Hybrid Decision Support in Strategic Product Planning: Leveraging Extreme Data for Early-Phase Innovation

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Abstract: Strategic product planning defines foresighted directions for product engineering by determining which ideas, technologies and concepts are pursued further. Decisions made in this phase strongly influence subsequent life cycle phases but are characterized by high uncertainty, fragmented information, and predominantly qualitative assessment practices. At the same time, increasing digitalization generates large, heterogeneous, and dynamic data from markets, engineering, usage, and sustainability domains. In this work, such information is understood as extreme data, as its heterogeneity, variety, and dynamics exceed the capabilities of traditional planning approaches. This paper investigates the potential of leveraging extreme data to strengthen hybrid decision support in strategic product planning. A structured literature review is conducted to identify key challenges. These challenges are analysed along the generic product life cycle to capture decision points, information flows, and information circularity. Relevant data sources are identified with respect to their relevance for strategic decisions. Based on this analysis, seventeen potentials for hybrid decision support are derived and clustered into five fields of action. The results indicate that extreme data can enhance strategic foresight, idea evaluation and portfolio decisions, lifecycle-spanning knowledge integration, engineering support for strategic decisions, and the adoption of AI-based methods.

Keywords:
Strategic Product Planning, Hybrid Decision Support, Extreme Data

1 Introduction

Strategic product planning (SPP) is the first phase of product creation and the entire product life cycle and sets foresighted engineering directions by deciding which ideas, technologies, and product concepts will be transferred to engineering [1]. Decisions made in this phase shape product architectures, market positioning, and engineering paths, thereby influencing all downstream life cycle phases [1,2]. Despite this central role, SPP is characterized by uncertainties, volatile environmental conditions, and fragmented information from heterogeneous life cycle domains [3]. As a result, decisions often remain qualitative, experience-based, and only partially traceable [4].

SPP operates in the area between market and engineering. This area includes activities such as strategic foresight, trend and technology analysis, idea generation, idea evaluation, and portfolio processes [1]. These activities require the integration of a wide range of information, including customer needs, technological maturity levels, environmental performance data, competitive dynamics, supply chain conditions, and internal capabilities. The increasing digitalization along the product life cycle expands the available information base and at the same time increases the complexity of decision-making [2,5].

This complexity poses a fundamental challenge: the information relevant to SPP is not only extensive, but also heterogeneous, dynamic, and spread across the entire life cycle. These forms of information

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represent extreme data [5]. This kind of data exceeds the capabilities of traditional planning methods, which commonly rely on static reports, expert judgments, or periodic analyses. Such data, even though it is characterised as extreme, therefore offers the opportunity to strengthen SPP's decision-making basis by supporting common methods with reliable data [3].

Hybrid decision support addresses this challenge by combining human expertise with AI-supported methods [5]. Existing approaches already demonstrate the potential benefits of AI in trend analysis, forecasting, scenario engineering, and generative design, but they remain narrowly defined and are not used holistically across tasks in SPP [5,6]. In addition, these approaches hardly exploit the potential of extreme data and do not sufficiently consider the information flows along the generic product life cycle (gPLC) [2]. Therefore, a systematic synthesis on how data can strengthen hybrid decision support in spite of extremities in SPP is missing, limiting the ability to structure decision-relevant information, integrate lifecycle perspectives, and transparently support SPP decisions.

To address this gap, this article builds on a structured literature review, an analysis of the SPP process, and the examination of relevant data sources. The contribution aims to structure and conceptualize how data-driven and hybrid approaches can support strategic decision-making in early product planning. The paper thereby provides a foundation for systematically identifying promising directions for future research and methodological engineering in hybrid decision support for SPP.

