A Design Theory for Blockchain-Based Reputation Systems: Trust and Coordination in B2B Markets

Der Fakultät für Wirtschaftswissenschaften der
Universität Paderborn
Zur Erlangung des akademischen Grades
Doktor der Wirtschaftswissenschaften
– Doctor rerum politicarum –

vorgelegte Dissertation
von
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geboren am 07. Februar 1992
in
Bad Mergentheim, Deutschland

2025

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Foreword

Trust is a risky advance, writes Niklas Luhmann—one of Germany's most influential sociologists and systems theorists, who also left a strong imprint on our region of Ostwestfalen. Trust reduces uncertainty so that coordinated action becomes possible.

In this spirit, Simon Hemmrich's doctoral thesis brings systems theory into dialogue with the design of information systems to explore how trust and reputation can be established in business-to-business markets. Drawing on core concepts from Luhmann's systems theory, Simon proposes a design theory for reputation systems that establish trust between actors in business-to-business markets, enabling efficient interaction.

Conceptually and technically, Simon's doctoral thesis breaks new ground by developing monetary ratings, counter-ratings, and selective sharing or trading of rating information as mechanisms that align incentives while preserving privacy through the built-in properties of blockchain technology. These ideas constitute an innovative information systems class, with systems theory and economic theory mapped to concrete design principles and IT artifacts.

Contrary to what its system-theoretical framing might suggest, the contributions of this thesis are not purely theoretical. Simon demonstrates how blockchain-based reputation signals can lower information asymmetries and promote business relationships in the field of professional consulting. Beyond consulting, these ideas may also benefit other business-to-business markets in which partners are initially unknown and information asymmetry about goods and services could lead to market failure if left unresolved.

For our research group, which has long been committed to the development of innovative digital services, this dissertation is a strong fit. It contributes new findings on service ecosystems and value co-creation with a system-theoretically grounded, blockchain-based reputation layer poised to enable more efficient matching, better incentives, and more productive value co-creation across organizational boundaries.

On a personal level, the relationship between an academic supervisor and a doctoral student also rests on trust—and it is, indeed, a risky advance in Luhmann's sense to recruit a new doctoral student, just as it is for a candidate to embark on a PhD. Simon has certainly demonstrated that my trust in him was well placed. What I value most about him is his talent for reading deeply into complex theoretical terrains and generating new, exciting ideas for advancing IS research from that foundation. He combines conceptual rigor with inventive system design. This blend of theory and artifact, of Luhmannian insight and blockchain technology's potential, yields a distinctively innovative reputation system that advances IS research while opening pathways for real-world coordination in digital markets.

I wish Simon every success on his future path—whether in a continuing academic career or as a trustworthy entrepreneur building his own start-up.

Paderborn, October 2025 Prof. Dr. Daniel Beverungen

The logical structure of reality is identical to the logical structure of consciousness.

Christopher Lagnan

If you want to find the secrets of the universe, think in terms of energy, frequency and vibration.

Attributed to Nikola Tesla

Your task is not to seek for love, but merely to seek and find all the barriers within yourself that you have built against it.

Jalāl ad-Dīn Muhammad Rūmī

New opinions are always suspected, and usually opposed, without any other reason but because they are not already common.

John Locke

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

Mark Weiser

Acknowledgements: I would like to thank Prof. Daniel Beverungen for granting me the freedom to pursue a topic outside the scope of ongoing projects and chair-related research. His openness provided the space for independent thinking that shaped this dissertation. I also thank Prof. Dennis Kundisch for his valuable critiques, which encouraged me to be more careful and precise in my work, and for his willingness to serve as second reviewer.

I'm grateful to all colleagues and co-authors I had the chance to work with—especially Ulvi Ibrahimli, whose curiosity and joy in research were contagious and made the process more rewarding. Special thanks to Brigit Petermeier for her support behind the scenes.

To my parents, Anne and Rolf Hemmrich. Thank you for always standing firmly behind me and for being an unwavering source of strength, support, and trust throughout this journey and beyond. Simply knowing that my family and friends are always there has been a steady source of reassurance. To Katharina, thank you for your patience, understanding, and for giving me the space I needed, even when that wasn't always easy for you.

Finally, my heartfelt thanks go to everyone who contributed to this journey. I feel fortunate to have worked on a topic I deeply believe in. Exploring system theory deeper has opened up new ways of seeing and thinking about the world.

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Abbreviations

ABMS	Agent-Based Modeling and Simulation
B2B	Business-to-Business
B2C	Business-to-Consumer
BCT	Blockchain Technology
C2C	Consumer-to-Consumer
eWOM	Electronic-Word-of-Mouth
DAOs	Decentralized Autonomous Organizations
DCO	Decentralized Collaborative Organization
DSR	Design Science Research
DSRM	Design Science Research Methodology
DP(s)	Design Principle(s)
ERP	Enterprise Resource Planning
GDPR	General Data Protection Regulation (Datenschutz-Grundverordnung)
GPS	Global Positioning System
IS	Information System or Information Systems (referred to the discipline)
LST	Luhmann's Systems Theory
MR	Meta-Requirements
SME	Small and Medium-Sized Enterprises
SST	Soft Systems Thinking
T	Trajectories
TCRs	Token-Curated Registries
TP	Testable Propositions
P1–P9	Paper 1 to Paper 9
PBE	Perfect Bayesian Equilibrium
RFID	Radio-Frequency Identification
RQ	Research Question
WOM	Word-of-Mouth
ZKPs	Zero-Knowledge Proofs
ZKPoK	Zero-Knowledge Proofs of Knowledge

Part A – Synopsis

1 Introduction

1.1 Background and Motivation

Many markets suffer from information asymmetries, where buyers cannot accurately assess the quality of goods or services before purchase. This information asymmetry issue relates to the well-known economic problem articulated by Akerlof’s (1970) Nobel Prize-winning *lemon market* problem, which describes how quality uncertainty fosters adverse selection. Consequently, sellers who provide low-quality products are not recognized and remain in the market. Since buyers lack reliable information about quality distribution, they assume poor quality and hesitate to pay price premiums. In conjunction with increased production costs, high-quality sellers are driven out of the market in favor of lower-quality ones, resulting in a downward spiral in quality.

The lemon market problem is an unresolved research challenge, as no effective and cost-efficient mechanism has been found to eliminate adverse selection in marketplaces (G. E. Bolton et al., 2024; G. E. Bolton et al., 2019; Greiner et al., 2021; Thierer et al., 2016). Lemon markets have been empirically proven to persist in B2C (Ghose, 2009; Scott et al., 2015) and B2B markets (Alhauli et al., 2022; Jan Devos et al., 2012). Therefore, assuming they are prevalent in many other B2B markets is reasonable, e.g., (Klör et al., 2015). The continued development of reputation systems is repeatedly mentioned as a promising solution to overcome lemon markets effectively (Spychiger et al., 2022; Thierer et al., 2016; Zavolokina et al., 2021; Zavolokina et al., 2018).

Reputation systems are described as an information system that “collects, distributes, and aggregates feedback about participants’ past behavior” (Resnick et al., 2000, p. 46). These systems enable buyers to rate product quality and sellers to send quality signals. Reputation systems employ *reputation mechanisms* that prompt participants to act trustworthily based on incentives and sanctions (Jøsang et al., 2007). These systems facilitate the building of reputation, e.g., for users, organizations, digital agents, or computer nodes (Battah et al., 2021). Reputation systems are widely adopted in B2C and C2C e-commerce to inform buyers about the quality of products or services. However, they are subject to significant limitations and adaptation barriers. For instance, although built to foster trust, studies assert that reputation systems have become a “major source of concern undermining trust” (Subramanian, 2018, p. 81). Nonetheless, in the future digital economy, reputation systems are expected to be the centerpiece of *every* digital market platform (Greiner et al., 2021; Kolleck & Teubner, 2024).

Research on reputation systems in the B2B context is still “very limited” (Dikow et al., 2015, p. 33), despite their growing importance to support B2B partner decisions for both sellers and buyers (Fauska et al., 2013; Kian et al., 2010; Parasuraman & Zinkhan, 2002; Sheikh et al., 2017). Calls to address this long-standing and significant gap in the development of reputation systems can be traced back 20 years, e.g. (Herhausen et al., 2020; Steward et al., 2018).[1] Almost no attention has been given to the design of reputation systems in academic research in IS. This pronounced neglect of research in the B2B context (Chatzipanagiotou et al., 2023; Chaurasiya, 2024; Gutt et al., 2019; Steward et al., 2023; Tóth et al., 2022) is all the more striking given that the B2B e-commerce market volume is about 20 times larger than for B2C markets (Statistisches Bundesamt, 2024a, 2024b).[2] The research void occurs despite substantially higher decision risks (Truong, 2019). This highlights the need for an information system that facilitates the exchange of ratings between businesses. Meeting this need requires overcoming limitations of existing systems and addressing B2B-specific challenges.

Blockchain technology is discussed as a solution to mitigate information asymmetry and enhance trust in lemon markets (Fremont & Jonathan, 2018; Zavolokina et al., 2021). This technology holds potential for a revolutionary impact on social and economic coordination and is expected to solve the limitations of traditional reputation systems (M. Becker & Bodó, 2021; Y. Cai & Zhu, 2016; Gonçalves et al., 2022; Seidel, 2018; Voshmgir, 2020). A blockchain represents a digital distributed ledger that provides transparent, tamper-proof, and decentralized data records, which excludes ex-post manipulation (Nakamoto, 2008). It enables all participants to independently verify transaction authenticity without relying on central authorities (Beck et al., 2017; Hawlitschek et al., 2018; Ostern, 2018). Blockchain characteristics are useful in environments with moral hazard (Arrow, 1986), e.g., when ratings are prone to ex-post manipulation (Y. Cai & Zhu, 2016; Rejeb et al., 2021). Yet, the utility of reputation systems is constrained by the oracle problem—a coordination challenge to reliably integrating offline information on a blockchain (Albizri & Appelbaum, 2021; Caldarelli, 2020).

Despite its potential, the design of trust-inducing blockchain-based systems remains almost entirely unexplored (Gregory et al., 2024; Große et al., 2024). Literature reviews clearly underscore this profound research void (Batwa & Norrman, 2021; Calvaresi et al., 2018; Gonçalves et al., 2022; Kölbel et al., 2022; Mohammed et al., 2024; Müßigmann et al., 2020; Soleimani, 2022; Y. Wang et al., 2019; Zheng & Lu, 2022). Finding the right incentives is considered the "biggest challenge of such systems" (J. Pereira et al., 2019, p. 101). To harness the potential of blockchain-based reputation systems, research needs to (re-)design the *whole system* and associated incentive structure (Beck et al., 2018;

[1] More evidence for this gap can be found in Aarikka-Stenroos and Makkonen (2014); Godes et al. (2005); Gutt et al. (2019); Parasuraman and Zinkhan (2002).
[2] In Germany, B2B e-commerce volume vastly surpasses B2C: €1.94 trillion compared to €88.3 billion.

Davidson et al., 2016; Fremont & Jonathan, 2018; J. Pereira et al., 2019; Spychiger et al., 2022; Tumasjan & Beutel, 2019; Y. Wang et al., 2019).

This dissertation pursues the design of a blockchain-based reputation system as an information system that mitigates adverse selection and supports trust formation in B2B markets. For this endeavor, social theories should be consulted (Hevner et al., 2004). However, theory candidates frame trust in overly rational terms, e.g., cost-benefit logic (Coleman, 1990; Colquitt et al., 2011), or do not explain how systems operate (Giddens, 1984, 1990). Accordingly, both theories do not consider the trust construct sufficiently, even though it is pivotal in reputation systems, which are originally rooted in trusted social trading systems (Rifkin et al., 2022; Tadelis, 2016b). Luhmann's systems theory on social systems (LST) is particularly suitable because it provides a well-founded explanation of trust and systems for (re-)conceptualizing reputation systems as complex social systems (Jalava, 2003). LST allows trust-building to be understood as a selective, observable communication mechanism. Building trust-enabling systems warrants a Design Science Research (DSR) approach (Hevner et al., 2004; Peffers et al., 2007) (Sec. 3.2). Thus, the design goal reads as follows:

Design a blockchain-based reputation system that addresses information asymmetries in B2B markets by enacting the trust mechanism of social systems.

The designed artifact is a reputation mechanism, classified as a *construct* in DSR (March & Smith, 1995). This mechanism is described in a design theory forming the basis for a novel class of information systems—blockchain-based business reputation systems (Hevner et al., 2004; Nunamaker et al., 1990). The theory describes how digital trust can be established, coordinated, and reinforced. Situated in a long-standing and unresolved problem space, the work contributes to IS by advancing theory, explicating the mechanism design, and providing an instantiation for trust-enabling infrastructures. Reputation systems are reconceptualized as selective, observed communication structures. This work theorizes the mechanism that combines monetary trust signals, counter-rating logic, and rating markets to improve trust coordination among strangers.

Across nine contributions, the dissertation delivers: 1) a collection of systems-theoretical concepts for IS, 2) a reconceptualization of reputation systems as social systems, 3) a reframing of trust formation as a forward-shifted risky advance, 4) an observer-dependent threshold to steer behavior, 5) the introduction of reputation information as a selectively private, tradable asset, 6) a digitally supported trust mechanism, 7) a nascent design theory for reputation (eco-)system, 8) a meta-theoretical integration of LST with explanatory economic theories, 9) a potential solution for coordination problems, 10) and an instantiation of a blockchain-based prototype for B2B use cases.

1.2 Research Problem and Objectives

Prior to the actual design of the reputation system, foundational work is required to identify and organize systems concepts and understand their function. This understanding helps bridge the gap between abstract system-theoretical concepts and their operationalization for design—a challenge that is generally insufficiently addressed in IS (Turpin & Alexander, 2014). Systems theory provides an extensive basis for systems concepts (Adams et al., 2014), though concepts are still fragmented (Sillitto et al., 2018). Although the IS discipline carries the term system in its name and is deeply rooted in systems theory (Markus & Saunders, 2007; Nolan & Wetherbe, 1980; L. D. Xu, 2000), the accessibility and practical application of systems theory concepts remain severely underdeveloped (Alter, 2004; Demetis & Lee, 2016, 2017). Despite being frequently mentioned in top-tier IS journals (Benbya et al., 2020; Markus & Saunders, 2007; Porra et al., 2005), the concepts remain largely absent as a source for guidance on how to design complex information systems (Demetis & Lee, 2016; Turpin & Alexander, 2014). The lack of a framework leaves researchers without clear pathways to apply this knowledge.

Accordingly, the first research objective is to explore systems-theoretical concepts to inform the design of complex information systems. Selected concepts will be the foundation for conceptualizing how the trust mechanism can be enacted to unfold within reputation systems. Consequently, the following research questions are derived:

Research questions for understanding systems concepts:

RQ 1.1: *What are the fundamental principles of systems functioning from a systems theory perspective?*

RQ 1.2: *Which systems theory concepts are suitable to guide the design of complex information systems?*

These system concepts need to be integrated into the theoretical understanding of trust and reputation. Understanding them is essential for designing effective reputation mechanisms since reputation is built on the logic of trust (Jøsang, 2007). The trust construct has been extensively researched, and trust characteristics are well understood from an academic point of view (R. Mayer et al., 1995; Schoorman et al., 2007). However, a significant gap remains in translating these theoretical insights into design principles (DP) for trust-enabling systems (Große et al., 2024). Design principles are needed to systematically transfer abstract knowledge into descriptive features within digital systems. So far, trust mechanisms are not integrated into reputation systems (e.g., no risk exposure, social safeguards, or selective observation) (G. E. Bolton et al., 2004; Jøsang, 2016; Milgrom, 1982; Nissenbaum, 2004). Without this social contexture, reputation systems overlook the underlying social trust relations, detaching social trust from its original conceptualization. This misalignment between '*natural social reputation systems'* and '*reputation systems as information systems'* undermines the ability of this information system class to accurately represent real-world trust dynamics (Brønn & Brønn, 2015; Nissenbaum, 2004). Thus, reintegrating the inherent characteristics of trust and social system principles appears indispensable to designing a novel reputation mechanism. This requires rethinking how reputation systems are conceptualized, since trusting is a relational, dynamic process, which captures the intricacies of human trust interactions (Dasgupta, 1988; Gambetta, 1988; Kroeger, 2011).

Accordingly, the second research objective is to analyze trust characteristics to integrate the social trust mechanism into reputation systems. For this purpose, this study consults LST and analyzes the trust dimensions of institutional trust/distrust (McKnight et al., 1998; Utz et al., 2023). Consequently, the following research questions are derived:

Research questions regarding trust:

RQ 2.1: *How can the inherent characteristics of trust be integrated into a digital reputation mechanism?*

RQ 2.2: *How can institutional trust dimensions be operationalized?*

The reputation mechanism can use blockchain technology to safeguard social interactions (Gregory et al., 2024). Therefore, blockchain's capabilities for building trust need to be examined. The building blocks a blockchain provides offer potential to tackle issues like data manipulation, information asymmetries, and insufficient trust-building (Awang Abu Bakar, Normi Sham et al., 2021; Ballandies et al., 2022; Han et al., 2022; Müller et al., 2020; Zavolokina et al., 2021). Nevertheless, how exactly blockchain technology should be operationalized is unknown. Utilizing this technology to resolve trust issues between companies is a research challenge (Filippi et al., 2020; Gonçalves et al., 2022; Gregory et al., 2024; Große et al., 2024; Holtz & Fradkin, 2020). This is primarily because the data input itself can be manipulated (Douceur, 2002) (Sec. 2.4.2). Consequently, providing proper incentives to ensure trustworthy data is indispensable to counteract the lemon market problem with blockchain technology (Gersbach et al., 2022; Große et al., 2024; Spychiger et al., 2022; Zavolokina et al., 2018).

Utilizing blockchain-based reputation systems requires an in-depth understanding of how blockchain features can meet the needs of B2B environments (Narang et al., 2019). Blockchain transparency and immutability ensure accountability and reduce information asymmetry, but simultaneously raise privacy concerns, which are seen as critical within B2B contexts (Govindan et al., 2024; Leung et al., 2023). Resolving the tension between transparency and data confidentiality is imperative since reputation data requires confidentiality (Aras et al., 2022; K. Zhu, 2002). This does not pose a conflict since social systems are open communication systems that maintain *operational closure* (Luhmann, 1995, p. 37). *However,* this issue imposes a non-trivial design challenge in using observable and non-observable monetary ratings, as envisioned in the reputation mechanism. Since content on a blockchain is by default transparent, it is unclear how monetary ratings can be implemented on a blockchain while maintaining rating data confidentiality in a blockchain network. Seemingly private transactions have been shown to be de-anonymized with forensics in blockchains (Biryukov & Tikhomirov, 2019; Filippi, 2016). Hence, resolving this issue requires an advanced cryptographic solution.

Accordingly, the third research objective is to leverage blockchain features to support trust-building while maintaining privacy in B2B reputation systems. This objective involves developing a reputation mechanism that balances transparency and confidentiality. In particular, the system should incentivize truthful reporting and thus provide reliable quality signals, leading to the following research questions:

Research questions regarding blockchain technology:

RQ 3.1: *How can a reputation mechanism be designed to encourage honest ratings?*

RQ 3.2: *How can monetary rating data be kept confidential on a blockchain?*

Based on a solid technical design, the reputation mechanism needs to be socially effective (Große et al., 2024; Sänger & Pernul, 2018). Hence, this phase examines whether the reputation mechanism fulfills its intended purpose by incentivizing truthful reporting and whether the designed mechanisms—such as tradable monetary ratings and counter-ratings—build and sustain trust. Evaluating whether the mechanisms function as intended is a pivotal step in the design process (Baskerville et al., 2015; Sonnenberg & vom Brocke, 2012; J. Venable et al., 2016). The evaluation incorporates buyer and seller perspectives to determine whether the designed system fosters truthful quality reporting.

Accordingly, the fourth research objective is to evaluate the reputation system's effectiveness and stakeholder perceptions of utility. The evaluation involves game-theoretic modeling and a simulation to assess whether the system effectively elicits truthful behavior and fosters trust. Also, the evaluation is supported by qualitative interviews. Consequently, the following research questions are derived:

Research questions for evaluation:

RQ 4.1: *How can the reputation system ensure trustworthy ratings?*

RQ 4.2: *How do buyers and sellers perceive the designed reputation mechanism?*

1.3 Structure of the Dissertation and Core Contributions

This cumulative dissertation comprises two main parts (Fig. 1). Part A provides the conceptual foundation and overarching framework for the research contributions. Because the research questions require conceptual exploration and empirical validation, a mixed-methods approach is adopted (Venkatesh et al., 2013) (Sec. 3.2). Part A consists of eight sections: Section 2 reviews theoretical foundations, including systems theory, reputation systems, B2B market characteristics, and blockchain foundations. Section 3 outlines the research foundations, justifies the research design, and presents the applied methods. Section 4 synthesizes findings and constructs the design theory. Section 5 presents core contributions across mechanism, conceptual, theoretical, and practical levels. Section 6 positions the research contribution with DSR. Section 7 provides a critical reflection on the study and outlines implications and future research. Section 8 concludes the work.

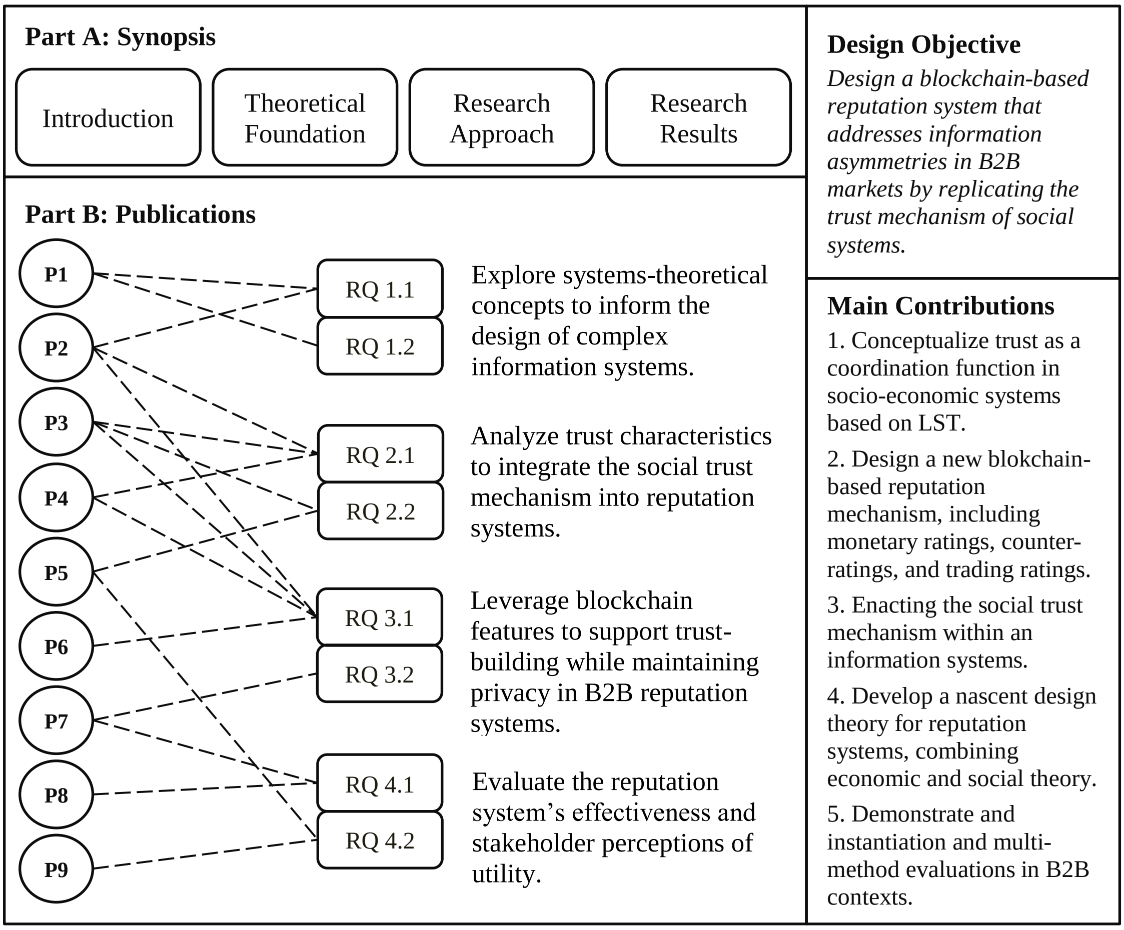

Figure 1: Structure of the Dissertation

Each paper (P1-P9) makes a stand-alone contribution, addressing one or more research questions (Fig. 1).

Part B comprises nine peer-reviewed papers that are either published or under review in academic outlets. The targeted outlets are ranked A-C in the VHB-JOURQUAL 4 for *Wirtschaftsinformatik*. The outlets include *Electronic Markets (EM), Communications of the Association for Information Systems (CAIS), Information Systems and e-Business Management (ISeB), Game Theory and Applications,* the *European Conference on Information Systems (ECIS),* the *Hawaii International Conference on System Sciences (HICSS),* and the *International Conference on Wirtschaftsinformatik (WI)*. The following outline describes each paper's role in shaping the cumulative research contributions, before providing an overview of these papers (Tab. 1).

P1: *Bridging Systems Theory and Information Systems – A Framework for Designing Complex Information Systems.* P1 develops a systems-theoretical framework for complex information systems, narrowing the longstanding gap between abstract systems theory and its applicability in IS. The paper consolidates 52 systems concepts into a coherent structure, indicates areas to analyze IS phenomena, and identifies 129 system design specifications, offering guidance for IS researchers to design, analyze, and theorize systems principles. P1 enables the targeted use of multiple system concepts, e.g., observation, communication, and selection for designing the reputation mechanism. P1 illustrates the applicability of the proposed concepts in the context of blockchain-based reputation systems. The concepts are used in P2 and theoretically inform P3 and P4.

P2: *Service Through Communication – Conceptualizing Service Systems with Luhmann's Systems Theory.* P2 explores the self-producing, abstract concept of service systems as self-sustaining communication structures. Drawing on selected concepts from P1, P2 provides an in-depth understanding of how social systems operate. This theoretical lens helps distinguish system types and reveals how foundational system mechanisms affect systems' behaviors. P2 contextualizes social systems as autopoietic communication structures, mainly using concepts of communication, observation, and selection from P1. This conceptual grounding informs the design and paves the way for P3 and P4 to operationalize these concepts into the reputation mechanism.

P3: *Reconceptualizing Blockchain-Based Reputation Systems – Applying Systems Theory with Basic Concepts.* P3 builds on the theoretical foundation laid in P1 and P2 to reconceptualize reputation systems as social systems, using an illustrative scenario of a marketplace. By using the method of systems thinking, P3 shows how systems-theoretical concepts can combine the trust mechanism while using blockchain, using properties like transparency, immutability, and decentralization. The paper outlines the reputation system's basic design. This conceptualization provides the basis for P4, where the mechanism is refined into concrete design principles.

P4: *Business Reputation Systems Based on Blockchain Technology – A Risky Advance*. P4 translates the conceptual foundation from P3 into concrete design principles for blockchain-based trust formation. The paper introduces two mechanisms: monetary ratings—where payments function as economically costly trust signals—and counter-ratings, which allow sellers to rate buyers in return and discourage exploitative behavior. These mechanisms operationalize trust as a risky advance, embedding risk and safeguarding into the trust-building process. P4 provides the foundation for technical implementations (P5,P6) and sets the stage for empirical evaluation (P5-P9).

P5: *Blockchain-Based Reputation Systems for Business-to-Business Services – Designing a Reputation Mechanism to Reduce Information Asymmetry in Professional Consulting.* P5 designs and technically instantiates a blockchain-based reputation mechanism. An instantiation of the artifact is implemented on an Ethereum TestNet, demonstrating its technical feasibility and showcasing how blockchain features can support trust building between B2B consultancies. The design integrates six institutional trust and distrust dimensions, operationalized through 23 factors to promote trustworthy behavior. Furthermore, P5 contrasts the design with B2C review systems, highlighting their limitations for B2B use and the improvements achieved by this new reputation mechanism. The empirical evaluation from the seller's perspective confirms practical relevance. Hand in hand with P6, P5 serves as the basis for technical refinements and further evaluation activities in P7-P9.

P6: *Designing Business Reputation Ecosystems – A Method for Issuing and Trading Monetary Ratings on a Blockchain.* P6 builds on the reputation mechanisms (P4,P5) and addresses the challenge of implementing monetary ratings on a blockchain while preserving data confidentiality. The paper presents a cryptographic method that allows only transacting parties to verify the authenticity of their rating exchange. By enabling secure issuance and selective trading of monetary ratings, P6 provides a technical foundation for trading monetary ratings in decentralized reputation ecosystems. The provided mathematical proof supports the assumptions taken in P5, P7, and P9 that monetary ratings can be used as transferable economic assets.

P7: *Does the Blockchain Technology Help to Reduce Information Asymmetries?* P7 explores how blockchain technology can reduce information asymmetries by linking quality signals immutably stored on a blockchain. The immutable storing of ratings enhances the credibility of signals and discourages strategic misinformation. The game-theoretical analysis of P7 shows that this setup can improve the coordination problem between rational agents and supports more efficient incentive-compatible equilibria, where agents are motivated to report truthfully. Thereby, P7 provides a strong empirical foundation for the signaling logic described in P4–P6 and reinforces the assumption that monetary trust signals can be reliably linked to truthful reporting.

P8: *Overcoming Lemon Markets with Business Reputation Ecosystem – A Multi-Agent Simulation on Monetary Ratings*. P8 employs a multi-agent simulation to evaluate how monetary ratings and counter-ratings mitigate information asymmetry in reputation ecosystems. By tying ratings to monetary transactions, the simulation links observed product quality to a company's reputation and its economic results, while counter-ratings deter opportunistic buyer behavior and enhance system fairness. The simulation demonstrates that these mechanisms promote truthful reporting and improve profitability for high-quality sellers. P8 empirically validates the design logic developed in P4–P6 and complements P7 by confirming that counter-ratings might achieve their intended function and that rating trade can be sustained.

P9: *The Value of Reputation Systems in Business Contexts – A Qualitative Study Taking the View of Buyers.* P9 explores how B2B buyers assess the practical value of a blockchain-based reputation system, focusing on monetary ratings, rating trade, and counter-ratings. The qualitative findings show that the system increases market transparency, reduces purchase uncertainty, and facilitates access to trust-related information. P9 complements the conceptual and technical contributions of P4–P6 and substantiates the simulation results from P8 through empirical user insights.

Table 1: Overview of Research Articles (P1-P9)

No.	Authors	Title	Outlet	VHB JQ4	Share
P1	Hemmrich, S., Ibrahimli, U., Winkelmann, A.	Bridging Systems Theory and Information Systems: A Framework for Designing Complex Information Systems	CAIS (resubmitted 2nd round)	B	0,55
P2	Beverungen, D., Pöppelbuß, J., Hemmrich, S., Iqbal, T.	Service Through Communication: Conceptualizing Service Systems with Luhmann's Systems Theory	Electronic Markets (resubmitted 2nd round)	B	0,30
P3	Hemmrich, S., Ibrahimli, U.	Reconceptualizing Blockchain-Based Reputation Systems: Applying Systems Theory with Basic Concepts	ECIS	A[3]	0,80
P4	Hemmrich, S.	Business Reputation Systems Based on Blockchain Technology: A Risky Advance	ECIS	A	1
P5	Hemmrich, S., Nissen, V., Beverungen, D., Pauls J.	Blockchain-based Reputation Systems for Business-to-Business Services: Designing a Reputation Mechanism to	ISeB	C	0,70

[3] This publication was accepted with minor revisions for presentation at ECIS 2025 but was not included in the conference proceedings, as the author did not attend the conference.

		Reduce Information Asymmetry in Professional Consulting			
P6	Hemmrich, S., Bobolz, J., Beverungen, D., Blömer, J.	Designing Business Reputation Ecosystems: A Method for Issuing and Trading Monetary Ratings on a Blockchain	ECIS	A	0,70
P7	Duman, P., Haake, C. J., Hemmrich, S., Koch, A., Kühn, S., Beverungen, D.	Does the Blockchain Technology Help to Reduce Information Asymmetries?	Decisions in Economics and Finance[4]	Not ranked	0,10
P8	Ibrahimli, U., Hemmrich, S., Zauke, S., Winkelmann, A.	Overcoming Lemon Markets with Business Reputation Ecosystems: A Multi-Agent Simulation on Monetary Ratings	WI	B	0,35
P9	Hemmrich, S., Schäfer, J., Hansmeier, P., Beverungen, D.	The Value of Reputation Systems in Business Contexts: A Qualitative Study Taking the View of Buyers	HICSS	A	0,60
∑					5,10

[4] This joint work was presented at several peer-reviewed academic venues, including the European Meeting on Game Theory (SING 20), one of the field's most prestigious and internationally visible conferences. It is intended for publication in the corresponding special issue of *Game Theory and Applications*, a specialized journal for high-level theoretical work. Although not listed in VHB-JOURQUAL, the journal is widely recognized in the game theory community for its academic quality and relevance.

2 Theoretical Foundations

2.1 Systems Theory

2.1.1 Systems Theory in Information Systems Research

Systems theory is a transdisciplinary theory for systems thinking and analyzing complex systems (Boulding, 1956; von Bertalanffy, 1968). Initially applied in biology and engineering, its concepts have been adapted across many disciplines, including management (Checkland, 1999; Mingers & White, 2010b), and sociology (Luhmann, 1995), among others. Due to its theoretical depth, systems theory is not a single theory but a collection of related system theories tailored to specific disciplines (Sillitto et al., 2018).

In IS research, the application of systems theory is limited and fragmented (Demetis & Lee, 2017; Onik et al., 2017). Alter's (2004) critique, *Desperately Seeking Systems Thinking in the Information Systems Discipline*, underscores the persistent lack of systems thinking within IS, echoed by Turpin and Alexander (2014) ten years later. These observations illustrate the discipline's ongoing "overall neglect" (Demetis & Lee, 2017, p. 163) of applying systems theory, despite IS having strong roots in systems theory (Markus et al., 2002; Merali, 2006; Mingers & White, 2010b; Nolan & Wetherbe, 1980; L. D. Xu, 1995). Only a few studies have suggested applying systems concepts for designing information systems, e.g., (Waguespack & Schiano, 2013; Warren & Adman, 1999). Still, systems concepts are considered "deeply imbedded in IS design" (Demetis & Lee, 2017, p. 164). Yet, the vast conceptual capacity of systems theory for designing information systems remains largely underutilized (Benbya & McKelvey, 2006a; Benbya et al., 2020; Demetis & Lee, 2017; Jaradat, 2015; Whitney et al., 2015).

Designing complex information systems demands a structured approach, for which systems theory offers valuable concepts (Adams, 2012; Markus et al., 2002; Nan, 2011). However, its application in IS has resulted in diverse and fragmented approaches (Alaa & Fitzgerald, 2013; Alter, 2013; Baskerville et al., 2022; Benbya & McKelvey, 2006a; Curşeu, 2006; Nan, 2011; L. D. Xu, 1995, 2000), which highlights the challenge of using systems theory for information systems design (Burton-Jones et al., 2021; Markus & Rowe, 2018). This fragmentation reflects a broader issue in IS research: the absence of a stable theoretical framework for theorizing in IS (Baskerville et al., 2015; Benbasat & Zmud, 2003; Burton-Jones et al., 2021; Gregor, 2006; Markus & Saunders, 2007). Systems theories encompass foundational concepts of systems, including, for instance, system-environment differentiation, observation, selection, communication, self-organization, or feedback loops (Adams, 2012; Luhmann, 1995) and many more (P1).

Information systems are *socio-technical systems*, a unity of distinct social and technical system parts, which collect, process, and provide information to support users' needs (Langefors, 1973; Lyytinen, 1987; Ropohl, 1979).[5] Since the *reputation system* is a broad term (Sec. 2.2.1), this study adopts a broad sense of design (Fig. 2). Note that an abstract system *cannot be directly* designed, but can only evolve indirectly based on changes in the system's environment (Luhmann, 1995, pp. 176–210) referring to this broad sense.

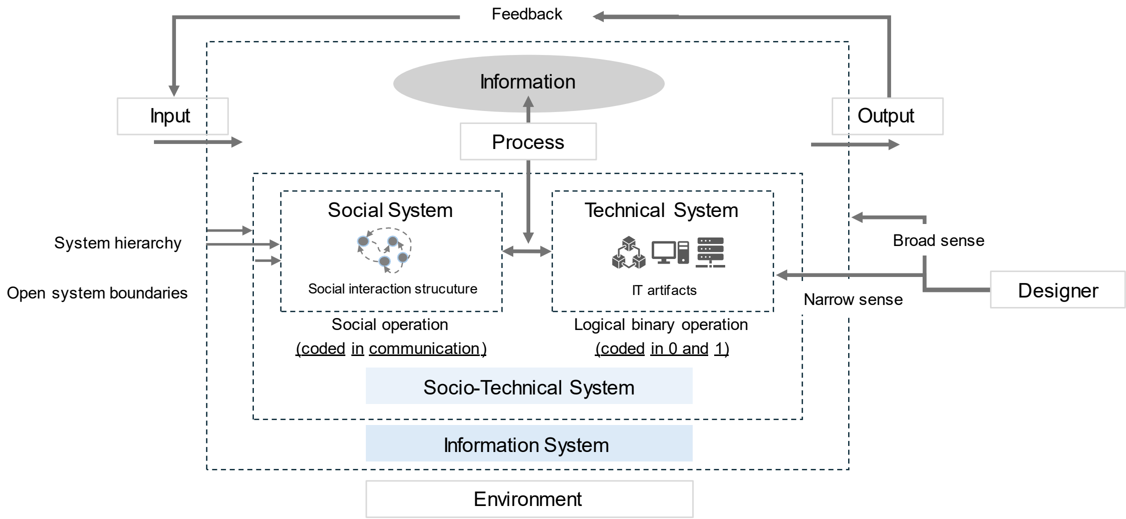

Figure 2: System Lens on the Information Systems Conceptualization (based on: Chatterjee et al. (2020) and A. S. Lee et al. (2015) (P1[6])

2.1.2 Luhmann's Systems Theory and Trust Conceptualization

LST offers a suitable foundation for addressing the design challenges of reputation systems, since they can be understood as social systems (Tadelis, 2016b). Connected to Luhmann's foundational work of trust, LST is particularly suitable for studying trust formation (Jalava, 2003; Luhmann, 2017). Also, LST holds underutilized but significant potential for IS research (Demetis & Lee, 2017). Although Luhmann does not offer a definition of social systems, he implicitly defines them through their difference from the environment and their mode of autopoietic reproduction.[7] Social systems use communication as their sole mode of operation and form expectation structures (Luhmann, 1995, pp. 12–59). Being operationally closed, they exhibit a kind of self-referencing path dependency in the continuation of communication (P2).

Through this lens, reputation systems are abstract communication systems in which expectation structures forming trust can evolve (Jalava, 2003; Luhmann, 1995, 47ff).

[5] When dealing with systems theory, one must respect the ontology of *different* system types as argued by Orlikowski and Baroudi (1991) and Orlikowski and Scott (2008), since the term system is often used for disparate systems with fundamentally different modes of operation, e.g., Münch et al. (2022).
[6] This Figure originates from a revised version of P1 in July 2025.
[7] Autopoiesis refers to a self-referential mode by which systems generate and reproduce their own elements.

Trust requires a commitment to vulnerability and involves the willingness to accept an uncertain outcome even though expecting benevolent behavior from others (Luhmann, 1995, 419ff). This uncertainty involves risk understood as a "risky advance" (Luhmann, 2017, p. 47), where the trustor initiates a communicative act without guaranteed success (Deutsch, 1958). Trust is a function that facilitates communication under conditions of observed risk (P2-P4). In a reduced set of system concepts[8], the design includes:

Observation: The system distinguishes relevant from irrelevant information by drawing system distinctions based on selections. Observation determines which communication, e.g., trust signals, becomes meaningful within the system boundary (Luhmann, 1993b).

Selection: Information is selected based on the system's internal expectation structures, thereby shaping which communications are processed (Luhmann, 1995, p. 127). Trust emerges when information aligns with the system's expectation structure, i.e., identifying a seller as credible (Jalava, 2003).

Communication: The system structure facilitates communication, shaped by observation and selection. Communication continuously reshapes a system's expectation structure by understanding the uttered information meaningfully (Luhmann, 1995, pp. 142–159).

Risky Advance: Trust inherently involves asymmetric risk exposure, requiring one party to act first and accept vulnerability (Luhmann, 2017, p. 38).

Safeguards: Formal mechanisms—such as identity verification, feedback moderation, or institutional control structures—act as *latent* control structures that stabilize expectation formation (Luhmann, 1995, p. 332). They provide the necessary preconditions for trust to evolve (Luhmann, 2017, pp. 39–44).

LST's concepts are tightly interwoven, forming a cohesive logic (Jalava, 2003; King & Thornhill, 2003). Put simply, observation feeds selection, selection shapes communication, and communication reconfigures expectations. This expectation forms structures that equal a system structure (Luhmann, 1995, 332, 345), making further communication expected, which reinforces trust or distrust. Reputation acts as a stabilizing force that fosters communication progress and underpins the formation of trust through re-relating communication (Luhmann, 2017). Trust is a process, in which utterances *can* become observable and *can* be selected within a system (P2).

[8] To maintain clarity, the dissertation focuses on a reduced set of system concepts. Additional system concepts that justify the system conception mentioned or explained within this dissertation contain *system boundaries, structural coupling, self-description, re-entry, elements and relations, system trust, feedback loops, adaptive tension, information redundancy, self-organized criticality, requisite variety, and inverse generativity* (P1-P3). The transfer and application of these concepts on reputation systems are discussed in P1 and P2.

2.2 Reputation Systems

2.2.1 Fundamentals of Reputation Systems

Reputation systems have their roots in social trading systems (Rifkin et al., 2022; Tadelis, 2016a, 2016b). This justifies reputation systems to be understood as social systems, as one part of a socio-technical system (Sec. 2.1.1). Understood as decision support systems, they enable participants to make informed decisions in contexts marked by information asymmetries and uncertainty (Jøsang et al., 2007; Shi et al., 2023). Reputation systems can reduce asymmetries and make interactions and others' experiences more transparent (G. E. Bolton et al., 2008; S. Liu et al., 2022; Thierer et al., 2016). In digital marketplaces where direct personal interactions are absent, reputation systems are fundamental for establishing trust (Dellarocas, 2005; Rice, 2012; Tadelis, 2016b). By providing rating data, reputation systems facilitate trust formation, reducing information asymmetries and enhancing market coordination (Loebbecke et al., 2007). For this purpose, reputation systems provide *reputation mechanisms* that sanction opportunistic behavior and incentivize trustworthy behavior (G. E. Bolton et al., 2004; Jøsang et al., 2007). These mechanism promotes benevolent actions and shape participants' expectations of positive future engagements, which improves trust and market efficiency (G. E. Bolton et al., 2019; G. E. Bolton et al., 2008; Dellarocas, 2005). In current systems, rating data serves as a proxy to identify unreliable entities (Dimoka et al., 2012; Tadelis, 2016a).

In B2C markets, platforms like Amazon and eBay demonstrate how reputation systems enhance market efficiency by providing transparent, crowdsourced ratings from buyers (Greiner et al., 2021; Mudambi & Schuff, 2010; Tadelis, 2016b). These systems aggregate and present user-generated feedback through textual reviews, numerical ratings, and aggregate ratings, and allow potential buyers to assess seller credibility and product reliability before engaging in a transaction (Cabral, 2012; Dellarocas, 2003). Accordingly, reputation systems provide quality signals and decision support to select capable sellers (G. E. Bolton et al., 2013; S. Chen et al., 2022; Steward et al., 2018). Positive ratings enhance cooperative behavior (S. Chen et al., 2022), increase the purchase likelihood of new buyers, and raise their willingness to pay price premiums (Ba & Pavlou, 2002; G. E. Bolton et al., 2004; Forman et al., 2008; Mai & Liao, 2021; Moreno & Terwiesch, 2014; D.-H. Park et al., 2007; Rice, 2012). Conversely, negative ratings can significantly reduce perceived trustworthiness and damage reputations (Dimoka et al., 2012), although findings on this effect are inconclusive (Steward et al., 2023).

Both trust and reputation are interdependent constructs that collectively underpin the effectiveness of reputation systems (Jøsang et al., 2007). Trust reduces uncertainty and facilitates cooperation (Luhmann, 2017; Zucker, 1986), allowing economic actors to engage in transactions despite risks (Deutsch, 1958; R. Mayer et al., 1995). Generally, trust arises and is strengthened through non-exploitative behavior that acknowledges and respects mutual vulnerability (Dasgupta, 1988; Gambetta, 1988). While trust processes always involve a *risky advance* as a *leap of faith* (Nikolova et al., 2015), reputation is a proxy to anticipate future actions and trust the trust of others (Gambetta, 1988; Resnick & Zeckhauser, 2002). Reputation reflects observed past behavior and serves as an informational foundation upon which (new) trust can develop (Luhmann, 2017). In this sense, reputation is a socio-economic signal for credibility that is hard to fake since it cannot be purchased because it emerges based on consistent, integrous, trustworthy behavior (B. K. Boyd et al., 2010; Connelly et al., 2011; Kirmani & Rao, 2000).

The term *reputation system* is applied inconsistently across disciplines, leading to conceptual ambiguity (Jøsang, 2016; Yao et al., 2012). Scholars often hold different views on what constitutes a reputation system and its specific operational domain and functions. Reputation-building variants related to reputation systems show different forms of understanding (Tab. 2). Review systems are considered a subtype of reputation systems, as they fall within their definitional scope (Resnick et al., 2000).[9]

Reputation systems are complex information systems that offer 14 design dimensions (Hendrikx et al., 2015). Since these systems are utilized across various environments (e.g., peer-to-peer, multi-agent, ad-hoc networks, online marketplaces, vehicle markets, and social networks), a fundamental distinction can be drawn between technical and socially embedded systems (Koutrouli & Tsalgatidou, 2015; Noorian & Ulieru, 2010).[10]

- Technically embedded reputation systems aggregate network data and compute trust between network nodes through technical metrics and algorithms independent of human observation (Jøsang & Goldbeck, 2009; Marsh, 1994).

- Social-embedded reputation systems involve social networks, relying on qualitative assessments and subjective feedback dependent on human observation (Jøsang et al., 2007; Mui et al., 2002).

[9] *Rating systems* mostly refer to vendor management systems, which store ratings without intending to disseminate this information. *Reputation and trust management systems* are sometimes considered reputation systems but do not involve social system structures. *Collaborative filtering systems* or *recommender systems* are distinct systems that can use data from reputation systems. The unstructured exchange of online opinions (eWOM) is typically understood as a phenomenon and is thus not a system.
[10] These differences are sometimes overlooked, despite fundamental differences in the system's operation. For a comparison of differing understandings, see Ghanbari et al. (2000) and Rezgui et al. (2003).

Table 2: Distinction of Related Concepts of Reputation Systems

	Typical Understanding	**Typical Focus**
Reputation Systems[11]	Collect, distribute, and aggregate feedback about an entity's past behavior (Resnick et al., 2000).	Providing mutual trust signals based on past behavior in online marketplaces.
Review Systems	Provide metrics to evaluate and aggregate online feedback, including numerical ratings and review texts (Dellarocas et al., 2004).	Aggregating and sharing user-generated text reviews on products in e-commerce.
Rating Systems	Rate a supplier's performance level according to the pre-defined criteria (Choy et al., 2003).	Internal company metrics are used to evaluate supplier performance.
Reputation Management Systems	Monitor, collect, evaluate, update, and disseminate reputation information about the behaviors of network nodes (Rezgui et al., 2003; Yamamoto et al., 2003).	Managing trust algorithms in distributed peer-to-peer computer networks to sustain privacy.
Trust Management Systems	Provide access structures in computational trusting peer-to-peer networks (Blaze et al., 1996).	Managing and evaluating access rights in multi-agent computer networks.
Collaborative Filtering Systems, Recommender Systems	Filter information to analyze users' behavior and preferences to derive data-based recommendations (Goldberg et al., 1992; Resnick & Varian, 1997).	Providing personalized recommendations based on user preferences in e-commerce.
Electronic-Word-of-Mouth (eWOM)	Any available online statement about an organization, product, or other subjects of interest (Hennig-Thurau et al., 2004).	Disseminating information (often reputation) in digital platforms and social networks.

Technical-embedded reputation systems computerize trust scores through algorithmic data aggregation and usually do not account for social relationships, focusing on technical privacy requirements, e.g., (Bazin et al., 2017; Jøsang & Goldbeck, 2009; Soska et al., 2016). Social-embedded reputation systems rely on human observation, where trust emerges from subjectivity, often technology-supported (Sänger & Pernul, 2018).

2.2.2 Current Knowledge of Designing Reputation Systems

Research has generated a rich body of knowledge on reputation systems. To systematically structure this knowledge for design, it is classified into (descriptive) *Ω-knowledge* and (prescriptive) *Λ-knowledge*. Originally introduced by Mokyr (2011) and adapted by Gregor and Hevner (2013), *Ω-knowledge* refers to the general theoretical understanding of what phenomena occur and how they can be explained. In contrast, *Λ-knowledge* provides guidance on how to apply a system. This distinction separates understanding-oriented from actionable design knowledge. In the following, relevant knowledge summarizes theory-based *Ω-knowledge* (Tab. 3), empirically based *Ω-knowledge* that is not directly linked to established theory (Tab. 4), and design-oriented *Λ-knowledge* (Tab. 5).

[11] The term *feedback system* is used synonymously, e.g., in Tadelis (2016b) and J. Yang et al. (2007), equal to *trust systems* in G. E. Bolton et al. (2004), Noorian and Ulieru (2010). But the terms can also be seen to be different. According to Yao et al. (2012, p. 2), *trust systems* measure the "willingness to depend", while reputation systems measure "expectation for good outcomes". In this study, they are understood as equal.

Table 3: Theory-based Ω-Knowledge for Reputation Systems

Theory	Ω-Knowledge
Signaling Theory	Observable and costly signals convey more credible information (Spence, 1973). Participants who bear the costs of sending *costly signals* are perceived as more trustworthy (Mudambi & Schuff, 2010). Sellers offering a costly signal in reputation systems, such as a monetary rebate, increase buyers' likelihood of making purchase decisions (Lingfang & Xiao, 2014).
Source Credibility Theory	The perceived credibility of a rating strongly depends on the trustworthiness of its source (S. Banerjee et al., 2017; C. M.-Y. Cheung et al., 2012; Pornpitakpan, 2004). When the identity and associated information of the rater are known, trust in the information provision is enhanced (Ekstrom et al., 2005).
Rational Choice Theory	Individuals decide by systematically weighing costs and benefits to maximize personal utility (G. S. Becker, 1976; Coleman, 1990). In reputation systems, actors behave strategically and rationally to optimize their economic outcomes (G. E. Bolton et al., 2013; Dimoka et al., 2012).
Transaction Cost Theory	Market participants incur transaction costs when engaging in economic exchanges (Coase, 1937; Williamson, 1985). Reputation systems reduce these costs by lowering uncertainty and enabling trust between unfamiliar parties (Pavlou & Gefen, 2004). When transaction costs decrease through reputation systems, the likelihood of successful interactions increases (Standifird & Weinstein, 2007).

Table 4: Empirically-based Ω-Knowledge for Reputation Systems

Topic	Ω-Knowledge
Quality of Information	Accurate and detailed reputation information is particularly valuable when uncertainty and cooperation costs are high (G. E. Bolton et al., 2005; Dimoka et al., 2012).
Rating Subject	While sellers' identities influence perceived product quality (Pavlou & Dimoka, 2006), product ratings are perceived as more informative (G. E. Bolton et al., 2024).
Rating Information	Multi-dimensional rating systems increase accuracy but may lead to information overload depending on the user interface and use context (Sänger & Pernul, 2018; C. Schneider et al., 2021; Seutter et al., 2023). Filtering options enhance decision quality (P. Y. Chen et al., 2018; Sänger & Pernul, 2018).
Review Depth	Comprehensive text reviews enhance perceived helpfulness, especially for search goods, whose quality can be assessed before purchase (Mudambi & Schuff, 2010).
Monetary Incentives	Incentives for rating submission increase the rating quantity (Burtch et al., 2018; Jurca & Faltings, 2003) but often reduce rating quality (Lafky & Wilson, 2020).
Uncontrolled Ratings	Many uncontrolled ratings with high text diversity diminish manipulation risk and increase the perceived rating veracity (Tóth et al., 2022). Active moderation of platform owners negatively impacts perceived trustworthiness (G. E. Bolton et al., 2024).
Fraud Costs	Reputation systems that impose higher costs for fraudulent behavior increase the trustworthiness of ratings (Dellarocas, 2000, 2005) and lead to more efficient reputation systems (Krügel & Paetzel, 2024).
Sybil Attack	In closed systems, manipulation via multiple fake identities is best prevented through rigorous identity verification (Douceur, 2002). In open systems, the best approach is to check past trust relationships, tracing back to different rating identities (Ekstrom et al., 2005; Malavolta et al., 2017; Mislove et al., 2012; Mohaisen et al., 2011).
Data Privacy	Transaction data and identities can be fully anonymized to protect privacy without compromising basic system functionality (Kalvenes & Basu, 2006).
Identity Disclosure	Raters who do not commit to a stable identity (or pseudonym) are perceived as less trustworthy (Friedman & Resnick, 2001). Preventing full anonymity reduces bad-mouthing and negative discrimination (Dellarocas, 2000).[12]

[12] These results stand in contrast to extensive technically-oriented research, which aims to mask identities (for economic actors), e.g., Bader et al. (2023), Bazin et al. (2017), and Hasan et al. (2022).

Rating Significance	The perceived importance of ratings varies with product complexity and decision context (Tóth et al., 2022). Recent reputation information is more informative but more prone to aggregation biases (Ivanova & Scholz, 2017)
Rating Helpfulness	Ratings marked as *helpful* are generally perceived as more trustworthy (Ghose & Ipeirotis, 2010).
Rating Weighting	When decision-makers can weigh reputation data based on personal rationale, trust in the decision increases (Ekstrom et al., 2005).
Purchase Decision	Reputation is a mediating trust signal for purchase decisions (G. E. Bolton & Ockenfels, 2012; Loebbecke et al., 2007). Positive ratings are more likely to lead to purchasing decisions than negative ones (Bajari & Hortaçsu, 2004; G. E. Bolton et al., 2019).
Re-Entry	Re-entering the system with a new identity can be effectively limited by high entry fees (Dellarocas, 2005; Friedman & Resnick, 2001).
Reciprocal Ratings	Customers tend to reciprocate fairly when they feel that they have received expected quality (C. M. K. Cheung & Lee, 2012; Gharib et al., 2019).
Effect of Reciprocity	Trust between transaction parties increases with positive reciprocity (G. E. Bolton et al., 2013), whereas negative reciprocity tends to escalate conflicts (G. E. Bolton et al., 2018).
Visible Indicators	The mere visibility of quality signals (such as badges) positively affects customer behavior, even when they do not read detailed review content (Hui et al., 2020).
Rating Disclosure	Partial rating disclosure does not necessarily disadvantage buyers in competitive markets and may benefit them when the supplier side is competitive (Shi et al., 2023).
Two-Sided Rating	Mutual, double-masked ratings enhance informational value but deter system participation due to the fear of retaliation by the rated entity (G. E. Bolton et al., 2018).

The following table summarizes the *Λ-knowledge* that provides prescriptive design knowledge for reputation systems (Tab. 5). Opposing findings require careful design consideration (Baskerville et al., 2015).[13]

Table 5: Design-Oriented Λ-Knowledge for Reputation Systems

Topic	Λ-Knowledge
Data Security	Use cryptographic methods and redundant storage of rating data to ensure data authenticity, integrity, and confidentiality (Yao et al., 2012).
Immutability	Ensure that users cannot modify published ratings or aggregated reputation scores (Vavilis et al., 2014).
Provided Information	Design features must maximize meaningful and helpful rating content (H. Hong et al., 2017).
Alignment of Incentives	Structure incentives to reward honest rating behavior and penalize manipulation (Dellarocas, 2005; Friedman & Resnick, 2001; Jøsang et al., 2007).
Entry Fee	Assign the lowest reputation to new entities and use refundable entry fees to deter strategic re-entry (Friedman & Resnick, 2001).
Rating Differentiation	Implement mechanisms to distinguish rating quality by source and detect unreliable ratings (Vavilis et al., 2014; Yao et al., 2012).
Time Offset	Update a reputation profile with a time offset to reduce moral hazard and improve cooperative behavior (Dellarocas, 2006).
Filter and Metadata	Filter ratings using metadata and known sources to exclude outliers and low-credibility ratings (Roy et al., 2024).
Incentives	Enforce incentives in the participants' interest (Große et al., 2024).
Unfair Ratings	Mitigate unfair ratings through objective performance metrics and aggregation of multiple uncoordinated sources (Jøsang et al., 2007).

[13] Differences in *Λ-knowledge* reflect the differing context. E.g., transparency is impactful for establishing trust and enabling informed decision-making, it conflicts with privacy protection (cf. Sec. 2.3.1; 2.3.3).

Fraud Reporting	Develop mechanisms that maximize the collective probability of accurate fraud reporting (Dellarocas, 2005; Dellarocas & Wood, 2008).
Fraud Detection	Reputation systems should have means to enable participants to detect inconsistencies in ratings (Dellarocas & Wood, 2008; Yao et al., 2012).
Aggregation and Volume	Structure the aggregation logic to generate meaningful ratings (Vavilis et al., 2014) and distinguish low-volume and high-volume transactions (Yao et al., 2012).
Rated Transactions	Display the number of non-rated transactions to assess a rating's significance (Dellarocas & Wood, 2008; Nosko & Tadelis, 2015).
Human Judgment	Use human judgment to enhance the overall interpretation of rating results (Große et al., 2024; Sänger & Pernul, 2018).

2.2.3 Limitations in B2C Environments

Since research on B2B reputation systems is scarce, B2C review systems must be the reference point for designing business reputation systems. Review systems are well-studied in B2C environments and exhibit well-known limitations (Tab. 6). These limitations are equally critical for the B2B context (Sec. 2.3.4).

Table 6: Limitations of B2C Review Systems (adopted from: P6)

Limitations	Description	Selected Literature
Fraud and Manipulation Vulnerabilities	Fake identities, manipulated ratings, attacks, ballot-stuffing, and bad-mouthing undermine trust in ratings.	(Y. Cai & Zhu, 2016; Dellarocas, 2000; He et al., 2022; Ivanova & Scholz, 2017; Jin et al., 2023; Lappas et al., 2016; Luca & Zervas, 2016; Mayzlin et al., 2014; R. H. Pereira et al., 2023; F. Schneider & Teubner, 2024; Swamynathan et al., 2010)
Lack of Incentives and Free-Riding	Users lack motivation, time, or incentives to provide ratings, leading to insufficient data.	(Adar & Huberman, 2000; Neumann & Gutt, 2019a; Y. Sun et al., 2017; J. Wang et al., 2018; Y. Yu et al., 2022)
Reputation Inflation and Other Biases	Ratings tend to be overly positive due to leniency, reciprocity, retaliation fears, strategic behavior, or social pressure.	(G. E. Bolton et al., 2013; Filippas et al., 2018; Fradkin et al., 2015; Hannák et al., 2017; Kolleck & Teubner, 2024; Nosko & Tadelis, 2015; Resnick & Zeckhauser, 2002; T. Teubner et al., 2017; Wan & Nakayama, 2014; Zervas et al., 2021)
Contextual Limitations	Ratings often fail to capture contextual complexity, resulting in inaccurate or misleading trust signals.	(S. Banerjee et al., 2017; G. E. Bolton et al., 2004; Z. Cheng et al., 2016; Hendrikx et al., 2015; H. Hong et al., 2017; X. Liu et al., 2023; Qiu et al., 2012; Wan & Nakayama, 2014)
Centralized Governance and Privacy Concerns	Centralized systems raise concerns about data ownership, manipulation, misuse, breaches, and privacy issues.	(Filippi, 2016; Gefen & Pavlou, 2006; Long & Liu, 2024; Lyon, 2014; J.-S. Park et al., 2018; Subramanian, 2018; Zyskind et al., 2015)

Reputation systems are highly susceptible to manipulation and fraudulent practices (Ansari & Gupta, 2021; Gössling et al., 2018; Jøsang & Goldbeck, 2009; Jøsang et al., 2007; Wan & Nakayama, 2014; Zhuang et al., 2018). Sellers have a strong financial incentive to create misleading information and actively seek ways to manipulate ratings (Luca & Zervas, 2016; R. H. Pereira et al., 2023). Fake reviews are a serious issue and are often systematically generated (Ivanova & Scholz, 2017; Wan & Nakayama, 2014).

They can be purchased cheaply, which makes manipulation attractive as long as the benefits from buying faked ratings outweigh the expenses of creating them (He et al., 2022; Y. Yu et al., 2022). A major risk in this context is the *Sybil Attack*, to which every open system is vulnerable (Douceur, 2002). In this scenario, single entities can create multiple fake accounts to re-enter the system with new identities (Dellarocas, 2005; Friedman & Resnick, 2001). These fake identities open attack scenarios, e.g., shilling, brushing, self-promotion, bad-mouthing, ballot-stuffing, flooding, and whitewashing (Dellarocas, 2000; Jøsang et al., 2007; M. Zhou et al., 2008). Despite countermeasures, e.g., (Duma et al., 2024; Roy et al., 2024; Swamynathan et al., 2010), it generally remains difficult to distinguish genuine from deceptive ratings ex-post (Shin et al., 2023). Fraud can persist when reputation mechanisms are weak (Snehasish Banerjee & Chua, 2023; R. H. Pereira et al., 2023; Tóth et al., 2022).

Ratings are underprovided, as they offer little benefit, and rating new products can have disadvantages for the rater (Dellarocas, 2005; Samuelson, 1954). Writing detailed rating reviews is time-consuming, and without incentives, most users opt not to provide a rating (Dellarocas & Wood, 2008; Jurca & Faltings, 2009; Y. Sun et al., 2017). In this free-riding problem, users rely on existing ratings to make decisions, but do not actively contribute ratings themselves (Adar & Huberman, 2000; G. E. Bolton & Ockenfels, 2012; Feldman et al., 2004; M. Zhou et al., 2008). Incentives can increase participation, but when provided by the rated entity or the platform owner (e.g., monetary rewards), they often distort rating accuracy, which leads to systematic biases (Kargozari et al., 2023; Neumann & Gutt, 2019b; J. Wang et al., 2018).

Reputation inflation, a phenomenon where ratings tend to be overly positive, is prevalent in most B2C reputation systems (Filippas et al., 2018; Zervas et al., 2021). For example, G. E. Bolton et al. (2013) report approx. 98 % positive ratings on eBay. Users are hesitant to leave negative reviews due to leniency or retaliation fears; consequently, they do not report bad experiences (G. E. Bolton & Ockenfels, 2012; Fradkin et al., 2015). This situation leads to two effects. First, inflated positive ratings become the norm, masking performance differences, which impedes differentiation between average and high-quality products (G. E. Bolton et al., 2019; Zervas et al., 2021; Y. Zhu & Grover, 2022). Second, only a comparatively small group of active users shapes ratings, which reinforces several biases (J. Wang et al., 2018). Additionally, biases arise from strategic manipulation, self-selection, reciprocity, leniency, or social influence, all of which undermine the trustworthiness of ratings (J. Chen et al., 2023; Fradkin et al., 2015; N. Hu et al., 2009; Jurca et al., 2010; Matherly, 2019; You & Sikora, 2014). Lastly, negative ratings can be removed due to legal reasons or platform policies (Đurović & Kniepkamp, 2022).

Most reputation systems in B2C contexts are insensitive to contextual factors, failing to account for specific trust dimensions or product complexity (G. E. Bolton et al., 2004; Gutowska et al., 2009; Pavlou & Dimoka, 2006; Wan & Nakayama, 2014). Reputation systems often rely on overly simplistic aggregation scores, erasing meaningful contextual information, and paving the way for malicious behavior (Ivanova & Scholz, 2017; Sänger & Pernul, 2018). Without detailed insights, reputation scores can mislead rather than guide buyers (M. Hu & Liu, 2004; Mcauley & Leskovec, 2013; Qiu et al., 2012). Taking social network relations into account is a largely overlooked aspect.

Many reputation systems are applied in centralized platforms, where operators retain control over which ratings are observable. This situation introduces risks of biased moderation and censorship, which "intensify the problem of information asymmetry" (Shi et al., 2023, p. 501) rather than resolving it. It is a recurring issue that commercial platform operators manipulate, remove, or withhold ratings for their advantage (Filippi, 2016; Y. Lim & van der Heide, 2015; Singhal et al., 2025; Soska et al., 2016; Subramanian, 2018; Ye et al., 2014). Consequently, users lack control over their ratings, and platforms can proactively suppress them. In addition, privacy concerns arise since platform operators collect vast user data with limited user control (Bernabe et al., 2019; Filippi, 2016; Hasan et al., 2022).

Despite their value (Greiner et al., 2021), reputation systems generally face several severe limitations. While the literature on these systems is extensive, concrete guidance for improving these systems is strikingly absent (G. E. Bolton et al., 2024; Sänger & Pernul, 2018). Hence, it is concluded that overcoming these limitations requires substantial redesign, moving beyond the current system class.

2.3 Business-to-Business Markets

2.3.1 Main Characteristics of B2B Markets

B2B markets typically involve complex products and services and are characterized by strategic non-transparency, high uncertainty, and substantial transaction costs, all of which drive pronounced information asymmetries between sellers and buyers (Garicano & Kaplan, 2001; Kittur & Chatterjee, 2023).

Usually, companies intentionally limit the disclosure of potentially business-sensitive information. High transparency requirements can discourage companies from engaging in electronic markets (Truong, 2019; K. Zhu, 2002, 2004). Non-transparency helps protect their proprietary knowledge and competitive positions (Akerlof, 1970; Glaeser, 2018). Transparency is particularly relevant for sellers since transparency determines the shift of market conditions. While *low-cost-high-quality sellers* are generally interested in sharing performance-related data; *high-cost-low-quality sellers* tend to withhold such information (Grossman, 1981; D. Kim & Cadogan, 2024; K. Zhu, 2002, 2004). Transparency that exposes cost structures discourages high-cost, low-efficiency sellers from participating in transparency-creating platforms (Nawaz & Wagner, 2025; K. Zhu, 2004). On the other hand, transparency is proactively used to attract new customers (Buell & Kalkanci, 2021; Kirmani & Rao, 2000). According to K. Zhu (2002), market transparency can negatively affect 1) pricing strategies, when price disclosure induces price pressure; 2) relationships, when business partnerships are exposed to competitors; 3) procurement strategies, when competitors can anticipate strategic moves.

High uncertainty is most prevalent during the initiation of business relationships, which are characterized by sparse, unknown social structures, spatial distance, regulatory requirements, and other interdependencies (Kittur & Chatterjee, 2023; Lanzolla & Frankort, 2016; Teece et al., 2016). New businesses frequently require sellers to invest in capital-intensive solutions to send quality signals (Kotlarsky et al., 2023). Assessing and selecting product qualities and sellers' capabilities is time-consuming and challenging (Grewal et al., 2015; Wuyts et al., 2009). In complex transactions, buying centers with domain experts are needed to help mitigate uncertainty (Webster et al., 1972). Another means to navigate uncertainty is to leverage trust (McKnight et al., 2017; Truong, 2019; L. Zhou et al., 2022). It is considered the most effective mechanism to reduce social uncertainty (Luhmann, 2017; Mehrwald et al., 2019). Trust reduces agency costs (M. C. Jensen & Meckling, 1976) and fosters collaboration (J.-Y. Son et al., 2006).

High transaction costs involve expenses such as search, negotiation, enforcement, and monitoring costs that collectively impede market efficiency (Coase, 1937; Picot et al., 2020; Williamson, 1985). Doing business usually demands extended negotiation, rigorous testing, regulation, and compliance check-ins, with high due diligence for vendor selection since a poor decision can lead to costly pitfalls (Fauska et al., 2013; Ho et al., 2010; Koh et al., 2012; McKnight et al., 2017; Oliveira & Roth, 2012; Truong et al., 2012). For this reason, contracts are employed but cannot completely prevent opportunism arising from information asymmetries (Abraham et al., 2016; Williamson, 1979). Therefore, trust is necessary to streamline operations and reduce transaction costs (Bromiley & Cummings, 1989; M. Granovetter, 1985; Pavlou, 2002; L. Zhou et al., 2022). Buyers typically rely on a few core suppliers for most of their procurement volume. In contrast, a much larger group of small, low-volume suppliers accounts only minimally for the overall purchase volume but makes up a large share of the supplier base (Bahameish et al., 2024). Cost-reducing structures are necessary due to high transaction costs, including 1) search and information costs from identifying capable suppliers and verifying their capabilities (Stigler, 1961; Williamson, 1985); 2) Bargaining and contracting costs from negotiating terms, drafting contracts, and aligning expectations (Alchian & Demsetz, 1972; Williamson, 1979, 1985); 3) monitoring and enforcement costs to ensure compliance with agreed terms, detect opportunism, and adapt contracts over time (Macneil, 1977; Williamson, 1979).

Besides these main characteristics, B2C and B2B markets typically exhibit other classic differences (Bruhn et al., 2014; Fauska et al., 2013) (Tab. 7).

Table 7: Differences in B2C and B2B Markets

Differences	B2C Markets	B2B Markets
Stakeholder Structure	Individual buyers and sellers (Bridges et al., 2005)	Complex organizational decision-making units (Johnston & Bonoma, 1981)
Decision-Making	Fast, individual decision-making (Singh, 2002)	Formalized evaluations, negotiations, and long, complex decision processes (Steward et al., 2023; Webster et al., 1972)
Transaction Frequency	High-volume, repetitive transactions (Kumar, 2008)	High- and low-frequency, strategic transactions (R. Dai et al., 2005)
Standardization	Standardized goods and services (Heim & Sinha, 2001)	Customized, complex product specificity (Williamson, 1975)
Price Sensitivity	Usually, high price sensitivity and immediate comparison (Choi et al., 2006)	Mixed price sensitivity with a focus on value, quality, and long-term costs (Erdem et al., 2001; Stock, 2005)
Trust Formation	Public user feedback and comparison of online reviews (Liwei Li & Wang, 2020)	Private vetting, contract-based safeguards, personal contact and referrals (Doney et al., 2007; X. Huang et al., 2008; Ratnasingam, 2005)
Relationship	One-off relationships (Dowling, 2002)	Short and long-term relationships, and customer retention (Friman et al., 2002; Gummesson, 2004)

While reputation systems cannot resolve all structural complexities inherent in B2B markets, they offer a trust-building mechanism that supports deliberate, selective transparency, reduces uncertainty, and lowers transaction costs in high-stakes transactions (Sec. 2.3.3). However, much potentially valuable information is withheld rather than shared in a targeted manner—primarily due to concerns over transparency—despite its potential to reduce uncertainty and transaction costs overall (P4).

2.3.2 Shortcomings of Trust Surrogates in B2B Environments

Companies often lack relevant information when evaluating prospective B2B partners. While sellers have efficient methods to reduce uncertainty (Kallberg & Udell, 2003; Safi & Lin, 2014), buyers must rely on trust surrogates when trust is absent. Companies turn to trust surrogates to expand their information base (J.-Y. Son et al., 2006). Trust surrogates serve as indirect proxies for trust, i.e., formal safeguards and governance mechanisms (Pavlou, 2002). They strengthen specific trust facets (Poppo & Cheng, 2018). The following table condenses the main weaknesses of surrogates (Tab. 8).

Table 8: Advantages and Shortcomings of Trust Surrogates

Surrogates	Examples	Strengths	Shortcomings	Selected Literature
Third Party-Verifiers	Third-party audits, industry associations, certifications	High credibility, regulatory alignment, impartial assessment	Limited availability of verifiers, high costs, time-consuming processes, bribery concerns	(Backhouse et al., 2004; Gao et al., 2017; Lansing et al., 2019; Lins et al., 2022; Lins et al., 2016; Pavlou, 2002; J.-Y. Son et al., 2006; Zucker, 1986)
Contractual Safeguards	Contracts, warranties, insurance	Legal enforceability, binding agreement	Only ex-post remedies, rigid structures, limited flexibility	(Lui & Ngo, 2004; Shen et al., 2020; Susarla et al., 2009; Woolthuis et al., 2005)
Market-Based Signals	Brands, awards, seals, web presence, public reputation	Easily accessible and recognizable	Susceptible to manipulation, signal distortion, and sometimes superficial indicators	(Cartwright et al., 2021; Gallus & Frey, 2017; Lins et al., 2024; Lowry et al., 2014; Tóth et al., 2021; Weng et al., 2024; Wuyts et al., 2009; J. Zhang & Du, 2020)
Experience-Based Endorsements	Personal referrals, references, testimonials, blogs, WOM, eWOM, social media	Peer-validated, socially more credible	Fragmented and hard to scale, context-specific, and limited informative value, potentially socially distorted or biased	(Aarikka-Stenroos & Makkonen, 2014; D. E. Boyd et al., 2023; Chatzipanagiotou et al., 2023; K. Cowan et al., 2023; Godes, 2012; Hada et al., 2024; Hada et al., 2014; Ishii & Kikumori, 2023; Jaakkola & Aarikka-Stenroos, 2019; Kikumori & Ishii, 2023; H. Kim, 2014; Zhao & Ke, 2023)
Internal Organizational Control	Internal audits and scoring, vendor management systems	Company-specific in-depth insights, tailored to internal processes	High effort, no external use of data, only data of known suppliers	(Choy et al., 2003; Gefen & Pavlou, 2006; Koh et al., 2012; Lins et al., 2016; Lins et al., 2015; E. Ng, 2010; Pathak, 2004; Steward et al., 2018)
Technological Set-ups and Data Analytics	Data-driven frameworks, algorithmic monitoring, sensor-based tracking	Automation of validation, transparency, scalability	Complexity, concerns about data sources and privacy, high setup costs	(A. Agarwal & Jayant, 2019; Ba & Pavlou, 2002; Khedr, 2024; Pavlou & Ratnasingam, 2003; van Nguyen et al., 2023; Yayla et al., 2015)

As these studies show, each trust surrogate has its strengths and shortcomings. Generally, buyers typically combine multiple surrogates simultaneously to offset respective shortcomings. Nonetheless, sellers have an interest in sending ostensibly high-quality signals without actually improving their performance, especially when true quality is hard to verify (S. E. Kaplan et al., 2007; Kerton & Bodell, 1995; Prabhu & Stewart, 2001; Q. Zhang et al., 2024). Consequently, lemon markets can emerge in markets marked by high non-transparency, and deceptive behavior becomes rational (Benner & Zenger, 2016; G. E. Bolton et al., 2019; Scott et al., 2015). This situation exacerbates information asymmetries, often leading to increased efforts to vet sellers (Benner & Zenger, 2016; Johnston & Bonoma, 1981; Mason & Sterbenz, 1994).

High information acquisition costs are a major issue. Data is often scattered across various sources, making it difficult to understand a prospective partner’s capabilities comprehensively. This fragmentation forces decision-makers to consolidate diverse data points, which increases complexity, time, and costs. Many trust surrogates require significant effort to obtain, verify, and interpret the necessary information (Teece et al., 2016; Wuyts et al., 2009). While third-party intermediaries provide credible and impartial assessments, their effectiveness is limited by high costs, data availability issues, and time-intensive processes. Although legally enforceable, contractual safeguards primarily function as ex-post remedies, offering little protection against partner selection risks. While easy to recognize, market-based signals are susceptible to marketing embellishment, selective disclosure, and manipulation (Koh et al., 2012; Lins et al., 2024). Experience-based endorsements rely on social credibility but are difficult to scale, fragmented across information sources, and prone to bias, limiting their overall value (Babić et al., 2016; Tsao et al., 2022). Internal control systems provide company-specific insights but require substantial effort, lack external validation, and do not share information with others (Lins et al., 2016). While technology improves scalability and transparency, unreliable data sources are a major challenge (cf. Sec. 2.4.2).

These shortcomings can be grouped into three categories: 1) high search and validation costs, 2) limited credibility or verification, and 3) constraints in information utilization. As a result, existing surrogates often fall short in mitigating uncertainty adequately, particularly when reliable, consolidated information is lacking. This situation underscores the need for IS research to design a system for inter-organizational exchange that provides accessible, trustworthy, and context-specific information.

2.3.3 Advantages and Adaptation of Reputation Systems in B2B Markets

B2B markets evolved into increasingly digital, complex, and globalized environments, where traditional mechanisms for building trust—such as personal relationships or long-standing partnerships—are often no longer viable (Pavlou, 2002). Especially in one-off or short-term transactions, establishing trust remains a central challenge (G. E. Bolton et al., 2005; Gregory et al., 2024; Große et al., 2024; Möller et al., 2024). Reputation systems offer a potential solution by fostering transparency, which is particularly valuable in B2B contexts. However, their adoption remains limited (Chatzipanagiotou et al., 2023; Dikow et al., 2015; Yili Hong & Pavlou, 2017; Luo et al., 2020), even though they can be understood as strategic instruments of business coordination (Gutt et al., 2019). Small and medium-sized enterprises (SMEs) stand to benefit the most, given their restricted access to information, limited processing capacity, and higher frequency of partner switching (Yoon et al., 2021).

Reputation systems can streamline the exploration, evaluation, and selection of suppliers by reducing information acquisition costs and minimizing the need for extensive internal assessments (S. Chen et al., 2022). Online reviews have become an increasingly important information source for B2B buyers (Tóth et al., 2022). About 80 % of B2B buyers actively search online, e.g., through online channels or reviews, to assess prospective sellers (Grewal et al., 2015; Seutter, 2022; Steward et al., 2023; Steward et al., 2019). Reading a trusted positive review is reported to increase the likelihood of a purchase by up to 90 % (Chatzipanagiotou et al., 2023; Kaemingk, 2025). Even negatively rated suppliers are considered in order to mitigate binding risks linked to other sellers (E. Anderson & Jap, 2005; Steward et al., 2018; Steward et al., 2023).

Reputation systems establish institutional mechanisms that help build initial trust without requiring long-standing relationships or prolonged vetting processes. This form of institutional trust allows companies to enter into collaborative arrangements that might otherwise appear too risky (Dimoka et al., 2012; Pavlou, 2002). Furthermore, rating data can enhance buyers' bargaining position by making supplier performance shortcomings visible (P5). Conversely, well-rated sellers can use their reputation to justify price premiums and negotiate from a position of strength (C. Shapiro, 1983).

Positive ratings also function as strategic quality signals, enabling suppliers to differentiate themselves in competitive markets (Gutt et al., 2019; Kotlarsky et al., 2023; Porter, 1997). This is particularly advantageous for high-quality providers in settings where actual quality is difficult to verify based on objective means (Montecchi et al., 2021). Moreover, accessible ratings foster transparency, support fair competition, and incentivize continuous improvement. Sellers can actively use feedback to refine offerings (Chatzipanagiotou et al., 2023; Gutt et al., 2019; Kwark et al., 2018; Ye et al., 2014).

Despite these benefits, only a few digital B2B platforms employ reputation systems. With the notable exceptions of *Capterra*, *G2*, *Clutch*, and *Alibaba*, such systems are largely absent. Even with these platforms, business reputation systems remain underutilized across most B2B sectors. *Capterra* and *G2* have found success in the software domain, where products are standardized and allow for structured reviews and comparative ratings. To boost review volume, *Capterra* offers incentives for submissions, which—despite generating content—also creates bias, inflates reputations, and raises concerns about credibility and review fraud (Kargozari et al., 2023). Although no research on *G2* is available, their apparent paid sales promotion for sellers most likely distorts rankings and undermines neutrality (G2, 2025). While focusing on service providers, *Clutch* exhibits comparable issues, including inflated ratings, paid placements, and insufficient identity verification (Clutch, 2025). These practices mirror the issues known from B2C websites (Y. Lim & van der Heide, 2015; Luca & Zervas, 2016; Roh & Yang, 2021; Shin et al., 2023; Singhal et al., 2025). *Alibaba* offers no direct rating incentives, and reviews are often notably brief but less controlled and more authentic (Tóth et al., 2022). Still, despite verification mechanisms, sellers manipulate sales volumes and ratings (Jin et al., 2023; Tóth et al., 2022). Equally, reputation inflation can be observed (Alibaba, 2025). Many sellers do not have transparent profiles, which limits source credibility (M. L. Jensen et al., 2013; Pornpitakpan, 2004).

Since the design of these B2B platforms is similar to those of B2C, it is reasonable to assume that the systems encounter the same limitations (Sec. 2.2.3). The weaknesses inherent in B2C system designs render them less suitable and heighten adoption barriers (Sec. 2.3.4). This situation underscores the need to (re-)design reputation systems to meet the demands of modern professional B2B markets (Long & Liu, 2024).

2.3.4 Adoption Barriers in B2B Markets

While reputation systems in B2C markets are widespread, B2B markets lack their adoption (Bader et al., 2023). B2C limitations (Sec. 2.2.3 – Tab. 6) seem to intensify in professional environments due to the more demanding market characteristics (Sec. 2.3.1). Although the limitations may be tolerable for B2C markets, higher stakes, strategic non-transparency, and confidentiality requirements turn them into substantial adoption barriers (Tab. 9). Tab. 9 categorizes adoption barriers of reputation systems in B2B environments. Tab. 9 exhibits strong parallels to the limitations outlined in Tab. 6.

Table 9: Adoption Barriers for B2B Reputation Systems

Barrier	Description	Selected Literature
Reluctance to Share Information	Companies hesitate to share data due to competitive risks, information leakage, and market vulnerability.	(Abbas et al., 2021; R. S. Hill & Zubielqui, 2023; Huong et al., 2016; Narang et al., 2019; Pressey & Ashton, 2009; Schomakers et al., 2020; Vuolasto & Smolander, 2024; K. Zhu, 2002, 2004)
Fraud and Manipulation Fears	Manipulation distorts trust and risks weak decisions.	(Darby & Karni, 1973; Hemmrich, 2023; Truong, 2019)
Limited Incentives for Submission	Little incentive for companies to submit ratings.	(Seutter, 2022)
Rating Aversion and Fear of Retaliation	Fear of negative ratings and retaliatory actions.	(Hemmrich et al., 2025; Hemmrich et al., 2024; Steward et al., 2023)
Multi-Dimensional Product Complexity	Complex products complicate performance evaluations and reduce comparability.	(Altayyar, 2017; Hemmrich et al., 2025; Saprikis & Vlachopoulou, 2015)
Centralized Governance Control	Concerns about data control, misuse, and biased moderation.	(R. S. Hill & Zubielqui, 2023; Pressey & Ashton, 2009)
Legal and Regulatory Risks	Negative reviews of risk defamation claims and contractual disputes.	(G. E. Bolton et al., 2018; Hemmrich et al., 2025)

One central barrier lies in companies' reluctance to disclose sensitive business information (Truong, 2019), including performance data, pricing models, or supplier relationships (P5,P9). Such disclosures can weaken a firm's bargaining position and expose it to strategic vulnerabilities, especially in industries where competitive advantage relies on proprietary knowledge (Schomakers et al., 2020; Vuolasto & Smolander, 2024). Transactional data may reveal patterns that competitors can exploit (Fabrizio & Kim, 2019; R. S. Hill & Zubielqui, 2023; Schumann et al., 2025; Truong, 2019). Nevertheless, firms with cost advantages may be more inclined to engage in transparent markets (Y. Cui et al., 2024; K. Zhu, 2004).

Concerns about manipulation are particularly pronounced in B2B settings (Truong, 2019) (P5). Yet empirical evidence suggests that trustworthy ratings can be achieved when buyers select sellers based on their credibility (Ekstrom et al., 2005).

Another barrier is the lack of tangible benefits for contributing ratings. Given the complexity of many business products and services, providing meaningful feedback often requires substantial effort and internal resources. Companies may view submitting ratings as an inefficient investment without a clear rationale (P9).

Companies are reluctant to be rated or rate others publicly (Tóth et al., 2021; Zavolokina et al., 2021). For sellers, induced transparency can eliminate beneficial market barriers (K. Zhu, 2002) and undermine buyers' loyalty (Belhadi et al., 2023). Negative reviews can—but must not—severely damage a company's reputation, jeopardize strategic partnerships, or trigger contract disputes (Babić et al., 2016; Steward et al., 2023). Still, even an average reputation can undermine a company's long-term viability (Luo et al., 2020). On the buyer side, hesitation is similarly present. Buyers may avoid honest ratings out of fear of retaliation or strained relationships (G. E. Bolton et al., 2018).

B2B products are often more complex and customized than most B2C products (Saprikis & Vlachopoulou, 2015). Thus, many products and services can be compared to a limited extent. Still, any information appears valuable to buyers (P9). Simple rating mechanisms risk oversimplifying complex product dimensions, while extensive text reviews may overwhelm users with information (C. Schneider et al., 2021; Seutter et al., 2023). When rating results are inconsistent, buyers try to resolve them (Steward et al., 2018).

Trust in B2B platform operators presents another barrier. B2B platforms raise concerns about data ownership, misuse, breaches, and privacy issues (Agahari et al., 2022). Often, companies distrust platform operators, fearing data manipulation or biased moderation (R. S. Hill & Zubielqui, 2023; Pressey & Ashton, 2009; Shin et al., 2023). Negative reviews can result in defamation claims or legal disputes (P5). Therefore, companies avoid such systems to minimize legal risks (J. Chandler et al., 2007).

In sum, the adoption of reputation systems in B2B markets is constrained by a combination of structural, behavioral, and legal barriers. Risk aversion, time expenditure, and other perceived disadvantages are significant obstacles (McKnight et al., 2017). These challenges can be understood as intensified forms of the B2C limitations (Sec. 2.2.3). However, additional concerns of data confidentiality must be explicitly addressed in system design. Companies require mechanisms to control what information is shared and with whom (Kalvenes & Basu, 2006). Excessive transparency can expose participants to competitive risks, while strong privacy obscures rating credibility (M. L. Jensen et al., 2013). Resolving this tension is critical for designing reputation systems.

2.4 Blockchain Technology

2.4.1 Technological Foundation and Economic Implications

A blockchain is a decentralized and chronological ledger that records digitally signed transactions between two or more entities, securely stored in cryptographically linked blocks (Beck et al., 2017; Y. Lu, 2022). Each block contains multiple transactions and is permanently linked to its previous block through cryptographic hashes, forming a chain of blocks (Nakamoto, 2008). This blockchain is maintained by network nodes that have an economic incentive to follow the consensus protocol, either by solving cryptographic puzzles (Proof-of-Work) or staking tokens (Proof-of-Stake) to validate transactions and add new blocks to the chain (Antonopoulos, 2017; Bentov et al., 2014; Narang et al., 2019). Altering past transactions is infeasible without controlling the majority of computing power (or the total stake). As long as sufficient nodes act independently, the network resists manipulation of stored data (Lipton & Treccani, 2022; Nakamoto, 2008; Tschorsch & Scheuermann, 2016).

Blockchains are typically categorized as permissionless (open) or permissioned (restricted), depending on who is allowed to access, read from, and write to the blockchain ledger (Helliar et al., 2020). Furthermore, privacy-preserving techniques can be used to hide certain transaction contents or transacting identities (Bernabe et al., 2019).

Notably, blockchain technology supports smart contracts (Szabo, 1997). A smart contract is self-executing code integrated into blockchain transactions (Buterin, 2014a). Smart contracts facilitate *‘programmable risk’* in hard-coded logic without needing an executing trusted instance (Gregory et al., 2024; Swan, 2017, 2019). By removing the need for such intermediaries, blockchain holds high potential for disintermediation and re-intermediation (Feulner et al., 2022; Fridgen et al., 2021; Mougayar, 2016). More advanced forms of smart contracts are envisioned to constitute Decentralized Autonomous Organizations (DAOs) that manage transactions autonomously while adjusting self-governing rules (Buterin, 2014a).

Beyond smart contracts, blockchain's architecture solves the double-spending problem (Davidson et al., 2018). This problem refers to the risk of copying data without securely identifying the original. The solution prevents unauthorized duplication and the exchange of digital assets, e.g., tokens and other valuable information (Nowiński & Kozma, 2017). Since the solution enables the trade of digital assets with programmable logic, it is announced for far-reaching economic implications (Davidson et al., 2018; Swan, 2017).

From a *New Institutional Economics* perspective, transaction costs primarily result from opportunism and information asymmetry (Williamson, 1985). Traditionally, companies control the associated risks through hierarchical governance and binding contracts (Carson et al., 2006; Foss & Weber, 2016). Blockchain can transform these organizational forms by providing a layer of technological governance (Davidson et al., 2016; Meijer & Ubacht, 2018) and transparency (Franke et al., 2024; Wigand, 2020). In this way, smart contracts can improve economic coordination by embedding self-enforcing rules directly into the network, which, in turn, reduces business transaction costs (Davidson et al., 2018; Gregory et al., 2024; Grosse et al., 2021; J. Pereira et al., 2019). Securing data and sending (costly) signals with this technology are expected to counteract information asymmetry. Both reduce adverse selection and moral hazard (Davidson et al., 2016; Meier & Sannajust, 2021). While the technology is expected to enhance economic coordination, it also introduces new challenges, including legal ambiguity, code vulnerabilities, and governance complexities (Rieger et al., 2019; Toufaily & Zalan, 2024).

