Harnessing Tacit Knowledge from Sustainable Product Engineering through Artificial Intelligence

Iris Graessler[1], Johanna Mansheim[1]*, Jan Pfeifer[1]

[1]Paderborn University, Heinz Nixdorf Institute, Chair for Product Creation, 33102 Paderborn
*Corresponding author. E-Mail address: johanna.mansheim@hni.uni-paderborn.de; Tel.: +49 5251/60-6252

Abstract: Tacit knowledge is particularly valuable in product engineering. Experiences reside in minds of employees and are not systematically documented but could have a significant influence on sustainable product engineering. Existing approaches do not offer sufficient support for harnessing technical tacit knowledge regarding sustainable product engineering. In this paper a three-step method is presented: The method contains knowledge acquisition, requirements extraction und requirements validation for quality assurance. Acquisition is performed by support artifacts like interview guidelines. Extraction is supported by Artificial Intelligence, converting statements into requirements. These requirements are validated using a specific questionnaire. The developed approach is applied in a funded project of the European Union (EU) with automotive industry partners. The method supports product engineers to collect tacit knowledge from experienced employees, transform unsystematic knowledge into standardized technical requirements and validate them. Application of this method enables creation of validated requirements that can be applied throughout the company and are not exclusively dependent on a single employee.

Keywords:
Tacit Knowledge, Sustainability, Product Engineering, Artificial Intelligence

1 Introduction

Leading industrial companies are placing rising emphasis on the sustainability of their products to address future developments. A significant proportion of a product's environmental impact is determined during engineering [1]. Formalized guidelines for engineering sustainable products are provided by ISO 14000 series such as Life Cycle Assessment in ISO 14040, allowing industrial companies to evaluate their products' sustainability [2]. Companies build their specific implementation frameworks based on such general standards and guidelines. Experiential knowledge is held by individual employees in product engineering. Experiential knowledge is undocumented and unsystematic [3]. Experiential knowledge is considered Tacit Knowledge (TK), and will always remain only partially usable for engineering sustainable products as it cannot be externalized completely [3]. Extracting TK provides support for product engineering for recurring challenges such as increasing complexity of products and changes due to new technologies, especially regarding sustainability [4]. To systematically counteract loss of TK, extraction of TK needs to be conducted in a structured and scalable manner. To be able to use extracted TK in engineering, its quality must be ensured.

To address these engineering challenges, a comprehensive approach is needed, assuming great potential in the utilization of Artificial Intelligence (AI) through Large Language Models (LLM). Currently, various individual methods for extracting TK exist in research and are already established in practice. These methods are formulated in general terms, not adapted to a specific technical topic and do not include quality assurance [5]. At the same time, LLM-based AI tools evolve technologically with great

International Symposium on Hybrid Intelligence in Product and Production Engineering, March 24–26 2026, Paderborn, Germany

potential to process unstructured information like natural language and even hand-written notes. The paper at hand is based on the assumption that this potential can help to overcome the high efforts of current practices in analyzing TK documentations. Based on the identified challenges and potentials, three research questions (RQ) are formulated:

RQ1: *What approaches are most beneficial for acquiring tacit knowledge in product engineering?*
RQ2: *Which methods and extracts from existing approaches need to be adapted to incorporate sustainability in engineering context?*
RQ3: *Which constituents are required in a) a questionnaire for acquisition and b) a prompt for extraction to generate automatized input to requirements specifications from technical tacit knowledge?*

To answer these RQs, the paper provides a brief overview of background in terms of state of the art, before introducing the applied scientific approach. The method for harnessing TK from sustainable product engineering and utilizing it in a requirements engineering project is proposed as a combination of acquiring, extracting and validating TK including results of a systematic literature review, method description and presentation of artifacts. An application with sample data and contributions by 20 experts is used for initial validation of the method, leading to conclusion and outlook.

