Self-Assessment Tool for AI Implementation in SMEs

Nadine Kaltschmidt
Department of Economics, Magdeburg-Stendal University of Applied Sciences, Germany
Nadine.kaltschmidt@h2.de

Fabian Behrendt
Department of Economics, Magdeburg-Stendal University of Applied Sciences, Germany

Abstract
Small and medium-sized enterprises (SMEs) face growing challenges, including geopolitical uncertainty, skills shortages, climate-related transformation, and structural change. At the same time, artificial intelligence (AI) offers considerable potential to improve efficiency, competitiveness, and resilience. However, many SMEs lack a systematic basis for identifying and evaluating suitable AI use cases along their value chain. Potential benefits are often accompanied by risks, such as dependence on external technology providers and limited transparency of AI-based decisions. This creates a need for practical decision-support tools that enable a holistic, process-oriented AI transformation. This study aims to design and evaluate an AI-based self-assessment tool that supports SMEs in analyzing organizational challenges, identifying AI potential, and deriving actionable recommendations. Following a design science research approach, the study draws on a problem and needs analysis as well as a review of existing maturity and AI adoption models for SMEs. The developed artifact integrates qualitative and quantitative dimensions such as process maturity, data availability, organizational capabilities, and strategic objectives. It is evaluated iteratively through expert feedback and pilot applications. The expected contribution is a validated, easily accessible tool for innovation management in SMEs that links strategy and implementation and extends existing AI maturity models through a process-oriented, recommendation-based perspective.

1. Introduction

1.1. Motivation
The future viability of firms is shaped by both external and internal factors. Externally, geopolitical uncertainty, global crises, demographic change, and technological progress, particularly in the context of the megatrend of artificial intelligence (AI), play a significant role (Zukunftsinstitut, 2025). Internally, innovation capability, corporate culture, workforce structure, and digital business strategies are key factors influencing firms' transformative capacity; these challenges affect SMEs to a particularly high degree (Institut für Mittelstandsforschung (IfM) Bonn, 2025). Regulatory requirements such as the EU-Green Deal (European Commission, 2019), the General Data Protection Regulation (European Union, 2016) and the AI Act (European Union, 2024) create additional pressure to adapt. SMEs therefore face the challenge of maintaining their capacity to act under uncertain conditions while simultaneously investing in technological and organizational adaptation (Kagermann et al., 2021). Against this background, digitalization is regarded as a key lever for competitiveness, efficiency gains, and the development of new business models. AI in particular affects different levels of digital value creation systems and, depending on the degree of integration, assumes supportive, optimizing, or adaptive functions (Davenport & Ronanki, 2018). It supports processes and decision-making in the sense of augmented intelligence (Kirste, 2019), thereby strengthening the efficiency, flexibility, and innovative capacity of digitally networked value creation systems (Lopez et al., 2023). In addition, the continued development of large language models and generative AI creates further potential for productivity gains and innovation in SMEs (Bitkom e.V., 2025). However, these opportunities are accompanied by considerable risks. These include the limited traceability of AI-generated decisions, data protection and privacy risks, dependencies on external providers, and regulatory uncertainties that complicate the integration of AI into business processes (Bitkom Research, 2023). In addition, deficits in the explainability of AI systems persist (Bitkom Research, 2023), alongside a considerable need to catch up in terms of competencies and future skills, particularly in small and medium-sized enterprises (Stifterverband, 2025). The successful introduction of AI therefore requires not only technical implementation but also appropriate organizational conditions, transparent evaluation criteria, and a practice-oriented approach based on concrete use cases (Aström et al., 2022; Jalowski et al., 2021). At the same time, firms face the challenge of continuously optimizing existing

http://dx.doi.org/10.25673/123533

processes while simultaneously building new technological capabilities. This tension is captured in the concept of organizational ambidexterity (Olivan, 2019). It is also evident that the transfer of AI research into business applications, particularly in SMEs, has so far been insufficiently successful (Plattform Lernende Systeme, 2024). This creates a need for structured, low-threshold, and practice-oriented support. Against this backdrop, the present study aims to develop and evaluate an AI-based self-assessment tool that supports SMEs in analyzing their current situation, identifying suitable AI application areas, and deriving process-oriented recommendations for action.