A blockchain is a highly reliable trust surrogate with built-in verification and validation mechanisms (Filippi et al., 2020; Hawlitschek et al., 2018; Lustig & Nardi, 2015; Ostern, 2018). As a reliable structure, the main benefit lies in creating trust (Große et al., 2024; Toufaily & Zalan, 2024; Zavolokina et al., 2024; Zavolokina et al., 2021), while it also reduces the need for other forms of trust (M. Becker & Bodó, 2021; Davidson et al., 2018; Schinle et al., 2020). However, blockchain-based transactions work only on complete contracts that are fully codifiable and executable on-chain, while many business transactions are governed by incomplete contracts that require human judgment (Davidson et al., 2016; Gregory et al., 2024; Hart, 1989; Voshmgir & Zargham, 2020). While monetary tokens are subject to a secure validation mechanism, other (potentially fabricated) information can be recorded on-chain. Accordingly, the utility of blockchain technology is limited to the extent of the information provided.

A blockchain ensures tamper-resistance, but lacks mechanisms to validate the correctness of real-world input data, known as the *oracle problem* (Caldarelli, 2020; Sheldon, 2021). Proposed solutions include secure source tagging (e.g., pictures, GPS, or RFID), technical-oriented reputation systems, data feeds, or trusted parties that validate data (Albizri & Appelbaum, 2021; Chang et al., 2020; Hassan, 2023; Pasdar et al., 2023; J. Pereira et al., 2019). Since only human judgment can resolve this issue, blockchains *must* remain inherently limited (Barr et al., 2014; Battah et al., 2021; Caldarelli, 2020; Franke et al., 2024; Gonçalves et al., 2022). A blockchain "cannot operate outside the sphere of computation" (Pazaitis et al., 2017, p. 113).[14] To bridge the gap, scholars increasingly emphasize integrating human judgment (Pastore et al., 2013; Sänger & Pernul, 2018). Nevertheless, the precise design of such mechanisms remains an open research question (Buterin, 2021; J. Pereira et al., 2019; S. Wang et al., 2019; Xia et al., 2018).

Consequently, a reliable mechanism is required to ensure that stored information reflects not only technical but also socio-economic reality (Hawlitschek et al., 2018; Toufaily & Zalan, 2024). Only human judgment can mitigate the oracle problem and help reduce information asymmetries and enhance coordination efficiency (Bons et al., 2020; Caldarelli, 2020; Lanzolla & Frankort, 2016).

2.4.2 Building Blocks for Blockchain-Based Reputation Systems

Research on blockchain and reputation systems is dominated by technical approaches (Gonçalves et al., 2022), with a strong emphasis on enabling *computational trust* between network nodes (Battah et al., 2021; Bellini et al., 2020). Technical-embedded blockchain-based reputation systems are well-developed and employ advanced privacy-preserving techniques (Hasan et al., 2022). While these technical-embedded reputation systems deal with the same limitations outlined in Sec. 2.2.3, they largely neglect trust issues concerning data origin (Greenspan, 2016; Sänger & Pernul, 2018).

Accordingly, this study examines social-embedded reputation systems (Sec. 2.2.1), also referred to as blockchain-*based* reputation systems (Y. Cai & Zhu, 2016). These systems are used on blockchains primarily because they are secure vehicles for storing ratings. Hence, the focus applied here is to design incentive structures *on top of* blockchain technology (Gregory et al., 2024; Große et al., 2024; Spychiger et al., 2022).

Next to cryptographical building blocks (P6), five technological capabilities are identified as central building blocks for designing the blockchain-based reputation mechanism:

[14] This echoes Ashby's *(1962) Law of Requisite Variety*, a system law that suggests that a system cannot process external complexity unless it possesses equivalent internal complex variety.

(1) Immutable Storage: Blockchain ensures tamper-resistant storage through cryptographic hashing, preventing modifications (Almasoud et al., 2020; Battah et al., 2021). Numerous studies demonstrate the storage of ratings, e.g. (Alhogail et al., 2021; Avyukt et al., 2021; Kugblenu & Vuorimaa, 2020; M. Li et al., 2021; Z. Liu & Li, 2020; Rahman et al., 2020; Ramachandiran, 2019; Shaker et al., 2021; Z. Zhou et al., 2021; Zulfiqar et al., 2021). Storing this information is argued to reduce information asymmetry (Zavolokina et al., 2021).[15] However, since blockchain only secures data *integrity* but not *veracity*, an incentive mechanism for truthful inputs is pivotal (Große et al., 2024; Voshmgir & Zargham, 2020).

(2) Token-Based Incentives: Token-based reward schemes are critical to stimulate sustained participation and truthful contributions. Tokens may be redeemable for monetary or non-monetary benefits, such as discounts, services, or access privileges (Doğan & Karacan, 2023; Kranz et al., 2019; Schwiderowski et al., 2024; Shakhnov & Zaccaria, 2023). Blockchain-supported incentives enhance data quality and reduce vulnerability to manipulation (Avyukt et al., 2021; Hunhevicz et al., 2020; Spychiger et al., 2022; Wei et al., 2020). A permissioned blockchain with a coordinating instance may be best suited for the reputation mechanism, as it enables stricter control of data sharing and the enforcement of governance rules (Spychiger et al., 2022).

(3) Smart Contracts: Smart contracts automate business commitments such as payments, reward allocation, or conditional feedback release (Ballandies et al., 2022, 2024; Zavolokina et al., 2021). They can escrow monetary value and trigger payments based on verifiable digital events (Asgaonkar & Krishnamachari, 2019; Gregory et al., 2024; Meier & Sannajust, 2021). When combined with privacy-preserving computation, including fully homomorphic encryption, sensitive data can be processed without public exposure (Almasoud et al., 2020; Bernabe et al., 2019).

(4) Pseudonymous Identities: In a public blockchain network, addresses of transaction participants are visible. By default, identities associated with an address can be verified or remain pseudonymous (unlinked to real-world identity) (Cousins et al., 2019). Participants can reuse the same address and establish a persistent identity, or generate new addresses for privacy reasons. However, despite changes of addresses, zero-knowledge proofs (ZKPs), and privacy-preserving systems (Hasan et al., 2022), technical forensics frequently manages to reveal real identities (Atlam et al., 2024; Narayanan et al., 2016). In permissioned blockchains, a trusted instance can ensure only authorized participants enter the system (Y. Cui et al., 2024; Doğan & Karacan, 2023). They allow

[15] The system shifts rather than resolves information asymmetry. While more data is made available, its reliability remains unverified, as it still originates from external sources whose completeness and truthfulness cannot be verified within the blockchain itself.

secure and private B2B collaborations (Narang et al., 2019). Verifiable credentials help prevent the creation of multiple identities (Doğan & Karacan, 2023; Hasan et al., 2022). Ring signatures can ensure the privacy of a rater as a person (Rivest et al., 2001).

(5) Token-Curated Registries: TCRs were originally suggested by Goldin (2017a, 2017b) to provide a curation mechanism where mutually unknown participants stake tokens to collectively validate and rank blockchain entries (Gajek, 2018). The curators stake tokens to vote on the expected order, receiving both their stake and a share of the fees. The incentive ensures that curators align their interests with the most expected outcome, which naturally converges toward the closest *'approximation of truth'* (Asgaonkar & Krishnamachari, 2018). This principle is known in economics as *Schelling point*.[16]

Related research argues that information asymmetry can be reduced through blockchain's immutable data recording (Notheisen et al., 2017; Spychiger et al., 2022; Zavolokina et al., 2021). Yet, these approaches shift the information asymmetry problem to the oracle problem, as they rely on external information sources (Sec. 2.4.1). Such approaches may fall short for many real-world scenarios as they suffer the same shortcomings of *third-party verifiers* (Sec. 2.3.2—Tab. 8). Gregory et al. (2024) goes one step further by implementing 'automated reciprocity' based on ex-ante determined technical conditions. A similar approach can be found in Große et al. (2024), which is adapted to the logistic domain.

In contrast to these approaches, reputation systems are more broadly applicable and can rely on distributed data sources, including human judgment (Jøsang et al., 2007; Sänger & Pernul, 2018). Consequently, they do not have to rely on institutional data sources or predefined technical conditions. The approaches mentioned above constitute the cutting edge of current research in this area. Yet, they primarily emphasize the reliance on blockchain's data storage capabilities rather than designing a reputation mechanism. However, the design of incentives is a pivotal ingredient for these systems, e.g., (Beck et al., 2018) but incentive design is still significantly under-researched for the design of these systems in IS (Große et al., 2024; J. Pereira et al., 2019; Spychiger et al., 2022).

[16] Two independent agents are likely to choose the option they believe others find most probable, see Schelling (2006).

3 Research Approach

3.1 Foundations

For every research endeavor, it is crucial to understand meta-theoretical assumptions and paradigms as they significantly influence the research approach and the designed information system (Hassan et al., 2018; Hirschheim & Klein, 1989). Meta-theory provides an overarching worldview from which meta-theoretical assumptions are derived, thereby shaping the structure of scientific inquiry (Bostrom et al., 2009). Paradigms are core constituents in the meta-theoretical landscape and encompass a research community's fundamental convictions—particularly regarding ontology, epistemology, and methodology (J. Becker & Niehaves, 2007; Kankam, 2019). Ontology refers to the nature of reality and the fundamental question of what constitutes reality (Hassan et al., 2018). Epistemology concerns the acquisition of knowledge based on the underlying ontology and what counts as valid research knowledge. A methodology provides a framework to translate epistemological stances into methods for applied research (Iivari et al., 1998). Depending on the ontological and epistemological assumptions, different methodologies and theories are deemed more appropriate. Still, methodologies and theories are not strictly bound to paradigms (Hassan & Mingers, 2018; Z. Zhu, 2022). Developing and refining theory is seen as the central purpose of IS research, employing methods to make sense of phenomena (J. S. Lee et al., 2011). Based on this understanding and reading Kuhn (1970), these interrelationships are depicted below (Fig. 3).

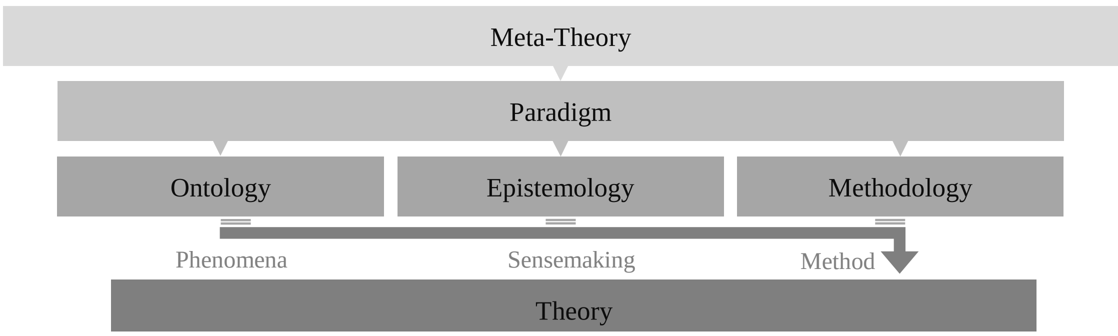

Figure 3: Research Model for Theory Development (based on Kuhn, 1970)

Meta-theoretical perspectives can cover individualism, holism, and systemism (Bunge, 2000). Individualism emphasizes autonomous actors, holism privileges structural totalities, while systemism integrates both by treating *systems as structures* (Reihlen et al., 2007). The last perspective is the "only cogent and viable alternative" (Bunge, 2000, p. 147) and matches with the historical roots of IS, where systems thinking has informed information systems design and the analysis (Avgerou, 2000; Burton-Jones et al., 2015; Chatterjee et al., 2020; Nolan & Wetherbe, 1980; L. D. Xu, 1995) (Sec. 2.1.1).

The IS research field is characterized by an evolving landscape of paradigms (Niehaves & Stahl, 2006), which represent a set of assumptions and beliefs shared within a scientific community that guide their research conduct (Jackson, 2003; Kankam, 2019). Paradigms can lead to ideological conflicts or even *paradigm wars*. Such tensions can foster scientific development (Kuhn, 1970). In IS, such a *paradigm war* has taken place during the debate on *rigor vs. relevance,* e.g., (Benbasat & Zmud, 1999; A. S. Lee, 1999), which reinforced the progression of DSR (Hevner et al., 2004; S. Weber, 2010).

In IS, paradigm pluralism is considered essential to cultivate a healthy research landscape and a reflective research community (W. Chen & Hirschheim, 2004; Hassan & Mingers, 2018; Hassan et al., 2018; Robey, 1996). Rather than existing in isolation, paradigms can complement each other, contributing to a more comprehensive understanding of IS phenomena (W. Chen & Hirschheim, 2004). Peripheral paradigms can introduce new puzzle pieces to the existing knowledge puzzle, reshaping the discipline's collective understanding (Hassan & Mingers, 2018; Kuhn, 1970).

The three major paradigms, widely accepted and used in IS, are *positivism*, *interpretivism*, and *pragmatism* (Goldkuhl, 2012; Kankam, 2019; Richardson & Robinson, 2007) (Tab. 10). Although DSR is often classified as a paradigm, it is more accurately described as a methodological framework situated in the paradigm of *pragmatism* (Goldkuhl, 2011; S. Weber, 2010). Similarly, *social and behavioral sciences* are labeled paradigms (Hevner et al., 2004), however, they are more accurately research fields (Kuhn, 1970, p. 182).

Table 10: Main Paradigms Adopted in IS, based on J. Becker and Niehaves (2007)

	Ontology	**Epistemology**	**Methodology**
Positivism	Reality exists objectively and independently from human experiences (Realism).	Knowledge through hypothetical, deductive testability of causal relationships, empirical observation, and measurement.	Hypothetico-deductive approach (commonly applied using the methods of surveys and experiments)
Interpretivism	Reality is (re-)constructed through human experience and social interaction processes (Constructivism).	Knowledge is constructed through the interpretation of subjective meaning through social actions.	Hermeneutic and inductive approaches (e.g., hermeneutics, grounded theory).
Pragmatism	Reality is shaped through practical outcomes of implemented concepts, e.g., artifacts (Pragmatic Realism).	Knowledge through practical application and evaluation of concepts in the real world, e.g., artifacts.	Iterative design and intervention that aims at practical solutions (e.g., mixed methods, action research).

Relevant to this study is the paradigm of *Pragmatism*. It emphasizes practical problem-solving by applying theoretical knowledge in practical contexts. Pragmatism is closely aligned with DSR, where real-world utility is prioritized over mere theorizing (Goldkuhl, 2012). Rooted in Simon's (1969) seminal work on *The Sciences of the Artificial*, DSR focuses purposefully on designing artifacts as interventions in complex environments.

Due to the interdisciplinary roots and the complexity of socio-technical phenomena in IS, no single paradigm can fully capture the multifaceted nature of research (Mingers, 2001; Niehaves & Stahl, 2006; Orlikowski & Baroudi, 1991; Robey, 1996). Therefore, IS as a discipline inherently supports pluralistic approaches, acknowledging the coherence and interplay of multiple paradigms (Hassan & Mingers, 2018; Mendling et al., 2021).

DSR serves as the methodology for developing information systems (Nunamaker et al., 1990; Peffers et al., 2007). This approach seeks to create a design theory by accumulating design knowledge that can be "applied, tested, modified, and extended through the experience, creativity, intuition, and problem-solving capabilities of the researcher" (Hevner et al., 2004, p. 76). DSR emphasizes the utility of problem-solving and fosters the systematic generation of design knowledge (Gregor & Hevner, 2013; Gregor & Jones, 2007a). The design process is typically executed through iterative cycles, searching for a solution to a problem class (Hevner et al., 2004). Design knowledge is distinguished into (descriptive) *Ω-knowledge* and (prescriptive) *Λ-knowledge* (Fig. 4).

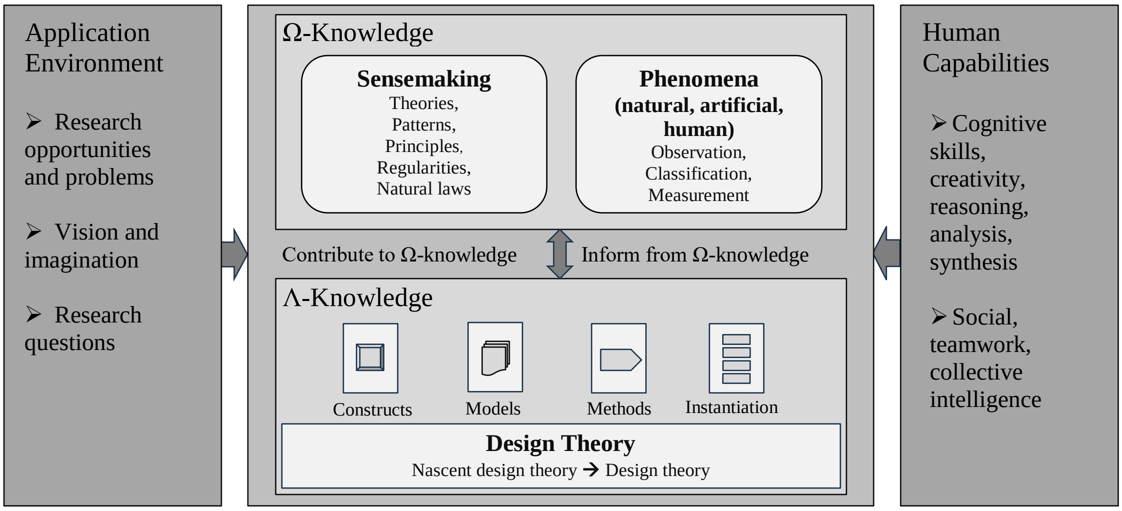

Figure 4: Knowledge Bases in DSR (adopted from Gregor and Hevner, 2013)

To ensure theoretical rigor in DSR, it is essential to clearly distinguish between different types of theory. Theories help translate conceptual ideas into cognitive models to make sense of specific phenomena (Weick, 1989). Gregor (2006) distinguishes five types of theory in IS. Relevant to this study are *theory for explaining* (type II), theory for *explaining and predicting* (type IV), and *theory for design and action* (type V). Type II theories involve complex frameworks that explain how the world functions, aiming for a comprehensive understanding. Type IV combines explanation and prediction to offer a systematic and testable view of phenomena. Type V provides principles to guide artifact development and evaluate their utility in practice. Lastly, a design theory provides an explanation of how and why a design should work and specifies the meta-design in terms of constructs, models, methods, and instantiations (Gregor & Jones, 2007a).

3.2 Justification

This section delineates the research approach to designing blockchain-based business reputation systems. Consistent with Bunge (2000), LST treats *social systems* as *structures* (Sec. 2.1.2). LST provides a meta-theoretical lens for IS (Demetis & Lee, 2016, 2017) and is valuable as a social theory to guide design reasoning (Hevner et al., 2004; Nunamaker et al., 1990; Walls et al., 1992). Therefore, it is employed as a guiding *kernel theory* for the DSR approach. A kernel theory is an explanatory or predictive theory from the natural, social, or design sciences, providing justificatory grounding for a design theory (Gregor & Jones, 2007a; Iivari, 2007; Walls et al., 1992). Systems theory is an explanatory theory eminently suited to understand complex systems in complex environments (Winthrop-Young, 2000). This perspective resonates with Simon's (1969) notion of building artificial systems in complex environments, underpinned by pragmatic design thinking. That is why the study follows the paradigm of *Pragmatism*.

Given the persistent problem of lemon markets and little knowledge on how to redesign this system class, the use of DSR is justified, as it aims to "address important unsolved problems in unique or innovative ways, or solve problems in more effective or efficient ways" (Hevner et al., 2004, p. 81). This study is firmly grounded in the relevance perspective of DSR, targeting a complex, impactful, real-world problem by developing a novel artifact (Tuunanen et al., 2024). As a *DSR construct*, the designed reputation mechanism is an intended *system structure* and a *meta-artifact* for the problem class of lemon markets, where quality is difficult to observe, and trust between unknown parties is hard to establish (Iivari, 2015; March & Smith, 1995; Nunamaker et al., 1990). The artifact builds upon other designed artifacts, including a model of the reputation mechanism (P4,P5), an instantiation of the reputation mechanism (P5), and a method for trading monetary ratings (P6) (Iivari, 2015; Bruls & Winter, in press).

In line with the *pragmatism* paradigm (Magnani, 2005), the artifact development is supported by abductive reasoning (Cronholm et al., 2023; J. S. Lee et al., 2011). It is a form of logical reasoning that combines deductive logic with inductive grounding, iterating back to conceptual reflection (Peirce, 1931). Abduction empowers researchers to derive testable propositions from upcoming conceptual patterns (Dubois & Gadde, 2002; Gregor & Jones, 2007a). It is particularly well-suited for early-stage research and complex designs, since it facilitates creativity and *learning through building* (S. Lu & Liu, 2012; Smuts et al., 2022; Weick, 1989; R. Winter & Aier, 2016). [17]

[17] Abductive reasoning underscores that the aim of DSR is not primarily to achieve falsifiability; rather, its main purpose is to guide problem-solving and the refinements of artifacts, as explained by J. S. Lee et al. (2011). While falsifiability is essential, see Popper (1977), it can be left to future inquiry, as argued by Hevner and Gregor (2022).

The *overarching process* of designing the reputation mechanism follows the DSR methodology of Peffers et al. (2007), which structures the design process into six iterative steps (Sec. 3.3.4). This research process reflects the cyclical knowledge refinement and matches the design goal and the research question (Baskerville et al., 2015). Methods applied in P1–P9 logically support this DSR research process (Fig. 5). Figure 5 illustrates the successive and method-driven progression of the research process. Semantically, the *develop/build* and *justify/evaluate* cycles can be understood as building and evaluating an artifact and developing and justifying a design theory (Hevner et al., 2004). After building an artifact, the resulting knowledge should be transferred and formalized into a design theory (Hevner et al., 2004; Walls et al., 1992).

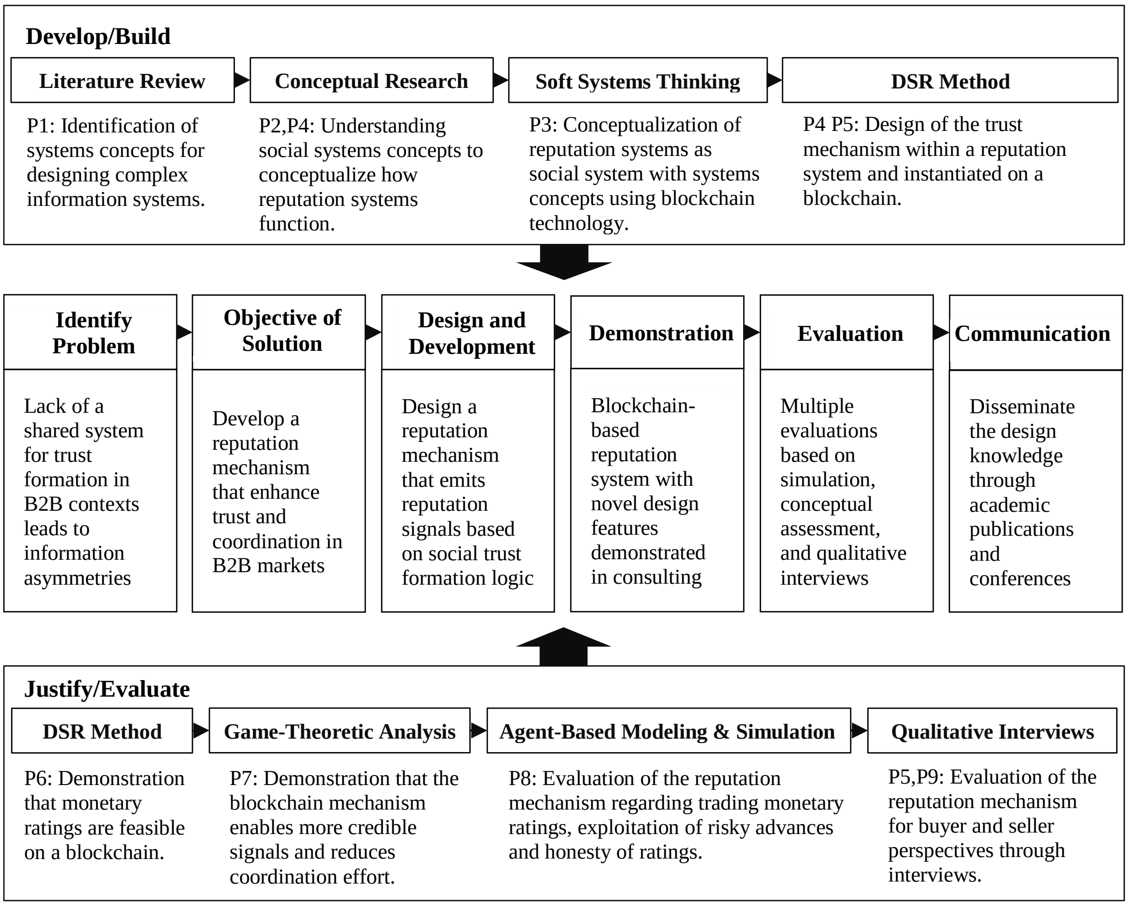

Figure 5: Multi-Method Approach Embedded in DSRM (Peffers et al., 2007)

This dissertation follows the advice to directly describe the *design theory* as the final research outcome (Baskerville et al., 2018; Bruls & Winter, in press). A design theory makes the insights from meta-artifacts transparent, generalizable, and integrable into the knowledge base of IS (Hevner et al., 2004; Iivari, 2015). Basically, a design theory comprises at least meta-requirements, a meta-design, one or more kernel theories, and testable propositions (Walls et al., 2004). The theory development process here follows the structure as proposed by Gregor and Jones (2007a). When the kernel theory is abstract, it often requires complementary explanatory grounding from other theories (W. Kuechler

& Vaishnavi, 2012). Since LST is a highly abstract *super theory*[18] (Luhmann, 1995, pp. 5–6), complementary economic theories suiting the B2B context are consulted. Effective theorizing relies on acknowledging artifacts' context-dependency while articulating the conditions under which a design is expected to work (Hevner et al., 2004; March & Storey, 2008). In this vein, contextualization is a central precondition for meaningful theorizing (Davison & Martinsons, 2016; zur Heiden & Beverungen, 2022).

The theory-driven construction uses abductive reasoning to validate during the design (Tab. 11). It derives generalizable solutions within the theory space of LST from the context of consulting and other B2B areas (P5,P9). Using different validation techniques (cf. Fig. 5), the research outcome is an *invention* (R. Winter & Aier, 2016) (Sec. 6).

Table 11: Classification of the Design Approach (adopted: Smuts et al., 2022)

Dimensions	**Characteristics**						
Meta-Artifact	Construct	Model	Method	Instantiation			
Sub-Artifacts	Construct	Model (no full DSR cylce)	Method	Instantiation			
Research Outcome	Construct	Model	Method	Instantiation	Design Theory		
Construction Mode	Build and Evaluate	Theory-Led Construction					
Validation	Parallel with Design (Abductive Reasoning)	Only at the End					
Procedure	Specialize in General Solutions	Generalize Specific Solutions	Combine Existing Solutions				
Validation Techniques	Experiment	Simulation	Prototype	Active Participation	Formal Proof	Case Study	Empirical Validation
Contribution	Routine Design	Improvement	Exaptation	Invention			

Methods must suit the tasks they aim to solve, which is why multiple methods are especially advisable for complex system designs (Vessey & Glass, 1998). Combined with the pragmatism paradigm and abduction, multi-methods have "led to a 'best answer'" (A. Mitchell, 2018, p. 103). This is in line with the pluralistic tradition in IS to use methods with different pragmatic stances (Mingers, 2001; Venkatesh et al., 2013). Mixed methods enable different but complementary insights into the same research subject (Creswell & Creswell, 2017). Researchers should apply diverse validation techniques to ensure the findings' internal consistency. Triangulation compensates for the limitations of individual methods and enhances the robustness of findings (Jick, 1979; Mingers, 2001). The mixed-methods approach used in this study comprises seven distinct methods.

[18] A *super theory* is an abstract, meta-theory that structures how reality is perceived and explained, see Winthrop-Young (2000).

3.3 Applied Research Methods

3.3.1 Literature Review

Literature reviews form the foundation of scientific work. They enable researchers to collect, structure, analyze, and synthesize what is known in a research field (J. Webster & Watson, 2002). Literature reviews show what is known, expose research gaps, and identify future work trajectories (Okoli & Schabram, 2010). Depending on the goal, literature reviews describe the state-of-the-art, develop research agendas, map concepts, provoke thoughts, resolve conflicts, build unified frameworks, or help theorize (Cooper, 1988; Y. Levy & Ellis, 2006; Paré et al., 2015). IS scholars emphasize that qualitative literature reviews should guide the creation of new knowledge (Schryen, 2015; Schryen et al., 2020). They also highlight the importance of reviewing system capabilities (such as system concepts) to design information systems (Schryen et al., 2017).

Based on Cooper's (1988) taxonomy, the search process can be structured in four steps (vom Brocke et al., 2015) (Tab. 12). Comprehensive systematic reviews often reach their limits in fields where research is highly fragmented (Paré et al., 2015). Inconsistent terms, scattered publications, and different academic traditions make it hard to apply a systematic literature review (Watson, 2015). In these cases, an iterative search is methodologically preferable (Boell & Cecez-Kecmanovic, 2014; vom Brocke et al., 2015). Accordingly, the review should follow the logic of a *narrative review*, which consolidates and synthesizes fragmented knowledge on domain-relevant concepts into a coherent framework (Paré et al., 2015; Schryen et al., 2020; Watson, 2015). To initiate this process, the review anchors on seminal publications selected for their conceptual relevance, which serve as starting points for iterative backward and forward searches (vom Brocke et al., 2015). Backward search traces the origins of a concept by reviewing keywords, references, and authors' prior work. Forward search examines more recent publications that cite the identified sources, uncovering how a concept has evolved (J. Webster & Watson, 2002). Both approaches ensure coverage and allow researchers to identify the most useful topics (Watson, 2015).

Table 12: Definition of the Search Scope (adapted: vom Brocke et al., 2015, p. 214)

Dimensions	Characteristics		
Process	Systematic|Sequential		Iterative
Sources	Citation indexing	Bibliographic database	Publications
Coverage	Comprehensive	Representative	Seminal works
Techniques	Keyword search	Backward search	Forward search

P1 applies an iterative literature review on seminal publications with a forward and backward search (Tab. 12). It develops a framework to guide IS researchers when they want to use systems theory for their study. The review collects, structures, conceptually integrates, and consolidates systems concepts from interdisciplinary sources. Guided by McBride's (2005) notion of epistemological scaffolding, the framework structures and synthesizes foundational systems concepts into a unified abstraction to support the analysis and design of complex information systems (Paré et al., 2015; Schryen, 2015).

3.3.2 Conceptual Research

Conceptual research is a theory-building method to advance systematic reasoning, abstraction, and synthesis of existing knowledge (Jaakkola, 2020). Unlike empirical studies, it does not rely on data collection and constructs. Instead, it contributes to theory by building concepts, resolving their ambiguities, exposing gaps, and refining new theoretical perspectives (Hirschheim, 2008; Jaakkola, 2020; Mora et al., 2008). Concepts are indispensable for IS research (Markus & Saunders, 2007). They form a bundle of meanings that follow logical rules "associated with certain events, objects, or conditions and used for representation, identification, communication, or understanding" (Meredith, 1993, p. 5), whereas constructs are seen as fictional entities abstracted from concepts for measurement (Hassan et al., 2022). That is why "constructs should follow concepts" (Hassan et al., 2022, p. 430), building upon solid conceptual research.

This method is particularly valuable when empirical evidence is scarce, fragmented, or difficult to interpret, e.g., when observable patterns are limited (Yadav, 2010). While often not labeled as such, conceptual research is widely practiced in IS (Mora et al., 2008). It supports the reinterpretation and realignment of empirical findings to enhance theoretical coherence (Yadav, 2010). Since the method can be applied across research paradigms, it can also inform design studies (Mora et al., 2007; Mora et al., 2008). By resolving conceptual uncertainty, conceptual research supports the early-stage considerations of system design (Antunes et al., 2021; Nunamaker et al., 1990). The quality of conceptual research depends on the internal coherence of arguments, consistent conceptual relationships, and the potential to guide future research (Jaakkola, 2020).

The results of this method can be "conceptual description, taxonomies and typologies, and philosophical conceptualization" (Meredith, 1993, p. 8) as well as "conceptual induction, conceptual deduction, and conceptual systems" (Meredith, 1993, p. 9). In particular, *conceptual systems* are characterized by multiple interrelated concepts forming a cohesive system structure. While complex, this result offers substantial explanatory power to understand complex phenomena, e.g., trust-building (Meredith, 1993).

Jaakkola (2020) outlines four core approaches to conducting conceptual research: *theory synthesis*, *theory adaptation*, *typology*, and *model*. Relevant to this study is *theory adaptation*, which readjusts a theoretical concept by informing it with another theoretical lens. Furthermore, a *model* captures the relationship between concepts to map and explain a focal construct, e.g., trust (Jaakkola, 2020). Thus, a *model* selectively abstracts and pragmatically reconstructs aspects of reality to serve explanatory purposes (Stachowiak, 1973).

P2 applies *theory adaptation* with the framework of *conceptual systems* to reinterpret the established *service system* concept through the lens of LST. The objective is to reconceptualize service systems through the lens of systems theory, clarifying the service system conceptualization as autopoietic communication system. This work discovers LST concepts that constitute service systems. Hence, it strengthens the capacity to study and understand systems principles based on LST. P4 constructs a *model* as a framework of *conceptual systems* to theoretically develop the conceptual logic behind the trust mechanism of risky advances, safeguards, control, and other system-related concepts. These findings serve as the theoretical foundation, formulating initial design principles. Thus, conceptual research provides the necessary abstraction.

3.3.3 Soft Systems Thinking

Soft Systems Thinking (SST) is a methodology within the broader systems thinking tradition for ill-structured and ambiguous problems in social contexts (Checkland, 2000). Systems thinking generally relies on holistic, integrative thinking and aims to solve problems that reductionist thinking cannot (Monat & Gannon, 2015). Therefore, it is recognized as a critical skill for solving “the most vexing problem of the 21st century” (Jaradat, 2015, p. 53). It has been highly regarded by IS founders as an effective approach to tackling complex problems in information systems development (Alter, 2004; Jackson, 2001; Mingers & White, 2010b; L. D. Xu, 1995).

SST is a heuristic that follows an iterative reflection process, beginning with constructing conceptual models with multiple stakeholders’ interests and comparing them to identify feasible and systemically desirable changes (Checkland, 2000). Compared to ‘hard’ systems approaches, with defined goals and measurable outcomes, SST adopts an interpretive stance suited for situations where objectives, stakeholders, and system boundaries are dynamic (Mingers & White, 2010b; L. D. Xu, 2000). This flexibility enables researchers to abstract stakeholder roles, identify communications, and map feedback relations (Checkland, 1999; Mingers & White, 2010b).

In the DSR context, SST is useful in the conceptualization phase, where it helps clarify what should be designed and why (Checkland, 2000; L. D. Xu, 1995). SST contributes to the early stage of the design process, helping to refine the artifact before construction (M. Winter et al., 1995). Accordingly, SST is particularly well-suited for conceptualizing blockchain-based reputation systems that span both technical and social layers, where the design challenge lies in bridging information asymmetries and the trust gap (Sec. 2.4.2).

SST encourages researchers to use conceptual modeling to explore system concepts and their impact on system behavior (Checkland & Poulter, 2020). Accordingly, this model helps structure thinking about, e.g., the system elements and relations, communication, observation, and selection boundaries (Luhmann, 1995). SST thereby corresponds with conceptual research, particularly with building *conceptual systems*, as explicated in Meredith (1993) (Sec. 3.3.2). In this way, SST provides a *conceptual system* that explains complex, under-theorized domains (Matook & Brown, 2017; Meredith, 1993).

P3 employs SST to conceptualize the basic structure of the blockchain-based reputation system with selected system concepts on a unified layer (social and technical). It helps identify and formulate relevant system concepts and system-level requirements and conceptualizes the relationships between users, trust signals, and the system design logic.

3.3.4 Design Science Research Method

DSR is the primary methodological approach for developing the reputation mechanism and associated artifacts (Sec. 3.1). Various DSR methodologies (DSRMs) exist for this purpose (J. R. Venable et al., 2017). A DSRM supports abductive reasoning, fostering the rigor and reliability of research outcomes (Cronholm et al., 2023). The DSRM of Peffers et al. (2007) provides a structured, neutral, and widely accepted process model that supports abductive, mixed-method approaches (Sec. 3.2). This DSRM belongs to one of five DSR genres (Peffers et al., 2018), each with its own standards, evaluation logic, and contribution focus (Deng & Ji, 2018).

The DSRM of Peffers et al. (2007) follows an iterative six-step procedure, which can be re-entered (Fig. 6). These iterations allow new insights to be integrated during the research process. The model supports multiple entry points, reflecting the iterative nature of the design process (Goldkuhl, 2012; Peffers et al., 2007).

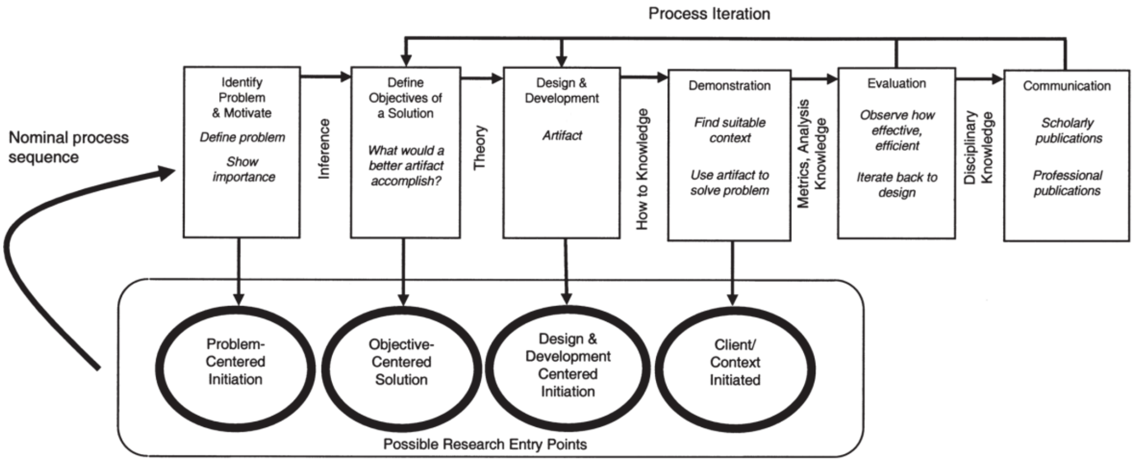

Figure 6: DSRM Process Model (Peffers et al., 2007, p. 54)

The application of DSR hinges on the rigorous evaluation of artifacts and the derivation of generalizable design knowledge (Hevner et al., 2004). The evaluation is not only a validation but an integral part of knowledge generation, which should also point to artifact weaknesses (Baskerville et al., 2018). Evaluation strategies should be carefully selected based on the artifact type, maturity level, and intended contribution (Sonnenberg & vom Brocke, 2012; J. Venable et al., 2012, 2016). In this vein, DSR guidelines should be used to ensure both scientific rigor and practical utility (Tab. 13). Furthermore, publication guidance can be found in Baskerville et al. (2018).

Table 13: Guidelines for the Design Process (adapted: Hevner et al., 2004)

Guidelines	Description
Artifact	DSR must produce a viable artifact as a construct, a model, a method, or an instantiation.
Problem Relevance	DSR should develop technology-based solutions to important and relevant business problems.
Design Evaluation	A designed artifact’s utility, quality, and efficacy must be rigorously demonstrated via well-executed evaluation methods.
Research Contributions	Effective DSR must provide clear and verifiable contributions for artifacts, design foundations, and/or methodologies.
Research Rigor	DSR relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Design as a Search Process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Communication of Research	DSR must be presented effectively both to technology-oriented as well as management-oriented audiences.

The embedded studies follow a cumulative DSR approach and contribute to the development and evaluation of the meta-artifact. P4 lays the conceptual foundation for the DSR process by identifying design challenges, formulating meta-requirements (Walls et al., 1992), and proposing initial design principles for the reputation mechanism (Gregor et al., 2020; Heinrich & Schwabe, 2014). Based on a conceptualized *model* of the reputation mechanism in P4 (cf. Sec. 3.3.3), P5 follows a full DSRM cycle (Peffers et al., 2007). The study contextualizes the design in the consulting domain and develops a functional instantiation. P6 also uses the DSRM by Peffers et al. (2007) and designs a method for the reputation mechanism where blockchain-secured ratings can be traded.[19] P4-6 contribute to the theorizing process by refining the meta-artifact components.

3.3.5 Game-Theoretic Analysis

A game-theoretic analysis is a formal method for examining strategic interactions between rational agents. It provides a deductive logic of how actors behave when their decisions depend on the expected behavior of others (Myerson, 1984). In IS, game theory is rarely applied, but it offers valuable insights into coordination, incentives, trust, and reputation mechanisms, e.g., (Ba et al., 2012; Elitzur & Wensley, 1997).

Game theory allows researchers to focus on the strategic logic of agents' behavior and goals (Maskin, 2008). It models utility-maximizing agents and equilibrium outcomes under strict rational assumptions (Bergemann & Morris, 2005; Myerson, 1984). Hence, it provides a rigorous, logical view of possible system outcomes and conditions under which a proposed mechanism is expected to be effective (Schelling, 1958).

The strength of game-theoretic analysis is its ability to identify how changed game settings affect agents' behavior and the associated system. Specifically, it enables an understanding of how information availability, reputation, or incentive structures influence cooperation, defection, or strategic manipulation (Ba et al., 2012; Myerson, 1984). Its contribution to IS research lies in offering type IV theory *for explanation and predictio*n (Gregor, 2006), which can be used to justify design decisions (Walls et al., 1992). Thus, the analysis can explore the effect of a novel mechanism before empirical evaluation (Sonnenberg & vom Brocke, 2012; J. Venable et al., 2016).

P7 applies game-theoretical analysis to model and compare strategic behaviors in sending trustworthy signals with and without a blockchain. The model is formalized as a static signaling game under asymmetric information. The results demonstrate that blockchain-secured ratings can shift strategic behavior towards truth-telling when combined with pre-committed monetary ratings.

3.3.6 Agent-Based Modeling and Simulation

ABMS is a simulation method to model and simulate agents' behavior in computational environments to explore how system properties arise from micro-level decisions (Macal

[19] Since the method is based on mathematical primitives, no formal evaluation process is necessary, see for instance: Baskerville et al. (2015); Cleven et al. (2009); J. Venable et al. (2016).

& North, 2005). In IS research, simulations are primarily used to test design assumptions and explore phenomena that are difficult to capture otherwise (Beese et al., 2019).

ABMS is particularly relevant for systems with evolving states where agents interact under uncertainty and bounded rationality. Unlike game-theoretical models (Sec. 3.3.5), ABMS explicitly allows agents to differ in goals and behaviors, and strategies. It enables the study of feedback loops, lock-in effects, and other emergent behavior (Macal & North, 2005). It is useful for testing whether a mechanism leads to stable behavioral patterns under non-equilibrium conditions, considering agents' adaptive behavior (Epstein, 1999).

A simulation is an *artificial*, *formative,* and typically *ex-ante* evaluation method in the DSR context (J. Venable et al., 2016). Thus, simulation contributes to rigor by testing if a setting operates as intended under controlled conditions (Beese et al., 2019; J. P. Davis et al., 2007). Its formative character is reflected in generating early insight that can reveal weaknesses within the design. This iterative refinement increases the meta-artifact quality and enables researchers to adjust mechanisms before real-world implementation (J. Venable et al., 2016). Simulation results depend on model structure, parameterization, and boundary conditions (Beese et al., 2019).

P8 implements the ABMS method to evaluate the reputation mechanism for repeated interactions. The approach follows the design guidance of Beese et al. (2019) and Rand and Rust (2011) and uses metrics for reputation systems as proposed by Schlosser et al. (2004). The results show that monetary ratings lead to market segmentation, where high-quality sellers dominate long-term interactions, and counter-ratings from sellers help deter buyers' misbehavior. The findings support the incentive logic from P4–P6 and extend the analysis in P7.

3.3.7 Qualitative Interviews

Qualitative interviews are an interpretive method for understanding how individuals perceive a specific subject of interest in social settings. IS research regularly uses this method to investigate perceptions, expectations, and behavioral rationales (B. Kaplan & Maxwell, 2005). It often reflects practicality and the user's perspective.

The qualitative research methodology supports inductive category formation and open interpretation, allowing knowledge extraction from interviews (Schultze & Avital, 2011). One of the most frequently used qualitative techniques is *semi-structured interviews*, which elicit rich insights and enable thematic comparison among participants (Myers & Newman, 2007). Qualitative data can be analyzed through various inductive coding techniques. *Open coding* identifies relevant categories for inductive category formation, *while axial coding* helps structure relationships between existing categories (Corbin & Strauss, 1990). *Qualitative content analysis* combines deductive and inductive category development within the coding scheme, making it suitable for structured data collection (Mayring, 2000). Guidelines and pitfalls for conducting interviews can be found in Myers and Newman (2007) and Sarker et al. (2013).

Qualitative research supports *formative or summative*, *artificial*, *ex-ante*, or *ex-post* evaluation in DSR (J. Venable et al., 2016). Unlike simulation and game-theoretic models, which rely on pure rational reasoning, qualitative interviews capture how real users interpret design features and anticipate use scenarios (Schultze & Avital, 2011). They offer a perspective grounded in domain-specific understanding (B. Kaplan & Maxwell, 2005). Accordingly, qualitative methods are particularly suited for exploring information systems design at an early stage (Beck et al., 2013; J. Venable et al., 2016). These methods refine the design by uncovering conditions for use, acceptance factors, and perceived value (B. Kaplan & Maxwell, 2005).

P5 and P9 apply *semi-structured interviews* to *formatively* evaluate the artifact from the seller's and buyer's perspectives. P5 applies *open coding*, organizing emergent topics into higher-level categories related to trust dimensions from the seller's side. Various facets of trust building are examined, and the reputation mechanism is detailed. P9 applies a *qualitative content analysis* to investigate the *perceived value* and *perceived costs* of using the system from the buyer's side.

4 Research Results: A Nascent Design Theory

4.1 Purpose and Scope

Following the theory development structure of Gregor and Jones (2007b), this section outlines the purpose and scope of a *design theory*, specifies its meta-requirements (Walls et al., 1992), and delineates its boundary conditions (Dubin, 1969).

The theory's purpose is to inform the design of a new information system class that addresses information asymmetry and fosters social trust. The class is primarily intended for settings where companies are unknown to each other, relationships are short-term, decision-making faces high uncertainty, and weak institutional capacities exist to build trust (Sec. 2.3.1). While current reputation systems suffer from limitations (Sec. 2.2.3), alternative traditional trust surrogates are not sufficient (Sec. 2.3.2). Business reputation systems are missing (Sec. 2.3.4). This situation indicates a knowledge gap for research on how business reputation systems can be designed. Accordingly, the design theory applies to a *reputation (eco)system*[20] "that collects, and distributes feedback and helps to determine the feedback's trustworthiness, whereby entities can observe and communicate selectively about each other's signals" (P6, p. 6). In this system class, rating information can be traded and selectively disclosed, thereby establishing complex interrelations between different ratings from different entities (P6).

Table 13: Meta-Requirements of the Design Theory (based on P4)

Meta-Requirements	Description
1) Business Relationships	The system should reflect the actual socioeconomic relationships and commitments between parties involved in the B2B exchange.
2) Trust Formation	The system should support trust-building between unknown actors by enacting the trust mechanism using the system concepts of observation, selection, communication, risky advance, and safeguards.
3) Sybil Attack Robustness	The system should be robust against manipulation, even in adversarial settings where actors collude, bribe, or create multiple identities to game the system.
4) Systemic Fairness	The system should incentivize honest and non-reciprocal rating behavior, ensuring participants cannot systematically benefit from biased ratings.
5) Performance Differentiation	The system should provide credible, meaningful signals about performance that support decisions in short-term business settings with high uncertainty.
6) Control over Disclosed Information	The system should enable parties to control which information is forwarded, shared, or withheld, ensuring context-sensitive information sharing in competitive environments.
7) Decentralized Infrastructure	The system should be based on a distributed system, avoiding a single powerful gatekeeper that can influence ratings.

[20] Following Hein et al. (2020) and Yoo et al. (2010), the suffix 'eco' refers to a system that co-creates value by establishing complex relationships among entities. This complexity of relations within the system contributes to its overall health (P1).

Based on limitations (Sec. 2.2.3) and adoption barriers (Sec. 2.3.4), meta-requirements are formulated (Tab. 13). These meta-requirements (MR) define the scope of the system class's essential requirements and guide design decisions in this theory (Gregor & Jones, 2007a). The added value of this theorized system class is limited by deliberate non-participation (e.g., due to high competition), low network effects, and difficulties in standardizing the rated subject. The theory is not primarily intended for settings characterized by stable, long-term relationships where institutional trust mechanisms are sufficient (Pavlou, 2002), even though this system class may still add value (P5,P9).

4.2 Theory Units for Theory Development

In line with Dubin's (1969) theory-building method, this section introduces *theory units* of the design theory. The units can be abstract *meta-theoretical concepts* that construct the phenomena of interest (here: trust and reputation) and serve as the meta-design within the theory (Gregor & Jones, 2007a; Walls et al., 1992). The system concepts act as theory units, including (*observation, selection, communication*) and concepts for trust building *(risky advance, safeguards)* (Sec. 2.1.2) (Luhmann, 1995, 2017) (P2) (Tab. 14).

Table 14: Selected[21] Theory Units of the Design Theory

Theory Units	Description
Observation	Distinguishes relevant from irrelevant information (e.g., trust signals).
Selection:	Filters and prioritizes observed information to reduce social complexity.
Communication	Connects both system operations, enabling the interpretation of trust signals.
Risky Advance	Initiates trust through vulnerability without guaranteed reciprocation.
Safeguards	Fosters trust by integrating latent risk-mitigating mechanisms into the system.

Fig. 7 illustrates how trust emerges through the process of communication from an LST lens (P3).[22] Trust evolves under double contingency, where each side must concede a risk while the outcome is uncertain (Luhmann, 2017, pp. 31–32). Thus, one side must take the first step and make itself vulnerable, not expecting to be exploited (Luhmann, 2017, pp. 47–48). The trustee (α) selects whom to trust and to what degree, based on prior observations (P4). The trustor (β) then observes this utterance as a trust signal and selects how to respond in the communication process (P2,P3). Trust can develop through an alternating process of mutual observation when vulnerabilities are not disappointed (Luhmann, 2017, p. 87). Trust thereby relies on safeguards, that is, explicit, organized, but latent control structures (e.g., institutions, technology) (Luhmann, 1990, 2017,

[21] While further system-theoretical concepts can be applied (P1;P2;P3), these three units are sufficient to model the trust mechanism.

[22] According to LST (Sec. 2.1.2), human beings are not constituents of social systems. While social systems cannot exist without human consciousness, they are constituted solely by communication, see Luhmann (1995, p. 59). For the sake of understanding—particularly in exploring the emergence of trust as discussed in an earlier work by Luhmann (2017)—the respective roles of these systems of consciousness are referred to as *trustor* and *trustee.*

pp. 51–64). Reputation can be understood as second-order trust (Jøsang et al., 2007), since reputation can be "formed by seeing how others trust" (Luhmann, 2017, p. 48). The *prospective trustor (γ)* can select whether to trust one or both communicating sides.

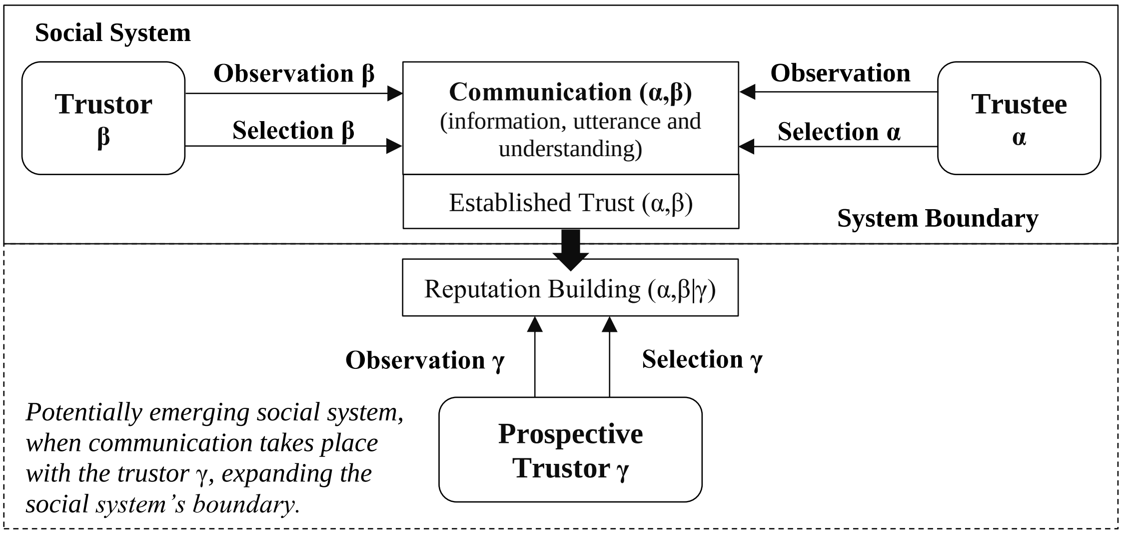

Figure 7: Systems Conceptualizations of Trust and Reputation Formation

Furthermore, a mandatory theory component is a set of *system outcomes* (Gregor & Jones, 2007a). Schematically, four system outcomes define the conditions under which a *prospective trustor (γ)* may trust (Fig. 8). The vertical axis represents the system's ability to reduce complexity through selection; the horizontal axis its ability to distinguish information through observation. *Uncertainty* describes the system outcomes, in which the system neither supports distinctions nor applies selections for a *prospective buyer γ*; trust cannot emerge. *Structural Blindness* refers to selection processes without sufficient observation into the system's environment, leading to misaligned ratings and distorted trust signals. *Signal Ambiguity* captures system-internal observation without sufficient selection logic, which results in ambiguous interpretations. *Trust-Building* denotes the desired system outcome in which observation and selection both support trust formation.

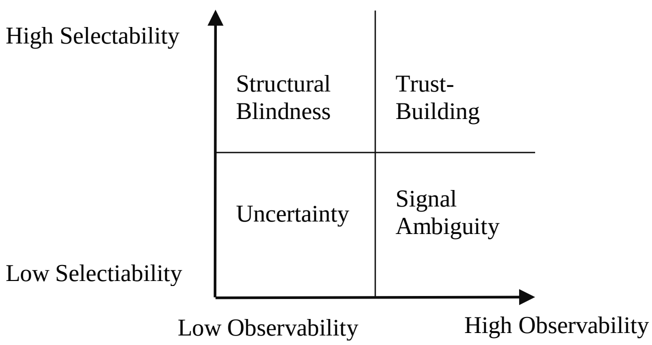

Figure 8: System Outcomes from a Prospective Trustor Perspective

4.3 Principles of Form and Function

Following Gregor and Jones (2007b) principles of form and function need to be described to characterize the system. The *form* refers to a system's structural composition, i.e., the operationalization of the *theory units* (Sec. 4.2—Tab. 14). *Function* explains how these forms interact within the system to achieve the system outcome (Rietz et al., 2019; Townsend et al., 2011). Each form is a derivation based on how a social system builds trust (Luhmann, 1995, 2017) (Fig. 9). The exact mapping of the systems concepts to DP1-6 is depicted in Appendix A, reflecting multiple trust dimensions (P5).

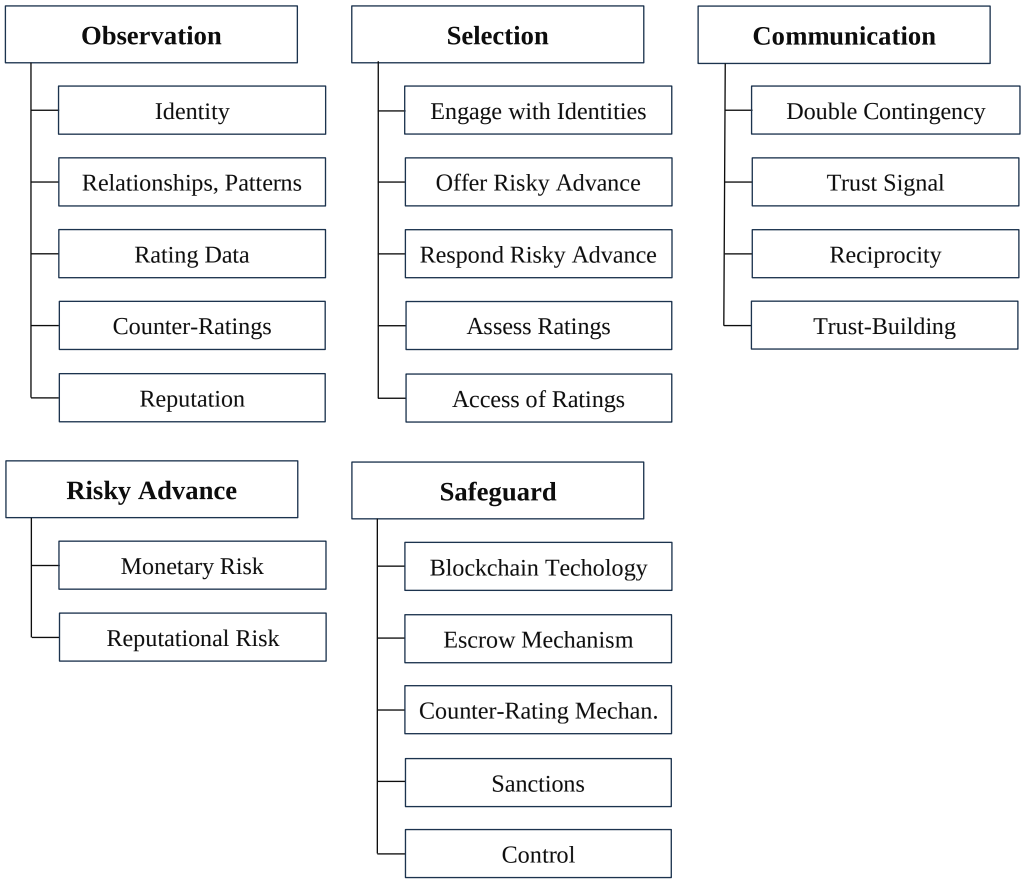

Figure 9: Operationalization of the Theory Units into Forms

These system operations can take different forms depending on the roles of trustee and trustor in respective situations. Buyer, seller, and prospective buyer repeatedly perform system operations (observation, selection, and communication), co-construct trust by oscillating risky advances and the reassurance and recourse offered by protective safeguards (M. S. Granovetter, 1973; Luhmann, 1988; S. P. Shapiro, 1987).

Based on the meta requirements, design principles translate operationalized *theory units (form)* into intended system behavior *(function)* (Tab. 15). The meta-artifact consists of six design principles (DP1–DP6), which have been derived from a combination of system-theoretical reasoning (Luhmann, 1990, 1995) and economic coordination logic.

The subsequent design principles (DP1–DP6) show *form* and *function* that mimic the trust mechanism in social systems naturally (Gambetta, 1988; Hardin, 2002). A more detailed version of Tab. 15 is provided in Appendix B, following Gregor et al. (2020).

Table 15: Overview of Design Principles According to Form and Function

Design Principles	Form	Function
DP1: Risky Advance (MR1,MR2,MR5)	Sellers offer a price discount and commit to being rated.	Send ex-ante trust signals while relying on safeguards and buyer reciprocation.
DP2: Voluntary Monetary Rating (MR2,MR3,MR4,MR5)	Buyers voluntarily issue (costly) signals in the form of monetary ratings.	Promote authenticity of trust signaling of both seller *and* buyers, encouraging voluntary, non-coerced ratings.
DP3: Counter-Rating (MR2,MR4)	The system detects repeated non-payment and allows sellers to issue counter-ratings.	Prevent strategic buyer exploitation, incentivize honest reciprocation, and safeguard reputation building.
DP4: Selective Signal Observability (MR2,MR6)	Buyers control whether, when, and to whom their ratings are disclosed or sold.	Protect sensitive information through operational-closed and selective communication, and foster trust-building without enforced transparency.
DP5: Trust Assessment (MR2,MR3)	Potential buyers can understand signals based on different indicators available to them.	Facilitate selective ratings assessment based on ratings associated identities regarding relational, behavioral, economic, and time indicators.
DP6: Decentralized Storage (MR1,MR2,MR5,MR7)	All rating commitments and executed ratings are stored and exchanged on a blockchain.	Ensure tamper-proof record-keeping, credible rating origin, and institutional trust safeguarded without an influencing platform intermediary.

Risky Advance (DP1): *To initiate trust under uncertainty, the system should enable sellers to issue a risky advance as a voluntary, pre-contractual commitment.* Trust is initiated through a risky advance in the form of a monetary rating as a share of the basic payment (Sec. 4.2—Fig. 7). Sellers selectively offer a price discount prior to the transaction, exposing themselves to the risk of non-compensation and reputation loss (Lingfang & Xiao, 2014). This action signals a seller's confidence in the offered performance and invites the buyer to reciprocate by releasing the withheld monetary compensation as offered by the seller (G. E. Bolton et al., 2013). The action constitutes the first communicative act, reflecting Luhmann's (2017) view that trust requires a risky advance (P4). The rating is held in escrow on a smart contract and can be released by the buyer upon satisfactory performance (P3,P5).

Voluntary Monetary Rating (DP2): *To ensure the trustworthiness of ratings, the system should allow buyers to issue monetary ratings after performance delivery voluntarily.* The buyer retains full control over whether to compensate sellers' risky advances. If the buyer releases a partial payment as a rating, it is recorded on the blockchain as an economic trust signal (Jurca & Faltings, 2003). The freedom to withhold payment is essential for the authenticity of the ratings, aligning with the notion that trust cannot be enforced (Gambetta, 1988; Luhmann, 2017). Buyers' rating decisions show four potential outcomes regarding seller performance (Fig. 10). *Fair Positive Ratings* and *Fair Negative*

Ratings are desirable outcomes. The other two should be avoided. *Exploitative behavior*, where the buyer withholds payments despite high performance, is counteracted through the safeguard described in DP3. *Lenient behavior,* where poor performance is rated positively, is unlikely to occur assuming rational behavior (G. E. Bolton et al., 2013) since buyers would pay more for poor performance (P5).

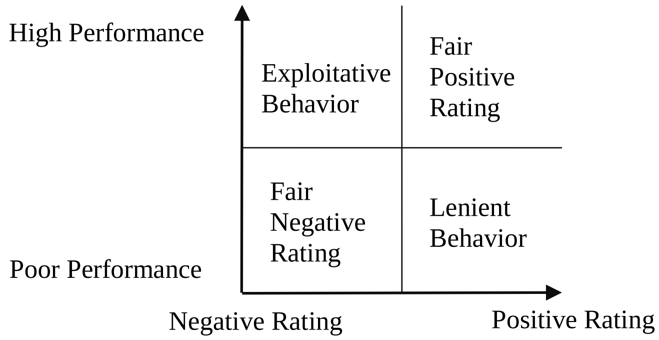

Figure 10: Buyers' Behavior Based on Performance and Rating Decision

Counter-Rating (DP3): *To protect sellers from opportunistic behavior, the system should enable counter-ratings when buyers repeatedly exploit sellers' risky advances*. The freedom to withhold payment creates potentially exploitative behavior and repeated refusal of a buyer to compensate a seller's risky advance. The affected seller *can* trigger a negative counter-rating (P4).[23] Once a defined threshold is exceeded (e.g., more than 10 % share of non-compensation), the buyer is flagged (for the time being) as potentially exploitative in the system, visible to other sellers (P5). As a result, other sellers are less inclined to offer a risky advance to this buyer, diminishing the buyer's potential benefits from system participation, such as receiving quality signals or saving costs by giving negative ratings (P4).[24] Counter-ratings reduce buyers' strategic misbehavior (P8).

Selective Signal Observability (DP4): *To protect strategic interests, the system should allow users to control their ratings' observability and the selective disclosure*. Rating information must be protected in competitive settings (Sec. 2.3.4). By using cryptographic primitives, buyers should retain full control to decide whether, when, and to whom their ratings are disclosed (P6). This mechanism reflects a deliberate balance between transparency and strategic discretion, ensuring signals are selectively observable but not universally exposed. When disclosure is withheld, the ratings' economic value (P9) enables the trading of rating information for profit (P6,P7).

Trust Assessment (DP5): *To enable trust formation, the system should provide observable ratings enriched with contextual, relational, and economic metadata***.** Analyzing buyer-seller relationships helps identify more trustworthy interaction patterns

[23] According to Bottom et al. (2002), when the penalty is perceived as justified, the seller may accept the rating as a form of financial compensation and refrain from retaliating with a negative counter-rating.
[24] In this sense, the buyer might also build a 'reputation' as a rater, who stays below the threshold.

(Ekstrom et al., 2005; Noorian & Ulieru, 2010), as trust is based on selective observation within complex social communication structures (P3). Second, buyers can select and assess ratings according to their source credibility and the observed identities involved (cf. Sec. 4.6). This implies comparing ratings from different raters (P5). Third, the monetary amount of 'risk-taking' amplifies the signal strength of sellers (Spence, 1973). Moreover, the ratio between basic and performance-related payments (Sec. 4.2—Tab.7) supports signal calibration by quantifying risk. In addition, semantic elements such as review text, counter-rating responses, and other metadata improve how ratings are interpreted (Mudambi & Schuff, 2010) (P5).

Reliable Storage (DP6): *To ensure tamper-resistance and verifiability, the system should store all rating commitments and outcomes on a decentralized blockchain network.* A *permissioned blockchain* anchors the trust-building logic with pseudonymous identities (P4) (Sec. 2.4.1). This safeguard ensures that, as long as this blockchain type is designed tamper-resistant, no party can manipulate, delete, or disavow ratings with smart contracts (P5). Using verifiable credentials in a blockchain enables costly and verifiable trust signals (Sec. 2.4.2), which support incentive-compatible equilibria by aligning the payoffs with truthful reporting (P7). Also, it prevents Sybil Attacks (Sec. 2.2.3).

4.4 Artifact Mutability

In line with Gregor and Jones (2007b), *artifact mutability* refers to how an artifact can evolve in a real-world setting based on the logic of the theory. Drawing on Simon's (1969) notion of evolving artifacts and O'Hear's (1989) idea of evolutionary trajectories (cf. Gregor & Jones, 2007a), mutability can be illustrated through refinements, which are understood as "suggestions for improving […] further work" (Gregor & Jones, 2007a, p. 324). Drawing on abductive reasoning (Sec. 3.2), mutability provides a lens through which artifact states can be theorized before implementation (Heinrich & Schwabe, 2014).

The trajectories express design tensions, each addressed through refinements, illustrating how a reputation system may unfold (Tab. 16). These refinements are no flaws but a logical design extrapolation of the design theory logic (B. Kuechler & Vaishnavi, 2008; W. Kuechler & Vaishnavi, 2012). Refinements align with the contextual reliability of the design that acknowledges the situated nature of designs (Storey et al., 2025). These refinements can extend or generate new DPs in further validation cycles (Gregor et al., 2020).

Table 16: Trajectories for Refinements Arising from Design Tensions

Trajectory	Design Tension	Refinements
T1 Monetary Commitment (DP1,DP2)	Upfront monetary commitments may deter cost-sensitive sellers from participating.	Allow non-monetary risky advances that rely (solely) on reputational exposure (Fig. 9). Provide bonus payments from buyers aligned with their interest to sell ratings (P4,P5).
T2 Economic Signaling (DP1,DP2)	Signal strength and cost are not strictly coupled.	Introduce differentiated rating amounts that reflect sellers' confidence|uncertainty (P4).
T3 Rating Generation (DP2,DP4)	Buyers are more interested in receiving (buying) ratings than generating them (P9).	Implement an '*access ratings for submitting ratings logic*'. Introduce tokens, surcharges, or throttling when no helpful ratings are generated.[25]
T4 Threshold Mechanism (DP3,DP6)	A static threshold may not reflect sellers' performance and buyers' incentivized rating distribution.	Implement adaptive thresholds based on counting overall rating outcomes.[26] Employ a governance mechanism to manage the threshold updates.[27] Combine with T3.
T5 Product Complexity (DP5)	Multi-dimensional subjects may be difficult to rate.	Decompose rating subjects into (simple) subcomponents and allow domain-specific aggregation logic (P5). Rate condition-based or within time frames. Combine with T2.
T6 Rating Disclosure (DP5)	Free-text reviews may leak sensitive information.	Implement staged disclosure of the rating.[28] Enable cryptographic redaction templates or role-based access for selective disclosure.
T7 Marketplace for Selling Ratings (DP5, DP6)	Buyers may struggle to assess the utility of a rating before purchase.	Introduce a marketplace with recommendation algorithms and rating bundles (P5). Employ TCRs to improve prospective buyers' selections of ratings.[29]
T8 Dispute Resolution (DP5)	The systems lack a central governance layer to resolve disputes.	Add an instance with governance rules to resolve conflicts (P5).[30] Implement a superordinate governance layer to legitimize data based on the blockchain's raw data.[31]
T9 Ownership of Ratings (DP4)	Ambiguity about who owns and may trade a rating (P6).	Define ownership and usage rights of generated ratings upon rating commitment.[32]

[25] Sold ratings are considered helpful by default unless disputed by the buyer within a fixed period.

[26] Rating outcomes (negative/positive) can be analyzed in a confidentiality-preserving manner using homomorphic encryption and protocol rules, e.g., H. Wu et al. (2024). The visibility of the counter-rating threshold should remain hidden until a sufficient number of ratings with non-trivial amounts have been collected (P6). Governance must determine whether past counter-ratings are revealed or not based on updates of the adaptive thresholds.

[27] Depending on the threshold level, it may be reasonable to enforce a payout even for negative ratings—where neither party receives the funds—in order to further reduce opportunistic rating behavior of buyers.

[28] Raters may encrypt rating contents with different keys and selectively grant access, allowing targeted disclosure to specific recipients to maximize profits. Offering should be content-based, not identity-based.

[29] A potential buyer can publicly solicit a recommendation for a specific product or service using TCRs. While TCRs are prone to capital concentration effects as noted by Asgaonkar and Krishnamachari (2018), these can be mitigated through capped stake amounts per entity and verified, thus independent, curators.

[30] Approaches to resolve disputes rooted in blockchain immutability are suggested by Allen et al. (2019).

[31] One may envision a superordinate institutional layer that *qualifies* data points recorded on a blockchain. This layer could serve as the basis for arbitration, compliance audits, or for legitimate dispute resolution protocols. Anchored to an institutional mechanism, e.g., legitimated vs. not legitimated, can complement technically immutable records with legitimization through one or more trustworthy instances and enable multi-level trust-assessing institutions. Technically, this can be achieved by excluding undesired entries from index structures, e.g., using hash-tables, see, for instance, Hillmann et al. (2020).

[32] Ratings sold by a seller may be perceived only as credible when accompanied by different ratings from different sources (P6). Furthermore, the transfer of the monetary rating amount can be stalled, enabling the seller to submit proof at a later time, thereby strengthening a buyer's incentive to distribute ratings.

4.5 Testable Propositions

Testable propositions (TP) explicate the theory-based causal design logic (Gregor & Jones, 2007a). They serve three purposes: 1) articulating design-induced cause-and-effect assumptions (Walls et al., 1992), 2) contributing to mid-range theorizing, 3) establishing a basis for theory refinement and empirical evaluation (W. Kuechler & Vaishnavi, 2012).

Table 17: Testable Propositions on the System's Underlying Core Mechanisms

Testable Proposition	Evidential Grounding[33]
TP1 (DP1): *If the system enables a seller to issue a risky advance prior to a contract, prospective buyers' perception of the seller's trustworthiness increases.*	● (P3,P4), ◆ (P9)
TP2 (DP2): *If buyers issue voluntary monetary ratings, then the perceived trustworthiness of ratings increases for prospective buyers.*	● (P3,P4), ◆ (P5)
TP3 (DP2): *If buyers are offered voluntary compensation (rating payment) for sellers' risky advances, then the likelihood increases that these buyers submit negative ratings to receive the escrowed rating amount unless counter-incentives (as outlined in DP3) effectively deter such behavior.*	● (P4), ■ (P8), ◆ (P5)
TP4 (DP3): *If the system defines a threshold beyond which a seller's negative ratings become visible to other sellers, then buyers refrain from submitting negative ratings that would exceed this threshold.*	● (P1,P4), ◆ (P9)
TP5 (DP3): *If a buyer's negative ratings of sellers are observable for other sellers, then the likelihood that other sellers avoid engaging this buyer increases.*	● (P4), ◆ (P5)
TP6 (DP4): *If buyers can selectively control the observability of their ratings, then the incentive to forward ratings increases.*	● (P4), ◆ (P5)
TP7 (DP4): *If buyers profit from selling ratings, then the incentive to forward ratings increases.*	● (P3,P4), ■ (P7, P8)
TP8 (DP5): *If the system provides contextual, relational, and economic metadata, then the perceived trustworthiness of the rating signal increases for buyers.*	● (P1,P3), ◆ (P5)
TP9 (DP6): *If monetary ratings are stored on a blockchain, then a buyer's rational behavior is more likely to converge toward honest rating reporting.*	■ (P7), ◆ (P5)
TP10 (DP6): *If rating commitments and outcomes are stored on a blockchain, then the trustworthiness of the rating signal increases.*	● (P4), ◆ (P5)
TP11 (general): *If a seller offers good quality, then the profits of these sellers increase over time.*	● (P4,P6), ■ (P8)
TP12 (general): *If a buyer has access to ratings by purchasing them,* then these buyers' *decision-making payoffs increase.*	■ (P7,P8)

Each proposition is primarily derived from design principles. The propositions bridge the design's internal logic with the explanatory and justificatory knowledge base (Arazy et al., 2010; B. Kuechler & Vaishnavi, 2008). Each TP is supported by at least one model-based or empirical piece of evidence, going beyond sole conceptual design logic (see footnote 33). The propositions build the foundation for future empirical testing (Gregor & Hevner, 2013; Walls et al., 1992).

[33] Evidential grounding is based on the type of evidence supporting each proposition: ● conceptual design logic (design rationale), ■ model-based evidence (instantiation, simulation, analytical modeling), ◆ empirical support (e.g., interviews, experiments). Evidential grounding is not limited to empirical validation but also includes conceptual and logic-based reasoning, see Gregor and Jones (2007b); Iivari (2007); Walls et al. (1992).

4.6 Justificatory Knowledge

Justificatory knowledge explains why a theory is expected to function by providing scientific support for the design. It is seen as the most important part of a design theory (Gregor & Jones, 2007a). Therefore, this section adopts[34] the multi-grounding approach to design theories following Goldkuhl (2004), which includes conceptual, value, explanatory, and empirical grounding to justify the knowledge (Fig. 11).

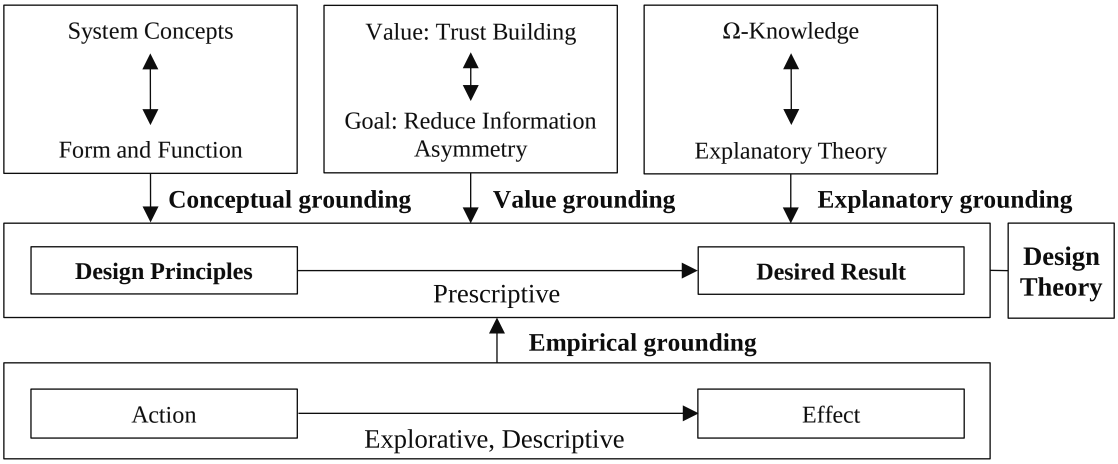

Figure 11: Grounding of the Design Theory (based on Goldkuhl, 2004)

LST provides the conceptual grounding for the artifact, framing it within a communication *structure* (P2). LST conceptualizes trust as a decentralized mechanism coordinated via observation, selection, and communication, which can be transferred to information systems (P2,P3). LST theory units inform the artifact's meta-design (Sec. 4.2), and design principles (Sec. 4.3). The system operationalizes risky advances through monetary ratings and incorporates safeguards like counter-ratings or visibility rules via communication, observation, and selection (P2,P3).

The alignment with value grounding ensures the artifact meets normative goals (Goldkuhl, 2004). The design is value-grounded in institutional trust dimensions, addressing normative expectations in professional B2B interactions, as shown in P5. The artifact incorporates 23 distinct institutional trust-supporting and distrust-reducing factors, mapped on six theoretical dimensions[35] following Utz et al. (2023) (P5). These dimensions fully integrate within the design and demonstrate a comprehensive trust logic.

[34] To maintain alignment with the design theory structure proposed by Gregor and Jones (2007) and avoid redundancy, only selected grounding processes are elaborated here. For the full spectrum of grounding processes, see Goldkuhl (2004, p. 67).
[35] The dimensions include cognitive-, knowledge-, and calculation-based trust, and skepticism-, control-, and vigilance-based distrust (P5).

Explanatory grounding completes abstract kernel theory with a set of *design-relevant explanatory predictive theories* (W. Kuechler & Vaishnavi, 2012), grounded on theory-based *Ω-knowledge* (Sec. 2.2.2—Tab. 3). These selected theories describe the anticipated functional impacts and are, to some extent, detached from P1–P9.

Signaling Theory explains that actors can mitigate information asymmetries by sending signals that are both costly and observable (Spence, 1973). DP1 embodies this principle. Risky advances make it unattractive for low-quality sellers to mimic high-quality behavior—an effect referred to as *signal fit* (Connelly et al., 2011; Kirmani & Rao, 2000). DP2 explicates a genuine risk of being rated negatively, which introduces a utility-based risk calculus (cf. Rational Choice Theory). The cost of potentially foregone revenue renders the signal credible (Spence, 1973). DP4 reinforces this signal fit by ensuring its salience is quantifiable and observable (Connelly et al., 2011). Signaling Theory predicts that such mechanisms differentiate trustworthy from untrustworthy actors—provided the signaling cost structure supports a separating equilibrium (G. E. Bolton et al., 2008; Kirmani & Rao, 2000). P7 formally validates this requirement, demonstrating that cost-dependent signaling can yield separating equilibria *when* using a blockchain. These effects occur irrespective of a buyer's incentive structure, indicating that the discriminatory power stems from the seller signal itself (P7).

Rational Choice Theory posits that actors seek to maximize expected utility by comparing anticipated benefits and costs (Coleman, 1990). DP1 ensures only those sellers who expect (long-term) utility offer risky advances (e.g., acquiring new buyers) to outweigh their potential costs (e.g., reputation loss) (Ba & Pavlou, 2002).[36] DP2 counterbalances leniency since rational raters refrain from giving excessive positive ratings due to the economic value of ratings. In addition, DP3 applies threshold-based sanctions to prevent misreporting. Raters' utility is maximized when 1) their negative ratings help save costs, 2) they do not risk profits to sell ratings (P8), and 3) they still benefit from sellers' signals (G. E. Bolton et al., 2008). Hence, occasional negative ratings appear rational for raters, while misreporting beyond a dynamic[37] threshold appears irrational. DP4 allows raters to monetize or withhold their ratings based on their utility calculus, given *footnote 32* is applied (P6). Rational raters choose to sell ratings when expected benefits (e.g., monetary compensation[38], reciprocal value (T3)) exceed the rater's costs (e.g., reveal sensitive information). These conditions are attainable in non-competitive environments (Sec. 4.1),

[36] A certain level of risk needs to be accepted to confer reputation value, see Kreps and Wilson (1982).
[37] When the quality distribution in a market fluctuates, the threshold should be dynamically adjusted (Sec. 4.4—T4). This aligns with the system concept of dynamic equilibrium (P1), see Combs and Vagle (2002).
[38] Empirical findings suggest that ratings are perceived as valuable and tradable assets, supporting the underlying assumption of economic utility (P5,P9).

while they can hold selectively in competitive settings (M. Cho & Jun, 2013; M. Levy et al., 2003; Shi et al., 2023; Tsoy & Konstantinov, 2023).

Source Credibility Theory explains that the persuasiveness of information depends on the source's perceived expertise and trustworthiness (Hovland et al., 1953; Pornpitakpan, 2004). Ekstrom et al. (2005) demonstrate that this theory can be operationalized in a B2B context, adding *familiarity between rater and buyer* and *organization affiliation* as factors. DP5 builds on this logic. Potential buyers can assess ratings based on their source credibility and rating behavior (J. Cho et al., 2009; Ekstrom et al., 2005). Buyers who compare non-aggregated ratings (and their monetary weight) across different sources can infer source credibility (Lingfang Li et al., 2020; Mohaisen et al., 2011), even with limited information available (G. E. Bolton et al., 2005). Raters with stable identifiers are perceived as more trustworthy and, therefore, more credible (C. M.-Y. Cheung et al., 2012; Friedman & Resnick, 2001). DP6 ensures this principle. While the system operates under pseudonymity, rational raters would disclose their identity for trading (cf. Rational Choice Theory). Raters who stake their credibility appear more trustworthy (Ekstrom et al., 2005; Glückler & Armbrüster, 2003). Source Credibility Theory predicts ratings are weighted more strongly by buyers with high source credibility (Pornpitakpan, 2004).

Transaction Cost Theory posits that organizations minimize the combined costs of coordination and safeguarding under conditions of bounded rationality and opportunism (Williamson, 1979, 1985). The system reduces *ex-ante* search and information costs by rendering quality observable via costly signals (cf. Signal Theory), while smart contracts reduce *ex-post* enforcement costs (Halaburda et al., 2019). Increased optionality may raise cognitive effort, thereby not directly reducing transaction costs (Williamson, 1993) (P5). Nonetheless, the system can facilitate bargaining by increasing performance expectations that streamline decision-making (Poppo & Zenger, 1998). Contracting costs might slightly increase due to more detailed rating specifications (P5), but smart contract formalization offers the potential for long-term cost reduction (Beck et al., 2018; Shermin, 2017). The enhanced transparency can discipline actors and reduce monitoring efforts (Bachmann & Inkpen, 2011; Jøsang et al., 2007). DP1 and DP2 jointly provide buyers with economically meaningful indicators of sellers' intent (G. E. Bolton et al., 2013). DP5 supports bargaining efficiency by anticipating ex-ante performance based on rating metadata (relational, economic, and temporal) (G. E. Bolton, 1991; Poppo & Zenger, 1998). Still, comparability between rating subjects is constrained when asset specificity is high and few ratings are available (Williamson, 1985).[39] Supporting DP6, it is shown that blockchain-based systems can reduce transaction costs (Roeck et al., 2020).

The design theory causal logic is backed by two empirical grounding layers. First, the design is substantiated through empirical studies mainly covering sellers' (P5) and buyers' perspectives (P9). Second, it draws on prior empirical *Ω-knowledge* (Sec. 2.2.2—Tab. 4).

From a seller's view, sellers acknowledge the concept of a risky advance, especially when ratings are expressed monetarily (P5). Despite the approval of DP1 and DP2, the effect on the negotiation effort remained inconclusive. Some sellers voiced concerns about increased operational overhead. Sellers emphasized the importance of selective disclosure, multidimensional representation of ratings, and their contextualization. These views align with DP4 and DP5, emphasizing that metadata plays a decisive role and sensitive data must remain individually controllable. Interviewees view selective disclosure, such as revealing only parts of a rating, adding textual context, or distinguishing sources, as essential, especially in competitive settings. In addition, raters should possess domain expertise.[40] While some interviewees acknowledged the logic behind DP3 to prevent opportunistic misreporting, others expressed reservations.[41] Nonetheless, the ability to react to negative ratings and the traceability of rater identities (DP6) were welcomed, as they ensure the integrity of rating behavior.[42]

From a buyer's view, the system is valuable in opaque markets and unanimously beneficial for knowledge-intensive services (P9). The rating payment was framed not as a seller-side risky advance but as an upfront investment by buyers (T1). This framing prompted skepticism regarding the compensation of rating expenses through resale. Thus operationalizing the rating payment mechanism as seller-side signal seems preferable with voluntary rating submission (DP1,DP2). Furthermore, buyers express discomfort about being rated by sellers. This aspect underscores the rationale behind the deterrence

[39]Asset specificity significantly limits the perceived usefulness of the system, which is too high (P5). Still an open question is whether the system yields a sufficiently rich set of meta-heuristics to extract meaningful data of related cases as it is currently practiced (P5). Network effects may plausibly contribute to reaching the necessary informational density.

[40] In this regard, considering Article 17 GDPR, it is advisable to provide access to qualified raters only, using ring signatures (Sec. 2.4.2).

[41] Concerns were also raised about potential retaliation and limited avenues for recourse in one-off transactions. Whether these concerns translate into systemic limitations needs to be seen. However, G. E. Bolton et al. (2018) indicate that negative reciprocity tends to escalate conflicts. A dispute resolution function, as outlined in Sec. 4.4—T8 and detailed in footnote 31, may therefore be a reasonable approach.

[42] The difficulty of objectively measuring consulting success and the variability in clients' expertise to assess service quality constrain the system's utility. This reflects a general problem in consulting, see Nissen and Dittler (2019). Even if performance cannot be objectively measured, ratings can still indicate a client's satisfaction; see Lam et al. (2004). While these issues do not undermine the design per se, they emphasize contextualization and third-party oversight.

mechanism aimed at preventing exploitative behavior by buyers (DP3). In this regard, counter-ratings introduce a (desirable) tension when the distribution of received performance ratings does not match a buyer's honest ratings intent (Sec. 4.4—T4). In such cases, it indicates that buyers strategically allocate their ratings to maximize outcomes while staying below the counter-rating threshold (P8). Although this strategy appears rational, it remains empirically undetermined whether this approach maintains the desired behavioral integrity of 'nearest-honest' reporting, aligned with rating differentiation in the real world. In such complex cases, Baskerville and Pries-Heje (2010) point to the use of Ockham's Razor, which would lead to the conclusion that buyers distribute ratings in line with true quality (TP9). Moreover, controlling ratings visibility appears important (DP4). Buyers stress the need for product filters, metadata, and credible sources, supporting DP5.[43] While most buyers value the option to sell ratings, their primary interest lies in consuming ratings. Thus, this finding reveals an interest imbalance, requiring counteracting this imbalance (T3).

Scientifically grounded arguments are integrated, empirically substantiating the underlying design principles through *Ω-knowledge* (Tab. 17). Trajectories are justified, as they may also contribute to the refinement of existing design principles or inform the derivation of new ones (Gregor & Jones, 2007a).

Table 17: Empirical Ω-Knowledge Integration

Topic	Empirical Finding	Design Principles, Trajectories	Justificatory Argument
Quality of Information	Reputation information is especially valuable in contexts with high uncertainty.	DP1, DP5, T2	Monetary ratings and incentives enhance information quality in B2B markets characterized by high uncertainty.
Rating Subject	Product ratings are more informative than identity ratings.	DP5, T5	Ratings center on products rather than seller identities.
Rating Information	Multi-dimensional ratings increase accuracy but require filtering.	DP5, T5	Ratings can be decomposed with partial monetary ratings.
Review Depth	Reviews enhance the perceived usefulness of ratings.	DP5, T3, T6	Review text can be included as a text file in the stored ratings (cf. Sec. 4.8).
Monetary Incentives	Monetary incentives increase rating volume but may reduce quality.	DP1, DP2, DP4, T3	Monetary incentives promote buyer participation (e.g., saving money). Rating monetization helps preserve rating quality by decoupling incentives from seller-directed reciprocity.
Uncontrolled Ratings	Rating diversity reduces manipulation; platforms' active moderation harms rating credibility.	DP1, DP2, DP5, DP6, T3, T8	Incentive structures foster rating submission and diversity. The blockchain's immutability ensures that rating data cannot be deleted.

[43] Some buyers showed limited interest in purchasing ratings when information was readily accessible.