2 State of the Art

SPP constitutes the interface between market, corporate strategy and product engineering by translating long-term strategic goals into concrete engineering directions and product ideas. Established models of SPP describe a structured narrowing of an initially open problem space toward a feasible engineering order, supported by portfolio considerations, foresight activities, and early concept evaluations [1,7]. Recent contributions emphasize that SPP increasingly needs to account for interdisciplinary products, product-service systems, and sustainability objectives, which significantly extend the scope and complexity of early planning decisions [1,8]. Beyond its positioning in the product lifecycle, SPP is characterized by its strong influence on downstream phases such as engineering, realization, and operation, as early decisions determine major cost, performance, and sustainability trajectories. At the same time, decision-making in SPP remains exploratory and knowledge-intensive, relying on expert judgment, workshops, and qualitative assessments rather than formalized data-driven methods [1].

A central challenge of SPP is coping with high uncertainty and fragmented information. Relevant inputs originate from diverse domains such as market engineering, technology trends, lifecycle considerations, and organizational constraints, which are rarely available in a consistent or structured form [7]. While foresight methods such as Scenario-Technique are widely used to support SPP, their application is often resource-intensive and dependent on expert knowledge, limiting their scalability and reproducibility [9]. Furthermore, existing planning approaches typically focus on isolated subprocesses, such as market analysis or technology assessment, without systematically integrating information across the entire product lifecycle. As a result, feedback from later phases such as usage, operation, or end-of-life is only partially considered in early planning decisions, despite its relevance for sustainability and circularity-oriented strategies [7]. This lack of information circularity reinforces subjectivity and hampers transparency in strategic decision-making.

In parallel to these challenges, ongoing digitalization leads to the generation of large, heterogeneous, and dynamic datasets across the product lifecycle. Along the gPLC[1], these include market data, engineering data, lifecycle assessment results, sensor data from usage phases, and sustainability-related indicators. Thus, comprehensive data models and the integration of processes form the basis for holistic insights into SPP [10,11]. In the context of SPP, such data can be understood as extreme data, as their volume, variety, and dynamics exceed the processing capabilities of traditional planning methods and manual expert-based evaluation [12]. Extreme data in SPP are not specifically extreme due to volume, but because of distributed origin and access, semantic heterogeneity, and temporal dynamics. Relevant information is scattered across different lifecycle phases and organizational units, making it difficult to identify which data is decision-relevant and how they should be interpreted in early planning contexts [7]. While digital twins and lifecycle data infrastructures promise improved information availability, their systematic use in SPP remains limited [1].

To address increasing complexity, hybrid decision support approaches combining human expertise with AI methods are gaining attention in research and practice. These approaches aim to leverage computational capabilities for data processing and pattern recognition while preserving human judgment, creativity, and contextual understanding [13]. Initial conceptual work demonstrates the suitability of hybrid approaches for selected planning tasks, particularly in strategic foresight and scenario analysis [9]. AI-based methods have been applied to automate consistency checks, cluster scenarios, or support trend analysis, thereby improving efficiency and transparency [9]. However, existing approaches predominantly address isolated tasks and remain domain-specific, focusing on foresight or evaluation activities rather than the entirety of SPP. Moreover, current hybrid decision support systems rather exclude extreme data instead of tackling extremities as a central data processing element. While large datasets are implicitly processed, little attention is paid to systematically identifying decision-relevant extreme data sources across the lifecycle and integrating them into SPP processes [12]. This reveals a research gap at the intersection of SPP, hybrid decision support, and extreme data utilization.

3 Method / Approach

Overall, existing approaches to decision support in SPP can be categorized into foresight-oriented methods, portfolio evaluation approaches, and lifecycle-related data models. However, these approaches predominantly address isolated sub-processes and do not provide a systematic integration of extreme data across the entire product lifecycle. This raises the following research question: *What potential for offering hybrid decision support in SPP is currently locked in data due its extreme characteristics?* T answere this question, this research follows a four-step conceptual approach, as shown in Figure 1.