1.2. Current state of research

Maturity models are an established approach to analyzing organizational and process-related stages of development (De Bruin et al., 2005; Becker et al., 2009). They structure a field of investigation into measurable influencing factors and arrange these along discrete stages of development in order to determine an organization's current state and identify potential for further development (Rosemann & De Bruin, 2005; Hammer, 2007; Paulk et al., 1993; Tarhan et al., 2016). The literature distinguishes between descriptive, prescriptive, and comparative maturity models (De Bruin et al., 2005). For practical application, it is crucial that such models are tailored to the target group and made accessible through self-assessments or online tools (Becker et al., 2009; Kühn et al., 2013). Since the Capability Maturity Model, maturity models have become established in numerous fields, including innovation management, product development, and business process management (Paulk et al., 1991; Paulk et al., 1993; De Bruin et al., 2005; Gausemeier et al., 2012; Niewöhner et al., 2021).

There is also an extensive body of research on the adoption and use of AI in companies, particularly with regard to SMEs (Schwaeke et al., 2024; Oldemeyer et al., 2024; Iyelolu et al., 2024; von Garrel & Jahn, 2023). The literature primarily highlights resource-related, strategic-organizational, technological, and culture- and competence-related barriers. These include, among others, a lack of financial and human resources, insufficient digital and AI-related strategies, fragmented IT infrastructures, data silos, low data quality, as well as skepticism and skills gaps among employees and managers (Oldemeyer et al., 2024; Govori & Sejdija, 2023). In addition, uncertainties arising from regulatory developments and liability issues further complicate adoption (Schwaeke et al., 2024). Overall, the adoption of AI in SMEs should therefore be understood as a socio-technical challenge in which the interplay of people, technology, and organization plays a central role (Hellmann, 2023).

Industry 4.0 check-ups and AI maturity check-ups already exist to enable an initial assessment of the level of digital development (Häberer et al., 2020; Mittelstand-Digital, 2024). These are based on maturity models that are now used across various domains (Paulk, 2009; Dahlin, 2020). While they provide structured starting points for assessing digital capabilities and AI maturity (Yams et al., 2020; De Bruin et al., 2005; Wendler, 2012), they also show clear limitations. Of 15 identified AI maturity models, only three have been sufficiently scientifically validated (Schuster et al., 2021). Furthermore, existing models do not adequately take into account the specific conditions of SMEs, such as limited resources, organizational dynamics, and scaling requirements. In addition, there is often no consistent pathway from maturity assessment to concrete, action-oriented support services, which results in process gaps (Jalil et al., 2024). Initial approaches to AI augmentation, such as the use of large language models (LLMs) to support maturity assessments, already exist, but are currently methodologically limited. Although the generated responses often appear linguistically convincing, their factual reliability is not consistently guaranteed (Schönmann et al., 2023). In addition, LLMs are subject to well-known limitations, such as implicit assumptions in cases of unclear input or biases in the results (OpenAI, 2022). The current state of research therefore suggests that LLMs should not be used for full automation, but rather as a supporting tool in the sense of AI augmentation (Schönmann et al., 2023).

This gives rise to the central research gap: to date, there is no scientifically grounded, SME-tailored, and design-oriented approach that integrates the human, technological, business, and organizational factors influencing AI adoption, translates them into maturity-based development frameworks, and operationalizes them in a low-threshold self-assessment tool with concrete recommendations for action. Likewise, it remains insufficiently clear which AI solutions or support measures are suitable for which levels of maturity. The novelty of this work lies in the integration of maturity modeling, AI adoption in SMEs, socio-technical factors, and AI augmentation. Unlike existing studies, this project does not merely describe barriers or measure technological maturity, but develops an integrated, maturity-based decision-making and learning tool for SMEs. The study therefore distinguishes itself from previous approaches through its design-oriented perspective and the translation of scientific findings into a practically usable self-assessment tool.