2 State of the Art

Sustainable product engineering considers the entire product life cycle [2]. Products have various environmental impacts, which accumulate over their product life cycle [2]. Environmental impacts can be divided into different impact categories such as climate change, acidification and human toxicity [1]. Environmental impacts must be already considered during the engineering phase [1]. To conduct sustainability assessments and take its results into account in engineering, a high amount of technical expertise is required [1]. This expertise often refers to the unconscious part of a person's knowledge and is considered Tacit Knowledge (TK). TK is not documented and is therefore intangible [6]. TK rises from experience and is expressed through intuitive actions [7]. These experiences allow future actions to be improved [7]. Verbalization of TK is difficult, partially even impossible [8]. Relevant examples in product engineering are the understanding of an issue and the development of a problem-solving strategy based on engineering know-how through personal knowledge and experience [4]. These problem-solving strategies are often required to make appropriate decisions in engineering processes [4]. In comparison to TK, explicit knowledge is communicated and documented. Explicit knowledge can be shared and is detachable from the person. For companies, both types of knowledge are crucial to success and of strategic importance in product engineering, for example for defining requirements [7]. The processing of TK can be very time-consuming. To utilize support from Artificial Intelligence (AI) regarding TK, machine-readable and, thus, explicit artifacts are needed. AI enables technical systems based on algorithms to solve tasks that require intelligence [9]. Generative AI is a subfield of AI that involves creation of new data. LLMs provide one framework for generative AI in the field of human and technical language processing. The answers of an LLM are generated based on statistical methods and training data to provide logical answers in terms of syntax and semantics [10].

3 Scientific Approach

To address these RQs, a five-step research approach is formulated. Through a systematic literature review (SLR), related work on harnessing TK in the context of product engineering is identified (1). Relevant approaches for the acquisition of TK are reflected in generic knowledge management literature and evaluated based on defined criteria in the context of sustainability (2). Based on recurring elements in related work, a method for comprehensive extraction and validation of TK is developed (3). The developed method is applied in an EU funded project with twenty experts from the automotive sector (4). Finally, the method is validated against the defined criteria (5).

4 Method for acquiring, extracting and validating Tacit Knowledge

This section delineates outcomes of the first three steps of the scientific approach. Results are divided into different subsections. Results of the SLR are presented and evaluated. The developed method and different artifacts are introduced and applied with twenty industry experts.

4.1 Systematic literature review

The SLR is used to identify relevant approaches for acquiring and extracting TK in product engineering. The SLR approach is based on the PRISMA schema [11]. The search string combines key words based on standard literature with Boolean operators "AND" and "OR". This search string consists of four areas: method, TK, knowledge extraction and engineering. Scopus and Web of Science databases were selected for their engineering-related content. Google Scholar is added to expand scope of results and ensure completeness. To supplement findings of other databases, number of documents from Google Scholar is limited to 100. The findings and search string of SLR are shown in Figure 1.

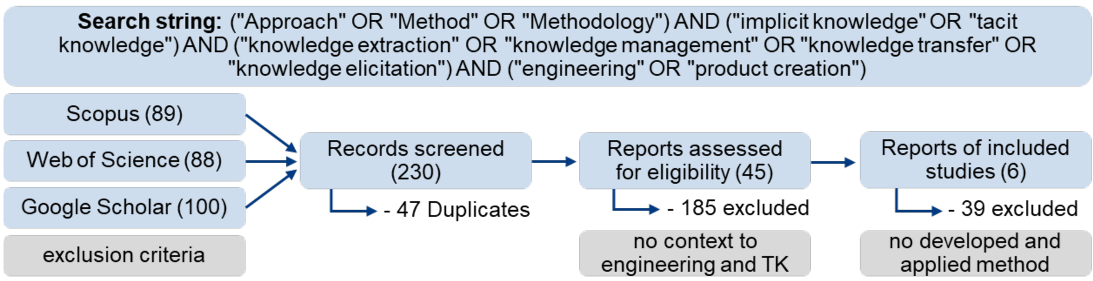

Figure 1: Results of the SLR

A total of 277 findings were retrieved. 47 duplicates were removed from results and 230 records were screened based on their titles and abstracts. 45 reports were assessed for eligibility in detail. The publications fulfil criteria such as context to TK, context to engineering and paper in English. Furthermore, an eligible publication needs to describe a method or approach that is developed, applied or validated. These criteria result in a total of six publications, whose approaches are examined in detail.

4.2 Evaluation of approaches and methods

The following evaluation considers the various knowledge acquisition and extraction methods identified in the six approaches. Overall, approaches have different orientations like development of a collaborative framework and application of a specific method. CURRAN et al. [12] develop a method for systematically reusing knowledge in a knowledge management system. SHANKAR et al. [13] define a framework based on the SECI model (socialization, externalization, combination, internalization) for transferring knowledge within companies. Both approaches refer to different methods such as expert interviews and observations for knowledge extraction, but do not provide detailed process models. Linking and application of methods remain unclear. KWONG and LEE [14] use narrative interviews to gather knowledge from experts in airline industry. WHYTE and CLASSEN [15] utilize storytelling, which is similar in application to narrative interviews. LIU et al. [16] use interviews that contain defined scenarios to obtain problem-solving suggestions from experts. This method is similar to the established critical incident technique. GARCIA-PEREZ and AYRES [17] develop a collaborative approach to knowledge representation. The first step in the preparation process is to conduct interviews to identify relevant use cases. In the next step, these use cases with unclear knowledge elements are addressed in group discussions.