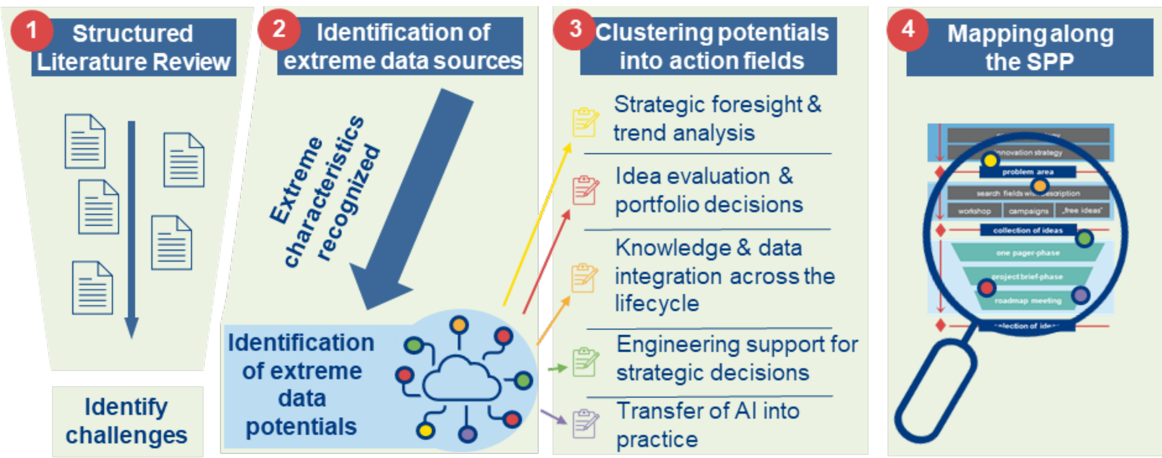

Figure 1: Methodological approach

The process starts with a structured literature review to identify challenges and decision-critical gaps in SPP. The underlying literature analysis is guided by the framework proposed by Machi and McEvoy, which is particularly suited for theory-oriented and concept-building research. Based on these findings, relevant data sources are identified and analysed with respect to their decision relevance along the SPP process. The recognized data characteristics serve as the basis for deriving potentials for hybrid decision support. Subsequently, the identified potentials are clustered into five fields of action reflecting similarities in decision logic, data characteristics, and the role of AI-supported analytical methods. Finally, the action fields and associated potentials are mapped along the phases and activities of SPP to illustrate where hybrid decision support can systematically contribute to strategic decision-making.

4 Results

This section presents the results of the literature-based analysis conducted in this study. The identified findings are structured along recurring challenges in SPP and their implications for the use of extreme data and hybrid decision support.

4.1 Challenges in SPP

To identify the key challenges in dealing with extreme data in SPP, a structured literature analysis was conducted following the conceptual synthesis approach by Machi and McEvoy. The aim was not to exhaustively catalogue all available publications, but to systematically identify, compare, and synthesize recurring challenges and argumentative patterns relevant to early-stage decision-making and decision support in SPP. To ensure transparency and reproducibility, the literature search followed a systematic and traceable procedure. Scientific databases including Scopus, Web of Science, and IEEE Xplore were searched using predefined combinations of keywords related to SPP, decision-making, extreme data, and AI- or model-based decision support. Titles, abstracts, and full texts were screened iteratively, allowing the refinement of search terms and thematic focus in line with emerging concepts, as suggested by Machi and McEvoy. Only publications that provided substantive contributions to at least one of the following aspects were included: (1) decision-making processes in SPP (2) data-related challenges in early engineering phases, and (3) AI- or model-based decision support processes. The evaluation reveals four recurring, cross-domain challenges that currently limit the systematic use of extreme data in SPP:

(1) Uncertainty and incomplete information in early strategic decisions

Several studies emphasize that strategic decisions in the early phase of the product life cycle are made under particularly high uncertainty, as reliable information on markets, technologies, costs, or usage scenarios is only available to a limited extent. At the same time, these decisions shape long-term engineering and product paths [14,15]. Although extreme data from market analyses, technology roadmaps, and sustainability assessments are generally available, they have so far been integrated into search fields, scenarios, and early evaluation steps only to a limited extent [3,16].