1.3. Research questions

The overarching research question is as follows: **Which human, technological, business, and organizational factors support the strategically guided process of AI adoption in SMEs, and how**

can these factors be translated into a maturity-based self-assessment tool to support organizational learning and development processes? To answer this main research question, the following sub-research questions are formulated:

1. **Human factors:** Which human factors, particularly competencies, acceptance, role understanding, and willingness to change, influence the strategic adoption of AI in SMEs?
2. **Technological factors:** Which technological factors, particularly data availability, IT infrastruc-ture, system integration, transparency, and usability, facilitate the AI adoption process in SMEs?
3. **Business factors:** Which business factors, particularly strategic fit, resource availability, expected benefits, and economic objectives, support AI adoption in SMEs?
4. **Organizational factors:** Which organizational factors, particularly leadership structures, processes, responsibilities, and innovation culture, facilitate the strategically guided AI adoption process in SMEs?
5. **Maturity perspective:** How can the identified influencing factors be structured into maturity levels of AI adoption in SMEs?
6. **Design-oriented perspective:** How can a self-assessment tool be developed based on the identified factors and maturity levels to support SMEs step by step in assessing their current status and gaining organizational insights regarding their AI adoption?

The objective of this dissertation is to develop and evaluate an integrated process model and an accompanying self-assessment tool based on the current state of research. The tool is intended to support SMEs in determining their AI maturity level, identifying suitable AI application areas, and deriving concrete, maturity-oriented recommendations for action. At the same time, it aims to promote knowledge transfer and the practical adoption of AI in workflows, products, services, and decision-making structures.

2. Methodological Approach and Research Design

The aim of this dissertation project is to provide systematic support for small and medium-sized enterprises (SMEs) in assessing their AI maturity and in the subsequent adoption of AI. AI maturity is understood here as an indicator that can be used to determine which AI-supported information systems and applications are feasible and realistically implementable under the respective conditions. In this context, information systems are regarded as practical application contexts for AI technologies, for example in the form of chatbots, automated workflows, intelligent analytics platforms, or knowledge-based assistance systems.

Design Science Research is adopted as the methodological framework. In contrast to behavioral science, which primarily aims to analyze and explain existing phenomena, design science focuses on the development and evaluation of applicable solution artifacts for real-world practical problems (Hevner et al., 2004). This research approach is particularly well suited to the present project, as it not only examines factors influencing AI adoption but also aims to develop a concrete methodology and toolkit. The overarching research methodology is the Design Science Research Methodology (DSRM) proposed by Peffers et al., as it enables the problem-driven and iterative development, demonstration, and evaluation of artifacts (Peffers et al., 2007). In this context, artifacts can be understood as constructs, models, methods, or instantiations (Hevner et al., 2004). The artifact to be developed within the scope of this work is conceived as an integrated ensemble comprising maturity-based evaluation logic, a process model, and a supporting self-assessment tool.

The research design is divided into three sequential phases. In the first phase, the theoretical foundation of the project is established through a systematic literature review and a bibliometric analysis of relevant scientific publications. The aim is to identify the state of the art, existing models, relevant success factors, barriers, and research gaps in the context of AI adoption and maturity models. In addition, case studies are used to align the theoretical findings with the practical requirements of SMEs. In the second phase, the methodology and the tool concept are developed on this basis. Within the DSRM framework, method engineering is applied for this purpose, as no existing method addresses the problem in sufficient breadth. Accordingly, existing methodological building blocks are adopted, adapted, or combined, while new components are developed only where existing approaches are insufficient (Gonzalez-Perez, 2007; Bucher et al., 2007; Mayer et al., 1992; Patel et al., 2004). In the third phase, the artifact is evaluated using a lab-to-field approach. First, the developed artifact is tested in a controlled laboratory environment with regard to functionality and usability. It is then tested in real-world business contexts in order to assess its practicality, acceptance, and utility. The evaluation is designed iteratively so that findings from both phases can be incorporated into the further development of the artifact.