In addition to methods identified through SLR, references in related work are reflected and complemented by further methods. While SLR results are related to the overall concept proposed in this paper, these methods for knowledge acquisition are derived from standard literature and are well established in qualitative research. The selected methods are shown in Table 1.

Table 1: Selected methods for acquiring tacit knowledge

Method	**Description**
Structured interview	stringent answering of questions from the prepared interview guideline, which cannot be deviated from [18]
Semi-structured interview	prepared interview guideline, which can be deviated from, with a mixture of structure and openness and a flexible focus of the questions [18]
Unstructured interview	open interview without interview guidelines [18]
Narrative interview	interview with open questions about personal experiences and experiential knowledge in detail; interviewee takes up most of the talking (narrative flow) [5,6]
In-depth interview	interview with comparatively more interventions by the researcher to identify rules, actions, types of actions and typologies; meaningful content must be determined in advance [18]
Critical incident technique (CIT)	interview in which the interviewee is asked specific questions about situations they have experienced to obtain a detailed description of the situation, behavior and resulting outcome; particularly positive and negative experiences [19]
Thinking aloud	thoughts are expressed parallel with a primary task to provide insight into problem-solving behavior of a test subject; task is focus and verbalization occurs alongside task [5]
Group discussion	discourse with six to ten participants to reflect different perspectives and to gather collective knowledge; researcher takes role of moderator [5]
Questionnaire	predefined number of questions sent to respondents; different types of questions, e.g. open questions with free text and questions answered by rating on a scale [20]

The list of methods provides a broad overview of methods for TK acquisition. The list of methods is evaluated with members of the EU funded project based on six criteria. Criteria include repeatable results (C1), text-based results (C2), anonymized results (C3), inherent process model (C4), low-effort adaptability (C5) and quality assurance of knowledge (C6). Degree of fulfilment of criteria is divided into completely fulfilled, partially fulfilled and not fulfilled. The results of the method shall be reproducible. C1 is completely fulfilled if results achieve the same structure and subject areas after repeated application. The experts' knowledge and the resulting outcomes of the method shall be represented in text form. C2 is completely fulfilled if results are available in text form immediately after application as an export. The criterion is partially fulfilled if results can be converted into text form (with an additional step). Sharing TK shall be possible anonymously to prevent participants from being influenced and potentially holding back. Results shall also be archived anonymously and do not allow any conclusions to be drawn about individuals. The criterion can be considered completely fulfilled if the results can be collected and archived anonymously to fulfill C3. The collection and processing of TK shall follow a methodical and inherent process model. C4 is completely fulfilled if the method specifies a systematic procedure for collection and processing of TK. Artifacts of the method shall be adapted with minimal effort. Additional questions and topics can be added or deleted. C5 is completely fulfilled if the method can be supplemented without changing the current version and with minimal resources. The knowledge gained shall be checked for correctness. Feedback shall be provided to pass on high-quality knowledge. C6 is fulfilled if the method provides a way of knowledge validation.

The results of evaluation of methods based on the criteria are shown in Table 3. The evaluation shows that all methods carry opportunities with regard to individual criteria. Some, like structured interviews, can be interpreted as more frequently applicable, others are adequate for very specific purposes like analysis of nonverbal actions. To cover all these characteristics, methods are combined in the developed approach. The method shall be adaptable to different setups in companies, with specific measures on knowledge management, business intelligence or quality management. None of the methods consider quality assurance of knowledge in their individual application. Quality and accuracy of knowledge is highly important for incorporating TK into technical processes in product engineering. By combining methods, control of TK should be considered and made possible. The methods that completely and partially fulfil most of the criteria are questionnaires, semi-structured interviews, narrative interviews and CIT. Based on the evaluation, these methods are selected as most beneficial for further use and considered suitable as a core of the TK acquisition approach (RQ1).