(2) Fragmented data landscapes and lack of information circularity

The literature shows a pronounced fragmentation of the available data across the entire life cycle. Information from engineering, simulation, production, operation, service, recycling, and the market environment is stored in separate systems, differs in structure, quality, and timeliness, and is rarely synchronized [2,5,17]. Due to its extreme characteristics, such as volume, heterogeneity, and dynamics, this data is difficult to consolidate into a consistent flow of information for SPP [5,17]. As a result, key relationships between market requirements, engineering, life cycle assessment, and circular feedback loops are insufficiently visible.

(3) Qualitative and opaque idea and portfolio decisions

In practice, idea and portfolio decisions remain largely qualitative, for example through expert panels, scoring models, or stage-gate processes [14,18]. Although these methods make use of expert experiences and enable structured discussions, they make only limited use of existing data and are susceptible to subjective bias. This leads to reduced transparency, limited traceability, and heavy reliance on implicit expert knowledge [7,16].

(4) Domain-specific AI applications without an overarching framework

The literature shows a variety of methodological approaches, such as generative design, graph-based concept evaluation, AI-supported innovation metrics, or automated trend analyses, which are promising for specific SPP issues [1,19]. Yet, these approaches support only such specific tasks, without a broader scope in SPP. However, these approaches remain largely domain-specific and method-driven, typically addressing isolated subtasks of SPP rather than being anchored across the entire SPP process. As a result, they provide only limited support for the systematic integration of heterogeneous and dynamic data sources and rarely consider extreme data as a central design element. Consequently, an integrative framework that combines extreme data, AI methods, and human expertise into a hybrid decision support system spanning the entire SPP process does not yet exist.

Tabelle 1: Data domains and sources in SPP and their characteristics of extremeness

Data Domain	**Exemplary Data Sources**	**Relevance for SPP**	**Characteristics of Extremeness**
Market Data	Customer feedback (reviews, social media), market studies, sales forecasts, competitor analyses, technology and trend reports [20]	Identification of search fields, market opportunities, and strategic risks	High heterogeneity of unstructured data, dynamic evolution of market signals, varying data quality
Engineering Data	CAD models, simulation results, variant and modular structures, textual requirements, design constraints, Life Cycle Assessment (LCA) results [21]	Assessment of technical feasibility, complexity, and architectural implications	Strong semantic complexity, implicit design constraints and interdependencies, limited interpretability at a strategic level
Product & Realisiation Data	Lifecycle-spanning sustainability, usage, and supply-network data, including continuously updated lifecycle assessment data streams, material and energy flow data across supplier interfaces, recyclability indicators[16]	Evaluation of long-term sustainability impacts and regulatory compliance	Lifecycle-spanning and cross-organizational data streams, continuous updates driven by external boundary conditions, high dependency on supplier interfaces
Use & Operation Data	Sensor data from product usage, maintenance and service records, failure statistics, usage profiles, customer feedback [22]	Feedback of real-world usage behaviour into early planning decisions	Large volumes of time-dependent sensor and service data, heterogeneous formats, context-dependent interpretation
Organiza-tional & Process Data	Project histories, portfolio decisions, resource allocations, engineering timelines [15]	Transparency and traceability of strategic planning and decision processes	Incomplete documentation of decisions and lessons learned, fragmented information across organizational units

In the second step, the analysis shifts from challenges in SPP to the data perspective required to address them. To operationalize the notion of extreme data in SPP, Table 1 summarizes exemplary data domains and sources across market, engineering, product lifecycle, and use phases, and describes the characteristics of extremeness. Rather than reflecting data volume alone, the degree of extremeness captures the specific challenges these data pose for SPP, particularly with respect to characteristics like heterogeneous formats, high volume, unknown quality, errors, gaps, or different languages in early planning stages [7]. Market, Engineering, lifecycle, and use-phase data are therefore classified as highly extreme, as they evolve dynamically and are often only partially accessible during SPP. Organizational data, while typically available at earlier stages, are comparatively more structured and are thus rated as moderately extreme. This classification provides a systematic basis for identifying where extreme data becomes decision-relevant in SPP and for deriving subsequent potentials for hybrid decision support.