Fraud Costs	Raising the cost of fraudulent behavior increases trust in rating outcomes and increases system efficiency.	DP1, DP4, T2, T6	Fraud cost for sellers increases due to the (necessary minimum) monetary value of ratings (cf. P6). Buyers' costs arise from threshold violations (and the limited marketability of future ratings). System exclusion prevents actors from extracting benefits from the system (raising their costs).
Sybil Attack	*Sybil Attacks* are prevented by identity verification, low initial reputation, and cross-referencing identities.	DP5, DP6, T7	A permissioned blockchain enables identity verification without pre-assigning reputation. Fake ratings tie up funds and become less sustainable as network effects grow. TCRs can cross-reference different collected ratings.
Data Privacy	Privacy can be preserved without compromising system functionality.	DP4, T4, T6	Cryptography supports the proposed functions and ensures the privacy of rating content.
Identity Disclosure	Stable pseudonyms enhance rater credibility; full anonymity does not.	DP5, DP6	A persistent identifier issued on a permissioned blockchain can be used to determine raters' credibility.
Rating Significance	Rating informativeness varies by product complexity and recency.	DP5, T5	Selectivity enables the comparison of the most meaningful rating components and allows the focus on recent ratings.
Rating Helpfulness	Ratings labeled as helpful are trusted more.	T3	Marking ratings as helpful strengthens signal salience and incentivizes quality-oriented rating behavior, which addresses motivational asymmetry.
Rating Weighting	Allowing users to weigh ratings themselves increases decision trust.	DP5	Selective assessment based on underlying data and individual choices of ratings enhances decision quality.
Purchase Decision	Reputation is a positive mediating trust signal for buyers' purchases.	DP1, DP2, T1	Sellers who are able to receive positive ratings are more likely to achieve higher sales.
Re-Entry	High entry costs reduce opportunistic re-entry.	DP6	Permissioned controls maintain identity consistency.
Reciprocal Ratings	Customers tend to reciprocate fairly.	DP2, DP3	Buyers tend to rate fairly based on the actual performance.
Effect of Reciprocity	Positive reciprocity increases trust; negative reciprocity fuels conflict.	DP1, DP2, DP3, T5, T8	Only sellers who are confident in their capabilities are expected to send trust signals. Negative reciprocity is limited by a threshold and can be managed by a third party.
Visible Indicators	Quality indicators influence trust—even without reading reviews	DP4, T6	The mere visibility of trading relationships and the existence of ratings can enhance customer trust, even without reading the ratings.
Rating Disclosure	Partial ratings disclosure does not necessarily reduce buyer advantages in competitive settings	DP4, T6	Selective disclosure enables strategically aligned rating sharing, which might allow the system to scale into more competitive settings.
Two-Sided and One-Sided Rating	Masked mutual ratings increase informational value but may reduce participation interest.	DP3, T4	Two-sided ratings yield partial benefits, help curb retaliation, which prevents the reduction of participation interest.

4.7 Principles of Implementation

Principles of implementation guide the practical use of the design (Gregor & Jones, 2007a). While not mandatory, they are valuable for design theories (Heinrich & Schwabe, 2014). They may include a description of how to establish a system (Aier & Fischer, 2011; Gregor & Jones, 2007a). The focus here lies on practical guidance, while prescriptive *Λ-knowledge* can be consulted independently (Sec. 2.2.2—Tab. 5).

As a platform instance, the system's levers should be configured in early phases to promote trust-building and foster network effects (Beverungen et al., 2021; van Alstyne et al., 2016).[44] This requires a balance in which sellers can issue credible trust signals while buyers have limited incentives for negative ratings (e.g., low risky advances, high counter-rating threshold). In other words, at this stage, buyer behavior should rather be encouraged to lean toward *lenient behavior* than *exploitative behavior* (Sec. 4.3—Fig. 10). Overall, the system should support a normative climate of trust-building (Ostrom, 1990) but also differentiate quality (Avery et al., 1999). The latter may become more worthwhile as adoption matures (T2). Communication between buyer and seller before the rating commitment is essential, which should aim for intended but not guaranteed positive reciprocity (G. E. Bolton et al., 2013; Gharib et al., 2019).

The trajectories provide several well-considered foundations for refining the system's effectiveness (Sec. 4.4). Integrating refinements might be indispensable for proper system implementation. These refinements include, for instance, adaptive or softly enforced thresholds that preserve buyer agency to rate correctly (T4) (Sec. 4.6), restricting rating purchases by buyers who have not submitted helpful ratings (T3), or determining who owns ratings (T9). Additionally, the system must use governance mechanisms to remain viable across contexts and time (Beck et al., 2018; Tiwana et al., 2010). Governance rules must be defined and enforced, e.g., through external oversight or smart contracts.

Several operational aspects should be considered. First, rating payments should be executed via fiat-backed stablecoins (P5). Second, ratings should follow standardized templates and predefined categories to reduce ambiguity, promote consistency, and minimize time and effort during submission and review (C.-W. Chen, 2017; Seutter et al., 2023) (P9). Rating descriptions should be mandatory and aligned with discrete rating scales to assess their expected helpfulness (Jabr & Rahman, 2022; Mudambi & Schuff, 2010). Third, privacy-preserving techniques, e.g., ring signatures, allow institutional actors to submit GDPR-compliant ratings (Mahmood & Vacius, 2020).

[44] In this sense, it should initially resemble a customer loyalty program, as described by Utz et al. (2023), that leverages long-term business relationships, even if its primary purpose is to support decisions.

4.8 Expository Instantiation

Expository instantiation is an optional part in the design theory development, either to uncover technical challenges or demonstrate design feasibility (Gregor & Jones, 2007a). Although a mock-up would have sufficed, a functioning prototype was developed. This instantiation was implemented on a permissionless *Ethereum Testnet* (P5).[45]

Core elements include the creation, approval, and execution of ratings, as illustrated by a UML activity diagram (Fig. 12). Buyer and seller create a rating commitment, allowing the buyer to submit a monetary rating within a defined time frame (DP2). While rating amounts can be kept private on a blockchain, as shown in P6 (DP4), full confidentiality cannot be guaranteed on Ethereum's native currency (Unterweger et al., 2018).[46] Thus, *at present*, rating commitments stored on a permissioned blockchain are recommended while using stablecoins.[47] The blockchain layer in the prototype serves to record rating-related transactions securely in a transparent yet privacy-preserving manner. Smart contracts store rating agreements, including base and performance-based payments, and rating commitments with deadlines (P5). Rating metadata is stored on-chain, while sensitive content like review texts can remain off-chain, referenced via signed hashes.

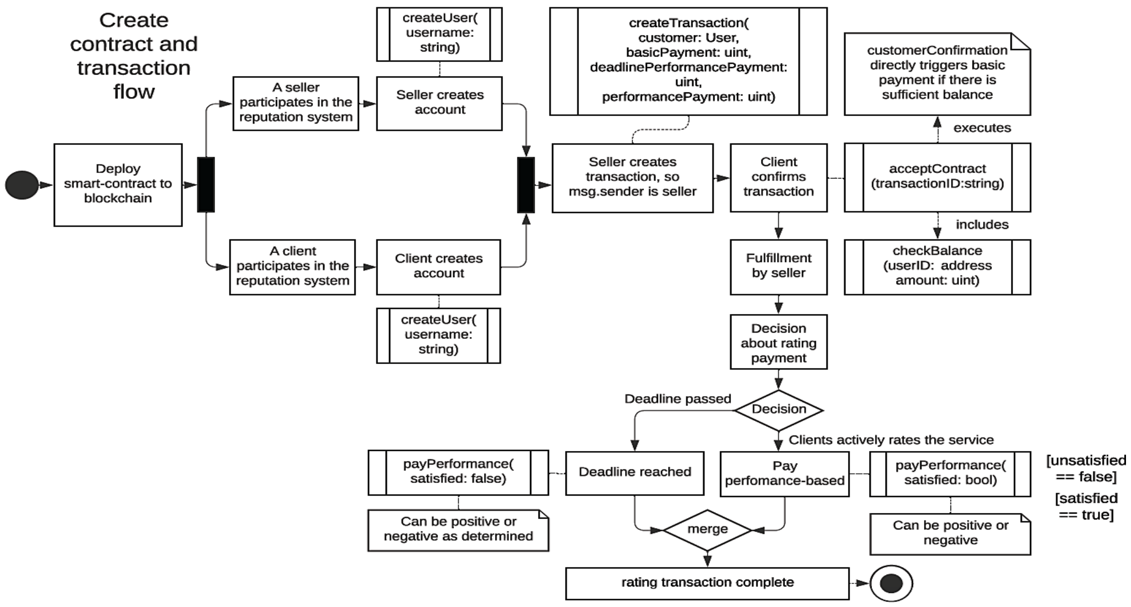

Figure 12: UML Activity Diagram of the Workflow of the Rating Process

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[45] Permissionless blockchains generally impose high requirements. Here, they are preferable because they enable native integration of stablecoins into smart contracts. The project was conducted and funded under the supervision of the Chair of Information Systems, particularly Business Information Systems.

[46] In Ethereum's native currency (Ether), outputs can be deterministically derived from inputs. *Privacy coins* address this issue but are currently not reliable regarding confidentiality, e.g., Möser et al. (2019), and often lack adequate smart contract functionality. Layer-2 solutions (and other blockchains) are a promising avenue to provide solutions; see Jamwal et al. (2024) for an overview.

[47] This can be achieved by storing a signed hash of the payment agreement on-chain, which ensures content integrity without disclosing sensitive details. Smart contracts might still be possible; see Henry et al. (2022).

The prototype features a functional graphical user interface (Fig. 13). In the field '*details*', users can enter texts (DP4) or enter timestamped, signed hash values (e.g., to reference review content), which can be stored off-chain (Lou et al., 2023; Z. Zhou et al., 2021).

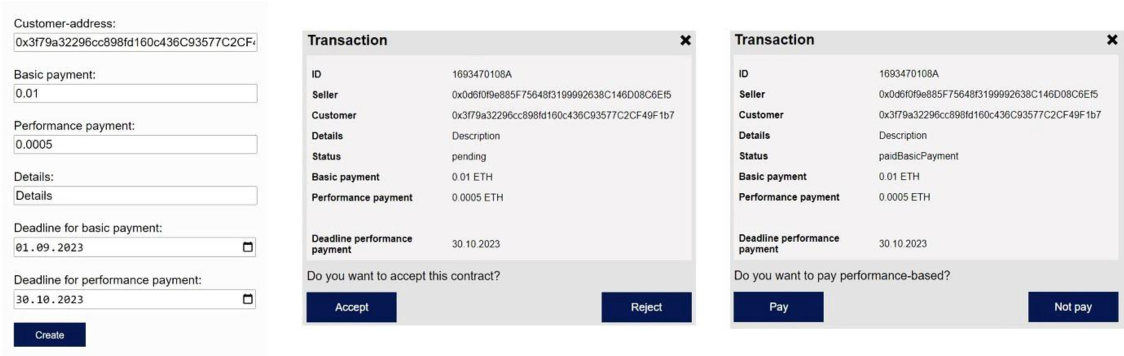

Figure 13: User Interface of the Reputation Mechanism (P5)

Additionally, the prototype can be integrated into an SAP test environment. As part of a student-led implementation project, various ABAP modules and function blocks were developed to simulate the entire procure-to-pay cycle (Fig. 14).[48] The functional prototype was implemented using a variety of function modules within the SAP test environment to simulate a trial run of the rating process using *TestEther*. The process covers a broad functional spectrum, from the formulation of the rating agreement to the inspection of monetary ratings by a potential seller on the SAP testnet. As just one example, Fig. 14 shows how a transaction for SAP purchase orders is created (left side). Different performance aspects can be rated separately according to their fulfillment level (T5). The aspects may include elements such as delivery, product quality, service performance, price-performance ratio, or reliability. This partially demonstrates how DP5 can be applied, although a rating history with real participants is missing, which would be a prerequisite for activating counter-ratings (DP3).

Seller	
Function	Description
Z_Load	Topping up the wallet address
Z_Get_User_Transaction	Displaying the transaction ID to the user
Z_Create_Transaction	Creating the transaction
Z_Accept_Contract	Accepting the transaction
Z_Buy_Details	Providing a description of the product or service
Z_Seller_Programm	Simulating the seller's perspective
…	…
Buyer	
Z_Filter_Product/Industry	Searching for the seller's rating
Z_Get_Balance	Displaying current account balance
Z_Rate_Trans	Initiating the rating flow
Z_Rate_Print / Service	Submitting a rating
Z_Get_Purchased_Ratings	Retrieving all transaction IDs
…	….

Figure 14: SAP Function Modules with Implementation Example

[48] As part of a university course project in the 2023 study module *Advanced Enterprise Systems*, the execution of the rating process was demonstrated in an operational setting.

5 Synopsis of Contributions

5.1 Mechanism-Level Contributions

This dissertation provides a theory-driven reconceptualization for reputation (eco)systems to overcome persistent limitations in current systems (Sec. 2.2.3—Tab. 6) (P5). It reframes trust-related information as a structured, selectively tradable coordination asset that can reduce information asymmetries in B2B transactions. The design yields six contributions—none of which have been proposed in this configuration before.

First, this study introduces economically weighted trust signals in the form of a risky advance. This design departs from the retrospective rating logic of related systems by sending quality signals embedded directly in the transaction. Thus, sellers can send quantifiable, monetary trust signals *before* contracting. Ratings embody a cost-bearing signal as a function of risk, filtering for high-quality sellers through a self-selection mechanism (Sec. 4.6). The monetary weight mitigates rating inflation by imposing *'costs'* on rating submissions. These costs encounter nearly costless rating submissions, which are seen as one root cause of fraud (Krügel & Paetzel, 2024).

Second, this study highlights the voluntary nature of ratings. Voluntary rating reflects a seller's risk, which helps build trust (Luhmann, 2017). Almost all previous approaches[49] consistently fail to integrate risk into the design of reputation systems. As a result, the capacity to build trust is limited to the extent that risk is limited (Litos & Zindros, 2017; Milgrom, 1982). Yet the design primarily proposed here focuses on human rating decisions. Technology can readily determine the outcome ratings (T5).[50]

Third, this study introduces a threshold to regulate observability. This threshold ensures that excessive negative rating behavior is exposed. Previous studies have not used observation-based thresholds to steer rating behavior. Here, an observer-dependent threshold mediates the problem of dispute escalations caused by negative reciprocity (G. E. Bolton et al., 2018). It prevents immediate escalation but still acts as a safeguard (Luhmann, 2017). The mechanism mimics the Nobel Prize-winning *revelation principle*.[51] Based on P7's evidence that incentives can foster truth-telling as a dominant

[49] The only known exception is Litos and Zindros (2017). However, their approach misses sufficient safeguarding, which might render their approach ineffective. Safeguards are necessary in trust-building systems according to Luhmann (2017).

[50] A technical-based approach was recently published by Gregory et al. (2024).

[51] Myerson's (1979) revelation principle demonstrates that truthful reporting is possible without central oversight. This paper is part of a series of works for which Myerson—together with L. Hurwicz and E. S. Maskin—was awarded the Nobel Prize for foundational contributions to mechanism design theory.

strategy, a threshold-based observation mechanism may improve buyers' rating effectiveness further (Sec. 4.6). Research on enforcing truthful reporting is not completely new (one exception is Jurca & Faltings, 2003, 2005, 2009)[52], but the conditional linkage to observation-based system thresholds is, which allows stronger selection pressure to be put on raters, if desired (Sec. 4.6,4.7).

Fourth, this study introduces the reconfiguration of ratings from public goods to selectively tradable market assets. Prior work treats ratings as public goods, e.g., (Chan et al., 2022; Lingfang & Xiao, 2014; Samuelson, 1954). However, their costless nature appears to be the main source of inflated rating signals (Friedman & Resnick, 2001; Resnick & Zeckhauser, 2002). Reconceptualizing ratings as private goods implies 1) they carry inherent weight, making them economically costly, 2) they become unambiguous, deterministic, quantifiable, and 3) they can be traded. Based on these features, markets for trading ratings can address the problems of low incentives and free riding (Sec. 2.2.3) (T3). Selective transparency addresses privacy concerns and aligns with broader B2B requirements for controlling the dissemination of ratings (Sec. 2.3.4).

Fifth, this study introduces a new starting point for rating generation. The design prompts buyers—not sellers—to become active drivers of trustworthy feedback. With few exceptions, i.e., platform owners (Chan et al., 2022), literature shows that rating incentives are provided by sellers, which usually induce a risk of positive rating bias, e.g., (Neumann & Gutt, 2019a; Y. Yu et al., 2022). By shifting the incentive source of rating generation to buyers, positive rating biases induced by sellers' incentives can be eliminated.

Sixth, the study uses permissioned blockchains for reputation systems. It helps defend against attack scenarios, including *Sybil Attacks* (Douceur, 2002). In research, storing ratings on blockchains is well-documented (Sec. 2.4.2). The novelty here lies in proving that it can also be done with monetary ratings (P6). Next to the general difficulty of building a fake rating network within a permissioned blockchain network (DP6), the economic value of ratings and the selection of buyers both impedes the creation of plausible fake ratings even more. Cautiously formulated, monetary weighting may help impede Sybil Attacks, since transactions are not costless (Sec. 7). TCRs can further resolve this issue (T7), opening a way for the system to function in an open environment.

[52] Although the inclusion of buyers as incentive providers is implicitly possible in Jurca and Faltings studies, they did not mention buyers as incentive providers.

5.2 Theoretical Integration and Conceptual Innovation

This dissertation develops a theory-driven foundation for a new generation of digital trust-enabling infrastructures. Central is a novel design logic that reframes reputation building as a coordination function within a *socio-economic information system*. One innovation lies in the use of technology-based communication structures shaped by economic signaling. The envisioned information system for B2B markets addresses shortcomings of trust surrogates by 1) reducing search and validation costs, 2) enhancing credibility through verifiable monetary-weighted ratings, and 3) leveraging available yet underutilized information for cross-organizational use (Sec. 2.3.2).

The system offers solutions to reduce the B2B adoption barriers (Sec. 2.3.4—Tab. 9). While some barriers can be alleviated by solving known system limitations (Sec. 5.1), other barriers require more targeted intervention through trajectories (Sec. 4.4). By sending an ex-ante risk signal, trustworthy sellers can be self-selected at an early business transaction stage, thereby curbing the difficulty of detecting manipulative behavior ex-post (Sec. 2.2.3). Another central issue is buyers' reluctance to generate and share ratings. The design theory accommodates this behavior by governing rating incentives (T3,T7) and rating disclosure (T5,T6). Likewise, the issue of multi-dimensional complexity can be reduced via T5, provided that service performance can be clearly described and supported by a manageable user interface (H. Wang et al., 2020). Overall, the system design shows the potential to overcome most[53] adoption barriers of B2B markets (P5).

The reputation system can unfold within a selectively-layered visible ecosystem—including elements such as commitment mechanisms, the sharing of ratings, rating component disclosure (T6), Token Curated Registries (T7), and a legitimacy layer (T8)—in which complex relationships co-create value (Hein et al., 2020; Jacobides et al., 2018; Yoo et al., 2010). The evolving ecosystem is described within the mutability of the design theory. Guided by mutable trajectories (T1-T9), a reputation ecosystem can evolve into a market by turning rating information into a priced, selectively tradable, non-public good. Conceptually new is that rating information can be strategically withheld, disclosed, and monetized. The design allows selective transparency, without enforcing transparency (Truong, 2019; K. Zhu, 2004).

Extending this market logic, the design also leverages blockchain infrastructure functions as an equilibrium-supporting device that discourages strategic lying (P7). This mathematically-proven improvement of coordination efficiency directly addresses the

[53] Legal risks have only been partially addressed. Concerns about the traceability of rating identities (P5) are not a problem when using ring signatures. However, open questions remain regarding the legal implications introduced by the use of blockchain technology and rating contracts; see Rieger et al. (2019).

phenomena of lemon markets (Akerlof, 1970). The design aligns the economic design for truth-telling that can help screen out low-quality sellers (Maskin, 2008; Myerson, 1979; G. Sun et al., 2022). Beyond market signaling, the design also responds to the *oracle problem*, the challenge of reaching credible information bases in decentralized settings (Caldarelli, 2020), rooted in the same coordination challenge.

This work reaches beyond IS relevance by offering a solution for the public goods problem as described in the seminal work by G. E. Bolton et al. (2004) on *trust engineering*. Yet, generating trust information is externalized, which leads to the underproduction of trust signals (Adar & Huberman, 2000; J. Wang et al., 2018). Hence, reputation mechanisms exhibit "a kind of public goods problem in that […] the benefits of trust and trustworthy behavior go to the whole community and are not completely internalized" (G. E. Bolton et al., 2004, p. 1587). Reframing trust-inducing information as a private good allows one to reverse the incentives logic. Potential buyers become the source of rating incentives by paying for them. This reversion internalizes the costs *and* benefits of rating generation to raters. By changing the incentive source, this research offers a potential solution to the "biggest challenge of such systems" (J. Pereira et al., 2019, p. 101), which is to find the right incentive structure for such systems (Sec. 1.1).

The design theory fulfills all components of a design theory as outlined by Gregor and Jones (2007a). The developed nascent design theory can be categorized as an early type IV theory (Gregor, 2006) that provides a testable and extensible foundation for mid-range theorizing on B2B trust formation for IS researchers (K. H. Lim et al., 2006; Merton, 1968; J.-Y. Son et al., 2006). This work fulfills established criteria for theory contribution. For instance, it introduces constructs to advance scarce theory (Aier & Fischer, 2011), is grounded in meta-theory, offers empirical insights (Weber, 2003), and provides rich explanatory power (Whetten, 1989), meeting criteria of meaningful theory contribution.

5.3 Integrative Synthesis and Scholarly Relevance

This dissertation redefines how reputation systems can be understood and designed. By reframing them as social systems[54] rather than mere feedback tools (Resnick et al., 2000), this work breaks with over two decades of tradition and questions dominant design assumptions of reputation systems in IS (Hendrikx et al., 2015; Rein, 2005; Vavilis et al., 2014). It shifts the theoretical perspective from evaluative to commitment-based systems. Yet, current systems are designed for neutral information exchange that *may* evoke trust

[54] This reframing is legitimate and aligns with the widespread conceptions of information systems as having a socio- and a technical system part (Sec. 2.1.1); see also Chatterjee et al. (2020) and Lyytinen (1987). Reputation systems are thus only a social system, operationally closed from the technological part, see Luhmann (1990).

or distrust, without intentionally cultivating trust based on committed risks. Given that reputation systems are expected to become the centerpiece of digital platforms (Greiner et al., 2021; Kolleck & Teubner, 2024), this work—as the first to describe this reconceptualization—may hold long-lasting scientific relevance (Wagner et al., 2021). Scholars can examine the coordination logic to foster trust, improve it, or adapt it.

Trust formation is grounded in LST and conceptualized as an indirect yet designable system property—relevant for any IS aimed at reducing uncertainty in digitally mediated relationships. The socially-oriented system design operates within bounded, self-referential informational domains, where information can be selectively disclosed and observed, and is pegged to the conditional logic of smart contracts. These features help coordinate strangers via endogenous incentive structures (G. E. Bolton et al., 2005; Gregory et al., 2024). IS research may be inspired to use similar endogenous incentives to steer behavior in other application areas. Collectively, the integration of LST with economic mechanism design opens new directions for designing coordination-based artifacts.

The increasing interdependence of platform-based coordination demands explanatory frameworks that move beyond deterministic operations (L. Zhou et al., 2022). While full behavioral outcomes can never be hard-coded into artifacts (Pentland & Feldman, 2008), this work showcases that emerging system patterns are not left to chance. Scholars might not only concentrate on designing technology, but also start design projects targeting the creation of system phenomena based on system principles (P1). For instance, DSR scholars can reimagine design elements, such as risk-bearing signaling, observer-dependent thresholds, or selective transparency, as deliberate design levers. Echoing A. S. Lee et al. (2015) critique of IT artifact-centrism, IS scholars may study mechanism-oriented IS artifacts with economic incentives leveraged by technology.

Another major contribution lies in "reengineering trust" (G. E. Bolton et al., 2013, p. 265). This reengineering enables the reduction of information asymmetries and addresses the coordination failure described as *lemon markets* (Akerlof, 1970), one of the most enduring problems in economics. Most importantly, ratings naturally absorb environmental information into a system. Thus, correctly configured, they offer extraordinary capabilities for solving coordination challenges (G. E. Bolton et al., 2013; Dellarocas, 2003). Likewise, the logic also holds the potential to mitigate the oracle problem (Sec. 2.4.1). Information generation can be positioned *outside* a technical system through human-generated incentive-aligned ratings (Sänger & Pernul, 2018).[55] Yet, in all cases, context-specific adaptation must be respected (Herwix & zur Heiden, 2022; Orlikowski & Iacono, 2001). Interdisciplinary scholars can investigate its application and specification for different contexts.

The proposed coordination logic is not confined to B2B ratings. It can be extended to B2C scenarios and other application domains characterized by epistemic uncertainty. The developed logic is also promising for machine-to-machine negotiation, where agents must assess both unfamiliar counterparts and negotiation subjects (Cao et al., 2015; Jennings et al., 2001). Beyond that, the coordination mechanism may inform adjacent domains such as recommendation generation, expectation formation, negotiation strategies, or attribution processes (P7). For instance, applying the logic to *recommendation content*—rather than to *rating content*—might improve person-related recommender systems.

Few studies have begun to explore how such systems may serve as economic instruments in B2B settings (Chaurasiya, 2024; Gregory et al., 2024; Große et al., 2024; Gutt et al., 2019; Koh et al., 2012; Luo et al., 2020). Complementary to these endeavors, this study presents a holistic stance actively involving all three sides in information exchange. As such, the study contributes to a growing—though still nascent—stream of IS research on trust-evoking ecosystems (Gregory et al., 2024; Große et al., 2024; Ishii & Kikumori, 2023). The proposed design opens up multiple avenues for research to explore the system's concrete instantiation in different B2B contexts.

This study uses system concepts of LST as an abstract lens on systems function and trust-building, integrating explanatory theories such as signaling (Spence, 1973), source credibility (Pornpitakpan, 2004), rational choice (Coleman, 1990), and transaction cost theory (Williamson, 1985). Together, they form a coherent theory corpus substantiated with economic explanations (Niehaves & Ortbach, 2016). Overall, this work demonstrates the utility of LST concepts for designing information systems. The use of LST implies that other systems concepts may also be fruitfully applied in the IS discipline (Waguespack & Schiano, 2013) (P1). A lens largely neglected so far in IS (Sec. 2.1.1). This dissertation offers a blueprint on how abstract system theory can be transformed into generative design logic. This may reposition systems theory from a reflective to a generative stance for analyzing, designing, and theorizing information systems and their

[55] In this context, the overall blockchain-based trust-promoting logic proves valid in practice, see Myerson (1979) (P7). It supports the growing claim that organizations may no longer be the superior mechanism "for market-based trust coordination issues" Seidel (2018, p. 40) and may be replaced successively by blockchains, see for instance: Davidson et al. (2016); Lumineau et al. (2021); Pedersen et al. (2019).

patterns (P1). IS scholars can learn from this study how abstract system theories can be operationalized.

This dissertation pioneers a design logic that combines abstract system concepts with DSR. Unlike traditional DSR approaches that build on behavioral assumptions or technical constraints (Hevner et al., 2004; R. Winter, 2008), this work shows how abstract system concepts and economic incentives can be co-designed into one functional logic. In this vein, P1 may open avenues of *system-theory-driven design* for IS scholars (Arazy et al., 2010; Markus et al., 2002; Markus & Saunders, 2007). Systems theory, esp. LST, as a peripheral paradigm that stands outside of mainstream science, is often marginalized or ignored (Sec. 2.1.1), yet exactly those theories hold the potential to challenge and transform established thought patterns in IS (Hassan & Mingers, 2018; Kuhn, 1970, p. 175). The relevance of systems theory for IS stems from the growing complexities of the digital world, which is argued to be best handled with it (Alter, 2004; Benbya et al., 2020; Demetis & Lee, 2017).

At an abstract level, this work indicates information systems may be conceptualized not only as *socio-technical* but as *socio-economic-technical systems. Hence,* this study points toward a path for integrating *economic mechanism design* (Hurwicz & Reiter, 2006) into DSR studies. This work invites IS scholars to reconsider the ontological role of information systems regarding socio-economic coordination based on technology. Yet, the socio-economic perspective is barely recognized in IS (Sah & Stiglitz, 1984).

In sum, theory contributions from Sec. 5.1–5.3 are distilled (Tab. 19).

Table 18: Overview of Core Contributions

No.	Core Contribution	Description	Contribution Type	Theoretical Foundation
1	Collection of Systems Concepts	Collection of 52 system concepts and 129 system specifications to guide the design and analysis of complex information systems.	Conceptual	Systems Theory
2	Reconceptualization of Reputation Systems as Social Systems	Reconceptualizing reputation systems as bounded, self-referential, employing a trust mechanism based on social system concepts.	Conceptual	LST
3	Trust as Risky Advance	Reframing trust as a forward-shifted commitment initiated under risk, enabling actors to signal trust.	Conceptual-Theoretical	LST; Signaling Theory
4	Observable-based Threshold	Introducing an observable-dependent threshold mechanism to steer behaviour	Conceptual-Theoretical	LST
5	Reputation Information as a Selectively Tradable Asset	Recasting reputation from a public good into a priced, marketable good, enabling selective disclosure and monetization in rating markets.	Economic-Theoretical	Information Economics; Public Goods Theory

6	Digital Facilitation of the Trust Mechanism	Operationalization through six design principles illustrated with 23 institutional factors to establish trust.	Design-Theoretical	LST; DSR
7	Design Theory for Trust-Enabling Systems	Development of a testable, extensible design theory with mutability logic and explanatory rationale for non-competitive B2B markets.	Design-Theoretical	LST; DSR; Explanatory Economic Theories
8	Meta-Theoretical Integration	Synthesis of LST with explanatory theories and Ω-knowledge into a coherent meta-design.	Meta-Theoretical	LST; Ω-Knowledge
9	New Approach for Coordination Failures	Suggested approach to mitigate persistent coordination problems, including Lemon Markets, Oracle Problem, and Public Goods Problem, through a new reputation mechanism.	Economic-Theoretical	Economic Coordination; Game Theory; Mechanism Design Theory
10	Application for B2B Markets and Blockchain Implementation	Prototype for B2B trust coordination, leveraging blockchain for incentive alignment, confidentiality, and decentralized control.	Design-Contextual	Related Literature; Ω-Knowledge

5.4 Practical Implications and Societal Relevance

While eWOM slowly gains traction in B2B settings (Belhadi et al., 2023; Chatzipanagiotou et al., 2023), trust-enabling information systems are largely absent (Große et al., 2024). In industries where offerings are comparable, stakes are high, and interpersonal trust is difficult to establish, reliable decision support is essential (Aras et al., 2022; Hada et al., 2024; Tsao et al., 2022). The proposed system targets this setting, though its exact form is subject to mutability (T1–T9). Once adopted, it might redefine how business relationships are formed (Beck et al., 2017; Narang et al., 2019; Sänger & Pernul, 2018). Managers need to understand how such systems operate, how to integrate them into operations, and how ratings affect business outcomes. Their strengths and limits relative to conventional trust surrogates should be considered (Sec. 2.3.2; Sec. 7).

Buyers gain a tool to reward performance, deter opportunism, and convert feedback into tradable informational assets. Ratings can complement contracts and signal accountability early in the procurement cycle (Moreno & Terwiesch, 2014; Padgett et al., 2020). Buyers can pay reduced prices when a seller's performance is below expectations, which can help rebuild cooperation (Bottom et al., 2002). Also, sold ratings offer a return on rating effort. However, establishing rating commitments might complicate contracting, e.g., when expectations diverge or rating conditions are hard to define (P5). Sharing rating data requires careful governance to avoid exposure or misuse (Shi et al., 2023; Truong, 2019).

For sellers, the system might serve as a strategic instrument (Gutt et al., 2019) or a marketing tool (Herhausen et al., 2020). Sellers' commitment to get rated signals confidence and credibility. Positive ratings can be expected to foster trust, attract new customers, justify price premiums, and defend margins. Monetary-backed ratings might have an even stronger trust-building effect than sole text reviews (Sec. 2.2.2). Sellers might use rating feedback to adjust offerings or differentiate themselves in competitive markets (Porter, 1997). Nonetheless, ratings issued by buyers carry inherent risks. Mitigation strategies like counter-ratings and also buyers' intention to sell ratings can reduce such risks (P7; T3), but do not eliminate risks completely. Sellers may choose to limit rating exposure (T2) or establish safeguards, for instance, by screening buyer ratings behavior before agreeing to be rated (T4) or peg rating results to objective measures (Gregory et al., 2024). Refusal to be rated is not necessarily a poor-quality signal.

Prospective buyers benefit from reduced search costs and screening costs (Bakos, 1997; Mai & Liao, 2021; Steward et al., 2019). Since reputation is hard to fake (Sec. 2.2.1), sellers' incentives might be shifted from marketing efforts toward direct investment in product or service quality. Buyers can cross-check providers' promises early in the procurement cycle and triangulate seller selection with low resource effort. Ratings can support early trust formation in new partnerships (Lanzolla & Frankort, 2016; McKnight et al., 2017; J.-Y. Son et al., 2006). Monetary ratings offer a discrete measure, but might also complicate interpretation when combined with review texts (C. Schneider et al., 2021; Seutter et al., 2023). Risky advances by sellers act as self-selection signals, indicating confidence and thus confer a certain credibility regarding their capabilities. In addition to this, rating variance as well as negative ratings can yield valuable insights (Steward et al., 2023; S. Zimmermann et al., 2018). When information is scarce or raters lack credibility, decision-makers should consult alternatives.

Monetary ratings provide a distinct informational dimension that is not captured by other rating attributes. They may significantly reduce the effort required to generate a rating, since they build a weighted and standardized information base for ratings. The system can replace selected portions of costly ex-ante negotiation with data-driven heuristics (Cao et al., 2015). Reputation ecosystems can show their value in dense, loosely coupled networks with frequently switching partners. This system may support trust in digitally mediated economies if deployed in algorithmic procurement or machine-to-machine settings. Businesses can engage flexibly, as raters, signalers, or observers, shape their involvement based on strategic priorities, transaction types, risk levels, and disclosure intentions (Chatzipanagiotou et al., 2023; K. Zhu, 2004).

Managers can start using the system in settings where trust is hard to establish, such as new supplier relationships, agency work, or short-term projects (Benson et al., 2020). Managers must be aware of pitfalls and be able to discern trustworthy ratings (Steward et al., 2018). Early implementations should focus on low-volume and low-risk contracts to test how ratings work for a company. Implementers can use different trajectories to adapt the system and balance perceived risk (T1-T9). However, initial implementation may face friction—buyers may hesitate to rate, and sellers may fear unfair treatment. Thus, principles of implementation should be considered (Sec. 4.7). Given its generic logic and low dependency on context-specificity, the system may scale into other areas facing coordination problems—including less trust-sensitive B2B fields, and others (Sec. 5.3). Adoption will likely depend on network effects and declining marginal costs to use the system (Katz & Shapiro, 1986; Zeithaml, 1988).

As blockchain technology gains wider adoption, solving oracle problems for decentralized applications becomes increasingly important (Buterin, 2021), for which this coordination logic is a solution candidate. Assuming a dense network, monetary weighting combined with selectivity (including TCRs) may practically help mitigate *Sybil Attacks* in open environments.

By viewing "reputation systems as a digital socio-economic institution," (Elfena, 2024, p. 131) this mechanism design can serve as a reference design for future systems of trust coordination, where institutional scaffolding erodes (Masum & Tovey, 2012; Schneier, 2012). As such, it may also complement traditional governance mechanisms and help structure economic interactions in settings where formal contracts or institutions are insufficient (Davidson et al., 2016, 2018; Earl & Potts, 2004; Thierer et al., 2016). Treating ratings *also* as private goods may prove more effective in increasing product and service quality in B2C settings (Bar-Isaac & Tadelis, 2008; Tadelis, 1999, 2016a).

Beyond organizational relevance, the system provides an institutional scaffolding for coordination in settings where institutional trust is weak. Analogous to money as a medium of remembered value (Alexander, 1987), reputation is a medium of remembered trust. Drawing on Ostrom's (1990) *governing the commons*, the system is an initial step to coordinate trust between actors under shared but modifiable governance. Different developmental trajectories illustrate how the system may give rise to genuinely self-organizing and sophisticated reputation environments over time (Ashby, 1947; Kauffman, 1993; van Lier, 2019). Reputation systems might become highly complex and evolve into fully-fledged social coordination systems, not so different from social systems (Takács, 2022).

6 Positioning the Proposed System as DSR Invention

The system class is positioned as an *invention* within the *Knowledge Contribution Framework* for DSR by Gregor and Hevner (2013). True inventions "are rare" (Gregor & Hevner, 2013, p. 345) and essential drivers of academic and practical progress, capable of opening new avenues for further problem-solving (Baskerville et al., 2018). An artifact qualifies as an invention when it is "recognizably novel" (Gregor & Hevner, 2013, p. 346) within a clearly underexplored problem domain, such as a first class of an information system in a domain. Inventions are *radical innovations* (Schumpeter, 1934), new to the world, where "the idea of the problem or opportunity, and the knowledge to solve it, have not been recognized before" (Hevner & Gregor, 2022, p. 5). The exceptionally high degree of innovation is demonstrated by objective criteria for IS research defined by Grover and Niederman (2021), since this research fulfills all twelve innovation types (Appendix C). Inventions address complex, wicked problems characterized by ill-defined requirements, contexts, and conflicting stakeholder interests (Buchanan, 1992; Gregor & Hevner, 2013). Also, to be classified as an invention, both solution and application maturity must be underdeveloped (Gregor & Hevner, 2013).

Solution Maturity. Existing reputation systems face inherent limitations such as manipulation, reputation inflation, lack of incentives, contextual insensitivity, and privacy concerns (Sec. 2.2.3). Despite often being accompanied by distrust, these systems are used, primarily due to the lack of better alternatives (Dellarocas & Wood, 2008; Swamynathan et al., 2010). These limitations indicate low to medium solution maturity.

Application Maturity. It is evident that the adoption of reputation systems in B2B markets is limited. B2B buyers rarely use reputation systems in their day-to-day business. Only a few B2B platforms exist, covering niche areas (Sec. 2.3.4). Platforms are compromised by paid listings and biased feedback and fail to meet the standards of trust and neutrality (Luca & Zervas, 2016; Singhal et al., 2025). Low adoption and usage indicate a low application maturity.

This work leverages blockchain to enable monetary-weighted, selectively shared trust signals. Departing from traditional reputation systems (Resnick et al., 2000), this system a) embeds economic stakes into ratings, b) enables selective information disclosure, c) allows monetizing ratings, and d) introduces counter-ratings with observer-dependent thresholds, through which the system mimics authentic trust (Milgrom, 1982).

This research achieves a level of innovation that aligns with the concept of an invention in DSR (Hevner & Gregor, 2022). Potential critics might argue that the meta-artifact draws on existing knowledge. However, Gregor and Hevner caution against narrow views of novelty, emphasizing that the essence of an invention lies in significant advancement —“a clear departure from the accepted ways of thinking and doing” (Gregor & Hevner, 2013, p. 345). This is readily supported by the analysis in Section 5.1 and the obvious absence of any comparable mechanism in B2B contexts. Features such as monetary ratings, sellers’ targeted exposure to risk in a reputation system to build trust, and trading ratings are unprecedented in existing B2B systems. Yet the artifact might be seen only as a *potential invention* (P5), as the solution is primarily theoretical, and increasing practical maturity remains to be seen.

7 Reflection, Limitations, and Future Research

Critical reflection is essential in research to uncover underlying assumptions, clarify limitations, and inform future work (Barata et al., 2023). The "most important work tends to be in the earliest phases, when […] stakes are highest for getting it right" (Henshaw, 2019, p. 67). This aligns with calls for work that is new, creative, and important (Hevner & Gregor, 2022; Nunamaker et al., 1990), tackles a demanding design space—a challenge many scholars shy away from (W. Chen & Hirschheim, 2004; A. S. Lee, 1999). Given this broad thematic scope, critiques are both expected and warranted, but must be interpreted relative to the contributions made (R. Agarwal & Lucas, 2005; A. S. Lee, 2001; Lyytinen et al., 2007; Rai, 2017).

Luhmann's work, despite its abstraction and critique as lacking actionable design content (Rucht & Roth, 1992), offers a compelling lens for conceptualizing trust as a system-inherent communication-based coordination mechanism. It is acknowledged that systems theory is highly complex. Accordingly, the reader may find parts of this dissertation intellectually challenging (Markus & Robey, 1988). This challenge is not uncommon among kernel theories. Precisely for this reason, explanatory economic theories are integrated to align abstract theoretical reasoning with implementable design logic (W. Kuechler & Vaishnavi, 2012). Due to the strong theoretical orientation of this work, the focus is placed on justifying the design theory rather than the artifact (Gregor & Hevner, 2013). As part of the meta-artifact (Sec. 3.2), evaluations are conducted in P5 and P6.

This study integrates two distinct yet complementary theoretical lenses, typical for reputation system research: rationality and trust (G. E. Bolton & Ockenfels, 2012; Dellarocas, 2005; Jøsang, 2007). While some scholars advocate for strict separation (Williamson, 1993), trust cannot be fully captured by classical assumptions of rationality. For instance, initiating a risky advance to build reputation appears first irrational from a rationalist viewpoint, from which reputation systems have traditionally been engineered, e.g., (G. E. Bolton et al., 2013; G. E. Bolton & Ockenfels, 2009). This study shows that trust and rationality are fruitful in combination and shed light on two sides of the same coin (Appendix D). Combining diverging perspectives often yields the most meaningful research outcomes (Mueller & Urbach, 2017).

Due to the limited availability of B2B-specific research, this study relies on insights from B2C and C2C contexts. Though conceptually similar, underlying assumptions may differ in interorganizational B2B settings. Moreover, realizing the system's potential depends on various legal, technical, and organizational preconditions, many of which are context-specific and underspecified. Initial empirical evidence supports the system's practical relevance (P5,P9). The system depends upon network effects and faces a cold start problem. Yet, the artifact has also not undergone field-based evaluation. Furthermore, the mechanism targets non-competitive environments with specific characteristics (Sec. 4.1). This covers only a comparatively small area of B2B segments. Although it is argued that the design theory logic appears to be extensible in more competitive settings, this assumption is unproven. Further studies need to examine and refine the results.

The design theory exhibits a complex logic structured around multiple trajectories to ensure contextual adaptability (A. Schneider et al., 2017; Storey et al., 2025). Still, they are grounded in Ω-knowledge (Sec. 4.6—Tab. 17) and align with the principle that "we do not have to know, or guess at, all the internal structure of the system components, but only that part of it that is crucial to the abstraction in the design theory" (Gregor & Jones, 2007a, p. 327). The trajectories' real-world applicability has yet to be demonstrated.

Usefulness "is the main validity claim of design theories" (Goldkuhl, 2004, p. 61), the first empirical findings suggest high usefulness in selected B2B application domains (P5,P9). However, generally, empirical validation is at an early stage. Sample sizes and contextual diversity of qualitative interviews are limited (P5, P9). The system exhibits high *theory validity* (Larsen et al., 2025). Nonetheless, proposition testability is provided, allowing concrete examination in further studies, which only a few IS studies offer (Salovaara et al., 2020). In novel domains, theory development should come before empirical studies (Iivari, 2007; R. Weber, 2003). This is supported by a contemporary understanding of theory as a lens for generating "tractable uncertainty and productive insights, rather than seeking certainty" (Burton-Jones et al. 2021, p. 306). Consistently, logical argumentation is argued as an equally valid form of knowledge generation in DSR, on par with empirical approaches (Iivari, 2007). Nevertheless, further validation is required. Likewise, agent-based simulations and game-theoretical analysis rely on simplified assumptions of rationality and agent homogeneity. Though helpful for conceptual elaboration, these assumptions may not reflect strategic ambiguity in the real world (Beese et al., 2019).

Regardless of game-theoretical predictions, buyers' rating behavior can deviate from the desired behavior. The assumption that ratings are indeed honest, as indicated by P7, has not yet been tested in real-world settings. Buyers may rate negatively for strategic purposes, such as gaining bargaining leverage, extracting pecuniary advantages, exerting pressure, or because they engage in bribery. Conversely, buyers might be overly cautious and use a buffer of unissued negative ratings to maintain strategic flexibility for submitting negative ratings in the future to account for threshold visibility or honesty (Sec. 4.6). While, in general terms, false positive ratings appear irrational and can be sanctioned with T3, they can still arise and remain undetected. This especially applies when buyers do not intend to share ratings or when cross-checking possibilities are constrained. In any case, negative ratings affect the threshold visibility counter. Therefore, refinements such as T3,T8 (see also footnote 31) might be indispensable. Also, sellers can determine who is allowed to rate (P5). Prospective buyers can consider the source credibility of raters (Ekstrom et al., 2005), make use of information solicitations (T7), or carry out stricter selection criteria.

Although a blockchain may not be needed (Meyers & Keymolen, 2023), several reasons justify its application (Pedersen et al., 2019; G. Sun et al., 2022). Particularly, a blockchain addresses the limitation of *Centralized Governance and Privacy Concerns* (Sec. 2.2.3), since it prevents undetectable selective moderation and suppressed ratings (Agahari et al., 2022; Avyukt et al., 2021). Blockchain protocols also limit informal influence, favoritism, or bribery, e.g., (Long & Liu, 2024; Subramanian, 2018). Truly decentralized blockchains are secure and reduce numerous attack vectors that central instances are vulnerable to (Nakamoto, 2008; Tschorsch & Scheuermann, 2016). The immutability of blockchains is not necessarily an adaptation barrier, since implementers can use techniques such as *soft deletion* for selective rating data mappings (footnote 31). Full disintermediation is not intended (P5), as blockchain systems must remain adaptable and compliant with regulatory requirements (Feulner et al., 2022).

Several unintended side effects warrant attention. One concern is the potential decline in social interaction (Pazaitis et al., 2017) and calculativeness of trust (Möllering, 2014). Put against these concerns, ratings still mitigate uncertainty and can support the emergence of personalized trust (G. E. Bolton & Ockenfels, 2009; Hollowell et al., 2019; Möhlmann et al., 2019). Yet the emerging effect is unknown. Furthermore, privatizing ratings may deteriorate costless information provision, which might reduce the willingness to share ratings for free. Alternative motivations for sharing free ratings might persist (Burtch et al., 2018; Hennig-Thurau et al., 2004; Seutter, 2022; Seutter et al., 2023; P. F. Wu, 2019). However, a negative effect in this regard appears probable when the system is widespread.

Several other aspects should be considered. It remains unclear to what extent the benefits of the system (Sec. 5.4) and T3 can overcome the general reluctance to share information (Fabrizio & Kim, 2019; McKnight et al., 2017; Truong, 2019). Yet, companies primarily view data sharing as an economically rational decision based on cost–benefit (Schumann et al., 2025), suggesting that market mechanisms serve to regulate the apparent demand for ratings (P5). When companies search themselves for information, they are more likely to share their information (P. Xu et al., 2009). While the monetization of ratings appears theoretically reasonable and has remained unquestioned in interviews (P5, P9), its viability in practice is untested. Incentive structures may vary with operative margins, pricing models, and visibility, which potentially affect ratings and fairness perceptions. Another aspect that has not yet been conclusively examined is individuals' willingness to subject themselves to being rated, even in institutional settings. Ultimately, system reliability hinges on network effects (Beck et al., 2008). In low-volume markets, limited trading opportunities weaken incentives to produce ratings and constrain the ability to cross-validate ratings (Ekstrom et al., 2005). Single quality signals seem not sufficient for complex business decisions. Finally, legal and ethical concerns are only slightly touched upon. These areas demand further scrutiny in future research.

These limitations suggest a range of fruitful research avenues. More crucially, future research should prioritize empirical evaluation of the system's core mechanisms (TP1–TP12). Each trajectory (T1–T9) opens distinct areas for future research. Prominently, research on (self-governed) observation stages, rating, and selection behavior appears interesting. Field studies and case studies can help examine actual behavioral responses. Experiments and simulation models may isolate the effects of visibility thresholds, monetary incentives, or collusion risk. Legal-oriented research can clarify how the system aligns with data protection, governance accountability, and normative standards in regulated environments. This includes mechanisms such as rating consent, auditability, and external governance structures (T8). On the technical side, selecting appropriate blockchain infrastructures and designing post-quantum-secure storage of ratings remains important. Another subsidiary yet uncertain but intriguing aspect is to examine whether monetary weighting, combined with high network density and selectivity, can withstand Sybil attacks in open networks.[56] Moreover, the design theory could be tested in several other B2B domains and new areas, such as agent negotiations, DAO governance, knowledge systems, etc., to refine the design. Applying the approach to the oracle problem with TCRs presents an especially impactful research frontier. In forward-looking scenarios, it will also be relevant to study how the system performs in more competitive or adversarial settings, and how viable it is without centralized oversight (T8). Lastly, the collected 52 systems-theoretical concepts offer numerous research directions beyond designing reputation systems and can inform IS research more broadly, e.g., for analyzing, designing, or theorizing complex information systems.

[56] The rationale for this consideration lies in the fact that money itself acts as a safeguard medium, see Luhmann (1976, 2017). It holds remembered trust in itself, which can act in a distributed network as a trust anchor. In addition to this, Douceur (2002) posits the widely accepted assumption that Sybil attacks are invariably possible in the absence of a central authority, except under highly unrealistic conditions. However, since Douceur did not consider monetary weighting, this mechanism may cautiously be interpreted as offering a practical path to encounter Sybil attacks (MR3). By introducing monetary weighting as an externality imposed by an outside system, it has the potential to influence the behavior of network nodes in an exogenous manner. This idea aligns with Luhmann's (2013) concept of structural coupling between systems, which describes how systems remain operationally closed but structurally dependent on specific environmental domains.

8 Conclusion

This dissertation develops a novel design theory for a trust-enabling reputation system in B2B contexts. It introduces monetary ratings as selectively tradable trust signals, operationalized through a blockchain-based coordination mechanism. This work aims to mitigate lemon markets and build trust between companies (McKnight et al., 2017; Thierer et al., 2016). By integrating systems theory with an economic coordination logic, this research redefines how reputation systems can be conceptualized and implemented in interorganizational digital environments using blockchain. The design mitigates the limitations of current systems and opens new pathways for establishing trust through risk in the form of a socio-economic asset.

The design indicates a pivotal evolutionary step from numerical to text-based and star-based ratings (Dellarocas, 2003; Pavlou & Dimoka, 2006) toward monetary ratings. Until now, research has solely concentrated on numerical scores, textual ratings, or star ratings, ignoring the potential of monetary ratings. This study is the first to describe reputation ecosystems, where monetary ratings can be traded, thereby offering a promising approach to the public goods problem inherent in traditional systems (G. E. Bolton et al., 2004).

Based on nine contributions, the proposed artifact responds to a potentially high-impact, underexplored problem domain (Hevner et al., 2004) and fulfills the innovation types for IS research formulated by Grover and Niederman (2021). Based on system principles, this study theorizes how trust formation can be fostered with a coordination logic using risky signaling, incentive alignment, and selective observability. This coordination logic might be useful for other domains. IS scholars can draw on a portfolio of 52 system concepts to craft *socio-economic-technical information systems* to create, analyze, and theorize about certain system effects.

Future research should validate the system's application empirically across industry domains. Beyond the B2B markets, its coordination logic invites transfer to automated procurement, DAO governance, or agent-based negotiation. By enabling the structured trading of quality signals, the system has the potential to reshape how organizations select partners, signal trustworthiness, and structure their digital relationships (Beck et al., 2017; Ekstrom et al., 2005; Herhausen et al., 2020; McKnight et al., 2017). In this sense, the work not only contributes to IS theory but also offers a blueprint for trust-enabling systems.

Appendix Part A

A Operationalization of System Concepts to Design Principles

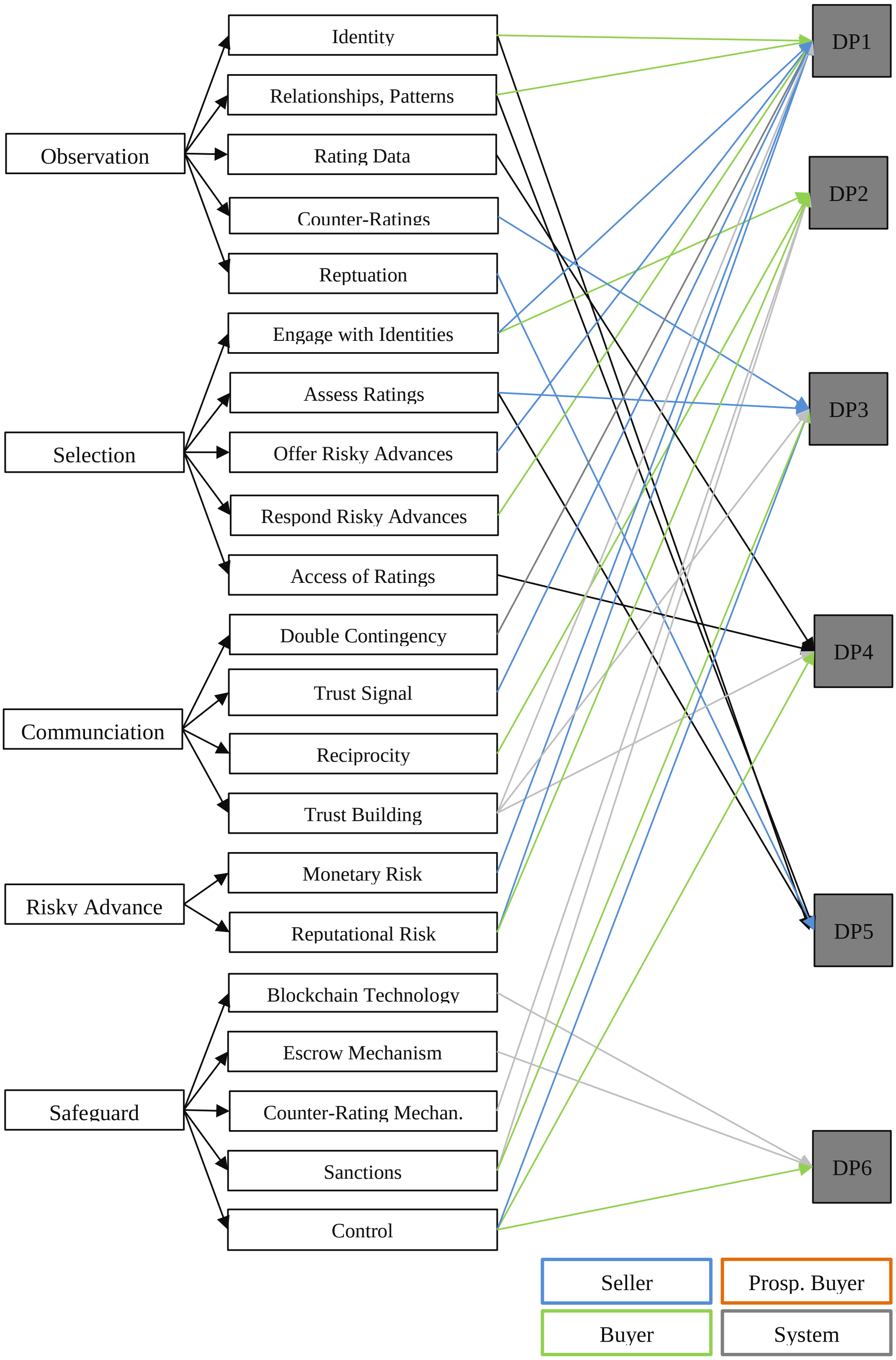

Figure 15: Mapping the Forms of the System Concepts to the Design Principles

B Extended Representation of the Design Principles

Table 19: Extended Representation of the Design Principles

Design Principle	Aim, Implementer, and User	Context	Mechanism (Form)	Rationale (Function)
DP1 – Risky Advance	*Aim:* Build initial trust *Implementer:* Seller *User:* Seller (initiator), Buyer (recipient)	Initial transaction with no prior trust relationship	Sellers offer a voluntary monetary rating (price discount) as an upfront commitment; held in escrow via smart contract	Establish initial trust for buyers through observable seller commitment
DP2 – Voluntary Monetary Rating	*Aim:* Enable voluntary trust expression *Implementer:* Buyer *User:* Buyer	Ex-post rating decision after rating commitment	Buyers voluntarily release monetary ratings as part of the payment recorded on-chain	Enable authentic, non-coerced trust signaling; provide economic trust signals
DP3 – Counter-Rating	*Aim:* Deter buyer opportunism *Implementer:* Seller (trigger) and system (automated flagging) *User:* Seller (reactive actor), Buyer (indirect actor)	Repeated buyer exploitation (non-payment of risky advances of sellers)	The system can react to repeated non-compensation; sellers can trigger counter-ratings and flag exploitative buyers	Deter opportunistic buyer behavior; reinforce fairness and reciprocal trust behavior
DP4 – Selective Signal Observability	*Aim:* Protect strategic information *Implementer:* Buyer *User:* Buyer	Trust-sensitive environments that require discretion	Buyers use cryptographic tools to control rating visibility and disclosure	Balance transparency with strategic discretion; enable private or traded trust signals
DP5 – Trust Assessment	*Aim:* Improve rating interpretability *Implementer:* System *User:* Buyer, Prospective Buyer	Decision-making based on rating information	Buyers assess ratings via relational, behavioral, and monetary metadata (e.g., history, identities, rating amount)	Support informed trust decisions by enabling contextual signal interpretation
DP6 – Decentralized Storage	*Aim:* Ensure verifiability and data integrity *Implementer:* System *User:* All actors	Need for verifiability and manipulation protection	All ratings and interactions are immutably stored on a permissioned blockchain	Ensure tamper-proof rating records; build institutional trust without relying on central platform authority

C Assignment of the Dissertation to the Eleven Types of Innovation

Table 20: Innovation Types of this Study (based on Grover and Niederman 2021)

Category	Innovation Type	Description	Fulfillment
Deriving	1. Filling a literature gap	Address the lack of B2B reputation systems as a recognized research gap.	✓
	2. Filling a problem gap	Tackle the real-world issue of adverse selection in B2B due to a lack of trust-enhancing mechanisms	✓
	3. Bricolage	Combine systems theory, DSR, blockchain, and trust research in a novel way to formulate a design theory	✓
	4. Differentiating subpopulations	Differentiate between B2B and B2C contexts with regard to trust mechanisms and system requirements	✓
	5. Changing level of analysis/stakeholder	Shift analytical perspective from individual rating mechanism to system rating mechanism; addresses firms as the primary stakeholders with complex behavior	✓
Extending	6. Extending current models	Introduce new elements such as *monetary ratings*, *counter-ratings*, and *selling ratings* to extend reputation system models	✓
	7. Technology extension	Use blockchain technology to create monetary ratings for tamper-resistant, decentralized business reputation systems	✓
	9. Using new theories	Employ LST to conceptualize trust in the social part of the information system. LST has not yet been used as a theoretical lens in DSR.	✓
	8. Using different methods	Design a method for issuing monetary ratings	✓
Re-Visioning	10. Future orientation re-visioning	Re-frame reputation systems as social communication systems rather than purely as technical aggregation systems	✓
	11. Blue ocean transformational	Theorize and challenge mainstream views of reputation system's design.	✓
	12. Perspective shift	Use systems theory as a design theory; Define a new system class of blockchain-based business reputation (eco)systems for B2B environments.	✓

D Two Theoretical Perspectives on Reputation System

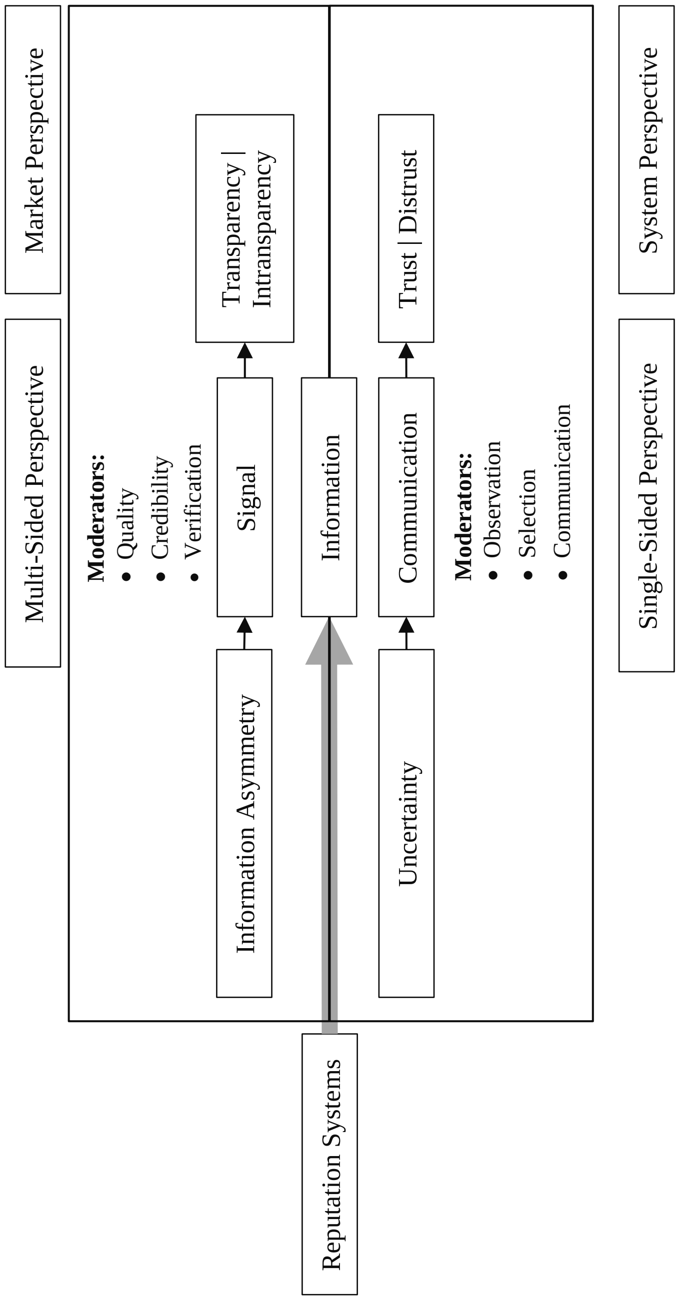

Figure 16: The Dual Role of Reputation Systems Regarding Information Asymmetry and Trust

Part B - Included Publications

9 Research Articles on the Design of a Blockchain-Based Reputation System

9.1 Bridging Systems Theory and Information Systems: A Framework for Designing Complex Information Systems

Paper Number	P1	
Title	Bridging Systems Theory and Information Systems: A Framework for Designing Complex Information Systems	
Publication Type	Journal Paper	
Outlet	Communications of the Association for Information Systems (CAIS)	
VHB JOURQUAL 4	B	
Authors	Hemmrich, Simon	55%
	Ibrahimli, Ulvi	40%
	Winkelmann, Axel	5%
Status	1st major revision (revised and resubmitted July 2025)	

Abstract. *Information Systems (IS) is rooted in systems theory. Systems theory offers powerful concepts to address challenges of increasing system complexity and non-systemic design principles in information systems. Despite its systemic roots, systems theory remains a peripheral topic in IS. The study addresses this gap by introducing a comprehensive framework of 52 systems-theoretical concepts to guide the design of complex IS artifacts. We synthesize scattered systems knowledge from diverse disciplines to provide a unified level of abstraction for complex information system design. We ascertain the utility of our framework by applying it to a use case of blockchain-based reputation systems to show how the systems lens informs the design of a novel and complex information system. We make several contributions to literature. The framework introduces a systemic perspective that encourages IS researchers to rethink the design of IS artifacts. Such a lens enables the transcending of disciplinary boundaries. It also contributes to literature by offering a unified level of abstraction grounded in systems theory that serves as a coherent basis for artifact design. The study also bridges the gap between DSR and systems theory by abstracting design principles to the systems level to generate more generally applicable design knowledge.*

9.1.1 Introduction

Information Systems (IS) researchers and practitioners alike face the persistent challenge of understanding and designing complex information systems (Merali, 2006). Information systems are mixed systems that involve hardware, software, data, people, and processes to collect, process, store, and disseminate information, which enables individuals and organizations to achieve their objectives effectively and efficiently (Mora et al., 2003; L. D. Xu, 2000). Lately, they have been marked by an exponential rise in complexity, ambiguity, and high levels of uncertainty (Jaradat, 2015). The advancements in IT sophistication, shifting user expectations as well as evolving organizational knowledge compound the challenges of designing information systems (Burton-Jones et al., 2021). As such, understanding how to navigate such system complexity has become crucial (Alter, 2004; Benbya et al., 2020; Jaradat, 2015; L. D. Xu, 2000; Zeigler, 1994). IS research has long been centered on the exploration of *systems* (Baskerville et al., 2015; Hevner et al., 2008; Hirschheim et al., 1995; Orlikowski & Baroudi, 1988). Early on, one primary basis for designing information *systems* is considered systems theory (Avgerou, 2000; Burton-Jones et al., 2015; Demetis & Lee, 2016; Mora et al., 2003; Nolan & Wetherbe, 1980; L. D. Xu, 2000). Systems theory unlocks a transformative line of thinking about the design of complex information systems artifacts (Fang et al., 2018; McBride, 2005; Onik et al., 2017) and is viewed as “a necessity to deal with the overwhelming systems complexity in the information era” (L. D. Xu, 2000, p. 105). The overarching concepts thereof are suited to holistically understanding the systemic blueprint of information systems (Hossain et al., 2020; Mingers & White, 2010b; Whitney et al., 2015; L. D. Xu, 2000).

Prior research finds that the information systems discipline has not availed itself of the body of knowledge on systems theory. Critics argue that a field bearing “systems” in its name would significantly benefit from more seriously integrating the systems lens into its core (Demetis & Lee, 2016). Such critical reflections are grounded in the origins of the early scholarly thinking on systems theory, like those of Boulding, who view systems theory as a skeleton to hang the flesh and blood of certain disciplines in the form of an orderly corpus of organized knowledge (Boulding, 1956). Such thinking enables theoretical abstraction beyond the confines of a design methodology (Demetis & Lee, 2016). Paradoxically, systems theory remains a peripheral topic in IS research (Demetis & Lee, 2016; Fang et al., 2018) despite its the systemic roots (Alter, 2004; Hassan, 2023; Merali, 2004, 2006; Mingers & White, 2010b; Nolan & Wetherbe, 1980; L. D. Xu, 2000). Further, the disparity between the discipline’s espoused theory of itself and the non-systemic theory-in-use loudens the lack of consensus about what truly qualifies as IS research (Alter, 2013; A. S. Lee, 2010). Discussion on meta-theory circulates for several years, and the status of theory development in IS undergoes intense debate (Burton-Jones et al., 2021; Hassan et al., 2023) while there are still ongoing calls to:

“reaffirm its commitment to developing foundational theories and offer bold new theoretical ideas and approaches to inspire and shape our field’s future” (Burton-Jones et al., 2021, p. 301).

One possible side-effect of such ideologically charged calls is critical introspection within the IS community to reflect on the essence of discipline. This discord collectively amplifies the need for a comprehensive systems framework in IS. While IS research has cultivated a body of knowledge on artifact design, development, and evaluation, e.g., (W. Kuechler & Vaishnavi, 2012; vom Brocke et al., 2017), the absence of systems theory-based frameworks as a unified degree of abstraction renders the design process fractured. This is potentially attributable to differing perceptions of system boundaries (Baxter & Sommerville, 2011) and the situational development of design principles that generate knowledge at varying abstraction levels (vom Brocke et al., 2017). A systems lens appears predestined to provide this unification in abstraction due to its interdisciplinary and holistic nature.

“In information systems, elements of systems theory have formed part of the conceptual fundamentals in all thematic streams. Terms such as system, subsystem, control,

boundary, and environment constitute the field's pervasive vocabulary." (Avgerou, 2000, p. 573).

Such a systems lens can also enable researchers to gauge the naturally evolving systemic changes and system-induced environmental requirements (Jaradat, 2015) in IS. Yet the IS discipline lacks an anchor of systems concepts necessary to capture the systemic nature of artifact design knowledge. The knowledge of systems concepts hitherto being fragmented further amplifies the ontological and epistemological ambiguities (Mononen, 2017; Onik et al., 2017; Robey & Mikhaeil, 2016). The study's central premise is thus to help IS researchers develop a profound understanding of systems concepts critical for designing complex IS artifacts at the highest possible unified level of abstraction. Past literature also emphasizes the importance of well-founded systems concepts to guide the knowledge creation in the IS domain (Kautz, 2012; Waguespack & Schiano, 2013)). Accordingly, we pose the following research question (RQ):

RQ: What are the relevant systems theory concepts that can be used in designing complex information systems?

To address this research question, we follow the General Systems Theory's inquiry to craft systems knowledge (Boulding, 1956). Drawing from seminal works in the domain (Adams et al., 2014; Benbya & McKelvey, 2006b; Ghosh et al., 2007; Luhmann, 1995; Onik et al., 2017; Peters, 2016; Whitney et al., 2015) we compile a comprehensive collection of 52 systems-theoretical concepts and consolidate them into a structured framework. In doing so, this study contributes to IS research in several ways:

First, by synthesizing systems concepts across various disciplines and positioning them within IS, the framework reduces the fragmentation of systems knowledge. It enhances accessibility, minimizes overlap, and aligns divergent perspectives, thereby improving the framework's utility for designing complex IS artifacts. Second, the framework introduces a systemic lens that encourages IS researchers to rethink the design of IS artifacts. It promotes a systemic perspective that enables researchers and practitioners to approach design challenges holistically. Third, the study also contributes to IS literature by offering a unified level of abstraction grounded in systems theory that serves as a coherent basis for the design of complex artifacts. Fourth, it also addresses the issues of increasing system complexity. Fifth, complementing the existing practices of abstracting design principles with foundational systems concepts contributes to bridging the gap between systems theory and design science research (DSR). Such practice would minimize the duplication of effort in different fields, promote unity of science, and improve communication of IS researchers across multiple fields of academia. Sixth, this study also lays a foundation for future theory development in IS. It advocates for a gradual infusion of systems-theoretical concepts into the discipline, guiding IS researchers to expand their methodological and theoretical toolkits and thus broadening the discipline’s horizon.

The paper proceeds with systems theoretical reasoning for IS in Section 2. Section 3 provides an overview of systems theories, while Section 4 details the research approach. In Section 5, we present the framework for complex information systems design. We then apply this framework to a business reputation system and draw design implications in Section 6. Section 7 provides a discussion of findings, contributions, and critical reflections. Finally, Section 8 concludes the study.

9.1.2 Systems Theoretical Reasoning for Information Systems

9.1.2.1 Systems Theory for Theorizing in Information Systems Research

Systems theory is a group of systemic propositions that are pulled together to aid in understanding systems. Those propositions stem from different disciplines, which render systems theory’s foundation inherently multidisciplinary (Adams, 2012; Adams et al., 2014). Information systems have evolved from the natural sciences of systems over time (Alter, 2004; Hassan, 2023; Merali, 2004, 2006; Mingers & White, 2010b; Nolan & Wetherbe, 1980; L. D. Xu, 2000). Systems research indicates that an information system consists of structured sub-systems that are found in natural sciences (Curtis et al., 1988; Warfield & Christakis, 1987) such as physics (von Bertalanffy, 1950), social systems (Luhmann, 1995), biology (Gell-Mann, 2002), anthropology (Abel & Stepp, 2003), management (Kast & Rosenzweig, 1972; A. Schneider et al., 2017), and more (Onik et al., 2017). This cross-disciplinary lineage suggests that natural science’s success can be replicated as information systems emulate the concepts of those systems (L. D. Xu, 2000).

A recurring theme in IS research is the field's struggle to develop a native theory. This challenge has often been attributed to the reliance on theories domesticated from other disciplines, which some argue diminishes originality in IS research (Grover & Lyytinen, 2015; Hassan et al., 2023). Some scholars argue that discipline should strive to understand the theorizing process (Gregor et al., 2020), while others state it is because of the lack of native IS concepts (Markus & Silver, 2008). Historically, well-developed concepts have underpinned solid theory building (Hassan, 2023). IS concepts are crucial for crafting propositions that facilitate generalization, abstraction, and application to new subject matter (Hassan, 2023; Hassan et al., 2019). Thus, the higher the developed concepts are of abstraction level, the more generally applicable IS knowledge can be generated that broadens the horizon of scholarly discourse of theory building in IS (Demetis & Lee, 2016; Hassan, 2023). The quest of systems theory is to achieve the highest level of abstraction (Demetis & Lee, 2016). Yet IS research rarely explores new, systems-related concepts (Markus & Saunders, 2007).

Systems theory provides the necessary means, i.e., concepts, to advance the work on systems theorizing (Bertalanffy, 1950; Boulding, 1956; Hammond, 2003) in IS (Demetis & Lee, 2016). It transcends the unidirectional, reductionist "boxes-and-arrows" depictions often observed in positivist IS research (Demetis & Lee, 2016; Hassan et al., 2023). It enables theorizing about the IS phenomenon “systemically,” i.e., holistically, where system elements are bidirectional, recursively re-entering the system and shaping its dynamics (Demetis & Lee, 2016; El Sawy et al., 2010). Unlike the approach of “analyzing”, which breaks down an information system to analyze individual properties, systems theory advocates “synthesizing” to understand the emergent whole—an approach aligned with interpretive theorizing (Demetis & Lee, 2016) . While interpretivism aligns more closely with systems theorizing than positivism, systems theory exceeds specific epistemologies through its high-level abstraction (Demetis & Lee, 2016). For instance, it allows for observer-relative studies (Yong Liu et al., 2017) where the act of observing is itself subject to observation, creating a layered framework of systemic sensemaking and contingent distinctions (Demetis & Lee, 2016; Luhmann, 1995). Such thinking promotes interpretive IS research and helps theorize the complex interactions within an information system at a higher-order abstraction, which can be handled with systems theories like holism or constraint theory (L. D. Xu, 2000). As a result, systems theory can serve as an antidote for silo thinking across many disciplines (Baxter & Sommerville, 2011) and promote the sharing of theory and concepts as it offers a holistic perspective to theorize about various systems (Adams, 2012; Malecic, 2016).

9.1.2.2 Systems Theory for Designing Information Systems

Many disciplines have benefited from adopting a systemic perspective to understand, theorize, and design systems (Henshaw, 2019; Mononen, 2017). IS can similarly benefit by embedding systems concepts (Robey & Mikhaeil, 2016) into its core, particularly in design science, to navigate introspection in a variety of ways: 1) investigate the isomorphy of concepts, laws, and models across various disciplines; 2) develop adequate theoretical models in fields that lack them; 3) minimize the duplication of effort in different fields; 4) promote unity of science by improving communication amongst IS, systems and design specialists (Adams, 2012).

DSR involves the production of design knowledge and artifact generation (Baskerville et al., 2015; Hevner et al., 2004) as innovative solutions to real-world problems (vom

Brocke & Maedche, 2019; vom Brocke et al., 2020). A recurring challenge in DSR is addressing the abstraction of deriving design knowledge (Baxter & Sommerville, 2011; Gregor & Hevner, 2013; Gregor et al., 2020). At the crux of the discussion is a common misconception regarding scholars describing the same complex systems using varying levels of abstraction. This stems from drawing system boundaries at different places (Baxter & Sommerville, 2011). For instance, socio-technical artifacts are frequently analyzed with a disproportionate focus on either the technical aspects (Eason, 2001), organizational context (Hollnagel, 1998), or user activity without considering their systemic interdependence (Demetis & Lee, 2016, 2017). This fragmented thinking is partly rooted in the situational development of design principles (vom Brocke et al., 2017) based on the contextual conditions and causal analysis (Gregor & Hevner, 2013), drawing, possibly, on non-IS or non-systemic prior knowledge (Gregor et al., 2020), rather than foundational systemic frameworks. As a result, this approach produces design knowledge at varying levels of abstraction, often lacking the theoretical generality required for broader systemic applicability (Gregor et al., 2020; vom Brocke et al., 2017). Explanations tend to remain context-bound and neglect the universal, lawful characteristics of complex systems (Baskerville et al., 2015).

Henshaw (2019) proposes rethinking the design of IS artifacts through the lens of systems theory. This enables capturing the systemic essence of the artifact design as a cohesive whole, i.e., a systemic phenomenon (Henshaw, 2019). Such an approach provides a unified abstraction level to the degree of systems concepts–a coherent basis for designing these complex systems in a more integrated manner, where the system properties based on which the system is designed are collectively rooted in systems-theoretical concepts (Syynimaa, 2017). Linking design principles to systems theory leads to a higher level of abstraction, which in turn results in the production of more generally applicable, systemic design principles (Kovacevic-Opacic & Marjanovic, 2024; W. Kuechler & Vaishnavi, 2012). To achieve this, it is vital to make systems-theoretical concepts more accessible through a structured framework. Such a framework helps IS researchers address information systems' complex and systemic nature. It is designed to foster consistency in design approaches, helping IS artifacts be understood and constructed within a comprehensive systems-theoretical paradigm (Burton-Jones et al., 2021; Dubrovsky, 2004; Gregor et al., 2020; Jones, 2014; B. Kuechler & Vaishnavi, 2011; J. R. Venable, 2006).

9.1.2.3 Systems Theory for Analyzing Information Systems

The goal is for IS artifacts designed with systemic abstraction to be leveraged for ex-post analysis and infused into practice, e.g., (Demetis & Lee, 2017; Henshaw, 2019).

However, a priori critiques, such as those by Robey and Mikhaeil (2016), caution that the abstract nature of some systems concepts might render them challenging for IS practitioners to analyze and apply. This lack of accessibility risks effective communication between academia and industry.

On the contrary, Demetis and Lee (2017) posit that the very versatility of systems concepts, which have transcended fields like law, sociology, economics, engineering, physics, etc., demonstrates their potential as a unified shared language. IS practitioners, often with multidisciplinary backgrounds, inherently engage with systemic constructs, such as client-server architectures, cellular biology, or planetary dynamics. These real-world parallels—between a system (e.g., a server, a cell, a planet, or a company) and its environment (e.g., clients, other cells, the moon, or a business context)—provide intuitive entry points for understanding and analyzing IS artifacts on a systems theory level.

A fundamental starting point in systems theory is distinguishing between a system and its environment. This establishes the system's self-referential nature and lays the groundwork for concepts like autopoiesis (Demetis & Lee, 2016). While such concepts may initially appear abstract and difficult to operationalize, Demetis and Lee (2017) highlight that focusing on simpler foundational elements—such as boundaries, feedback loops, and system-environment interactions—can make systems thinking more accessible and practical for IS analysis.

Applying a systems lens allows IS researchers and practitioners to analyze nested dependencies and dynamic interactions within complex systems. This perspective acknowledges that IS outcomes emerge from their design and the evolving interdependencies and interactions within their environments. By respecting the systemic nature of IS, systems thinking helps uncover patterns and interrelationships, making it a valuable analytical tool for capturing and understanding these complexities (Alter, 2013).

9.1.3 Overview of Systems Theories

Systems theory is an interdisciplinary foundational theory for understanding systems in nature, society, or artificial (Capra, 1997; Henshaw, 2019; Simon, 1969). It posits that entities are interconnected wholes comprising interdependent elements that fuse into an "interacting unicum of phenomena, where the individual properties of the single parts become indistinct" (Mele et al., 2010, p. 126). Hence, as a whole, "a system is a set of interrelating elements" (Ackoff, 1971, p. 662) where holistic properties emerge that analysis alone cannot detect. Communication within the system happens when states or properties of system elements are distinct in the context of specific relations. When the elements share the same state or relationship, no meaningful interaction occurs, as there is no dynamic to drive a change or process (Demetis & Lee, 2016). In IS, a system is conceptualized as a dynamic network of interrelated and interdependent components that interact to process, transfer, and adapt information. These components work together within ever-changing environments, influencing and being influenced by organizational structures and processes. This perspective highlights the critical role of systems theory, which views systems as evolving entities rather than static constructs. Effective information systems leverage feedback loops and relational changes to enable adaptive responses to environmental shifts. Feedback loops provide mechanisms for self-regulation, allowing systems to assess their performance and make adjustments to align with organizational goals. Relational changes within the system's components facilitate adaptability, ensuring the system remains relevant and effective in dynamic contexts. For a comprehensive explanation of the foundations of systems in IS, we relate to Merali (2004), Mele et al. (2010), Mingers and White (2010b), and Ackoff (1971). Systems theory uses seven axioms based on which information systems can be understood, analyzed, and influenced (Tab. 21) (Adams et al., 2014; Whitney et al., 2015).

Table 21: Seven Axioms of Systems Theory (Adams et al., 2014)

Axioms	Description
Centrality	Systems have a hierarchical order of constituting elements, while communication and control happen between subsystems or the systems inherent elements.
Contextuality	Systems observe (and are observed) according to their environment, informing the dynamic actualization of internal elements.
Goal	Systems follow a purposeful behavior using pathways by connecting their elements to existing structures.
Operational	Systems operate according to their system character (guiding differences) (Luhmann, 1995) and must be addressed in situ.
Viability	Systems aim to ensure continued existence by outbalancing key parameters.
Design	Systems design is never fully balanced in terms of relations and resources.
Information	Systems select, modify, create, and transfer information.

Many extensions next to basic concepts like communication, emergence, and feedback have been proposed to expand the pool of systems thinking concepts. Over time, scattered attempts have been made to integrate systems concepts in the IS domain, noteworthy from General Systems Theory (Boulding, 1956), Complex Adaptive Systems (Gell-Mann, 1994; Holland, 1992b), and Work System Theory (Alter, 2013), and some others.

General Systems Theory (GST). Pioneered by Kenneth Boulding (1956), GST represents a foundational paradigm for understanding systems across diverse domains. It is to serve the purpose of a meta-level language for theory to address systemic problems (Checkland, 2000) and promote the unity of science across different disciplines (Boulding, 1956). GST inspired a lot of other research streams, especially systems thinking and systems engineering. As an interdisciplinary framework, it transcends disciplinary boundaries by identifying common patterns that can be applied to different types of systems (Whitney et al., 2015). Conceptual synthesis helps recognize these parallels (Bunge, 1983; Nevo & Wade, 2010). GST on a purely theoretical scale received some recognition from IS (Gregor, 2006; Markus & Rowe, 2018) but is barely used within the domain. One exception is Alter (1999, 2013), who uses general system theory concepts in his Work System Theory. Another connection to GST can be found in Complex Adaptive Systems Theory (Umpleby, 2009; van Assche et al., 2019).

Complex Adaptive Systems (CAS). CAS explores the behavior of complex systems characterized by non-linear interactions, self-organization, and adaptation (Nan, 2011). Rooted in biological evolution and computational modeling, CAS uses agent-based models to simulate and understand the dynamics of non-linear complex systems, providing insights into key phenomena such as emergence, self-organization, and co-evolution (Dooley, 1997). Although CAS has been applied in IS research, its adoption remains fragmented (Onik et al., 2017). Notable instances of CAS application include the investigation of agile software development (Vidgen & Wang, 2009), information systems development process (Kautz, 2012), or information structures (Khanna & Venters, 2013).

Work System Theory (WST). Steven Alter's WST offers a nuanced perspective on the design and operation of work systems within organizations. Alter emphasizes the need for flexibility, adaptability, and human-centered design in IS development by focusing on the socio-technical aspects of work systems (Alter, 2014, 2018). WST has found some acceptance in IS, particularly for research on aspects of socio-technical systems (Bednar & Welch, 2020) and workarounds (Wolf et al., 2020).

Beyond the theories above, several other theoretical perspectives contribute to understanding systems within the IS domain. These include Beer's recursive embedded Viable Systems Model (Beer, 1984), Checkland's Soft Systems Methodology (Checkland, 2000), Luhmann's far-reaching Social Systems Theory (Luhmann, 1995), and more (Ashby, 1947, 1956). Each perspective offers unique insights into the structure, behavior, and evolution of systems in organizational and technological contexts, which can enrich the theoretical landscape of IS research.

9.1.4 Research Approach

In this study, we construct a conceptual framework that consolidates accumulated knowledge in systems thinking to situate the relevant systems concepts within the IS domain. Frameworks are the researcher's map of the domain being studied, consisting of the main concepts and their propositions (Hassan, 2023). They maintain structure, guide the scholarly work, and contribute to the cumulative knowledge base in a particular domain (Palvia et al., 2003). The method's inclusive nature facilitates combining knowledge across different fields of systems scholarship (Palvia et al., 2003) to anchor its concepts within an interdisciplinary field like information systems (Gorry & Scott Morton, 1971; Tarafdar & Davison, 2018).

Following Mingers's (2004) recommendation of pragmatism, we introduce a framework that organizes the most prevalent systems concepts for a more practical representation of reality (Hassan et al., 2023; van de Ven, 2007). Given the fragmented nature of systems concepts (Onik et al., 2017), this structured framework brings coherence to widely dispersed ideas. We perform the framework construction on interpretive epistemological ground – a cascading set of models and metaphors that serves as an interpretive scaffold (McBride, 2005; Walsham, 1995) for sensemaking in complex socio-technical interactions. It allows generalizable insights that can be applied to other design contexts in IS (McBride, 2005).

In lieu of conducting systematic literature research – which would be limited due to the strong fragmentation and ambiguous search terms (e.g., "system"; "theory") (Williams et al., 2017) – we conducted extensive iterative forward and backward searches through seminal works. This approach allowed us to focus specifically on high-quality, conceptually relevant IS research (vom Brocke et al., 2015). We primarily adhere to the concepts provided by Adams et al. (2014), Luhmann (1995), and additional carefully selected papers (Benbya & McKelvey, 2006b; Onik et al., 2017; Peters, 2016; Whitney et al., 2015), where we consolidate different system concepts into a manageable form. To align those concepts with the nature of accumulated knowledge in IS, we reformulate descriptive concepts in a design-oriented way. It is crucial to note that, depending on the system type, one can only design certain aspects or only the environment of the system. We explain each foundational concept's fundamental systemic purpose and provide a short explanation. We outline subordinate concepts and delineate specifications for designing IS at a systems abstraction. We reference relevant IS literature where these concepts can or have been applied and refer to potentially affected IS topics. By doing so, we also identify gaps in IS literature.

9.1.5 A Framework of Systems Concepts for Information Systems Design

We struggle to understand the interrelations among the systems concepts and their functional purpose due to the knowledge basis on systems theory being vastly scattered and underexplored in the IS context. Our framework addresses these challenges by restructuring the body of knowledge on systems concepts and eliminating redundancies.

Consistent with prior literature (Abbasi & Chen, 2008; J. Li et al., 2020), our framework guides the study of systemically behaving information systems. Drawing from General Systems Theory (Boulding, 1956), the framework includes system concepts rooted in diverse disciplines like physics, chemistry, biology, psychology, sociology, economics, etc. We first present the foundational system concepts, followed by an extensive collection of subordinate concepts that build upon these foundations.

Table 22: Foundational Concepts in Systems Theory

System Concept (and Associated Effect)	**Main Purpose**	**Brief Description**
Autopoiesis (Self-Organization) (Ashby, 1947; Luhmann, 1995; Varela et al., 1974)	Organizing structures within a system.	Autopoiesis refers to a system's ability to self-produce and maintain its organization through internal processes. This concept is applied to the continuous generation of communication. Systems are autopoietic when they reproduce their elements through internal communication networks, defining their boundaries and interactions with their environment.
Communication (Information Exchange) (Luhmann, 1995; C. E. Shannon, 1948)	Process information within a system.	As per C. E. Shannon (1948), communication involves the technical process of encoding, transmitting, and decoding information to minimize noise and ensure efficient transfer. Communication is encoded and decoded in systems using the triad of information, utterance, and understanding, which forms the basis of social interaction.
Complexity (Chaos and Uncertainty) (Lorenz, 1963; Simon, 1962)	Deal with internal and external complexity.	Complexity arises from the intricate interactions and interdependencies among a system's numerous components. This leads to unpredictable behavior, emergent properties, and a high degree of variation in the system's responses to external and internal changes. Complexity encompasses the multiple layers of structure, the diversity of elements, and the dynamic nature of their interactions within a system.
Dynamic Equilibrium (Regulation) (Le d'Alembert, 1743; von Bertalanffy, 1968)	Regulation to maintain the system balance/state.	Dynamic equilibrium regulates and maintains the system's balance amidst changing environmental conditions. Controlled by adjusted regulation, dynamic equilibria are fundamental for systems' adaptation and self-organization to their environment. Dynamic equilibrium plays a crucial role in managing complexity and facilitating resilience.
Emergence (Order) (Holland, 2000; Simon, 1962)	Creation of new system properties.	Emergence refers to the process where a system displays properties, behaviors, or patterns that are not present in the individual components but arise from their interactions. It explains how complex order emerges from the interactions of subordinate elements. These emergent properties are novel and cannot be fully understood or predicted by analyzing isolated components.
Feedback Loop (Circular Causality) (Bateson, 2000; Korzybski, 1933; Wiener, 1948)	Learning from (complex) loops to achieve certain system states.	Feedback loops, or circular causality, refer to a process where a system's output feeds back into the system as input, influencing subsequent behavior. This loop can either reinforce (positive feedback) or counteract (negative feedback) changes within the system. Feedback creates a cycle of cause and effect that can either stabilize or destabilize the system. Feedback loops are essential in understanding how systems regulate themselves, adapt to changes, and evolve.

Hierarchy (Control) (Checkland, 1999; Wiener, 1948)	Surveillance and control of subordinate system instances.	Hierarchy refers to the organizational structure of system elements arranged in levels where higher levels exert control over lower ones. This concept emphasizes the distribution of authority and responsibility within a system to manage complexity and facilitate efficient operation. The hierarchical arrangement enables effective control, ensuring coordination and coherence within the system while subordinate elements support the superordinate ones.
Observation (Selection) (Foerster, 2003; Luhmann, 1995)	Overcoming contingency in the system's own environment.	Darkness is the unobserved state in the environment of a system. Observation refers to a system recognizing and using its environment by observing it. Observation enables systems to grasp their environment, recognize patterns, anticipate changes, and make decisions. Any observation reintroduces the distinction imposed by the observer.
Part-Whole-Interaction (Unity) (J. C. Smuts, 1926; van Gigch, 1978)	Combining individual components into a cohesive and adaptive whole.	Part-Whole-Interaction refers to the idea that systems and their properties should be viewed as wholes, not just as a collection of parts. This concept emphasizes that the interactions and relationships between parts create emergent properties that cannot be understood by examining the parts in isolation. Holism and unity are interconnected, as unity underscores the integration and interdependence of components within a system, leading to a cohesive and functioning whole.
Structure (Path-Dependency) (Parsons, 1951; Pierson, 2000; Simon, 1969)	Continuation of the system's trajectory based on past events.	Structures are time-related relationships that connect the system elements. Path dependency explains how these structures evolve since past events influence them. The current structure of a system is the result of accumulated past actions and events, which shape the system's present form and future possibilities.
Structural Coupling (Dependence) (Luhmann, 1991a, 1995)	Configuration of structures to other environments or other systems.	Structural coupling refers to the interdependence between a system and its environment, where the system's organization adapts to maintain coherence amidst environmental changes. Structural coupling denotes the ongoing mutual influence and adaptation between a system's internal structure and its environment, ensuring functional harmony and viability.
System Border (System-Environment Difference) (Parsons, 1951; von Bertalanffy, 1968)	Permission or prevention of the entry of matter, energy, or information.	System borders refer to the demarcation that separates a system from its environment, defining what is internal versus external to the system. System-environment exchange describes the interactions and exchanges of information, energy, or materials across this boundary, indicating what belongs to a system and how it adapts and responds to external influences.