Table 3: Evaluation of selected methods

Methods/Criteria	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
Structured interview	●	◐	●	◐	○	○
Semi-structured interview	◐	◐	●	◐	●	○
Unstructured interview	○	◐	●	○	●	○
Narrative interview	◐	◐	●	◐	●	○
In-depth interview	◐	◐	●	◐	◐	○
CIT	◐	◐	●	◐	●	○
Thinking aloud	◐	◐	●	◐	◐	○
Group discussion	○	○	○	◐	●	○
Questionnaire	●	●	●	◐	●	○
Key: C = Criteria ● = completely fulfilled ◐ = partially fulfilled ○ = unfulfilled						

4.3 Method for harnessing Tacit Knowledge in Sustainable Product Engineering

With reference to RQ2, a three-step approach is developed based on results of the SLR (see Figure 2). The method contains knowledge acquisition, requirements extraction und requirements validation. The three phases are performed sequentially. In **knowledge acquisition**, experts are interviewed using semi-structured interviews according to KATENKAMP [18]. Openly formulated questions are asked to collect knowledge about sustainable product engineering. To extract relevant data and information within product engineering, various topics like materials and assembly are addressed in the interview guideline. In addition to technical categories, narrative questions and CIT questions are used at the beginning of interview. These two methods were selected as being suitable for use alongside the semi-structured interview. Narrative questions and CIT intend to encourage interviewees to talk freely about their experiences and prepare them for specific questions. Result of the first phase is documented machine-readable TK. TK can be recorded as transcripts in individual documents and a table. TK takes on an initial explicit character through documentation but remains unstructured. Statements may be duplicated and contradictory, which means that recorded knowledge should not be archived and used in this form.

In **requirements extraction,** a LLM converts acquired TK into requirements. Requirements are structured according to the SOPHIST requirements templates [21]. The detailed prompt (cf. parallel work in [22]) is used to provide context to the AI and to explain the task and response format in detail. For example: "In sustainable product engineering, screw connections should be used instead of riveted connections.". Attributes such as "ID", "domain of expertise" and "lifecycle phase" are assigned to the requirements. Use of AI ensures rapid processing and sorting of unstructured data. The level of expertise can be used as a basis for initial prioritization of requirements: Requirements obtained from statements of the interviewees with expert knowledge and extensive knowledge are more likely to be correct; requirements obtained from statements made by interviewees with basic knowledge, little knowledge and no knowledge require more detailed validation. In **requirements validation**, requirements are checked for validity using a questionnaire as an evaluation form. Through a five step Likert scale [20] identified requirements are validated for plausibility and cross-employee knowledge is utilized. Application of the developed approach facilitates conversion of TK into validated requirements. Validated requirements can be transferred to a database in a defined format.