4.2 Identified potential of hybrid decision support in SPP

The analysis identified 17 different areas of potential for hybrid decision support in SPP. These include, for example, cluster algorithms for structuring large quantities of idea inputs [16] and hybrid dashboards for providing transparent evaluation metrics [14]. All identified potentials were consolidated into five fields of action that structure their relevance along the planning process (Figure 1).

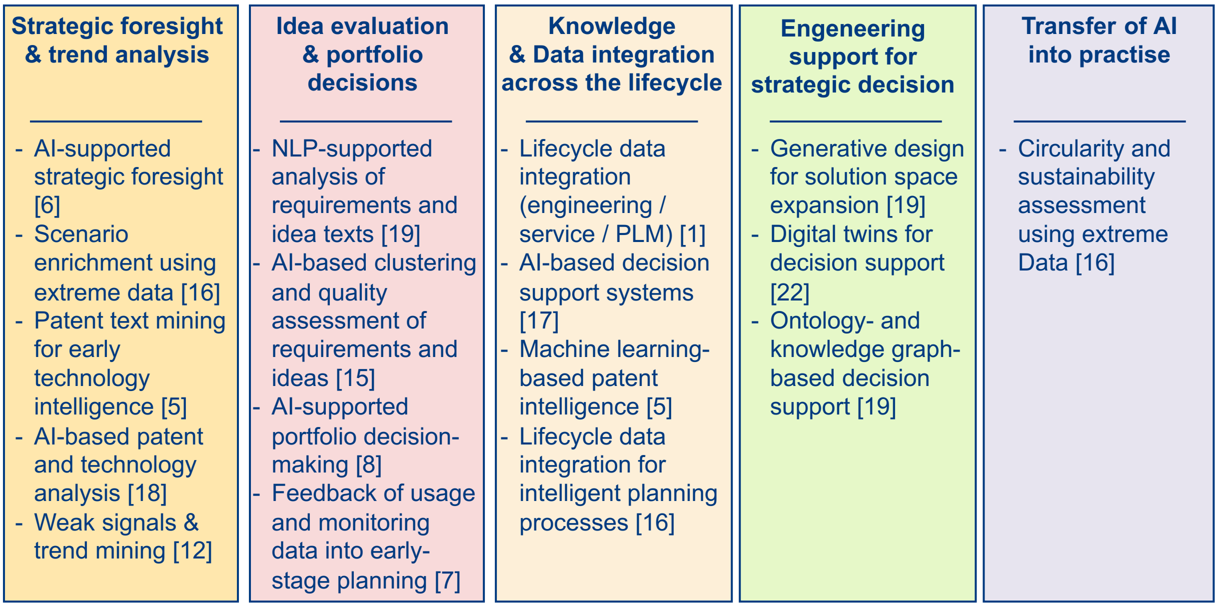

Figure 2: Clustering potentials into fields of action

Strategic foresight & trend analysis in SPP benefits greatly from AI methods that can analyse large, heterogeneous, and dynamic data sets. Extreme data, including market information, usage data, scientific publications, patents, social media signals, and technological maturity indicators, enables more precise identification of trends and search fields. AI-supported trend analyses reveal potential by performing pattern recognition on unstructured data and making engineering visible at an early stage [17]. In addition, the Scenario-Technique can be systematically expanded through the integration of data-based evidence, with AI-supported analysis methods identifying weak signals and structured trend engineering, thereby reducing uncertainties in strategic orientation [9]. Similarly, patent- and technology-related text mining approaches enable the efficient derivation of technology trends and innovation potential from global databases. These potentials strengthen strategic advance planning by systematically using extreme data sources to derive robust search fields and long-term technology paths.