In the following framework (Tab. 23), we present what we believe to be the most comprehensive collection of system-theoretical concepts to date, with similar concepts thoughtfully aggregated. The framework offers an analytical lens that guides the understanding of the systems associated with common phenomena. Yet this lens can also help to analyze other phenomena, effects, or outcomes. Finally, we derive systems specifications that combine systems knowledge with insights from IS literature. Through an iterative process, we constructed, refined, and categorized these specifications by concept context and distinct properties. The defining criterion for a new concept category was its unique capacity to explain system properties not addressed in the same manner by other concepts. The focus lies in reorganizing the systems knowledge to position its concepts in the domain of IS design rather than critically assessing the concepts per se.

Table 23: Framework of Systems Concepts for Information Systems

	Subordinate Concepts	Analytical Lens	Systems Specifications for Information System Design
Autopoiesis (Self-Organization)	**Self-Organization, Spontaneous Order** (Ashby, 1947; Prigogine & Stengers, 1984): Organization without external influence.	Understand how autopoiesis contributes to self-organization and autonomy of systems (decentralization, dynamic stability, innovation).	• Foster unplanned, non-formal structures for heterogeneous interactions without control (Kautz, 2012). • Allow interaction with autonomous decisions, reorientation, and restructuration (Merali, 2004). • Govern elements in the system by the information carried within themselves or according to their structure/surface (D. Boyd, 2020; Ghosh et al., 2007).
	Reproduction (Luhmann, 1995; Zeleny, 1977): Creation of new instances or copies of a system.	Analyze the role of reproduction in diversifying systems (mutation, services, products).	• Introduce variation, mutation, and selection into the reproduction of system elements (Merali, 2004, 2006). • Consider the different evolution speeds of associated systems (D. Boyd, 2020)
	Co-Evolving (Jantsch, 1980; Kauffman, 1993): Systems adapt and develop together.	Study how systems evolve through mutual adaptation and development (evolution, innovation).	• Allow functions to evolve independently (D. Boyd, 2020). • Provide a sufficient environment where the functions of elements can co-evolve (D. Boyd, 2020). • Combine routines, capabilities, and measures to regulate the internal rate of change (Vidgen & Wang, 2009).
Communication (Information) Exchange)	**Communication** (Luhmann, 1995; Parsons, 1951): Effective exchange and organization of system processes.	Explore how communication facilitates effective system organization (innovation, knowledge, communication channels).	• Interrelate specific system elements or foster communication between system parts. • Amplify or attenuate communication (Merali, 2004) • Provide multiple information channels and facilitate short (or long) interaction (Curşeu, 2006; Katz & Shapiro, 1986; Kautz, 2012). • Communicate through open channels or holes (Ghosh et al., 2007). • Determine the forms of communication programs and code (Luhmann, 1995).
	Input-Output Transformation (Klir, 1969; Wiener, 1948): Transform system input into outputs.	Examine how systems transform input into outputs (resources, efficiency, transformation).	• Alter input or output parameters by interventions (Merali, 2004) • Provide the necessary environmental input for the system's configurations. • Implement rhythmic synchronization protocols to ensure temporal alignment of critical processes.
	Change Rate, Coordination Rhythm (Benbya & McKelvey, 2006a; Dumont, 1967; Fisher, 1930): Synchronize and regulate activities.	Analyze time patterns, synchronization, and agility to regulate system activities (time pattern, synchronization).	• Set change rate to adapt to the environment (Benbya & McKelvey, 2006a). • Set fixed time intervals for information exchange (Benbya & McKelvey, 2006a; Kautz, 2012). • Timestamp changes to trace operations and resource allocation (Banathy, 1989). • Increase the speed and volume of information transmission (Merali, 2006).

Complexity (Chaos)	**Requisite Variety, Requisite Complexity** (Ashby, 1956; Boisot & McKelvey): Necessary variety and complexity to respond effectively to changes.	Understand how much diversity a system needs to flourish (complexity reduction, micro diversity, network effects).	• Ensure sufficient controlled variety for reaction possibilities by implementing sufficient control variety (Ashby, 1947). • Create or allow the evolution of complexity to reduce complexity elsewhere (Benbya & McKelvey, 2006a; A. Schneider et al., 2017). • Use large, open crowds as a guarantor of variety in a system for processing, rating, solving, and creation (Geiger et al., 2011).
	Requisite Parsimony (G. A. Miller, 1956): The minimal complexity required for a system to operate efficiently.	Identify the minimal complexity required for a system to operate (efficiency, complexity reduction).	• Identify and define essential key parameters/variables (Merali, 2004). • Detect and use invariants as proxies that serve as replicas of system behavior (Ghosh et al., 2007). • Streamline, standardize, and simplify elements. • Employ minimalistic design principles to reduce unnecessary complexity.
	Incompressibility (Chaitin, 1975; Cilliers, 2002): The essential complexity that cannot be simplified further.	Analyze the system's flexible response and capacity concerning essential complexity (capacity, identity).	• Ensure system components are as simple as possible without losing necessary functionality (Beeson & Davis, 2000). • Use complexity metrics to identify and retain only the indispensable aspects of the system.
	Causal Intricacy (Lindblom, 2018): Systems have complex cause-and-effect relationships.	Examine the complex cause-and-effect relationships (complexity, feedback paths).	• Map multiple sources of causalities and feedback loops (Benbya & McKelvey, 2006a; Kautz, 2012). • Interlink feedback loops in multiple ways (Merali, 2004). • Use system nested diversity to protect the system (Ghosh et al., 2007; Sharman et al., 2004).
	Entropy (Clausius, 1865; C. E. Shannon & Weaver, 1949): The Level of disorder and randomness.	Understand how fluctuation affects the system's disorder (differentiation, order).	• No concrete systems specifications were found.
	Diffusion, Differentiation (Fourier, 1888; Luhmann, 1995; Rogers, 1962): Natural spread of information or substances.	Study the system's spread of information, behavior, or substances (fluctuation).	• No concrete systems specifications were found.
	Recombination, Inverse Generativity (Hofstadter, 1999; Holland, 1992a) Creating new configurations by combining and repurposing existing elements.	Analyze the effects of recombining certain system (structures of) elements (innovation, value creation, products, services).	• Recombining the same system elements with different variety levels to produce different outcomes (Baldwin & Woodard, 2009; Beverungen et al., 2018; Vial, 2023) • Create advanced functions by combining simpler functions (D. Boyd, 2020). • Integrate heterogeneous or homogenous resources with different properties (Peters, 2016). • Use modularity that supports easy recombination and repurposing of existing elements.

Emergence (Order)	**Preferential Attachment** (Barabási & Albert, 1999): Elements tend to connect more frequently with highly connected elements.	Study how topology, aggregation, and information flow are affected (topology, aggregation, information flow).	• Steer newly arriving entities to smaller (or bigger nodes) (Benbya & McKelvey, 2006b). • Increase connectivity, reach, and information transmission range (Merali, 2006).
	Connection Costs, Square-Cube Law (Carneiro, 1987; Holland, 1992a; Meadows et al., 2018; Zipf, 1949): Effort and resources required to establish and maintain connections.	Examine how system connection costs influence the system's efficiency, element distribution, connection costs, or security (efficiency, coherence, block building).	• Set system boundaries to restrict further growth of connections (Benbya & McKelvey, 2006b). • Remove and add new components or elements in the system to work more efficiently (Georgiadis et al., 2002; Hanseth & Lyytinen, 2010).
	Morphostatic Elaboration (Archer, 1996; Buckley, 1967; Wolpert, 1969): Keeping or refining the form of a system over time.	Analyze how systems maintain or refine their form over time (purpose, consistency, personality).	• Add or prune connections selectively to create new network dimensions or functions (D. Boyd, 2020). • Develop new functions or features while retaining basic identity, organization, or structure (Peters, 2016).
	Dissipative Structure (Prigogine, 1980): Forming structures that use energy flows to maintain or create order despite non-equilibrium states.	Understand how emergent patterns and structures maintain stability and adaptability in dynamic environments (structure).	• Allow system behavior outside admissable performance limits (Garlan & Schmerl, 2002; Ghosh et al., 2007). • Identify semistable patterns of changing behavior (Beeson & Davis, 2000; McBride, 2005). • Implement gateways to guide information flow to other system parts or systems (Geiger et al., 2011; Hanseth & Lyytinen, 2010).
	Tipping Points, Bifurcation, Edge of Chaos (Lyapunov, 1992; Poincaré, 1893; Prigogine & Stengers, 1984; Schelling, 2006): Key points on which a small change causes significant system shifts.	Analyze network effects, sudden collapse, and changeover concerning critical thresholds in system behavior (network effects, collapse).	• Identify or implement critical points on which the system switches to new emergent behavior (positive or negative) (McBride, 2005; Williams et al., 2017). • Induce small actions that cause large consequences (Beeson & Davis, 2000). • Isolate structures that can result in significant changes (Benbya & McKelvey, 2006a; McBride, 2005; Merali, 2004).
	Order (Haken, 1983; M. Mitchell, 2009; von Bertalanffy, 1968): Systems develop distinct structures and repetitive patterns.	Study patterns and behaviors that emerge within systems (patterns, structures).	• Recognize change as a natural way to preserve or improve order in the system (Beeson & Davis, 2000) . • Model complex dynamics to reveal emergent structures and build on this (Merali, 2004). • Implement feedback loops that promote the emergence of orderly and stable system behaviors.
	(Inverse) Power Laws, Zipf`s Law, Pareto Distribution (Newman, 2005; Pareto, 1964; Watts & Strogatz, 1998; Zipf, 1949): Regular distribution patterns observed in various systems.	Analyze regular distribution patterns revealing underlying principles and dynamics (distribution, efficiency, capability).	• Allocate resources to the expected probability distribution of occurrence (Merali, 2006; Whitney et al., 2015). • Focus on highly connected nodes for, e.g., fault resolution (Merali, 2006).

Feedback Loop (Circular and Delayed Causality)	**Reinforcement Loops, Balancing Loops** (Sterman, 2002): Feedback loops that either increase (reinforce) or stabilize (balance) system behavior.	Analyze the effects of positive and negative feedback loops on system behaviors (exponential growth, self-reinforcement, signaling).	• Reintroduce certain loops to reinforce or balance system behavior (Fang et al., 2018; Henfridsson & Bygstad, 2013). • Use feedback loops to align and disalign internal processes (Amarilli et al., 2023; Valetto & Kaiser, 2002). • Send and receive positive or negative signals about the system's operation (Ghosh et al., 2007; Spence, 1978).
	Re-Entry (Recursion) (Beer, 1984; Luhmann, 1993b): Feedback loops where a system's outputs are fed back as inputs.	Examine self-reinforcement, obsolescence, and renewal of information dynamics (sustainability, repository).	• Reuse the same system components as input (R. Agarwal & Tiwana, 2015; Kovacevic-Opacic & Marjanovic, 2024; Vial, 2023). • Update and recycle old system information under novel conditions (Kallinikos, 2006).
	Synchronization, Resonance (Huygen, 1673; Luhmann, 1995): Synchronize activity patterns when interacting.	Understand how synchrony and resonance occur (integration, harmony, parallelization).	• Improve effective harmonic communication in the system (Mele et al., 2010). • Develop synchronization protocols to align operations across distributed system components.
Hierarchy (Control)	**Requisite Hierarchy, Systems-of-Systems** (Aulin‐Ahmavaara, 1979; Maier, 1998): The necessary level of hierarchical organization to maintain structures.	Study the effects of hierarchy on system organization (chain-of-command, system levels, dependence).	• Establishing necessary levels of authority and control, coordinating the actions on lower levels (Combs & Vagle, 2002; Ghosh et al., 2007; Knop et al., 2002). • Detect disappearing components, the absence of messages, or missing responses(Ghosh et al., 2007). • Integrate superordinate and subordinate system instances (Merali, 2004).
	Fractals, Bounded Generativity (Mandelbrot, 1982): (Self-similar) Patterns that repeat at different scales.	Recognize self-similar patterns that repeat at different scales within systems (self-similarity).	• Use growth boundary to stabilize the system (Fürstenau et al., 2023). • Use the repetition of patterns of higher-level behavior on lower levels or vice versa. • Build up superordinate structures from subordinate structures.
	Subsystems, Modularity (Parsons, 1951; von Bertalanffy, 1968): Breaking down systems into smaller (interchangeable) units.	Understand how modularity enhances adaptability and efficiency (robustness, specialization).	• Integrate and decompose modules to decrease interdependencies and complexity (R. Agarwal & Tiwana, 2015; Eessaar, 2014; Kovacevic-Opacic & Marjanovic, 2024). • Break down or integrate into smaller interconnected modules and components for variety and flexibility (Kovacevic-Opacic & Marjanovic, 2024).
	Control (Wiener, 1948): Processes for regulating a system's operation.	Examine processes regulating operation to achieve certain outcomes (effect, dependence).	• Monitor the system's performance relative to its goals and adjust parameters or strategies accordingly (Checkland, 2000). • Delegate jurisdiction and responsibility (Kautz, 2012). • Implement feedback loops to adapt to changes.
	Redundancy of Potential Command (McCulloch, 1965) Multiple components within a system can take control.	Analyze the potential for multiple components to take over control (pleiotropy, teamwork).	• Providing multiple command options to achieve desired outcomes (Kautz, 2012). • Implement failover mechanisms that allow backup components to assume control in case of primary component failure.

Dynamic Equilibrium (Self-Regulation)	**Homeorhesis (External Stability)** (Jantsch, 1980; Waddington, 1957, 1968): Return to system trajectory after external disturbance.	Understand what mechanisms make systems return to the previous trajectory (parameters, regulation, infection).	• Use adaptive algorithms to restore system functionality (Merali, 2004). • Replicate elements excessively to send signals and reprogram system information (George et al., 2003).
	Homeostasis (Internal Stability) (Cannon, 1929; Wiener, 1948): Return to a stable system state after internal disturbance.	Examine how systems return to a stable state (parameters, regulation, error).	• Withold substituting system protocols for operation when errors occur (Combs & Vagle, 2002). • Delete specific or all system programs and restart the system (Ghosh et al., 2007; Yiguang Hong, 2002). • Maintain (multiple) dynamic equilibria internally in the system.
	Ambidextry, Exploitation & Exploration (O Reilly & Tushman, 2004): Ability to exploit current resources while exploring new possibilities.	Study the balance between exploiting resources and exploring new possibilities (innovation, productivity).	• Balance the use between internal and external resources (Vidgen & Wang, 2009; Volberda & Lewin, 2003).
	Self-organized Criticality, Adaptive Tension (Bak, 2013; Prigogine, 1955): Self-regulated balance between stability and the ability to adapt.	Understand how systems achieve a self-regulated balance (reconfiguration, regrouping, robustness).	• Stimulate adaption with exogenous environmental tension (Benbya & McKelvey, 2006a; Hanseth & Modol, 2021). • Use external tension to induce preservative behaviors (Benbya & McKelvey, 2006b). • Increase the capacity for distributed storage, processing, and reconfiguration (Merali, 2006).
	Information Redundancy (Pahl et al., 2011; C. E. Shannon & Weaver, 1949): Duplication of (critical) elements for reliability.	Examine the trigger of duplication of critical elements within a system to prevent system failures (data storage, backup).	• Provide superfluous information in the system (e.g., data storage) to increase reliability against noises or internal defects (Georgiadis et al., 2002).
	Relaxation Time (Recovery), Self-Healing (Clemson, 1984): Time required for a system to recover.	Study the time support required for a system to recover to its normal state (sustainability).	• Implement self-healing features to quickly respond to new conditions (Ghosh et al., 2007). • Use models (internal or external) to monitor system behavior and self-heal the system from faults or attacks (Ghosh et al., 2007).
	Adaptive Capacity| Responsiveness (Bertalanffy, 1950; Capra, 1997; Forrester, 1997): The capability to adjust to changing conditions.	Examine the capability of systems to adjust to changing conditions swiftly (learning).	• Structure the system around processes rather than fixed states (Alter, 1999, 2014, 2021). • Structure the system involving past environmental responses (Kautz, 2012). • Build adaptive capacity into the system, allowing it to respond to changing environmental conditions.
Observation (Selection)	**Darkness, Blind Spot, Contingency** (Luhmann, 1995; Spencer-Brown, 1994): Aspects that a system cannot or does not observe.	Understand aspects that are hidden, overlooked, or not readily apparent (encryption, information asymmetry).	• Make some information purposefully unobservable by cutting connections. • Encrypt essential information within the system. • Stimulate the system to make behavior observable.

	Selection (Darwin, 1859; Fisher, 1930; Luhmann, 1995): The selection process of certain information and ignoring others.	Examine how systems selectively process information, reducing complexity (choice, progress, evolution, fitness).	• Determine what can be observed and which selection processes can be carried out. • Prioritize and select relevant information for processing and decision-making. • Filter irrelevant data and focus on critical inputs.
	External Observer (Luhmann, 1995): An observer outside a system who distinguishes the system from its environment.	Study the role of an external observer in distinguishing a system from its environment (perspective, difference, bias).	• Satisfy the observer's expectation through the implemented design thresholds between separate operating systems (Waguespack & Schiano, 2013). • Understand the designer as a second-order observer(Henshaw, 2019). • Implement feedback loops that incorporate insights from external observers to improve system design.
	Self-Referentality (Bateson, 2000; Foerster, 2003; Luhmann, 1995): The capacity of a system to refer to itself (self-description).	Understand a system's capacity to refer to and regulate itself (information, understanding, self-regulation).	• Refer the description of information to an information domain of an element and as meta-description to other meta-descriptions to generate new information patterns (D. Boyd, 2020; Kallinikos, 2006). • Abstract and update the information status based on disposition and depreciated information (Kallinikos, 2006).
Part-Whole-Interaction (Unity)	**Elements and Relations** (Luhmann, 1995): Fundamental units and their interaction.	Analyze the fundamental units and interactions (specification, relationships).	• Determine what elements and relations constitute a system(Garrity, 2001; Merali, 2004). • Explore and visualize relationships between entities for other entities (Basole, 2009; McBride, 2005).
	Minimum Critical Specification (Cherns, 1976, 1987): The least detail necessary for system components to work.	Understand the minimum detail necessary for a system to function (components, parameters).	• Establish minimum requirements for system functioning (Kautz, 2012). • Specify the same (identical) elements applied on a great scale using the same system program on a single layer (Ghosh et al., 2007; Nagpal et al.). • Standardize the elements in the system.
	Local Optimization, Sub-Optimization (Hitch, 1953): Optimizing efficiency in one place leads to weaker performance elsewhere.	Analyze the trade-offs between optimizing efficiency in one part and drawbacks in others (reaction time, specialization).	• Balance optimization efforts to maximize overall effectiveness. • Design the system where each element operates independently based on local information.
	Complementarity (Bohr, 1928): Interdependence or mutual reliance between system parts or elements.	Study the interdependence and mutual reliance between different parts or elements (micro diversity).	• Plan and design systems (asymmetrically) to support or supplement other systems (P. Wang, 2021; Whitney et al., 2015). • Complement a system's abilities with another compatible system to synergize each other abilities (Nevo & Wade, 2010).
Structure (Path-Dependency)	**Equifinality (Convergence)** (von Bertalanffy, 1950): Different paths lead to the same outcome independent of the initial state.	Understand how different paths can lead to the same outcome (goal, standardization).	• Find valid alternative structure paths to attain the same final state (Demetis & Lee, 2016; Rolland & Hanseth, 2021). • Impact system trajectory with specific events (artificial or random).

	Multifinality (Divergence) (Buckley, 1967): A single starting point can lead to multiple outcomes.	Examine what allows systems paths to change multiple outcomes (goal, disparity).	• Permit different, mutually exclusive end goals of a system (Demetis & Lee, 2016). • Structure element combinations based on previously created elements (D. Boyd, 2020).
	Bounded Rationality (Simon, 1955): Limited decision-making capacity due to processing constraints.	Understand the limitations of decision capacity (incentives, goal, behavior).	• Consider individuals acting with differing rationalities according to available information (Mingers & White, 2010b; Stacey et al., 2000). • Incentivize or sanction certain behaviors to align behavior (Hanseth & Lyytinen, 2010).
	Purposive Behavior (Viability) (Beer, 1984; Rosenblat & Stark, 2016): System behavior is interpreted as to achieve a goal.	Study how system behavior is interpreted to achieve specific goals (meaning, competition).	• Different observers perceived a different purpose of the system (Kovacevic-Opacic & Marjanovic, 2024). • Determine the system's goal (Garrity, 2001). • Neglect unimportant functionalities to achieve a specific goal.
Structural Coupling (Dependence)	**Decoupling and Recoupling** (Glassman, 1973; Orton & Weick, 1990): Separation and reconnection of elements within a system.	Analyze the cause for the separation and reconnection of elements (system integration, inter-system communication).	• Modularize loosely coupled system parts (Benbya & McKelvey, 2006a; Eessaar, 2014; Hanseth & Lyytinen, 2010; Kautz, 2012). • Couple systems appropriately with other systems to enable a coordinated exchange of information. • Use the system's environment (including other systems) to directly feed or not feed the system (Normann, 2001; Vestues & Rolland, 2021).
	Connectedness, Hebb's Law (Hebb, 1949): Joint activity connects elements or enforces existing connections.	Understand when joint activity occurs and why they connect elements or reinforce existing connections (learning, linking).	• Activate connections between elements to create a selective network (Merali, 2004, 2006). • Reinforce beneficial connections based on joint activity.
	Interpenetration (Luhmann, 1995): Overlap of different kinds of systems.	Study which systems and their elements use the same resources (system-system relationship).	• Employ systems to support the generation of feedback loops of other systems (McBride, 2005). • Insert boundary objects for exchange information at the system border (M. C. Dong et al., 2017).
	Guiding Difference, Requisite Saliency (Boulding, 1966; Luhmann, 1995): The primary distinction used to guide systems operations and its salient parameter.	Identify salient elements and their functions and the primary distinction of a system (operator, system border, difference).	• Define clear operational system boundaries to understand the system's operational realization (McBride, 2005; Merali, 2004). • Delineate when elements belong to the system to differentiate the system from its environment (Garrity, 2001; Merali, 2006).
	Operational Closure (Luhmann, 1991a, 1995): Self-contained functionality or operation within a system.	Understand self-contained functionality or operation within a system (interoperability, immunity).	• Translates external information into the (sub)-system's internal codes and processing rules, ensuring that external data is compatible with the system's internal logic (Banathy, 1989; D. Boyd, 2020). • Apply different codes for separate processes (Banathy, 1989). • Defend attacks with barriers separating external and internal environments (Ghosh et al., 2007).

This extensive collection with 129 system specifications offers an overview of various, sometimes lesser-known, applications of system concepts in IS(-related) literature as prescriptive knowledge for system design and analysis. Where concepts lacked relevance or applicability, such as apoptosis (self-destruction of a cell) and double binding (bonding between atoms), we excluded them. However, these concepts may still hold potential for future research in information systems.

9.1.6 Example for Design of Blockchain-based Reputation System

To ascertain the practical utility of our framework, we apply a selected set of identified concepts to the design project of business reputation systems (Hemmrich et al., 2023). Business reputation systems, as a rather new system class, present unique design challenges (Hemmrich et al., 2024). Because it also carries ample possibilities for refinement (Ibrahimli et al., 2024), the project is a suitable context for applying our framework. We navigate a series of design tasks and demonstrate how system-theoretical concepts can inform and enhance the design process.

Business reputation systems are designed to assess product or service quality, discern trustworthy ratings, and shape reputation information to augment business relationships. They aid buyers in finding reliable sellers and enable sellers to showcase their competence. This system introduces five novel features: monetary ratings, where payments serve as ratings; selling ratings to peer buyers; blockchain-based storage for securing monetary rating data; risky advance to foster trust; and a counter-rating mechanism to prevent malicious rating behavior. We begin by detailing the mechanics of each feature and outline their distinct contributions to the system's functionality. Then, we abstract these features to a systems-theory level by applying our framework (Tab. 24).

Monetary ratings: The buyer and seller engage in a transaction where the seller consents to be rated by the buyer based on the quality of the product or service. This transaction includes two financial components: (1) base payment and (2) rating payment. The base payment, made by the buyer, is essential to the transaction and is discounted by the rating payment. The rating payment is an optional, variable component that the buyer may choose to make to rate the seller. The rating payment quantifies the rating by assigning it a monetary value. By tying ratings to financial transactions, this mechanism is intended to reduce the likelihood of reciprocal or inflated ratings, as the rating involves a direct financial commitment from the buyer (Filippas et al., 2018).

Selling ratings: Buyers can sell their rating information, that is, whether they made a rating payment, to peer buyers. Buyers are hence incentivized to submit ratings as they are enabled to monetize their feedback, which creates a self-sustaining motivation to rate honestly (Hemmrich et al., 2024). Over time, buyers who consistently submit honest ratings build credibility, enhancing the value of their rating information to peers. Buyers can profit from selling rating information, so their reliance on sellers for incentives is dampened. This helps to mitigate biased ratings that often result when buyers feel compelled to provide positive feedback in return for financial rewards from sellers (Neumann & Gutt, 2019a). By distancing financial incentives from the seller's influence, the system aims to foster a more balanced and accurate rating environment.

Blockchain-secured ratings: Rating agreements are stored immutably on the blockchain. This renders ratings irrefutable and safeguards them from corruption, post-facto changes, or attacks. It also helps to uphold the authenticity, integrity, and consistency of documented agreements.

Risky Advance: In joining the reputation system, a seller agrees to offer a product or service at a discounted price, with the expectation of receiving the discount amount back in the form of a rating-based payment if the seller delivers the anticipated quality (Hemmrich, 2023). However, this arrangement makes the seller vulnerable, as he/she risks not being compensated for the discount upfront. Nonetheless, it serves as a strong trust signal, demonstrating a seller's confidence in earning the expected compensation and helping reduce the buyer's uncertainty.

Counter-rating: A question arises regarding how to handle buyers who engage in exploitative rating behavior, systematically withholding rating payments despite receiving good quality. To counter this, sellers can issue a counter-rating in the form of a star rating (Hemmrich, 2023). This counter-rating becomes visible once it reaches a threshold determined by a sufficient number of sellers reporting a negative rating for that buyer. Sellers who observe a poor reputation for a buyer's rating behavior may then choose to avoid future transactions with them.

Overall, ratings embody the reputation that users rely on to evaluate the system's trustworthiness. Consistent with the systems theory of social systems (guiding difference) (Luhmann, 1995), entities providing these ratings exist outside the reputation system itself. They contribute to a reputation ecosystem by supplying rating information for others. This ecosystem helps to select, observe, and communicate about each other's signals, enabling entities to interpret information in ways that shape their perception of system trustworthiness (Hemmrich et al., 2023). Hence, crafting such rigorous systems necessitates a solid foundation of abstraction at the systems level. Table 4 illustrates how we apply specifications to design reputation systems. The output knowledge (right column) outlines how each system concept (left column) informs and substantiates the design of business reputation systems. This enables a better understanding of the systemic laws that affect the features and what to look out for in a specific design.

Table 24: Application of Systems Concepts to Business Reputation Ecosystems

Concept	Design Implications for Business Reputation Ecosystems
Requisite Variety, Requisite Complexity: Use large, open crowds as a guarantor of variety in a system for processing, rating, solving, and creation (Geiger et al., 2011).	***Knowledge:*** Reputation information can be seen as a core system element of reputation systems. It requires a large and diverse user base, as a guarantor of information richness, to ensure a requisite variety of reputation information. A broad user base contributes to an information pool that reflects the full range of goods and services. ***Design:*** The variety of reputation information should exceed the variety of offerings to support users in forming comprehensive judgments and making well-informed decisions. This information environment should have a sufficient structural complexity that allows various reaction possibilities and responsiveness to changes. Hence, with requisite variety and depth of ratings users are enabled to draw conclusions about complex service compositions.
Recombination, Inverse Generativity: Recombining the same system elements with different variety levels generates different outcomes (Baldwin & Woodard, 2009; Beverungen et al., 2018; Vial, 2023).	***Knowledge*:** A diverse range of outcomes can be generated when reputation insights drawn are based on the varying recombination of the system elements in reputation systems. When system participants are enabled to creatively recombine rating information or other reputation elements, they expand the information pool, potentially adjusting existing ratings or adding new layers of insights atop historical data. This process enables adaptive updates as actors' trading decisions continuously reshape the contextual relevance of ratings tied to products or services. ***Design:*** In this dynamic environment, existing and new information from different varieties should, therefore, be recombined to generate new reputation information, which allows for more nuanced and context-sensitive judgments about goods or services.
Self-Organized Criticality, Adaptive Tension: Stimulate adaptation with exogenous environmental tension (Benbya & McKelvey, 2006a; Hanseth & Modol, 2021).	***Knowledge:*** Complex systems maintain balance through tension, e.g., irregular, change, or disturbance. Such systems under continuous pressure, where the tiniest push can lead to either a small ripple or a big wave of change, usually settle into a balanced state where they make constant adjustments. Similarly, reputation systems must be able to constantly adapt themselves to avoid disruption through malicious actor behavior – e.g., free riders who exploit discounted prices and never give fair ratings. ***Design:*** To counter such actions, systems should incorporate a self-regulating mechanism, such as counter-ratings, in this case. When dishonest buyers accumulate a threshold of counter-ratings, sellers can identify and restrict them, maintaining system balance without needing third-party intervention. Hence, counter-ratings serve as a defense mechanism of such systems to "push back" against system disequilibrium caused by systematic exploitative behaviors.
Reinforcement Loops, Balancing Loops: Introduce feedback loops to reinforce or balance system behavior (Fang et al., 2018; Henfridsson & Bygstad, 2013).	***Knowledge:*** Feedback loops are critical for ensuring system sustainability by aligning individual actions with collective outcomes. Positive reinforcement loops reward actors for behaviors that align with system goals, such as providing accurate and reliable ratings. Balancing loops counteract behaviors that deviate from the desired outcomes, ensuring that negative tendencies like dishonest ratings are minimized. This interplay between reinforcement and balancing creates a self-regulating mechanism that stabilizes the system over time. ***Design:*** Reputation systems should contain a feedback mechanism to align the actors' behavior with the system's intent by rewarding positive actions and penalizing negative ones to sustain the overall long-run functioning of the system. For buyers, rating honestly is reinforced as they depend financially on the peer buyers' search for quality information about sellers (reinforcement loop). They would also avoid bad counter ratings by sellers that would ruin their

	reputation and jeopardize their trade relations with peer buyers, hurting them financially (balance loop). Similarly, sellers are motivated to maintain high performance to secure positive ratings. Over time, this enables them to adjust prices while still attracting buyers.
Information Redundancy: Provide superfluous information in the system (data storage, communication channels) to increase reliability against noises or internal defects (Georgiadis et al., 2002).	***Knowledge:*** Although negatively connotated, redundancy is vital for robust system design, ensuring reliability and safety. When a system element fails, duplicates can seamlessly take over its function. In reputation systems, redundancy must ensure resilience against system failures or data loss by maintaining backup data channels and communication pathways. ***Design:*** In an open reputation ecosystem, seamless data exchange between nodes allows the system to withstand disruptions. Information redundancy aids in detecting false or inaccurate ratings by cross-referencing data across multiple copies, reinforcing system integrity. For this issue, blockchain technology can enhance resilience by storing redundant copies of information across decentralized nodes.
Selection: Determine what can be observed and which selection processes can be carried out (Luhmann, 1995).	***Knowledge:*** Selection processes are foundational in reputation systems as they determine the information that actors consider relevant. By filtering observations and interactions, actors focus on data that maximizes decision-making efficiency and minimizes uncertainty. This selective observation enhances the relevance and accuracy of the exchanged information, ensuring that system participants can tailor their actions and decisions based on reliable and context-sensitive reputation insights. The concept emphasizes the importance of observation and selection for the system's functionality. ***Design:*** In reputation systems, actors must be enabled to selectively collect, process, and act upon reputation data. For instance, sellers can observe buyers, collect and process information on their rating behavior (e.g., counter-rating mechanism), and select which buyers they want to be evaluated by. Similarly, buyers can select to whom they resell information, while potential peer buyers can observe and select sources from which to receive ratings.

This application shows how abstract systems theoretical concepts can inform the design of complex information systems. The use case demonstrates how the design of selected information system elements can collectively be abstracted to the degree of systems theory as a unified level of abstraction. We derive design implications from this use case that reflect the prescriptive nature of the framework. Hence, we contribute to the prescriptive knowledge base in the intersection of systems theory and IS research (Gregor & Hevner, 2013) by consolidating scattered systems knowledge and showing how the framework can guide the design of other complex information systems.

9.1.7 Discussion

The process of synthesizing concepts from a multiplicity of scientific fields, like physics, chemistry, computer science, biology, sociology, politics, art, or economics, into a highly abstract systems lexicon (Demetis & Lee, 2016) built the basis for the cumulative tradition of organized knowledge in systems thinking. In systems theory, the purpose has been to seek the highest levels of abstraction possible. This quest has manifested the need to tackle the phenomenon of understanding and designing complex systems (Demetis &

Lee, 2016). As the IS field has matured, its focus has progressively shifted from the artifact per se to levels of abstraction that underlie its design (Gregor & Jones, 2007; B. Kuechler & Vaishnavi, 2008; W. Kuechler & Vaishnavi, 2012). The lack of systems frameworks as a unified degree of abstraction renders this design process unstructured. This abstraction challenge aligns with the historically rooted native theory and concepts crisis in IS (Demetis & Lee, 2016; Hevner et al., 2004; Somers, 2010). Apart from the individual works like Checkland (2000) and Alter (2013), there are no impactful systems movements in the IS domain (Demetis & Lee, 2017) that guide the systemic design of IS. This development has an ironic tinge given that IS as a discipline and many core concepts are fundamentally grounded in systems theory (Alter, 2004; Hassan, 2023; Merali, 2006; Mingers & White, 2010; Nolan & Wetherbe, 1980; Xu, 2000).

The systems concepts compiled in this study serve to understand universal and lawful patterns in complex system design (Onik et al., 2017). While some already are second nature in IS, they exhibit varying degrees of overlap and contrast. Overlap becomes visible when concepts are applied to different system types—abstract versus tangible, biological, energetic, social, or artificial systems—or from systems' salient characteristics, reflecting "requisite saliency" (Boulding, 1966). Though this overlap may be perceived as a limitation, it simultaneously provides a necessary level of variance to address the complexity inherent in information systems, akin to the "requisite variety" principle (Ashby, 1956). Moreover, certain concepts may seem mutually exclusive—such as control versus self-organization—yet others mediate these apparent contradictions. For instance, the *operational closure* concept bridges the dichotomy between open and closed systems (Luhmann, 1991), showcasing the integrative potential of systemic perspectives.

9.1.7.1 Contributions and Implications for IS

Comprehensive systems theoretical framework for IS. This paper makes several contributions to IS literature. It extends the current literature by providing an extensive collection of 52 system theoretical concepts as a framework to guide the design of information systems. Aligned with GST's mission to craft systems knowledge (Boulding, 1966), this collection provides a nuanced synthesis of fragmented systems knowledge. It renders systems concepts more accessible to improve system design across various information systems classes (Hevner et al., 2004). The framework's rich composition of concepts, positioned in the IS context, potentially addresses all facets of design phenomenon in systemically behaving information systems. By pooling knowledge from various information systems and systems theory strands, we reduce redundancy and overlap in concepts, identify connections, and harmonize divergent perspectives. These efforts collectively improve the framework's utility for complex IS designs to foster systemic depth in information systems.

Introduction of systemic perspective and fostering systems thinking. In that sense, the framework introduces a systemic perspective that encourages IS researchers to rethink the design of IS artifacts. Providing a comprehensive overview of systems concepts equips IS researchers with a systemic lens that aligns the foundational roots of IS discipline with the design of increasingly complex IS artifacts. This perspective enables the transcendence of traditional disciplinary boundaries, fostering a rich understanding of how systems concepts can also be applied to theory development (Jaradat, 2015) and inference of design principles.

Systems theory as a unified level of abstraction. This study also contributes to IS literature by offering a unified level of abstraction grounded in systems theory that serves as a coherent basis for designing IS artifacts. The framework crafts a cross-referential theoretical underpinning and a shared language that fosters synthesis beyond subject-specific categorization in IS (Alter, 2013; Hirschheim & Klein, 2003). A common issue arises when scholars produce design knowledge at varying levels of abstraction (vom Brocke et al., 2017) instead of using consistent terminology for the same system, inter alia, due to ambiguity in defining system boundaries (Baxter & Sommerville, 2011; Merali, 2004). By adopting a broader, systems-level viewpoint, this study sets the stage for unified abstraction through systems concepts, enabling more integrated and holistic design approaches.

System complexity. The framework also helps address the increasing complexity of systems we deal with in IS, especially in design terms, e.g., (Hanseth & Lyytinen, 2010; Merali, 2006). The dynamic and multifaceted nature of the information systems overwhelms existing design approaches since they promote situational development of design principles (vom Brocke et al., 2017) based on the contextual conditions and causal analysis (Gregor & Hevner, 2013), drawing on prior knowledge (Gregor et al., 2020), rather than drawing them from foundational frameworks. While this approach can be practical for specific systems like socio-technical systems, it falls short in handling the complexity of cross-system translation (Orlikowski & Baroudi, 1988). To bridge this gap, we propose complementing the existing practices of abstracting design principles with foundational systems concepts. The framework presented in this study provides a means to approach this issue. We, therefore, encourage IS scholars to consider adopting systems concepts as core concepts in addressing increasing system complexity.

Bridging DSR and systems theory. By further abstracting design principles to the systems level (Kovacevic-Opacic & Marjanovic, 2024), more generally applicable design knowledge can be produced for a broad range of systems (W. Kuechler & Vaishnavi, 2012). In that sense, the study bridges the gap between DSR and systems theory (Baskerville et al., 2015). It facilitates the development of adequate theoretical models, minimizes the duplication of effort in different fields, and helps promote the unity of science (Boulding, 1956; Orlikowski & Baroudi, 1988), thus improving communication between IS researchers and related domains.

Groundwork for future research in IS. This study also lays a foundation for future research and theory development in IS by gradually infusing systems-theoretical concepts into the discipline. By reconciling fragmented academic efforts and organizing core and sub-concepts (Hassan et al., 2023) the study provides a structured approach to understanding and applying systems theory in IS. Beyond IS, our framework can potentially enhance cross-disciplinary communication, paving the way for broader collaboration and knowledge sharing across domains.

9.1.7.2 Critical Reflections

Boundary conditions. We define the boundary conditions of the research during our reasoning process by setting the focus on the design of the information systems. Although the constructed framework may as well be used to theorize and analyze information systems, as outlined in section 2, we prioritize the design lens as it allows readers to more easily understand the essence of applying systemic perspective in IS. It is more readily applicable to a use case where we see the highest level of contribution.

System concepts for design vis-à-vis design principles. Further, it should be noted that the design implications we derived by applying the systems concepts to a case of reputation systems may resemble design principles from the domain of DSR. They may be perceived as similar because they both focus on what the system should allow actors to do (Gregor et al., 2020; vom Brocke et al., 2017). Yet, they are different in nature. While design principles are context-specific, dynamically tied to the nature of the specific artifact, and "develop[s] knowledge at various levels of abstraction" (vom Brocke et al., 2017, p. 3), our concepts describe the systems nature of IS artifacts. They are collectively rooted in systems theory, which we present in a unified form of abstraction.

Ontological challenges. The diversity of information systems, including socio-technical, organizational, and work systems, introduces ontological challenges due to their unique characteristics and meanings. The broad scope of the term *information systems* complicates precise contextual differentiation within the systems space (Alter, 2013;

Somers, 2010). As a result, the framework presented in this study may not serve as a one-size-fits-all solution for designing all system types equally. Future research should investigate combinations and configurations of these concepts to address ontological challenges, as their utility often emerges through their interplay. This study primarily focuses on consolidating systems concepts rather than prioritizing or differentiating them within specific contexts.

Practicality. Designing abstract systems is a challenging task. IS artifacts may often fail to produce the desired patterns of action or outcomes (Pentland & Feldman, 2008). Thus, one needs to reflect on the creation and handling of IS artifacts of an abstract systemic nature (e.g., business reputation ecosystems, agentic AI-powered systems, etc.) and their implications for design. Unlike concrete systems, abstract systems are inherently intangible (Banathy, 1989), rely on interpretative knowledge, hypothetical relationships (J. G. Miller, 1986), and reasoning, and cannot be explicitly constructed (Beeson & Davis, 2000; Stacey et al., 2000). Their dynamic behaviors, such as communication content, cannot be directly controlled. While the systems-theoretical laws presented in this study offer ways to address these challenges, the abstract nature of the concepts may hinder their practical application. The high abstraction level makes translation into actionable development for systemic artifacts difficult. Acknowledging this difficulty, we nevertheless consider this a valuable challenge in advancing the design of complex information systems.

Epistemological challenges. Transferring certain „systems concepts in their entirety to the domain of information systems“ (Merali, 2004, p. 438) is often fraught with epistemological challenges. An entry point is the ontological distinction between abstract and tangible systems. For instance, the concept of operational closure, central to autopoietic (self-producing) systems, segments systems based on their operational modes. Viewed through this lens, socio-technical systems are not singular entities but a combination of distinct systems—social and technical—operating autonomously within their boundaries. This distinction stresses the approaches that have strong paradigmatic attachments. Consistently, a standardized lens might initially lead to confusion about how system concepts should be understood and to which systems they should refer. We believe the framework carries high potential to offer initial stabilization and orientation regarding different system concepts for the IS discipline in the long run.

Identity crisis of IS discipline. There is a scholarly discussion about the identity crisis in the IS discipline as an ongoing theme grounded in limited consensus about its native theory, core concepts, or boundaries (Benbasat & Zmud, 1999; Riemenschneider & Armstrong, 2021; Somers, 2010). This debate encompasses issues such as studying non-

IS-related phenomena within the IS domain and frequently borrowing theories from other disciplines. Such practices have contributed to confusion regarding the essence of the field (Somers, 2010). We recognize systems theory offers a promising avenue to reflect the discipline's essence and substance. While systems concepts have been periodically highlighted, they have yet to establish themselves as a defining identity for IS (Teo & Srivastava, 2007). By anchoring its concepts and utilizing them to generate IS knowledge, the field can better communicate the concepts' unique value in crafting complex information systems.

The collection of systems concepts in this study serves as an initial step to show which systems concepts exist and how they can be leveraged to design information systems. Yet, as L. D. Xu (2000) pointed out over two decades ago, much remains to be done to craft a comprehensive systems theory for IS to become powerful and applicable to all information systems domains.

9.1.8 Conclusion

Systems theory has been regarded as a sine qua non for designing information systems (Burton-Jones et al., 2015; Demetis & Lee, 2016; L. D. Xu, 2000). In the face of growing system complexity, systems theory offers indispensable tools for managing the intricacies of the information era (L. D. Xu, 2000). Systems theory has paradoxically remained in the shadows of IS research (Demetis & Lee, 2016) despite being evolved from systems concepts (Alter, 2004; Mingers & White, 2010b; L. D. Xu, 2000).

This research aims to consolidate dispersed systems concepts into a comprehensive framework positioned within the IS domain. We propose a framework that provides a high-level abstraction for designing complex information systems, encourages IS scholars to rethink existing design approaches, and equips them with tools to address increasing complexity (Mononen, 2017). By introducing systems theory concepts, this paper guides researchers and practitioners to design systemically operating complex information systems. Furthermore, we examine the prescriptive nature of the design implications from a systems perspective, contrasting these with existing design principles. We also propose systems theory as a unifying foundation and reflect on the ongoing identity crisis within the IS discipline. The paper contributes to the cumulative knowledge creation in IS and attempts to establish a shared systemic language for theory-building and design endeavors (Grover & Lyytinen, 2015). This study focuses specifically on the application of systems theory to IS design. Future research is encouraged to explore the potential of systems theory in theorizing and analyzing complex information systems (Demetis & Lee, 2016, 2017). Overall, this work invites researchers and practitioners to engage in a collaborative discourse to promote systems thinking, thereby broadening the horizon of the IS discipline to address the challenges of increasingly complex systems.

9.2 Service Through Communication: Conceptualizing Service Systems with Luhmann's Systems Theory

Paper Number	P2	
Title	Service Through Communication: Conceptualizing Service Systems with Luhmann's Systems Theory	
Publication Type	Journal Paper	
Outlet	Electronic Markets (EM)	
VHB JOURQUAL 4	B	
Authors	Beverungen, Daniel	30%
	Pöppelbuß, Jens	30%
	Hemmrich, Simon	30%
	Iqbal, Taskeen	10%
Status	2nd major revision (revised and resubmitted)	

Abstract. *Service research has evolved into an interdisciplinary research field that bridges diverse disciplines, including information systems (IS) and marketing. Nearly two decades ago, the service system concept was introduced as a foundational abstraction in service research, drawing on ideas from the service-dominant logic (S-D logic) of marketing. Despite its widespread adoption in service-based IS research, the service system concept lacks a solid theoretical foundation, resulting in conceptual ambiguities and overlaps with related constructs, such as service ecosystems. Moreover, it has largely remained a static analytical lens, insufficiently addressing dynamic service phenomena, including value co-destruction. To address these limitations, we propose Luhmann's systems theory (LST) as a robust explanatory framework for conceptualizing service systems as autopoietic (self-creating) systems in which communication serves as the fundamental mechanism that drives value co-creation. We derive five theoretical propositions from this re-conceptualization that clarify conceptual ambiguity and allow researchers to explore dynamic service phenomena in greater depth. Due to the general approach taken by LST, our conceptualization provides a theoretically grounded and interdisciplinary foundation for advancing service research.*

9.2.1 Introduction

Over the recent three decades, research interest in service and the service sector has steadily grown across disciplines, including marketing, information systems (IS), mechanical engineering, computer science, and many more. Reflecting a general shift from production economies towards information and service economies (Castells, 2010), two powerful academic initiatives guided the interdisciplinary service research over the last two decades in particular: First, the service-dominant logic of marketing (S-D logic) reframed the dominant conceptualization of value creation, moving it from goods exchange to service-for-service exchange and challenging classical economic concepts that regarded service as unproductive labor (Vargo & Lusch, 2004). Second, the introduction of the service system concept substantiated IBM's quest to establish a new science of service as an academic discipline that educates future leaders to create value, resolving the duality of goods and services with a unified paradigm for value creation (Chesbrough & Spohrer, 2006; IBM, 2011; Lusch et al., 2008). Together, these initiatives left a strong legacy, establishing a new vocabulary for interdisciplinary research on service, management, and marketing.

During this time, the service system concept was proposed as the fundamental unit of analysis in service research, defined as "a configuration of people, technologies, and other resources that interact with other service systems to create mutual value" (Maglio et al., 2009, p. 395). However, the concept's theoretical underpinnings remained unclear, providing only loose references to general systems theory (GST) as a "foundation for thinking about the formal structure of service systems" (Jim Spohrer et al., 2008, p. 8). Perhaps due to this lack of theoretical embedding into a general theory about the structures and dynamics of systems, the concept has since drifted in its meaning and purpose. Taking an "institutional and dyad-to-network-to-systems turn" (Vargo & Lusch, 2016, p. 6), recent works particularly highlight the importance of a service ecosystem perspective "to allow a more holistic, dynamic, and realistic perspective of value creation, through exchange, among a wider, more comprehensive (than firm and customer) configuration of actors" (Vargo & Lusch, 2016, 5f). In this context, a service ecosystem is generally understood as a "relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional logics and mutual value creation through service exchange" (Vargo & Akaka, 2012, p. 207), emphasizing their complex and dynamic nature and the relevance of institutions (rules and norms) for co-creating value (Letaifa & Reynoso, 2015; Vargo & Akaka, 2012). Entities as diverse as cities, industries, and market organizations can be understood as both service systems (Jim Spohrer et al., 2008) and service ecosystems (Sarno et al., 2024; Vargo & Lusch, 2017), leading to ambiguities if these concepts can be used synonymously or if they refer to different levels of aggregation (Barile et al., 2016; Pöppelbuß et al., 2022; Storbacka et al., 2016; Wieland et al., 2012). Hence, profound inconsistencies seem to remain in defining and operationalizing service systems as a basic abstraction of service research (Brozović & Tregua, 2022; Frost & Lyons, 2017; Mustak & Plé, 2020). This is problematic for interdisciplinary research at the intersections of service research and information systems, as a uniform understanding and vocabulary are lacking to define what a service system is and is not.

To harmonize service system conceptualizations across disciplines, various contributions have been made to establish aspects of different systems theories in service research (Barile et al., 2016; I. Ng & Andreu, 2012; Jim Spohrer et al., 2008; Vargo & Lusch, 2016) following up on a service system's initial reference to GST (Maglio et al., 2009). GST is a powerful yet abstract super theory that strives for universality (Boulding, 1956; von Bertalanffy, 1972). Its concepts have proliferated in many academic disciplines (Löbler, 2016; Maglio et al., 2009), providing a unifying theoretical lens for service research across disciplines (Wieland et al., 2012; L. D. Xu, 2000). A particular strength of systems theories is that they enable the analysis and design of wholes, complementing reductionist research approaches (I. Ng et al., 2011). A system theory lens enables a better understanding of the complexity and indeterminacy of service systems and service ecosystems (Barile et al., 2016; I. Ng & Andreu, 2012), which could help resolve current conceptual ambiguities.

However, these approaches have overlooked properties of service systems as social systems, which differ substantially from the properties of technical systems as focused in, for instance, complex adaptive systems or the viable systems approach (see the appendix for a comparison of different strands of systems theories). Therefore, we propose revisiting, extending, and substantiating the original concept of the service system concept with Luhmann's system theory (LST), a particularly comprehensive and well-known theory of social systems that has been largely overlooked in information systems and service research so far. LST provides a novel perspective on service systems by viewing them as autopoietic social systems, that is, self-reproducing systems with communication as their central reproduction mechanism. Adopting this theoretical stance, we address the following research: What implications does LST offer for conceptualizing service systems?

We answer this question with a re-conceptualization of the service system concept as an autopoietic system in which benefactors (service providers) select and utter pre-selected resources as value propositions to be understood by beneficiaries (service customers) as value-in-use, altogether completing a communication process that is subject to time. The novelty of this definition is that it focuses on communication as the central mechanism that constitutes the value co-creation among any set of benefactors and beneficiaries within a reciprocal relationship. The dynamic properties of service systems govern the reciprocal acts of communication among these actors over time. Communication between service systems can also lead to the emergence of higher-order service systems, which can be understood as service ecosystems on a higher level of aggregation. As such, service ecosystems and service systems are self-similar, i.e., they use the same mechanisms and theoretical properties.

This paper offers three core contributions. First, we revisit and extend current conceptualizations of service systems with the lens of social systems, developing theoretical propositions that align with the principles of LST. The propositions lead us to develop an updated definition of a service system, answering calls in the literature to apply system theory concepts to service phenomena (Maglio et al., 2009; Mele et al., 2010; I. Ng et al., 2011; Tracy & Lyons, 2013). Second, we discuss the scholarly value of this re-conceptualization for advancing information systems and service research in fundamental ways (Rai, 2017). Our conceptualization helps identify the interplay of different aspects, such as (technological) resources, communication, and service, providing service researchers with a more detailed analytical lens. Communication is the central mechanism behind value co-creation, which sheds new light on dynamic service phenomena, such as value co-destruction and the emergence of institutions. Focusing on communication as the central mechanism provides aesthetic value as powerful simplicity to ensure successful service interactions between providers and customers (Rai, 2017). Third, the notion of service systems as social systems also has implications on digital innovation, service design, and service systems engineering, emphasizing recent works, e.g., (Vink et al., 2021) that render service systems and service ecosystems not fully designable but rather emergent in the here and now.

The paper is organized as follows. Section 2 reviews the foundations of systems theories in the service discipline before introducing foundational concepts of LST. In Section 3, we build on LST's concepts to develop five theoretical propositions, leading to an updated conceptualization of service systems as autopoietic systems with communication as the key mechanism that is required to provide and capture service. Section 4 discusses the implications of this re-conceptualization for service research. Section 5 concludes the paper with a call for more interdisciplinary research based on LST's conceptual foundations.

9.2.2 Theoretical Foundations

9.2.2.1 Systems as a Theoretical Lens in Service Research

9.2.2.1.1 The Notion of a System

An abundance of system conceptualizations has been discussed in various disciplines (Adams et al., 2014; Friendshuh & Troncale, 2012), creating considerable ambiguity about the properties of a system (Malecic, 2016). This confusion also relates to the plethora of research streams springing from the science of systems (Boulding, 1956; von Bertalanffy, 1950), which has, in turn, inspired approaches such as cybernetics (Ashby, 1991; Wiener, 1948), the system-of-systems concept (Ackoff, 1971), autopoietic biological systems (Maturana & Varela, 1980), autopoietic social systems (Luhmann, 1995), complex adaptive systems (Gell-Mann, 1994; Holland, 1992b), organized behavior systems (Alderson, 2006), viable systems (Barile & Polese, 2010a), systems thinking (Checkland, 1999; Emery et al., 1978; Weinberg, 1975), amongst many others.

As regards the very notion of a system, the Latin *systēma* and Greek *sustēma* are the word's origins, which can be translated as a composition of parts or a set of things or ideas (Oxford Dictionary, 2025). Over a hundred systems definitions have been proposed since (Sillitto et al., 2018), spanning fields as diverse as philosophy, social sciences, natural sciences, and engineering (Rousseau & Calvo-Amodio, 2019). A system is generally recognized as a whole, comprising elements and relations between them (Rousseau & Calvo-Amodio, 2019; Sillitto et al., 2018). A system is most fundamentally defined through its elements, which are purposefully connected (von Bertalanffy, 1971).

Accordingly, a system is defined as “a set of interrelated elements [...] composed of at least two elements and a relation that holds between each of its elements and at least one other element in the set.” (Ackoff, 1971, p. 662). From this definition, each of a system’s elements is connected directly or indirectly to every other element in the system , while the system’s properties emerge from the interplay between its elements (Ackoff, 1971).

9.2.2.1.2 Systems Theories in Service Research

Systems theory has been taken up in many of the academic disciplines that engage in service research, including marketing, economics, computer science, information systems, engineering, and social science, to name just a few (Maglio et al., 2019). Wieland et al. (2012) suggest that GST, or the viable systems approach (VSA), can support exploring the dynamic and complex nature of service systems. Similarly, Barile and Polese (Barile et al., 2012; 2010a; 2010b) adopt the VSA lens and elaborate on conceptual overlaps between S-D logic, VSA, and service research. Viable systems aim to survive in their environment by dynamically interacting with all relevant entities that offer critical resources for their function and viability (Badinelli et al., 2012; Beer, 1972). Barile and Polese (2010b) also track the roots of VSA to earlier contributions to systems theory, e.g., to GST by von Bertalanffy (1950) and Luhmann’s (1995) theory of social systems, and call to investigate the dynamics of service at a system’s level based on systems theory. Furthermore, Wieland et al. (2012) recognize that service ecosystems are complex service systems, similar to complex adaptive systems (CAS), which are “composed of interrelated parts, interacting with its environment, subject to resulting feedback effect, evolving over time adaptively to fit the pressures imposed on it” (Holbrook, 2003, p. 2). A CAS exhibits self-adjusting capabilities often described as structural adaptations, which emerge in response to environmental change (Onik et al., 2017). Recently, Vargo et al. (2023) used CAS to conceptualize service emergence as an institutional phenomenon in service ecosystems, referring to feedback between the interactions of system elements (which for them are actors and resources) and the outcomes of their interactions (value-creating activities, service-ecosystem properties). Still, none of these conceptual lenses from systems theory has been used to re-conceptualize the notion of a service system itself.

In our quest to explore social system features of service systems, we follow numerous authoritative calls to substantiate core concepts of service research with systems theory (Briscoe et al., 2012; Lusch et al., 2016; Mele et al., 2010; I. Ng et al., 2009; Wieland et al., 2012; L. D. Xu, 2000). Connecting with the overarching lens of systems theory might also enable service research to bridge boundaries between disciplines (Larson, 2016; J. C. Spohrer et al., 2011). In the extant research, the VSA (Beer, 1984), structuration theory

(Giddens, 1984, 1990), and LST (Luhmann, 1995) were proposed as particularly suitable approaches (Löbler, 2016) (see the appendix for a comparison). Further advances have been made toward providing a stronger embedding into systems theory (Godsiff, 2010; Polese et al., 2017; Vargo & Akaka, 2012). However, these approaches only focus on specific theoretical angles and selected properties of systems rather than re-conceptualizing the service system itself. Undoubtedly, digging deeper into the extensive body of knowledge of systems theory offers great potential to advance our understanding of the service system concept's nature and mechanisms (Barile & Polese, 2010b; Löbler, 2016; Peters et al., 2020; Wieland et al., 2012).

9.2.2.2 Luhmann's Systems Theory

9.2.2.2.1 Prospects of Luhmann's Systems Theory for Service Systems

After carefully considering and contrasting different system theories and approaches to systems science, we posit that LST (Luhmann, 1995, 2002, 2013, 2018) provides a promising and fresh perspective on the service system concept that has been largely overlooked so far (except for Löbler, 2016). This theoretical approach is promising as it recognizes the social properties of service systems. Based on the concept of autopoiesis, which describes living systems (i.e., organisms), Luhmann established a sophisticated general theory of social systems that are abstract and self-reproducing in nature. Autopoiesis refers to the ability of systems to create and maintain themselves through the continuous regeneration and actualization of their elements. Luhmann's edifice of ideas is considered one of the most—if not the most—developed theoretical bodies dealing with systems theory (Albert, 2016). For instance, Luhmann's ideas have also been taken up prominently in the IS field to examine how technology reconfigures human-technology relations (Demetis & Lee, 2018) and in organization science to justify Eigenzeit as a new lens on the temporal complexity of organizing (Blagoev & Schreyögg, 2025).

LST enables us to view service systems through the lens of autopoiesis (Maturana & Varela, 1980, p. 101), highlighting dynamic mechanisms such as self-reproduction, operational closure, and self-organization. These properties allow service systems to maintain their identity by generating and regenerating their core elements—service—through their own internal operations. Since a service system focuses on service—"the application of specialized competencies (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself" (Lusch & Nambisan, 2015, p. 161)—it differs from allopoietic (technological) systems involving tangible resources, while autopoietic and allopoietic systems can interpenetrate (overlap).

Still, LST is consistent with the properties of service systems. First, the concept of autopoiesis fits well with the idea that service systems are self-contained and self-adaptive and have self-X features, like self-organization (van Assche et al., 2019), which service research aims to elucidate (Vargo et al., 2023). Second, LST focuses on abstract rather than concrete systems (Luhmann, 1995, p. 442), which fits well with the claim to use a service system as a basic abstraction (Jim Spohrer et al., 2008). LST's abstract conceptualization also aligns with the proposition that "services are exchanged for services" (Vargo & Lusch, 2004, p. 7), reflecting Bastiat's (1860) great economic law. Third, LST can consider the overlap that has been proposed between social systems and service systems (Edvardsson et al., 2011; Wetter-Edman et al., 2014), even if it departs from the current service system conceptualization in which elements with different system references, such as "people, technologies, and other resources" (Maglio et al., 2009, p. 395), have been merged into one single service system concept. In contrast, LST emphasizes separating different system elements—such as service, communication, or resources—into different systems. While these systems can still interpenetrate (overlap), LST is mindful of separating different types of elements, enabling researchers to investigate the mechanisms with which these elements play together. We conclude that LST provides a theoretical view consistent with current service thinking and introduces new theoretical angles into the scientific debate.

9.2.2.2.2 Foundational Concepts of Luhmann's Systems Theory

Luhmann's extensive writings provide numerous theoretical concepts. We group core concepts as static and dynamic to convey an easier understanding (Table 25). Static concepts refer to the structure of a system, whereas dynamic concepts refer to mechanisms of autopoiesis. Although the list of concepts we review in this paper is extensive, we still omit some LST concepts (e.g., bounded rationality and double contingency) that we consider less significant for this paper. We visualize the concepts in Figure 17 and summarize them in Table 25. At the end of each paragraph, we refer to the LST concepts of service systems.

Regarding static concepts, systems constitute themselves by establishing a difference from their environment (Luhmann, 2013, pp. 29–30). Each system has a guiding difference that exhibits a system reference, defining a single type of element in this particular system (Luhmann, 1995, p. 177). For instance, elements of action systems are action elements; elements of communication systems (which equal social systems) are communication elements (Luhmann, 1995, pp. 137–175); this implies that the single type of element permissible in a service system is service elements. A system boundary demarcates a system towards its environment (visualized as thin double lines in Figure

17). → **The system boundary demarcates a service system from other service systems or systems of other kinds in its environment.**

Systems consist of elements and relations mirroring a dynamic structure in time. Luhmann implicitly views events (Allport, 1940; Morgeson et al., 2015) as the underlying element of an evolving system on which higher-order systems (e.g., action systems, communication systems) can be built. More specifically, social systems are communication systems that consist of communication elements, referring to elements of actions and thus to elements of events (Luhmann, 1995, 104,139). When an event is interpreted as action, an action system emerges; if actions are interpreted as communication, a communication system (= social system) emerges (Luhmann, 1995, pp. 164–171). → **Service systems emerge when a beneficiary understands communication as valuable, which implies that a system that solely facilitates communication (= social system) must be in place.**

Systems become complex when elements (e.g., events, actions, communication) can no longer be linked directly to every other element in a system (Luhmann, 1995, pp. 20–24). This means that events can belong to a (sub-)system and might also belong to environments of other systems. Therefore, it is essential to "distinguish between the environment of a system and systems in the environment of this system" (Luhmann, 1995, p. 17). → **Service systems can interact with other systems (e.g., other service systems) while remaining distinct from their environment.**

A system's environment is always more complex than a system itself (Ashby, 1991). Each system can be disassembled into sub-systems, thereby marking itself as an environment of its subsystems. When reuniting the subsystems through communication, a system emerges again as a whole (Luhmann, 1995, p. 7). Overlaps of different (sub-)systems refer to interpenetration. Interpenetration is an inter-system relationship concept between systems situated in the same environment. It means the same elements can belong to multiple systems simultaneously. In Figure 17, systems A and B share some elements, while these elements connect and form relations between them. Hence, service systems can have underlying elements that they share with other systems. → **Service systems can interpenetrate with other types of systems.**

The concept of self-description serves to describe a system's observed elements. Referring to the difference between a system and its environment, a system must have and uphold a description of itself (Luhmann, 1995, p. 9; Rosen, 1977). The system's description mirrors its guiding difference (e.g., service) to stand out from its environment and describe its behavior. Internally, this description enables a system to define its own rules for ordering, selecting, and processing information (Luhmann, 1995, p. 165). → **The guiding difference of a service system is the distinction of whether a communication is meant to be and perceived as a service.**

Systems are self-referential (Varela, 1975). A system refers ‘everything’ originating from the system’s environment (e.g., selected information) to its own elements (self-reference). Every system operation has elements to refer to and build upon. Still, systems are open to environmental influences, even operationally closed, as their environment cannot directly intervene in a system’s operations (Luhmann, 1995, p. 444). Because of this operational closure, a system must generate its complex operations (its dynamic structure) to handle interference originating from its environment. → **Assuming that service systems are self-referential and operationally closed, they cannot be designed from the outside but only through selection and observation.**

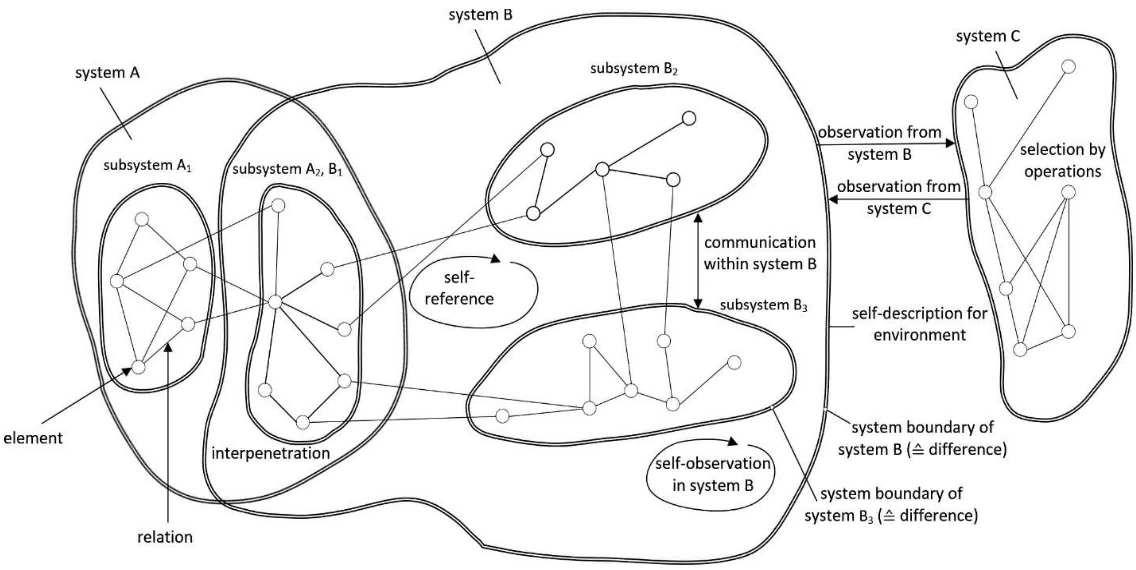

Figure 17: Outline of Selected Core Concepts of LST (building on Luhmann 1995)

As regards the dynamic concepts of LST, observing refers to indicating and distinguishing between important and unimportant environmental irritations (Luhmann, 1995, p. 65). Through observation, the system’s environment is used to re-adjust a system’s boundaries and identify which elements belong to the system. A system can observe itself and other systems in its environment. For simplicity, an actor—seen as an external system—can observe other systems. Depending on an observer’s vantage point, observation can take place as first-order observation (inside the system; internal observer) or second-order observation (outside the system; external observer) (Figure 17). → **Service systems can be observed internally (e.g., from the perspectives of benefactors and beneficiaries involved in service exchange) and externally (e.g., by external actors not involved in the service exchange).**

Systems are self-organizing. This means that system elements arrange themselves depending on the current system state. As soon as elements A and B form a connection, they determine the positioning of a further element C. By adding more elements, the system starts to self-organize its elements. As an autopoietic system, a system reproduces itself through its own elements. → **The determinants of self-organization are reflected by the institutional arrangements (i.e., the rules, norms, and symbols) that are shaped by and shape the service system's structure.**

System elements are connectable and are constantly being rearranged. A system has the connective capacity to integrate new elements within its boundary (depending on observation and selection). By integrating new elements, a system's variable boundary determines which elements change or maintain their states. Elements as semantic abstractions have no permanent existence but must be reproduced continuously. That is why elements must constantly establish new connections and thus reproduce new elements for the system to exist (Luhmann, 1995, p. 11). → **Service systems must reproduce themselves through service.**

Focusing on social systems, Luhmann considers communication as the only operation that can provide this connective capacity (Luhmann, 1995, p. 243). Communication is a single operation in a social system that organizes elements. It consists of the synthesis of (1) the selection of information, (2) the utterance of information, and (3) the understanding of information (Luhmann, 1995, p. 40). Communication in a social system is only initiated when observation occurs, enabling communication within the system. → **Service must rest on communication, meaning that service involves the selection and utterance of value propositions by benefactors that beneficiaries understand as valuable.**

Systems process information selectively. When communication occurs in a system, it performs selections to steer information flows to cope with the upcoming complexity. When a system observes another system and, thus, processes new information, this information is interpreted in line with the systems' guiding difference, establishing new processing conditions for the entered information (Luhmann, 1995, p. 17). → **Communication elements originating from the environment are interpreted as service elements within a service system, while communication is necessary to uphold the service system.**

Systems operate in time. That is, relations emerge among elements to establish order over time. In this way, time allows elements to react asymmetrically to indeterminacy. As time passes, elements refer back to each other. This temporal backlink leaves behind system structures (Luhmann, 1995, pp. 286–294), letting structural patterns emerge, ensuring relatively constant connecting lines to guide further elements (Luhmann, 1995, pp. 345–346), creating a path dependency also known as institutions. → **Path dependency is relevant to service systems as new service elements refer back to previous service elements, which are previous service experiences.**

In autopoietic systems, elements self-organize themselves with the help of the current system structure (Luhmann, 2013, p. 76). While observation occurs, structures are built to set the system's elements in motion, initiating their self-organization. Structures ensure the cohesion of the elements and are necessary for the system to operate, which means maintaining its elements and relations (Luhmann, 1995, p. 134). Systems can be structurally coupled to other systems, depending on their own operations, without merging with other systems. Instead, each system remains operationally closed, meaning it functions based on its own internal processes and logic. Still, a system can be "irritated" or influenced by another system, adapting its behavior or structure. For example, social system structures are structures of expectations manifesting in the form of patterns that guide social action. Relations and structure differ (Luhmann, 1995, p. 283) in the sense that structures are time-related and thus complex, while relations are not time-related, applying a more static perspective on systems elements. → **Service systems guide service exchange, which are patterns of resource integration.**

Selections made by the system re-enter the system and determine future communication, as well as other selections made in this system (Luhmann, 1995, p. 125) that are observed. Whatever is observed, the observer "reintroduces the distinction of observer and observes into the object of observation" (Luhmann, 1995, p. 120). This leads to circularity in the selection process within a system, creating a path dependency (structure) of element creation (Luhmann, 1993b). → **Service elements re-enter the system to bridge time until the service composition is fully understood.**

Table 25: Selected Core Concepts of LST (Luhmann 1995, 2002, 2013, 2018)

LST Concepts	Core Statement	Description
Static Concepts		
Systems as being different from their environment (system reference)	Systems constitute themselves as being different from their environment.	Systems can only exist as a distinctive identity in relation to an environment (Luhmann, 2013, pp. 29–30). A system is always clearly distinct from its environment, constituting itself as being different from its environment (Spencer-Brown, 1994). Each system has a *guiding difference* towards its environment, indicating its reference and way of processing and selecting information.
System complexity	Systems become complex when elements can no	Complexity arises if two elements can only be connected using other elements in between(Luhmann, 1995, p. 24). Complexity refers to (a) the number of

(elements and relations)	longer be linked to every other element.	elements, (b) the number of relations among the elements, (c) the difference between elements and their relations, and (d) the temporal change of relations in a system (Luhmann, 2013, p. 124). The environment is always more complex than a system (Ashby, 1991).
Subsystems (systems differentiation)	Systems consist of elements that have relations and can exhibit subsystems that have their own environment.	Sustaining a difference from its environment, a system can further differentiate itself by establishing subsystems, each constituting an environment within the system. Reuniting the subsystems by resolving the differences, a system emerges again as a whole (Luhmann, 1995, p. 7). As a result, a system of a higher order emerges (Luhmann, 1995, p. 22).
Interpenetration and system boundary	Different systems can build on the same elements, but systems do not have identical element relations.	Interpenetration is an inter-system relationship between two or more systems sharing the same environment. It describes the use of the same elements at the same time in different systems. When there is a system boundary, the system references differ, and accordingly, the selection mechanism within the system and the relation configuration between these elements are also different(Luhmann, 1995, pp. 214–215).
Self-description	Systems create and use self-descriptions to identify and handle their elements.	The concept of self-description refers to a system describing itself—and its behavior—in an environment(Luhmann, 1995, p. 456). Internally, it helps the system to keep its own rules for ordering and processing information(Luhmann, 1995, p. 165).
Self-reference	Systems can only handle information in relation to themselves.	Every system operation presupposes its own elements to refer to and to build upon. Thus, new elements are being created by building on previous elements only (Luhmann, 1995, p. 437).
Openness and operational closure	Systems are open to influences from the environment but, at the same time, closed to distinguish themselves from their environment.	A system draws its boundaries and stabilizes itself by constantly deriving information from its environment and establishing its own internal relations.(Luhmann, 1995, pp. 48–50). In this way, a system is open and closed at the same time. It is open to the possibility of making selections from the environment and closed in that it uses only its own internal operations within the system (Luhmann, 2013, pp. 63–70).
Dynamic Concepts		
Observing and observer	Everything in a system must be distinguished and identified by an observer.	Observing is defined as the "formal terms of distinction and indication" (Luhmann, 2013, p. 105). A system observes to carry out distinctions in this system or in relation to its environment. In this way, a system determines the elements that belong to it. Observation is equal to the operative distinction of what elements belong to a system (Luhmann, 2013, pp. 101–120).
Self-organization	System elements arrange themselves depending upon the current system state.	As soon as element A and element B form a connection, they determine the role of a further element C. By adding more elements, elements relate, and the system starts to observe its own elements. Observing then triggers a self-organization process (Ashby, 1991), and the system communicates internally to carry out its autopoiesis.(Luhmann, 1995, xxix-xxx,34).

Structural coupling	Systems can be structurally coupled, depending upon the operational processes of the other system.	Systems maintain distinct boundaries while selectively integrating external influences and aligning their operations. They can be influenced by the processes of other systems, which can lead to changes in internal behavior or structure while retaining their distinct identity (Luhmann, 2002, pp. 83–101).
Communication	The system communicates to establish new connections in the system.	Communication is the process of making selections within a system. While selective operations presuppose a description in the form of an utterance, an utterance is itself a performed selection. In this way, communication is a threefold process consisting of information, utterance, and understanding(Luhmann, 1995, pp. 140–143).
Selectivity and information processing	Systems select and process information by using their structure.	Information is created and occurs only in systems (Luhmann, 2013, pp. 92–93). The flow of information functions as a selection mechanism to indicate and create new system elements(Luhmann, 1995, p. 40) by using its own system structures.
Operating in time	Systems constantly change their state and the relations of their elements over time.	A system constantly reconstitutes itself by actualizing its relations and elements. As time passes, it sets further conditions for elements and their relations, which can only be updated at the next point in time. A system constantly forms new relations and elements, choosing between repetition and change. Some elements are reproduced, and others disintegrated, creating new element relations(Luhmann, 1995, pp. 39–43).
Re-entry	What has already been observed in a system serves as a distinction for what is observed later.	A peculiarity of observation is that the observed is re-entered, as the observer forms part of the observation. Whatever is observed, the observer "reintroduces the distinction of observer and observed into the object of observation" (Luhmann, 2013, p. 120). This is how subjectivity is installed in systems.

9.2.3 LST as a Foundation for Service Systems

9.2.3.1 Five Propositions for Re-conceptualizing Service Systems

Subsequently, we use LST to re-conceptualize the concept of the service system. We develop five theoretical propositions guiding this process, culminating in an updated definition of the service system concept. Theoretical propositions are testable statements deductively derived from theory, in our case, from LST. Similar approaches have been frequently used to develop the foundational premises and the axioms constituting S-D Logic (Lusch & Vargo, 2006; Vargo & Lusch, 2004, 2008, 2016). Still, LST cannot be readily applied to re-conceptualizing service systems, but there is a conceptual gap between both strands of research because Luhmann never explicitly dealt with service systems as systems in the sense of the LST. Also, Luhmann did not consider technology, such as IT artifacts or information systems, in his conceptualization of systems—which he viewed as social systems—but treated them as allopoietic components that need to remain in a system's environment. Subsequently, we provide this missing link, drawing from the rich conceptual foundations to identify implications for re-conceptualizing the service system concept.

We illustrate each proposition with the example of connected mobility, a smart service system based on a digitally networked car (Beverungen et al., 2019). A smart car is equipped with various sensors that identify its internal properties (e.g., velocity, state of charge) and surroundings (e.g., road conditions and other vehicles in the car's proximity) to self-adjust its velocity. It offers remote access for the manufacturer to retrieve usage data and make system diagnoses. The data are also used to optimize the car's autonomous functions since autonomous driving depends on data from numerous vehicles. The car also provides users access to additional services like remote upgrades, predictive maintenance, insurance services, and autonomous driving.

1) Service is the only guiding difference of a service system.

LST states that systems have one single system reference that constitutes them as difference from their environment. This system reference also defines the type of element part of the system. From an LST point of view, the sole system reference of a service system is service, making service its only element type. As an abstract system, a service system comes into being only if a human observer interprets other types of elements, such as resources, actions, or communication, as service. While a service system is operationally closed, service can also relate to elements of other systems (e.g., action systems, communication systems) through interpenetration. For a service system to emerge from these other element types, a beneficiary must observe these elements, and a complete communication process—consisting of selection, utterance, and understanding—must be present.

Service systems can include nested structures, i.e., they can comprise service elements that are service systems themselves. The boundary of a service system is dynamic in the sense that a service system can connect to other element types, incorporating these as service. However, these elements can only be included as service in a service system due to the premise of a singular system reference (Luhmann, 1995, pp. 135–136). “Systems are selected, not as a bunch of objects, but as ordering perspectives from which a relationship between system and environment is accessible” (Luhmann, 1995, p. 136).

An LST view implies that other element types cannot be part of service systems but must remain elements of other system types. For instance, a system of living beings can only reproduce living beings, not service elements (following Luhmann, 1995, p. 427). Similarly, resources, frequently mentioned in service system definitions—including people, technologies, organizations, and information (Maglio & Spohrer, 2013)—cannot, by definition, be elements in an autopoietic self-organizing service system. Rather, resources must be allopoietic systems "capable of producing only 'the other' rather than itself" (Zeleny, 2006, p. 12). Resources must remain in a service system's environment and can belong to other types of (allopoietic) systems (Schatten & Bača, 2010). It follows that when service systems appear to exhibit social and technical features simultaneously, we deal with more than one system. These do not intermingle but are structurally coupled. In other words, social and technical structures exhibit a difference, not a unity, since social structures are operationally closed to technical operations (and vice versa).

This perspective profoundly differs from current conceptualizations of service systems that include elements irrespective of their system references. We posit that differentiating element types and system types that play a role in service science makes an LST-enabled conceptualization of a service system a sharper theoretical lens since specialized phenomena can be attributed to a single system reference (e.g., looking at resources or actions), while others can be viewed as an interplay of systems that display different system references. For instance, differentiating actions (action systems) from service (service systems) can enable researchers to identify how service is interpreted from actions in processes of communication; this view enables researchers to identify why service is sometimes successfully co-created, and sometimes remains unsuccessful, while the underlying actions remain the same.

Taking the example of connected mobility, this proposition implies that neither the beneficiary nor resources like a car or the computing infrastructure are elements of a service system. Connected mobility emerges from a beneficiary's observation and understanding of the interplay of elements with other system references—such as actions, information, and people—as service, constituting a service system. When these elements are combined (e.g., when traveling), and a beneficiary observes and understands this combination as service (e.g., appreciating their arrival or enjoying their travel), a service system emerges, overlapping with the other systems. The service system can be nested, combining service elements on different levels of abstraction—the entertainment system, the interior, the state of charge—all of which can be observed and understood as service.

2) A service system emerges from understanding information as a service.

LST states that systems are operationally closed, limiting them to using their own operations. Still, systems can interpenetrate (overlap) with other system types, allowing them to deal with other types of elements. When different systems interpenetrate, elements (e.g., action, communication, or resources) can be observed and unified into new system elements (e.g., service). LST posits that observation is a selective operation

(Luhmann, 1995, p. 184) that focuses on a system's environment, interpreting the environment as resources destined for setting up communication. Because of operational closure, a service system cannot make causal interventions in its environment but must remain inside its own system.

From a LST perspective, a service system can be understood as a higher-order system in which service emerges from combining other abstract elements, such as action elements, communication elements, or events. Pointing beyond a socio-technical systems view that joins different element types into the same system (Bostrom & Heinen, 1977; Ropohl, 1979), service systems are supra-systems that overlap with other systems (i.e., social and technical systems). While different types of systems are environments for each other and cannot interact directly, the more abstract service system can establish a relationship between them, presupposing the process of observation that distinguishes and identifies the combined elements as service. LST refers to this overlap between service and social systems (Akaka & Vargo, 2014a) as interpenetration (Luhmann, 1995, pp. 214–217). Resource integration includes two steps: observing resources in the environment and selecting communication by purposefully indicating (i.e., viewing the other elements as) service. Put differently, beneficiaries integrate resources (Bruce et al., 2019; Peters, 2016; E. W. Zimmermann, 1933), thereby building the structure for service (Barile et al., 2016; Barile et al., 2012).

This proposition serves to glue together different element types that matter to service, such as people, actions, information, and resources. Still, it highlights differences among these elements, emphasizing no causal relationships between them. Since resources, actions, and people need to be observed and coded as service by a human observer or beneficiary before service emerges, the sole presence of these elements is no guarantee that service will eventually emerge. Similar observations have long been made in service research. For instance, S-D logic highlights that "value must always be determined by a beneficiary," while the traditional IHIP criteria emphasize the perishability of services, referring to the inability to store services for future use, which makes timely resource utilization critical for value creation (Lovelock & Gummesson, 2004; Zeithaml et al., 1985). Concerning this issue, LST introduces strong theoretical concepts and mechanisms to the debate, enabling researchers to elucidate the detailed mechanisms at play.

In the connected mobility example, the service system emerges when a beneficiary observes and understands the combination of resources (e.g., car, data, maintenance, route, state-of-charge) and actions (e.g., autonomous driving, directions, recommendations) as service. The service system establishes a new relationship that connects elements from systems with other system references (e.g., information systems, action systems) because a beneficiary observes and understands this relationship as value-in-use (e.g., traveling). Observation and understanding are the prerequisites for benefactors and beneficiaries to integrate their resources, constituting a service system that emerges from coding these elements as a smart mobility service. If, however, a car remains standing in a garage, the same resources remain unobserved and do not lead to a service system emerging.

3) Communication is the core mechanism driving value co-creation.

In LST, the only suitable operation for social systems is communication (Luhmann, 1995, p. 243), which is the synthesis of the selection of information, the utterance of information, and the understanding of information (Luhmann, 1995, p. 40). Communication occurs only when an utterance is observed and understood (Luhmann, 1995, p. 165). For this reason, communication goes beyond actions since actions can remain unobserved and, therefore, unnoticed. Different types of systems (e.g., living systems like humans or social systems like organizations) can observe service systems in their environment; observations are subject to limited interests, structures, and the information processing capacities of observers (as observing systems).

For service systems, value propositions can be viewed as information offered to stimulate value co-creation (Eggert et al., 2018). Value propositions might remain unredeemed for a time, waiting to be observed by beneficiaries. They might also be bound to resources or fade away (P. Hill, 1999) if non-observed. While the actual assignment of value-in-use to a service element depends on observation, value is co-created only if the communication process is complete. Beneficiaries observe events (e.g., value propositions selected and uttered by the benefactor) in their environment, which they understand as valuable, interpreting them as action, communication, and, finally, as service. Because of differences in observation, the same value proposition might create different value-in-use for different observers or even fail to do so. Service-for-service exchange is initiated when an observer outside a service system engages in value co-creation through their actions, which need to be observed and understood by others. Utterances serve the utterer (benefactor) as a promotion to describe themselves, thus confirming (re-entering) their distinction from their environment. Simultaneously, observers (beneficiaries) bring their distinctiveness to the system, re-interpreting the benefactor's utterances. In this way, value is co-created, setting up new conditions for service communication. However, as service systems are selective and remain indifferent towards most of their environment, many actions are not observed and understood and are not interpreted as service. Transforming 'events' related to 'actions' into 'service' based on 'communication' is the constitutive function of a service system.

Focusing on communication as information, utterance, and understanding (Luhmann, 1995, pp. 140–143) has profound implications for our understanding of service systems. Current conceptualizations of service systems point to different mechanisms of system reproduction (As' ad et al., 2024; Fehrer et al., 2024; Ojasalo & Kauppinen, 2024; Vink et al., 2021). We posit that viewing communication instead of action as the basic mechanism of service system re-production provides a much sharper theoretical lens. Action is a weaker concept than communication since actions can remain unobserved and fail to have any effects on others (Luhmann, 1995, p. 165). Adverse phenomena in service research, such as value co-destruction, could be analyzed in terms of failing or incomplete communication processes, which would provide a new angle to the debate that goes beyond the actions performed by benefactors and beneficiaries.

Considering the example of connected mobility, a predictive maintenance service is a value proposition that is selected and can be uttered by a car company as a benefactor. Customers may interpret this utterance differently, creating variety in their understanding of the value proposition. While some customers understand the value offered by predictive maintenance, leading to a service system emerging, others do not understand it to be valuable or even fail to observe the value proposition. Since the communication process remains incomplete in the latter case, the resources and actions of benefactors are not identified as service.

4) Service systems are autopoietic systems that reproduce themselves through service.

LST distinguishes autopoietic systems (which reproduce themselves) from allopoietic systems (which produce something other than themselves, e.g., machines) (Maturana & Varela, 1980). An autopoietic system withstands environmental irritations by changing its internal structure, thus maintaining its guiding difference and creating new elements. Autopoiesis implies that a system reproduces only using internal operations. Nevertheless, an autopoietic system can use allopoietic components to reproduce itself (Maturana & Varela, 1980).

As an autopoietic system, a service system reproduces service since systems can only reproduce their own elements (Luhmann, 1995, p. 11). Technology (Akaka & Vargo, 2014b), such as smart products (Beverungen et al., 2019) or software applications, are allopoietic components (i.e., resources) that remain situated in a service system's environment, while a service system reproduces itself through (new) service being observed. Digitalization allows service systems to handle greater complexity by leveraging IT-driven processes, mitigating the complexity gap, which is the disparity between a system's capacity to process and manage complexity and the increasing intricacy of its environment. This gap arises when the dynamic nature of external influences exceeds a system's ability to adapt or process information efficiently. By integrating advanced technologies and IT-driven processes, service systems can enhance their capacity for observation, communication, and structural adjustments, thereby bridging this gap and maintaining operational effectiveness (Robra-Bissantz & Schlimbach, 2023).

For service systems, an autopoietic service system implies that a service system persists as long as beneficiaries and benefactors observe each other, and thus, communication takes place between them. The ongoing communication creates a cumulative service experience subject to path dependency. That is, the actors refer to potential previous service encounters (or communicative events) when interacting. A service system collapses if the actors cease to observe and understand the other's value propositions, irrespective of their actions.

For instance, no mobility service can exist without a beneficiary understanding its benefits or a manufacturer who wants to offer smart connected cars. Operand resources like the actual car, data, or information systems are allopoietic elements that remain situated in the environment of the service system, waiting to be observed.

5) Due to their reliance on communication, service systems are subject to time.

LST assumes that communication is threefold—selecting, uttering, and understanding information—while systems incessantly change their state and the relations of their elements over time. Selection, utterance, and understanding can happen at different points in time; for instance, an utterance can bridge time when actions that are one means to utter information resonate long enough, waiting to be understood. Since communication is subject to time, a system is always in an asynchronous state and can never operate entirely synchronously. Hence, utterances require a time delay to be understood (see also P. Hill, 1977), and this time offset is permanent.

For service systems, binding value propositions to service is subject to the time required by a complete communication process, including information, utterance, and understanding. Since the same value proposition can be understood by multiple beneficiaries at different times, it leads to a multiplicity of service systems; while an action can happen once, value-in-use can be observed several time intervals later, which might influence the value-in-use and service observed by beneficiaries.

LST highlights the crucial role of time that, as we posit, has been insufficiently addressed in service research. In most studies, time has been abstracted away, focusing on value propositions, interactions, and value-in-use as timeless concepts. For instance, neither S-D Logic nor current conceptualizations of service systems recognize time as a factor in service research. This view stands in stark contrast to anecdotal evidence of day-to-day service processes. Clearly, it makes a difference at which time you enter a hospital to receive medical treatment or at which time you consume a repair service.

Considering connected mobility, a car manufacturer might offer predictive maintenance and this value proposition to its customers. While some beneficiaries understand this value proposition up-front, others might understand it later, maybe after their car broke down. Still, others might never understand this service, leaving the value proposition unredeemed. Predictive maintenance is a value proposition that builds on always-on interactions of benefactors and beneficiaries, subjecting them to a different rhythm than classic reactive maintenance services. Thus, the respective service encounters are subject to time in different ways.