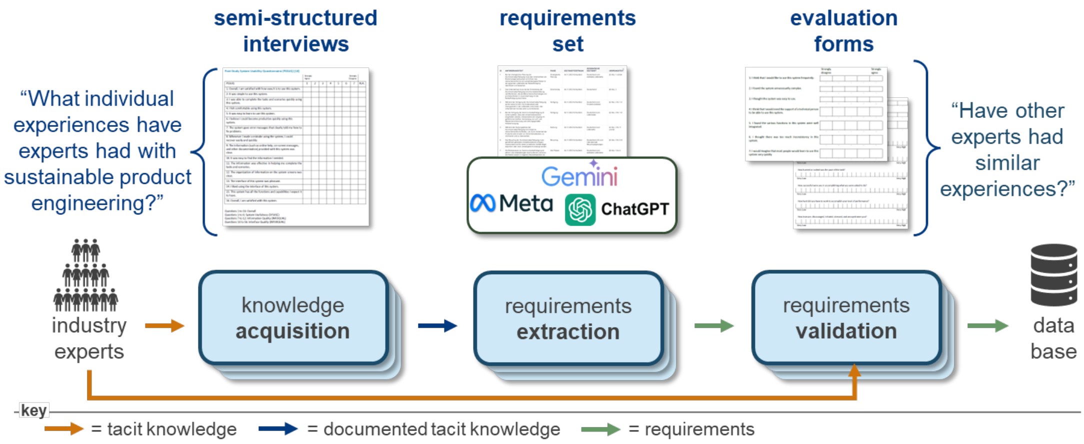

Figure 2: Developed method for harnessing tacit knowledge

4.3.1 Interview guideline for TK acquisition

An interview guideline is developed as part of the first step "knowledge acquisition". The interview guideline enables systematic querying of TK in expert interviews. Its first part consists of a brief introduction of interviewer and context. In the second part, CIT [19] and narrative questioning technique [5] are applied. These techniques get experts into narrative flow and into thinking intensively about their actions. In the third part, the interview guideline is created taking technical guidelines into account. Important areas of product engineering are considered in relation to sustainability. The main-feature list of VDI/VDE 2206 [23] contains various relevant criteria for product engineering, such as interfaces, manufacturing and recycling. The interview guideline is divided into areas according to the main features. In the interview, for example, experiences with disassembly-friendly joining methods can be requested under topic of 'assembly'. Within these areas, explicit and targeted experiences are queried in comparison to the first part. Areas from the main-feature list are supplemented by VDI 4800 [24] and VDI 2243 [25]. In areas of materials, manufacturing and assembly, for example, questions are asked on topics of lightweight construction, reparability and modularization. These topics are taken from VDI 4800 [24], which covers resource efficiency and resource conservation. The area of recycling can be enriched with further questions from VDI 2243 guideline [25] on recycling-oriented product engineering. Questions in each area are preceded by a five-point Likert scale [20]. Interviewees use this scale to assess their level of knowledge. This scale includes the levels "no knowledge", "little knowledge", "basic knowledge", "extensive knowledge" and "expert knowledge". This assessment enables classification and evaluation of knowledge elements during requirements extraction. To better illustrate technical questions, they are posed using a product example from industry partner. An excerpt from the interview guideline is shown in Figure 3.

Interview guidelines can be converted into a questionnaire to make TK extraction less resource intensive. Such questionnaire can therefore be conducted without another person acting as an interviewer. Questions from the interview guideline can be transferred verbatim into a questionnaire. A free text field is provided as a response option. This allows experts to answer questions without restriction. The Likert scale for assessing expertise can also be included in a questionnaire.

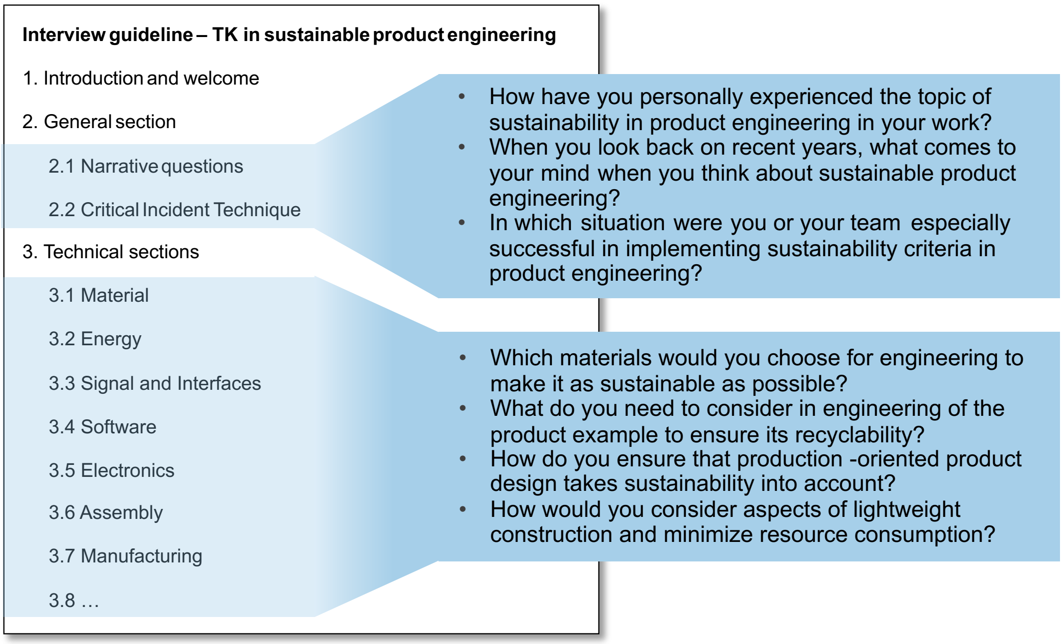

Figure 3: Exemplary questions from the interview guideline

4.3.2 Prompt for requirements extraction

In the next step, requirements are extracted from documented TK (cf. RQ3). An Excel spreadsheet serves as the source document. Often even this means a realistic type of data source; in other cases, requirements are exported from requirements management tools like DOORS or Polarion to Excel. Extraction is performed using an LLM. Due to large volume of textual data, use of an LLM saves time during text analysis. ChatGPT 5.0 is selected as LLM based on previous research with technologies like support vector machines and transformer models [26], resulting selection criteria, literature research and technical tests. The query to ChatGPT is based on a prompt. This prompt is created in advance and refined through tests with ChatGPT. Revisions like precise columns of the table to be analyzed and sample formulations for requirements are made. The prompt is divided into sections that are intended to provide ChatGPT with adequate previous knowledge to solve the task. The CO-STAR framework according to PENG et al. is used to structure the prompt and is extended to include role [27]. To ensure that individual parts are clear for AI despite long text, hashtags are used [28]. The structure of the formulated prompt is shown in Figure 4.