The **evaluation of ideas** and concepts in SPP has traditionally been highly subjective. Extreme data and AI methods offer potential to make evaluation processes more objective, comprehensible, and evidence-based. Natural language processing (NLP) enables the automated analysis of requirements and idea texts and supports the identification of semantic similarities, conflicts, or quality characteristics [2]. In addition, AI-based clustering allows large quantities of ideas or requirements to be organized in a more structured manner and provides decision-makers with transparent groupings, which is particularly helpful in early screening processes [19]. Explainable AI approaches increase the traceability of data-based portfolio decisions and enable sensitivity analyses that clearly reveal the influence of specific criteria [18]. Similarly, usage and monitoring data from operations or services can be fed back into early evaluation via extreme data pipelines, enabling a more realistic assessment of market potential, risks, and life cycle impacts [23]. This opens up substantial potential for evidence-based prioritization of strategic projects.

A key potential of hybrid decision support exists in the **integration of data** across the entire product life cycle. Extreme data is generated in engineering, production, service, operation, return, and recycling but has so far hardly been used for strategic decisions. The concept of information circularity within the gPLC shows that available data streams contain valuable indicators about product use, failure behavior, maintenance costs, and sustainability impacts [16]. The Information Circularity Assistance Framework demonstrates how AI methods, digital twins, and semantic information models can be linked to support strategic decisions with cross-lifecycle information. Another potential arises from the use of knowledge graphs to link heterogeneous data sources, revealing relationships between requirements, technologies, components, and usage scenarios [6]. Machine learning-based patent analyses also enable systematic early technology reconnaissance and can enrich strategic roadmaps with data-based evidence [2]. These potentials strengthen the quality of decision-making by making extreme data sets structurally accessible and strategically usable.

Engineering methods such as simulation, digital twins, or early transfer of AI approaches like ontology-based knowledge models open up new potential for SPP, especially when combined with extreme data. Generative design processes use AI to generate alternative concept solutions and significantly expand the solution space in the early stages. In this context, digital twins provide a data-rich representation of physical products and systems, which can be coupled with simulation models to systematically support strategic decisions on sustainability, performance, and costs [17]. Ontology- and knowledge graph-based decision support systems enable the linking of requirements, functions, technologies, and usage scenarios in consistent information structures, thereby transparently displaying strategic dependencies. Machine learning methods extend this by recognizing patterns in engineering data and automating or improving strategic analyses, such as concept evaluation. Overall, these potentials enable stronger feedback from engineering into SPP and thus a more fact-based derivation of future product architectures.

In order of hybrid decision support and extreme data having a **practical impact in SPP**, organizational, methodological, and cultural prerequisites must be taken into account. Studies show that companies often have difficulty with anchoring data-driven methods in decision-making processes, even though their benefits are proven [17]. Therefore, approaches such as explainable AI methods that provide decision-makers with transparency and confidence are essential for the effective adoption of hybrid decision support in SPP [13]. Further potential arises from circularity and sustainability assessments that use extreme data from operations and services to inform strategic decisions in line with ecological and regulatory requirements [1]. In addition, organization-wide concepts for collaboration between data science, engineering, and management can promote the successful use of hybrid systems. The potential of this field of action thus addresses the organizational transformation necessary to establish databased decision support in a sustainable manner.