Table 26: Propositions on Service Systems as Outlined by LST

#	**Proposition**	**Example: Smart Mobility**	**Theoretical implications**	**Foundation in LST**
1	*Service* is the guiding difference and the only element type constituting a service system.	Neither actors (e.g., manufacturer, user) nor resources (e.g., a car) are elements of a service system; the service emerges from the resources' combined effects (e.g., distance traveled), subject to a beneficiary's observation and understanding.	Service systems only have service (understood as a process) as their constituting elements. Operand and operant resources used to co-create service are part of the environment.	Systems as being different from their environment (system reference) Elements and relations (system complexity) Self-reference
2	A service system emerges from establishing relationships between communicative events being observed as 'service' between abstract systems.	A service system emerges only if a beneficiary observes and understands the combination of diverse resources (e.g., car, technician) and actions (e.g., repair) as a service being performed. Service establishes a new relationship, connecting the involved communicative events resulting from resources.	Service systems are higher-order systems that interpenetrate with other systems (e.g., action systems) or resources. Service systems are built on a communication system where 'service' is communicated. The resources contributed by either actor are important; however, they are part of the service system's environment.	Subsystems (systems differentiation) Interpenetration and system boundary Observing and the observer Openness and operational closure
3	Value co-creation in service systems rests on communication between	The car and the manufacturer's resources (e.g., data, algorithms, technicians) utter value propositions that can be	Value co-creation depends on a communication process involving the mutual utterance, observation,	Observing and the observer Connective capacity Communication

	benefactors and beneficiaries.	observed and understood by beneficiaries. Beneficiaries' utter demands (e.g., traveling) and resources (e.g., defect car), to be observed and understood by a benefactor (and vice versa). Beneficiaries may observe and understand service differently. A service system overlaps with a social system that emerges based on communication. For example, a benefactor utters and one or more beneficiaries understand each other's value propositions.	and understanding of information. Communication is subject to selective information processing and constrained by the attention level and the resources applied to the observation. The actions of the benefactor must be observed and understood by the beneficiary to constitute value. The amount of value co-created is subject to the beneficiary's selective information processing.	Selectivity and information processing
4	Service systems are autopoietic systems that reproduce themselves through service.	A service system persists as long as the benefactor and beneficiary communicate. A service system collapses if the actors no longer observe or understand the partner's value propositions; there can be no mobility service without a beneficiary requiring mobility or without a manufacturer who provides cars.	Service systems describe and reproduce themselves through observed service (i.e., value propositions uttered, observed, and understood) and their relations to other service elements in the system. Technical structures always remain resources that are situated in a service system's environment. Technology is an allopoietic component that is situated in the environment of a service system. A service system is not a socio-technical system consisting of people and technology, but a supra-system that interpenetrates with various actors' shaped environment.	Self-reference Self-description Self-organization Connective capacity Re-entry
5	Time divides initiated action and observed communication, allowing service to emerge.	A service system emerges when a benefactor observes and understands the value-in-use generated by the service process (e.g., a car computing a route). Benefactors can be absent while a service process is performed, e.g., a software update of their cars.	Communication and, thus, service provision is subject to time offsets due to the duration of observation and understanding. Action and communication are asynchronous, even if the time offset can be infinitely small.	Communication Selectivity and information processing Operating in time

9.2.3.2 Implications for the Service System and Service Ecosystem Concept

Building on the five theoretical propositions derived from LST, we define a service system as follows: *A service system is an autopoietic system in which benefactors (service providers) select and utter pre-selected resources as value propositions to be understood by beneficiaries (service customers) as value-in-use, altogether completing a communication process that is subject to time.*

We depict this conceptualization of a service system in Figure 18. Service requires at least two actors: a benefactor (service provider) and a beneficiary (service customer). Before a service system emerges, other types of systems must be in place, such as social systems or information systems. A service system can then interpenetrate with these systems. A service provider selects information on elements from other systems (e.g., resources) to set value co-creation in motion. This selection is then uttered as a value proposition through language or actions.

Beneficiaries must observe that a value proposition is made. As soon as the information uttered is understood as value-in-use by a beneficiary, one or more service elements are created and attached to the service system, restructuring the service system in an autopoietic process that simultaneously sets the scene for selecting new information as service. The process of selection, utterance, and understanding is subject to time. With understanding, the communication process of selection, utterance, and understanding is complete (Luhmann, 1995, p. 40). Communication constitutes value co-creation among any set of benefactors and beneficiaries as a reciprocal relationship. The dynamic properties of service systems, i.e., re-entry, structural coupling, and operating in time, emerge from and govern the reciprocal acts of communication among these actors.

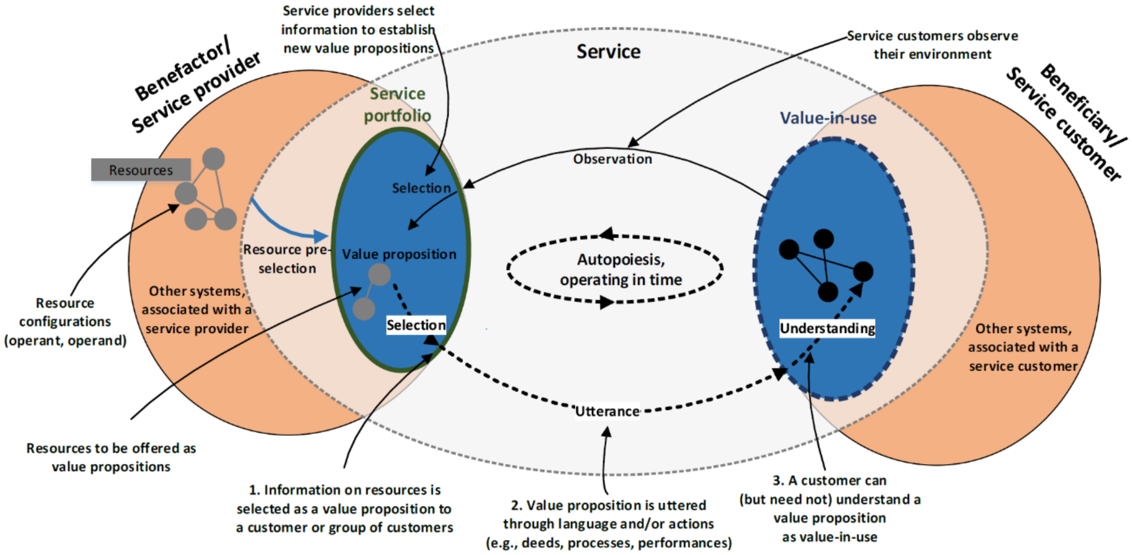

Figure 18: Conceptualizing a Service System Based on a LST Lens

We posit that service systems can be nested and connected with other service systems. We refer to the space in which this happens as a service ecosystem (Figure 19). A service ecosystem is often viewed as a "relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange" (Vargo & Lusch, 2016, pp. 10–11). In a service ecosystem, service systems can create higher-order (super) service systems through communication, as outlined above: information is uttered by one service system and then observed and understood within another service system, interpreting the uttered information as value-in-use. We posit that service ecosystems are embedded into society as a larger system that can be seen as an environment. As proposed in LST, their relation is reciprocal: Society provides its institutional properties (Edvardsson et al., 2011) that provide irritations interpreted by service ecosystems, while service ecosystems also influence the emergence of society. In this way, service ecosystems are situated on a meso level of aggregation (Vargo & Lusch, 2017) between the value co-creation of service systems on a micro level and society (situated in the environment) on a macro level. Service ecosystems allow for identifying a middle ground for value co-creation in specific industries (e.g., retail, baking) or digital realms that reach beyond dyadic service systems, such as public data spaces.

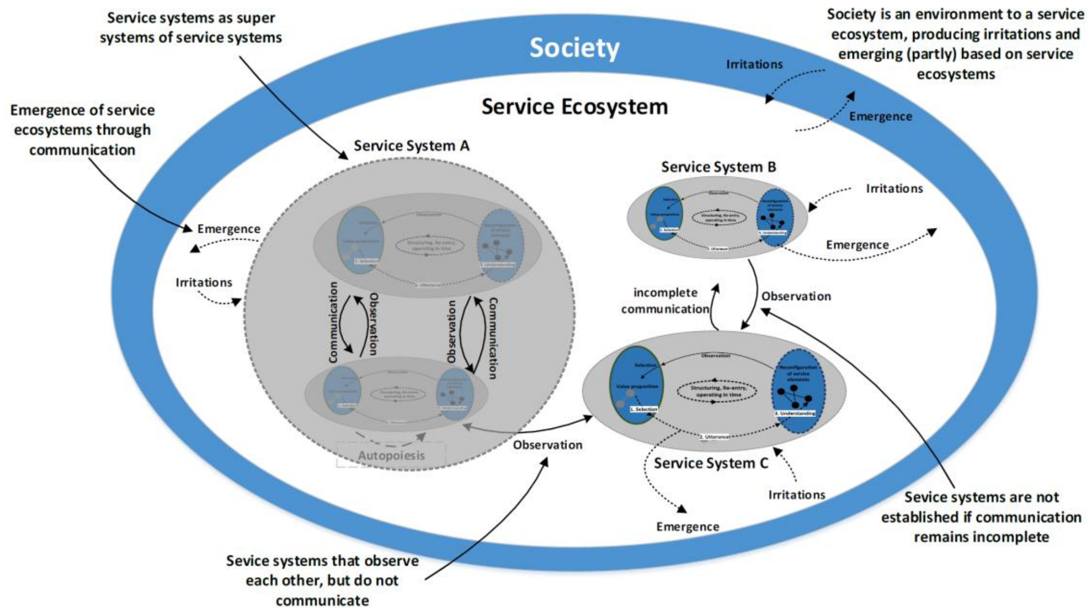

Figure 19: Service Ecosystems as a Meso Level of Aggregation between Service Systems and Society

9.2.4 Discussion

9.2.4.1 Service systems include service only, while relating to other system types

We see a crucial advantage of using an LST lens in its potential to substantiate and clarify the service system concept and its relationship with similar concepts, including service ecosystems. Currently, both concepts lack theoretical embedding and clarity, making service research ambiguous, fragmented, and self-referential, e.g., (Huotari & Hamari, 2012; Maglio & Spohrer, 2013; Maglio et al., 2009; Stanicek & Winkler, 2010). The original service system papers (Maglio et al., 2006; Jim Spohrer et al., 2008) do not provide a theoretical embedding into systems theory, even if calling on others to establish this link. As one of the most prominent systems theories, LST provides a unifying, well-developed, and widespread theoretical lens (Demetis & Lee, 2016) that has been largely overlooked in service research so far. This lens emphasizes the social system properties of service systems, bridging boundaries between academic disciplines involved in service research. An LST lens can also differentiate but still link closely related concepts of service systems and service ecosystems (cf. Figure 19). A service ecosystem is a super-system of service systems, while both types of systems are self-similar (Leinster, 2011), i.e., they use the same mechanisms and theoretical properties. This view of setting both systems into relation strongly differs from the (often implicit) viewpoint that the service system concept could be abandoned in favor of the service ecosystem concept (Brozović & Tregua, 2022; Frow et al., 2014; Vargo & Lusch, 2011). On a macro level, society is an environment that can produce irritations to be observed, selected, and processed on a service ecosystem or service system level. LST provides crucial concepts for understanding the interplay of micro, meso, and macro service layers, pointing considerably beyond more generic frameworks, limited to the interplay of service systems and their environment (Edvardsson et al., 2011).

LST enables this theoretical clarification due to its hallmark principle that every system must have one single guiding difference to establish itself as different from its environment, e.g., (Luhmann, 1995, p. 455). For service systems, this guiding difference is service. This axiomatic view departs from earlier definitions of service systems that contain multiple elements with different system references—e.g., people, organizations, information, and technology (Jim Spohrer et al., 2008). We argue that mixing up systems with different guiding differences leveraged the conceptual confusion about the service system concept and its relation with other system concepts. LST allows to zoom into the service system concept to distinguish service from other types of elements, including people, organizations, information, and technology as resources (Maglio et al., 2009) that are selected, uttered, and can be understood as service by a beneficiary, all networked to service based on the principles of a system's structural coupling (Luhmann, 2013, pp. 83–101). Of course, resources and their combinations remain indispensable for service. Nevertheless, distinguishing different types of systems—such as social systems, service systems, or maybe resource systems—enables researching the mechanisms connecting them to bring about service, where service researchers struggle to find a compelling, theoretically robust explanation of 'services activities' (Skålén & Trischler, 2024). These mechanisms are obfuscated in current definitions of service systems and service ecosystems, e.g., (Huotari & Hamari, 2012; Immonen et al., 2016; Jim Spohrer et al., 2008; Sudbury-Riley et al., 2020; Vargo & Lusch, 2008), which abstracted from their interplay. We argue that identifying how different types of systems interpenetrate and interplay to establish service allows for a more specific, nuanced, and conceptually consistent analysis of service phenomena. For instance, a human's observation using a meaning system (Luhmann, 1995, p. 38) can be structurally coupled to a digital platform (Robra-Bissantz & Schlimbach, 2023), which is a resource. Structural coupling highlights how service systems maintain autonomy while adapting to interactions with other systems, forming dependencies that facilitate mutual influence without merging into one unified system (Luhmann, 1995, p. 85).

Obviously, social systems and service systems interpenetrate significantly since they both rely on communication as a basic mechanism. For differentiation, we argue that service is communication that beneficiaries perceive as beneficial, aligning with prominent definitions of service (P. Hill, 1977, 1999; Vargo & Lusch, 2004). A social system is established through communication and precedes a service system. At the moment at which uttered information is understood as valuable, the observed system's elements become service elements, and thus, a service system emerges. In this way, communication as information, utterance, and understanding prompts a service system to emerge only if all three aspects are fulfilled and also the communication is perceived as beneficial, which aligns with current service thinking (Lovelock & Gummesson, 2004; Vargo & Lusch, 2004).

However, our conceptualization gently refutes the common assumption that social systems and service systems are completely identical, e.g., (Edvardsson et al., 2011; Löbler, 2016). Instead, our conceptualization gives service systems a narrower scope, centering on beneficial outcomes for a defined beneficiary or group. Their outcome-driven orientation makes service systems distinct in purpose and function, with structural formations directed toward generating service outcomes, setting them apart from the broader communicative dynamics of social systems.

9.2.4.2 Beyond action, communication allows for fresh investigations and introduces a new conceptualization of time into service systems

From the LST perspective, service itself is not merely an application of resources but a fundamental communicative act. This perspective diverges profoundly from the resource- and action-centric view prominent in Vargo and Lusch's (2004) foundational S-D Logic, where service is defined as the application of operant resources (knowledge and skills) to benefit another actor, emphasizing resource integration and value co-creation. Foregrounding communication complements related arguments from Edvardsson et al. (2011), who describe service systems as resource configurations (Brozović & Tregua, 2022), yet challenge their assumption that resource integration alone is sufficient to co-create service.

An LST view implies that the mechanism that binds together different types of systems is communication—including information, utterance, and understanding—not action. While the crucial role of communication has started to be discussed, action vocabulary (e.g., performances, deeds, processes, or competencies (Vargo & Lusch, 2004) is still viewed as the generative mechanism of value co-creation in mainstream service research. However, actions—unlike communication—do not include understanding (Luhmann, 1995, pp. 168–177). Thus, current literature that focuses on actions implicitly limits service research to phenomena in which actions find resonance (Luhmann, 2013, p. 54), meaning that they are observed and understood as valuable by a beneficiary. This is not necessarily the case. Consider, for instance, a repair shop to which you do not bring your car or a TV show you never watch. In these instances, service providers apply their operand and operant resources to offer value propositions to clients. However, few service customers observe these utterances, and even fewer understand them as valuable, which is essential for a service system to emerge. In service research, which is still dominated by action vocabulary (Edvardsson et al., 2012; Skålén & Trischler, 2024), these incomplete communication processes could still be considered as service—they are consistent with the definition that service is “the application of specialized competences (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself” (Vargo & Lusch, 2004, p. 2).

We posit that accepting communication as the basic mechanism that creates service provides a pivotal advantage to research service phenomena in which communication processes remain incomplete or dysfunctional. For instance, value co-destruction—which is often assumed to be the consequence of untrustful actions (e.g., taking advantage of others) (Echeverri & Skålén, 2011; Plé & Cáceres, 2010; Prior & Marcos-Cuevas, 2016)—could instead be interpreted as a dysfunctional communication process that remains incomplete despite the actors’ best efforts towards value co-creation. Our line of thinking proposes that value co-destruction (Echeverri & Skålén, 2011; Järvi et al., 2018; Plé & Cáceres, 2010) (Echeverri & Skålén, 2011; Järvi et al., 2018; Plé & Cáceres, 2010) might also happen unintentionally, since for instance, information about resources can be inadequately selected, insufficiently uttered, remains unobserved, or is misinterpreted (i.e., not understood properly). A system keeps exploring and testing new possibilities since "every accident, every impulse, every error is productive’’ (Luhmann, 1995, p. 116), even though they are not beneficial. However, destructive power can affect the structure of the service system, at which point they can build up new services more effectively. In this sense, fruitless paths of possibilities might retrofit dysfunctional communication structures and facilitate better ones, such that ineffective forms of value creation disappear over time while new forms emerge. For example, communication has been argued to sometimes fail on digital platforms, prompting system selection processes to restructure to meet user expectations more effectively (Robra-Bissantz & Schlimbach, 2023). Communication is cumulative, whereby it recursively builds on previous communication and constrains all future elements of communication (Luhmann, 1995, pp. 163–171). If it is re-established, communication might also remedy value co-destruction. Since communication happens in situ, service systems would alternate between value co-creation and co-destruction, depending on how communication progresses in the very moment—here and now. We argue that through its focus on communication, an LST lens provides new vistas to study and understand this fragile and intriguing interplay (Lumivalo et al., 2024).

Another crucial implication of differentiating selection, utterance, and understanding as part of communication is introducing a new conceptualization of time into service systems. Departing from ephemeral actions (P. Hill, 1999), meaning that they dissolve quickly if they remain unobserved, communication allows researchers to study service subjects to long time offsets between utterance and understanding (J. D. Chandler et al., 2019). For instance, schools provide education as a valuable service that sometimes falls on deaf ears of pupils. It might be years later that they will understand their education as valuable and complete communication. Early service research has reflected similar service properties by pointing to the perishability of resources and actions (Zeithaml et al., 1985); however, it does not consider communication as a unifying concept. From a communication viewpoint, service is perishable in the sense that an utterance that remains unobserved permanently leaves communication incomplete and fails to lead to the emergence of a service system. While we do not wish to contradict the observation that the initial IHIP criteria were incomplete and lacked empirical grounding (Lovelock & Gummesson, 2004), we argue that re-investigating literature on perishability with a communication lens could help to reconcile this deprecated body of knowledge with current service research (Edvardsson et al., 2005; Grove et al., 2003; Sampson, 2010). Similar observations could be made regarding intangibility (here: service systems rely on communication, but communication might include observing and understanding selected physical actions), heterogeneity (here: understanding is subject to autopoiesis in the observing system, leading to heterogeneous outcomes), and inseparability (here: service requires communication as an inseparable process of information, utterance, and understanding, subject to time). Still, LST's focus on communication is surprisingly consistent with, yet offers pivotal insights to related work that foregrounds the non-ownership properties of service, positing "that services offer benefits through access or temporary possession, instead of ownership, with payments taking the form of rentals or access fees" (Lovelock & Gummesson, 2004, p. 20).

9.2.4.3 Autopoiesis links resources, including technology, to value-in-use

From an LST perspective, a service system is an autopoietic (self-producing) entity that emerges from a network of communicative interactions between benefactors and beneficiaries. LST posits that all elements are internally generated in an abstracted autopoietic system, and the system maintains its identity by continually reproducing itself through its own operations. This self-referential characteristic enables what we refer to as self-X features of service systems, such as self-organization, self-regulation, and self-sustaining, which others view as properties of service ecosystems (Akaka et al., 2013; Vargo & Akaka, 2012; Vargo & Lusch, 2016). Autopoiesis implies that service systems are operationally closed; they can only observe and interpret external elements through their internal operations (Luhmann, 1986). We posit that this operational closure is key to understanding why service is always uniquely determined by a beneficiary, which is one of the axioms stated by S-D Logic (Vargo & Lusch, 2016). Due to the axiomatic status of this proposition, S-D Logic did not provide a deeper theoretical foundation for this claim. An LST view, however, provides a compelling explanation that is rooted in systems theory, substantiating S-D Logic's claim.

Operational closure does not mean that a service system is cut off from its environment. Operations in the observed environment irritate the service system when re-creating its structure through a selection process (Luhmann, 1995, p. 141). This perspective treats resources as external elements, observed and selectively integrated based on the system's internal communicative processes. Through recursive communication with their environment (e.g., feedback from customers or real-time data), service systems can autonomously adjust their processes or reconfigure their structure to optimize service quality (Barile & Polese, 2010b; Mora et al., 2009). This feedback loop is not simply a reaction but a process by which the service system actively maintains and evolves its structure based on ongoing communication (Vink et al., 2021). The system reorganizes itself internally by selectively incorporating feedback that resonates with its operational difference toward the environment, thereby supporting both the stability and adaptability of the system's structure (Barile & Polese, 2010b). This self-organizing process is fundamentally tied to the system's ability to reproduce its own elements (service) through internal operations (Mingers, 1989). In service systems, this occurs when beneficial communication is continued and internalized, and service elements emerge as new communication constructs. Existing identification structures are decisive in determining whether and how new services are created (J. D. Chandler et al., 2019). In this way, the boundary of a service system is fluid yet structurally maintained by ongoing communication. This is consistent with the claim that a service system's identity is defined not by a fixed set of resources but by the patterns of interaction and communication that sustain it (Storbacka et al., 2016). For service system design, this means that the effectiveness of, e.g., new customer data and technological changes depends on how well these inputs can be processed and selected within the system's existing communication patterns (Pentland & Feldman, 2008), which substantiates why a service system can ignore or underutilize valuable information if it cannot be linked to the system's existing structure and operational boundaries (Robra-Bissantz & Schlimbach, 2023).

An autopoietic view on service systems profoundly departs from current definitions that view service systems as allopoietic systems, describing them as combinations of tangible and intangible components, such as technologies, people, and organizations (Maglio et al., 2009; Jim Spohrer et al., 2008). An allopoietic view excludes autopoietic-based self-

X features of service systems that were declared and spread in the literature as properties of service ecosystems (Brozović & Tregua, 2022; J. D. Chandler et al., 2019; Nazemi et al., 2024; Vargo & Lusch, 2016). For instance, self-organizing capabilities enable service systems to respond flexibly to environmental changes, which is critical in dynamic or unpredictable contexts (J. D. Chandler & Vargo, 2011). Still, for a service system to be autopoietic, it must exclusively consist of service elements capable of self-reproduction (Luhmann, 1995, 286,449). Only service elements capable of participating in recursive communication processes can contribute to autopoiesis. Thus, while autopoietic properties like self-organization and self-regulation are often attributed to service ecosystems (Vargo & Lusch, 2016), they cannot be intrinsic features of service (eco-)systems.

Recognizing service systems as autopoietic necessitates rethinking their analysis and design, particularly their reliance and selection on external elements and system boundaries. LST supplies a framework to investigate how autopoietic service system structures originate, unfold, and sustain as autonomous systems shaped by different observation checkpoints in time, not by the actions of integrating resources alone.

Viewing service systems as autopoietic systems also has profound implications for understanding the role of (information) technology in service systems. From an LST perspective, technology always functions as an external operand resource facilitating communication between service systems and their environment. As an allopoietic system, technology depends on external impulses, without which they would cease functioning (G. Teubner, 1989). It is seen as a neutral structure that is embedded in the social complex of meaning and, at the same time, efficiently reduces social disturbance variables that allow "faster and better-coordinated information acquisition" (Luhmann, 1997, p. 788). As a causal simplification, such systems are disjoint from their environment (Japp, 1998; Luhmann, 1990, pp. 223–228). LST centers human observation as necessary for value creation, positioning it as the defining mechanism of service systems boundary. From this perspective, observation involves not just perceiving data but interpreting it within a meaning system—a capability inherently tied to human consciousness (Luhmann, 1993a, 1995, p. 263). We posit that observation in service systems is inherently a social operation, while technical systems can only carry out distinctions but not indicate social action that refers to a meaning system (Luhmann, 1990, 2013, pp. 101–120) and finally to quantum-induced consciousness (Langan, 2002). It follows that only consciousness-driven operations can truly observe and thus understand service. It follows that technology—as long as it remains non-sentient—must always remain an operand resource in a service system. In contrast, observation, used by consciousness, resides as (the only) operant resource within humans (Luhmann, 1992, 1993a). Endorsing this view, structuration theorist Giddens posits that we cannot evade human distinctiveness (Giddens & Pierson, 1998, pp. 82–83), which lies at the very core of observation.

This view of technology as a passive (operand) resource stands in contrast to some recent approaches towards positioning AI as a potential co-creator of value within service interactions, e.g., (Akaka & Vargo, 2014a; Demetis & Lee, 2018; Manser Payne et al., 2021). While technology enhances communication and supports decision-making, we argue that it cannot become an observer in its own right, according to LST (Luhmann, 1995, p. 437) since it can only make a value proposition but not recognize value. It lacks the required degree of connective capacity to observe and react to undetermined environmental irritations and must, therefore, remain a trivial machine (Foerster, 1993, pp. 245–257). We posit that even if technical systems might still improve considerably, they can never self-organize as long as they lack the ability for self-reference, consciousness, and intentionality (Langan, 2002; Luhmann, 1995; van Lier, 2013), preventing them from autopoietic self-reproduction (Maturana & Varela, 1980) and, finally, from attributing meaning and communication. In this way, information technology remains a "*functioning simplification in the medium of causality*" (emphasis in original Luhmann, 1991b, p. 97), and service that relies solely on interactions with technology remains self-service. Rather than being an internal component of service systems, technology serves as both a boundary object (Razmdoost et al., 2023; Star & Griesemer, 1989) and an enabler for communication, shaping how service systems establish, observe, and differentiate in digital environments.

Still, technology remains constitutional for modern service. The relationship between technology and service systems exemplifies structural coupling—where technology impacts system behavior but remains an external influence, given the system’s operational closure. This facilitation is vital for service systems, which rely on effective observation to differentiate themselves and maintain autopoietic self-reproduction. This way, the service system implements autopoiesis by evolving through self-directed processes rather than predefined, static configurations, supporting adaptability and resilience in changing environments (Robra-Bissantz & Schlimbach, 2023). Digital technologies play a pivotal role in facilitating and managing communication, highlighting their role in reflecting the service system's emergent nature (Breidbach & Brodie, 2017).

9.2.4.4 Value creation and institutions are inextricably linked by communication

Departing from the early definitions of service systems, service ecosystems were proposed as a new concept that, as the authors argued, links value co-creation with the institutions that set the rules, norms, and beliefs in which value co-creation is performed

(Vargo & Lusch, 2011). Further research identified the emergent properties of these institutions as shared institutional arrangements (Vargo & Lusch, 2016). However, the extant research falls short of identifying the generative mechanisms that bring about institutionalization. While we acknowledge that, once again, actions-related vocabulary were argued to be this mechanism (Vargo & Lusch, 2016)—drawing on structuration theory (Giddens, 1984)—we refer to our arguments above to state that actions cannot be the single generative mechanism, since actions can remain unobserved, thus having no effect on establishing institutions.

From the LST view (Luhmann, 1995, p. 139), communication is the generative mechanism for the emergence of institutions. Luhmann's main writings, in effect, deal with the question of how social relations are created and how they emerge based on communication, which—as he argued convincingly—is the only possible operation that can bring institutions as consolidation of expectations to life (Luhmann, 1995, p. 160). In line with our observation that communication is the basic mechanism of value co-creation (proposition 3), communication is a duality that brings about value co-creation in every service system and simultaneously creates the institutions governing value co-creation. Thus, the role of communication is similar to the duality between structure and agency promoted by structuration theory (Giddens, 1984), yet relies on another mechanism: communication. This view profoundly departs from and extends current conceptualizations of institutions and institutional logic associated with service, offering new research vistas that rely on exploring the profound implications of institutionalization offered by communication.

9.2.4.5 Service systems emerge here and now, reaching beyond their design

The concepts provided by LST shed new light on the nature of digital innovation (Kohli & Melville, 2019), service systems engineering (SSE) (Böhmann et al., 2014), and service design (Joly et al., 2019). Traditionally, SSE has been viewed as purposeful acts of design that shape (some would even say: determine) value co-creation among service providers and customers, with novel IT-enabled services being a typical outcome of purposeful innovation activities (Kohli & Melville, 2019). Recent approaches highlight the importance of design for emergence (Vink et al., 2021), noticing that design cannot fully prescribe how value will be co-created. Instead, designers shall equip a service system to grow beyond their design by implementing mechanisms for their adaptation.

An LST view equips researchers with theoretical concepts to investigate how the design of other systems (e.g., communication systems, actions systems, information systems) interplays with the (hoped-for) emergence of (autopoietic) service systems based on communication. While an autopoietic view implies that we cannot engineer service systems directly, service systems engineering can “facilitate the emergence of desired value cocreation forms.” (Vink et al., 2021, 172). Based on the observation that communication is the core operation for value co-creation, we clarify that this claim towards a design for emergence essentially means design for engaging in proper communication. In other words, we posit that designers can anticipate the expected interplay of resources that can then be observed and understood as service, leading to the emergence of a service system. Thus, the LST view does not downplay neither the role of design as a deliberate and purposeful action nor the role of technology as an important resource. Rather, our perspective serves to correctly identify their roles, respecting the mechanism that governs the emergence and autopoietic reconstitution of service systems.

This insight is echoed in current studies on IS design, highlighting the need to view technology not as a static element but as an active role in the structuring, emergence, and encouragement of service interactions (Breidbach et al., 2014; Breidbach et al., 2013; Demetis & Lee, 2018). LST spotlights designers cannot purposefully design a service system when it unfolds according to their own observation and communication. Similar observations have been made regarding the design of routines in workplaces (Pentland & Feldman, 2008). This focus on the indirect role of design does not contradict but updates current perspectives of SSE (Böhmann et al., 2014; Cavalieri & Pezzotta, 2012; Tien & Berg, 2003) and service design (Joly et al., 2019). Systems theory reminds us that systems engineering is inherently non-deterministic, and its outcome is neither fully controllable nor predictable, as emphasized by Vink et al. (2021). In a similar vein, Robra-Bissantz and Schlimbach (2023) argued that digital platforms evolve autonomously, often beyond designers' original intent, emphasizing that indirect design through adaptable communication structures is paramount.

9.2.4.6 LST has pivotal implications on S-D Logic’s axioms

As indicated above, our re-conceptualization helps substantiate the foundational premises and axioms—unproven statements on which theory is based—of S-D logic (Lusch & Vargo, 2015). While axioms are not intended to be proven, we argue that providing a deeper theoretical foundation is highly desirable for the quest to establish a consistent and overarching service theory, as Lusch and Vargo (2006) advocate. Reviewing the implications for the five fundamental premises (FP1, FP6, FP9, FP10, and FP11) (Vargo & Lusch, 2016) reveals that our LST-informed propositions can substantiate the axioms of S-D logic while the axioms can remain fairly unchanged.

Still, we argue that the propositions provide a much-needed systems theoretical foundation (Barile & Polese, 2010a; Briscoe et al., 2012; Godsiff, 2010; Lusch et al., 2016; Mele et al., 2010; I. Ng & Andreu, 2012; Polese et al., 2017; Vargo & Akaka, 2012; Vargo et al., 2017; L. D. Xu, 2000) for the axioms rooted in LST that is compatible with current S-D Logic vocabulary (Figure 20).

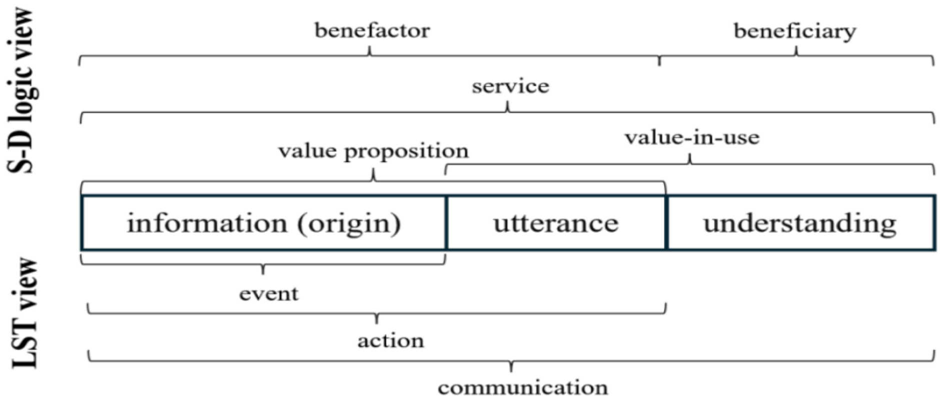

Figure 20: Service Vocabulary from the Viewpoints of S-D Logic and LST

New aspects introduced by our propositions (Table 3) highlight the crucial role of communication in establishing service as the fundamental basis for exchange (FP1) and observation as a crucial prerequisite for value co-creation through communication (FP6). Acknowledging communication's constitutive role in service, LST explains why value must always be uniquely and phenomenologically determined by the beneficiary and why this process is subject to a new understanding of the time that passes to complete communication (FP10). These insights provide new explanations for observation and communication as basic mechanisms behind resource integration (FP9).
Apart from value co-creation, communication also shapes institutions and institutional arrangements, pointing at the dualistic role of communication (FP11).

Table 27: Implications of the LST View on the Axioms stated by S-D Logic

S-D logic Axioms	Implications from an LST View
Service is the fundamental basis of exchange (FP1).	Service is the guiding difference that constitutes a service system. Communication is the generative mechanism for service.
Value is co-created by multiple actors, always including the beneficiary (FP6).	Service is autopoietic, building on communication that is observed and perceived as valuable by a beneficiary.
All social and economic actors are resource integrators (FP9).	All economic actors need to observe and communicate to co-create service.
Value is always uniquely and phenomenologically determined by the beneficiary (FP10).	Service is autopoietic, building on communication that is perceived as valuable by a beneficiary. Beneficiaries use their own operations to interpret value beyond benefactors' influence, establishing service. Communication is subject to time.

Value co-creation is coordinated through actor-generated institutions and institutional arrangements (FP11).	Institutions that govern value co-creation emerge based on communication. Since value co-creation also builds on communication, institutions and value co-creation are inextricably linked.

9.2.5 Conclusion

Service research has established itself as a research discipline in its own right that bridges boundaries between disciplines like (service) marketing, social science, computer science, information systems, and engineering. We firmly believe that no single discipline can analyze and design the mechanisms in service research fully enough to claim the completeness and generalizability of their theoretical insights. Systems theory was frequently named as the natural candidate for a theory that can serve to provide a common ground for multiple disciplines to research service, but no convincing attempt has been made so far to explore its full potential.

In this conceptual paper, we reviewed LST—a prominent and complete systems theory that applies to social systems—to identify theoretical properties that can substantiate service research. Following LST, we defined the service system as an autopoietic system in which benefactors (service providers) select and utter pre-selected resources as value propositions to be understood by beneficiaries (service customers) as value-in-use, altogether completing a communication process that is subject to time. Drawing on the assumptions that service builds on communication and that service systems are autopoietic systems, we developed five propositions that encouraged us to revisit and extend current definitions of the service system and service ecosystem concepts, taking up authoritative calls for action. Based on the extended definitions, we revisit the axioms of S-D logic with the concepts supplied by LST, strengthening their role as a common reference point in service research.

We see LST as a strong and complementary theoretical lens through which core concepts in service research can be substantiated. Still, we acknowledge three limitations. First, even when discussing many concepts of LST, we could not discuss all its aspects in detail, e.g., bounded rationality or double contingency. Further research is required to explore the implications of these concepts for service research. Second, establishing a general systems theory that unites all systems theories is a vision that has remained unachieved and might never be fulfilled. Hence, other researchers might use other systems theories to further substantiate the service system abstraction. We want to stimulate this scientific discourse as a community task to increase the theoretical validity of the core concepts used in our discipline. Third, we acknowledge that Luhmann has been criticized for abstracting the concept of autopoiesis to social systems, even if closer investigations revealed that such criticism is unjustified. Still, even LST leaves some important aspects discussed in service research unanswered. Particularly, the role of human actors in service systems and the interplay of social systems (autopoietic systems) with technology (allopoietic systems) need to be discussed further to contextualize LST in service research.

We call on subsequent research by interdisciplinary teams to explore the array of theoretical concepts supplied by LST and other systems theories more fully. We trust that doing so can provide a fresh perspective to research service phenomena—like the interplay of value co-creating and co-destruction—and serve to consolidate our body of knowledge based on the strong conceptual foundations of systems theory.

E Appendix P2 Explaining and Justifying the Selection of LST

LST offers a strong theoretical lens through which core concepts in service research can be further substantiated. To outline the relevance of LST in comparison to existing system theories, it is important to analyze the existing theories and derive implications regarding their similarities and fundamental differences. In this regard, we want to take a closer look at Giddens structuration theory, adaptive structuration theory, complex adaptive systems, and viable systems theory. Starting off with Giddens's structuration theory, we can outline that the primary unit of analysis is the individual actor and their agency within social structures. Structuration theory emphasizes the interplay between structure and agency. It highlights how individuals reproduce and transform social structures through their actions and practices. It sees agencies as an essential component in creating and maintaining social systems. Luhmann's system theory focuses more on the autonomy and self-referential nature of social systems as the primary unit of analysis. It examines how social systems operate, communicate, and self-reproduce through a network of interdependent subsystems. While Structuration theory focuses on the actions (routines) taken by humans that are influenced by social structures. LST focuses on communication (not action) as a central means of system reproduction. One fundamental difference that favors LST is that the structuration theory focuses on institutional arrangements over time, but LST also considers one-time encounters as service systems.

Adaptive structuration theory (AST) is the adaptation of structuration theory, which originated in IS and focuses on the structuring properties of technology. Accordingly, AST significantly emphasizes technology and its impact on social systems. It examines how individuals and groups adapt their behaviors, structures, and practices in response to technology. AST recognizes the role of technology in shaping and influencing social structures and explores the iterative process of adaptation. AST offers insights into the adaptation of individuals and social structures in response to technology but does not address boundary conditions. Hernes and Bakken (2003) argue that boundaries are essential in defining systems as the boundary is a neutral marker of where one system ends and another begins. According to Luhmann, social systems maintain boundaries. He further describes the role of boundaries as follows: ‘Using boundaries, systems can open and close at the same time, separating internal interdependencies from system/environment dependencies and relating both to each other.

These boundary conditions or constraints are not defined in AST. (Thomas & Bostrom, 2010) argue that adaptive structuration theory remains silent when predicting technology adaptation, but it offers a framework to capture elements pertinent to causing technology adaptation. Their study found even when technology structure is not a primary cause, technology adaptation can occur due to external constraints and trust and relationship inadequacies. Neglecting external constraints or boundaries can be misleading in this regard.

Similarly, complex adaptive systems (CAS) also lack the ability to define boundaries (which on the contrary is very sophisticated in LST). Similarly, (Cilliers, 2002) argues defining boundaries is not easy for CAS. The dynamic behavior of CAS reflects interactions within and between a system and its environment. Knowing system boundaries can be interesting and would help to define service-related boundaries in service systems. However, it must be considered that in CAS, multiple systems and their components can overlap, interact, and are often embedded in each other (Chu et al., 2003; Holland, 1992a).

Other than LST, the VSA does not address the self-referential aspect in a system. (Mingers & Brocklesby, 1997) argue that they cannot see anything in the theory of viable systems that implies self-production of components. In addition, they emphasize that it is difficult to satisfy the requirement of self-reference in a viable system. Therefore, Beer must include principles and axioms to maintain the self-referential property.

Applying LST makes the autopoietic features of systems theory accessible to service research. Concepts like interpenetration, operational closure, self-organization, or re-entry have no counterparts in service research yet. LST can provide common ground for research on service, but no convincing attempt has been made so far to explore its full potential. In this conceptual paper, we review LST, the most prominent and complete systems theory that applies to social systems, to identify theoretical properties that substantiate our discipline of service research.

Despite LST not receiving much attention among service researchers, we argue that its focus on social systems makes it a particularly promising theory to substantiate the service system abstraction since service systems and social systems are closely intertwined (Edvardsson et al., 2011). To us, this work appears closest to reaching the abstraction level required to establish the principal concepts of a general systems theory (Troncale, 1978, 1985) and to provide a 'skeleton of science' (Boulding, 1956). LST reveals interdependencies among systems, provides an exceptionally high level of generalization, and is predestined to be applied to other systems in other disciplines (Luhmann, 1995, pp. 1–3). Drawing on Demetis and Lee (2018), who discussed the implications of LST for information systems, we posit that LST can also inform further conceptualizing of the service system and service ecosystem concepts. Further differences and commonalities among the theories are summarized in the following table.

Table 28: Comparison of Different System Approaches

Concept	**Luhmann's Systems Theory (LST)**	**Structuration Theory (ST)**	**Adaptive Structuration Theory (AST)**	**Viable Systems Approach (VSA)**	**Complex Adaptive S ystems (CAS)**
Origin	Sociology	Sociology	Information Systems	Management	Computer Science
Focus	Social systems, autopoietic systems	Constitution of society as social structure and its multi-faceted interplay with human agency	Adaptation of structuration theory for IS, focusing on the structuring properties of technology	Business organizations as systems that are managed to adapt to and survive in a volatile environment	Technical systems consisting of large numbers of actors/agents that produce simultaneous signals
Leitmotif	Social systems constitute themselves as a difference from their environment. They are restricted to using their own operations to re- constitute themselves, while they can observe and be observed by their environment. Communication is the basic operation enabling a system to re-constitute its elements and relations in a process of self-organization,	Social structure comes into being and is reproduced only through human action. Vice versa, social structure enables and constrains human action. Both are connected in a dynamic interplay, referred to as duality of structure. The knowledgeability of humans is bound by the unconscious and by unacknowledged conditions and unintended	IT, work tasks, and the environment are sources of social structure. Thus, not all structures are purely virtual. The social structure provided by IT refers to structural features and the spirit of the feature set of IT. Interactions between users and technology are subject to a dialectic of control, in which both are shaped by the	Organizations are systems that can be coordinated and managed to function in and adapt to volatile environments.	The actions of agents depend on the signals they receive. That is, the agents have an IF/THEN structure: IF [signal vector x is present] THEN [execute act y]. The act may itself be a signal, allowing quite complicated feedback, or the act may be an overt action in the agent's environment.

	making it an autopoietic system.	consequences of action. Routine is the predominant form of day-to-day social activity. Social reproduction is subject to contextualized interaction. Social identities are markers in the virtual time-space of structure. Social identities are markers in the virtual time-space of structure. Agents are knowledgeable about their actions and continuously reflect on their conduct.	other. Appropriations refer to visible actions that evidence deeper structuration processes.		
Definition of a system	A system constitutes itself as a difference from its environment.	No explicit definition	No explicit definition	An organization is viewed as a system	Systems are complex configurations of agents
Types of elements	Specific elements in line with a system's guiding difference	No explicit definition	No explicit definition	No explicit definition	Any
Static concepts	Super- and subsystems, interpenetration, self-description; self-reference; operational closure	Social structure, routine, context, social identities, power, agents	IT; work tasks; environment; structural features and spirit of the feature set of IT	Five subsystems required by an organization to function effectively	Agents, rules, modularity, self-similarity, openness, complexity, indeterminacy, density, connectivity
Dynamic **concepts**	observing and observer; self- organization; connective capacity;	Human action, rules, resources, structuration,	Structuration, appropriation	Communication, management, control, adaptability, self-regulation	Path dependence, adaptation, evolution, parallelism, conditional action, subroutines

9.3 Reconceptualizing Blockchain-Based Reputation Systems: Applying Systems Theory with Basic Concepts

Paper Number	P3
Title	Reconceptualizing Blockchain-Based Reputation Systems: Applying Systems Theory with Basic Concepts
Publication Type	Conference Paper
Outlet	European Conference on Information Systems (ECIS 2025)
VHB JOURQUAL 4	A
Authors	Hemmrich, Simon 80% Ibrahimli, Ulvi 20%
Status	Accepted with minor revision[57] (resubmission planned for WI 2026)

[57] This publication has been accepted on ECIS 2025 with minor revision but was not published there, since a conference visit was not permitted. A revision was not conducted.

Abstract. *In marketplaces, reputation is built upon observable qualities, such as evidence of customer satisfaction, which signal trustworthiness. Reputation systems, here conceptualized as abstract social systems, leverage systems-theoretical concepts to facilitate trust formation. However, current scholarly discourse on reputation systems is predominantly technical, often neglecting integrated incentive mechanisms of social and technical layers. Addressing this gap, our study employs a systems-theoretical perspective to harmonize social and technical design layers at a unified level of abstraction, offering a novel framework for blockchain-based reputation systems. By applying key concepts from social systems theory—observation, selection, communication, system trust, and elements/relations—we propose a reconceptualization of reputation system design that aligns social and technical layers. Our findings show that systems thinking provides a cohesive abstraction level, making it valuable for crafting new IS artifacts. We contribute to cumulative knowledge of conceptualizing and designing information systems by illustrating how systems concepts can scaffold more integrative IS design.*

9.3.1 Introduction

Effective reputation mechanisms help maintain functioning markets by restoring and sustaining trust among market participants (Tadelis, 2016a). Such mechanisms have been used over the ensuing decades to close sales deals. Nowadays, such mechanisms used in online marketplaces create reputation systems paramount for providing a trustworthy exchange environment (Moreno & Terwiesch, 2014). These systems enable the quality to be judged and justify the pricing prior to the transaction (Tadelis, 2016a). Nevertheless, reputation systems face hitherto a series of unresolved challenges such as fake ratings, lack of incentive to submit ratings, bad-mouthing, reputation inflation, and cold-start problems (Hemmrich, 2023; Tavakolifard & Almeroth, 2012). These challenges undermine such systems' working, reliability, and credibility (Subramanian, 2018).

Reputation is built upon observable qualities in the marketplace, such as demonstrating customer satisfaction. Reputation-building takes place within the concept of reputation systems, commonly defined as a system that "collects, distributes, and aggregates feedback about participants' past behavior" (Resnick et al., 2000, p. 46). Here, reputation systems are viewed as abstract social systems (Ackoff, 1971), where systems concepts of observation, communication, selection, and system trust contribute to forming expectations of trust (Luhmann, 1995). Alongside the social layer, there is a technical layer commonly used on platforms, which structures the operations of associated social systems and facilitates the representation of social reputation tokens(Giddens, 1990).

Creating incentives for trustworthy and reliable reputation systems—e.g., through the possibility of rating the business services—is essential (Ba et al., 2001; Tumasjan &

Beutel, 2019). Yet, because the scholarly work on reputation systems is primarily technical, the social design layer among people using the technology is often neglected (Battah et al., 2021). Thus, there are hardly suitable incentive mechanisms (Ahn et al., 2018; Gruhler et al., 2019; Kugblenu & Vuorimaa, 2020) that combine social and technical design layers. The emergence of blockchain technology is discussed to help solve the problem of fake ratings by securely documenting rating information (Battah et al., 2021; Y. Cai & Zhu, 2016; M. Li et al., 2021; L. Liu et al., 2017; Mehrwald et al., 2019; Tijan et al., 2019; Zavolokina et al., 2021). A blockchain is regulated on a decentralized consensus mechanism, building a reliable, transparent, and immutable basis for business transactions (Böhme et al., 2015; Chong et al., 2019). Reputation systems are viewed as a potent use case for applying blockchain technology (Almasoud et al., 2020; Dennis & Owenson, 2016; Efanov & Roschin, 2018; Narang et al., 2019). Combining blockchain technology with adequate incentives offers a promising stage for building trustworthy reputation systems (Y. Cai & Zhu, 2016; Möhlmann et al., 2019).

Well-designed reputation systems hold disruptive innovative potential when they help create a harmonized social incentive structure combined with robust technical architecture (Buchanan, 2019; Checkland, 1999; M. C. Davis et al., 2014; Mingers & White, 2010a; Mononen, 2017; Nunamaker et al., 1990; L. D. Xu, 2000). Yet, it remains a major research issue to design reliable, trustworthy reputation systems (Hemmrich, 2023; Pastore et al., 2013). Despite the emerging body of research on blockchain-based reputation systems, the missing social layer signifies the need for a conceptual basis using a holistic perspective, like systems theory, to guide the design of such systems. The systems thinking perspective provides an avenue to address this issue. It helps develop information systems (L. D. Xu, 1995) by studying the effectiveness thereof as a whole. A systems theoretical perspective renders abstract and complex (incentive) structures accessible by studying both social and technical design layers on the same abstraction level (Checkland, 1999; Jaradat, 2015). This study explores how systems theory can help design blockchain-based reputation systems. Hence, we pose the following research question:

RQ: *How can systems theory help guide the design of effective blockchain-based reputation systems?*

Business reputation systems are viewed as a new innovative system class (Gregor & Hevner, 2013), where both solution maturity (i.e., a mechanism that sends money-based trust signals) and application maturity (i.e., effectively deployed business reputation systems in the real world) are low (Hemmrich et al., 2025). Monetary ratings are a novel idea that allows the incorporation of risk, inherently linked to the trust mechanisms, in the reputation system (Litos & Zindros, 2017; Luhmann, 1995) and imparts an intrinsic weighting of the rating. Another new idea is selling ratings to selected actors or exchanging them for other ratings combined with a decomposable transaction history, inducing agents to act more trustworthy (Hemmrich, 2023; Jurca & Faltings, 2003).

We refer to recent research on business reputation systems that try to replicate social trust mechanisms (Hemmrich, 2023; Hemmrich et al., 2023; Narang et al., 2019), rate monetarily, and selectively sell rating information to peer buyers (Hemmrich et al., n.d.). Our study engages social systems theory (Luhmann, 1995) to reconceptualize reputation system design through the concepts of observation, communication, selection, and system trust, offering three primary theoretical contributions. First, we identify a second design layer—the social layer—rooted in observation, communication, selection, and system trust—that can complement reputation mechanisms vis-à-vis purely technical solutions. Second, we exemplify the essence of the contribution of the social layer in reputation systems by navigating through a cascading set of decision points in a controlled market scenario. Third, through systems thinking, we offer a new theoretical underpinning for the reputation mechanism of monetary ratings and selective sales of ratings. Hence, we contribute to the cumulative tradition of applying systems thinking and IS research knowledge by showing how systems concepts can help reconceptualize information systems.

The next section presents the related literature, followed by an outline of the research approach in the third section. Section four presents the concepts of social systems theory. In section five, we apply the abstraction of these concepts to a market scenario. Next, we discuss how such abstraction can contribute to constructing next-generation reputation systems based on blockchain technology. Finally, limitations and the future research agenda are discussed.

9.3.2 Related Literature

The initial suggestion to use a blockchain in a reputation context from Vandervort (2014) dates back to 2014. Following this, Carboni (2015) suggested a reputation model in which service providers and customers sign a voucher if satisfied with a service. Later, further technical systems such as privacy-preserving and Sybil-attack-resistant systems are proposed, e.g., for a decentralized anonymous marketplace (Bazin et al., 2016, 2017; Soska et al., 2016). These systems rely on blockchain technology as it has a built-in layer to verify transactions mathematically, which is a solid bastion against manipulation. Yet, fraudulent rating behavior remains challenging to detect since ratings are inherently subjective and lack solid ground truth (Y. Cai & Zhu, 2016).

For this reason, Denns and Owen (2016) designed a binary rating system using blockchain technology to isolate human subjectivity. However, some scholars reason these systems must include human interaction to better capture a subjective service quality (Mui et al., 2002) and call for more sophisticated reputation mechanisms involving social actors. Since then, more elaborate technical systems have been developed, for instance, to record feedback without disclosing reputation scores or identities (Zhai et al., 2016) and mitigate malicious behavior (Yuan Liu et al., 2017), yet research on blockchain reputation systems still lacks a social lens, that is, attempts to reconceptualize the social layer into the incentive structures. Most work concentrates on pure technical solutions, leaving out social aspects (Battah et al., 2021). On top of the subjectivity and social actor trade-off, ratings or review quality are at times viewed critically due to the distorted incentive structures in place that potentially lead to inflated reviews in one or the other direction (Filippas et al., 2018). Yet still, they are seen as the closest proxy for assessing service quality.

Blockchain-based reputation scores are envisioned as a pathway to facilitate new value exchange systems, social sharing, and decentralized cooperation (Allen, 2017; Pazaitis et al., 2017). Putting these building blocks together is essential to extend the cumulative knowledge in this research field (Davidson et al., 2016). There is a need to rethink the current approaches that fall short of providing trust outside a blockchain (Battah et al., 2021; Greenspan, 2016). For this purpose, we complement the conceptualization with system thinking to guide the design of blockchain-based reputation systems.

9.3.3 Research Approach

This study aims to conceptualize a blockchain-based reputation system grounded in systems thinking principles. We use the interpretive research paradigm (Mora et al., 2008), which helps to generate new concepts (or constructs) when designing innovative software solutions (Gregg et al., 2001). Conceptual design research, a recognized non-empirical approach within IS, enables the design of real-world artifacts without necessitating their physical construction (Sonnenberg & vom Brocke, 2012). Among four approaches for conceptual studies — namely *theory synthesis*, *theory adaption*, *typology*, and *model* (Jaakkola, 2020), we adopt *theory adaptation* to extend the current understanding of reputation systems as purely technical IS by incorporating a social perspective to address theoretical gaps (Jaakkola, 2020; MacInnis, 2011). Systems thinking, which examines interdependencies and dynamics within complex systems, offers an effective method to simplify and abstract both social and technical layers (Caulfield & Maj; Jackson, 2001). Abstraction through systems theory has consistently proven valuable in addressing complex systems in IS (L. D. Xu, 2000), serving as an effective tool in the conceptual design process to achieve a unified level of abstraction that enhances systems thinking within IS (Kamarudin et al., 2016). We use soft systems thinking to address the complex socio-technical dynamics in the social layer of reputation systems (Checkland, 2000), an approach well-suited for studying ill-structured, human-centric systems. It enables exploration of both social and technical aspects by mapping human interactions with technical artifacts which makes it ideal for studying the development and design of blockchain-based reputation systems. By applying system-theoretical concepts to illustrate a marketplace scenario involving multi-layer interactions, we anchor abstract theoretical concepts in a practical, real-world context and hence facilitate understanding of the complex socio-technical dynamics of such information systems.

We begin by explaining the theoretical background of the systems concepts on an abstract level before putting them into the perspective of reputation systems to explain how they build a reputation in an example of a marketplace (level of analysis). Following that, we detail how these systems address the issues of trust (research outcome) (Meredith, 1993; Mora et al., 2008). Using social systems theory, the ambiguous use of the term reputation system and the dominance of technical approaches are engaged by framing the concept of reputation systems with a typical marketplace situation. This illustration appears necessary to comprehensively exemplify the highly abstract theory concepts for the reader and show the applicability of systems thinking for this endeavor.

9.3.4 Systems Theoretical Concepts

Reputation systems are perceived as abstract structures that operate within social systems. Social systems theory, comprising five key system concepts, aids in understanding the mechanics of social systems and how reputation is built as a social phenomenon.

1) Observation: Systems emerge through observing within a defined scope of observation. Only what is observed becomes part of the observing system, in which it is further selected and communicated (i.e., processed within a system). Observed elements—such as data on a screen, interactions, or symbols—are subject to a symbolic generalization imposed by the observer (Luhmann, 1995); (see also Giddens, 1990). This generalization represents the unity of a system element (in this case, reputation) gathered from a range of subordinate observations (Luhmann, 1995). *In a reputation system, the core system element—'reputation'—emerges from observing communication in the system that signals trust relations.*

2) Selection: Systems continuously select information from their environment to reduce internal complexity. This selection process determines which information is processed to set boundary conditions on the system's information pathways for refining and guiding its operations (Luhmann, 1995). Selection also occurs within the scope of observation and reflects the observer's values (Luhmann, 1993b). *In reputation systems, selective information forwarding and reception allow an external observer (i.e., not involved in the transaction) to observe and understand relevant information. The observer selectively processes communication information—such as identity, behavior, transaction relations, and others—to form the essence of reputation.*

3) Communication: Systems rely on communication to exchange information and to assign meaning interpreted through actions, offers, and self-descriptions, often conveyed through symbolic tokens (Giddens, 1990). Communication reduces contingency and thus decreases uncertainty about future interactions, initiating further communication that impacts the system's ongoing state (Luhmann, 1995). *The information conveyed can indicate an 'actor's capabilities and should be interpretable. Trust builds through communication anchors in preceding communicative events and reinforces relational stability within the system.*

4) System trust: Social systems achieve stability through trust, which is reinforced by the understanding that dishonesty lead to sanctions. Trust is built on incremental risk-taking and mutual confirmation, one party stepping in to take the first risk (Luhmann, 1995). System trust depends on explicit, organized control of information selection, with human judgment underlying each piece of information (Luhmann, 2017). *Observing a successful approach to overcome uncertainty and, thus, risks foster trust, gradually building a reputation as trustworthy through a sequence of communication events.*

5) Elements and relations: Systems are composed of elements (e.g., reputation) and the relations that connect these elements. Elements selectively refer to one another, building relations between elements that help determine each element's quality (Luhmann, 1995). *In reputation systems, the quality of a reputation is shaped by its observed relations with other reputation information elements.*

9.3.5 Systems-level Abstraction of Reputation Systems through a Market Scenario

9.3.5.1 Reputation Systems in Marketplace Scenario

In a physical marketplace, traders offer their goods at individual market stands. Buyer A, a newcomer seeking to purchase wine, finds it challenging to judge the quality of wine offered by Sellers B and D. Conveniently, in front of Seller B's wine rack, Buyer A notices a glass vessel with a tag that reads: *"Please leave a small tip if you enjoyed the* *wine. I offer good quality at a discount price and trust that you'll show your appreciation with a little extra."* Buyer A observes that many other market sellers also display similar vessels with tags in front of their goods. In this marketplace, each seller slightly lower their prices, trusting that satisfied buyers will tip as an ex-post demonstration of product quality.

In front of Seller B's stand is a nearly full vessel. Buyer A observes this and, drawing an impartial conclusion, decides that Seller B must be the better choice, at least compared to Seller D, whose vessel is not as full. Buyer A then chooses to buy wine from Seller B at a low price. Later that day, after tasting the wine and finding it to be excellent, Buyer A leaves a generous tip in Seller B's vessel (Fig. 21).

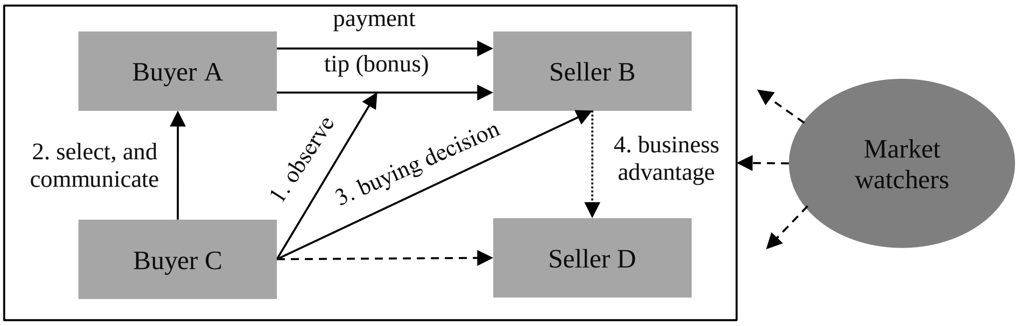

Figure 21: Reputation Building Mechanism with Payment Tips

On another day, Buyer C, another first-time buyer in the market, comes to purchase wine. He notices the same small tag on Seller B's wine rack and sees the nearly full vessel. Buyer C also sees a group of market watchers observing the market stands. These market watchers keep detailed records of every transaction between buyers and sellers. Buyer C checks the records and realizes that they are identical across all the watchers. Market watchers track the identities of every buyer and can quickly detect if someone is attempting to cheat or unfairly promote a particular seller. Using this transaction history, the watchers analyze which buyers appear trustworthy by comparing the tips (ratings) left for goods purchased from different sellers. They can even estimate the amount of a tip a buyer leaves, although they cannot see the exact amount. All recorded information is then published on a market board and made visible to everyone.

Buyer C becomes suspicious of the additional payments and decides to investigate further. He notices that someone left a large tip for Seller B. When he inquires, the market watchers direct him to Buyer A, who gave the generous tip. Buyer A agrees to meet with Buyer C, and during their conversation, Buyer A, a wine connoisseur, shares valuable insights about Seller B's products, recommending the purchase. Buyer C finds Buyer A trustworthy, so he follows his advice and buys from Seller B. As a result, Seller B gains a business advantage over Seller D by demonstrating public endorsements from satisfied and trustworthy buyers. Additionally, Buyer C appreciates the helpful information and compensates Buyer A for his time and expertise.

This scenario can be applied to blockchain technology, where market watchers act as blockchain nodes that maintain detailed records of transactions and ensure the verifiability of both transactions and identities to prevent fraud. In this system, buyers and sellers are transaction partners, with blockchain technology facilitating their exchanges. The description above suggests that a rater (in this case, Buyer A) may remain pseudonymous, with their real identity only revealed upon confirmation by Buyer A. The tip can be viewed as an additional transaction on the blockchain, linked to the initial payment, and serving as a seller's rating. While the exact amount of the tip may not be directly observable (it can remain hidden), it is possible to verify that the tip falls within a certain range (Koens et al., 2018). A larger tip indicates a fully satisfied buyer (Cronin et al., 2000).

9.3.5.2 Systems-level Abstraction of Reputation Systems

We now translate this scenario piece-by-piece into systems-level concepts and render them more tangible and distinguishable from a purely technical lens.

1) Observation: The boundaries of reputation systems shift based on the observer's scope. While Buyer A is satisfied with the available information, Buyer C seeks additional details, thus expanding the scope of the observed reputation system. Hence, reputation is perceived as a phenomenological, individual, and subjective construct that varies according to the 'observer's perspective. *This contrasts with fixed reputation scores, which are not dependent on the observer but are predefined by the technology*.

2) Selection: Buyers act as observers and have the ability to choose whom they trust within the reputation system. They determine which information to select when assessing a 'seller's reputation. Reputation, therefore, is a selectively constructed phenomenon where the information considered can be contextually specified and selected (Filippi, 2016; Nissenbaum, 2004). In this scenario, Buyer C selects Buyer A as a reference to seek further context-specific information. *This targeted selection and sharing of personal, first-hand information is a defining feature of a social reputation system, a dynamic that is overlooked in technical approaches, where scores are accumulated.* tangible and distinguishable from a purely technical lens.

3) Communication: Buyers can communicate about the quality of sellers' products or services. They can ask follow-up questions and seek additional information. Sellers, in turn, communicate their confidence in the quality of their offerings by exposing themselves to risk, thereby signaling trust. Communication enables buyers to gather more detailed information and, if necessary, assess the trustworthiness and competence of the seller to evaluate quality personally. *By definition, technology alone cannot provide the nuanced human insights that often make a difference in a purchase decision.*

4) System trust: Trust manifests in several forms in this scenario. First, there is trust from Seller B toward prospective buyers, such as trusting that they will not miss out on profit (through discounted prices) or damage their reputation (by failing to receive tips). Second, Buyer A trusts the honesty of the tips provided. Third, Buyer C trusts the control measures established by the market watchers and the expertise and judgment of Buyer A. Observing the successful trust of others—such as not being disappointed by the quality of the wine—can serve as an indicator of reputation. *Thus, systems trust provides a reliable foundation for observation, communication, and selection, making building personal trust between buyer and seller easier.*

5) Elements and relations: A reputation system is interlinked, where the creation of a reputation depends on the reputation of others. In other words, reputation is shaped by the opinions of those who already have established reputations (Bromley, 2001; Jøsang et al., 2007). For instance, Seller B can gain a high reputation if Buyer A, who has a good reputation, speaks positively about him. *The transaction history (relations) of sellers or buyers with a reputation (element) can be used to determine the meaning of other reputation information.*

9.3.6 Discussion

This work highlights the underexplored social layer of blockchain-based reputation vis-à-vis technically oriented approaches through the systems theory perspective. Social systems theory pieces together a set of theoretical concepts relevant to the current state of understanding of reputation systems, rethinking such information systems from a social perspective. Designing reputation systems based on systems thinking is rather unpopular due to its abstraction complexity. Hence, we offer an illustrative, albeit abstract, view of the intended artifact to ease understanding (Matook & Brown, 2008). We show how systems thinking can be deployed to conceptualize design knowledge prior to implementation (Chatterjee et al., 2020; Sonnenberg & vom Brocke, 2012). Below, we provide a succinct summary of abstracted knowledge for reputation systems.

1) Observation: Reputation is observer-dependent and is not necessarily represented by an aggregated score, as is often assumed in reputation systems. Distributed observation helps counteract inaccuracies or fraudulent activities (Tong & Zhang, 2009).

2) Selection: Information can be selected and contextualized with input from a peer. Social context enriches the meaning of reputation (Hendrikx et al., 2015).

3) Communication: Communication can be directed in a focused manner, enabling a system to describe a company's capabilities and allowing individuals to assess information with added context.

4) System trust: Observing others' behavior—such as discounting or tipping—fosters trust in a person based on system trust rooted in naturally occurring system mechanisms (Luhmann, 1995). Market reputation can develop from observing actions, with trust being built as parties risk vulnerability (e.g., sellers rely on tips without guaranteed compensation), allowing buyers to signal trustworthiness through their tips.

5) Elements and relations: The transaction history between peers helps to indicate reputation quality. To acquire additional elements of reputation information, one may need to pay or engage in further transactions with a partner (Jurca & Faltings, 2003).

More broadly, reputation can be conceptualized as an assessment involving the selective sharing, communication, observation, and selection of information, all grounded in systems' trust and the observed exchange of values (such as goods, services, or money) on a blockchain (Checkland, 2000). This research contributes to the evolution of self-organizing systems based on blockchain technology, facilitates a more accurate representation of social exchange, and supports the emergence of highly complex reputation systems (Ballandies et al., 2022; Ueki et al., 2024; van Lier, 2020). Such complex systems may include mutual reputation, where buyers also build reputations, for example, by regularly paying tips (Ueki et al., 2024). This feature could encourage the creation of mutual-trust reputation systems that could pave the way for more sophisticated B2B business reputation systems, which are currently heavily under-researched and not widely adopted (Dikow et al., 2015; Gutt et al., 2019; Seutter, 2022).

We provide three main contributions: We demonstrate that a social reputation layer can operate on top of blockchain nodes. Unlike traditional approaches, which focus on purely technical solutions or digital equivalents of word-of-mouth and review systems, this research highlights that reputation systems can be understood as inherently social systems that facilitate genuine trust between economic actors. Integrating a social layer into the technical layer opens up new design possibilities, such as enabling individual coordination, embedding real social trust into the system's innate design (Hemmrich, 2023), and incorporating broader institutional trust considerations (Davidson et al., 2016; Glaser et al., 2019; Pennington et al., 2003).

Second, we exemplify the essence of the social layer in reputation systems by navigating through a cascading set of decision points in a controlled market scenario. In this scenario, we showcase an underexplored yet straightforward design approach where tipping acts as a rating mechanism to build a reputation within the marketplace. While commonly observed in restaurant settings, tipping as a reputation signal is not yet recognized as a viable design option to indicate product or service quality. Additionally, selectively selling ratings offers an intriguing economic design option, which allows rating buyers to be compensated for rating creation (Hemmrich et al., n.d.).

Third, based on this scenario, we show the relative ease with which systems theory concepts can be applied to online marketplaces. This approach could be further extended to other systems concepts (Adams et al., 2014). Hence, we show that systems thinking can effectively help design new information system artifacts since it offers a unified level of abstraction. Consequently, we contribute to the cumulative body of knowledge in systems theory and IS research by illustrating how systems concepts can help reconceptualize information systems.

Concerning the practical implications, the study invites consideration of which industry sectors might be most suitable for implementing blockchain-based reputation systems. Given evidence from recent simulation studies showing benefits for both buyers and sellers in such systems (Hemmrich et al., 2025; Hemmrich et al., 2024), practitioners should consider aligning incentives while addressing additional sector-specific considerations (e.g., legal, technical, economic, and psychological aspects). These systems could be particularly beneficial in industries where customers face high uncertainty around relatively standardized services—such as logistics, construction, and software—where current incentives may be inadequate to encourage feedback (Seutter, 2022). Early examples can be seen on platforms like Twitch and YouTube, where tipping mechanisms support creators. The social system layer could enhance business reputation systems for both trust-building and marketing purposes, reducing customer uncertainty while increasing pricing potential and expanding client bases (Pavlou, 2002). Context-specific adaptation will be crucial to successfully operationalize these systems (Hemmrich et al., 2025).

Future research is encouraged to explore more advanced designs for reputation systems through systems thinking. Potential areas include formalizing payment amounts, rating mechanisms from both buyer and seller perspectives, identity verification and pseudonymization, token-based incentives for submitting ratings, selective information aggregation, and other aspects of the technical layer. Key future research topics include (1) Investigation into tip-based rating payments, as these could be tiered at different levels for more informative, performance-dependent compensation structures; (2) Smart contracts could be used to establish tipping conditions linked to other data sources, such as RFID technology, creating more dynamic and automated interactions between different types of reputation data.

9.3.7 Conclusion

This study demonstrates how systems thinking can unify social and technical design layers at the same abstraction level (Checkland, 1999; Jaradat, 2015) and offers insights for designing blockchain-based reputation systems. By integrating ratings into transactional exchanges, reputation becomes a quantifiable transaction grounded in social trust, built upon the foundational principles of communication, observation, and selection (Battah et al., 2021). Additionally, the embedded monetary value enhances security by making fraudulent attacks more challenging in a supervised transaction environment. While this mechanism could theoretically operate without a blockchain, the technology enables innovative, decentralized reputation mechanisms with monetary ratings, reliably storing ratings without centralized control (Tschorsch & Scheuermann, 2016).

Addressing the information systems discipline's need to conceptualize new, technology-enabled systems for unmet information needs (Gregor & Hevner, 2013; Herhausen et al., 2020; Nunamaker & Briggs, 2012), this research illustrates how systems thinking can streamline the design of information system artifacts by providing a unified abstraction layer. This work contributes to advancing systems theory and IS research by showing how systems concepts can help re-envision information systems, using social scaffolding to lay the groundwork for next-generation reputation systems (Möhlmann et al., 2019; J. Pereira et al., 2019).

This work has several limitations. Primarily, its conceptual nature results in high abstraction, which may hinder the direct extraction of practical implications. Additionally, while we present a theoretical foundation, we do not provide empirical validation. However, empirical support for related systems exists, as performed by other scholars (Hemmrich et al., n.d.; Hemmrich et al., 2024), and a prototype has been developed for a similar reputation mechanism (Hemmrich et al., 2025). Another limitation lies in the assumption that buyers will leave tips as a form of rating; however, (Hemmrich, 2023; Hemmrich et al., 2023) suggests that certain incentive schemes could encourage tip submissions to solve the associated problem of free riders.

Furthermore, this study does not account for other motivations behind (not) tipping, such as tactical, strategic, or competitive reasons, beyond buyer satisfaction. Future research should focus empirically validating and further developing this reputation mechanism.

Studies might include game-theoretical analysis, experimental methods, surveys, or instantiation studies to explore the ’system’s practical applications and robustness.

9.4 Business Reputation Systems Based on Blockchain Technology: A Risky Advance

Paper Number	P4
Title	Business Reputation Systems Based on Blockchain Technology: A Risky Advance
Publication Type	Conference Paper
Outlet	European Conference on Information Systems (ECIS 2023)
VHB JOURQUAL 4	A
Authors	Hemmrich, Simon 100%
Status	Published

Abstract. *Reputation is indispensable for online business since it supports customers in their buying decisions and allows sellers to justify premium prices. While IS research has investigated reputation systems mainly as review systems on online platforms for business-to-consumer (B2C) transactions, no proper solutions have been developed for business-to-business (B2B) transactions yet. We use blockchain technology to propose a new class of reputation systems that apply ratings as voluntary bonus payments: Before a transaction is performed, customers commit to pay a bonus that is granted if a service provider has performed a service properly. As opposed to rival reputation systems that build on cumulated ratings or reviews, our system enables monetized reputation mechanisms that are inextricably linked with online transactions. We expect this system class to provide more trustworthy ratings, which might reduce agency costs and serve quality providers to establish a reputation towards new customers, building on second-order trust.*

9.4.1 Introduction

Online business requires buyers to trust that sellers will deliver a product or service as promised. However, buyers have incomplete information about the seller's capabilities and are exposed to the risk of not being satisfied as expected. A way to reduce this uncertainty is to establish trust (Luhmann, 2017) or reputation (Jøsang et al., 2007), increasing the buyer's confidence in a buying decision (Sullivan & Kim, 2018). Trust is a social construct and refers to "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (R. Mayer et al., 1995, 712). Reputation is an observable public opinion about an entity standing out from a group (Jøsang et al., 2007). It can be established with reputation systems that are information systems (IS).

Reputation systems reliably collect, store, and distribute information about an entity's past behavior (Y. Cai & Zhu, 2016; Resnick et al., 2000). An entity might refer to a person, a group, or an organization. Reputation systems purvey reputation to provide objectified measures to assess trustworthiness subjectively (Jøsang, 2016; Jøsang et al., 2007), particularly to select trustworthy entities for buying decisions based on ratings from unknown agents (Resnick & Zeckhauser, 2002). Thus, reputation systems include ratings or reviews to inform third parties. Review systems feature plain text reviews and other metrics, while in rating systems, a product or service is rated typically, e.g., with a star rating. Both types are often used in a B2C context to indicate a seller's reputation (Gutt et al., 2019; Moreno & Terwiesch, 2014). Well-known examples that integrate both types are amazon.com and yelp.com.

Reputation has been proven to play an important role in business deals, supporting buying decisions and allowing sellers to achieve higher prices (Ba & Pavlou, 2002; Moreno & Terwiesch, 2014). Many value propositions in a B2C context are rated every day, including products, accommodations, shares, rideshares, mini-jobs, and more. However, although these systems are designed to reflect reputation and establish trust, they are also infused with “spam, tampered ratings and reviews, and paid reviews” (Subramanian, 2018, p. 81), since ratings are disconnected from the actual transaction.

Surprisingly, no global reputation system is available for companies to rate each other’s products or services on a daily basis. Since millions of transactions are performed among companies every day using digital technologies, a profound basis for rating other companies’ performance would be available. However, very few efforts have been made to design such systems (Dikow et al., 2015; Gutt et al., 2019), even though “creating a reliable, trustworthy distributed record system, or ledger, may be fundamental to how we organize interpersonal and inter-organizational relationships” (Beck et al., 2017, p. 381). Reputation systems help to solve the famous lemon market problem (Thierer et al., 2016), where asymmetric information between providers and customers leads to an adverse selection of bad products while driving good products out of the market (Akerlof, 1970).

Blockchain technology is discussed to deliver a missing link to design better and robust reputation systems (Y. Cai & Zhu, 2016; Catalini & Gans, 2016; Möhlmann et al., 2019). Blockchain technology is known to establish trust between economic actors without the need to install a trustworthy intermediary. A blockchain is built on a distributed peer-to-peer network to provide a reliable, public, and tamper-proof infrastructure to conduct trustworthy and secure transactions (Nakamoto, 2008). This technology defines new ways to trust each other, prompting IS research to revisit trust as a construct (Beck et al., 2016; Ostern, 2018). Related research views this technology as a trust-free transaction system (Beck et al., 2016) or a trusted code (Simser, 2015). Research on blockchain-based reputation systems currently focuses on designing algorithmically secure and anonymous systems (e.g., Bag et al., 2018; Bazin et al., 2017). However, purely technological approaches struggle to induce reliable data on-chain from the outside world (Greenspan, 2016), disregarding off-chain reputation mechanisms.

We posit that reputation is a subjective phenomenon that builds on social relations, so off-chain trust mechanisms must be considered alongside technological mechanisms. However, until now, the trust perspective on blockchain technology is rarely addressed in top IS journals (Ostern, 2018), although IS research can explain how to establish trust with this technology (Risius & Spohrer, 2017; Seidel, 2018). While there have been calls for finding design mechanisms to build reliable blockchain-based reputation systems

(Voshmgir & Zargham, 2020), an unresolved challenge is to enable individualized reputation and design proper incentive mechanisms (J. Pereira et al., 2019). Thus, we derive the research question: How can we use the trust concept for designing business reputation systems?

Therefore, we set out to revisit the trust construct and explain how the closely related concept of risk can be combined with blockchain-secured transactions to establish trust in B2B transactions. Our approach aims to represent trust relations backed with safeguards to help others to trust. Based on our initial findings, we provide two core contributions to this research-in-progress paper. First, we review and clarify the role of trust concerning blockchain technology. Second, we introduce the idea of leveraging a risky advance as a trust signal by a service provider offering a price discount while getting paid with voluntary bonuses, thereby demonstrating its capability and building a reputation. This idea is innovative since it breaks with established approaches to review or rate a seller retrospectively after transactions have been concluded. Monetary payments as ratings have three advantages. They allow us as researchers to conceptualize a system with a tangible risky advance representing one-sided trust relations. The amount of payments allows us to differentiate the significance of ratings as a parameter. The economic value of ratings is likely to increase the expressiveness of positive ratings since they cost money and might mitigate reciprocity issues.

In Section 2, we review the core concepts of trust, risk, and reputation, along with their role in existing reputation systems, before reviewing key properties of blockchain technology. We summarize and justify our research method in Section 3. In Section 4, we sketch out the idea for designing a blockchain-based B2B reputation system using the reputation mechanism of a risky advance that helps to ease trust between unknown business agents. Section 5 discusses the research contribution and concludes the paper, sketching the path ahead for a new class of reputation systems.

9.4.2 Related Research

9.4.2.1 Trust and Risk, System Trust, and Reputation

Trust is a multidimensional social construct studied extensively in the social context. It refers to various aspects of cognition, emotion, and behavior. Trust is highly subjective and varies depending on the purpose and context. It is indispensable for social interactions and reduces decision uncertainty. As a social lubricant, trust also enables fluid business exchange (Arrow, 1974; H. Sun, 2010).

In general, trust is an expectation about the actions to be performed by others—unlike calculus, and it starts before it is possible to monitor the actions of another actor (Williamson, 1993). As a priori concept, trust always comes with the risk that trust is unwarranted (Luhmann, 2017). It goes hand in hand with a voluntary willingness to take a risk, to lose something that appears valuable, even if a trustor does not expect to be disappointed (Deutsch, 1958; R. Mayer et al., 1995; Schoorman et al., 2007). Thus, there must be something at stake for trust to be built (Kee & Knox, 1970; Schoorman et al., 2007), indicating a constitutive relation between risk and trust (Chetty et al., 2021; Siegrist, 2021). When one makes a voluntary risky advance in a certain matter, it eases giving trust of the other party particularly (Gambetta, 1988; Luhmann, 2017).

System trust is decisive in reputation systems (Pennington et al., 2003). It is independent of a person's risk tendency or motives (S. P. Shapiro, 1987). As a form of distributed trust, it emerges in social systems and is based on explicit and organized control mechanisms, according to concrete requirements. These concrete requirements include safeguards built into the system to preserve the fragility of trust by sanctioning adverse behavior (Luhmann, 2017). In this way, a reputation system works as a collaborative sanction system that discourages untrustworthy behavior (Jøsang et al., 2007).

Trust is closely related to reputation. It is a positive, cognitive assessment by an individual towards another individual or entity, while reputation relates to a group's positive, distributed opinion (Bromley, 2001; Jøsang et al., 2007). Like trust, reputation is contextual, valuable, takes time to build, and is destroyed quickly (Dasgupta, 1988). Reputation occurs only compared to other potential trustees and can help foster trusting a specific trustee. When there is not enough information on whom to trust, peers that have already built trust are consulted—even if they are strangers—as long as they are in a similar position as the trust seeker. Demonstrating to have trusting customers representing a reputation can cause new, yet uncertain customers to trust (Moreno & Terwiesch, 2014).

Trusting in fellow customers who, themselves, trust a provider creates a transcitive relation of trust. Trust transitivity states that trusting a thirid person depends mainly on what extent a referral is trusted (Jøsang, 2016; Jøsang et al., 2007) (Figure 22). First-order-trust refers to trusting a recipient directly, while reptauton is a form of second-order trust derived fromobserving peers' first-order trust.

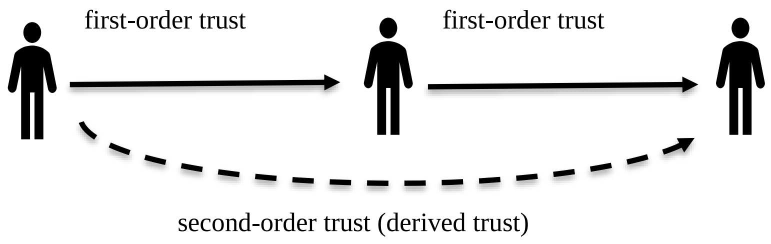

Figure 22: Trust Transitivity Principle: (modified: Jøsang et al. 2007)

9.4.2.2 Trust Inscribed in Information Systems

Early research in IS investigates reputation in game-theoretical settings, splitting up into research on reputation systems to model trustworthiness between (computational) network nodes and research to assess the trustworthiness of sellers/service providers in e-commerce, e.g., through review systems.

Trust and reputation have been ascribed to network nodes (e.g., computer nodes, companies) as well as to things (e.g., vehicles), departing from their original conceptualization as emotional or cognitive concepts. Since trust is inherently based on cognitive processes, modeling trust has no solid validation point in the computational context. Still, modeling trust in these systems has its raison d'être for designing reliable and secure IS (Jøsang, 2016). Computational trust—a quantity or score— refers to an online node's technical capabilities and network contribution from calculated propagated ratings (Jøsang et al., 2007). See Bellini et al. (2020) for a comprehensive view of current reputation systems.

For e-commerce, Jøsang et al. (2007) recognize risk as an inherent characteristic of reputation systems, distinguishing classes of trust according to the risk context. Risk includes, for instance, the risk of not making a good buying decision (decision trust), not being satisfied with a service or product (provision trust), not being part of an honest system (system trust), having no sufficient control mechanisms (reliable trust), and the risk to select false identities (identity trust). However, the concept of risk is often considered a sideline phenomenon in reputation systems (F. Li et al., 2012), even provided that conceptualizing risk shifts the underlying trust mechanism in reputation systems drastically (Litos & Zindros, 2017). For computational reputation networks, risk conceptions are often considered implicitly as a computational network score. However, this also has the disadvantage that reputation is not specifically but globally condensed, which contradicts the social view of trust as an individual construct. Integrating risk in rating processes is hardly discussed in online marketplaces (e.g., Amazon.com or eBay.com) or other business reputation systems. This faint consideration of risk in reputation mechanism might be a reason for false reviews, fraud, and customers' reluctance to trust ratings provided on online marketplaces since a seller and buyers have nothing to be risked in the rating process. Therefore, we conceptualize a reputation system with a risky advance to strengthen buyers' ratings, and make it at the same time easier for trustworthy sellers to win over new customers.

9.4.2.3 Blockchain Technology as an Enabler of Reliable Trust

A blockchain is a distributed ledger recording digital transactions between nodes in a network securely. Transactions are hashed, stored in blocks, and appended to a previous block, establishing an ever-growing chain of blocks, in which transactions can hardly be changed (Buterin, 2014b). Every node holds a copy of the current state of the blockchain, representing an immutable ledger that is stored in the distributed network (Nakamoto, 2008). Transactions are transparent in the network, and parties can verify them easily. Based on this, smart contracts can be committed on a blockchain, providing a reliable basis for automated business exchange (Buterin, 2014b). Blockchains shift trust away from the contractor to the entire blockchain network if the network and the smart contracts are deemed reliable (J. W. Kim, 2020; X. Li et al., 2008; Seidel, 2018). A blockchain can help foster trust, as it has the following features:

- *Immutability* refers to reliable transactions secured as (relative) tamper-proof records in a blockchain. Parties can verify executed transactions themselves, eliminating the need for a central authority to validate transactions. In a blockchain-based reputation system, ratings can be stored reliably, and no single actor can change, nor disavow a rating (Y. Cai & Zhu, 2016).
- *Distributed trust* in a blockchain network (Seidel, 2018) is a form of system trust. System trust is established with a series of control mechanisms, comprising validation mechanisms in the network to approve transactions, so that reputation ratings (as transactions) can be verified.
- *Decentralization* lowers an intermediary's ability to restrict and control activities in a system (Filippi, 2016). A decentralized blockchain network with many independent validators makes most attack scenarios virtually impossible. Manipulating blockchain-secured ratings of transactions is highly unlikely.
- *Transparency* relates to the visibility of transactions, including transaction content, limited to protecting users' privacy. Privacy also allows pseudo-anonymity so that users can decide with whom to share private data. For reputation systems, parties can apply different pseudonyms that cannot be linked, signing a transaction with different personal keys (Filippi, 2016).

These features imply that contractual agreements cannot be changed without the approval of the counterparty, reducing the need to monitor or check the contractors' actions. In this way, a blockchain can reduce agency costs by providing a basis of reliable trust for business exchange (Murray et al., 2019) and prevent strategic lying about ratings. Similarly, rating agreements can be secured on a blockchain.

9.4.3 Method

In this research-in-progress paper, we conceptualize a reputation system for the B2B context. Our idea is based on theoretical literature on trust. Implementing a risky advance mechanism in blockchain-secured transactions, which serve as an immutable, trusted, decentralized, and transparent ledger can help to build second-order trust represented as reputation.

Conceptual research is a non-empirical research method (Mora et al., 2008) for developing a theory based on reflecting on existing theoretical concepts. This paper's theoretical concepts comprise different types of trust and risk. Based on these concepts and core properties of blockchain technology, we conceptualize how a risky advance can be implemented in an IS to ease decision trust in B2B settings. Additionally, we implement control to safeguard the risky advance of a service provider.

The conceptual findings build the first steps of a more comprehensive design science research project (Peffers et al., 2007), in which we plan to build and evaluate a blockchain-based reputation system that instantiates the findings presented in this paper. For this endeavor, the theoretical concepts discussed here will be used as kernel theories to develop, implement, and evaluate an innovative IS artifact (B. Kuechler & Vaishnavi, 2008). We use our theoretical perspective on trust and known problems in related reputation systems to build design principles for implementing a software prototype. Other researchers can build on these design principles and integrate risk (and thus trust) in the rating process of sellers.

9.4.4 Conceptualizing Blockchain-Based B2B Reputation Systems

9.4.4.1 Requirements and Design Principles

Related literature summarizes six main problems related to current reputation systems (Bellini et al., 2020; Jøsang et al., 2007): (1) low incentive for evaluation, (2) positive and reciprocal evaluations, (3) too many ratings (ballot-stuffing), (4) change of identity (whitewashing), (5) unfair valuations, and (6) discrimination (bad-mouthing). Revising how trust as a construct works (observation, selection, and risk assignment in a systemic context) (Luhmann, 1995, 2017), we build on these problems to identify requirements and design principles (Gregor et al., 2020) to design a blockchain-based business reputation system (Table 1).

Table 29: Requirements and Design Principles for Business Reputation Systems

	Requirements	Design Principles
a)	Business relationships	A reputation system should represent the true socioeconomic relationship of the transacting parties.
b)	Economic commitment	A reputation system should give evidence of the economic commitment between the transacting parties.
c)	Information contextualization	A reputation system should provide non-cumulated information and allow contextual information to be filtered and selected.
d)	Performance differentiation	A reputation system should allow for portraying performance differentiation among service providers.
e)	Linkable services	A reputation system should allow linking different service objects.
f)	Selection of ratings	A reputation system should allow a buyer to select which ratings are forwarded.
g)	Open system	A reputation system should be open to new participants.
h)	Raters' fairness	A reputation system should allow responding to a rater's bad rating.
i)	Systemic fairness	A reputation system should support a system equilibrium of fair ratings.
j)	Peer-to-peer system	A reputation system should be based on a distributed system, avoiding a single powerful gatekeeper that can influence the ratings.

9.4.4.2 Concept

We investigate reputation systems to establish trust based on transactions between business parties, while we do not consider reputation systems on the blockchain validation layer itself. We will now briefly explain how the idea works, in general, before building on the identified design principles. We propose establishing bonus payments between the transacting parties, enabling a service customer SC(x) to pay a part of the liabilities only if they are satisfied with the service delivered by a service provider SP. With this risky advance, we integrate risk in the transaction, since a SP risks a loss of profit by not receiving the bonus share; but also risks reputation, since the transaction can be visible to others. In this way, we consider what we learned about trust in theory, which is that trust and, thus reputation, can be created more effectively by exposing oneself to being vulnerable (R. Mayer et al., 1995). In doing so, SP also raises the trust expectation of a SC(x) to fulfill a service as promised, encouraging prospective customers' SC(p) decisions to do business with this SP. If not satisfied, a SC(x) can decide to pay only a basic payment (trans(y)) to the SP, but no bonus payment (trans(x)). If satisfied, the SC(x) might pay trans(x) to acknowledge proper service provision (Figure 23).

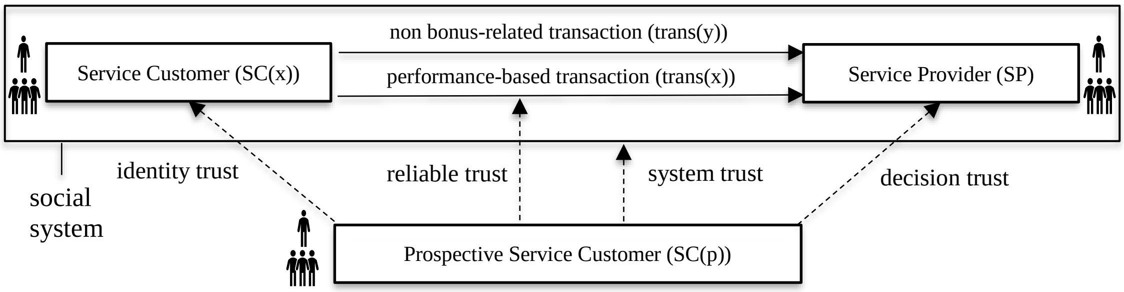

Figure 23: Trust in a Performance-based Reputation System

The payment transactions are visible for other SC(p)s, who use the payment history of a SP as a basis to decide if they want to transact with this SP. The SC(p) will interpret the received trans(x) (in relation to trans(y)) as a rating of the SP's past performance. The SC(p) can compare a requested service with (similar) services rated. We can expect that the willingness of SC(p) to conduct business with SP would increase when the SP receives trans(x) from different SC(x) on a regular basis since this points to several satisfied SC(x). Vice versa, a SP can demonstrate receiving trans(x), gaining a trust advantage over competing SPs that received fewer transactions or lower bonuses. The SP will unlikely make a risky advance and enter into a business with a SC(x) that pays bonuses infrequently or whom he does not trust. Therefore we will introduce a safeguard to indicate exploitive SC(x) (see *h); i)*). Observing the transaction history, a SP can assess the risk of not receiving a trans(x) from a SC(x), which prevents him from engaging with exploitive SC(x)s.