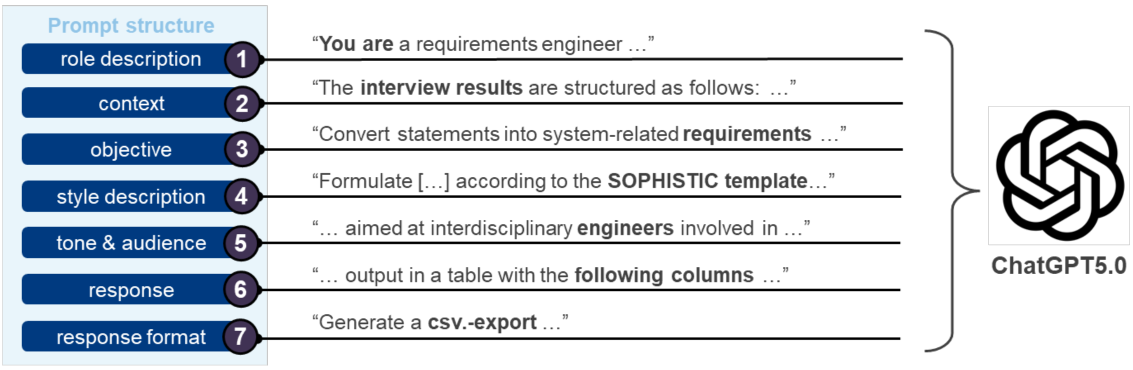

Figure 4: Structure of the formulated prompt

First, a "role description" is added to the framework. It describes the person represented by AI. "Context" provides AI with background information about the scenario. "Objective" precisely defines the task for AI model so that AI can best meet expectations. Next is the "style description" to define a template. “Tone“ determines type of wording, e.g. formal. The description of an “audience” explains who the answer given is aimed at to meet expectations. “Response” defines exactly what the output should look like. Response can be, for example a table and a specific file format. ChatGPT is utilized as an agent performing requirements engineering tasks. To provide context for AI, the prompt states where statements in the resulting table (see “response format” csv in Figure 4) come from and how the table is structured. Further refinement of this table in the final step can be achieved by including “task”, “level of expertise”, “life cycle phase” and “style”. Task describes which columns should be analyzed and provides an example of how to derive requirements. In addition to requirements, level of expertise of interviewee and life cycle phase to which the requirement relates should be specified to influence solutions of AI in a targeted manner. The individual life cycle phases are used in accordance with GRAESSLER and POTTEBAUM [29]. Style defines the appearance of requirements using the SOPHIST template [21] and specifies criteria that requirements should meet. Tone and audience help to tailor the response to a specific use case. The audience ‘engineers’ generates greater attention to technical terms and a technical perspective. Last section of the prompt explains format of desired responses. Requirements should be displayed in a table. The individual columns with desired content are listed. This allows AI to output requirements directly in the expected form to be used for evaluation.

4.3.3 Questionnaire for requirements validation

A questionnaire is used to check requirements in terms of correctness. The extracted requirements are listed in this questionnaire and grouped by topics like assembly. Experts can evaluate requirements using a five-point Likert scale [20]. Objective correctness of requirements is classified using the levels “I completely agree”, “I agree”, “I disagree”, “I completely disagree” and “I don't know”. A text box below allows additional information about requirements to be added and corrections to be made. These corrections are collected after the questionnaire has been completed and used to revise initial requirements. Requirements can be weighted based on evaluations. Requirements that are rated as incorrect by majority of experts should be removed from collection. Requirements about which majority of experts are uncertain should be reviewed through research and consolidation with additional experts. Requirements that are rated as correct by majority of experts can be included in a database.

5 Initial validation of the developed approach

The method described in section 4.3 is applied in an EU funded project. Semi-structured interviews based on the developed interview guideline[1] are conducted with twenty selected experts. During application, diversity of interview results highlighted importance of flexibility in the interview guideline. Results are then checked by an employee of the industry partner and revised if necessary to ensure that no sensitive data is disseminated. Results are then compiled in form of an Excel spreadsheet and can be evaluated. Data is anonymized to prevent any conclusions about specific individuals being drawn from an evaluation of the table. Extraction of requirements using AI worked after revisions to the prompt. ChatGPT 5.0 evaluates the table based on the final prompt and formulates requirements.