Figure 3 relates the previously derived fields of action and their associated potentials to the SPP process. Building on the clustering of potentials presented in the preceding section, the figure illustrates how these action fields manifest across the phases and core activities of SPP. Based on the gPLC, lifecycle-related information flows are transferred to the SPP process, making decision-relevant interfaces and feedback loops visible. The analysis focuses on the early phase of SPP, represented by the first three control points shown in Figure 3. These control points encompass the problem framing, idea generation, and idea selection stages, which are characterized by high uncertainty and strategic relevance. [1]

The individual potentials, shown as discrete markers, indicate concrete points within the SPP process where extreme data and AI-supported methods can contribute to hybrid decision support. Their positioning highlights that potentials identified within the same field of action occur at multiple stages of SPP, ranging from early strategic problem framing to idea evaluation and selection decisions. This emphasizes that the areas of action are not tied to individual process steps but are spread across several steps. The visual aggregation of potentials along the process reveals cross-cutting patterns: some fields of action predominantly support early strategic reasoning, while others connect early planning decisions with downstream lifecycle and engineering considerations. Rather than introducing new clusters, the figure demonstrates how the previously identified fields of action interact with existing SPP structures and where multiple fields converge at key decision points. Overall, Figure 3 emphasizes the process-wide relevance of the action fields and illustrates how hybrid decision support enriched by extreme data can be systematically embedded into early phase SPP processes. The figure thereby supports the identification of priority intervention points without duplicating the content-based clustering of potentials.

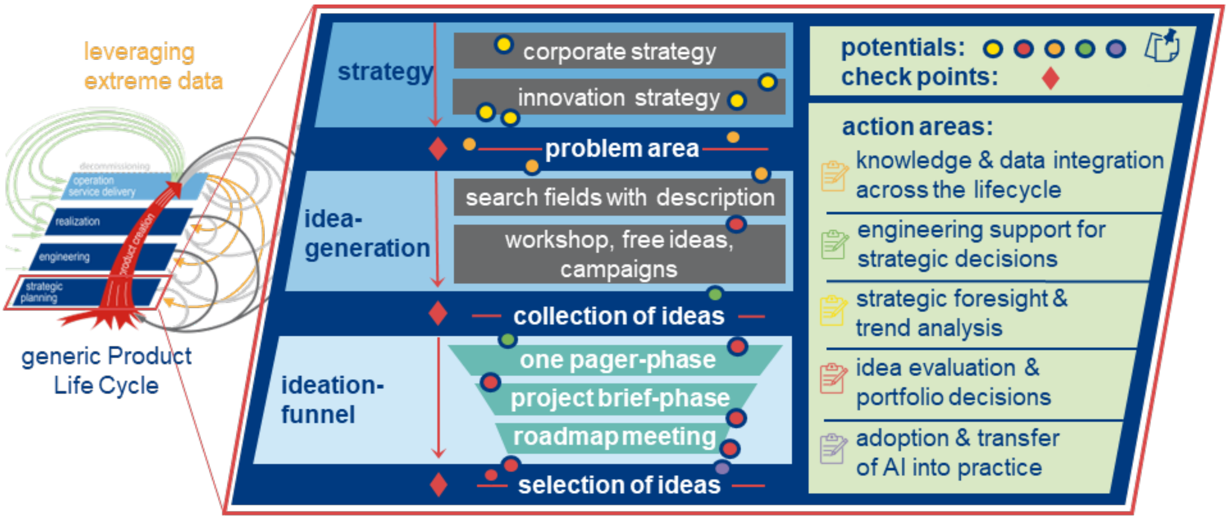

Figure 3: Areas of action for hybrid decision support in strategic product planning

4.3 Application and Discussion

This paper addressed the question of what potential the use of extreme data offers for hybrid decision support in SPP. The results indicate that extreme data can systematically strengthen hybrid decision support in early planning phases by improving strategic foresight, increasing transparency in idea and portfolio decisions, enabling lifecycle-spanning knowledge integration, and supporting the consideration of engineering-related implications at a strategic level. These potentials are consolidated into five fields of action, which together provide a structured framework for integrating data-driven insights and human expertise in SPP decision-making. Across the identified action fields, a central insight is that extreme data primarily shifts the nature of strategic reasoning rather than replacing established practices. In strategic foresight and trend analysis, for example, data-driven approaches enhance weak signal detection and scenario robustness, yet they remain dependent on expert interpretation to ensure plausibility and relevance. Similarly, in idea evaluation and portfolio decisions, AI-based analyses increase transparency and consistency but do not eliminate normative judgments related to strategic priorities, risk tolerance, or organizational constraints and decision contexts.