Based on the information provided by SC(x), a SC(p) can decide to engage with a SP. Therefore, a SC(p) needs to trust in the SC(x)'s identity (identity trust), in the immutability of the transaction (reliable trust), and that the SC(x) and SP do not conspire (system trust), before trusting a SP (decision trust). Identity trust can be achieved by verifying identities that are deemed trustworthy; reliable trust is obtained with an immutable ledger. System trust relies on establishing systemic mechanisms rooted in business parties' economic self-interest. We posit that our system needs to be built on the following design principles:

a) Business relationship: Each transaction is recorded on a blockchain, providing a full picture of reputation. The lack of an incentive to elicit ratings (Neumann & Gutt, 2019b) is fixed by deriving reputation from every on-chain transaction. Only metadata is public, while transaction details are hidden.

b) Economic Commitment: The parties establish a smart contract that specifies the bonus payments and is made visible to others. This clear economic commitment is quantified with the payment value and the money at risk for a SP. The smart contract also enables the integration of a counter-rating mechanism for ratings perceived as unjustified, controlling who can give a counter-rating (see *h)*).

c) Information contextualization: Blockchain data can be filtered to identify services fitting a SC(p)'s purchase intent. The SC(p) selects relevant metadata according to a service description supplied in a smart contract and may apply additional evaluation metrics. Importantly, the selection choice of SC(p) includes that the raters' identity (SC(x)) is known or deemed trustworthy, based on verifiable ratings.

d) Performance differentiation: Services are described in a smart contract to indicate different value propositions. In particular, the trans(x) payment amount can be contracted on different levels, depending on how much risk a SP is willing to take for building a reputation.

e) Linkable services: A SP can create one or more seller identities, representing various service categories (Blömer et al., 2018; Zhai et al., 2016). Positive ratings of a service linked to an address/identity can promote customers' trust in the corresponding service provider's service.

f) Selection of ratings: A SC(x) is able to decide with whom to share ratings and not to disclose sensitive information to a competitor. This can be achieved with privacy-preserving techniques to hide the exact transaction amounts (Hemmrich et al., 2023). Equally, the SC(p) decides which rating to pick up to prevent being tricked by a fraudulent SC(x) or SP. Viewing a transparent transaction history, a SC(p) can learn over time which identities are trustworthy. After a sufficient information basis exists, SC(p) might place trust in specialized intermediaries to filter for honest addresses that fit his own assessment.

g) Open system: In a public blockchain network, parties can always join and leave the reputation system. Private spaces might be set up to exchange information about services conducted between SC(x) and SP to inform a SC(p). A SC(p) might pay the SC(x) for additional information to achieve an information advantage (e.g., for knowing SC(x)s true identity, and service details) to reduce the risk of engaging with a bad SP. A SC(x) can prove to have this information without revealing it.

h) Raters fairness: To overcome the problem that a SC(x) exploits the risky advance offered by SP, we propose a counter-rating mechanism. When a SC(x) does not pay a trans(x), the SP receives a one-time certificate to counter-rate the SC(x). This certificate allows a SP to rate to what extent the SP considered the omission of a trans(x) rating justified. For this counter-rating, a star-based rating might be used, revealing more information about the exchange relationship for another observing SP to decide whether to offer a risky advance for a particular SC(p).

i) Systemic fairness: Even if the quality of a service is good, an opportunistic SC(x) always has no interest in paying a trans(x). To establish fairness for counter-ratings, we propose a systems balance mechanism, making unpaid trans(x) visible depending on a threshold. Bad ratings get revealed if a SC(x) regularly decides not to pay trans(x). We suggest defining a threshold (e.g., 90%), at which counter-ratings become visible, as determined by the blockchain protocol rules shared in the network. This display incentives SC(x)s to pay trans(x) to at least 90% to SPs that offered a risky advance because else the exploitive behavior of a SC(x) becomes visible in the reputation system. Consequently, a SC(x) would try to stay below this threshold in order to continue doing business with SPs and being trusted. However, once revealed, every SP can view counter-ratings as revealing a SC(x) excessive exploiting behavior. Intuitively, SPs will pick SC(x)s, who can prove to pay trans(x) regularly to other SPs. This serves as a safeguard for SPs' risky advance, building trust (Luhmann, 2017). Avoidance of a SC(x) to pay too much (unobservable down to the threshold) and selective SP probably lead to a fair system equilibrium, filtering bad actors. Lastly, the threshold should correspond to the quality distribution in a market, at which counter-ratings would be visible to separate high-quality SPs from bad-quality SPs.

j) Peer-to-peer system: Blockchain technology builds on a distributed network that replaces the need for an intermediary, alleviating problems like data breaches, censorship, fraud, or high commission fees.

9.4.5 Discussion and Conclusion

We proposed an incentive scheme for reputation systems based on a risky advance of a service provider to his customer, thereby, using safeguards built on a blockchain to establish decision trust. We expect that this system can provide high-quality SPs with a competitive advantage over weaker-performing competitors, promoting good service quality. Compared with existing rival systems, our approach exhibits five main differences. First, ratings become an inherent part of business transactions, whereas current systems disconnect transactions from ratings. Second, ratings are carried out with payments, making the ratings quantifiable. Third, implementing the system with blockchain facilitates reliable trust, since ratings are immutable, transparent, trustworthy secure. Fourth, we propose a performance differentiation threshold to set incentives and sanction mechanisms aiming to establish a systemic equilibrium. Fifth, services can be rated quicker than writing a review, and service ratings can be differentiated regarding different services.

Blockchain technology can help to make these new reputation mechanisms feasible, paving the way for a new system class of reputation systems. Blockchain-based reputation systems provide control mechanisms to select and verify information service customers and service providers provide. Modifying ratings and strategic lying about ratings, e.g., when selling rating information, is impossible, presupposing a reliable blockchain network. Selecting trustworthy ratings is essential, but might be challenging initially, reflecting a cold-start problem. However, we assume that a marketplace for trading information about the trustworthiness of ratings will form since rating information has an economic value.

We acknowledge that this system might also be applied without blockchain technology. However, we posit that blockchain technology makes particular sense here because rating information is sensitive data, and centralized instances are always exposed to the risk of being compromised, among other disadvantages (Locher et al., 2018; Subramanian, 2018). However, please note that with this technology comes a limitation regarding conflict resolution. Some conflicts are hard to solve since data is stored immutably on the blockchain. However, we assume that a seller who allows himself to be rated accepts this and has a positive relationship with a rating service customer, expecting positive ratings.

Limiting attacks would also be important, and possible attack scenarios should be comprehensively researched to find eventual weak spots in the incentive scheme. Sending trust signals in the form of a risky advance, which is safeguarded through making bad behavior visible, can probably make a positive outcome for both, the service provider and the service customer, more likely. This is because customers want to get or stay in the position of getting trust signals (through the risky advance), while a service provider can expect positive ratings. However, a customer is able to give bad ratings, but, viewed from an overall system perspective, would do it as a rational actor (to stay in the system) only to a limited degree. If he decides otherwise, probably no seller would want to interact with him anymore. Parameters for disclosing bad rating customers need to be adjusted accordingly to the quality distribution in the market.

We assume that agency costs (e.g., monitoring a service provider’s actions, searching for trustworthy service providers, and committing to trustworthy service customers) can be reduced with this system. We build this concept primarily for one-time business deals, making it more attractive to switch business partners. However, this concept might be adjusted to repeated business transactions extending its usefulness.

The multilateral design of incentives provided with this reputation system might result in a system equilibrium. Indeed, we see it as a potential solution to the famous lemon market problem (Akerlof, 1970). Developing such systems might be helpful to counteract adverse selection in business markets. A blockchain can help secure reputation systems, preventing business parties from compromising them. Thus, our blockchain-based system might level information asymmetries by establishing trust and reputation on a systems level promoting good service quality. Whether a system equilibrium is realized with our system needs to be explored in more profound settings, like game theory or lab experiments. This would contribute to complementing the design and evaluation of the proposed system.

9.5 Blockchain-based Reputation Systems for Business-to-Business Services: Designing a Reputation Mechanism to Reduce Information Asymmetry in Professional Consulting

Paper Number	P5	
Title	Blockchain-based Reputation Systems for Business-to-Business Services: Designing a Reputation Mechanism to Reduce Information Asymmetry in Professional Consulting	
Publication Type	Journal Paper	
Outlet	Information Systems and e-Business Management (IseB 2025)	
VHB JOURQUAL 4	C	
Authors	Hemmrich, Simon	70%
	Nissen, Volker	15%
	Beverungen, Daniel	10%
	Pauls, Josias Daniel Miño	5%
Status	Published	

Abstract. *Reputation systems to rate companies' performances remain largely unexplored in research and are scarcely used in business-to-business (B2B) practice. Such systems are essential for businesses seeking trustworthy partners, as they help reduce information asymmetry, lower buyers' transaction risks, and allow high-quality service providers to justify premium pricing. Unlike traditional review-based systems in the business-to-consumer (B2C) context, we propose a B2B reputation mechanism in which buyers commit to a rating payment before a transaction. Once the buyer finalizes the rating, this payment is executed and recorded on a blockchain as an immutable, secure ledger. Our system mimics natural trust-building mechanisms with ratings that are 1) monetary-based, 2) stake-based, 3) non-aggregated, 4) involve counter-ratings, 5) selectively sellable, 6) individually comparable, 7) stored on a blockchain, 8) and monitored by a third instance. This system provides a novel approach to fostering trust in B2B transactions by reducing information asymmetry and transaction risk. We illustrate the mechanism's application in the consulting sector. Our analysis has identified 23 institutional trust and distrust dimensions that promote establishing institutional trust through the proposed mechanism. Qualitative interviews suggest that, while complex and challenging to apply, this mechanism can foster trust in B2B transactions. Given the low maturity in the application domain—rating professional business services with business reputation systems—and solution domain—using monetary stakes for ratings, this system stands as a potential invention.*

9.5.1 Introduction

Consulting services, including IT or management consulting, are professional services delivered by one or more qualified persons hierarchically independent of the client advised. As a professional service, consulting is a knowledge-intensive service that is marketed as a complex, intangible value proposition. The results are usually strategically crucial for customers and impact their organizations long-term. The goal of a consulting service is to interactively define, structure, and analyze problems with a client to develop, plan, facilitate, and, if desired, implement new solutions (Nissen, 2018, 2019).

Beyond search qualities that clients can quickly assess, consulting services are particularly subject to experience qualities and credence qualities (Darby & Karni, 1973). Professional service is subject to the *uno-actu principle*—it is simultaneously co-created and consumed (Hennig-Thurau, 2004). These aspects make it difficult for clients to estimate a consultant provider's quality of service before the service is performed. Leveling this information asymmetry is conceptually tricky, and doing so creates substantial costs on the client's side (Nissen, 2018), while the risk associated with making poor buying decisions cannot be reduced fully. Viewed from the other side, a consulting company needs to signal high-quality service provision to their clients to justify premium prices (Nissen, 2018), which is difficult to accomplish (Müller-Stewens et al., 1999).

Quality signals used often to level the information asymmetry include brands, references to other customers, loyalty programs, success stories, certificates, and other indirect surrogates (Utz et al., 2023). Still, these signals often remain qualitative, and their value cannot be measured objectively and monetarily. In the worst case, unresolved information asymmetry leads to the emergence of a lemon market in which high-quality service is driven out of the market (Akerlof, 1970).

Information asymmetry can be reduced by reputation systems (Thierer et al., 2016) that provide a transparent and accessible record of a service provider's past actions, thereby signaling the quality of their services. A reputation system "collects, distributes, and aggregates feedback about participants' past behavior" (Resnick et al., 2000, p. 46). In a B2B context, research on reputation systems is still very limited (Dikow et al., 2015; Seutter, 2022). In the B2C domain, reputation systems have been viewed as review systems that feature text-based reviews and star ratings. However, they lack applicability in a B2B context (Gutt et al., 2019) due to conceptual shortcomings that promote, amongst others, a lack of incentives to submit ratings, biased ratings, fake ratings, whitewashing, and bad-mouthing (Ansari & Gupta, 2021; Jøsang et al., 2007). A business reputation system must incentivize rational rating behavior, enable selective sharing and choice of ratings, and allow comparing service quality while coping with complexity, different stakeholder interests, and nontransparent price policies (Dellarocas, 2003; Ekstrom et al., 2005; K. Zhu, 2002). Setting adequate incentives for business parties to submit fair, unbiased, and honest ratings remains an unsolved challenge (Y. Cai & Zhu, 2016; Han et al., 2022; Heinis et al., 2022; Hemmrich et al., 2024; Herhausen et al., 2020; Mantas et al., 2017; Swamynathan et al., 2010).

In related research, blockchain technology has been argued to provide a robust architecture against manipulation to cope with quality uncertainties (Y. Cai & Zhu, 2016; Zavolokina et al., 2021). Although still in the early stages, we use blockchain technology to implement a reputation mechanism, providing a reliable means for business reputation systems (Hemmrich, 2023; Möhlmann et al., 2019). If a blockchain is combined with a reputation system and a trusted party, three goals can be reached simultaneously (Filippi et al., 2020; Locher et al., 2018; Lumineau et al., 2021; Spychiger et al., 2022): 1) secure ratings, 2) dispute resolution, and 3) stakeholder participation. However, implementing the reputation mechanism on blockchains is subject to technical challenges, particularly ensuring ratings' secure and efficient handling. In our study, we pursue two research questions:

(RQ1): How can a business reputation system overcome the limitations of traditional B2C feedback mechanisms in a B2B environment?

(RQ2): How can a blockchain-based reputation system with monetary stakes reduce information asymmetry in B2B transactions, particularly in knowledge-intensive services like consulting?

To answer these questions, we examine the deficiencies of current B2C systems and design a new reputation mechanism that mimics trust through monetary stakes and safeguards. Second, we conceptually design and review the mechanism's technical feasibility and explore its effects on six dimensions of institutional trust and distrust (McKnight et al., 2017; Moody et al., 2017; Utz et al., 2023). Our goal is to design a reputation mechanism that builds on blockchain using money as a rating and trust signal (Hemmrich, 2023; Hemmrich et al., 2023), providing a trustworthy and quantified quality signal that reduces information asymmetry—and thus a client's risk—ex-ante of selecting low-quality consulting services. We expect the system will benefit small and medium-sized consultancies, while more established firms might join the community later.

The paper is organized as follows. Section 2 identifies a research gap and discusses the theoretical background of information asymmetry and possible remedies in a consulting context. In particular, we touch on trust, risk, and reputation before presenting a blockchain as an enabling technology. In Section 3, we summarize and justify our design science research approach. Section 4 describes the reputation mechanism and its implementation on the Ethereum blockchain. Section 5 reports a theoretical-conceptual and qualitative evaluation that illustrates the reputation mechanism's benefits for professional consulting. We present our theoretical and practical contributions, challenges, and research opportunities in Section 6 before concluding the paper in Section 7.

9.5.2 Theoretical Background

9.5.2.1 Towards Designing Business Reputation Systems in a B2B Context

In reputation systems, buyers can share experiences about a particular seller with each other, making it difficult for sellers to brand themselves with high quality in a credible way. Related literature on review systems in e-commerce suggests that positive online reviews significantly impact product sales and customer loyalty and improve quality in electronic markets (Moreno & Terwiesch, 2014). In principle, sellers who accumulate positive online reviews can signal higher customer satisfaction and are more likely to increase sales and justify higher prices (Pavlou & Dimoka, 2006). Similarly, these feedback systems provide sellers with valuable information on customers' needs, preferences, and experiences (Tadelis, 2016b).

Reputation systems ought to be designed to dissolve information asymmetry between sellers and buyers effectively (Ye et al., 2014). Their design can involve verifying the identity of feedback providers and reviews and implementing dispute resolution mechanisms (Burtch et al., 2021). Importantly, reputation systems should encourage users to contribute valuable and accurate data. A reputation mechanism that sets proper incentives is essential for creating trustworthy rating data (Dellarocas, 2005; Moreno & Terwiesch, 2014), just like sanctioning malicious behavior also plays a critical role (Jøsang et al., 2007). Discounts granted by sellers have been found to incentivize buyers to submit ratings (Lingfang & Xiao, 2014) and might influence trust decisions in the provider (Hemmrich, 2023).

Considerable literature deals with review systems in B2C business settings (Pavlou and Dimoka 2006) or refers to reputation systems as technical networks (Bazin et al., 2017; Hasan et al., 2022). While both research bodies refer to reputation systems, they use different conceptualizations of trust (Jøsang, 2016). Research that explicitly discusses the design of reputation systems in a B2B context is rare, and the few available papers focus on review systems (König et al., 2022; Poniatowski et al., 2019) or electronic-word-of-mouth (Chatzipanagiotou et al., 2023). Most of these papers are descriptive and do not report on designing IT artifacts. A notable exception is the approach by Carboni (2015), who built a feedback system on Bitcoin based on vouchers. Others discuss that mutual trust may be expressed in terms of money using *bitcoin* (Litos & Zindros, 2017). However, both approaches lack an embedding into a concrete scenario and appear unsuitable for B2B scenarios. Shaker et al. (2021) show how to secure text reviews on the Ethereum blockchain but do not discuss B2B scenarios or a reputation mechanism.

From this overview, we conclude that very little is known about how business reputation systems ought to be designed to reduce information asymmetry in B2B transactions. Based on principles of economic theory and building on blockchains as an enabling infrastructure, we set out to design a novel reputation mechanism that implements a performance-related payment to rate service quality in the context of professional consulting.

9.5.2.2 Trust, Risk, and Reputation in Professional Consulting Services

From the perspective of new institutional economics that acknowledges the imperfections of markets and provides means to resolve them, consulting is an intangible contract good. Due to information asymmetry caused by the role of experience and credence qualities in a consultant service, creating *trust in a provider* is essential for conducting a transaction. This institutional-based trust is “the subjective belief with which organizational members collectively assess that favorable conditions are in place that are conducive to transaction success" (Pavlou, 2002, p. 218). This kind of trust reduces decision uncertainty and always comes with a risk of disappointment, even though it is unexpected (Luhmann, 2017). Trust is built from the seller's side by intentionally communicating (vulnerable) *beneficial* signals and (secured) *credible* evidence (Pavlou, 2002). These trust signals can be beneficially communicated as a risky advance in the form of an unexpected but potentially missed profit of a provider, reliably secured within a credible source of evidence (Hemmrich, 2023; Pornpitakpan, 2004).

Institutional trust is closely linked with an organization's reputation. Reputation is evaluative and helps clients estimate how far a seller's performance can meet their expectations. Demonstrating a history of past institutional trust relations accumulates to an organization's reputation (Fuglsang & Jagd, 2015). The most critical reputation driver for consulting providers is the quality of the service they deliver (Nissen & Dittler, 2019), which is in line with the saying, "Quality is the best marketing tool." High-quality documentation can differentiate a seller from its competitors (Porter, 1997). Hence, consulting companies must signal service quality to entice and convince new clients. Signals often used to this end include establishing long-term business relationships, building a reputation, providing appropriate contractual arrangements, establishing solid brands, and other signals that provide credible information (Gallouj, 1997). With these signals, consulting is marketed as a promise of high performance and is then co-created by consultants and clients (Wright & Kitay, 2002).

Still, there remains an information asymmetry before a consulting service is sold. A consulting provider knows about its staff's skills, abilities, and experience and the company's track record of past projects. However, clients lack this knowledge, while hiring consultants is an expensive, often strategically important investment. Hence, clients are exposed to considerable risk if the result falls short of expectations, leading them to demand more convincing trust signals to remedy the information asymmetry (Nissen, 2019). So far, consulting firms primarily use websites, image advertising (brochures, advertisements), or printed success stories from previous projects. A fundamental deficiency limiting these approaches is that providers can edit or otherwise influence this information, casting an improperly favorable perspective on the consulting provider (Neumann & Gutt, 2019a). Consequently, new clients do not always trust these signals and rely primarily on personal relations, a selection consultant, or the consultancy's reputation when selecting a new partner (Glückler & Armbrüster, 2003).

We posit that small and medium-sized consultancies have reason to embrace innovative reputation systems to overcome trust barriers and signal their quality to potential customers. To compensate for the lack of trustful information, clients rely on public reputation to reduce uncertainty, experience-based trust, and networked reputation. However, public reputation alone is insufficient when selecting a consulting provider. Personal relations can form a trustworthy basis for selecting time-consuming and slow consultancies (Glückler & Armbrüster, 2003). Credible recommendations exchanged among clients can provide a substitute in the form of a networked reputation (Armbrüster & Glückler, 2007; Glückler & Armbrüster, 2003). However, such credible recommendations are often not available. What is needed is a reliable (digital) reputation mechanism that offers credible information (Heinis et al., 2022).

9.5.2.3 Blockchain Networks as an Enabling Technology for Reputation Systems

A blockchain is a distributed ledger that securely records digital transactions among network nodes. Transferred transactions are hashed and stored in blocks attached to build an immutable chain of blocks. Once committed to the blockchain and valid, blocks get distributed throughout a blockchain network, which prevents unauthorized changes, creating an immutable ledger (Nakamoto, 2008). Since a new block's reference refers to a previous block, it is almost impossible to manipulate the content in a truly distributed network (Tschorsch & Scheuermann, 2016). In a blockchain network, transaction information is transparent, and stakeholders can verify it easily. Using smart contracts, programmed business logic can be executed securely without requiring a trusted third party (Buterin, 2014b). In a blockchain, rating information can be reliably collected, stored, and distributed (Y. Cai & Zhu, 2016). At its core, a blockchain has features that appear to be well aligned with the functionality desired from a reputation system (Govindan et al., 2024; Hemmrich, 2023; Zavolokina et al., 2021):

Immutability refers to transactions secured as tamper-proof records in a blockchain. Parties can verify executed transactions, ratings can be stored reliably, and no actor can change or disavow a rating (Y. Cai & Zhu, 2016).

Distributed trust in a blockchain network (Seidel, 2018) is a form of system trust. It is essential for a blockchain to work reliably, and it can be established with control mechanisms comprising validation mechanisms to approve transactions while ensuring that ratings are securely stored and distributed in the network (Pennington et al., 2003).

Decentralization reduces the ability to attack and control activities in the system (Filippi, 2016). A blockchain network with many independent validators renders most attack scenarios virtually impossible.

Transparency relates to the visibility of transactions in the network. Transaction relations and content are, in principle, visible. Content can be hidden to protect users' privacy (Filippi, 2016).

9.5.3 Research Method

We set out to design, implement, and evaluate a reputation mechanism that can contribute to leveling the information asymmetry inherent to a professional consulting service *before* a contract is concluded. The reputation mechanism is envisioned to generate trustworthy, reliable, quantified, and monetary ratings that appoint reputation to consulting providers in a B2B context, enabling institutional trust of clients. We organize this research process as a design science research (DSR) approach, building on Hevner et al. (2004) and the DSR model proposed by Peffers et al. (2007) (Fig.24).

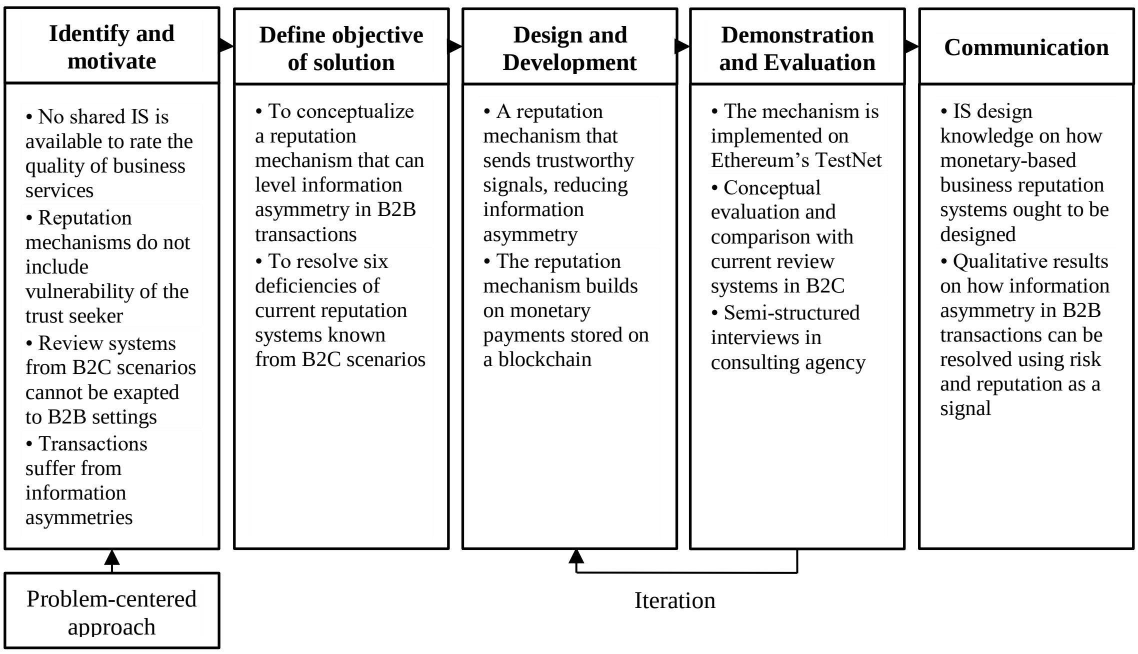

Figure 24: Overview of our DSR Approach (based on: Peffers et al. 2007)

In terms of the knowledge contribution framework (Gregor & Hevner, 2013), we position our approach as a *potential invention* since "little understanding of the problem context exists and […] no effective artifacts are available as solution" (p. 346). It is conceptually unclear how the quality of a business service can be rated, and no *business reputation system* (Hemmrich et al., 2023) has been established for B2B transactions, even beyond the consulting domain. To inform our design (Sonnenberg & vom Brocke, 2012), we start with consulting the literature on review systems established in the B2C field. While these systems cannot be transferred to a B2B scenario due to their conceptual shortcomings, we figure their review is a reasonable starting point for deriving design requirements that can guide the further design of a novel reputation mechanism.

Theoretically, we root our design in new institutional economics lemon market theory and refer to reputation, trust, and risk as established theoretical concepts (Hemmrich, 2023; Luhmann, 2017) that can guide the conceptualization of the mechanism. We then designed and deployed the reputation mechanism to the Ethereum blockchain's Testnet to demonstrate its proper function. The evaluation is performed in two steps. First, we elicit the reputation mechanism's potential to level information asymmetries with institutional trust in a conceptual review and compare it with the mechanisms provided in other review systems (J. Venable et al., 2016). Second, we perform a qualitative-empirical evaluation based on semi-structured interviews (Myers & Newman, 2007) with consulting companies as the mechanism's primary target group. Based on the interviews, we build an *illustrative scenario* (Peffers et al., 2012) by mapping important aspects of the interviews. We discuss how the reputation mechanisms ought to be designed and what conditions must hold for the mechanism to work. We discuss potential benefits for consulting providers and clients to prepare subsequent qualitative evaluations (Sonnenberg & vom Brocke, 2012).

9.5.4 Designing a Reputation Mechanism for Providing Quality Signals for Consulting Services

9.5.4.1 Design Requirements

We summarize six common deficiencies of the review system currently used in a B2C context (Tab. 30), all of which have been frequently discussed in the literature (Bellini et al., 2020; Jøsang et al., 2007). We describe each deficiency briefly to identify requirements that our reputation mechanism and the surrounding reputation system must address. We complemented these insights with design requirements for reputation systems that we identified from the related literature (Hemmrich, 2023; Vavilis et al., 2014). Both perspectives resulted in identifying six design requirements that guided the further development of our reputation mechanism.

Table 30: Deficiencies and Design Requirements (based on: Jøsang et al. 2007)

Deficiencies	Descriptions	Design Requirements for the Mechanism
(1) Little incentive to generate ratings	A client has no or insufficient incentives to rate a provider’s service after it is concluded. Relevant ratings are not filed, leaving the information incomplete.	a) Raters must have incentives to elicit ratings. b) The rating submission procedure should be time-efficient. c) Rating information must remain confidential when the rater denies sharing it publicly.
(2) Positive and reciprocal ratings	Positive ratings are often based on politeness or the hope for positive returns. Too many positive ratings can lead to an unjustified reputation.	d) The significance of a rating must be assessable. e) The mechanism must balance uncertainty between users.
(3) Too many ratings (ballot stuffing)	Clients provide too many ratings, falsifying the basis of reputation. Ballot stuffing serves self-promotion (5) or bad-mouthing (6).	f) The system must be robust against attacks but open to new participants. g) Every rating must be verifiable.
(4) Change of identity (whitewashing)	A bad reputation can be undone by re-entering the system with a new identity.	h) A new identity must have no reputation and must be verifiable. i) Relations between actors and ratings are traced.
(5) Fake ratings (self-promotion and unfair ratings)	Ratings are explicitly used to increase or lower a provider’s reputation.	j) Raters must have incentives to generate meaningful ratings. k) Raters can respond to unfavorable ratings. l) Raters must be able to judge a rating properly.
(6) Discrimination (bad-mouthing)	A client rates one particular provider poorly and all others well. Vice versa, a service provider delivers good quality for all customers except one.	m) Every rating commitment is recorded. n) Ratings are provided with contextual information. o) Ratings can be selected individually.

9.5.4.2 Conceptual Design of a Monetary and Quantifiable Reputation Mechanism

The conceptual design of the reputation mechanism builds on using performance-dependent payments as ratings of a consulting provider’s quality. Each rating is secured on a blockchain, providing a trustworthy and immutable ledger. We focus the design of the reputation mechanism on consulting firms to gauge the mechanism’s applicability from a research perspective (B. Kuechler & Vaishnavi, 2011).

In line with typical customer behavior in B2B service contexts (Lam et al., 2004), we can assume that a performance-related payment reflects a customer’s satisfaction with a service. Compared to ratings issued on review platforms used in a B2C context (e.g., text, star ratings), a performance-based payment carries an inherent weight better than qualitative metrics for indicating a provider’s service quality. The amount of the performance-related payment’s share is negotiated before the contract on the consulting service is concluded. If the client is dissatisfied, the payment is not made or is not made entirely. In this way, the provider accepts the risk of being paid less (Hemmrich, 2023). This risky advance is a substantial trust signal (Gambetta, 1988; Luhmann, 2017).

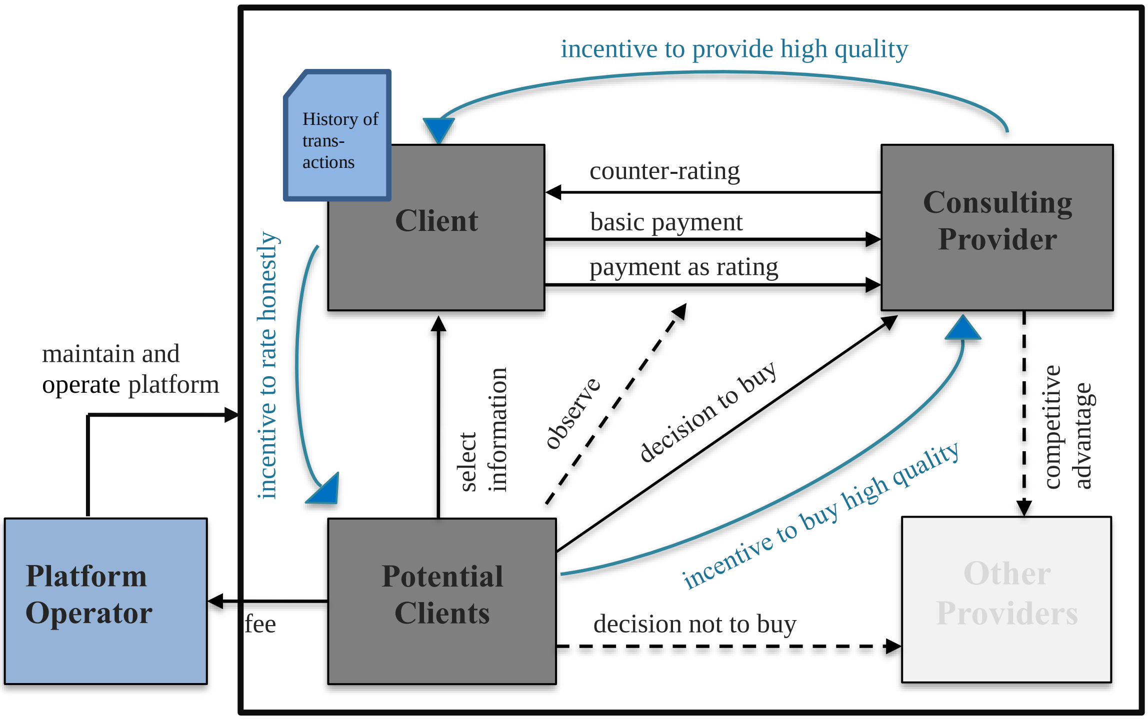

Figure 25: Conceptualization of the Reputation Mechanism

Before the service is co-created, a client and consulting provider agree to rate the provider's quality based on a basic payment and an additional voluntary payment that is used as a rating (Fig. 25). To overcome the client's uncertainty, the consultant offers the service with a discount expected to be compensated when the client pays the performance-related payment (Bar-Isaac & Tadelis, 2008; Nikolova et al., 2015). The consulting provider intends to receive the full payment, thus building a reputation to draw new clients, but risks being rated poorly, even if performing well. In return, the clients' buying uncertainty is reduced. The higher the variable rating share relative to the transaction's value, the greater the providers' risk and the demonstration of the providers' confidence in the quality delivered. The payment levels can be set in stages, permitting ratings on different levels of service components without disclosing the actual amounts paid. Disclosing the ratio of the two payments proves the payment is not a trivial cheap rating. The payment agreement is stored in the blockchain like other additional feedback information, which can be stored and secured as a hash. The benefits of using a blockchain include: a) sensitive rating information is not visible, b) the exact transaction amounts (rating) must not be shown to others, and c) a platform operator or any other party cannot manipulate the rating (Hemmrich et al., 2023). The feedback can be in text or a filled-in form to a detailed review text (Shaker et al., 2021). Assuming that a new client is looking for a consultant firm, this client can check a consulting provider's reputation based on the payment ratings issued by other clients. The new client pays a fee to retrieve this information from a platform operator that governs the blockchain-based platform, from which a share is given to the rater as an incentive to submit ratings. The rater can ultimately approve which information is shared with a requesting buyer and, in this way, can sell ratings selectively (Hemmrich, 2023).

In line with theory, it is essential to include additional safeguards in the system to sanction adverse behavior (Jøsang et al., 2007; Luhmann, 2017). Therefore, we implement the concept of counter-ratings to protect a provider from unjustified unfavorable ratings (non-performance-related payment) from a client. For every negative rating a client issues, a consultant provider can report the rating as justified in the form of a star rating. When the average of the counter-ratings falls below a certain threshold—e.g., below two stars out of five—all submitted counter-ratings become visible, and other potential providers and the platform operator will notice a probably exploitative client. The platform operator can then intervene and might decide to exclude this client. The platform operator can also settle potential disputes. The counter-rating allows a certain degree of freedom to disappoint trust expectations without direct sanctioning (Gambetta, 1988) set by a provider by offering a price discount.

The counter-ratings should not become directly visible as long as they exceed a certain threshold, granting a client the ability to rate a consultant's service poorly now and then. We expect clients to make a performance-related payment most of the time to stay above this threshold and remain part of this system (get high effort from the rated provider). Still, they can pay less if their expectations remain unmet (Bottom et al., 2002). The threshold must be set appropriately to meet the quality distribution in the consulting market. Avoidance of a client getting kicked out of the system when falling below the threshold and the difficulty of convincing clients to renounce paying less (no positive rating) in case of poor performance leads to the expectation that clients' rating behavior is honest. Also, a consultancy can choose which clients can submit ratings to send trust signals about their capabilities while being exposed to the risk of not being rated well. Thus, the system implements a form of *mutual institutional trust* between provider and client (Kroeger, 2011), determined by their past transaction histories, which balances information asymmetries.

We posit that this mechanism benefits all actors, stating the following testable propositions:

- **For consultant providers**: Providers can generate additional profit by justifying a price premium if positive ratings are received regularly. The provider can attract even more potential buyers since the possibility of rating reduces a client's uncertainty (in the case of poor performance, the current client pays less).
- **For existing clients:** Clients reduce the risk of the consulting firm not providing good quality. If the performance is not satisfying, the client pays less for the service received.
- **For prospective clients:** New clients reduce risk and lower the probability of contracting low-quality consultants.

9.5.4.3 Implementation of the Reputation Mechanism on the Ethereum Blockchain Network

As a demonstration, we implemented the reputation mechanism on the Ethereum TestNet *Sepolia*. In the prototype, all addresses and, thus, transaction histories of the participants are visible (pseudo-anonymity). We explicitly refrained from using anonymizing identities since the contextual information about the transaction relationships of the actors helps to determine the trustworthiness of ratings (G. E. Bolton et al., 2004). Also, we avoided the issue of transaction relationships being often traceable despite anonymization techniques (Filippi, 2016).

The blockchain prototype works similarly to the one proposed by Shaker et al. (2021) and Ramachandiran (2019) for product reviews. The other systems store reviews as a transaction hash on the blockchain, while our system stores two encrypted monetary transaction commitments, from which the performance-related payment is pegged to an expiration date (Hemmrich et al., 2023). If no bonus is paid within the specified time frame, it is considered a negative rating. The money transfers of the rating should use a stable coin or (stable) fiat money since cryptocurrencies are subject to considerable fluctuation.

We built the prototype as a DApp on the Ethereum blockchain for technical demonstration purposes only. One can write an individual rating smart contract as a rating application using the Ethereum Virtual Machine that converts high-level code into machine code. This code is registered and executed, enabling business transactions with encrypted messages secured in a blockchain. Smart contracts allow writing and connecting a rating contract to a user interface or carrying it out when specific digital events (e.g., digital service fulfillment) occur. The consultant provider and client make a payment commitment on a smart contract for the client to rate the provider's services by creating a payment and a performance-related payment (executed from a bank account). This triggers a certificate for the consultant to perform a counter-rating (e.g., star-based rating) to rate a client in return.

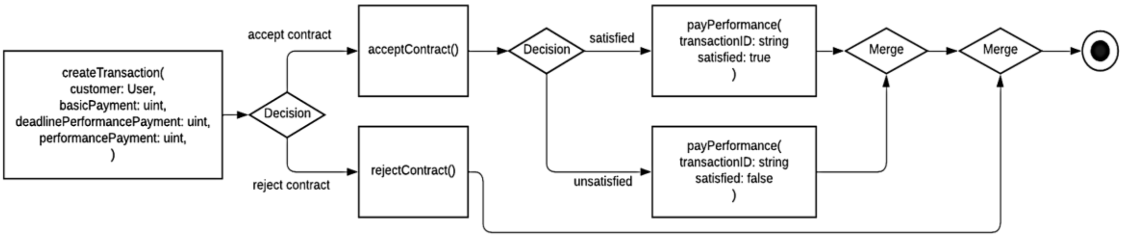

Figure 26: An Exemplary Process Modell for the Reputation Mechanism

Only authorized users can participate in the rating process. First, the client must complete the transaction, which displays the status fulfilled. Once this has been achieved, the client can decide to make the performance-based payment (Fig. 26). The rating commitment is then stored on a blockchain, whereby a client can choose to pay the performance-based payment, generating a positive rating (Fig. 27). If not, the counter-rating opportunity will be unlocked for the consultant in the form of star ratings. A smart contract checks the average number of stars given to a client as a counter-rating. It indicates to the platform operator that it is a potentially exploitive rating client when the average number of ratings falls below a given threshold, e.g., two stars. Any textual rating content *(txt)*, like details of the consulting performance, can be stored as a hash in the blockchain (as metadata) so no party can change it.

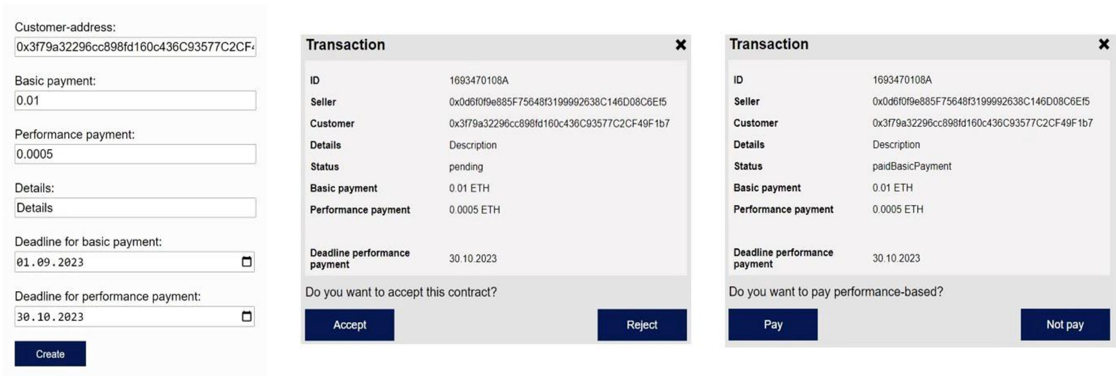

Figure 27: User Interface of the Reputation Mechanism

Since the client and provider do not want to reveal the exact transaction amount (the consulting price), they only need to define a lower bound on the payment amount with proof ranges. This lower bound (*basic pay min*) prevents the creation of trivial ratings without any relevant transaction amount. With a deniable zero-knowledge proof, the buying client can reveal the ratio ($\frac{performance\ pay}{basic\ pay\ min}$) between the basic payment and the *performance pay* without showing the actual amount. Even though we did not implement the zero-knowledge procedure in this prototype, there is logical reasoning that it works on Ethereum (Hemmrich et al., 2023). Further technical details like data structure, network, and consensus algorithm are left out here. They are irrelevant to the mechanism.

9.5.5 Evaluation

9.5.5.1 Conceptual Evaluation

Reflecting on the properties of our reputation mechanism, we structure its evaluation in two parts, taking up advice on performing *ex-ante* evaluations of IT artifacts (J. Venable et al., 2016). In a conceptual evaluation, we identify how our design reflects institutional trust dimensions and how the proposed system remedies shortcomings of current reputation systems used in B2C scenarios. In a follow-up empirical evaluation, we mainly elucidate consulting companies' views on the reputation mechanism to identify how it can stimulate trust and its weaknesses. We position both parts as artificial evaluations to formatively "identify weaknesses and areas of improvement for an artifact under development." (J. Venable et al., 2012).

We analyze the reputation mechanism's potential to facilitate trust by mapping institutional trust and distrust dimensions (X. Cheng et al., 2021) with the design requirements (Tab. 31) addressing conceptual deficiencies of these systems. Specifically, we refer to the institutional trust/distrust dimension (Utz et al., 2023) (cf. Tab. 31) to demonstrate our mechanism's potential to increase institutional trust and decrease institutional distrust.

Table 31: Increasing Trust and Decreasing Distrust Strengthening Institutional Trust Dimensions, cf. Utz et al. (2023)

Institutional Trust/Distrust Dimensions	Description
▲Cognitive-based trust	Cognitive assessment of the impersonal structure in place to anticipate successful interaction (McKnight et al., 1998; S. P. Shapiro, 1987).
▲Knowledge-based trust	Accumulated knowledge through experiences or a given interaction history (McKnight et al., 1998).
▲Calculation-based trust	Conscious judgment of (often economic) outcomes while pondering the associated risk and effort (Williamson, 1993).
▼Skepticism-based distrust	Inclination to question situations and facts until sufficient evidence is presented.
▼Controlled-based distrust	Exerted control by using measures to make aspects transparent and reveal attributes of trust subject.
▼Vigilance-based distrust	Heightened alertness and suspicion about potential deception.

By mapping each of our design requirements to one or more trust/distrust dimensions (Tab. 32), we investigate how this mechanism increases trust (▲) or decreases distrust (▼). We found 23 institutional trust factors that link to the reputation mechanism to establish trust. The mechanism is rooted in a multi-layered trust mechanism based on intentional communication signals, observing ratings given the specific context, and guiding selection behavior according to the estimated source's credibility.

Table 32: Reviewing Design Requirements with Trust|Distrust Dimensions

#	Requirements	Mapping the Design Requirements to Six Institutional Trust/Distrust Dimensions
1	**Incentives to submit ratings**	▲Calculation-based trust: Clients are offered a discount for which they do not have to repay, whereby negative ratings must be taken into account. ▲Calculation-based trust: Clients can sell and profit from sharing ratings.
	Time effort for rating submission	▲Calculation-based trust: Clients are compensated for time effort when they sell their ratings.
	Decision to share ratings	▲Calculation-based trust: Clients can sell and profit from sharing or exchanging their ratings for other ratings (or associated tokens). ▼Controlled-based distrust: Clients control with whom they share sensitive data.
2	**Assess the rating significance**	▲Knowledge-based trust: Potential clients can assess the rating significance based on the addresses involved and the monetary rating amount.
	Reduce uncertainty for all parties involved	▲Cognitive-based trust: Potential clients' uncertainty is reduced by providing a better market overview (Hemmrich et al., 2024). ▲Cognitive-based trust: Providers can send beneficial signals and provide credible evidence to foster clients' cognitive trust (Ba & Pavlou, 2002) while relying on counter-rating and secure smart contracts (Zou et al., 2019). ▲Knowledge-based trust: Rating clients can rely on the mechanism to not reveal negative ratings unless they exceed a certain threshold. ▲Knowledge-based trust: Providers can select only known, trustworthy clients or use the transaction history to select unknown clients to be rated. ▲Calculation-based trust: Providers ponder the risk of monetary loss and reputation against achieving a higher reputation. ▼Skepticism-based distrust: Clients trust providers who substantiate their performance promises with a risky advance. ▼Controlled-based distrust: Providers control rating opportunities selectively.
3	**Robustness against attacks; rating verification**	▼Vigilance-based distrust: All parties can report unfair behavior to the third instance. Retroactive manipulation becomes nearly impossible for transacting parties since the ratings are secured on a distributed blockchain.
	Rating verification	▼Vigilance-based distrust: Potential clients can verify ratings.
4	**Identity verification**	▼Vigilance-based distrust: All parties can verify the addresses of identities.
	Tracing of identity and transactions	▲Knowledge-based trust: All parties can determine the trustworthiness of ratings or identities by tracing transactions.

		▼Skepticism-based distrust: Potential clients' skepticism about fake ratings can be reduced when rating transaction relations are made transparent and approvable.
5	**Incentive to generate meaningful ratings**	▲Calculation-based trust: Rating clients as a business organization stands by their credibility, not to lie. ▼Vigilance-based distrust: A third party can exclude fraudulent actors.
	Response to ratings	▼Skepticism-based distrust: Providers can comment and respond to negative ratings with (negative) counter-ratings.
	Correct rating judgment	▼Controlled-based distrust: Potential clients can control which ratings they exclude or request more information from an entity.
6	**Immutability of commitments**	▲Cognitive-based trust: The client and provider know their rating commitment is stored immutably on the blockchain. No party can change or dispute a rating.
	Deliver rating context	▲Knowledge-based trust: Potential clients (and the third instance) can, based on contextual information, analyze and learn which ratings are relevant for them.
	Selection of ratings	▲Knowledge-based trust: Potential clients can select, compare, and compile interesting and credible ratings.

We posit that the requirements rely on specific trust dimensions: Cognitive-based trust needs understanding, knowledge-based trust needs knowledge, calculation-based trust needs economic incentives, while reducing skepticism-based distrust needs trust signals, control-based distrust needs transparency, and vigilance-based distrust needs verification. Each dimension is addressed at least twice in our artifact, which confirms profound coverage of all trust factors. Although potentially effective due to numerous trust-strengthening factors, trust literature suggests additional determinants to improve trust further (X. Cheng et al., 2021). Notably, *e) "reduce uncertainty for all sides"* appears particularly important, emphasizing that balancing uncertainty between the parties is crucial. When uncertainty is reduced on one side, it may inadvertently create a degree of uncertainty elsewhere (Luhmann, 2017). While the focus remains on trust-enhancing factors, the mechanism must also be designed to mitigate potential distrust arising from other contexts.

Tab. 33 presents conceptual differences between our B2B reputation system and the B2C review systems currently used. We highlight how the proposed blockchain-based monetary reputation mechanism can resolve current systems' deficiencies. While the comparison draws on B2C systems to highlight their conceptual deficiencies, the proposed reputation refers to a B2B context. Given the overlap in challenges between B2B and B2C environments, such as biased or fake ratings, our mechanism may also be applicable in B2C contexts later. We posit that we offer an entirely new approach to remedy deficiencies (1), (2), and (5) while we consider the improvement of (3), (4), and (6) as relatively minor.

Table 33: Comparison of Current Review Systems and the New Reputation System

Deficiencies	Current B2C Review Systems	Blockchain-Based Monetary Business Reputation Systems for B2B Context
(1) Little incentive to generate ratings	Often rewards from rated parties. All ratings are publicly available.	Ratings are kept private and can be sold, providing an economic incentive to generate them.
(2) Positive and reciprocal ratings	Positive ratings are easy to obtain, leading to *reputation inflation* (Filippas et al., 2018).	Ratings have an inherent monetary weight, leading to more rational rating behavior, while counter-ratings counteract the exploitation of discounts.
(3) Too many ratings (ballot stuffing)	Ratings are produced on large scales without diligent examination.	Ratings are verified with an address strictly tied to a monetary business transaction, and smart contracts can automate rating decisions.
(4) Change of identity (whitewashing)	Agents can join the system and create a new identity at any me (Friedman & Resnick, 2001).	A third instance verifies ratings and identities, while a transparent history allows one to judge and trust selective ratings or identities of known companies.
(5) Fake ratings (self-promotion and unfair ratings)	There are entire marketplaces for trading fake reviews and machine-generated text reviews.	Ratings are compared based on quantifiable monetary measures and transaction addresses, which enables ratings from this address to be compared.
(6) Discrimination (bad-mouthing)	Undue ratings can remain or are usually deleted after automated bot inspection or legal proceedings.	Rating data is not deleted and may be analyzed individually in a professional business environment, while a third instance settles upcoming disputes.

Imperfectly, business reputation systems are still in their infancy and will encounter many other multi-layered challenges due to their unique characteristics of services/products, business complexity, technical complexity, mutual profit intentions, strategic behavior, competitive stances, and others. See: (Aras et al., 2022; Dellarocas, 2000, 2005; Filippi et al., 2020; Glas et al., 2018; Govindan et al., 2024; Hemmrich et al., 2023; Mantas et al., 2017; K. Zhu, 2002). Additionally, the evolving nature of legal frameworks and technological constraints like blockchain's immutability will further determine the development and implementation of business reputation systems, probably adding more layers of complexity.

9.5.5.2 Qualitative-Empirical Evaluation

Following our conceptual evaluation, we conducted eleven semi-structured interviews with an IT consultancy in Germany as a qualitative-empirical evaluation. While the reputation mechanism needs to be evaluated based on the perspectives of consulting companies and their clients, we begin with the providers' perspective since they are subject to greater risk. Also, the usefulness of a reputation system for buyers has been explored in previous research (Hemmrich et al., 2024). An *illustrative scenario* (Peffers et al., 2012) guides the evaluation and demonstrates the artifact's applicability. Therefore, we focus on a hypothetical consulting scenario with semi-structured interviews to explore the system's benefits and challenges. We map statements that fit the design requirements, support or challenge the design, and indicate the specific use of the system (Peffers et al., 2012). To cover different perspectives, we interviewed consultants, marketers, sales employees, and project managers (Tab. 34).

Table 34: Overview of the Informants

Professional Title	Acronym	Years in Position
Senior Process Engineer & Integration Consultant	C1	7
Integration Consultant	C2	2,5
Integration Consultant & Enterprise Architect	C3	7
IT-Consultant esp. Logistics	C4	13
Middle Manager in Technology Consulting	C5	2
Key Account Manager for Large Enterprises	AM1	10
Senior Account Manager for Large Enterprises	AM2	4,5
Key Account Manager for New Clients	AM3	3,5
Project Manager & Team Leader	PM	11
Corporate Brand Manager, esp. Events	MK1	4
Director of Marketing for Germany	MK2	1,5

The interviews explored critical factors relevant to the system's applicability. The findings (Tab. 35) do not indicate substantial changes to the original reputation mechanism but illustrate how the mechanism can be applied. Our reflections on the design demonstrate that the mechanism fulfills the requirements in 4.1 (Tab. 30). We also refer to the extant literature to support and contextualize the empirical findings.

Table 35: Empirical Evaluation, Leading to Detailing the Reputation Mechanism

Requirements	Key Statements from Informants	Implications and Detailing of the Reputation Mechanism
Incentives to submit ratings	**Monetary incentives:** There probably is no better incentive than [...] to tie it to money for both sides. (C1)	The mechanism evades the rating predicament that the rated entity itself rewards the rater.
	Jeopardizing reputation: If a project does not go well, it hurts everyone […] also the customer's side. (AM1)	The design enables a client to control whom to sell a rating.

Time effort for the rating	**Time effort:** Once the reputation system is relevant, you will make time for it. (C5)	Consultant providers need time to negotiate rating commitments. However, network effects are necessary to make the system relevant in a market.
Decision to share ratings	**Sharing ratings:** What is the incentive to make information available for sale? (AM1); The reference customer bonus program does not provide enough incentives [to share ratings]. (AM2)	Since ratings have an economic value, potential clients probably pay for ratings. Refining the incentive structure, potential clients should buy/view ratings only if they submit ratings themselves, enabling ecosystems to trade ratings.
	Share of disclosure: How much information are they [clients] willing to divulge? […] It is a fundamental difference between private and business environments. (C5)	Clients and providers may decide to share only parts of the rating content. Rating buyers should select which information they share.
	Value of rating: Writing a complete field report or anything like that. It is worth a lot. (AM3)	Complementing the payment rating with text reviews significantly increases the rating's value.
Assess the rating's significance	**Rater expertise:** It depends on [...] whether the customer has someone who can assess it correctly. (C4)	Clients should only be permitted to give ratings for aspects they have experienced.
	Measure: You need measurable factors to make such a rating. (C2)	Detailed performance metrics about a service can strengthen the significance of ratings. By structuring metrics of service provision, single aspects can be rated with certain monetary amounts or by adding other heuristics.
	Rater subjectivity: There is always inevitable subjectivity involved. (MK1)	The problem of subjectivity will remain since ratings are always subjective, making faking ratings difficult.
	Standardization: You standardize it [...], and you can see, okay, this is a good or bad rating. (AM3)	Ratings should be presented multidimensionally and standardized, considering business complexity.
Reduce uncertainty on both sides	**Estimation of relevance:** Get a bit of an impression beforehand of what is actually in [the rating]. (MK1)	Ratings should carry essential facts for interested clients searching for a provider.
	Rating quality: With the services you buy, you never know whether you are buying a pig in a poke. (AM1)	Due to subjectivity, it seems necessary to compare different ratings from different raters.
	Concern about reputation damage: Can it [negative ratings] not be super damaging for the individual [provider]? (C3)	Consulting providers should not let exploitative clients rate them. They choose trustworthy clients (based on their transaction history) but have to accept the risk of being rated negatively. Providers may request other trust safeguards before the rating process is started. Counter-rating and a third instance could help to prevent false ratings.
	Transparency: It might be more public and accessible for potential customers to get hold of it [stories with hearsay]. That can also be an	As a transparent ledger, the system may provide a market overview for potential clients without showing every detail.

	advantage because it is more transparent. (C4)	
	Legal check: Somebody with legal glasses should look over it. (C4)	The procedure must be compliant to General Data Protection Regulation (GDPR).
	Trust signal of seller: You should actually be so convinced that you say, okay, yes, let's rate me. (AM3)	Reputation systems have to balance uncertainties (providers bear a higher risk now), which hinders providers from making overblown promises and allows them to send trust signals.
	Marketing: You can say, "Hey, look, we have five out of five stars." (MK2)	The reputation system can work as a marketing tool.
Robustness against attacks	**Bypassing the system:** I definitely see that [collusion] is a relevant point, and something like that can happen. (C4); You get extra money from me and then write me a good rating. (MK1)	Open systems cannot prevent collisions fully; a consulting provider can always pay a client for positive ratings outside the system.[58] Still, a rating buyer decides which ratings to consult and can compare and learn about their quality (see also selection of ratings). When colluding, parties would risk reputation, exclusion from the system, and impairment to sell ratings or products. Providers and buyers want to stay in the system due to the delivered benefits. Internal whistleblower systems and compliance may contribute to inhibiting fraud.
Rating verification	**Offline verification:** Customers contact other customers, call and ask, "Okay, how [...] did it go with the provider?" (C3)	Ratings can be easily verified. The reputation system can provide basic information and help find other clients who need more information.
Identity verification	**Anonymization:** You should ensure that not everybody can rate and that someone who rates can remain anonymous. (AM3); I do not think you can do that with plain names. (C3)	A third instance controls who can participate. Using ring signatures[59], persons who rate can stay anonymous, while it can be ensured that only authorized addresses can contribute ratings.
Tracing identity and transactions	**Comparable references:** When we have a potential customer, he always asks for comparable references. […] I then try to find a project that is as similar as possible to an existing customer. I never succeeded. (AM2)	Tracing identities secures the credibility of the rating source, and digital reputation systems and an overwatching third instance can catch free-riders more efficiently. Transaction histories, identities, and the monetary weight of ratings allow for assessing the plausibility and correctness of a rating.
Incentive to generate meaningful ratings	**No interest to lie:** There is [...] no interest [to lie] because a company's reputation is, of course, completely different than that of an anonymous private person. (C3)	An intentionally false submitted rating would be recorded and permanently connected to the company's identity. Raters stand by their credibility and public reputation.[60] Parties seek to maintain their reputation. Misbehavior would become observable.
	Rationalize behavior: No customer has a voluntary and	Monetary costs make it unattractive to provide benevolent ratings without reason.

[58] This problem is also known as the sybil attack, which cannot be fully prevented according to Douceur (2002).
[59] Ring signatures enable an entity to sign a message anonymously by hiding the signer within a group, ensuring unlinkability and privacy. For more details, e.g., Odoom et al. (2023)
[60] This is particularly true for professional consulting firms, see Glückler and Armbrüster (2003)

	intrinsic motivation to pay a provider more than they absolutely have to. (AM1)	
Response to ratings	**Justify negative ratings:** You must monitor for bad ratings [...] and refute them or justify yourself. (AM2)	Providers must be able to react to negative ratings. A provider receives a one-time certificate that allows back-rating when receiving negative ratings.
Correct rating judgment	**Commented ratings:** You get two views [client rating and provider comment] and can derive what helps you. (AM1)	The reputation system should include a response function to disprove, admit, or clarify service provisions that have not met expectations, making ratings more informative.
Immutability of rating commitment	**Define objective criteria:** I have to incorporate this procedure into the contract so that when it comes to the payment [...], we have objective criteria to measure it. (AM1)	Rating criteria should be defined at the beginning or need to be readjusted in the course of service provision.
Deliver rating context	**Environment:** In what environment was such an assessment made? (PM)	The system should use filters or text sections describing the services. Pre-categorized forms help to differentiate, approximate, and compare ratings without giving too detailed information.
Selection of ratings	**Rate the ratings:** Yes, that [rating a rating] would definitely improve it [the significance of a rating]. (C2)	Rating the monetary ratings themselves might help to determine their helpfulness before buying them.
	Compare ratings: As a potential customer, I would probably buy two, three, or four ratings and not just one to be able to compare the providers. (C4)	Since ratings are not aggregated into a score, single ratings can be compared. Over time, a client or a secondary information market can learn which ratings are helpful and thus adapt their future selection behavior to find more credible ratings.

The implications from Tab. 35 highlight that using the reputation mechanism surpasses the design requirements and that a broad range of factors are involved. In the following, we provide a selection of condensed interview excerpts of formative statements. By emphasizing core topics, we distill our interview data to highlight key insights about the reputation mechanism, which can serve as a foundation for performing the next design cycle.

Trust signals: Signaling profound quality is particularly relevant if the business relationship is one-off, i.e., no follow-up business is expected. Consulting agencies can differentiate themselves from their competitors, sending a trust signal by agreeing to be rated (AM3). This signal documents providers' expectations that their clients find their service quality appropriate. However, to function properly, the reputation system should prevent providers from charging the total payment while treating variable payments as a pure bonus; doing so may diminish the impact and credibility of the signal (C1, C4, C5, AM1, AM2, MK2).

Marketing tool: The informants view the reputation system as relevant. Credible proof of past service quality can be a convincing argument to win new customers and have a positive long-term effect on the market (Moreno & Terwiesch, 2014; Thierer et al., 2016). This claim is supported by C1, C2, C5, MK1, MK2, AM2, and PM, who see a potential competitive edge for high-quality consulting providers using a reputation system. Depending on market size, making providers' performances visible gives rise to an electronic market that attracts customers who would not become aware of these providers. Credible ratings may enable providers to reduce their marketing costs and foster their efforts to build trust and reputation (MK1, MK2, MK3).

Measureability: One particular problem is that success in consulting is often challenging to measure (C2, C3, AM1, AM2), and especially outside IT consulting, it usually can only be estimated long term (C4, PM). The system's usefulness depends on the project's subject area, complexity, and other factors (C1, C2, C4, C5, AM1, AM2, MK1, PM). If a time lag is expected before the manifestation of its positive results, a time offset with step-by-step performance-related payments might be a solution during an ongoing project (C1, C2, C4). However, even when receiving unfavorable ratings (refer also to *Manipulation*), a provider can take valuable insights to improve service quality (C1, C5). The risk of receiving unjustified ratings might prompt consulting companies to refrain from making exaggerated promises and provide more measurable targets (C3, PM).

Informed decisions: Clients can benefit from better insights into the service quality consulting providers offer (C2, C5, AM3). For potential clients, this information offers a profound basis for making informed decisions for a tendered consulting project (AM1, AM3). For a client, it seems reasonable to individually collect ratings to pick a suitable provider (C2, C3, C4, AM3, MK1). Rating data could lead to an increased fit between providers and clients and thus foster better results in the long term. Rating data is assumed to be less biased than reference cases provided by consulting providers. So it should provide a more accurate picture of a provider's performance (C1, C2, C5, AM1, AM3). Furthermore, informants emphasize the importance of providing context information and the opportunity to compare ratings and approve that the mechanism can send credible trust signals, improve trustworthiness, and increase market transparency. One aspect they only indirectly touch upon is that network effects are necessary for sufficient rating information to be available (C3, C4, C5, AM2).

Institutionalized trust: Ratings always refer to concrete consulting teams. Especially in larger firms, it is not sure that the same people are available to serve other clients (C2, C5). However, this argument applies to all common forms of quality surrogates used in consulting today (such as project references). A certain uniformity in consultants' expertise (e.g., methods and tools used) within the same provider company can be assumed (C1, PM).

Paying for good performance: Generally, clients are interested in sustaining a stable business relationship with high-quality consultant providers (Barchewitz & Armbrüster, 2004). The temptation for clients not to pay for a positive rating despite receiving good quality could be particularly strong when no future collaboration with a provider is planned. Clients who rarely contract consulting companies might be tempted not to pay for good performance, even if satisfied with the service provided (C1, C4, AM2). The same argument is not seen as an obstacle for clients who are better off financially (C2). Susceptible clients themselves might have to build a reputation as trustworthy raters or deliver safeguards to counterbalance the uncertainty of a consulting provider engaging with them (C4).

Performance-based payments: Neither consultants nor clients use performance-based payments currently (C4, C5, AM2). Additionally, providing ratings requires time and resources (C1, C4, C5, MK2), and not all clients possess the expertise to accurately assess consultant services (C1, C3, C4). Using the reputation mechanism, a client can pay less if unsatisfied with a service. However, it remains uncertain how clients will utilize this option to mitigate uncertainty and the risk of opportunistic behavior (AM2, C4, MK1). Correctly setting the performance-based payment ratios is non-trivial, which could complicate price negotiations in consulting (C5, AM2) but might also inform price negotiation on both sides (C1, C2).

Manipulation: Interviewees raised concerns about tricking the system, increased contractual complexity, and lack of raters' expertise (AM3, C1, C3, C4, PM, MK1, MK2). Safeguarding a system against manipulation is often voiced as an advantage of blockchain-based systems, even if it refers only to content security and not content creation. The informants propose measurement standardization, response options, anonymizing persons, and a second layer for rating the ratings to solve these issues. For instance, providing verified ratings from different clients underscores the overall rating value, while single ratings have only limited information value (C2, C3, C4, MK1, AM3). Based on this, we recognize the usefulness of including a third instance that can monitor (based on counter-ratings) a client's negative rating behavior to prevent them from exploiting the system for their benefit.

9.5.6 Discussion

9.5.6.1 Theoretical Contribution

This research delivers pioneering insights into designing reputation systems that foster institution-based trust while reducing institution-based distrust. Specifically, we propose a novel blockchain-based reputation mechanism that digitally replicates trust in the context of professional consulting services. The proposed design directly tackles the dual challenge of fostering trust while mitigating distrust by incorporating mechanisms that create transparency, accountability, and balanced incentives with blockchain technology. This cutting-edge design is built upon eight features: (1) monetary-based mechanisms, (2) stakes as risky advances, (3) non-aggregated feedback, (4) counter-ratings as trust safeguards, (5) selective rating sales, (6) individual rating comparability, (7) pseudo-anonymous blockchain addresses, and (8) monitoring by a neutral instance. By leveraging blockchain's decentralized and tamper-proof infrastructure, the system addresses critical trust barriers in B2B environments, such as ensuring rating integrity**,** safeguarding sensitive information through selective sharing, and maintaining pseudo-anonymity. These features offer several substantial new ideas for designing business reputation systems, contributing design knowledge to a limited body of literature (Cassia et al., 2021; Gutt et al., 2019; Herhausen et al., 2020). The inclusion of financial risk (through monetary stakes) and counter-ratings operationalizes trust by linking it to measurable sanctions and incentives, a significant departure from existing systems**.** The system's selective sharing and individual comparability of ratings protect sensitive information while enabling tailored and actionable insights. These innovations foster a robust digital reputation mechanism that mitigates information asymmetry and promotes fair, accountable interactions in B2B settings. While this study focuses on consulting in the B2B context, the proposed reputation mechanism may also improve review systems used in B2C interactions.

Ultimately, our mechanism represents a new class of reputation systems, fulfilling the design science goal of creating novel artifacts "where the idea of the artifact itself is new" (Gregor & Hevner, 2013, p. 346). In contrast to the current definition of reputation systems (cf. Resnick et al. 2000), our system introduces two major departures: (1) selective distribution of information and (2) non-aggregated feedback mechanisms. Therefore, and due to the high degree of novelty with several new ideas and the lack of jointly shared trust-building information systems among companies, we conclude that this system potentially represents a recognizable new type of information system. Our study contributes to both the application domain—no business reputation systems have yet been adapted to rate professional services (using blockchain technology)—and the solution domain, where no sufficient mechanism currently exists to implement trust signals based on risk, which is inherent to trust (Luhmann, 2017). As the level of maturity in both areas is low, we classify this type of system as a *potential invention* (Gregor & Hevner, 2013). Advancing this reputation mechanism also lays a foundation for future innovations in business reputation ecosystems as industrial data spaces tailored to dynamic and competitive environments where ratings can be traded selectively (Hemmrich et al., 2023).

Building on the construct of trust (Luhmann 2017), we incorporate multiple dimensions of institutional trust in the reputation mechanism (refer to Tab. 32) (Utz et al., 2023). Unlike Utz et al. (2023), who introduced a blockchain-based customer loyalty program to increase trust, our approach targets the reputation mechanism itself. It builds on 23 institutional trust factors, balancing uncertainty between providers and customers. By mapping these trust factors to fulfill specific design requirements (refer to Tab. 32), we demonstrate how trust might be systematically enhanced in B2B relationships. For instance, non-aggregated feedback and counter-ratings address transparency and accountability gaps, while pseudo-anonymous blockchain addresses ensure secure, privacy-preserving transactions**.** Therefore, the system can act as a digital marketing tool, addressing a significant research gap (Herhausen et al., 2020). Even if we admit that trust cannot be digitized entirely, our findings shed light on how trust and risk can be mimicked with digital agents (Cao et al., 2015; Osman et al., 2014; Patil & Gaud, 2021).

This research directly contributes to the broader literature on trust, reputation systems, and industrial data ecosystems by addressing trust barriers, such as information asymmetry and lack of accountability, through innovative design features (Ba & Pavlou, 2002; Ekstrom et al., 2005; Gansser et al., 2021; McKnight et al., 2017; Möller et al., 2024; Tadelis, 2016b; Utz et al., 2023). Prior work has largely neglected the integration of risk as a trust signal in reputation mechanisms[61] (Hemmrich, 2023). Unlike earlier studies, which primarily set general trust principles (Vavilis et al., 2014) or design guidelines (Große et al., 2024), this work introduces measurable mechanisms like performance-based payments and counter-ratings that operationalize trust economically. Using performance-based payments as a direct rating mechanism fundamentally differentiates this system from classical text-based review systems research. Since ratings have an economic value (G. E. Bolton et al., 2004), potential clients probably pay for ratings (Jurca & Faltings, 2003). Different aspects of a rated business service can be standardized using multidimensional metrics and heuristics (P. Y. Chen et al., 2018; Reece et al., 2007; J. Son et al., 2020). Integrating both sides' positive and negative

[61] One noteworthy exception is Litos and Zindros (2017), who explicitly suggest integrating risk in transactions.

financial consequences brings trust-building closer to economic considerations (Hurwicz & Reiter, 2006; Maskin, 2008), stimulating research to study more nuanced incentive structures with economic-aligned behavior for designing information systems.

Our results reaffirm that trust is vital in reducing information asymmetry in professional services, such as consulting. Perceived service quality directly affects customer satisfaction and trust, which is pivotal in creating customer loyalty (Edward & Sahadev, 2011; Kassim & Abdullah, 2008). Signals currently used as surrogates are limited, e.g., customer loyalty programs, to demonstrate service quality initiated by the providers, making them susceptible to manipulation (Neumann & Gutt, 2019a). Our system encourages buyers to actively share ratings through tangible benefits, such as discounts, profit from selling ratings, or access to other ratings, while a seller can enhance reputation, boosting their sales and margins (Ba & Pavlou, 2002; Moreno & Terwiesch, 2014).

9.5.6.2 Practical Contribution

Our practical contribution is a new reputation system for professional consulting services. The proposed system introduces a mechanism to incentivize submitting ratings and manage information asymmetry in B2B transactions (Hemmrich et al., 2024). Our reputation system incorporates performance-based payments as a small portion of the total transaction fee. At the core of our design, performance-based payments are stored as ratings on the blockchain, incentivizing buyers to share and trade their ratings, thereby providing potential economic benefits for all parties involved. Providing these incentives the mechanism reduces the practical issue of biased and fake ratings (Filippas et al., 2018; Neumann & Gutt, 2019a) and may encourage providers to avoid making unrealistic promises, focusing more on the right quality, which is critical for professional services. In general, the mechanism allows the selective sharing of rating information, which is especially essential in competitive environments where a company does not want to share market information with everyone (K. Zhu, 2002). For strategically relevant information, the use of such a system is still not to be expected. Instead, this system can be used primarily in areas where the disclosure of information is not a disadvantage or the exchange of information benefits both sides (Dellarocas, 2003; Gutt et al., 2019).

Introducing counter-ratings offers a practical advantage to ensure fairness. Providers are less likely to receive inflated positive ratings, while clients benefit from a safeguard against unfairly negative ratings. Unlike most reputation systems, which typically provide a one-way rating, counter-ratings may induce considerations for more rational ratings. However, counter-ratings introduce complexity into the system, potentially leading to strategic behavior and eventually also to more rational choices (Narang et al., 2019; Xin et al., 2022). Yet, negative reciprocity can ensure that companies rate little or deliberately negatively, whereby their solvency may also have an influence on paying the rating amount (Dellarocas et al., 2004). Still, an agent-based study indicates that this mechanism can provide incentives to buyers to rate more honestly (Ibrahimli et al., 2024) and might, as known in the B2C sector, tend to act fairly (Nguyen & Meng, 2013). Whether this system is vulnerable to trustless strategic calculations (Williamson 1993) or promotes genuine performance and trust remains to be seen.

In current B2C review systems, obtaining ratings is often free or incentivized by indirect rewards, which usually leads to biased feedback (Neumann & Gutt, 2019a). In contrast, it puts the rating amount at risk (stake). This underscores the assigned value of a rating, making the rating more significant. However, it is unclear how high the rating amount should be set. It will likely depend on various factors, such as the topic and complexity of the consulting assignment, the industry, the preferences issued by the client, or even a specific client (i.e., a person).

9.5.6.3 Challenges and Limitations

We acknowledge that economic incentives may not always align with the behavioral patterns occurring in markets (Cassia et al., 2021; Rindfleisch et al., 2010). Regarding our system, one serious issue is collusion through offering money for positive ratings (cf. Tab. 35)) (Ibrahimli et al., 2024). This problem is not unique to this mechanism but applies to other surrogates of trust building, where facts are embellished (Neumann & Gutt, 2019b). Interestingly, providing false positive ratings would require convincing a client to pay more despite receiving poor performance, which seems unlikely. In this context, the rating volume might play a decisive role. By making the reputation of the rating entity itself observable, we believe this counteracts the collusion issue, making collusion costs higher than the expected benefits (Jurca & Faltings, 2005). Internal whistleblower systems and compliance measures may further inhibit fraudulent behavior (Stubben & Welch, 2020). Furthermore, the problem of subjectivity will persist, as ratings are always subjective, making faking ratings difficult (N. Hu et al., 2014). It seems necessary to compare different ratings from different raters (L. Huang et al., 2014). Moreover, the system is intended to store the rating data of many providers, where their performance can be compared and analyzed, enabling more differentiated assessment of ratings, thereby excluding potential fake ratings (H. Cai & Zhang, 2019; Salminen et al., 2022; Z. Yang et al., 2016). We expect that source credibility (Ekstrom et al., 2005; Hovland et al., 1953) and data volume will be critical in obtaining accurate data. Reaching a critical mass of participants and ratings is essential to generate sufficient, meaningful data. The costs of collusion must exceed the expected benefits (Jurca & Faltings, 2005).

The proposed counter-rating also faces challenges related to the potential and *deliberately induced* dilemma of raters if they are no longer able (do not want) to rate a performance negatively, even if this appears justified, due to fear of being perceived as free-rider by giving too many negative ratings. This situation resembles *dilemmas* in game theory (Hardin, 1971). How this dilemma manifests in practice must be tested, and future research must ensure that the counter-mechanism works in the intended way since raters may provide dishonest ratings for financial gain and strategic advantages (Panagopoulos et al., 2017).

In an era of virtually unlimited access to information, a decline in customer loyalty and an increase in price sensitivity and willingness to switch providers are observed in many industries. Whether this will also apply to the consulting industry remains to be seen. Switching a provider is countered by human risk aversion, particularly if subjecting a client to significant financial risk, suggesting consulting clients will stick to familiar providers with whom they share positive experiences. It is questionable if a consulting provider is willing to subscribe to a system that does not guarantee that clients pay for proper quality. Another issue is how decisions are made in disputes or contested ratings, especially when stakeholders have conflicting interests. Third parties could take on an arbitration role here and help catch free-riders more efficiently (Uzzi, 1997).

The reliance on blockchain technology comes with its own set of challenges. The immutability of blockchain data conflicts with existing legal frameworks, such as GDPR, which mandates the "right to be forgotten" and the ability to modify or delete personal data (Tatar et al., 2020). This legal contradiction needs careful consideration, affecting the system’s compliance in different jurisdictions (Rieger et al., 2019). While zero-knowledge proofs (zk-SNARKs) could allow for private computation of reputation data, these techniques are complicated (Steffen et al., 2022). A simpler, though still imperfect, solution would be obtaining explicit user consent to permanently store rating data, ensuring users understand the implications of participating in the system.

9.5.6.4 Research Opportunities

While this study offers significant theoretical and practical contributions, several limitations highlight opportunities for future research. Specifically, we identify three key areas where further investigation can advance the field. By concentrating on these areas, future research can address key limitations of our study while advancing the broader understanding of trust and reputation mechanisms in digital ecosystems.

Behavioral Impacts of Trust Signals in B2B Interactions: Although our study incorporates institutional trust factors, the behavioral dynamics of trust signals—such as how stakeholders perceive and respond to counter-ratings, pseudo-anonymity, and selective sharing—warrant further exploration. Understanding these behavioral effects at various stages of transactions (e.g., business match, initial negotiation, contract execution, or post-performance review) is critical to improving the design and adoption of reputation systems for B2B environments.

Economic Models for Incentivized Trust Systems: Our system operationalizes trust through monetary stakes and counter-ratings. However, it remains to be seen if better designs for mimicking digital trust and providing the right incentives exist. Future research should develop and test economic models that balance participant incentives and study the height of monetary amounts while minimizing strategic manipulation. Empirical studies, including simulations, lab experiments, and real-world trials, should refine these mechanisms and validate their effectiveness across B2B contexts.

Scalability and Performance of Blockchain-Driven Reputation Systems: While blockchain offers transparency and security, its scalability and performance in supporting large-scale reputation systems require further investigation. Future studies should evaluate the technical feasibility and cost implications of implementing such systems in industrial data ecosystems and extended design opportunities (Hemmrich et al., 2023). Interesting aspects relate to transaction speed, storage efficiency, integration with existing enterprise systems, tokenization, and cryptocurrencies.

9.5.7 Conclusion

We see our reputation mechanism as a pioneering approach to establishing business trust relationships with reputation systems (Hemmrich et al., 2023; Narang et al., 2019). Our work marks a first step to economic ratings using monetary stakes compared to numerical and textual ratings. We designed and evaluated a reputation mechanism based on a blockchain test net that can provide a trustful and quantified signal for a consulting service. The signal can level information asymmetry before concluding a contract for a consulting service, lowering a customer's risk and increasing a provider's opportunity to justify premium prices for excellent service quality. In this way, market failure, as described in a market for lemons (Akerlof, 1970), might be avoided for the benefit of both actors. First, empirical insights suggest that reputation systems might indeed profoundly reorganize business relationships (Beck et al., 2017; Narang et al., 2019) when it is possible to benchmark the service quality relatively quickly. Our approach might also be used to level information asymmetry for other scenarios. Future research needs to explore how actors in markets adopt this mechanism.

9.6 Designing Business Reputation Ecosystems: A Method for Issuing and Trading Monetary Ratings on a Blockchain

Paper Number	P6	
Title	Designing Business Reputation Ecosystems: A Method for Issuing and Trading Monetary Ratings on a Blockchain	
Publication Type	Conference Paper	
Outlet	European Conference on Information Systems (ECIS 2023)	
VHB JOURQUAL 4	A	
Authors	Hemmrich, Simon	70%
	Bobolz, Jan	20%
	Beverungen, Daniel	5%
	Blömer, Johannes	5%
Status	Published	

Abstract. *Many market transactions are subject to information asymmetry about the delivered value proposition, causing transaction costs and adverse effects among buyers and sellers. Information systems (IS) research has investigated how review systems can reduce information asymmetry in business-to-consumer markets. However, these systems use textual data or star ratings that cannot be readily applied to business-to-business markets, are vulnerable to manipulation, and suffer from other conceptual shortcomings. Building on design science research, we conceptualize a new class of reputation systems based on using payments as monetary ratings for each transaction stored on a blockchain. We show that our system assures content confidentiality so buyers can share, sell, and aggregate their ratings selectively, establishing a reputation ecosystem. Our prescriptive insights advance the design of reputation systems and offer new paths to understanding how payments can be used as signals that reduce information asymmetry in B2B transactions.*

9.6.1 Introduction

Business transactions presuppose buyers to trust that sellers will deliver a product or service as promised. However, before a transaction, buyers are often uncertain about a seller's ability and willingness to perform as expected (Truong, 2019). This uncertainty is particularly relevant for person-intensive, high-cost business services like consulting, recruitment, or individual software development (Cronin et al., 2000; Lam et al., 2004). The uncertainty reflects an information asymmetry among buyers and sellers. Sellers know their abilities but often need to spend considerable effort to convince buyers to trust them, since new buyers cannot assess their quality in advance. Particularly for market transactions, buyers rely on publicly available market information and might still end up contracting low-quality sellers. This effect is known as the lemon market problem leading to adverse selection in a market, where high-quality offerings are pushed out of the market while low-quality offerings prevail (Akerlof, 1970).

Quality signals can contribute to leveling information asymmetries (Bauer et al., 2022). Among others, quality signals include brands, references, quality seals, or warranties. Reputation feedback is another quality signal that has the potential to solve the lemon market problem (Thierer et al., 2016). It is shared in reputation systems, which are information systems that systemically incentives and sanction trustworthy behavior and collect, distribute, and aggregate feedback (Jøsang, 2016; Resnick & Zeckhauser, 2002). Setting the right economic incentives is crucial to make these systems work (Buechler et al., 2015; Jurca & Faltings, 2009), but if they do, reputation systems can provide better quality signals that correlate more with the underlying product quality when they are based on a blockchain (Bauer et al., 2022; Spychiger et al., 2022). Consistently, blockchain technology can be considered a breakthrough technology to design business reputation systems (Y. Cai & Zhu, 2016; J. Pereira et al., 2019; Voshmgir, 2020). With a blockchain-based reputation system, buyers reduce their risk of making bad buying decisions. High-quality sellers, on the other hand, can use these systems to signal the quality of their goods and services in the market, justify higher prices, gain new customers, and build a reputation (Ba & Pavlou, 2002; Moreno & Terwiesch, 2014).

Current IS research focuses on review systems—a sub-form of reputation systems—used frequently on commercial platforms such as Airbnb or Yelp. Review systems often use user-generated text and star ratings to allow customers to make better buying decisions, e.g., book a suitable vacation rental. Usually, all reviews are public and provided for free, providing immense value to platform owners while attracting additional customers due to the emergence of direct network effects. In business-to-business (B2B) markets, no comparable system is available due to a series of shortcomings: First, current systems suffer from profound limitations, e.g., rating fraud, insufficient incentives to provide honest ratings, and reliance on a central platform, among others (Jøsang et al., 2007; Subramanian, 2018). Second, sellers try to decrease transparency in B2B markets to differentiate their offerings from their competitors for dynamic pricing and capitalize on the value of sales (K. Zhu, 2002). Third, buyers are reluctant to share ratings about products or services publicly, drawing no advantage from it (Jurca & Faltings, 2003). Rivals might benefit from shared information, while some companies fear exposing their business data or revealing the quality of certain suppliers to competitors (K. Zhu, 2002).

In light of the potential benefits of such systems, related research has identified a strong need to design business reputation systems (Y. Cai & Zhu, 2016; Catalini & Gans, 2016; Dikow et al., 2015; Möhlmann et al., 2019). Taking up these calls and in line with design science research (Hevner et al., 2004; Nunamaker et al., 1990); our research goal is to design a new method (March & Smith, 1995) that allows companies to share monetary-based ratings with other market participants selectively. The envisioned system enables buyers to 1) rate sellers with monetary payments for each business transaction, 2) selectively sell and buy ratings to identify high-quality sellers, and 3) make better buying decisions. Using monetary ratings might contribute to solving some of the shortcomings of reputation systems because monetary ratings reflect customers' value-in-use, encapsulate economic information, carry an inherent weight as a signal, allow portraying asymmetric risk relations (Hemmrich, 2023), are quantifiable and individually assessable, and are harder to fake due to their inherent monetary value. Our system enables buyers to sell rating information to other buyers, generating pay-ins that can offset their pay-offs associated with providing monetary ratings. Rating confidentiality is guaranteed by the built-in features of a blockchain. The method enables companies to hide, or share (and, thus, sell) their monetary-based ratings selectively with other market participants without having to disclose other details on their transactions. Selling ratings might provide an important incentive for buyers to share their ratings, while it allows sellers to build a reputation through receiving positive ratings. In regard to the conceptual weaknesses of rival systems used in B2C markets, we point out that trading monetary ratings can contribute to solving three major limitations. Fake ratings, lack of incentive to submit ratings and a controlling central instance. Also, our method can help to counteract other deficiencies, such as reciprocity issues and reputation inflation, without a need to rely on a trustworthy intermediary.

The paper is structured as follows. In Section 2, we discuss related research and briefly summarize the core principles of blockchain technology. In Section 3, we describe and justify our research method. In Section 4, we discuss deficiencies of current reputation systems primarily used in B2C markets. To remedy these deficiencies, we outline the design of a new type of reputation system, starting with a cryptographic method to hide and share ratings on a platform. This demonstration evidences that this artifact can be implemented in current blockchains. In Section 5, we discuss our contributions to theory and practice, before concluding the paper in Section 6.

9.6.2 Research Background

9.6.2.1 Reputation Systems

Focal points of research on reputation systems are examining and designing them (Dellarocas, 2005; Moreno & Terwiesch, 2014) and the related concepts of trust and markets (Jøsang et al., 2007; Tadelis, 2016b). However, IS-related research mainly discusses review systems (Gutt et al., 2019) or word-of-mouth (C. M. K. Cheung & Lee, 2012). In computer science, related research proposed privacy-preserving techniques (Bazin et al., 2016; Blömer et al., 2018), which has also recently involved blockchain technology (Bellini et al., 2020; Camilo et al., 2020). Also, other works show how to secure the integrity of text reviews on a blockchain (Zulfiqar et al., 2021).

Related research has remained fragmented and has not developed reputation systems that can be used in B2B markets. While many papers motivate improvements that need to be made to current systems, e.g. (Dennis & Owen, 2015), monetary payments have not been considered as ratings, nor selling ratings to other stakeholders in a market. Still, designing reliable reputation mechanisms remains an open issue (Y. Cai & Zhu, 2016; Tumasjan & Beutel, 2019; Voshmgir & Zargham, 2020).

First steps have been made on a path to establish monetary ratings in reputation systems. For instance, DeFigueiredo and Barr (2005) propose a reputation system based on monetary security deposits that another party could withdraw, but as proof of trust, refrains from doing so. Similarly, Litos and Zindros (2017) equate trust with risk to conceptualize a decentralized platform, on which trust is quantified with a monetary deposit issued among peers. By depositing money, the risk (and, thus, trust) becomes visible in the network to assess a subjective indirect trust relation (Litos & Zindros, 2017). However, in these systems money does not serve as a rating, but is considered as a security deposit to represent indirect trust. Also, both approaches do not consider that raters might sell *their* rating information to others.

In multi-agent simulations, selling reputation information is discussed as an incentive for sharing reputation information. Selling reputation information makes the reputation mechanism incentive-compatible to report ratings trustfully (Jurca & Faltings, 2003). While money can be an incentive to provide ratings (Buechler et al., 2015), monetary benefits are currently often granted by the seller that is rated itself, so ratings are often biased in the seller's favor (Fradkin et al., 2015; Neumann & Gutt, 2019a). Switching the benefactor of paying the ratings from a seller to a neutral prospective buyer might resolve this dilemma.

9.6.2.2 Blockchain Technology

A blockchain is a distributed ledger in which data references can be distributed and securely stored in a network. The network nodes take the role of a distributed third party, bound to the rules of consensus protocols. A consensus protocol ensures that nodes agree about the transactions stored in each block, building a blockchain. After reaching a consensus, the data recorded on the blockchain becomes immutable (Pilkington, 2016). Blockchains are commonly used to implement cryptocurrencies (Nakamoto, 2008). The distributed ledger is used to record currency transactions, where the immutability property ensures that currency cannot be double-spent. Modern privacy-preserving cryptocurrencies—e.g., (Fuchsbauer et al., 2019; Sasson et al., 2014)—use cryptography to hide transaction data from the blockchain while preserving the desired properties of a cryptocurrency (i.e., coins can only be spent by their owner, coins can only be spent once, transactions are publicly verifiable). Blockchain eliminates the need for a central trust authority to validate transactions (Lustig & Nardi, 2015).

Blockchain technology enables distributed applications—such as a reputation system for business, providing an openly accessible public ledger without a central trust instance—based on two essential features:

- *Manipulation resistance*: Information stored on a blockchain is secure and cannot be changed. This property ensures that no entity can manipulate a rating.

- *Proof of information*: Using cryptographic techniques, users can prove to possess some information without having to reveal it. This property allows to control which rating is disclosed.

9.6.2.3 Limitations in Current Review Systems

Although review systems have been researched for more than a decade, some weak spots remain:

1) Only a small proportion of transactions are rated at all, while generating meaningful ratings is time-consuming and costly. Ratings usually rely on voluntary feedback, but buyers have little incentive to share their experiences with others (Dellarocas, 2005; Resnick et al., 2006), and giving ratings comes with an effort (Jurca & Faltings, 2009). Thus, most users do not submit feedback. Especially, dissatisfied users refrain from giving ratings (Dellarocas & Wood, 2008). Accordingly, poor performance, cases of misconduct, or exploited business relations are not recorded, paving the way for opportunistic behavior. To stimulate the generation of high-quality feedback, platform operators or sellers try to incentive buyers to submit feedback in exchange for discounts (Jurca et al., 2010). However, when sellers attract customers with coupons, vouchers, or other rewards, ratings are usually biased in the seller's favor (Neumann & Gutt, 2019a). Luring raters with rewards makes them (feel) committed to submitting a good rating so that negative ratings become unlikely (Neumann & Gutt, 2019b). However, precisely the potential risk of not being rated positively signifies the high value of reputation (Kreps & Wilson, 1982).