Table 4 shows five examples of requirements that are derived from the statements made in interviews. They are all related to sustainability and refer to different life cycle phases. Requirements provide general constraints for engineering. The requirements do not contain any specific technical details such as length of a component and specific materials. This is due to imprecise information provided by interviewees. In the interviews, participants only provide general context on sustainable engineering. If interviewees express themselves unclearly, AI can hardly draw logical conclusions from their statements. Accordingly, a standardized response format is necessary. This provides AI with uniformly

[1] https://zenodo.org/records/18360632

structured responses, which AI can analyze much more precisely. Validation of requirements using questionnaire was also successful. Questionnaire is implemented in a digital version using Microsoft Forms. Results allowed requirements to be grouped. Incorrect requirements are excluded immediately.

Table 4: Derived requirements from the interview statements

ID	Requirement	Life cycle phase	Level of expertise
1	The system should quantify energy usage during operation and output energy usage as a parameter.	Use	High
2	The system should only use materials whose sustainability characteristics have been verified in the material database.	Engineering	Expert
3	The system must be designed in a way that allows for the segregated separation of the main components by type for material recycling.	Decommissioning	High
4	The system must consist mainly of recyclable and corrosion-resistant materials whose surface is suitable for low-pollutant disposal and recycling.	Engineering	Basic
5	The system must avoid permanent connections such as adhesive bonds.	Engineering	High

The developed method meets the defined criteria from 4.2. The prescribed process involving various artifacts such as the prompt ensures that results are presented and evaluated in the same way. The interview guideline ensures that all experts are asked same set of questions, thereby supporting consistency across interviews (cf. C1). Extracted TK can subsequently be presented in text-based formats, such as tables or transcripts, enabling further processing by AI (cf. C2). To promote unbiased feedback, the questionnaire is conducted in a fully anonymous manner, and only a neutral interviewer is present during interviews (cf. C3). Overall, the approach follows a structured three-step process (cf. C4), while remaining flexible, as questions and additional topics can easily be incorporated into both interview guideline and questionnaire (cf. C5). Finally, a questionnaire is used to validate identified requirements and to ensure accuracy (cf. C6). The approach was successfully applied. TK extraction can be conducted either by semi-structured interviews or questionnaires. This approach allowed the concept to be tested through its application. Improvements like a standardized response format and more precise technical questions in interviews are elaborated to address problems encountered during application.

6 Conclusion and Outlook

In this paper, a method is described to facilitate conversion of tacit knowledge into validated requirements. Methods for acquiring and extracting TK are analyzed and evaluated. Most suitable methods for acquiring and extracting TK are semi-structured interviews advanced with narrative questions, CIT and questionnaires. An approach is developed from evaluation results using these methods. In the first step, TK is collected using an interview format. Technical guidelines are consulted to focus the approach specifically on sustainable product engineering. To ensure the accuracy of requirements in the final step, a feedback mechanism in form of a questionnaire is proposed. To enable an initial classification of requirements, interviews include an individual assessment of experts' knowledge on each topic area. Extracting requirements with AI offers a low-effort alternative to manually reviewing large amounts of data. AI requires a detailed prompt including sufficient context and a precise description of the expected answer to derive requirements. Overall, LLMs offer an efficient way to extract requirements. However, these requirements should not be accepted without validation. Future research will explore expanded use of LLMs and GPTs, for example through chatbot-conducted interviews, where this further automation enables scalability in companies with many employees and reduces effort required to extract TK. The developed approach supports engineers in sustainable product engineering by providing systematic technical knowledge that has been acquired through TK.

7 Aknowledgements

The research leading to these results has received funding from the European Union's Horizon Europe Program under the Digi4Circular Project, grant agreement n° 101177586. Results are reflected by the scope of DFG SPP2443 (coordination, PN521148212).