The analysis further reveals that knowledge and data integration across the lifecycle represents both a major opportunity and a critical limitation. While linking heterogeneous data sources enables improved traceability and continuity of strategic decisions, it also introduces significant methodological and organizational complexity. Engineering support for strategic decisions demonstrates how generative design and digital twins can broaden solution spaces beyond human cognitive limits; however, these approaches rely on structured input data and validated modelling assumptions, which are often unavailable in early strategic phases. Adoption and transfer considerations highlight that hybrid decision support is not solely a technical challenge. Organizational readiness, user acceptance, and methodological transparency emerge as decisive factors for realizing the identified potentials. Without addressing these aspects, even technically advanced approaches risk remaining isolated applications rather than becoming integral elements of SPP.

The proposed framework has been exemplary applied in context of a german manufacturer of kitchen appliances during early-phase SPP. In conducted workshops, strategic search fields and product ideas for future appliance generations were assessed under conditions of high uncertainty, by considering market requirements, technological developments, and sustainability objectives. To support these decisions, heterogeneous data sources were taken into account, including customer feedback from service and usage data, engineering related information on existing product architectures, and lifecycle-related data on energy consumption and regulatory boundary conditions. Structuring the identified data according to the identified fields of action has supported transparent discussions of trade-offs between functionality, energy efficiency, and product strategy, and has laid the foundation for further hybrid decision support. This example illustrates how extreme data can be used to complement expert judgment in early SPP without implying empirical validation of the framework's effectiveness. Overall, the analysis shows that extreme data does not constitute a standalone solution. Instead, value is gained by supporting hybrid decision-making by complementing human expertise with data-driven insights. At the same time, the analysis confirms that existing research remains fragmented and largely domain specific. This lack of methodological continuity across the entire SPP process underscores the need for integrative frameworks that systematically combine extreme data, AI methods, and human judgment.

5 Conclusion and Outlook

This research examines how data even with extreme characteristics can contribute to hybrid decision support in SPP. By combining a structured literature review with an analysis along the gPLC, seventeen distinct potentials were identified and consolidated into five action fields covering strategic foresight, idea evaluation and portfolio decisions, lifecycle-wide knowledge integration, engineering support for strategic decisions, and the transfer of AI-based methods. Together, these results provide a structured overview of where and how extreme data can support decision-making in SPP. The findings indicate that the value of extreme data does not lie in data availability alone, but in its systematic integration into hybrid decision support approaches. Extending inputs by data that is extreme deepens the informational basis of strategic reasoning by connecting heterogeneous and dynamic data sources across lifecycle phases. When combined with human expertise, this enables more transparent, traceable, and evidence-informed decisions in SPP, while preserving the exploratory and interpretative character of early SPP. The results further show that current approaches remain fragmented and predominantly focused on isolated tasks. The identified action fields therefore represent starting points for structuring future research rather than ready-to-use solutions. Advancing these fields requires the engineering of methodological frameworks that explicitly address information circularity, decision-relevant data selection, and the interaction between analytical models and human judgment. Future research will focus on operationalizing the identified potentials into concrete methods and tools for SPP. This includes developing integrated data pipelines across lifecycle phases, designing hybrid decision support concepts that are robust under uncertainty, and empirically evaluating their impact on planning quality and decision transparency in SPP contexts. By addressing these challenges, extreme data enriched hybrid decision support can contribute to a more systematic and resilient discipline of SPP.

6 Aknowledgements

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