2) Ratings can be manipulated easily or submitted intentionally incorrectly. Online rating fraud is a well-documented problem in B2C markets and undermines trust in these markets (Ansari & Gupta, 2021; Dellarocas, 2005; He et al., 2022; N. Hu et al., 2011; Ivanova & Scholz, 2017). Buying intentionally wrongly submitted ratings (fake ratings) is cheap and often easy (He et al., 2022). It impacts the perceived trustworthiness of ratings significantly and harms the trust in the entire market (He et al., 2022; Y. Wu et al., 2020). Since ratings strongly affect buying decisions, sellers are inclined to manipulate ratings. Fake ratings can also be used to discriminate against competing buyers purposefully (R. Cui et al., 2020; Lappas et al., 2016; Mayzlin et al., 2014). Since unfair ratings and discriminating behavior may be hard to distinguish from personal taste, there is a risk of moral hazard that must be encountered with sophisticated reputation mechanisms (Dellarocas, 2000).

3) Reciprocity and fear of retaliation cause reputation inflation. Well-intentioned reciprocity or fear of retaliation distorts reputation mechanisms (G. E. Bolton et al., 2013).

Reciprocal feedback helps to record mutually beneficial transactions between parties, but it can also distort ratings' actual quality (G. E. Bolton et al., 2013). Fear of retaliation prevents parties from giving bad ratings, even if they do receive poor quality, either because they fear getting negative feedback in return, or fear that other parties would refrain from doing further business with them (G. E. Bolton et al., 2013; Dellarocas & Wood, 2008; Luca, 2017). Often, this fear leads to strong rating distortion, with ratings becoming overly positive (G. E. Bolton et al., 2013; Ert et al., 2016; Resnick & Zeckhauser, 2002). This phenomenon is called reputation inflation (Filippas et al., 2018) and deprive ratings of a reasonable basis for differentiation (Zervas et al., 2021).

4) The change and the creation of new identities enable a forged reputation. Creating new fake identities or changing the identity allows users to manipulate ratings (Dellarocas, 2003). Fake identities are always an issue in open systems without a central, trusted authority (Douceur, 2002). Having control over many fake identities enables one to generate fake ratings and thus promote reputation, submit unfair ratings, and discriminate against competitors (Douceur, 2002; Friedman & Resnick, 2001). Also, leaving the system after one transaction (free-riding) as soon as the initial reputation declines and creating another clean identity can be a problem.

5) Informational value gets lost when reputation information is condensed into a global score. Many reputation systems condense reputation into a single trust score eliminating multiple contexts (Hendrikx et al., 2015). However, reputation is represented more accurately by social embeddedness (Durkheim, 1960; M. Granovetter, 1985). By aggregating reputation information, a great deal of relevant context for trust decisions is lost. Therefore, cumulative measures seem not appropriate, since they lack contextual information (G. E. Bolton et al., 2004). The context is vital since reputation is a subjective phenomenon and is created from context (Mui et al., 2002; ur Rehman et al., 2019). Reputation might differ according to the observers' subject of interest (L. Huang et al., 2014). Knowing the context, information can be processed in more detail (Hirshleifer & Teoh, 2003) and informational value improves significantly (Filippi, 2016; Nissenbaum, 2004; Pavlou & Dimoka, 2006). For instance, aggregating reputation on the level of an entity is helpful as an individual estimate of trustworthiness but does not yield objective information about a product. Trust mediators, like the Better Business Bureau that assess the trustworthiness of an identity, are helpful but do not provide differentiated product ratings. Experiments in the B2B context also support the need to compile ratings in a unique fashion (G. E. Bolton et al., 2004; Ekstrom et al., 2005) presupposing a set of raw data to build subjective trust decisions on.

6) Privacy and data are exploited by platform intermediaries. Reputation systems are often offered on digital marketplaces and operated by a (more or less) trusted intermediary that owns the platform. While intermediaries generally mitigate some of the problems mentioned above—e.g., prevent fake identities, ballot stuffing, or whitewashing—they can also be weak spots (Subramanian, 2018). Intermediaries open up attack vectors to manipulate or remove data and can be bribed, while they are increasingly suffering from fake ratings (He et al., 2022; Wan & Nakayama, 2014). They might be vulnerable to data breaches or censorship, while they sometimes charge high fees (Catalini & Gans, 2016). Also, some intermediaries are inclined to exploit their customers' data in their own self-interest, irrespective of the customers' desire for data privacy (Filippi, 2016; Lyon, 2014; Soska et al., 2016; Zyskind et al., 2015).

By describing these problems—mainly drawing from related research on review systems—it becomes clear that the challenges concerning reputation systems are multifaceted. Therefore, we decided to focus on three particularly severe problems: a) cheap fake ratings can be bought, which we address with a monetary weight of ratings that can be traded and distinguished from purchased and cheap ratings; b) little incentive to submit rating information (especially in the B2B context), which we address through the opportunity to sell rating information to other buyers; c) dependence on a central platform provider, which we address by using blockchain technology.

9.6.2.4 Positioning this Work as to Designing Reputation Ecosystems

The purpose of this paper is to elucidate how a reputation system can be designed for a B2B market, enabling companies to perform monetary ratings on their business transactions. The ratings are stored confidentially and immutably on top of a blockchain, while they can be sold to inform other market participants. The pay-ins generated from the sale could level or exceed the pay-out for conducting ratings. Against the backdrop of current definitions of reputation systems (Resnick & Zeckhauser, 2002), we refer to this system class as an ecosystem (Jacobides et al., 2018).

Ecosystems are characterized by entities that co-create value while building complex relations among them to exchange value (Hein et al., 2020; Yoo et al., 2010). The rating information constitutes this value for companies (e.g. monetary-based ratings, or text reviews). For sellers by building a reputation in an ecosystem based on complex relations among different entities. For buyers getting quality signals and trading (information about) these quality signals. Entities can select and aggregate rating data according to their needs.

Thus, following (Resnick & Zeckhauser, 2002), we define this type of system as a *reputation ecosystem* that collects, and distributes feedback and helps to determine the feedback's trustworthiness, whereby entities can observe and communicate selectively about each other's signals, e.g., about their payments as ratings and aggregate this information selectively. Intending this system to work in a B2B market, we speak of a *business reputation ecosystem*. These systems can be blockchain-based and might comprise monetary-based features and other metrics, but they may also comprise other data, such as text or star ratings (Fig. 28). In contrast, review systems are typically free of charge and display ratings publicly, relying on qualitative data.

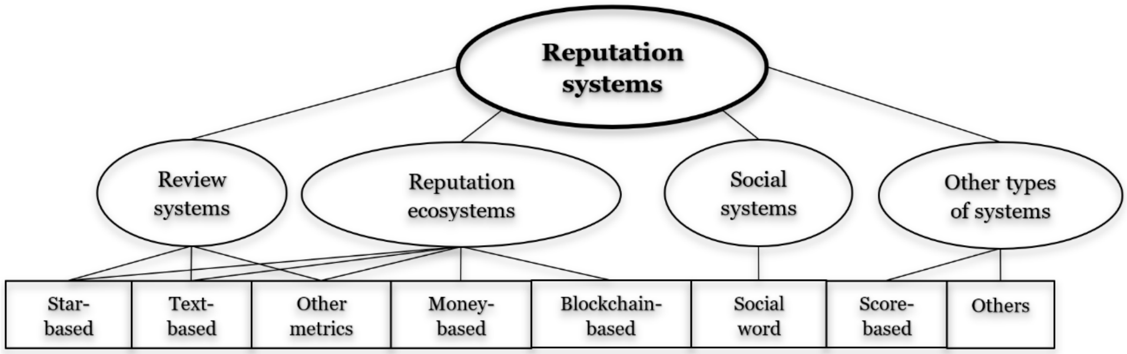

Figure 28: Reputation Ecosystems as a Particular Class of Reputation Systems

9.6.3 Research Method

Sharing fair and honest ratings about a product or service in the business context is a yet "unsolved and important business problem" (Hevner et al., 2004, p. 82) and warrants a Design Science Research (DSR) approach (Nunamaker Jr et al., 2015). Generally, the DSR paradigm (Hevner et al., 2004; March & Smith, 1995; Nunamaker et al., 1990) seeks to identify relevant problems and build and evaluate meaningful artifacts to help to solve such problems (Gregor & Hevner, 2013; A. S. Lee et al., 2015). Establishing reputation feedback in B2B markets is important to mitigate information asymmetries, opposing the emergence of lemon markets (Akerlof, 1970; Thierer et al., 2016). Our method is a design science artifact (March & Smith, 1995) positioned as an improvement (Gregor & Hevner, 2013), since the solution maturity is low and the application domain maturity is high. Building on the design science research methodology (Peffers et al., 2007), we summarize our research method as follows (Fig. 29).

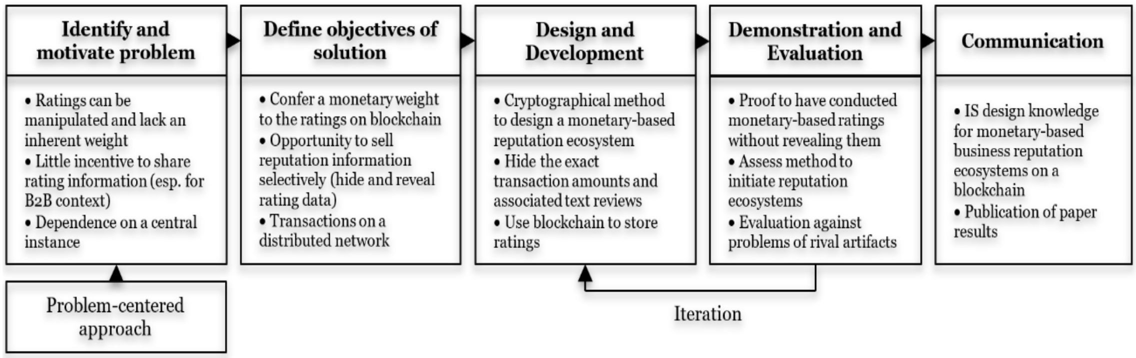

Figure 29: Overview of the Research Process (based on Peffers et al., 2007)

We took a problem-centered approach to identify and motivate the problem. Since no comparable reputation systems in business are described in research yet, we relate our concept mainly to the literature on rival artifacts in B2C markets, review systems. Three well-known limitations of these systems include fake ratings, missing incentives to submit honest ratings, and dependence on a platform provider. These limitations hinder current systems from being used in B2B markets to evaluate other companies' qualities, with which no transaction has taken place previously.

Our ultimate objective is to design a complete reputation system that can be used in a B2B market to establish payments as monetary ratings, establishing an ecosystem of trust among sellers and buyers. While buyers can trade their rating information with other buyers for money, sellers can document their ratings to establish a reputation and justify higher prices for their goods and services. Designing a profound incentive schema and elucidating users' acceptance are also important for establishing a prescriptive design theory (Gregor & Jones, 2007a) for this new system class. While developing the full-scale system is, beyond the scope of this paper, we focus on designing a technically feasible method.

Implementers can use the method to hide and sell their rating information to other buyers. We build this method based on cryptographic commitments, privacy-preserving cryptocurrencies, and zero-knowledge proofs. Following the advice of (Vaishnavi et al., 2017), we relate our method to no specific cryptocurrencies to make it applicable in different contexts. One can prove that ecosystems applying our method will work cryptographically securely. Consistently, we evaluate our method by providing cryptographic evidence for its correctness and security. This formal proof and logical reasoning represents the evaluation itself (Cleven et al., 2009; Hevner et al., 2004; Sonnenberg & vom Brocke, 2012; J. Venable et al., 2016). To further evaluate the external validity of our method, we conceptually compare the system with other rival artifacts. The class of reputation ecosystems envisioned here provides core insights for managing and trading rating information in business networks that are subject to no or little trust. IS researchers and professionals can apply the resulting knowledge to guide design processes in more specific use cases (van Aken, 2004) or build on our results in other contexts.

9.6.4 Artifact Description

9.6.4.1 Method Overview and Objectives of a Solution

For designing a new class of business reputation ecosystems as another future artifact, we combine monetary-based ratings with the ability to share rating information without making them visible to others.Consider a *basic transaction* on a blockchain in which a buyer ("buyer 1") pays an amount v_{buy} to a seller ("seller 1") for a good or service, while seller 1 consents to being rated and allows buyer 1 to pass on the rating. Afterward, buyer 1 *rates* the quality positively in a second transaction (*rating transaction*) by paying an additional amount v_{rate} to seller 1 (Fig. 30).

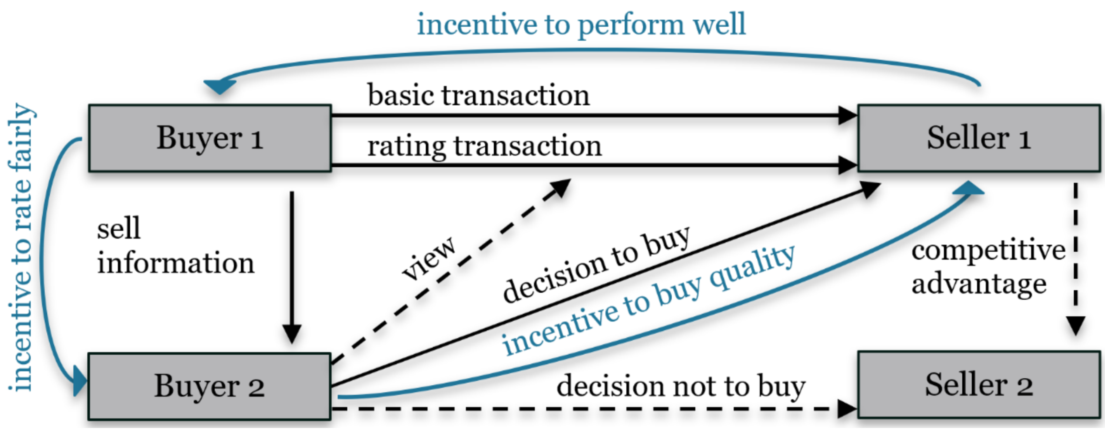

Figure 30: The Reputation of Seller 1 can be Documented with Quantified Monetary Ratings.

The ratio v_{ratio} = v_{rate}/v_{buy} between the rating transaction v_{rate} and the basic transaction v_{buy} expresses buyer 1's satisfaction with the quality provided by seller 1. The higher v_{ratio}, the weightier the rating. For example, if buyer 1 is very satisfied, the rating transaction might be 10% of the buying price v_{buy}, i.e. v_{ratio}= 0.1$. Vica versa, if buyer 1 pays nothing, i.e., v_{ratio} = 0$, the rating reflects strong dissatisfaction.

Because ratings have an economic value (Wise & Morrison, 2000), and businesses are hesitant to share ratings with competitors, we design the system in a way that ratings remain *hidden*, enabling a buyer 1 to sell ratings only to selected peers (i.e., buyer 2). Buyer 1 can *choose* to whom to sell the rating, namely v_{ratio}, without a need to reveal v_{buy} or v_{rate} hiding the exact payment amounts. Buyer 1 can also prove that the basic transaction amount v_{buy} passes some non-triviality threshold v_{min}, i.e. $v_{buy} \geq v_{min}$ to exclude insignificant ratings, without having to reveal the exact amount v_{buy}. Buyer 1 can *sell* this rating information v_{ratio} and that $v_{buy} \geq v_{min}$ about a seller to other potential buyers ("buyer") providing buyer 1 an economic incentive to share ratings. We assume from now on that buyer 1 is willing to sell ratings to earn money and buyer 2 is interested in buying them to support decision-making.

Based on buyer 1's identity, knowledge, and rating quality, buyer 2 can decide to buy rating information. After a while, buyer 2 learns about the rating quality of a particular buyer 1 and can also compare bought ratings from different buyers. On this basis, buyer 2 will get a better basis for decision-making. We define four objectives of a solution, guiding the implementation of *secure* reputation ecosystems.

(O1) Ratings remain hidden until sold. All transaction data (v_{buy},v_{rate},v_{ratio}) is hidden from the public and is only known to buyer 1 and seller 1.

(O2) Selling rating data does not reveal exact values of v_{buy} or v_{rate}. When buyer 1 decides to reveal v_{ratio} and v_{min} to buyer 2, of course, buyer 2 learns that $v_{buy} \geq v_{min}$ and $v_{rate}/v_{buy} = v_{ratio}$. However, buyer 2 is not able to infer anything about v_{buy} or v_{rate} beyond that (keeping prices confidential).

(O3) Buyer 1 cannot lie about the submitted rating data. After buyer 1 submits a rating as rating transaction, buyer 1 is committed to that rating. Buyer 1 is *unable* to prove inconsistent data $v_{ratio}' \neq v_{rate}/v_{buy}$ or $v_{min} > v_{buy}$. In particular, neither buyer 1, nor a third party can change a rating (e.g., selectively reveal different ratings to different buyers 2). Also, buyer 1 cannot sell ratings for transactions that are not exceeding a trivial amount v_{min} (e.g., if the amount was so small to not even cover the typical price of a unit of the good/service, the rating should not be trusted).

O4) Buyer 2 cannot resell buyer 1's rating information. After buyer 2 receives v_{ratio} (and v_{min}) from buyer 1, it should be infeasible for buyer 2 to sell the information to a third party without involving buyer 1 (or seller 1).

Because we want the reputation ecosystem to work in an open environment—not requiring a central trusted instance—and ensure manipulation resistance, we build the ecosystem upon blockchain technology and several cryptographic concepts.

9.6.4.2 Cryptographic Building Blocks

Commitments. As presented above, the amounts (v_{buy},v_{rate}) transferred in basic/rating transactions must be hidden from the public. However, one still needs to record v_{buy},v_{rate} in a reliable way, to fulfill the requirement that buyer 1 must not be able to change their ratings once they have been submitted. Cryptographic *commitments (Brassard et al., 1988)* guarantee this. A commitment *C* is an object that (1) hides a unique value *v* that cannot be changed, while (2) not revealing any information about that value. Creating the commitment creates a secret *commitment key k* as a byproduct. With the commitment key *k*, one can efficiently check what value is hidden inside the commitment *C*, while everyone who does not know *k* cannot infer any information about *v* from *C*. One can think of a commitment as an encryption of *v* or a hash *H(v, k)* for a random unpredictable commitment key *k*.

In order to record the transaction values v_{buy},v_{rate} securely on the blockchain, one can record a *commitment* C_{buy} to v_{buy} and a commitment C_{rate} to v_{rate} instead. By this C_{buy} and C_{rate} do not reveal any information about v_{buy} and v_{rate} publicly. Only the stakeholders involved in the transaction (buyer 1 and seller 1) can use the commitment key *k* to make sense of the commitments.

Privacy-preserving cryptocurrency. It is technically challenging to make the transactions conventional secure, e.g., prevent double-spending, because, in our desired setting, the blockchain validators do not even know what amounts are being transferred. However, this problem has been solved by privacy-preserving cryptocurrencies such as Zerocash (Sasson et al., 2014) and Mimblewimble (Fuchsbauer et al., 2019).

We do not focus on the specifics of these privacy-preserving cryptocurrencies because we want to make the system more universally usable to work with any cryptocurrency that fulfills those requirements. Therefore, our system works with any cryptocurrency that fulfills these *requirements*:

- The amount of coins transferred in any transaction is hidden from the public. Only the sender and receiver of a transaction know how many coins were transferred. This necessarily implies that the current account balances of senders and receivers are hidden as well.
- Every transaction contains a publicly available commitment *C* to the (hidden) number *v* (“value”) of coins transferred. The sender and the receiver hold the commitment key *k* for *C* to read the transaction secured in the network.
- The identity of the sender and receiver in a transaction is publicly visible (while just the amount being transferred is hidden).

The first requirement is generally a feature of privacy-preserving cryptocurrencies (Fuchsbauer et al., 2019; Sasson et al., 2014). Regarding the second requirement, not every cryptocurrency *directly* stores a commitment to the transfer amount *v* alongside a transaction. However, such a commitment can often be either (1) efficiently derived from all the other data (such as in Mimblewimble, using homomorphic properties of the commitment scheme) or (2) it is available in some commitment-like format (such as Zerocash). For simplicity, we assume that the commitment is directly available. With small modifications, our system works essentially for all (typical) privacy-preserving cryptocurrencies.

Finally, the third requirement is not an explicit goal of privacy-preserving cryptocurrencies, but it is trivial to establish using standard techniques such as digital signatures. Buyer 1 can simply sign the transaction with a secret signing key to publicly establish the sender's role in the transaction. We omit the details here but conclude that all three requirements can be achieved by typical privacy-preserving cryptocurrencies.

Zero-knowledge proofs of knowledge (ZKPoK). As discussed above, it must be infeasible for a buyer 1 to lie about the submitted rating. With commitments, buyer 1 could simply reveal the commitment key *k* and allow buyer 2 to check that the revealed rating data v_{ratio},v_{min} is indeed consistent with what was recorded on the blockchain in the commitments C_{buy} and C_{rate}. However, at the same time, we want buyer 1 to be able to hide the exact values of v_{buy},v_{rate} from buyer 2 and the public, so this approach is not viable (since revealing the commitment key reveals the exact contents of C_{buy} and C_{rate}, namely v_{buy} and v_{rate}). Instead, buyer 1 will *prove* to buyer 2 that the information v_{ratio},v_{min} is correct *without* revealing v_{buy},v_{rate}. This requirement can be enabled by *zero-knowledge proofs of knowledge* (ZKPoK) (Goldwasser et al., 1989). A ZKPoK is an interactive protocol, where buyer 1 and buyer 2 exchange messages. This protocol allows buyer 1 to convince buyer 2 of some statement about hidden data v_{rate},v_{min}, without actually revealing the hidden data (Quisquater et al., 1990). However, 1) buyer 2 is not able to learn anything about the v_{ratio},v_{min} other than that the proven statement, i.e. the rating data, is correct (*zero-knowledge*), while 2) buyer 1 is not able to convince buyer 2 of a statement for which it does not know valid hidden data (*poof of knowledge*).

We will furthermore require our ZKPoK to have a third property: deniability (Pass, 2003). Deniability is a non-standard requirement of ZKPoK, which says that after buyer 2 has witnessed the execution of the ZKPoK protocol with buyer 1, buyer 2 *cannot* convince a third party that the proven statement is true. Standard constructions of ZKPoK do generally not have this property. Indeed, for non-interactive ZKPoK (such as SNARKs, STARKs, etc.), being *publicly* verifiable by *anyone* is even considered a feature, which is incompatible with deniability, which says that the proof must only be convincing for buyer 2, not to anyone else. However, one can generally modify any reasonable ZKPoK to provide deniability (Pass, 2003). Using deniability property prevents reselling of information: Because the proof is deniable, buyer 2 will not be able to convince any third party that the rating data is indeed correct.

9.6.4.3 Technical Description of the Method

Buying and rating. The buying and rating process can be described as a smart contract that binds the basic and the rating transactions together. The basic transaction, in which buyer 1 pays seller 1 v_{buy} coins for a good or service, is executed via a privacy-preserving cryptocurrency. This results in a commitment C_{buy} to v_{buy} being written to the blockchain. Afterward, buyer 1 pays an additional v_{rate} coins to seller 1, again using the privacy-preserving cryptocurrency, resulting in a commitment C_{rate} to v_{rate} being written to the blockchain. A smart contract binds the two transactions together so that it is clear what basic transaction a rating transaction references. Note that even for a negative rating $v_{rate} = 0$, a rating transaction (over 0 coins) is submitted to the blockchain. The reason for this is that fully omitting the rating transaction for $v_{rate}= 0$ would *publicly* signal a negative rating, but the rating result must not be known publically. The state of the blockchain after this process is depicted in (Fig. 31). Note that objective O1 (cf. Sec. 9.6.4.1) is fulfilled: C_{buy},C_{rate} are secure commitments, so they do not reveal any information about v_{buy}, v_{rate}. The privacy-preserving cryptocurrency also does not reveal any information about v_{buy},v_{rate} to the public.

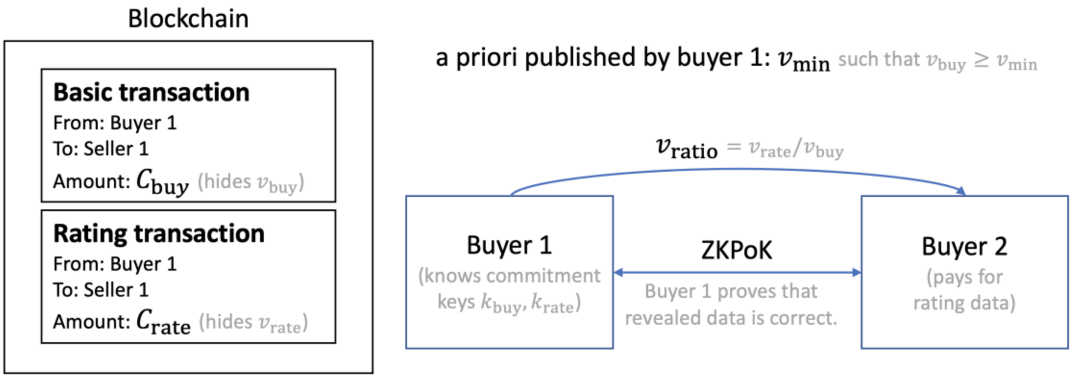

Figure 31: The Process of Buyer 1 Selling Rating Data to Buyer 2, and Proving the Data's Correctness

Selling rating data. First, if buyer 1 wants to sell the rating information, buyer 1 needs to choose a value v_{min} of the basic transaction s.t. $v_{buy} \geq v_{min}$. In the simplest case, v_{min} is simply related to the price of a single unit of seller 1's service. In more complex cases, buyer 1 may explicitly advertise having bought a larger amount, e.g., for at least 1000 coins, in which case v_{min} = 1000$ might be a reasonable choice. It is on buyer 1 to decide whether to choose v_{min} as high as possible (close to the paid v_{buy}), making the rating amount more exact, or to choose v_{min} relatively low, in which case buyer 1 reveals less information about the price paid for the basic transaction. We assume v_{min} is published to prospective buyers 2. When buyer 2 wants to buy rating data from buyer 1, buyer 2 approaches buyer 1 and points to buyer 1's transactions on the blockchain that buyer 2 wants to have revealed. If buyer 1 is willing to share rating data with buyer 2, buyer 2 pays buyer 1 for the rating (e.g., via traditional bank transfer or cryptocurrency). In that case, buyer 1 and buyer 2 then engage in the process depicted in Fig. 31: Buyer 1 reveals $v_{ratio} = v_{rate}/v_{buy}$ to buyer 2 (as well as stating that $v_{buy} \geq v_{min}$). To provide authenticity of v_{ratio} and v_{min}, buyer 1 then uses the commitment keys k_{buy}/k_{rate} to prove with a deniable ZKPoK, the following statements about buyer 1's hidden values v_{buy},k_{buy}/k_{rate} to be true to buyer 2:

- The commitment key k_{buy}shows that the commitment C_{buy} in the basic transaction hides v_{buy}.
- The commitment key k_{rate} shows that the commitment C_{rate} in the rating transaction hides v_{rate}.
- For the revealed value v_{ratio}, it indeed holds that $v_{ratio} = v_{rate}/v_{buy}$.
- For the public value v_{min} and the secret value v_{buy}, it indeed holds that $v_{buy} \geq v_{min}$.

The ZKPoK has the zero-knowledge property, so it does not reveal the exact values of the hidden data v_{buy} or v_{rate},fulfilling objective O2. With this ZKPoK, buyer 1 proves not to lie about the rating data, which is guaranteed with the proof of knowledge property, fulfilling objective O3 (cf. Sec. 9.6.4.1). Because the ZKPoK is deniable, buyer 2 is not able to resell buyer 1's rating convincingly, fulfilling objective O4.

9.6.5 Discussion

With our method, based on established cryptography, it becomes evident that we can build reputation ecosystems technically. With the designed method for storing and trading rating information on a blockchain and the sketched reputation ecosystem, we propose new solutions to resolve three major problems of reputation systems currently used in B2C markets, as summarized above.

a) Current reputation systems are compromised by cheap fake ratings. Fake ratings are a massive problem in review systems since sellers can mandate actors to generate fake reviews cheaply. Even if many of the current platforms struggled hard to prevent fake reviews, the problem prevails (He et al., 2022). While we acknowledge this issue may cannot be solved completely in an open system (Douceur, 2002), our study might contribute to new approaches to make fake ratings less likely to occur.

First, endowing ratings with monetary payments binds substantially more money to issue fake ratings. Second, buyer 1 cannot provide different ratings for different buyers 2, since it is not possible to manipulate a transaction after it has been committed to the blockchain—unless, of course, the blockchain is compromised itself. Third, the rating values are not aggregated immediately (like star ratings or reputation scores on review systems), but ratings can be aggregated and selected by buyer 2 individually. Accordingly, buyer 2 can choose to buy ratings only from other buyers that are considered trustworthy instead of relying on aggregated scores. Since many transactions on B2B markets are valuable, we posit that the effort to search and identify trustworthy buyers 1 is warranted by the additional benefit gained from this process. By accessing experience, own market information, comparing different ratings, and testing ratings submitted by other buyers, buyer 2 will learn over time which buyer 1 delivers useful data. Once buyer 2 identifies trustworthy addresses, they can refer to their ratings as trust anchors, which enables them to identify more honest actors/ratings in the network. In this way, an ecosystem of trust is established over time, reducing information asymmetry and uncertainty in the market. Fourth, since rating information has a high economic value in business (Wise & Morrison, 2000), we can expect information markets or institutions to emerge (Spychiger et al., 2022), which help the companies engaged in the market to identify honest actors in the reputation ecosystem.

Switching the perspective, we consider that buyer 1 might try to trick the system by selling fake ratings. However, such data would remain immutably stored on a blockchain, linked to the addresses that issued the data. Providing misleading ratings would sooner or later prompt buyer 2 quit further buying ratings that were issued by a fraudulent buyer 1. Even if this buyer 1 decides to re-enter the system with a new address and create new fake ratings, such an address would not be considered trustworthy as long as not enough ratings have been issued with other honest sellers. For this reason, connecting fake ratings to honest sellers would be difficult, since all sellers have to commit to being rated. We posit that honest seller 1 would avoid contracting with such addresses, fearing their loss of reputation.

Finally, setting up a bot network to promote a seller would be hard to accomplish, as soon as trustworthy addresses are known and networked. Fake addresses would need to be connected to honest addresses to indicate trustworthiness. This would be hard to accomplish, since honest sellers would refrain from associating with actors they have never transacted with. Once network effects set in, it will get increasingly hard for a malicious actor to submit plausible fake ratings. Buyer 1 can use sampling techniques to find trustworthy sellers regarding ratings of different buyers 1 to confirm the trustworthiness of a seller's address. In addition, as has already been touched on above, such fraudulent actions are prevented, because buyer 2 can select the addresses to buy information from and aggregate ratings individually.

b) Current reputation systems provide insufficient incentives to submit ratings. Current systems lack sufficient incentives for players in a market to submit ratings. Sellers entice buyers to submit ratings which leads to distorted ratings. Buyers usually have no incentive to share rating information in a business context (Jurca & Faltings, 2003). Adding an incentive directly to buyer 1 to sell ratings and earn money should compensate, or even exceed, the effort associated with providing trustworthy ratings. Also, our system incentives buyer 1 to provide ratings for buyer 2 (while ratings might not be in favor of seller 1) to sell more ratings. While this system will work in non-competitive environments, competitors might mutually refuse to exchange ratings (K. Zhu, 2002). Still, solutions might be found to align conflicting interests e.g., involving trusted institutions (see also c)). Furthermore, the ability of sellers to sell ratings themselves can undermine the profits of a buyer 1 and might be reflected in prior negotiations between buyer 1 and seller 1. Still, buyer 1 may have more information to offer. For instance, text reviews that give further information (Shaker et al., 2021; Zulfiqar et al., 2021). The quality of ratings might affect the price a buyer 1 can charge when selling a rating, strengthening the incentive to submit meaningful ratings. Since the system promises advantages for buyers 1 (get a trust signal, and potentially earn money) and high-quality sellers 1 (build reputation, justify higher prices, and win new buyers), we posit that sufficient incentives may exist for the ecosystem to work.

c) Current reputation systems depend on a commercial platform provider. Current review systems are subject to platform providers that operate a digital platform. Their centralized governance, however, opens up attack vectors that might compromise the system. Manipulation, censorship, or the unwarranted exploitation of user-generated data are risks worth noting. To avoid the manipulation of sensitive rating data, we posit that a blockchain provides a profound infrastructure on which a reputation ecosystem can be built. A core feature of blockchains is the immutability of the stored data (Catalini & Gans, 2016; Tumasjan & Beutel, 2019). Still, we acknowledge, the proposed system could be implemented without a blockchain, however, losing the advantages a blockchain offers.

Next to potentially resolving three conceptual problems of current review systems, we also contribute other improvements for designing reputation ecosystems. First, proposing money as ratings, a buyer 1 thinks twice about giving a positive rating because every positive transaction costs money. Therefore, reciprocity can be diminished, counteracting reputation inflation, and ratings become differentiable and quantifiable. Second, expecting positive ratings, seller 1 might compensate buyer 1 with a price discount. Hence, a buyer 1 can buy a product cheaper, whereby he is rewarded for advertising. For this, buyer 1 ensures this with its credibility, while seller 1 can excel with a higher reputation. This construction turns the dynamic into that a seller also must trust a buyer (Hemmrich, 2023). Introducing trust as a concept for rating submission has hardly been discussed so far (F. Li et al., 2012). Third, since a rating transaction has to be committed from both sides and blockchain data can be analyzed, discriminating ratings are reduced. Every discriminatory behavior will be recorded. Finally, monetary ratings are much faster submitted than writing a review.

Current research on reputation systems considering the B2B context is very limited (Dikow et al., 2015; Gutt et al., 2019). While we frame this kind of system for personal-intense business services, it might also work in other scenarios. It seems to make sense, especially in cases when the uncertainty about the performance is high, enough transactions take place and the players are willing to sell ratings or exchange them for their own ratings. In a business reputation ecosystem, buyer 2 can request ratings and buyer 1 has more control over whom to share them, increasing the willingness to share this information (Boissieu et al., 2021). However, seller 1 can try to promote oneself with fake ratings, at least in an open system, or prompt buyer 1 to rate only certain transactions to hide sensitive data from competitors. Taking the fact that business environments have competitors as well as non-competitive buying peers, institutions, decentralized autonomous organizations (DAOs) (Buterin, 2014a), or other mechanisms might play a major role in determining the trustworthiness of rating sellers and organizing the sharing of rating information (Möhlmann et al., 2019).

Conventionally, buyers 2 choose familiar, trusted sellers that have not yet built up expertise in the pertaining field (Uzzi, 1997), since they do not know which other sellers suit them. An ecosystem can change this circumstance by affecting matching and resource allocation in a market. Particularly, low-cost sellers can profit through their cost efficiency from such systems, preferring transparency, while high-cost sellers choose opaque environments to hide their costs (K. Zhu, 2002). We expect that in a functioning system, high-quality sellers achieve a competitive edge over weak-performing competitors, promoting good service quality. Ultimately, this system may reduce marketing efforts for capable sellers when they show positive ratings from different buyers, which would be more credible than promoting themselves through marketing. Testing ratings become a cheaper economical means than actually buying a product. This would shift testing a non-digital product to testing digital ratings, or thought-ahead testing certain credentials. Lastly, such systems could also bring risks, such as increased performance pressure, fear of retaliation when rating, inadvertently leaked data, or others.

9.6.6 Conclusion

We designed and evaluated a method that enables stakeholders to build business reputation ecosystems. The core idea is to use monetary payments as ratings, stored and made accessible on a blockchain.

We posit that these core features make our system more suitable for B2B markets, since buyers might have a compelling incentive to submit truthful ratings, can better control and share their rating information, and can rely on transparent relations and immutable data that encourage honest behavior, on which ratings can be tested and analyzed without relying on a commercial platform owner. Moreover, our approach exhibits four main differences compared to rival systems. First, ratings become inherent parts of business transactions, whereas rival systems disconnect buying transactions from ratings. %Rival approaches are subject to various biases (e.g., buyers often only rate transactions that were exceptionally positive or negative). Second, ratings are carried out with payments, making the ratings quantifiable. Third, using payments as ratings, bind capital when building up a bot network impeding some attack scenarios. Fourth, reputation is not condensed into one global score and buyers can select ratings according to transparent transaction history and compare them with one another. Furthermore, this system class may lead to a professionalization of business rating submissions and requests, compensate uncertainty of buyers for engaging with sellers, and be used as a marketing tool by delivering a profound data basis.

With this paper we provide a first essential building block for designing reputation ecosystems. We posit that our method can serve well to solve some of the major conceptual problems that prevent using current review systems from a B2C market on B2B markets. Even if our method cannot solve the emergence of fake ratings in open systems completely, we argue that our system makes such fraudulent behavior much more costly and unlikely to occur when such a data set is analyzed. That said, the mechanisms proposed here can only work in a reasonably large network of companies submitting ratings, providing a start for reputation ecosystems to emerge. These initial steps might be hard to take, since digital platforms usually suffer from cold-start problems.

We see our research as an impetus for our community to research the design of business reputation ecosystems. Monetary ratings are novel in research, and by demonstrating this method, we raise more questions than we provide answers. We call for economic, empirical, and practical-oriented research on the proposed system. Technical-oriented research can investigate to prove and reveal the distribution of ratings, implementing DAOs, ratings about ratings, or other decentralized oracle solutions to sort and rank ratings. An interesting research question is whether a seller can be prevented from passing on monetary-based ratings. Other research might investigate different variations of conducting payments as ratings, mapping performance metrics or content of ratings, or the influence on business relationships.

9.7 Does the Blockchain Technology Help to Reduce Information Asymmetries

Paper Number	P7	
Title	Does the Blockchain Technology Help to Reduce Information Asymmetries	
Publication Type	Journal Paper	
Outlet	Game Theory and Applications (Special Issue for SING 20[62])	
VHB JOURQUAL 4	Not ranked[63]	
Authors	Duman, Papatya	35%
	Haake, Claus-Jochen	30%
	Koch, Alexander	10%
	Kühn, Sarah	10%
	Hemmrich, Simon	10%
	Beverungen, Daniel	5%
Status	Accepted Presentation on the Conference European Meeting on Game Theory (SING 2020). Based on this the associated submission to the Association Game Theory and Applications is planned in the near future.	

[62] The SING is the leading European Meeting on Game Theory, originally initiated by researchers from Spain, Italy, the Netherlands, and Germany.

[63] This joint work was presented at several peer-reviewed academic venues, including the European Meeting on Game Theory (SING 20), one of the field's most prestigious and internationally visible conferences. It is intended for publication in the corresponding special issue of *Game Theory and Applications*, a specialized journal for high-level theoretical work. Although not listed in VHB-JOURQUAL, the journal is widely recognized in the game theory community for its academic quality and relevance.

Abstract. *We examine the problem faced by a buyer seeking to purchase an experience good without prior knowledge of its stochastic quality. An expert who owns the product can be paid to provide a signal about its quality. Our analysis explores the impact of introducing a credible signaling mechanism for the buyer. Specifically, we propose using blockchain technology, which ensures immutability, decentralization, privacy, and transparency, to store the signal. Our findings reveal that this approach reduces the number of possible equilibria while preserving the "good equilibrium", in which information is both acquired and accurately transmitted. Consequently, the use of blockchain technology mitigates the equilibrium coordination problem and improves the provision of credible information.*

9.7.1 Introduction

Availability of correct information is one of the central aspects in economic interaction. In his seminal paper, (Akerlof, 1970) demonstrates in a simple model for the market for lemons that asymmetric information leads to market failure. In essence, two agents want to trade a product, but the buyer does not have sufficiently accurate information on the product quality, and hence on personal utilities.

The analysis of trade under asymmetric information is at the heart of contract theory which aims at designing mechanisms that incentivize agents to reveal their private information through taking specific observable actions. For example, signaling mechanisms, as introduced by Spence (1973), allow the informed agent to send a message or signal to the uninformed one. Although it cannot be verified directly that the agent submits the credible signal, signaling costs are set up in a way that it is in the agent's best interest not to misrepresent information. In practice, therefore, costless signals only provide limited advice to potential buyers, e.g., (online) rating systems that are almost costless to use (Dellarocas, 2003). Similarly, the problem of limited informativeness occurs when the costs of a signal (e.g. a rating) is either independent from the signal itself or information on the signal costs cannot credibly be shared. As a result, signaling games typically show a large number of (separating and pooling) equilibria.[64]

As an illustration of this problem we return to (online) rating systems that are supposed to inform potential buyers about the quality of a product. Typically, the costs of releasing a rating are low and not connected to the product quality so that we observe more and more the emergence of fake reviews (He et al., 2022) jeopardizing its original intent (Tadelis, 2016b). From a technical perspective Mohawesh et al. (2021) survey the

[64] For our context, Fudenberg and Tirole (1988) show that the notions of Perfect Bayesian Equilibrium and Sequential Equilibrium are equivalent and P. Bolton and Dewatripont (2004, p. 103). state: "In signaling games, the difficulty is not to find a PBE. Rather the problem is that there are too many PBEs.

possibilities of detecting fake reviews by analyzing review texts. However, such methods are designed for detection, not prevention.

From a general perspective, a part of the problem is that information (e.g., on product quality) and action (e.g., give a rating) are decoupled. A device like blockchain[65] provides an interesting possibility to link both, information and action, by storing actions (in particular payments revealing information on incentives) in a way that this information is traceable, public, immutable, and a trusted third party is not required as intermediary (Franke et al., 2024). Moreover, acquisition of information stored in the blockchain can be designed costly, so that it is part of a buyer's strategic choice to acquire a signal or not (X. Yu et al., 2023; Q. Zhang et al., 2024).

In this paper, we want to investigate, whether the blockchain technology (BCT) can be used to reduce information asymmetries in economic transactions. More precisely, we employ a simple model in which a buyer wants to buy a product of unknown quality. Assuming that the good is an experience good, its true quality cannot be observed prior to purchase. However, the buyer may receive information from another agent, named expert[66], who has already bought the product and therefore is informed about the true product quality. In a “traditional modeling”, the buyer may pay the expert for a quality assessment, and then base his[67] buying decision on the expert's signal. In this model, the expert's costs of providing any signal are independent of the signal. As we will demonstrate later (Proposition 1), the corresponding two-person game exhibits multiple sequential equilibria in pure strategies, so that a severe coordination problem occurs.

We compare the results with those in a model, in which the blockchain technology is avail- able. More precisely, the seller, who is not modeled as an active agent, allows the expert to buy the product either at regular or at discounted price.[68] The expert decides which price to pay for the purchase after experiencing the product quality, and that payment is stored in a blockchain. Therefore, the signal that she sends has a direct impact on her overall payoff. Phrased differently, the cost of a signal depends on the signal. Instead of “just asking” the expert about the product quality, the buyer now has the

[65] This technology emerged from previous research on digital signatures Rivest et al. (2001), the Merkle tree by Merkle (1980), cryptographically secure time-stamping with blocks Haber and Stornetta (1991), and the precursors of digital money, see Back (2002); W. Dai (1998). Beyond its use as an infrastructure for cryptocurrencies, such as bitcoin, built-in features in the blockchain technology include immutability, decentralization, privacy and transparency, and distributed trust Filippi (2016); Nakamoto (2008); Seidel (2018); Swan (2015).
[66] Here, the term “expert” refers to an agent, who has already bought the product and has therefore experience with it and can assess its quality.
[67] Throughout this text, we use ’he’ and ’she’ to differentiate between two types of agents (expert - she, buyer - he). This choice of pronouns does not imply any gender-specific characteristics or biases regarding the individuals discussed.
[68] We may also think of the expert as the first buyer of the product

possibility to pay for observing the stored transaction between the expert and the seller. In particular, signaling high quality (via paying regular price) now comes at a higher cost for the expert, thus increases her signal's credibility (Pornpitakpan, 2004).

The direct implication is that the existence of a device that stores immutable information, which is observable at a given cost, helps to reduce a coordination problem between an expert and an uninformed potential buyer. The “good equilibrium”, i.e., the expert always pays the price that matches the quality of the product, and the buyer acquires information, then perfectly correlates his buying decision on the signal, is still an equilibrium, however reachable with fewer coordination effort. In the game induced in the model with BCT, we show that there are fewer sequential equilibria compared to the game without BCT (Proposition 2).

As one application, a trading system with experts that are offered special purchase conditions can be designed to better inform buyers about product qualities. From an information economics perspective, such a system works because the cost of a signal becomes observable, and as a result signal credibility is enhanced. Many online platforms feature reputation systems to reduce uncertainty in transactions (Rice, 2012) and promote trust in sellers (Moreno & Terwiesch, 2014). The more reliable the implemented reputation mechanism is, the more it enhances trust in buying decisions (Honhon & Hyndman, 2020; Jøsang et al., 2007). Still, reputation systems are prone to strategic manipulation, especially due to false quality signals induced by low-quality sellers (G. E. Bolton et al., 2013; G. E. Bolton et al., 2004; Kennes & Schiff, 2007).

Implementing reputation systems on a blockchain is considered the most reliable way to store feedback information and exclude manipulation (Bellini et al., 2020; Y. Cai & Zhu, 2016; Hawlitschek et al., 2018). A blockchain is a tamper-proof, chronological ledger implemented as a distributed database for transactions secured by cryptographic mechanisms and governed by a consensus protocol (Beck et al., 2017). A community of computing nodes produces a blockchain by exchanging and storing digital transactions that are recorded in blocks, building an ever-growing chain. Cryptographic mechanisms guarantee that transactions can be verified and any unauthorized change of transaction data is easy to detect. The consensus protocol provides economic incentives that ensure only valid transactions are stored in the blockchain. In a truly decentralized network, distributed consensus mechanisms provide an extraordinary degree of tamper- resistance, removing the necessity to include a trusted third party for checking transactions' legitimacy and authenticity (Nakamoto, 2008; Tschorsch & Scheuermann, 2016).

From the contract theory perspective, P. Bolton and Dewatripont (2004), Kreps and Sobel (1994), or Kőszegi (2014) provide extensive survey on how to incentivize agents to reveal private information. As one expects, there remains a trade-off between incentive compatibility and efficiency. Mamada (2022) follows an interesting approach to solve the market for lemons problem by considering signal indices already defined in Spence Spence (1973) that can costly be observed. For used cars this means that the state of air-conditioning can costly be verified, which is correlated with the quality of the car. He shows that if the price falls into a specific range, cars with bad air- conditioning are driven out of the market. Unlike in our approach, there has to be an opportunity to test the product prior to purchase.

Gersbach et al. (2022)) discuss a model with severallow and high quality sellers and one buyer, who potentially wants to buy more than one product. They set up a four stage mechanism, in which prices depend on the actions of all sellers and show that in equilibrium all high-quality sellers send a different signal than low-quality sellers. Compared to our work, we focus on the revelation of quality information through the interaction of (two) buyers.

In supply chain manufacturing, a blockchain can be used to store the quality of a product itself. In such models, information disclosure through BCT is a strategic choice and will only be used by high-quality sellers (Q. Xu & He, 2023; Q. Zhang et al., 2024). However, in our model, product quality is not verifiable prior to purchase and cannot credibly be shared, so that the agents are dependent on quality signals.

The paper is organized as follows: Section 2 introduces the two games with imperfect infor- mation without (Model 1) and with (Model 2) deploying a blockchain technology. While Section 3 briefly reviews the concept of sequential equilibria, the results are presented in Section 4. Section 5 concludes. All calculations of equilibria are relegated to the appendices.

9.7.2 Model

In this section, we set up two models describing the interaction between two buyers of the same product, the quality of which is unknown. More precisely, a seller offers one unit of a pro- duct at a given price $p > 0$ and delivers the product in either good or bad quality. We assume that the product is an experience good meaning that a buyer can only observe its quality after consumption, i.e., only after a purchase. The buyer's utility from consumption expressed as will- ingness to pay is $B > 0$, when the product quality is high, and 0 otherwise. In order to reduce information asymmetries, the buyer can retrieve information on the product quality from an ex- pert (or experienced buyer), who has already bought and assessed the same product. The expert's utility from consumption is either r > 0 or 0 given that the quality is high or low, respectively. Both, the expert and the buyer, have use for at most one unit of the product.

As we are primarily interested in mechanisms for information transmission from the expert to the buyer, we model the quality of the product as a chance move with the known priors q for high quality and *1 — q* for low quality. The expert and the buyer are assumed to be risk-neutral, and the seller is not modeled as an active decision-maker, so that product quality is not a strategic choice. To eliminate the effects of long-term reputation, we think of a one-shot interaction taking place anonymously, e.g., on an online platform.

In what follows, we introduce and compare two versions of the way in which information can be transmitted to the buyer. In both models, the sequence of actions is described as a sequen- tial move game with imperfect information. First the expert buys the product and is therefore perfectly informed about the realization of the chance move. While the expert knows the pro- duct quality, the buyer has no information about it. However, he knows that the expert observed the quality. This asymmetric information environment is the key feature in our models. Before buying the product the buyer may acquire a signal about the product quality from the expert. The difference between the models lies in how information is signaled and how the signals are designed.

In both models, there is an incentive for the expert to report truthfully. While in the first model the buyer has to completely rely on the expert's signal, in the second model we use BCT to store the expert's signal, i.e., the real payment. With blockchain, the signal is confirmed and can be retrieved by the buyer. The goal of the analysis is to investigate how the set of equilibria changes when the blockchain is employed.

Model 1: Reported Quality

Figure 32 illustrates the game tree in Model 1. The game starts with a chance move with pro- babilities q and *1 — q* choosing high or low quality, respectively. We assume that the expert then buys the product at price p and directly assesses its quality, i.e., she observes the outcome of the chance move. Depending on whether the true quality is high or low, the expert makes a decision on which quality level to report to the buyer when asked.[69] More precisely, given the true quality is “high” (“low”), the expert either chooses *H+ or L+ (H- or L-)* to signal high or low quality.[70]

[69] To have a greater similarity of the game trees of the two models, this decision is modeled prior to the buyer's decision whether or not to acquire information from the expert.

[70] While *H* and *L* refer to the experts action, the superscript “+” (“—”) means that the true quality is “high” (“low”).

From now on, all remaining decisions are taken by the uninformed buyer. He first has the option to acquire *(ac)* information from the expert by paying her an amount $x > 0$ or refuse (*ref*) to do so. After that, he takes a final decision on buying or not buying the product. Formally, he chooses an action buy^{+},buy^{-}, or buy^{0} for buying the product, after receiving a signal of *high quality*, *low quality*, or *no signal on quality*, respectively. Similarly, the actions nb^{+}, nb^{-}, or nb^{0} refer to not buying the product.[71] Due to the unobservability of the chance move and possibly unacquired information, the buyer has four information sets, displayed in different colors.

At each terminal node, the payoffs for expert (top line) and buyer (bottom line) are displayed. They are determined as follows: Independent of the product quality, the expert pays the price p. Her net utility is $v – p$ when the realization of the chance move is high, and $0 – p$ otherwise. If the buyer buys the product, he pays the same price p. In case the bought product is of high quality, he receives u, and 0 for a low quality product. If he does not buy the product, his utility is 0. Whenever the buyer chooses *ac* and therefore the expert sends a quality signal, a fee $x > 0$ is transferred from the buyer to the expert.

So far, the expert is not provided with incentives to tell the truth, because the fee x she may receive is independent of the signal she gives. In addition, the expert receives a bonus $r > 0$ paid by the platform, when the buyer bought the product and the report was truthful. We may think of the buyer approving or not the acquired information, but do not model it as an explicit action.[72] The platform (owner) is not explicitly modeled as an agent. As the platform is interested in having a working system that allows buyers to acquire information from the expert and receive a correct response, there is good reason to pay the bonus r. From a far-sighted perspective, such a possibility can attract future buyers to use the platform.

In sum, the payoffs depend on the utility received from a high quality product (u or r), the price of the product p, and possibly on the fee x and bonus r. The following assumptions capture specific scenarios for which we will analyze equilibria in the next section.

---

[71] Here superscripts do not refer to the true quality of the product but to the information provided ("+" for "high" signal, "—" for "low" signal) or not provided ("0" for no signal) by the expert.
[72] As the game is over after the approval, it is not necessary to incentivize the buyer to tell the truth here.

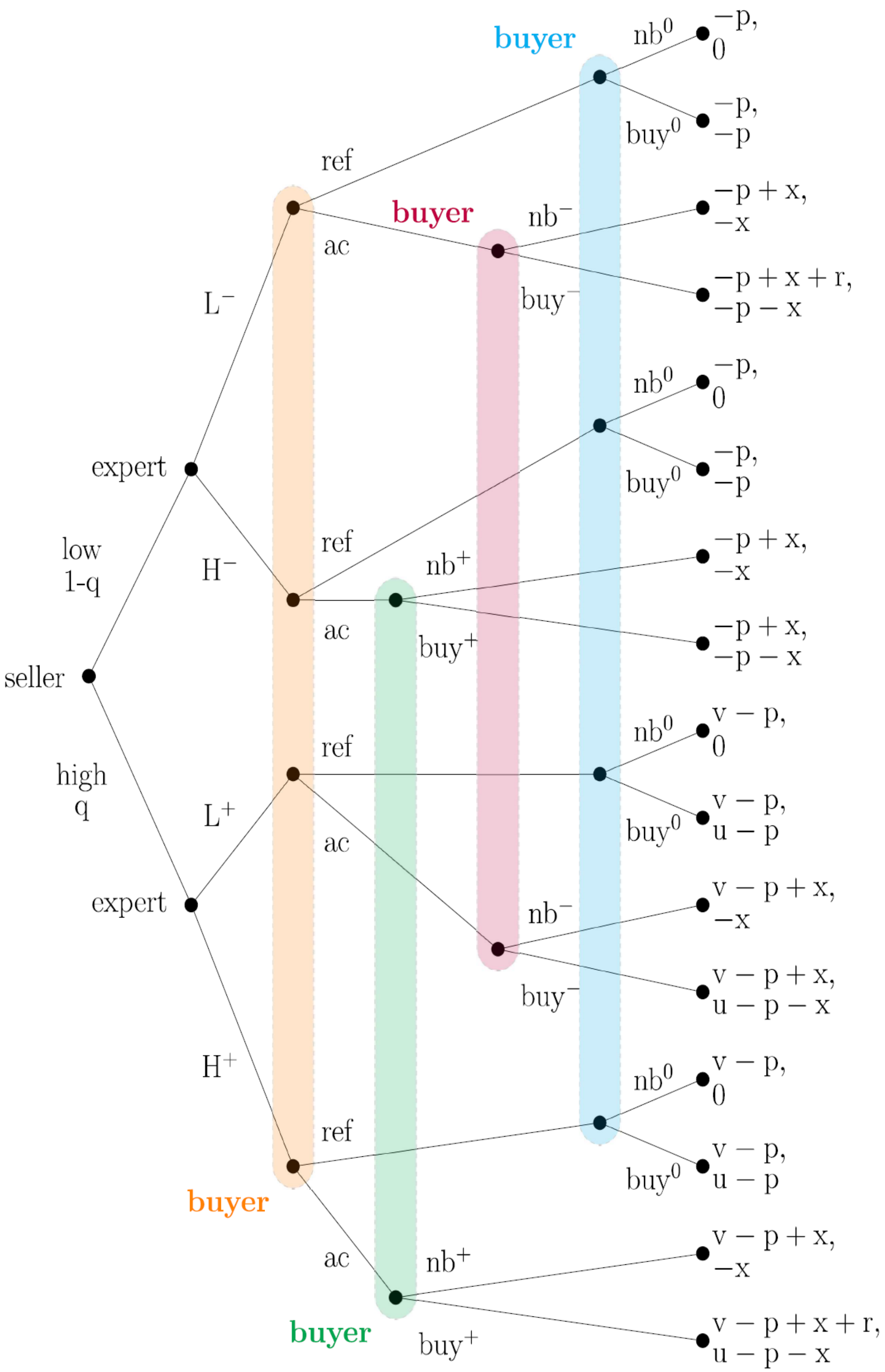

Figure 32: Game Tree in Model 1: Quality Reported

Al $uq - p > 0$ and $vq - p > 0$

Al' $uq - p < 0$ and $vq - p > 0$

A2 $(1 - q)p > x$

A2' $q(u - p) > x$

Assumptions *A1* and *A1'* are mutually exclusive. *A1* guarantees that the expected utility from buying the product exceeds the price for the buyer. It can be viewed as a participation constraint and implies that a completely uninformed, risk-neutral buyer does buy the product.[73] In contrast, assumption *A1'* requires the buyer not buy the product, when he is uninformed. In either assumption *A1* and *A1'*, the buyer expects to have a positive net utility from buying the product $(u - p > 0)$.

Assumptions *A2* and *A2'* relate the fee x to the buyer's expected net utility or net loss. Assumption *A2* can be rewritten to $q(u - p) + (1 - q)(0 - p) < q(u - p) - x$, which means that the expected utility from buying the product without information is lower compared to having the correct signal at cost x. Phrased differently, it ensures that paying the fee is better than receiving a low quality product. Otherwise, there would be no incentives to ask an expert. Assumption *A2'* ensures that the fee is smaller than the expected utility gain, so that paying x is overcompen- sated by receiving a high quality product. Interestingly, when subtracting the 1.h.s. in *A2* from the 1.h.s. in *A2'* we get $q(u - p) - (1 - q)p = qu - p$ which is positive (negative) under *A1 (A1')*. A direct implication is given in the following lemma.

Lemma 1. *Assumption A1 and A2 together imply A2'. Assumptions A1' and A2' jointly imply A2.*

In essence the key characteristic of Model 1 lies in the fact that the buyer can choose to base his buying decision on information that cannot credibly be transmitted from the expert to the buyer, as he cannot learn the result of the chance move without buying the product.

Model 2: Information access via Blockchain

The game tree in Model 2 is depicted in Fig. 33. What changes is the type of signal from the expert and the access to information. We now assume that a two-price contract is

[73] Technically, it implies that the action buy^0 dominates the action nb^0 in the corresponding (blue) information set.

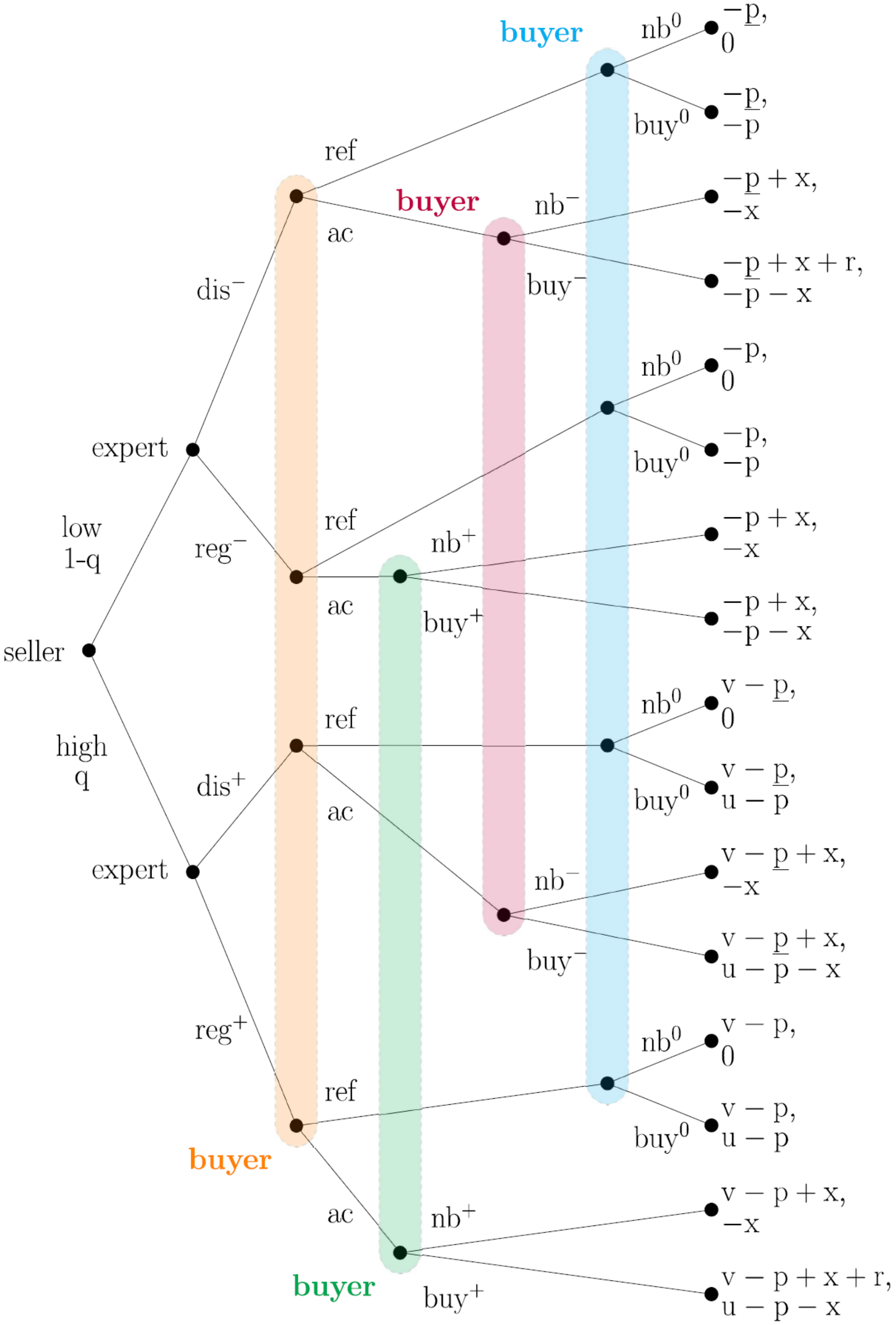

Figure 33: Game Tree in Model 2: Information Access via Blockchain

offered from the seller to the expert. That means, she buys the product, assesses its quality, and can then either pay the regular price *p* (action *reg*) or a specified discounted amount

$\underline{p} < p$ (action *dis*). The final payment to the seller is stored in a blockchain so that it cannot be modified anymore and can be retrieved from a third party. This stored information is used as the signaling feature of the model. The difference to Model 1 is that the price paid by the expert serves as the signal. Hence, signaling high quality by paying the regular price instead of a discounted one comes at a cost for the expert. This is in line with the general idea of signaling information in economics. The more costly a signal is, the more credible it is (Pornpitakpan, 2004). In this model, signaling the high quality by paying the higher price preserves the chance of receiving the bonus payment r at the end.

The buyer chooses to acquire information (action *ac*) or not (action *ref*) from the blockchain at a fee *x* paid to the expert. In the former case, he knows whether the expert made the regular or the discounted payment. A regular payment (discounted payment) of p ($\underline{p}$) is supposed to signal high (low) quality. But information on payment can credibly be obtained thanks to the use of a blockchain.

The sequence of the buyer's actions is identical to the first model, so we keep the same notation for actions and payoffs. The main difference in the payoffs is that the expert can choose to pay either p or $\underline{p}$. Again, at the very end the expert may receive a bonus r, if the buyer acquired information, bought the product, and approved accuracy of the signal.

Additional to Assumptions *A1-A2* (or *A1'-A2'*), it is instructive to introduce the following intuitive assumption on the bonus payment r:

A3 $r > p - p$.

Assumption *A3* guarantees that it is more attractive to pay the regular price and receive the bonus r than to pay the discounted price. Otherwise, the expert has no incentive to pay the regular price p.

9.7.3 Strategic Behavior

To economize on notation, the expert and the buyer are also denoted as agent 1 and 2, respectively. A *pure strategy* for agent i (i=1,2) is a mapping that takes each of agent *i's* information sets to one of the feasible actions therein. In Model 1, we can therefore describe the expert's possible pure strategies by $S^{1,1} := \{H^+, L^+\} \times \{H^-, L^-\}$. In Model 2, her pure strategies are given by $S^{2,1} := \{reg^+, dis^+\} \times \{reg^-, dis^-\}$. The set of the buyer's pure strategies is the same in both models and given by $S^2 = S^{1,21} = S^{2,2} := \{ac, ref\} \times (buy^+, nb^+\} \times (buy^-, nb^-\} \times (buy^0, nb^0\}$.

We analyze agents' strategic behaviors by inspecting the extensive form games with imperfect information as described in Model 1 and 2. From a static viewpoint, the agents choose their plans of action prior to the game and the game play results from execution of these plans. In the normal- form game the strategy sets are the pure strategies as above and payoffs at a strategy profile are formed by following the path that is visited by the application of the actions in the strategy profile. This way we can identify Nash equilibria (NE) of the normal-form game. However, this static view neither takes the sequentiality of decisions nor imperfect information into account. More- over, the number of Nash equilibria is typically large, so a refinement of the Nash equilibrium concept strengthens the predictive power and typically reduces the number of equilibria. Yet, as both versions of the game (from the two models) admit only a single subgame, the subgame perfect equilibrium concept has no further bite compared to Nash equilibria (of the normal-form game). We therefore discuss the concept of sequential equilibria introduced by Kreps and Wilson (1982) next.

A *behavioral strategy* b_i *for agent i* specifies a probability distribution over the feasible actions in each information set, in which agent *i* chooses. A pure strategy of agent i is a special behavioral strategy, which assigns in each information set a probability of 1 to the action chosen in the pure strategy (and hence 0 to all other actions). A behavioral strategy of agent *i* is *completely mixed* if it assigns a positive probability to each of the feasible actions in each of an agent's information set. A *belief* β_i|3; of agent *i* includes for each information set of that agent a probability distribution over the nodes included in the information set. A pair $\beta = (\beta_1,\beta_2)$ of beliefs for both agents is a belief system. A tuple (b, β) = $((b_1,b_2),(\beta_1,\beta_2))$ consisting of a profile of behavioral strategies and a belief system is termed an *assessment*. To define sequential equilibria we first discuss the following properties for an assessment (b,β).

Sequential Rationality Within each information set h_i of agent *i*, the probability distribution $b_i(h_i)$ over actions in h_i maximizes the agent's expected payoff given the belief $b_i(h_i)$ over nodes in that information set and the behavioral strategy profile *b*.

Bayesian Consistency The belief system $\beta = (\beta_1,\beta_2)$ is generated by the strategy profile via Bayesian updating. That means, given the probabilities in b = (b_1,b_2) to take actions, the belief of deciding at a specific node in information set h is the probability of reaching that node conditional on reaching some note in *h*.

Sequential rationality requires the agents choose behavioral strategies that maximize their payoffs given their beliefs about the node at which the decision has to be taken. Bayesian up- dating means that given the strategy choices, agents' beliefs are formed in a compatible way. However, it could happen that by the application of a behavioral strategy profile, an information set is not visited at all. In those information sets h, the belief formation via Bayesian updating is not possible. It means that a rationality condition based on Bayesian updating per se makes no sense, so that $b_i(h)$ cannot be identified as an optimal choice in h. For such cases, we need a more sophisticated form of consistency.

Consistency There exists a sequence (b^m, β^m) $m \in \mathbb{N}$ of assessments in which b^m is completely mixed and β^m is Bayesian consistent so that $lim_{m\to\infty}(b^m, \beta^m)$ = (b,β) holds.

Now, we are ready to define our equilibrium concept:

Sequential Equilibrium A *sequential equilibrium (SE)* is an assessment (b,β) which satisfies Sequential Rationality and Consistency.

If the behavioral strategies are such that all information sets in the game tree are reached with positive probability, Bayesian consistency and consistency coincide. Hence, consistency is triv- ially satisfied. Then in equilibrium, sequential rationality and Bayesian consistency ensure opti- mal decisions w.r.t. correct beliefs. If an information set h is reached with zero probability, belief formation according to Bayesian updating as well as rational choice is not possible. Nonetheless, the equilibrium action choice in *h* is rationalizable, if it maximizes the agent's payoff given plau- sible beliefs, i.e., beliefs $\beta^m m \in \mathbb{N}$ which are formed via behavioral strategies beliefs $(b^m) m \in \mathbb{N}$ being close to the equilibrium strategies b. Completely mixed strategies b^m for any $m \in \mathbb{N}$ guarantee that every information set is reached with positive probability, so that the plausible beliefs W stem from Bayesian updating.

When comparing sequential equilibria in the extensive form game with (pure) Nash equilibria of the normal-form game, it is easy to see that any sequential equilibrium is a Nash equilibrium, which is due to sequential rationality.[74] Conversely, not every Nash equilibrium needs to be a sequential one. Intuitively, a Nash equilibrium may include actions that are not sequentially rational in an information set as a “threat” to make the opponent stay away from a particular strategy choice and not reach that information set. Therefore, the sequential equilibrium concept is insensible to this form of non-credible threats. Roughly speaking, increasing the degree of rationality built in the equilibrium concept reduces the number of equilibria.

[74] Sequential rationality means that deviating to another strategy reduces the payoff, as it is not optimal in one information set.

9.7.4 Results

The "desired" or "good" behavioral strategy is arguably the one in which the expert reports or pays according to the true quality, then the buyer acquires information and buys according to the signal he receives. The buying decision when no information is available is governed by Assumption $A1$ (buy) or $A1'$ (not buy). Let us denote this behavioral strategy by b^{des}. Besides the question, whether bde' is part of some sequential equilibrium (together with a consistent belief system) we are interested in finding out whether the use of BCT reduces information asymmetries. We use the following route to answer this second question: For the games in Model 1 and in Model 2, we compare the numbers (and sets) of sequential equilibria, i.e., investigate if employing the blockchain method helps to reduce coordination issues. Attaining uniqueness of the equilibrium in Model 2 is certainly to much to hope for, because the strategy profile, in which the expert never pays the regular price and the buyer does not acquire information, will always form a sequential equilibrium. The expert cannot improve her payoff, because she can never receive the bonus r and the buyer cannot be better off as the expert's strategy choice does not reveal any information. To compare numbers of equilibria, we restrict attention to pure sequential equilibria, as there are at most finitely many.[75] The sequential equilibrium concept is a refinement of the Nash equilibrium concept applied to the normal-form derived from the sequential move game(s). To start, there is a large number of pure Nash equilibria. The game in Model 1 has 10 pure Nash equilib- ria with 2 different equilibrium outcomes.[76] In Model 2 (with blockchain technology) we have 6 Nash equilibria in pure strategies, again with 2 different outcomes. For details see Table 37 and for the computation see Appendix F.

The following two propositions provide the results for Model 1 and Model 2. These results demonstrate that (a) moving to the sequential equilibrium dramatically reduces the number of equilibria and (b) the coordination problem simplifies through the use of BCT, because informa- tion can credibly be shared and actions (payment) are linked with the signal.[77] The Nash and sequential equilibria in Model 1 and 2 are displayed in Table 36, he proofs are relegated to the appendix.

[75] That means, each equilibrium satisfies the requirements of a sequential equilibrium from the previous section. In particular, there is no mixed sequential equilibrium that provides a greater payoff to some agent given the equilibrium beliefs.
[76] The outcome of an assessment is a probability distribution over the terminal nodes of the game tree.
[77] Technically,we identify actions in Model 1 with actions in Model 2 in the canonic way. Therefore, we get a bijection of strategies in the models that allows us to compare sets of equilibria.

Table 36: Sequential Equilibria of both Models under the Assumptions A1, A2, A3 or Al', A2', A3'

	Player 1		Player 2	NE		SE	
	Model 1	Model 2	Model 1 and 2	Model 1	Model 2	Model 1	Model 2
Under the assumptions $A1$, $A2$, and $A3$							
I (b^{des})	H^+L^-	reg^+dis^-	$ac\ buy^+nb^-buy^0$	✓	✓	✓	✓
II	H^+L^-	reg^+dis^-	$ac\ buy^+nb^-nb^0$	✓	✓	×	×
III	L^+L^-	dis^+dis^-	$ref\ buy^+buy^-buy^0$	✓	✓	✓	✓
IV	L^+L^-	dis^+dis^-	$ref\ nb^+buy^-buy^0$	✓	✓	✓	✓
V	L^+L^-	dis^+dis^-	$ref\ nb^+nb^-buy^0$	✓	✓	×	×
VI	L^+L^-	dis^+dis^-	$ref\ buy^+nb^-buy^0$	✓	✓	×	×
VII	H^+H^-	reg^+reg^-	$ref\ buy^+buy^-buy^0$	✓	×	✓	
VIII	H^+H^-	reg^+reg^-	$ref\ nb^+nb^-buy^0$	✓	×	×	
IX	H^+H^-	reg^+reg^-	$ref\ buy^+nb^-buy^0$	✓	×	✓	
X	H^+H^-	reg^+reg^-	$ref\ nb^+buy^-buy^0$	✓	×	×	
Under the assumptions $A1'$, $A2'$, and $A3$							
XI	H^+L^-	reg^+dis^-	$ac\ buy^+nb^-buy^0$	✓	✓	×	×
XII (b^{des})	H^+L^-	reg^+dis^-	$ac\ buy^+nb^-nb^0$	✓	✓	✓	✓
XIII	L^+L^-	dis^+dis^-	$ref\ buy^+buy^-nb^0$	✓	✓	×	×
XIV	L^+L^-	dis^+dis^-	$ref\ nb^+buy^-nb^0$	✓	✓	×	×
XV	L^+L^-	dis^+dis^-	$ref\ nb^+nb^-nb^0$	✓	✓	✓	✓
XVI	L^+L^-	dis^+dis^-	$ref\ buy^+nb^-nb^0$	✓	✓	✓	✓
XVII	H^+H^-	reg^+reg^-	$ref\ buy^+buy^-nb^0$	✓	×	×	
XVIII	H^+H^-	reg^+reg^-	$ref\ nb^+nb^-nb^0$	✓	×	✓	
XIX	H^+H^-	reg^+reg^-	$ref\ buy^+nb^-nb^0$	✓	×	×	
XX	H^+H^-	reg^+reg^-	$ref\ nb^+buy^-nb^0$	✓	×	✓	

Proposition 1 (Sequential equilibria without BCT).

1. Under Assumptions A1 and A2, there are 5 sequential equilibria in pure strategies of the game in Model 1 given my E^1 —— {I, III, IV, VII, IX}.

2. Under Assumptions A1' and A2', there are 5 sequential equilibria in pure strategies of the game in Model 1 given by $E^{1'}$ = {XII, XV, XVI, XVII, XX}.

3. Under either set of assumptions, A1 and A2 or A1' and A2', there is a belief system β^{des} such that (b^{des}, β^{des}) is a sequential equilibrium.

Proposition 2 (Sequential equilibria with BCT).

1. Under Assumptions A1, A2, and A3, there are 3 sequential equilibria in pure strategies of the game in Model 2 given by the set E^2 = {I, III, IV}. further, $E^2 \subset E^2$.

2. Under Assumptions A1', A2', and A3, there are 3 sequential equilibria in pure strategies of the game in Model 2 given by the set $E^{2'}$ = {XII, XV, XVI, XX}.

3. Under either set of assumptions, A1, A2, and A3 or A1', A2', and A3, there is a belief system β^{des} such that (b^{des}, β^{des}) is a sequential equilibrium in the game of Model 2.

The propositions show in particular that the desired strategy profile b^{des} is (a part of) a se- quential equilibrium in both Model 1 and Model 2. Recall that the two sets of assumptions reflect the cases, in which the buyer has a positive or negative expected utility from buying the product without any further knowledge.

A comparison of the propositions shows that the use of BCT used for information retrieval shrinks the set of equilibria. Interestingly, when we take a closer look at which equilibria drop out, it turns out that using BCT eliminates all equilibria, in which the expert reports high quality in case that the quality is low (in Model 1 there are such equilibria; see last two columns of Table 36). It follows that an (equilibrium) action of paying the discounted pice is an accurate signal for low quality when using BCT. This observation is independent of the buying incentives of an uninformed buyer.

The number of equilibria can, however, not be reduced to one. This is because the strategy, in which the expert always pays the discounted price and the buyer never acquires information is an “unavoidable” equilibrium strategy. But, the desired equilibrium strategy is payoff dominant (cf. Table 37 and Table 38), and this fact reconciles with the left over coordination problem in Model 2. Thus, also from this perspective, the desired equilibrium is desired by the two agents as a group.

9.7.5 Discussion

Our paper shows that storing quality signals in a blockchain with signal dependent costs reduces incentives for strategic lying between informed and uninformed agents, as verifiable payments serve as cost-backed quality signals. Due to its built-in features of immutability, decen- tralization, transparency, and distributed trust, BCT provides a reliable infrastructure for quality signals.

Our analysis is kept simple and limited to a one-shot interaction between two players. In other words, our model with anonymous agents does not accommodate considerations for reputational effects as they were studied in the seminal paper by C. Shapiro (1982). However, future endeavors could involve devising a repeated game setup wherein our models serve as the foundation for the stage game. Giving up anonymity of agents, in such a model we could explore in how far BCT helps to build up (long-term) reputation.

As an implication, the quality signal can leverage the design of superior reputation systems that base on BCT, improving data-sharing platforms (Hawlitschek et al., 2018) and collaboration platforms (Narang et al., 2019). Our approach builds on payments as reliable quality signals, in- centivizing buyers to reveal the real quality of a product. When a secure transaction environment is established, buyers might also sell their ratings to other market participants or exchange them for other ratings. Envisioning a scenario that allows buyers and sellers to trade quality signals (Hemmrich et al., 2023), our results may have a profound impact on how companies organize their relationships (Beck et al., 2017), do marketing (Herhausen et al., 2020), select sellers or buyers (Ekstrom et al., 2005; McKnight et al., 2017), and create social welfare (Arrow, 1950). Aligning the payoffs with acting honestly in an open system also allows the creation of trustfully generated digital information and assets without institutionallegitimacy, promoting digital rating representations of non-digital real-world objects (J. Pereira et al., 2019). These quality signals may reduce information asymmetries and help with selection problems starting with the market for lemons (Akerlof, 1970) up to data oracles (Caldarelli, 2020).

F Appendix P7: Determination of Nash and Sequential Equilibria under A1 - A3

Appendix G provides the calculations and hence proofs of Propositions 1 and 2 under the assumptions A1, A2, and, whenever applicable, A3. In Appendix H we display the same analysis under assumptions A1', A2', and A3. Finally Appendix I treats the case Bq — p = 0, in which a completely uninformed buyer is indifferent between buying and not buying the product. Nash equilibria in the games of Models l and 2 Model 1 is informationally equivalent to the simultaneous move game in which the expert has the 4 strategies (H^+H^-), (H^+L^-), (L^+H^-), (L^+L^-) and the buyer's strategy set {ac, ref} × (buy$^+$, nb$^+$} × {buy$^-$, nb$^-$} × {buy^0, nb^0} has 16 members as he has 2 possible actions at each of his four information sets. Model 1's pure strategy Nash equilibria are found via the normal-form representation of that simultaneous move game. Those equilibria are readily determined by payoff comparisons and are shown in Table A.2. We reach the Nash equilibria in the game in Model 2 via similar argumentation (see Table A.3). Here the expert's strategies are (reg^+reg^-), (reg^+dis^-), (dis^+reg^-), (dis^+dis^-). The game in Model 1 has 10 Nash equilibria in pure strategies, while the game in Model 2 has 6 Nash equilibria.

Bayesian Consistency

Next, we will search for the sequential ones among those equilibria. We denote the expert and the buyer as Player 1 and 2, respectively. Let b_1,b_2 be their completely mixed behavioral strategies. The corresponding Bayesian consistent beliefs will be computed as follows: β^1 $m \in \mathbb{R}^4$ represents the beliefs of Player 2 at the first information set from left (orange). β_1^1 is the belief that the decision node at the bottom is reached, i.e., the product quality is high and Player 1 has played H^+, while β_2^1 is the belief that the second decision node from bottom is reached, i.e., the product quality is high and Player 1 has played L^+. In case of the low quality product, Player 2 believes that Player 1 has played H^-L^- with probability β_3^1, β_4^1, respectively. Under the assumption that b_1,b_2 are completely mixed, the belief β^1 can be computed via conditional probability:

$$\beta^1 = (\beta_1^1, \beta_2^1, \beta_3^1, \beta_4^1) = (sq, (1-s)q, t(1-q), (1-q)(1-t)) \qquad (A.1)$$

Where s = b_1 (H^+), t = b_1 (H^-) represents the beliefs of the buyer at the second information set from left (green). When this information set is reached, Player 2 believes with probability β_1^2 that the decision node at the bottom is reached. Similarly, the belief β^2 can be computed via conditional probability:

$$\beta^2 = (\beta_1^2, \beta_2^2) = \left(\frac{sq}{sq + t(1-q)}, \frac{t(1-q)}{sq + t(1-q)}\right). \qquad (A.2)$$

$\beta^3 \in \mathbb{R}^2$ represents the beliefs of the buyer at the third information set from left (pink). Via similar argumentation, one can see that

$$\beta^3 = (\beta_1^3, \beta_2^3) = \left(\frac{q(1-s)}{q(1-s) + (1-q)(1-t)}, \frac{(1-q)(1-t)}{q(1-s) + (1-q)(1-t)}\right). \qquad (A.3)$$

The fourth information set of Player 2 is represented in blue. The belief vector of Player 2 for this information set is β^4, and the beliefs in reaching decision nodes from bottom to top are as follows:

$$\beta^4 = \left(\beta_1^4, \beta_2^4, \beta_3^4, \beta_4^4\right) = (sq, (1-s)q, t(1-q), (1-t)(1-q)). \qquad (A.4)$$

Sequential equilibria in the game of Model 1

For any Nash equilibria in Model 1, one can easily construct the equilibrium strategy as a behavioral strategy. Then, that behavioral strategy b along with a belief system β must satisfy Consistency and Sequential Rationality. To do so, for any h, we must find a β, so that together they satisfy Sequential Rationality. Then, a sequence of assessments (b^m, β^m) $m \in \mathbb{N}$ of completely mixed b^m, Bayesian consistent β^m converging to b,β is necessary. If an equilibrium is not sequential, it will be justified here why this is the case. Below in Table A.4, one can see that 5 out of 10 Nash equilibria in Model 1 are sequential equilibria. The corresponding belief systems and the assessment sequences that allow us to confirm sequential rationality and consistency are shown in Table A.5.

It remains to show that the other Nash equilibria are not sequential equilibria. We show this separately.

- **Equilibrium II:** For any $b_1^m(H^+), b_1^m(H^-) \in (0,1)$, $\mathbb{E}_2[\text{buy}^0] > \mathbb{E}_2[\text{nb}^0]$ as $\mathbb{E}_2[\text{buy}^0] = (u - p)\beta_1^4 + (u-p)\beta_2^4 + (-p)\beta_3^4 + (-p)\beta_4^4 = (u-p)q - p(1-q) = uq - p > 0 = \mathbb{E}_2[\text{nb}^0]$. By

sequential rationality, this equilibrium cannot be a sequential equilibrium.

Table 37: The Normal-Form Representaticon of Model 1 in which the Players' Best Responses are Marked

Buyer (Player 2) \ Expert (Player 1)	H^+H^-		H^+L^-		L^+H^-		L^+L^-	
$ac\ buy^+buy^-buy^0$	$uq-p-x$	$(v+r)q-p+x$	$uq-p-x$	$vq-p+x+r$	$uq-p-x$	$vq-p+x$	$uq-p-x$	$(v+r)q-p+x$
$ac\ buy^+nb^-buy^0$	$uq-p-x$	$(v+r)q-p+x$	$(u-p)q-x$	$(v+r)q-p+x$	$pq-p-x$	$vq-p+x$	$-x$	$vq-p+x$
$ac\ buy^+buy^-nb^0$	$uq-p-x$	$(v+r)q-p+x$	$uq-p-x$	$vq-p+x+r$	$uq-p-x$	$vq-p+x$	$uq-p-x$	$(v+r)q-p+x$
$ac\ buy^+nb^-nb^0$	$uq-p-x$	$(v+r)q-p+x$	$(u-p)q-x$	$(v+r)q-p+x$	$pq-p-x$	$vq-p+x$	$-x$	$vq-p+x$
$ac\ nb^+buy^-buy^0$	$-x$	$vq-p+x$	$pq-p-x$	$(v+r)q-p+x$	$(u-p)q-x$	$vq-p+x$	$uq-p-x$	$(v+r)q-p+x$
$ac\ nb^+nb^-buy^0$	$-x$	$vq-p+x$	$-x$	$vq-p+x$	$-x$	$vq-p+x$	$-x$	$vq-p+x$
$ac\ nb^+buy^-nb^0$	$-x$	$vq-p+x$	$pq-p-x$	$(v+r)q-p+x$	$(u-p)q-x$	$vq-p+x$	$uq-p-x$	$(v+r)q-p+x$
$ac\ nb^+nb^-nb^0$	$-x$	$vq-p+x$	$-x$	$vq-p+x$	$-x$	$vq-p+x$	$-x$	$vq-p+x$
$ref\ buy^+buy^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$
$ref\ buy^+nb^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$
$ref\ buy^+buy^-nb^0$	0	$vq-p$	0	$vq-p$	0	$vq-p$	0	$vq-p$
$ref\ buy^+nb^-nb^0$	0	$vq-p$	0	$vq-p$	0	$vq-p$	0	$vq-p$
$ref\ nb^+buy^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$
$ref\ nb^+nb^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$	$uq-p$	$vq-p$
$ref\ nb^+buy^-nb^0$	0	$vq-p$	0	$vq-p$	0	$vq-p$	0	$vq-p$
$ref\ nb^+nb^-nb^0$	0	$vq-p$	0	$vq-p$	0	$vq-p$	0	$vq-p$

Table 38: The Normal-Form Representation of Model 2 in which the Players' best Responses are marked.

Buyer (Player 2) \ Expert (Player 1)	reg^+reg^-		reg^+dis^-		dis^+reg^-		dis^+dis^-	
$ac\ buy^+buy^-buy^0$	$uq-p-x$	$(v+r)q-p+x$	$uq-p-x$	$(v-p+\underline{p})q-\underline{p}+x+r$	$uq-p-x$	$(v+p-\underline{p})q-p+x$	$uq-p-x$	$(v-r)q-\underline{p}+x+r$
$ac\ buy^+nb^-buy^0$	$uq-p-x$	$(v+r)q-p+x$	$(u-p)q-x$	$(v-p+\underline{p}+r)q-\underline{p}+x$	$pq-p-x$	$(v+p-\underline{p})q-p+x$	$-x$	$vq-\underline{p}+x$
$ac\ buy^+buy^-nb^0$	$uq-p-x$	$(v+r)q-p+x$	$uq-p-x$	$(v-p+\underline{p})q-\underline{p}+x+r$	$uq-p-x$	$(v+p-\underline{p})q-p+x$	$uq-p-x$	$(v-r)q-\underline{p}+x+r$
$ac\ buy^+nb^-nb^0$	$uq-p-x$	$(v+r)q-p+x$	$(u-p)q-x$	$(v-p+\underline{p}+r)q-\underline{p}+x$	$pq-p-x$	$(v+p-\underline{p})q-p+x$	$-x$	$vq-\underline{p}+x$
$ac\ nb^+buy^-buy^0$	$-x$	$vq-p+x$	$pq-p-x$	$(v-p+\underline{p}-r)q-\underline{p}+x+r$	$(u-p)q-x$	$(v+p-\underline{p})q-p+x$	$uq-p-x$	$(v-r)q-\underline{p}+x+r$
$ac\ nb^+nb^-buy^0$	$-x$	$vq-p+x$	$-x$	$(v-p+\underline{p})q-\underline{p}+x$	$-x$	$(v+p-\underline{p})q-p+x$	$-x$	$vq-\underline{p}+x$
$ac\ nb^+buy^-nb^0$	$-x$	$vq-p+x$	$pq-p-x$	$(v-p+\underline{p}-r)q-\underline{p}+x+r$	$(u-p)q-x$	$(v+p-\underline{p})q-p+x$	$uq-p-x$	$(v-r)q-\underline{p}+x+r$
$ac\ nb^+nb^-nb^0$	$-x$	$vq-p+x$	$-x$	$(v-p+\underline{p})q-\underline{p}+x$	$-x$	$(v+p-\underline{p})q-p+x$	$-x$	$vq-\underline{p}+x$
$ref\ buy^+buy^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$q(v-p+\underline{p})-\underline{p}$	$uq-p$	$q(v+p-\underline{p})-p$	$uq-p$	$vq-p$
$ref\ buy^+nb^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$q(v-p+\underline{p})-\underline{p}$	$uq-p$	$q(v+p-\underline{p})-p$	$uq-p$	$vq-p$
$ref\ buy^+buy^-nb^0$	0	$vq-p$	0	$q(v-p+\underline{p})-\underline{p}$	0	$q(v+p-\underline{p})-p$	0	$vq-p$
$ref\ buy^+nb^-nb^0$	0	$vq-p$	0	$q(v-p+\underline{p})-\underline{p}$	0	$q(v+p-\underline{p})-p$	0	$vq-p$
$ref\ nb^+buy^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$q(v-p+\underline{p})-\underline{p}$	$uq-p$	$q(v+p-\underline{p})-p$	$uq-p$	$vq-p$
$ref\ nb^+nb^-buy^0$	$uq-p$	$vq-p$	$uq-p$	$q(v-p+\underline{p})-\underline{p}$	$uq-p$	$q(v+p-\underline{p})-p$	$uq-p$	$vq-p$
$ref\ nb^+buy^-nb^0$	0	$vq-p$	0	$q(v-p+\underline{p})-\underline{p}$	0	$q(v+p-\underline{p})-p$	0	$vq-p$
$ref\ nb^+nb^-nb^0$	0	$vq-p$	0	$q(v-p+\underline{p})-\underline{p}$	0	$q(v+p-\underline{p})-p$	0	$vq-p$

Table 39: Sequential Equilibria in Model 1 under A1-A2

NE in Model 1 under $A1$-$A2$			
	Player 1	Player 2	Seq. Equilibrium
I	H^+L^-	$ac\ buy^+nb^-buy^0$	✓
II	H^+L^-	$ac\ buy^+nb^-nb^0$	×
III	L^+L^-	$ref\ buy^+buy^-buy^0$	✓
IV	L^+L^-	$ref\ nb^+buy^-buy^0$	✓
V	L^+L^-	$ref\ nb^+nb^-buy^0$	×
VI	L^+L^-	$ref\ buy^+nb^-buy^0$	×
VII	H^+H^-	$ref\ buy^+buy^-buy^0$	✓
VIII	H^+H^-	$ref\ nb^+nb^-buy^0$	×
IX	H^+H^-	$ref\ buy^+nb^-buy^0$	✓
X	H^+H^-	$ref\ nb^+buy^-buy^0$	×

- **Equilibrium V and VI:** For any completely mixed strategies b^m with $s_m = b_1^m(H^+) \to 0, t_m = b_1^m(H^-) \to 0$, consider the corresponding Bayesian consistent belief at the third information set as in (A.3): $\beta^{m3} \longrightarrow (q, 1-q)$. By sequential rationality, Player 2 plays buy^- at his third information set as $\mathbb{E}_2[\text{buy}^-] = (u-p-x)q + (-p-x)(1-q) = uq-p-x > -x = \mathbb{E}_2[\text{nb}^-]$.