References

[1] T. C. McAloone and D. C. A. Pigosso, "Ökodesign," in Pahl/Beitz Konstruktionslehre, B. Bender and K. Gericke, eds.: Berlin, Heidelberg: Springer, 2021, pp. 975–1021.
[2] ISO 14040, "Environmental management - Life cycle assessment. Principles and framweork", Geneva, 2006.
[3] F. Lehner, "Wissensmanagement. Grundlagen, Methoden & technische Unterstützung", 8. Aufl., München: 2025.
[4] H. Wang and G. Peng, "Collaborative Knowledge Management Through Product Lifecycle. A Computational Perspective", 1st ed. 2023, Singapore: Springer Nature Singapore; Imprint Springer, 2023.
[5] G. Mey and K. Mruck, eds., "Handbuch Qualitative Forschung in der Psychologie. Band 2: Designs und Verfahren", 2. Auflage, Wiesbaden: Springer Fachmedien, 2020.
[6] U. Reisach, C. B. Nakhosteen, C. Erlach and W. Orians, "Wissenstransfer bei Fach- und Führungskräftewechsel. Erfahrungswissen erfassen und weitergeben", 2. Auflage, München: Hanser, 2025.
[7] C. Erlach, A. Mittelmann, C. B. Nakhosteen, M. Della Schiava and G. Terhoeven, "Praxis Wissenstransfer. Erfolgsstrategien und bewährte Lösungswege", München: Hanser, 2025.
[8] S. Porschen-Hueck, "Austausch impliziten Erfahrungswissens. Neue Perspektiven für das Wissensmanagement", Wiesbaden: VS Verl. für Sozialwissenschaften, 2008.
[9] S. Matzka, "Künstliche Intelligenz in den Ingenieurwissenschaften. Maschinelles Lernen verstehen und bewerten", Wiesbaden: Springer Vieweg, 2021.
[10] J. Fuchs, C. Helmerich and S. Holland, "Transforming System Modeling with Declarative Methods and Generative AI", in AIAA SCITECH 2024 Forum: Reston, Virginia: American Institute of Aeronautics and Astronautics, 2024.
[11] Page, M. J. et al., "Updating guidance for reporting systematic reviews: development of the PRISMA 2020 statement", Journal of clinical epidemiology, vol. 134, pp. 103-112, 2021.
[12] R. Curran, W. J. Verhagen and M. J. van Tooren, "A multidisciplinary implementation methodology for knowledge based engineering: KNOMAD", in Expert Systems with Application, 2010.
[13] R. Shankar, S. Acharia and A. Baveja, "Soft-system knowledge management framework for new product development", in Journal of KM, 2009.
[14] E. Kwong and W. B. Lee, "Knowledge elicitation in reliability management in the airline industry", in Journal of KM, vol. 13, no. 2, pp. 35-48, 2009.
[15] G. Whyte and S. Classen, "Using storytelling to elicit tacit knowledge from SMEs", in Journal of KM, 2012.
[16] L. Liu, Z. Jiang and B. Song, "A novel two-stage method for acquiring engineering-oriented empirical tacit knowledge", International Journal of Production, 2014.
[17] A. Garcia-Perez and R. Ayres, "Collaborative development of knowledge representations - A novel approach to knowledge elicitation and transfer", in 9th European Conference on KM, 2008, pp. 217–224.
[18] O. Katenkamp, "Implizites Wissen in Organisationen. Konzepte, Methoden und Ansätze im Wissensmanagement", Wiesbaden: VS Verl. für Sozialwiss, 2011.
[19] H. Hughes, "Critical Incident Technique", in Exploring methods in information literacy research, S. Lipu, K. Williamson and A. Lloyd, eds.: Wagga Wagga, N.S.W: Centre for Information Studies Charles Sturt University, 2007.
[20] N. Baur and J. Blasius, eds., "Handbuch Methoden der empirischen Sozialforschung", 3. Auflage, Wiesbaden: Springer VS, 2022.
[21] R. Kluge, "Die SOPHISTen Schablonen für alle Fälle", 1.th ed.Nürnberg: SOPHIST GmbH, 2013.
[22] I. Graessler and J. Pfeifer, "Performance evaluation of Large Language Models in extracting requirements sets from technical documents", International Symposium on Hybrid Intelligence in Product and Production Engineering, 2026.
[23] VDI/VDE 2206, "Development of mechatronic and cyber-physical systems", Berlin: Beuth Verlag, 2021.
[24] VDI 4800, "Ressourceneffizienz und Ressorcenschonung. Methodische Grundlagen, Prinzipien und Strategien", Düsseldorf: Beuth Verlag, 2023.
[25] VDI 2243, "Recycling-oriented product development", Düsseldorf: Beuth Verlag, 2002.
[26] I. Gräßler, D. Preuß, L. Brandt and M. Mohr, "Efficient Extraction of Technical Requirements Applying Data Augmentation", in 2022 IEEE International Symposium on Systems Engineering (ISSE): IEEE, 2022, pp. 1–8.
[27] J. Peng, H. Zhongyuan, Z. Huan, Y. Jingyan and L. Chang, "A multilingual text detoxification method based on few-shot learning and co-star framework", CLEF 2024, 2024.
[28] S. Lemeš, "Prompt Engineering", in Artificial Intelligence in Industry 4.0: The future that comes true: Academy of Sciences and Arts of Bosnia and Herzegovina, 2024, pp. 159–170.
[29] I. Graessler and J. Pottebaum, "Generic Product Lifecycle Model: A Holistic and Adaptable Approach for Multi-Disciplinary Product–Service Systems", Applied Sciences, vol. 11, no. 10, p. 4516, 2021.