- **Equilibrium VIII and X:** For any completely mixed strategies b^m with $s_m = b_1^m(H^+) \to 1, t_m = b_1^m(H^-) \to 1$, consider the corresponding Bayesian consistent belief at the second information set as in (A.2): $\beta^{m2} \longrightarrow (q, 1-q)$. By sequential rationality, Player 2 plays buy^+ at his second information set as $\mathbb{E}_2[\text{buy}^+] = (u-p-x)q + (-p-x)(1-q) = uq-p-x > -x = \mathbb{E}_2[\text{nb}^+]$.

Sequential equilibria in the game of Model 2

Consider again a completely mixed behavioral strategy (bi. b2) and the Bayesian consistent belief system g as described above. In Tables C.13 and A.7 we see that 3 out of 6 Nash equilibria are sequential and the corresponding belief systems. We remark that Equilibrium I shows the desired behavioral strategy and that the set of sequential equilibria in Model 2 is included in the set of those in Model 1.

Table 40. Belief Systems for Equilibria in Model 1 under AI-A2: For the Sequence of Assessments, the Corresponding Bayesian Consistent Beliefs are Calculated as in (A.1)-(A.4)

Equilibrium	Belief System	Assessment Sequence ($m \geq 2$)
I	$\beta^1 = (q, 0, 0, 1-q)$ $\beta^2 = (1, 0)$ $\beta^3 = (0, 1)$ $\beta^4 = (q, 0, 0, 1-q)$	$b_1^m(H^+) = 1 - 1/m, b_1^m(H^-) = 1/m$ $b_2^m(ac) = 1 - 1/m, b_2^m(buy^-) = 1/m$ $b_2^m(buy^+) = b_2^m(buy^0) = 1 - 1/m$
III	$\beta^1 = (0, q, 0, 1-q)$ $\beta^2 = (q, 1-q)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (0, q, 0, 1-q)$	$b_1^m(H^+) = b_1^m(H^-) = 1/m$ $b_2^m(ac) = 1/m, b_2^m(buy^+) = 1 - 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1 - 1/m$
IV	$\beta^1 = (0, q, 0, 1-q)$ $\beta^2 = (0, 1)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (0, q, 0, 1-q)$	$b_1^m(H^+) = 1/m^2, b_1^m(H^-) = 1/m$ $b_2^m(ac) = b_2^m(buy^+) = 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1 - 1/m$
VII	$\beta^1 = (q, 0, 1-q, 0)$ $\beta^2 = (q, 1-q)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (q, 0, 1-q, 0)$	$b_1^m(H^+) = b_1^m(H^-) = 1 - 1/m$ $b_2^m(ac) = 1/m, b_2^m(buy^+) = 1 - 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1 - 1/m$
IX	$\beta^1 = (q, 0, 1-q, 0)$ $\beta^2 = (q, 1-q)$ $\beta^3 = (0, 1)$ $\beta^4 = (q, 0, 1-q, 0)$	$b_1^m(H^+) = 1 - 1/m^2, b_1^m(H^-) = 1 - 1/m$ $b_2^m(ac) = 1/m, b_2^m(buy^-) = 1/m$ $b_2^m(buy^+) = b_2^m(buy^0) = 1 - 1/m$

The reasons behind the failure of the other equilibria are as follows:

- **Equilibrium II:** For any $b_1^m(reg^+), b_1^m(reg^-) \in (0,1)$, $\mathbb{E}_2[\text{buy}^0] > \mathbb{E}_2[\text{nb}^0]$ as $\mathbb{E}_2[\text{buy}^0] = (u-p)\beta_1^4 + (u-p)\beta_2^4 + (-p)\beta_3^4 + (-p)\beta_4^4 = (u-p)q - p(1-q) = uq - p > 0 = \mathbb{E}_2[\text{nb}^0]$. By sequential rationality, this equilibrium cannot be a sequential equilibrium.

- **Equilibrium V and VI:** For any completely mixed strategies b^m with $s_m = b_1^m(reg^+) \to 0, t_m = b_1^m(reg^-) \to 0$, consider the corresponding Bayesian consistent belief at the third information set as in (A.3): $\beta^{m3} \longrightarrow (q, 1-q)$. By sequential rationality, Player 2 plays buy^- at his third information set as $\mathbb{E}_2[\text{buy}^-] = (u-p-x)q + (-p-x)(1-q) = uq - p - x > -x = \mathbb{E}_2[\text{nb}^-]$.

G Appendix P7: Determination of Nash and Sequential Equilibria under A1', A2', and A3

We proceed as in the previous section and give the distinction between Nash and sequential equilibria in Model 1 (Model 2) in Table 41 (Table B.43) as well as the corresponding belief systems in Tables 42 and 44 followed by the contradictions that the remaining Nash equilibria are not sequential.

Table 41: Sequential Equilibria in Model 2 under AI-A3

NE in Model 2 under $A1$-$A3$			
	Player 1	Player 2	SE
I	reg^+dis^-	$ac\ buy^+nb^-buy^0$	✓
II	reg^+dis^-	$ac\ buy^+nb^-nb^0$	×
III	dis^+dis^-	$ref\ buy^+buy^-buy^0$	✓
IV	dis^+dis^-	$ref\ nb^+buy^-buy^0$	✓
V	dis^+dis^-	$ref\ nb^+nb^-buy^0$	×
VI	dis^+dis^-	$ref\ buy^+nb^-buy^0$	×

Table 42: Belief Systems for Equilibria in Model 2 under AI-A3: For the Sequence of Assessments, the Corresponding Bayesian Consistent Beliefs are Calculated as in (A.1)-(A.4)

Equilibrium	Belief System	Assessment Sequence ($m \geq 2$)
I	$\beta^1 = (q,0,0,1-q)$ $\beta^2 = (1,0)$ $\beta^3 = (0,1)$ $\beta^4 = (q,0,0,1-q)$	$b_1^m(reg^+) = 1-1/m, b_1^m(reg^-) = 1/m$ $b_2^m(ac) = 1-1/m, b_2^m(buy^-) = 1/m$ $b_2^m(buy^+) = b_2^m(buy^0) = 1-1/m$
III	$\beta^1 = (0,q,0,1-q)$ $\beta^2 = (q,1-q)$ $\beta^3 = (q,1-q)$ $\beta^4 = (0,q,0,1-q)$	$b_1^m(reg^+) = b_1^m(reg^-) = 1/m$ $b_2^m(ac) = 1/m, b_2^m(buy^+) = 1-1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1-1/m$
IV	$\beta^1 = (0,q,0,1-q)$ $\beta^2 = (0,1)$ $\beta^3 = (q,1-q)$ $\beta^4 = (0,q,0,1-q)$	$b_1^m(reg^+) = 1/m^2, b_1^m(reg^-) = 1/m$ $b_2^m(ac) = b_2^m(buy^+) = 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1-1/m$

Again, the set of equilibria shrinks when moving from Model 1 to Model 2. Under the as- sumptions the desired strategy here requires the buyer not to buy the product when uninformed. It is part of the sequential equilibrium II and prevails in both models.

Reasoning for the non-sequential equilibria in Model 1:

- **Equilibrium I** For any $b_1^m(H^+), b_1^m(H^-) \in (0,1)$, $\mathbb{E}_2[\text{buy}^0] < \mathbb{E}_2[\text{nb}^0]$ as $\mathbb{E}_2[\text{buy}^0] = (u-p)\beta_1^4 + (u-p)\beta_2^4 + (-p)\beta_3^4 + (-p)\beta_4^4 = (u-p)q - p(1-q) = uq - p < 0 = \mathbb{E}_2[\text{nb}^0]$. By sequential rationality, this equilibrium cannot be a sequential equilibrium.

- **Equilibrium III and IV** For any completely mixed strategies b^m with $s_m = b_1^m(H^+) \to 0, t_m = b_1^m(H^-) \to 0$, consider the corresponding Bayesian consistent belief at the third information set as in (A.3): $\beta^{m3} \longrightarrow (q, 1-q)$. By sequential rationality, Player 2 plays nb^- at his third information set as $\mathbb{E}_2[\text{buy}^-] = (u-p-x)q + (-p-x)(1-q) = uq - p - x < -x = \mathbb{E}_2[\text{nb}^-]$.

- **Equilibrium VII and IX** For any completely mixed strategies b^m with $s_m = b_1^m(H^+) \to 1, t_m = b_1^m(H^-) \to 1$, consider the corresponding Bayesian consistent belief at the second information set as in (A.2): $\beta^{m2} \longrightarrow (q, 1-q)$. By sequential rationality, Player 2 plays nb^+ at his second information set as $\mathbb{E}_2[\text{buy}^+] = (u-p-x)q + (-p-x)(1-q) = uq - p - x < -x = \mathbb{E}_2[\text{nb}^+]$.

Table 43: Sequential Equilibria in Model 1 under the Assumptions A1', and A2': it is easy to see that there are 10 Nash Equlibria in Pure Strategies under the Assumptions

NE in Model 1 under $A1'$, and $A2'$			
	Player 1	Player 2	SE
I	H^+L^-	$ac\ buy^+nb^-buy^0$	$\times$
II	H^+L^-	$ac\ buy^+nb^-nb^0$	$\checkmark$
III	L^+L^-	$ref\ buy^+buy^-nb^0$	$\times$
IV	L^+L^-	$ref\ nb^+buy^-nb^0$	$\times$
V	L^+L^-	$ref\ nb^+nb^-nb^0$	$\checkmark$
VI	L^+L^-	$ref\ buy^+nb^-nb^0$	$\checkmark$
VII	H^+H^-	$ref\ buy^+buy^-nb^0$	$\times$
VIII	H^+H^-	$ref\ nb^+nb^-nb^0$	$\checkmark$
IX	H^+H^-	$ref\ buy^+nb^-nb^0$	$\times$
X	H^+H^-	$ref\ nb^+buy^-nb^0$	$\checkmark$

Table 44: Belief Systems for Equlibria in Model 1 under A1', and A2': for the Sequence of Assessments, the Corresponding Bayesian Beliefs are Calculated as in (A.1)-(A.4)

Equilibrium	Belief System	Assessment Sequence ($m \geq 2$)
II	$\beta^1 = (q, 0, 0, 1-q)$ $\beta^2 = (1, 0)$ $\beta^3 = (0, 1)$ $\beta^4 = (q, 0, 0, 1-q)$	$b_1^m(H^+) = 1 - 1/m, b_1^m(H^-) = 1/m$ $b_2^m(ac) = b_2^m(buy^+) = 1 - 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1/m$
V	$\beta^1 = (0, q, 0, 1-q)$ $\beta^2 = (q, 1-q)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (0, q, 0, 1-q)$	$b_1^m(H^+) = b_1^m(H^-) = 1/m$ $b_2^m(ac) = b_2^m(buy^+) = 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1/m$
VI	$\beta^1 = (0, q, 0, 1-q)$ $\beta^2 = (1, 0)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (0, q, 0, 1-q)$	$b_1^m(H^+) = 1/m, b_1^m(H^-) = 1/m^2$ $b_2^m(ac) = 1/m, b_2^m(buy^+) = 1 - 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1/m$
VIII	$\beta^1 = (q, 0, 1-q, 0)$ $\beta^2 = (q, 1-q)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (q, 0, 1-q, 0)$	$b_1^m(H^+) = b_1^m(H^-) = 1 - 1/m$ $b_2^m(ac) = b_2^m(buy^+) = 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1/m$
X	$\beta^1 = (q, 0, 1-q, 0)$ $\beta^2 = (q, 1-q)$ $\beta^3 = (1, 0)$ $\beta^4 = (q, 0, 1-q, 0)$	$b_1^m(H^+) = 1 - 1/m, b_1^m(H^-) = 1 - 1/m^2$ $b_2^m(ac) = 1/m, b_2^m(buy^-) = 1 - 1/m$ $b_2^m(buy^+) = b_2^m(buy^0) = 1/m$

Nonsequential equilibria in Model 2:

- **Equilibrium I:** For any $b_1^m(reg^+), b_1^m(reg^-) \in (0,1)$, $\mathbb{E}_2[\text{buy}^0] < \mathbb{E}_2[\text{nb}^0]$ as $\mathbb{E}_2[\text{buy}^0] = (u-p)\beta_1^4 + (u-p)\beta_2^4 + (-p)\beta_3^4 + (-p)\beta_4^4 = (u-p)q - p(1-q) = uq - p < 0 = \mathbb{E}_2[\text{nb}^0]$. By sequential rationality, this equilibrium cannot be a sequential equilibrium.
- **Equilibrium III and IV:** For any completely mixed strategies b^m with $s_m = b_1^m(reg^+) \to 0, t_m = b_1^m(reg^-) \to 0$, consider the corresponding Bayesian consistent belief at the third information set as in (A.3): $\beta^{m3} \longrightarrow (q, 1-q)$. By sequential rationality, Player 2 plays nb^- at his third information set as $\mathbb{E}_2[\text{buy}^-] = (u-p-x)q + (-p-x)(1-q) = uq - p - x < -x = \mathbb{E}_2[\text{nb}^-]$.

H Appendix P7: Determination of sequential equilibria when uq — p = 0

Under the assumption uq — p = 0, i.e., the uninformed buyer is indifferent between buying and not buying, Model 1 has 18 pure strategy Nash equilibria that can be found via the normal- form representation of that simultaneous move game in Table 37. Similarly, there are 10 pure strategy Nash equilibria of Model 2 via Table 38. What is different to the previous sections is that all Nash equilibria are also sequential equilibria. Moreover, the set of sequential equilibria in either model is the union of the sets of sequential equilibria given in Appendix F and Appendix G.

We present for each model separately the sets of equilibria and demonstrate that they are sequential.

Table 45: Sequential Equilibria in Model 2 under A1', A2' and A3'

NE in Model 2 under $A1'$, $A2'$, and $A3$			
	Player 1	Player 2	SE
I	reg^+dis^-	$ac\ buy^+nb^-buy^0$	×
II	reg^+dis^-	$ac\ buy^+nb^-nb^0$	✓
III	dis^+dis^-	$ref\ buy^+buy^-nb^0$	×
IV	dis^+dis^-	$ref\ nb^+buy^-nb^0$	×
V	dis^+dis^-	$ref\ nb^+nb^-nb^0$	✓
VI	dis^+dis^-	$ref\ buy^+nb^-nb^0$	✓

Table 46:Belief Systems for Equilibria in Model 2 under Al', A2', and A3: For the Sequence of Assessments, the Corresponding Bayesian Consistent Beliefs are Calculated as in (A.1)-(A.4)

Equilibrium	Belief System	Assessment Sequence ($m \geq 2$)
II	$\beta^1 = (q, 0, 0, 1-q)$ $\beta^2 = (1, 0)$ $\beta^3 = (0, 1)$ $\beta^4 = (q, 0, 0, 1-q)$	$b_1^m(reg^+) = 1 - 1/m, b_1^m(reg^-) = 1/m$ $b_2^m(ac) = b_2^m(buy^+) = 1 - 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1/m$
V	$\beta^1 = (0, q, 0, 1-q)$ $\beta^2 = (1, 0)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (0, q, 0, 1-q)$	$b_1^m(reg^+) = 1/m, b_1^m(reg^-) = 1/m^2$ $b_2^m(ac) = b_2^m(buy^+) = 1/m$ $b_2^m(buy^-) = b_2^m(buy^0) = 1/m$
VI	$\beta^1 = (0, q, 0, 1-q)$ $\beta^2 = (1, 0)$ $\beta^3 = (q, 1-q)$ $\beta^4 = (0, q, 0, 1-q)$	$b_1^m(reg^+) = 1/m, b_1^m(reg^-) = 1/m^2$ $b_2^m(ac) = b_2^m(buy^-) = 1/m$ $b_2^m(buy^+) = 1 - 1/m, b_2^m(buy^0) = 1/m$

Before going into the details of why all equilibria are sequential, an observation regarding to the equilibrium behavior of Player 2 is worth noting: Unlike Appendix A and Appendix B, Player 2 is indifferent between the alternatives at the fourth information set, i.e., $\mathbb{E}_2[\text{buy}^0] = \mathbb{E}_2[\text{nb}^0]$ for any b, β as $\mathbb{E}_2[\text{buy}^0] = (u-p)\beta_1^4 + (u-p)\beta_2^4 + (-p)\beta_3^4 + (-p)\beta_4^4 = (u-p)q - p(1-q) = uq - p = 0 = \mathbb{E}_2[\text{nb}^0]$.

- **Equilibrium I:** Consider the following completely mixed behavioral strategies: $b_1^m(H^+) = 1 - 1/m \to 1, b_1^m(H^-) = 1/m \to 0$, and $b_2^m(ac) = 1 - 1/m \to 1$, $b_2^m(buy^+) = 1 - 1/m \to 1, b_2^m(buy^-) = \frac{1}{m} \to 0, b_2^m(buy^0) \in (0,1)$. The corresponding Bayesian consistent belief

Table 47: The Sequential Equilibria of Model 1 when uq = p

NE in Model 1 when $uq = p$			
	Player 1	Player 2	SE
I	H^+L^-	$ac\ buy^+nb^-buy^0$	✓
		$ac\ buy^+nb^-nb^0$	✓
II	L^+L^-	$ref\ buy^+buy^-buy^0$	✓
		$ref\ nb^+buy^-buy^0$	✓
		$ref\ nb^+nb^-buy^0$	✓
		$ref\ buy^+nb^-buy^0$	✓
		$ref\ buy^+buy^-nb^0$	✓
		$ref\ nb^+buy^-nb^0$	✓
		$ref\ nb^+nb^-nb^0$	✓
		$ref\ buy^+nb^-nb^0$	✓
III	H^+H^-	$ref\ buy^+buy^-buy^0$	✓
		$ref\ nb^+nb^-buy^0$	✓
		$ref\ buy^+nb^-buy^0$	✓
		$ref\ nb^+buy^-buy^0$	✓
		$ref\ buy^+buy^-nb^0$	✓
		$ref\ nb^+nb^-nb^0$	✓
		$ref\ buy^+nb^-nb^0$	✓
		$ref\ nb^+buy^-nb^0$	✓

system is constructed as in Appendix A as follows: $\beta^{m1} \to (q,0,0,1-q) := \beta^1, \beta^{m2} \to (1,0) := \beta^2, \beta^{m3} \to (0,1) := \beta^3, \beta^{m4} \to (q,0,0,1-q) := \beta^4$.

- **Equilibrium II:** Consider the following completely mixed behavioral strategies: $b_1^m(H^+) = b_1^m(H^-) = \frac{1}{m} \to 0$, and $b_2^m(ac) = \frac{1}{m} \to 0$, $b_2^m(buy^+), b_2^m(buy^-), b_2^m(buy^0) \in (0,1)$ for any $m \geq 2$. The associated beliefs with b^m satisfying Bayesian consistency are $\beta^{m1} \to (0,q,0,1-q) := \beta^1, \beta^{m2} \to (q,1-q) := \beta^2, \beta^{m3} \to (q,1-q) := \beta^3and\beta^{m4} \to (0,q,0,1-q) := \beta^4$. Then, Player 2 is indifferent at all information sets except the first one.

- **Equilibrium III:** Consider the following completely mixed behavioral strategies: $b_1^m(H^+) = b_1^m(H^-) = 1 - \frac{1}{m} \to 1$, and $b_2^m(ac) = \frac{1}{m} \to 0$, $b_2^m(buy^+), b_2^m(buy^-), b_2^m(buy^0) \in (0,1)$ for all $m \geq 2$. The associated beliefs with b^m satisfying Bayesian consistency are $\beta^{m1} \to (q,0,1-q,0) := \beta^1, \beta^{m2} \to (q,1-q) := \beta^2, \beta^{m3} \to (q,1-q) := \beta^3and\beta^{m4} \to (q,0,1-q,0) := \beta^4$. Again, Player 2 is indifferent at all information sets except the first one.

The observation which was done above for Model 1 remains valid for Model 2, i.e., Player 2 is indifferent between the alternatives at the fourth information set.

- **Equilibrium I:** Consider $b_1^m(reg^+) = 1 - \frac{1}{m} \to 1, b_1^m(reg^-) = \frac{1}{m} \to 0, b_2^m(ac) = 1 - \frac{1}{m} \to 1$, $b_2^m(buy^+) = 1 - \frac{1}{m} \to 1, b_2^m(buy^-) = \frac{1}{m} \to 0$ and $b_2^m(buy^0) \in (0,1)$. Based on this behavioral strategies, Bayesian consistency implies β^m, the computed beliefs above: $\beta^{m1} \to (q,0,0,1-q) := \beta^1, \beta^{m2} \to (1,0) := \beta^2, \beta^{m3} \to (0,1) := \beta^3, \beta^{m4} \to (q,0,0,1-q) := \beta^4$.

Table 48: The Sequential Equilibria of Model 2 when uq = p

NE in Model 2 when $uq = p$			
	Player 1	Player 2	SE
I	$reg^{+}dis^{-}$	$ac\ buy^{+}nb^{-}buy^{0}$	✓
	$reg^{+}dis^{-}$	$ac\ buy^{+}nb^{-}nb^{0}$	✓
II	$dis^{+}dis^{-}$	$ref\ buy^{+}buy^{-}buy^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ nb^{+}buy^{-}buy^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ nb^{+}nb^{-}buy^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ buy^{+}nb^{-}buy^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ buy^{+}buy^{-}nb^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ nb^{+}buy^{-}nb^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ nb^{+}nb^{-}nb^{0}$	✓
	$dis^{+}dis^{-}$	$ref\ buy^{+}nb^{-}nb^{0}$	✓

- **Equilibrium II:** Consider $b_1^m(reg^+) = b_1^m(reg^-) = \frac{1}{m} \to 1, b_2^m(ac) = \frac{1}{m} \to 0, b_2^m(buy^+)$, $b_2^m(buy^-), b_2^m(buy^0) \in (0,1)$. These strategies lead to the Bayesian consistent beliefs in the way described above, so $\beta^{m1} \to (0, q, 0, 1-q) := \beta^1, \beta^{m2} \to (q, 1-q) := \beta^2, \beta^{m3} \to (q, 1-q) := \beta^3, \beta^{m4} \to (0, q, 0, 1-q) := \beta^4$.

9.8 Overcoming Lemon Markets with Business Reputation Ecosystem: A Multi-Agent Simulation on Monetary Ratings

Paper Number	P8	
Title	Overcoming Lemon Markets with Business Reputation Ecosystem: A Multi-Agent Simulation on Monetary Ratings	
Publication Type	Conference Paper	
Outlet	International Tagung Wirtschaftsinformatik (WI 2024)	
VHB JOURQUAL 4	B	
Authors	Ibrahimli, Ulvi	45%
	Hemmrich, Simon	35%
	Zauke, Simon	15%
	Winkelmann, Axel	5%
Status	Published	

Abstract. *Business reputation ecosystems are a widely untapped research field. In these ecosystems, agents can selectively exchange (monetary) ratings to inform about the experienced quality in a market. We build a model for conducting a multi-agent simulation (ABMS) that can be used to simulate and evaluate business reputation ecosystems as a new system class. We explore the factual occurring voluntary payment to create positive (pay) or negative ratings (no pay), selling ratings selectively to alleviate information asymmetry, and the workings of counter-ratings to prevent buyers' dishonest ratings. Thereby, we analyze the occurrence of dishonest ratings, the extent of price adjustments, and reputation sensitivity, among others. Simulation results show that high-quality sellers and buyers who sell ratings benefit from such a system, whereas low-quality sellers have disadvantages. The results indicate that counter-ratings prompt buyers to rate sellers honestly, albeit incurring the monetary cost for positive ratings.*

9.8.1 Introduction

Information asymmetry between buyers and sellers can lead to a downward spiral of the provided quality in business-to-business (B2B) markets (Akerlof, 1970; A. Banerjee et al., 2020). Reputation systems can reduce or even reverse this dynamic (Rice, 2012; Thierer et al., 2016). As information systems (IS), they collect, aggregate, and disseminate information about a product (Resnick et al., 2000). In the business-to-consumer (B2C) context, they demonstrated practical usefulness in the form of review systems (Gutt et al., 2019) or recommender systems (Jannach & Jugovac, 2019) for marketplaces like Amazon or eBay. Despite their significant benefits and daily use for product search, reputation systems poorly exist in B2B settings (Dikow et al., 2015; Gutt et al., 2019; Mai & Liao, 2021; Poniatowski et al., 2019). Several design weaknesses contribute to the underutilization of these system classes in B2B markets (Hemmrich et al., 2023; Seutter et al., 2023). These include inter alia low incentives to submit ratings (Neumann & Gutt, 2019a), the prevalence of distorted or reciprocal ratings, and the system's vulnerability to fake or unfair ratings (Ansari & Gupta, 2021; Mayzlin et al., 2014). Furthermore, businesses fear revealing capable suppliers to competitors and are challenged to compare products and services as well as to align conflicting stakeholder interests. Often, there is deliberate non-transparency regarding price and quality from the sellers' side (K. Zhu, 2002). Nevertheless, the research indicates that low product quality, delayed transactions, or volatile supplier performance are detrimental to forming trust, a critical factor in data exchange in B2B setups (McKnight et al., 2017). Consequently, we argue that such instances of intercompany misconduct necessitate establishing robust reputation systems in a B2B context. Reputation systems are viewed as essential technologies that digital ecosystems rely on to build or restore trust and foster corporate collaborations between agents (Dikow et al., 2015).

Designing business reputation ecosystems as a new system class (Hemmrich et al., 2023) is an upcoming advance to address the previously mentioned weaknesses (Hevner et al., 2008). In this new system class, companies—denoted as agents—collect and distribute ratings, which they can selectively communicate to one another. Two novel ideas proposed by Hemmrich (2023) are particularly relevant to this paper. 1) Sellers offer product discounts, expecting buyers to compensate by paying the full price. Buyers can freely and selectively choose to grant this compensation through positive ratings, effectively costing them the discounted amount.[78]1 On the other hand, sellers perform counter-ratings to penalize the exploitative rating of such buyers (e.g., when they do not pay the pre-agreed money), which becomes only visible (upon threshold) if the buyer consistently fails to pay the offered discount. Payments linked to ratings establish a direct quantifiable connection between a rating and a business transaction, incorporating a reputation mechanism that quantifies trust between agents (Hemmrich, 2023). 2) Buyers own their ratings and decide to whom (typically other buyers) they sell the rating information for profit. This incentive offers an alternative to hitherto seller-induced incentive schemes with potentially biased ratings (Neumann & Gutt, 2019a). Systems in which agents can validate stored quality information based on these ratings are generally superior to those that test only for honesty (Kennes & Schiff, 2007; McKnight et al., 2017). The ability to select ratings individually also appears essential for a business reputation ecosystem to function effectively (Hemmrich et al., 2023; Marti & Garcia-Molina, 2003).

We employ Agent-Based Modeling and Simulation (ABMS) to study and evaluate the effects of the proposed system class (Beese et al., 2019). A simulation is a particularly suitable means of investigating novel designs not implemented in the real world and assessing IS-induced phenomena (e.g., selection behavior of agents of trustworthy sellers) before practically instantiating an artifact (Sonnenberg & vom Brocke, 2012). Moreover, agent-based simulation enables configuring heterogeneous agents with self-learning adaptive strategic behavior. This capability closely mirrors the chain of complex interactions that take place within such information systems. The engineering of environment variables allows for evaluating the effectiveness of such IS in real B2B settings (Rand & Rust, 2011). The IS scholarship also reflects on its epistemic status – that is, mechanism-based methods are viewed as credible approaches for studying novel socio-technical IS phenomena and making epistemic inferences (Beese et al., 2019). Therefore, simulation furnishes strong scientific rigor (Beese et al., 2019; J. Venable et al., 2016). No simulation study has examined this kind of system class with monetary

[78] In this paper, the term "buyers" refers to purchasing companies in the B2B context. To avoid potential confusion, we will refer to buyers in B2C transactions as "consumers" where necessary.

ratings or counter-ratings. To gain prima facie empirical evidence of whether such a system functions, we formulate the following research question (RQ):

How do the incentives offered by monetary reputation ecosystems contribute to reducing information asymmetry between agents?

The paper continues by describing the theoretical background comprising information asymmetry, reputation systems, and ABMS. The subsequent section deals with agent-based model setup and parameters, followed by outcome analysis, evaluation, and discussion before concluding the study.

9.8.2 Research Background

9.8.2.1 Information Asymmetry

Akerlof's seminal work on 'The Market for Lemons' explores the impact of information asymmetry, exemplified in car markets. Sellers know more about product quality than buyers, leading to buyer uncertainty and reduced willingness to pay high prices. High quality is not recognized and disincentivizes sellers from offering higher quality, leading to a downward spiral of quality dominated by low-quality "lemons" (Akerlof, 1970). This effect of information asymmetry is also seen in most B2B transactions (A. Banerjee et al., 2020), where sellers cannot prove quality upfront. One form of signaling quality before is through reputation (Lingfang Li et al., 2020; Mui et al., 2002; C. Shapiro, 1982). Signaling quality with reputation can contribute to mitigate this problem (Fig. 34) (J. Devos et al., 2012). Reputation affects the perceived quality and is a known promoter for enhancing selling products successfully (Ba & Pavlou, 2002; Saeedi, 2019). Adverse selection and moral hazard can be addressed through pre- or post-contractual measures (Mavlanova et al., 2012) while trusting buyers contribute to a company's reputation and instill trust in uncertain sellers (Jøsang et al., 2007).

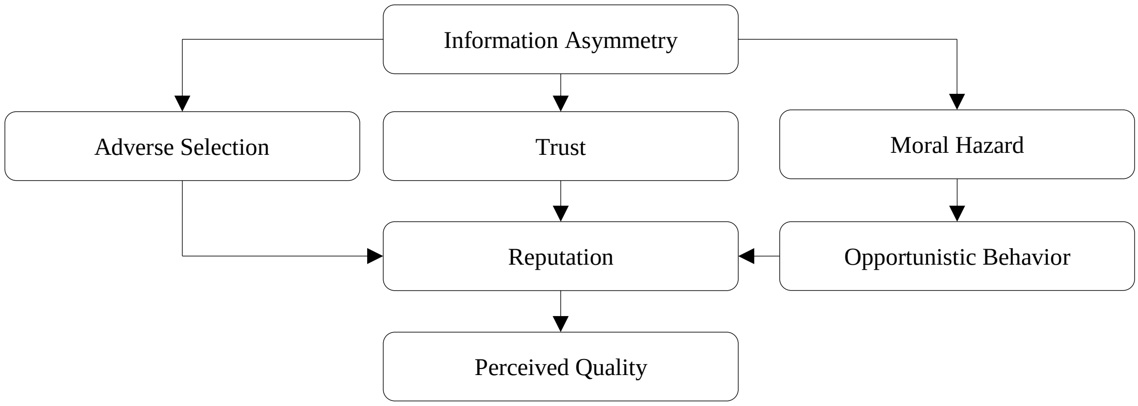

Figure 34: Lemon Market Theory: Nomological Network for Antecedents of Perceived Quality (J. Devos et al., 2012)

Reputation systems help signal good quality, thereby reducing information asymmetry and building trust (Saeedi, 2019; Thierer et al., 2016). Positive ratings from a positive reputation lower perceived risk for buyers, thus making them more willing to engage in transactions previously deemed too risky (Moreno & Terwiesch, 2014; C. Shapiro, 1982). The reliance on reputation increases willingness to transact with sellers, fostering economic stability and growth (Biong, 2013; Ghose & Ipeirotis, 2010). High-quality sellers aim to build a positive reputation for higher profits, while low-quality sellers try to avoid or manipulate ratings to appear more favorable (Salminen et al., 2022; C. Shapiro, 1983). Reputation systems, rooted in real-tested product quality, combat information asymmetry effectively (Kennes & Schiff, 2007). While reputation may not perfectly reflect quality (C. Shapiro, 1982), ratings from peer buyers in a reputation system serve as the best approximation (Moreno & Terwiesch, 2014; S. P. Shapiro, 1987). Trustworthy identities, such as known companies, contribute to the credibility of their ratings (Marti & Garcia-Molina, 2003; Whetten, 1997), promoting efficient and trustworthy markets (Kreps & Wilson, 1982).

9.8.2.2 Reputation Systems in B2B Context

Business reputation systems are yet to evolve in the future in the business context (Seutter, 2022). Notably, B2B transactions between companies present unique challenges compared to B2C contexts, such as differences in purchase intention, decision-making, complexity, information asymmetries, payment processes, product characteristics, usage, supplier relationships, and logistics (S. Chen et al., 2022; Choy et al., 2003; McKnight et al., 2017). Hence, business reputation systems face greater challenges than B2C systems in incentivizing rating agents, as submitting ratings involves resource commitment and time (Hemmrich et al., 2024). Consequently, the justification for rating efforts should align with a tangible business benefit (notably monetary incentives (N. Miller et al., 2005)). Additional challenges include the rater's experience or expertise in rating products (Dikow et al., 2015) and concerns about competitive disadvantages, potentially leading to hesitancy in sharing information (K. Zhu, 2002). Competitive situations may also influence rating submission, as companies might be reluctant to enhance the reputation of good suppliers, fearing the loss of a strategic advantage (Neumann & Gutt, 2019b). However, this concern is less pronounced in low- or non-competitive environments. *Selective* forwarding of information, where the original buyer verifies the authenticity of a rating, is considered a viable solution (Hemmrich et al., 2023).

As depicted in Fig. 35, the reputation system involves a seller offering a buyer a rating opportunity, with the payment as a rating being optional and indicative of the seller's delivered quality. Other buyers can observe monetary ratings received by a seller and request this information based on the trustworthiness of the identity. In contrast to B2C reputation systems, where the identity of the rating agent is less relevant, for business ratings, the identity significantly influences the trustworthiness of the given rating (Jøsang et al., 2007; Marti & Garcia-Molina, 2003). Ratings from renowned companies are deemed more trustworthy, given the perceived reluctance to risk their public reputation for a forged rating (Keh & Xie, 2009; van der Merwe & Puth, 2014), particularly when stored immutably (Hemmrich, 2023). A counter-rating mechanism in the form of a star rating restricts the visibility of negative ratings at first, becoming apparent only after excessive negative ratings across all sellers, determined by a visible threshold (Hemmrich, 2023). Moreover, the buyer has the discretion to confirm or refuse to pass on the requested rating, balancing the benefits (receiving compensation and potentially other ratings) against potential detriments (disclosing relevant information to competitors). Buyers selectively submit information about a seller's product quality, and other buyers can learn which identity of buying agents appears trustworthy, building a simulated self-learning adaptive system (Sabzian et al., 2018).

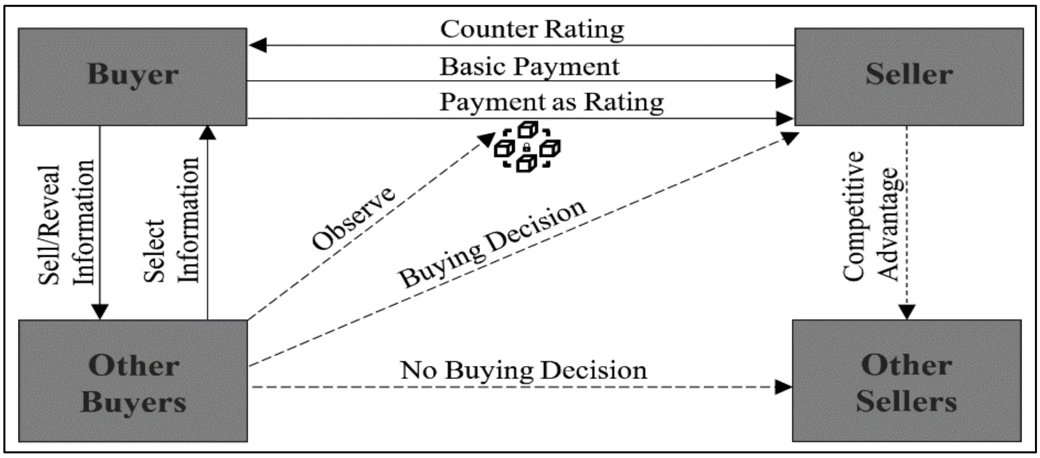

Figure 35: Mechanisms of the Business Reputation System (Hemmrich et al., 2024)

The context of B2B entails specific agent interactions. The following incentives should hold to show that our model works and can achieve solid simulation results (demonstration). Companies evaluate costs and benefits and must reproduce three incentives in the system design for agents (Hemmrich et al., 2023): (1) Sellers with a high reputation command a price premium in the long term, expecting higher profits than non-participation; (2) Buyers can profit by selling rating information, which means their revenue can exceed rating payments; (3) Buyers minimize losses by avoiding sellers that fail quality expectations.

9.8.3 Research Method

9.8.3.1 Agent-based Modeling and Simulation

Agent-based models are a particularly good fit to examine new properties of systems with simulations, forming the ABMS method (Wall, 2016). ABMS method helps understand complex patterns that emerge in markets due to the presence of many individual agents (Rand & Rust, 2011). It is a system design tool to investigate economic effects in dynamic markets with information asymmetries and to develop new theoretical insights (J. Q. Dong, 2022; Poggio et al., 2001). In the agent-based approach, properties of a system occur from individual, autonomous agents and their interactions in a shared environment (Macal, 2016).

Agents are discrete and identifiable individuals with assigned characteristics and rules that determine their behavior and decisions in a defined environment. They interact with their environment, including other agents, restricted to predefined rules. Agents recognize the characteristics of other agents, act autonomously in a goal-oriented manner, and compare the outcomes of their behavior with their goals. This way, they can store what they learned and adapt to experiences (Macal & North, 2009). Agents can have different capability levels: individual if-then execution (e.g., drive and stop), dynamic autonomous according to their state (e.g., refuel), interactivity with the environment (e.g., tow another car), adaptivity and learning based on experience (e.g., foresighted driving) (Macal, 2016).

9.8.3.2 Application and Evaluation Framework

We apply ABMS as a research method to empirically test how the described incentives contribute to reducing information asymmetry in monetary reputation ecosystems. For the research setup of simulation in IS research, our approach is based on the guidance of Beese et al. (2019) and Rand and Rust (2011). We first derive a conceptual model that serves as a foundation for the simulation. Based on this, we generate model parameters to run simulation scenarios with variations in agent numbers, the occurrence of dishonest ratings, the extent of price adjustments, the regulation of trading with ratings, and mechanisms for calculating the reputation of sellers.

The ABMS software NetLogo was chosen based on criteria like free availability, widespread use in research, moderate development effort, graphical display of simulation results with export options in textual data format, and portability.

In the application phase, we show that the model helps create the intended incentives (described in 2.2) necessary for the simulation and, thus, the ecosystem to function. In the evaluation phase, we assess to what extent the monetary reputation ecosystems reduce information asymmetries in a B2B market scenario. For this purpose, one can evaluate the model in terms of utility (main purpose), fitness (future permanence), and usefulness (practical use) (Gill & Hevner, 2013). We evaluate the model's utility to develop an understanding of the dynamics of information asymmetries in B2B markets using the metrics of Schlosser et al. (2004). The fitness of the model will be assessed as the reputation ecosystem evolves and new requirements emerge (Gill & Hevner, 2013), so this metric is skipped at this stage. To evaluate the model's usefulness, we study the behavior of the agents, e.g., to generate honest ratings for blacklisting sellers, and whether they achieve benefits within this system. Our model undergoes summative evaluation after the application phase. We avoid earlier formative evaluation due to the deterministic programming of the ABMS as a discrete system (R. E. Shannon, 1998). The chosen evaluation strategy allows for simulating different market scenarios with moderate time expenditure within this artificial evaluation (J. Venable et al., 2016).

9.8.4 Agent-based Model for Simulation

9.8.4.1 Agent Properties and Model Parameters

The agent-based model represents a decentralized market with seller and buyer agents, each representing a company. Sellers, $S=\{s_1, s_2, ..., s_n\}$, offer homogeneous products of varying quality, cost and price. Quality is modeled with a normal distribution (μ=50, σ=30). Quality, combined with a normally distributed random factor, co-determines production costs per product. Sellers set prices 20 percent above their costs, allowing for price adjustments. Buyers, $B=\{b_1, b_2, ..., b_m\}$, have properties like quality expecta-tion *quality* exp_b*~N(50,30)*, budget per purchase, price-reputation sensitivity, probabil-ity of unfair rating behavior, and star rating. The price-reputation sensitivity coefficient influences the purchase decision, a uniformly distributed random number (0,1), which prevents bias with sufficiently generated agents. Values below (or above) 0.5 indicate a preference for price (or reputation). Opportunistic rating behavior in the model occurs when b_j (any buyer) withholds the rating payment despite the s_j (any seller) meeting or exceeding the b_j's expectations. The likelihood of such behavior is a normdistributed-uted random number (μ=0) with a (later) specified standard deviation (*sd-malicious-behavior* [0.00,1.00]). Buyers possess $star - rating_b$[0.0,5.0] to regulate such behavior, which is the arithmetic mean of all received ratings.

In buyer-seller interactions within the ABM, the negotiated rating payment (*rpay* $amount_s^b$) and basic payment (*price reduced by rpay* $amount_s^b$) vary for each pair (b, s) upon negotiation b_j computes the selection probability of *sj* based on budget and price sensitivity (excluding blacklisted sellers where $quality_s$*<quality* exp_b*), price compared to mins* × *price sensitivity* $coef_b$. Other buyers can acquire reputation information from buyers through purchases or trading rating information. If b_j possesses reputation information about s_j, the selection probability involves adding the price comparison metric to the product of locally calculated reputation for s_j and b_j's reputation sensitivity (*price compared to mins* × *price sensitivity* $coef_b$) + *reps* × *reputation sensitivity* $coef_b$. The rating payment amount is modeled with a continuously equally distributed random number ranging from 5 to 20 percent of *S*'s price. The transaction's non-performance-dependent component (basic payment, *bpay*) is derived by subtracting the generated rating amount from the *sj*'s price. In addition, each buyer agent holds distinct properties: *transaction* $history_b$, *own reputation informationb, bought reputation* $information_b$, and *all reputation* $information_b$.

Model parameters facilitate the simulation of various scenarios. Four parameters af-fect sellers' pricing behavior post-monetary transactions. If the share of received per-formance (rating) payments surpasses a certain threshold, there is a price increase. Conversely, if the share falls below a threshold, prices decrease. Six model parameters regulate the trade with ratings. The *premium-for-sale-of-reputation information* [-1.00,1.00] determines the premium or discount for buyer agents' selling ratings. The model prevents an excessive number of ratings from being sold via a single provider (*nr-max-purchasable-repinfo-per-seller* [1,100]) and sets an upper limit for buyers from whom rating information can be purchased (*nr-max-buyers-to-buy-repinfo-from* [0,50]). Buyers can purchase a limited number of additional ratings (*base-nr-purchas-able-reputation-information* [0,20]) beyond their offer to buy. The *threshold-purchase-amount* [1,100] determines the minimum basic payment amount a buyer must pay so that trading with rating information becomes possible, and *reputation-information-to-buy* determines the criteria (newest, oldest, or all ratings) for purchasing rating information from another buyer.

To perform an artificial simulation scenario, we establish a set of base model parameters such that the subsequent variations of individual parameters can be ex-post evaluated against the base model. Some examples include: *sd-malicious-buyer-behaviour*=0.10; *threshold-buyer-star-rating*=3.0; *premium-for-sale-of-reputation-infor-mation*=0.20; *good-seller-share-of-rpays-received*=0.80; *price-premium-after-good-seller-performance* = 0.05; *bad-seller-share-of-rpays-received*=0.40.

9.8.4.2 Model for Simulation

Setup. The agent behavior is simulated in ten procedures, executed consecutively in a unit of time (*tick*) (Fig. 36). Here, the simulation generates seller and buyer agents with corresponding properties. Before the first tick run, no *bj* has any reputation information about s_j.

Matching. If no tick has yet elapsed, the first procedure is choosing a seller. In the first tick, each buyer *b* chooses a random *s* and creates a link to *s*. From the second tick onwards, each buyer initially creates a set of sellers within their budget and builds a link to each seller. Subsequently, a *selection* $probability_b$ a is calculated for each link. Only the link with the highest *selection* $probability_b$ remains. In the next process, sellers delete the links to buyers who have a $star - rating_b$<*threshold-buyer-star-rating* to prevent a possible systematic dishonest rating.

Payment Process. The remaining sellers and buyers calculate the amount of the rating payment in *negotiate-rpay*. This is followed by payment of the basic amount, *bpay*. Before *rating-process*, buyers inspect the quality of the product and decide whether they rate it negatively or positively (paying rpay). Based on the result, buyers make or do not make the rating payment and store this information in their transaction history. In another step, buyers can blacklist sellers. Based on rating payments received, sellers adjust their prices. Finally, the data on seller reputation are saved, and all links between sellers and buyers are deleted.

Trading with Ratings. *trade-reputation-information* is only executed if at least one tick has already been passed. Here, each buyer collects ratings that are within their budget from a set of *S*. This set contains sellers who performed at least one sale, are not on the buyer's blacklist, and for whom these b_j have bought at most as many ratings as technically possible. When a tick starts, b_j randomly selects a seller s_j from this set. Subsequently, each b_j has a maximum set of other buyers b_j for this seller s_j, defined by the model parameter *nr-max-buyers-to-buy-repinfo-from*, who have already inter-acted with this *sj* and had a transaction via *threshold-purchase-amount*. If a buyer does not find suitable other buyers, their set stays empty. Each b_j in this set sells, depending on *reputation-information-to-buy*, the oldest, newest, or all available ratings of the de-sired seller from *own reputation* $information_b$. to the other rating b_j. Each buyer stores the purchased ratings and calculates a reputation value for each potential seller and stores this individually in *all-reputation* $information_b$.

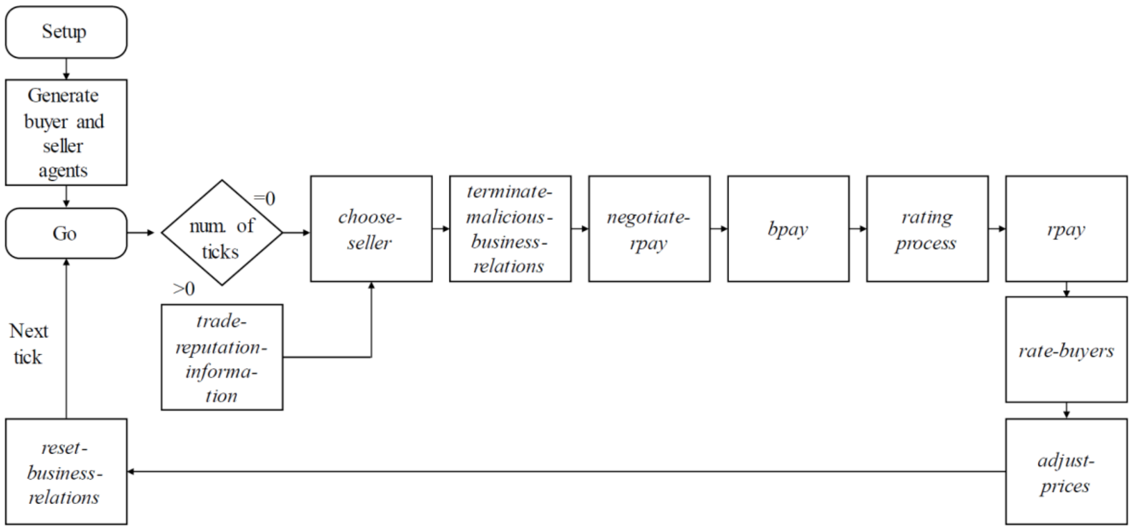

Figure 36: Model of Simulating Payment as Ratings Between Agents

9.8.5 Simulation Outcome

9.8.5.1 Application

Following the setup phase, seller (N=30) and buyer agents (N=50) are created with their properties in the time unit ticks=0. We observe heterogeneity among sellers in terms of quality, cost, and price and among buyers regarding quality expectations and budgets. The scenario is initially simulated over 50 ticks to gauge the results of seller behavior.

The sellers' profit is calculated from the rating and basic payments received minus the cost per unit multiplied by the number of sales. Due to a few outliers, we study median profit instead of average. The analysis shows that sellers with above-average product quality run at a loss after 50 ticks, albeit a smaller loss than low-quality sellers. To assess the long-run effects, we extend the simulation by an additional 150 ticks. We find that high-quality sellers eventually become profitable, whereas low-quality sellers suffer even greater losses. This finding highlights that consistently offering high-quality products pays off in the long run within a money-based reputation mechanism.

Looking at buyers, the difference between made rating payments and revenue from the sale of ratings is relevant as a profit metric. After 50 ticks, this difference averages positive and increases as buyers interact with more sellers. Buyers made the rating payments 80 percent of the time. The cluster analysis reveals that buyers with the highest probability of dishonest rating surprisingly achieve high profits initially, yet this effect diminishes in the long term. Also, reputation-sensitive buyers tend to be more profitable than price-sensitive buyers. These findings emphasize that buyer profitability is positively shaped by the interplay of distinct features of the reputation system.

Thus, we observe that the model works as intended. The first incentive (1) is validated as high-quality sellers achieve higher profits when the reputation system is switched on, and low-quality sellers benefit when switched off. The second incentive (2) also occurs, as buyer profits are positive on average and median. To test the third incentive (3), we measure each rating trade as to how much each buyer spends on buying rating information about sellers that do not meet their quality expectations and compute how high the losses would have been if they had bought from those sellers. After 200 ticks, for all buyers, the sum of potential losses incurred when choosing a bad seller exceeds the cost of buying the respective ratings. Thus, (3) incentive is also observed.

9.8.5.2 Evaluation

Evaluating the *utility* of choosing a capable seller, the reputation bias is computed as suggested in Schlosser et al. (2004) with small modifications. The bias measures how much the average reputation of each seller deviates from the reputation it should re-ceive. The mean reputation bias is computed based on the base setting of the model parameters. The average mean reputation bias achieved in ten simulations is 0.30 (Fig. 37). To observe the influence of variations of relevant model parameters on reputation bias according to One-Factor-At-a-Time (OFAT) sensitivity modeling, six param-eters are selected that govern the trade with ratings and reputation building: *nr-max-purchasable-repinfo-per-seller* ([10,100] with an interval of 10), *nr-max-buyers-to-buy-repinfo-from* ([1,45] with an interval of 5), *base-nr-purchasable-reputation-infor-mation* ([1,20] with an interval of 1), *threshold-purchase-amount* ([10,100] with an in-terval of 10), *reputation-information-to-buy* and *rep-computation-method* (all methods, see section 4.1). Subsequently, for each parameter we perform ten simulations (100 Ticks each), holding other parameters constant at the base model setup. We later set variables at values that individually generated the lowest average reputation bias and performed ten more simulation rounds. The optimized parameter setting indeed leads to overall reduced reputation bias (Figure 37).

To evaluate the *usefulness*, we study the effect of buyers' dishonest rating behavior

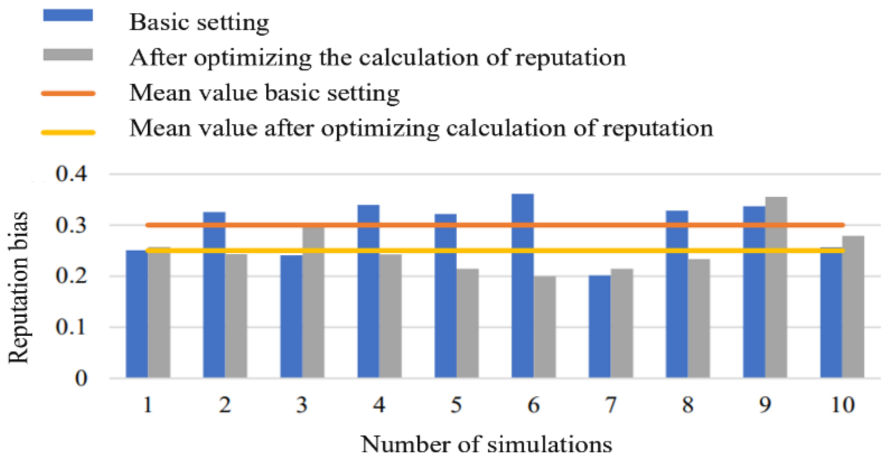

Figure 37: ABMS Reputation Bias Comparison with Basic Model Setup

through reputation bias and buyers' mean profit with a bias-optimized model parameter setting. The results show that reputation bias and buyers' mean profit increase with the probability of dishonest ratings. Buyers who often rate dishonestly have lower expenses for making rating payments than those who never or rarely rate dishonestly. However, a poor star rating discourages sellers from transacting with those buyers. Nonetheless, dishonest buyers can still profit from selling rating information. To address this, we adjusted the model parameter so that buyers do not purchase ratings from other buyers whose star ratings fall below $\mathrm{threshold-buyer-star-rating}_b$. We observe that although the buyers with the lowest probability of dishonest rating receive the highest profit, those with the highest probability still manage to generate high profits.

9.8.6 Discussion and Implications

The study provides simulation-based empirical evidence that the concept of money-based reputation systems in B2B markets can effectively incentivize participation. The results of this study have several implications for the research. We find that, albeit with short-term losses, sellers who consistently offer high-quality products benefit from participating in such a system in the long run. The fact that buyers typically make the rating payments in most cases implies that, in the long run, they are likely to find a seller that matches their quality expectations in such systems. This, coupled with the finding that fair rating buyers receive the highest profit from trading the rating information, indicates an overall reduced information asymmetry regarding the seller quality compared to the lemon market at the “cold start” The system incentivizes buyers to rate honestly, and honest buyers benefit the most from the monetary reputation system. However, dishonest raters also make significant profits. One likely explanation is that dishonest buyers often avoid paying rating payments, positively impacting their net profit. The adjusted star rating emerged as a suitable instrument to alleviate this problem as the model with a star rating shows lower reputation bias than the one without such an instrument. Yet future research needs to design a more robust counter-mechanism, as buyers may rate dishonestly not only for financial but also for strategic purposes (Panagopoulos et al., 2017).

On the other side, our study presents practical implications. The model developed can serve as a prototypical testing framework on, for example, digital B2B marketplaces for capital goods or E-Commerce platforms. Our model can be used to inform platform design and policies aimed at optimizing platform-based matchmaking and promoting trust in B2B transactions. Understanding the buyer-seller dynamics through the lens of reputation systems can help platforms design algorithms that highlight reputable sellers and allow buyer profits, thereby fostering a trustworthy digital marketplace. Nonetheless, certain caveats are to be considered. The fact that buyer profit increases as they interact with more sellers (Section 5.1) suggests a buyer's tendency to switch sellers frequently to sell more rating information. Thus, it is advised that practitioners design a countermeasure to address potential intercompany malpractices. Also, the dishonesty remains undetected when untruthful rating information is not sold to other buyers on such platforms. A remedy could be encouraging purchasing and comparing multiple ratings (Hemmrich, 2023).

Altogether, our work contributes to scholarly discourse within IS research by studying how B2B agents are incentivized to participate in money-based reputation systems. It sheds light on how the monetary nature of such ecosystems reduces information asymmetry. Through the lens of multi-agent simulation, our research offers a more nuanced empirical understanding of monetary reputation ecosystems in the B2B arena.

9.8.7 Conclusion

This study explores the design, functionality, and impact of monetary transaction-based reputation systems on information asymmetry to be used in B2B markets.

The study demonstrates the model's functionality by simulating a comprehensive market scenario and provides an initial evaluation of the concept of the business reputation ecosystem. It shows that it provides the necessary incentives for participation. Also, the information asymmetry is reduced since buyers, in the long run, are likely to find a seller that matches their quality expectations, and fair-rating buyers receive the highest profit from trading with ratings. Yet introducing a risky advance here in the form of monetary ratings is necessary to help digitize trust, as it entails a risk for sellers of receiving poor ratings and, consequently, less payment (Hemmrich, 2023). Our study reveals that the counter-rating instrument helped minimize dishonest rating behavior. However, the continued profitability of dishonest buyers indicates a need for future research to address this market failure comprehensively. The simulation model presented can unlock the potential of business reputation ecosystems. It sets the stage for further research on developing more robust reputation systems with dynamic agent parameters and exploring real-world applications of monetary reputation systems.

Our study comes with certain limitations. Given the choice of the ABMS as a research method, abstraction decisions were necessary. The abstractions include infinite supplier budgets and do not model the possibility of suppliers charging prices below production costs. Also, a more robust financial penalty mechanism is necessary for strategic dishonest ratings as it distorts such a system (Panagopoulos et al., 2017). For the results to be extrapolated to real-world situations, it must be verified whether the chosen abstraction leads to deviating agent behavior compared to real test subjects. In addition, future research still needs to address issues such as dynamic parallel adjustment of the model parameters and handling positive dishonest ratings.

9.9 The Value of Reputation Systems in Business Contexts: A Qualitative Study Taking the View of Buyers

Paper Number	P9	
Title	The Value of Reputation Systems in Business Contexts: A Qualitative Study Taking the View of Buyers	
Publication Type	Conference Paper	
Outlet	Hawaii International Conference on System Sciences (HICSS 2024)	
VHB JOURQUAL 4	A	
Authors	Hemmrich, Simon	60%
	Schäfer, Jannika	25%
	Hansmeier, Philipp	10%
	Beverungen, Daniel	5%
Status	Published	

Abstract. *Reputation systems for companies to rate each other's performance are largely unexplored in research and hardly available in practice. However, these systems are relevant for prospective buyers to find a trustworthy seller. This observation applies especially to short-lived business relationships where fulfilling the performance promise is subject to a high degree of uncertainty. This paper explores the value of a reputation system for a business-to-business (B2B) context and focuses on three novel solutions for designing reputation systems. These solutions include selling ratings, conducting ratings as payments, and employing a counter-rating mechanism. We interview buyers to fathom the added value of these solutions in different contexts. Our findings suggest that such a system is useful for companies acting in less transparent markets and also helps when companies already have a good market overview. Depending on the market conditions and business context, the perceived value of the proposed system varies.*

9.9.1 Introduction

Business companies lack a solid information system to select capable sellers or signal high capabilities. Therefore, business reputation systems will become highly relevant as an overarching decision support system for companies in the B2B context as soon as they allow buyers to make more informed buying decisions and enable sellers to profile with high quality.

In business-to-consumer (B2C) contexts like Amazon.com, these systems provide interested parties with information about others' experiences with products and services. Transferring reputation systems into B2B contexts can, amongst others, provide similar benefits, like increasing sales rates or improving product quality assessment (Ba & Pavlou, 2002). Despite their assumed importance for businesses, very little theoretical work exists on designing reputation systems for business contexts (Dikow et al., 2015; Gutt et al., 2019). This gap also fits the observation of a 'digital marketing capability gap' in the industrial context (Herhausen et al., 2020), which these systems can fill when they work properly (Sampath et al., 2006; Steward et al., 2018). Reputation systems might have *value* for buying decisions in the B2B context and may fundamentally transform business operations (e.g., marketing and supplier selection). These information systems can potentially withdraw *information asymmetry* between business companies (Y. Cai & Zhu, 2016; Thierer et al., 2016).

However, transferring such systems into B2B scenarios is difficult since current systems applied in B2C scenarios are still subject to various challenges (Jøsang & Goldbeck, 2009). Remarkably, there is a lack of incentives for participants to submit ratings; they are often biased with unfair ratings, while fake ratings remain a huge issue (Ansari & Gupta, 2021; Dellarocas, 2003; Fradkin et al., 2018; He et al., 2022; Neumann & Gutt, 2019a; Resnick & Zeckhauser, 2002). On top of that, B2B environments are even more complex, showing various peculiarities (S. Chen et al., 2022; Dellarocas, 2003; K. Zhu, 2002). Existing literature has not yet found adequate incentives for business parties to submit and share fair, unbiased, and honest ratings (Y. Cai & Zhu, 2016; Möhlmann et al., 2019; J. Pereira et al., 2019; Ryan, 2017).

Aiming to encounter these issues, we inspect the value of an initial advance to transfer reputation systems to business contexts as proposed by (Hemmrich, 2023; Hemmrich et al., 2023), building mainly on three novel solutions. First, a buyer can decide to sell a rating before sharing it. With this incentive, buyers are expected to be more interested in providing fair and honest ratings in non-competitive environments by increasing the profit of selling ratings. Second, buyers utilize payments as ratings, imbuing the rating with an inherent weight. Third, the system applies a counter-rating mechanism to prevent system exploitation of dishonest or unfair buyers.

In our qualitative study, we explore the value of the proposed system in varying business contexts through in-depth interviews with buyers in the role of business owners and employees. By collecting and analyzing their experiences and opinions, we gain general knowledge of how buyers assess the value of these solutions to design and build business reputation systems. Our research question is: "*How do buyers in B2B contexts assess the value of reputation systems based on the proposed ideas?*" By qualitatively exploring this issue, we aim to provide a first understanding of the complex design requirements for business reputation systems'.

Our findings indicate that our examined solutions to design reputation systems offer value (total perceived value) in different business contexts, especially for small-sized buying companies in less transparent markets. It may also help larger companies in some cases, even though it seems to strongly depend on factors like the industry sector, market size, and the buying process. To this end, we contribute hypotheses about the main criteria and dimensions buyers apply when judging the system's value to prepare the ground for further empirical work.

This paper unfolds as follows. Section 2 presents the theoretical background and explains the proposed solutions. Section 3 describes the research method, followed by Section 4, which displays our study's results. Section 5 discusses the perceived costs and benefits, while section 6 concludes the paper.

9.9.2 Theoretical Background

9.9.2.1 Information Asymmetries in the Buying Process

Information asymmetries exist in business transactions when a buyer does not obtain enough information about the quality delivered by a seller, while the seller knows its quality (Akerlof, 1978). In such cases, buyers have limited capabilities to assess the quality ex-ante of the transaction and are exposed to the risk of being dissatisfied. Information asymmetries in decision-making-related business transactions cause buyers to be subject to the risk that sellers do not deliver a product as expected. This problem exists especially in short-term online transactions, where low-quality sellers have a low risk of being detected for providing bad quality (Sullivan & Kim, 2018). To avoid inefficiencies and high agency costs for controlling an agent caused by information asymmetries, establishing a reputation and, thus, trust with reputation systems are proven measures to mitigate information asymmetries (Jøsang, 2007; Thierer et al., 2016).

While trust can be understood as one's positive expectation of another individual's actions (Williamson, 1993), reputation refers to the positive experiences of others towards an entity (Bromley, 2001). Evaluating reputation and trust with the definition of value for buyers as applied here, the value of these constructs lies primarily in reducing information asymmetry to make better buying decisions (Dimoka et al., 2012). By collecting, distributing, and aggregating feedback in the form of ratings, reputation systems provide relatively objectified measures for determining the capabilities of unknown parties (Resnick & Zeckhauser, 2002). Buyers can assess the trustworthiness of sellers and forward their experiences to other buyers. Still, current reputation systems remain ineffective in solving the adverse selection problem, so poor-quality sellers prevail in many markets (G. E. Bolton et al., 2004; Ghose, 2009; Hemmrich et al., 2023; Thierer et al., 2016).

9.9.2.2 Value as Construct in the Decision-Making Process of Buying

Value is a multilevel construct, and various definitions exist. We follow an economic interpretation as an "overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988, p. 14). This understanding of the study's central construct to assess the system is supplemented by Dodds et al. (1991) theoretical classification of a total perceived value (TPV). It is the outcome of a subjective assessment in which the perceived benefits (PB) are compared against perceived costs (PC). Taken together, perceived value refers to a subjective cost-benefit analysis. When PB outweighs PC, TPV is positive, and the proposed reputation system is worth using from an interviewee's perspective.

Reputation systems are applied in various contexts to incentivize desired behavior. Their primary benefit is helping reduce risk and associated uncertainty when interacting with strangers (Dimoka et al., 2012). Reducing risk is particularly important in non-transparent online marketplaces, where buyers have little information about sellers, e.g., when they are located in different countries (K. Zhu, 2002). Information about past sales lets a buyer expect the seller's future quality, decreasing buying uncertainty. Buyers are more likely to engage in a business deal if they believe sellers to continue to deliver a certain quality (Moreno & Terwiesch, 2014). Vice versa, buyers refrain from engaging with sellers, who are expected to provide insufficient quality.

Critical determinants of perceived costs are the effort required to use a reputation system and the perceived reliability of the system (Wan & Nakayama, 2014). If buyers expect submitting and retrieving ratings to take significant time and resources, they may be less likely to use the system (Neumann & Gutt, 2019b; Nosko & Tadelis, 2015). Equally, when buyers feel the reputation system is unreliable and provides inaccurate or misleading information, they are less likely to use it (Dimoka et al., 2012; Rice, 2012).

9.9.2.3 Proposed Solutions

The three proposed solutions are part of a venture to tackle current issues to transfer reputation systems in the business context (Hemmrich et al., 2023). When a buyer provides a positive rating and sells it to a prospective buyer, it increases the seller's reputation, thereby decreasing a buyer's uncertainty about engaging with this seller (Figure 38).

Monetary ratings: Buyers use monetary-based ratings to confer ratings an inherent weight and make them quantifiable. Therefore, a business transaction is divided into two parts. One part is considered the basic payment, while the second part manifests the actual rating (payment as rating). A monetary payment counteracts the inflationary issuance of positive ratings since ratings cost the rating buyers money, and identities can be selected individually, respective to their estimated trustworthiness (Forman et al., 2008). When the business transaction relates to a particular identity, one can check only submitted ratings from this identity (Hemmrich, 2023; Pornpitakpan, 2004).

Incentives to submit ratings: Buyers can sell ratings to interested parties, e.g., other buyers or information markets. Hence, a buyer who sells a rating is directly incentivized to submit a rating. The intention to sell further ratings to (the same) buyers adds a sustainable incentive to rate honestly. Taking the game-theoretical assumption of an infinite game in non-competitive environments, a rating buyer aims to provide honest ratings to hold his reputation accountable to sell more ratings in the future (S. Chen et al., 2022). Hence, this solution should contribute to solving the problem that an incentive to submit ratings is set directly from the seller's side, biasing ratings (Neumann & Gutt, 2019a). Instead, a potential buyer pays other current buyers for rating information and thus provides an incentive to generate ratings (Hemmrich et al., 2023).

Rating fairness: Sellers consent to be rated to prevent unauthorized buyers from submitting ratings. Also, the seller can react and counter-rate a buyer's rating when the seller receives a bad rating. Thus, a seller can submit a counter-rating (e.g., text rating) on how he feels a received bad rating is justified. The counter-ratings will become observable once a buyer's ratio between good and bad ratings exceeds a certain threshold (Ismail et al., 2003). Sellers can check this threshold to avoid exploitative buyers. Still, a buyer can now and then rate negatively without being detected by sellers, staying beneath a certain threshold. It can be expected that rational buyers will opt to a) stay beneath the threshold to stay in the game and be allowed to rate a seller reflecting a trust signal from this seller and b) try to generate more ratings and rate honestly in non-competitive environments to increase profits from sold ratings. On the other hand, a buyer's free-shot opportunity (rate negatively) is expected to make ratings more (risky and thus) meaningful and remedy the problem of reputation inflation (only favorable ratings) (Filippas et al., 2018). The seller's risk of being negatively rated underscores the value of a reputation and confirms potential buyers' trust that the system is unbiased (Hemmrich, 2023; Kreps & Wilson, 1982; Luhmann, 2017).

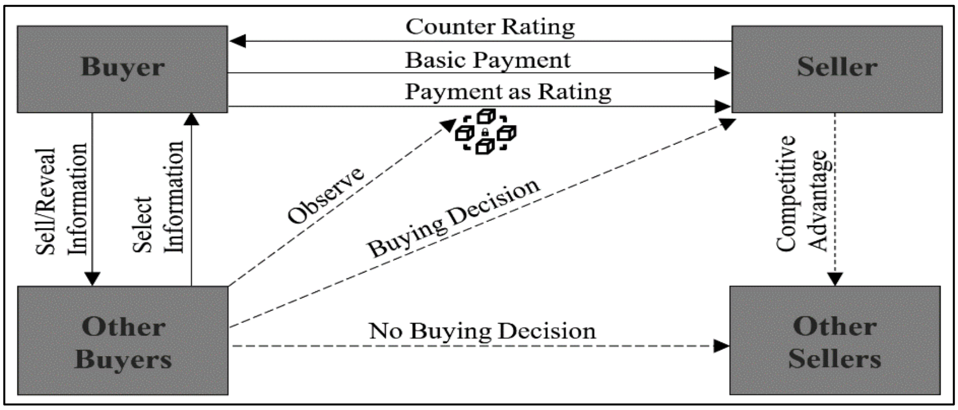

Figure 38: Mechanisms of the Proposed Reputation System (adopted: Hemmrich et al., 2023)

Reputation data can be used as a database to compare and evaluate ratings from diverse buyers. Sold ratings can be tested, compared among one another, and might be rated themselves (e.g., thumbs up or down). After having a profound data basis and network effects set in, it can be expected to be relatively easy to identify malicious raters (Forman et al., 2008; Lappas et al., 2016).

9.9.3 Research Method

It is unclear in which scenarios reputation systems are valuable. Therefore, it is vital to capture first under which circumstances this information system would be of value before commencing with its implementation (Sonnenberg & vom Brocke, 2012).

We adopt an empirical and explorative approach with different industry sectors and company sizes to address the proposed research question. This approach will help to generate theoretical and conceptual assumptions. Qualitative research enables to develop in-depth understanding of the particular phenomenon of B2B reputation systems. Concretely, it covers eight one-person interviews concerning B2B reputation systems in our study design. The interviewees have varying industrial backgrounds and are recruited through personal contact. As the interviews are collected during June 2022, this data can be classified as cross-sectional (Döring & Bortz, 2016). Furthermore, we follow a purposive sampling approach in the natural habit of the interviewees (Marshall, 1996), who must be procurement experts (Tab. 49).

Table 49: Overview of the Surveyed Companies

Company	Industry Sector	Company Size
Company A	Wholesale	Very large
Company B	Chemistry	Large
Company C	Food Production	Large
Company D	Electric manufacturer	Medium
Company E	Health	Medium
Company F	Food Retail	Small
Company G	Construction	Small
Company H	Nutritional supplements	Small

Regarding the data collection, we conduct semi-structured, qualitative interviews under the premise of openness (Döring & Bortz, 2016; H. O. Mayer, 2013). The interview questionnaire includes six elements containing information and questions about (1) the company, esp. the purchasing process; (2) the industry, esp. the market participants and overall transparency; (3) the concept description (the proposed business reputation system); (4) potential use cases; (5) the perceived value, and (6) emerging critique from buyers and sellers.

Finally, the interview material is analyzed for content paraphrasing, passages summarizing, core content synthesizing, and extracting inductive categories following Mayring's (2000) qualitative content analysis. The identified concepts incorporate the company's purchasing process, industry characteristics, reputation system usability factors, perceived benefits, and perceived costs.

9.9.4 Results

This study aims to generate insights into how B2B buyers assess the value of the proposed reputation system, with TPV defined as the ratio of PB and PC (Dodds et al., 1991). Here, 'how' refers to the perceived value derived from using the proposed reputation system and, on the other hand, to the criteria or dimensions by which the buyers assess the value of the business reputation system. The results are displayed in a visual form in Figure 39 below. The aspects are listed in descending order of perceived importance from the interviewees' perspectives.

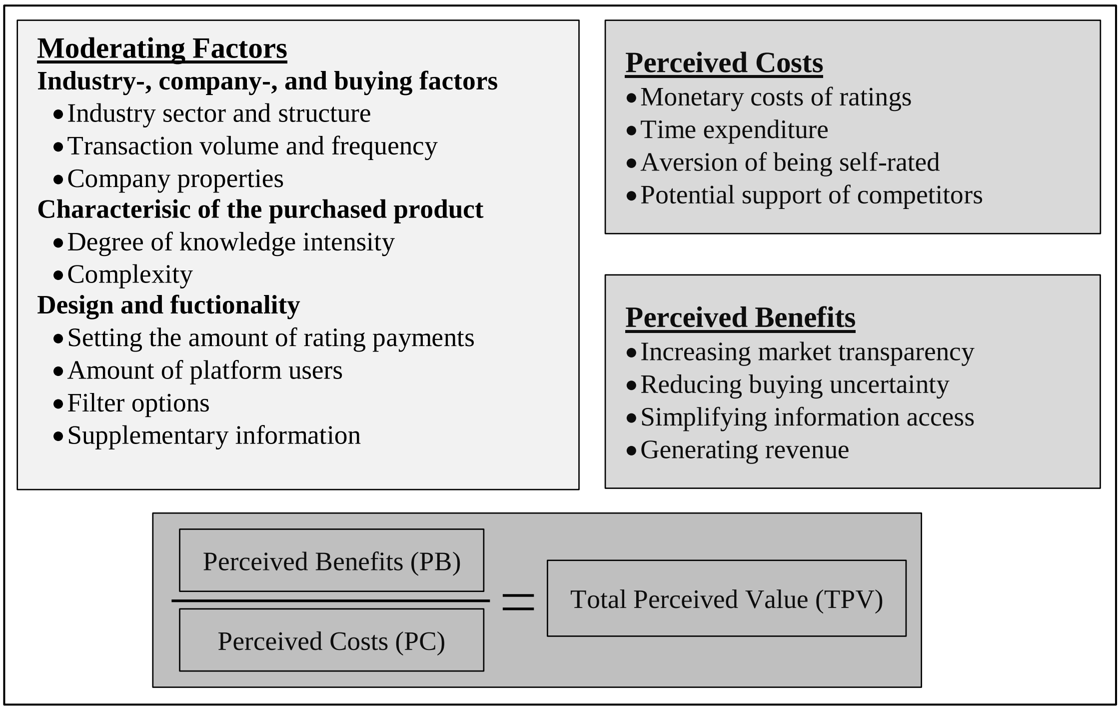

Figure 39: Study Results of Perceived Benefits, Costs, and Moderating Effects

In addition to the dimensions applied when assessing TPV, based on PB and PC, results can be derived on whether the respondents assign value to a reputation system and the proposed solutions. The results are displayed in Table 50. At this point, it needs to be underlined that these results refer to those transactions related to the company's main products. Independent of primary products, we ask every buyer to assess the reputation system's value for knowledge-intensive services. We assume greater value due to a higher buying uncertainty of such services (Lam et al., 2004). Unanimous, all buyers surveyed see the system here as clearly valuable.

Table 50: Value for the Reputation System for the Surveyed Companies

Company	**Valuable for companies main products**	**Valuable for knowledge-intensive services**
Company A	No	Yes
Company B	Partly	Yes
Company C	Yes	Yes

Company D	Partly	Yes
Company E	Partly	Yes
Company F	No	Yes
Company G	Yes	Yes
Company H	Yes	Yes

Company A is referenced to have its rating system and quality-ensuring processes established. Company B knows its suppliers well, acting in a market with only a few suppliers. However, the interviewee recognizes the value of finding suppliers not directly related to the company's main product in unknown markets. Company C also knows its suppliers well but indicated the value of using this system to inform about suppliers' current problems and considered it to improve their bargaining power. At Company D, most distributors are known, but the system seems valuable if additional information is provided, e.g., specific filter options. For company E, the system would not be relevant for all products, only for certain products, if quality criteria are met accurately. For company F, distributors are either known or easy to test, and the system does not provide value for their main products. Company G finds the system useful since the market is intransparent and sound quality is hard to identify. The market is equally intransparent for Company H, and the system appears useful for identifying high-quality providers.

9.9.5 Discussion

9.9.5.1 Perceived Benefits

Four main determinants substantiate the PB: increased market transparency, reduced transaction uncertainty, simplified information retrieval processes, and the possibility of generating additional revenue. Market transparency stood out as the most relevant PB, exemplified by the following statement.

"The less I know about the market and the more intransparent the situation, the more valuable the reputation system." Company D.

This statement underlines the reputation system has great potential for increasing market transparency and reducing transaction uncertainty. Company B remarks that market transparency is a prerequisite for successful buying operations. All interviewees strongly agree that the system increases market transparency and see the main benefit in improving or gaining new market knowledge. The latter seems particularly interesting for new market entrants, as bigger companies B, C, and E explicitly articulated. These companies know their suppliers well and have a good market overview. Smaller buyers, who typically have a bad market overview, see the advantage primarily in creating market transparency. The reputation system might help companies, independent of the industry, increase transparency efficiently in new markets. Accordingly, we derive the following hypothesis.

H_{1a}: The better the market overview, the more the system's benefit lies in gaining knowledge about the quality of suppliers in untapped markets. H_{1b}: The weaker the market overview, the more the system's benefit lies in gaining knowledge about the quality of suppliers in the operating market.

The benefit seems particularly helpful in crowded markets with many different suppliers or highly complex markets associated with buying uncertainty. Results show that increased transparency is expected to decrease purchase uncertainty. The observation also supports that a high value is always attributed to the reputation system for knowledge-intensive services, known for high buying uncertainty (Lam et al., 2004). Thus, we expect the system to have a supportive effect on buying decisions there.

Furthermore, Company H emphasized the benefit of selecting reliable buyers.

"In any case, the information is of value [in our industry]. Particularly to obtain information about the reliability of sellers but also about product availabilities." Company H.

The main criterion for selecting reliable sellers depends on the degree of transparency and, thus, on transaction uncertainty. Thus, we formulate H_2.

H_2: The higher the perceived transaction uncertainty, the higher the perceived benefits.

The second aspect that fundamentally affects reputation system usage is the simplified information retrieval processes. The respondents see a primary benefit of the reputation system when additional information on the products is provided, e.g., whether a specific manufacturer or distributor has a particular product in their portfolio. A filter function for products is desirable, so only those providers are displayed with ratings that offer the desired product.

"I enter what I need, and the system tells me which distributors sell it. That would be helpful." Company D.

Based on these considerations, we conclude that simplifying the information retrieval process about suppliers' reliability and product availabilities is a primary source of PB. Here, the tendency is clearly towards the more information within the reputation system, the better. Considering this finding in the discussion about TPV, we derive the subsequent hypothesis.

H_3: The more the perceived information retrieval is facilitated through the reputation system, the higher the perceived benefits.

This hypothesis results again in the assumption that information retrieval is complex in those markets. On the other hand, the hypothesis indicates some implications regarding the system's functionality and design. The buyers evaluate the benefits even better if more information is provided. Information about the manufacturer's or distributor's product or service and product availabilities are particularly interesting here.

Another central mechanism of the system is the possibility of selling the information obtained regarding suppliers' quality and reliability. Buyers 'invest' a certain amount of money executing a positive 'transaction as rating.' They can subsequently sell this same rating to multiple other buyers within the reputation system, generating profit.

"The expenditure of time is only justified if I can generate additional profit." Company A.

This statement allows for the assumption that this monetary incentive is, in fact, necessary to induce buyers within the system to commit a certain amount of time to carry out ratings. This opportunity to generate additional revenue constitutes a third dimension of PB for buyers when they assess the system's value. However, it is striking that, although information trading is a central mechanism, it does not seem to be too crucial in the respondents' assessments. We believe this dynamic may be profoundly different when looking at high-competitive markets. Still, H4 can be formulated as follows.

H_4: The higher the perceived potential for generating additional revenue, the higher the perceived benefits.

When conducting the interviews, we observed that the buyers were more interested in receiving information than giving information. However, we consider this mechanism as an incentive for participating in the system and submitting ratings and thus may be one fundamental factor for the system to be used. However, given that this mechanism is instead viewed as a prerequisite for the usage, it should also be seen as just that and not as a central benefit-generating aspect like increased transparency (H_1), or reduced transaction uncertainty (H_2).

We could not identify a common consensus on the selling price of ratings, even though there was no question that it has an economic value in every market. We conclude that the price is primarily affected by the product or service.

9.9.5.2 Perceived Costs

Company A's statement above indicates that time costs play a significant role when assessing the reputation system's value. The time and effort consumed for providing a rating need to be justified. This fact leads to the cost dimensions buyers consider when evaluating the system's value. For submitting ratings, a time investment is required. Time effort is seen as PC for the system, for which compensation is demanded to justify these PCs. Company E acknowledges in this context the existence of time costs but evaluates these in a much more relative way due to the simplified information-gathering process:

"It's just a shift in the time spent. You get information faster and save time, which you later use in the information exchange process. The time required would be the same." Company E.

In any case, the respondents interviewed consider time costs to play a significant role in evaluating PC and, thus, the TPV. Although the significance for PC is assessed differently from our interviewees, hypothesis H5 reads as follows:

$\boldsymbol{H_5}$: The higher the perceived time costs to use the system, the higher the perceived costs.

H_5 builds on an aspect originating from the reputation system's functionality. That means that these time costs accrue independently of the industry. It would be helpful to keep the time required to provide ratings low, thus keeping the PC for a buyer low while increasing the TPV. This aspect also points to how the system should be designed regarding functionality and features. Providing sophisticated filter options or a simplified trading process can consume less time, lowering PC and increasing TPV.

Furthermore, one interviewee questioned how much value a rating information is worth.

"Who is then willing to pay money for this information? [...] The information definitely has a value, but am I willing to pay the value?" Company F.

This statement points to another central component of PC: the costs of buying a rating. For buyers, the price of a good or service is vital for decision-making. The fact that for obtaining ratings, an extra fee needs to be paid to get information on a seller's reliability on top of the actual price is rated critical by some respondents. For company F, e.g., this fact is a knockout criterion, even though for its industry, it would help massively gather a better market overview, and although the mechanism offers the possibility even to generate profits in principle. Company E characterizes this matter:

"I think the most challenging part is that you must tip first. Difficult – because there's always that risk that you won't get it back again." Company E.

Hence, we conclude that a rating investment affects the PC negatively. In the reputation system's TPV valuation, this matter is reflected in a reduction of TPV as PC increases due to the perceived risk of potential monetary losses. Thus, H6 can be derived about PC-relevant dimensions and their effect:

H_6.: The higher the perceived risk of not getting back the rating investments to perform a positive payment rating, the higher the perceived costs.

H_6 allows for formulating practice recommendations. Since this seems to be a severe obstacle to using such a system, we consider it a worthwhile research avenue to examine how buyers assess the system when a seller offers a discount instead of a tip, expected to be compensated by a rating buyer. Price discounts and expecting monetary ratings can also be used as a trust signal by the seller; for instance, the seller offers the product at a lower price, considering the monetary rating a withdrawal, not an investment. This setting of the reference price probably switches the whole dynamic of cost perception.

In addition, some companies argue to avoid using such a system because they feared being rated inadequately and expressed concerns about helping competitors. However, both facets did not appear to have a specific cost dimension but referred to an unspecific caution. Consequently, no hypotheses were formulated in this regard.

9.9.5.3 Moderating Factors

As moderating factors, we identified industry-, company-, and procurement process-dependent factors and factors related to the reputation system's design and functionality as well as the product's characteristics. These factors moderate the interplay of PB, PC, and TPV.

For industry-, company-, and procurement process-dependent factors, the industry's role in which the company operates is the most relevant moderator. The industry refers mainly to the degree of market transparency or whether it is a buyer's or a seller's market. Company E outlines this as follows:

"If you need a very specific product that you can only get from one manufacturer anyway, a reputation system is irrelevant." Company E.

The above statement shows that the PB derived from lowered transaction uncertainty H_2 and facilitated information retrieval H_3 are less critical in a seller market context.

The company itself seems to play a moderating role as well. On this, one respondent stated:

"The bigger the company, the better you know the market already. But if I'm a company and I'm very local, and now I want to expand and have a local footprint, but don't have a clue [about the market] - then of course that [the reputation system] is worth gold." Company B.

Additionally, it was mentioned several times that the more long-term oriented the relationship is, the less benefit is achieved through the reputation system. Such representative statements show that in terms of the company's impact, the company size and its quality standards relativize the relevance of the level of PB or PC. Accordingly:

M_1: H2-H4 lose in strength while H5-H6 are intensified (1) when a high bargaining power of suppliers characterizes the market; (2) when the buyer's company's size or established processes can ensure quality standards; or (3) when a long-term relationship is desired.

From this, we can draw practical conclusions. A reputation system is particularly of value in markets with many suppliers and (small) firms without sophisticated quality-ensuring processes and markets with one-off or short-term business relationships.

The characteristics of the purchased product primarily refer to the degree of the knowledge intensity of the product or service to be purchased. This aspect is of major relevance since all eight respondents attribute a high value to the reputation system in the context of knowledge-intensive services such as management consulting or education services. The value (TPV) is assessed by weighing the hypotheses formulated under H_{2-6}. Due to the nature of knowledge-intensive services, e.g., a high number of trust properties of the promised service, the PBs are perceived as more and PCs less relevant. Therefore, we found proof in all interviews, whereby we gained the impression that the PB was even higher for small companies. The following representative statements underpin our impression:

"If you need a management consultancy [...], then it is of great value if you have the right one and if there are people who can evaluate that [...]. This information is worth a lot." Company G.

"I would definitely be willing to pay [for reliable information]. These investments [educational courses] make you think twice or even three times." Company F.

Accordingly, we define M_2 and conclude that reputation systems may be of particular interest for knowledge-intensive services.

M_2: H_{2-4} are intensified, and $H_{5,6}$ are mitigated for knowledge-intensive services, leading to a very high PB in this context.

Also, factors for the design and functionality of the reputation system were mentioned, and the respondents have stated several aspects, either intensifying or weakening PB and PC in reputation system usage. Those mainly refer to preferences regarding the information price setting approach, additional value through, e.g., supplementary product information, filter options, or the platform's reach. Several implications in this context can be derived from these eight interviews. For example:

"I need to judge the validity of the other buyers' statements. It would be important that they identify themselves with what they do, i.e., how long have they been with the company, what function do they have [...]?" Company D.

M_3: H_{2-4} are intensified, and $H_{5,6}$ are mitigated if the reputation system's functionality, features, and design meet potential users' demands.

In sum, TPV is positive when the PB outweighs the PC. The mediating factors can heavily influence the coinage of PB and PC and play a decisive role in determining whether a reputation system is of value to a company. The proposed solutions seem to positively and negatively affect the TPV for buyers. The idea of selling ratings was perceived as something positive, monetary ratings appeared neutral, and counter-evaluations tended to be seen as unfavorable by the interviewees. However, in the interviewees, it cannot be pinned down to a specific aspect. There seems to be a general aversion to being rated by sellers. We interpret this result as a positive sign that a buyer would try to stay beneath a threshold to avoid ratings becoming visible to other sellers.

9.9.6 Conclusion

Reputation systems seem to be a valuable tool for promoting trust and cooperation in several business contexts. The study aimed to determine how buyers assess reputation systems' value in B2B contexts against three newly proposed solutions to design business reputation systems. These solutions include selling ratings, conducting ratings as payments, and using counter-ratings. We interviewed informants from eight companies representing different industries and sizes, receiving manifold insights into various business contexts. In our initial setting, we explored the added value of these solutions for reputation systems in these business contexts and collected insights on perceived benefits (PB) and perceived costs (PC) to assess the total perceived value (TPV).

Our findings suggest that such a system is useful for companies acting in less transparent markets and also helps in some situations when companies already have a broad market overview. We exploratively identified value and cost dimensions, as well as moderating factors. All need to be examined in more detail to understand better their role in the value assessment of business reputation systems. The perceived value of the investigated reputation system varies depending on the market conditions and the business context. Unequivocally, all buyers find the system valuable for assessing the quality of knowledge-intensive services. We take this as confirmation of our assumption that the value of such systems increases the higher the buying uncertainty is. As the interviewed buyers indicate, the three solutions seem promising for designing a new class of reputation systems – business reputation systems. This system class might have a profound economic impact if they are put into use and work.

Our insights help structure the most significant value drivers in varying contexts helping researchers better understand the dynamics of business reputation systems, and contribute to the knowledge base on how reputation systems need to be designed in terms of functionality and features to increase the value for buyers. Due to the relatively small sample size, this study is limited in grasping the full complexity of every business context, leaving some business aspects untouched.

Reputation systems for B2B contexts will likely become a hot topic in future information systems research, leaving plenty of room for further research questions, including design and business management aspects. Further research should aim to improve the system design and examine designing business reputation systems with the lens of real-world applicability. Furthermore, we encourage future research to investigate the value of such systems for sellers and the applicability and usefulness of the proposed design solutions in more specific business scenarios. Other research perspectives might complement our initial lens on business reputation systems by studying potential implications on decision behavior, humans, companies, procurement, negotiation, marketing, (lemon) markets, economics, or others.

Declaration of Authorship

I hereby declare that I have written the submitted dissertation entitled *Designing Blockchain-Based Business Reputation Systems: A Design Theory for a New Information System Class* independently and without unauthorized assistance. I have used only the sources and aids indicated by me. All passages taken either literally or in substance from other works have been clearly marked as such. For language refinement and improved readability, I made limited use of AI-based writing assistance tools (Grammarly and ChatGPT) to improve linguistic clarity, grammar, and style. These tools were not used to formulate arguments or contribute to the intellectual substance of this work. The thesis reflects my independent academic effort and understanding.

Boxberg, October 7, 2025

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