Alternative methodological approaches were considered but proved only partially suitable for the project's objectives. A purely behavioral-scientific approach or an exclusively quantitative survey design might explain factors influencing AI adoption, but it would not produce a usable solution artifact. Purely exploratory qualitative approaches,

by contrast, would be suitable for identifying needs and perceptions of problems, but would not ensure the systematic development and evaluation of a self-assessment tool. Against this background, the combination of Design Science Research, method engineering, and iterative lab-to-field evaluation proves to be the most suitable methodological approach for both generating scientific insights and developing a practically usable tool for SMEs.

3. Results and Discussion

The self-assessment tool, based on a Retrieval-Augmented Generation framework (Béchard & Marquez Ayala, 2024), constitutes the central artifact of this study for the systematic assessment of AI maturity in SMEs. Its purpose is to provide companies with a structured and easily accessible framework for assessing their current status with regard to artificial intelligence, identifying relevant opportunities in key business processes, and deriving appropriate recommendations for action. In line with the research objective, the tool combines diagnostic, reflective, and recommendation-oriented functions. The assessment focuses on four core dimensions: processes, data, competencies, and technical prerequisites. The conceptual design of the tool builds on established approaches to organizational AI readiness, which describe a company's ability to use AI in terms of technological prerequisites, organizational activities, structural constraints, and strategic objectives (Holmström, 2022). In addition, the tool draws on AI adoption models specifically tailored to SMEs, in particular the AI adoption model for SMEs proposed by Bettoni et al., which highlights the interplay of technological, organizational, and environmental factors influencing implementation (Bettoni et al., 2021). Furthermore, insights from digital maturity models are integrated to enable a structured self-assessment of organizational development on the basis of defined criteria (Petzolt et al., 2022). Another important theoretical foundation concerns data usability for AI. Existing frameworks on "AI-ready data" show that data can only be used productively for AI applications if it meets minimum requirements in terms of quality, structure, metadata, and governance (Majithia et al., 2025).

Against this background, the AI self-assessment tool is not limited to measuring AI maturity in an abstract sense. Rather, it explicitly links maturity assessment to concrete application opportunities for AI. Based on the results, relevant use cases can be identified and matched with suitable demonstrators or prototypes in the AI UX Lab. In this way, the tool serves not only as a diagnostic instrument but also as a mechanism for connecting organizational needs with feasible and context-sensitive AI solutions.

3.1. Dimensions and structure of the AI self-assessment tool

The **first dimension** addresses the company's processes. It captures key business processes in areas such as marketing, human resources, operations, and finance. The aim is to map the current process situation, identify bottlenecks and recurring challenges, and document desired target states. Relevant application areas include, for example, sales planning, onboarding, quality assurance, and budget planning. The process dimension is of particular importance because AI potential can only be meaningfully assessed when it is linked to concrete operational workflows and real organizational problems. The **second dimension** concerns the data basis. Here, the tool assesses whether suitable data is available or can be generated for the identified process areas. This includes the availability of sales, image, personnel, and financial data, as well as their format, quality, timeliness, and technical accessibility. Assessing the data basis is crucial because the success of AI applications fundamentally depends on the availability and usability of appropriate data resources. The **third dimension** comprises competencies within the company. These include formal qualifications, practical experience in dealing with data and AI, internal expertise, as well as the potential to involve external partners when needed. Existing studies on AI readiness suggest that human and organizational capabilities are decisive success factors for the sustainable implementation of AI in SMEs (Böhme et al., 2024). Accordingly, this dimension captures both the current level of competence and the organization's ability to learn and build capabilities over time. The **fourth dimension** relates to technical prerequisites. These include the existing IT infrastructure, such as ERP and HR systems, production-related information systems, interfaces, cloud services, as well as aspects of IT security and data protection. The aim is to determine to what extent the current technical environment supports the introduction, integration, and operation of AI-based systems.

Overall, the tool provides more than just a snapshot of the organizational status quo. It establishes a link between a company's specific initial conditions and the requirements of potential AI demonstrators. The digitally collected responses are translated into an automated evaluation, resulting in a company-specific maturity profile. This profile forms the basis for identifying suitable AI applications and assigning relevant demonstrators in the AI UX Lab (Figure 1).

3.2. Use of the tool in the AI UX Lab

Within the AI UX Lab, the AI self-assessment tool fulfills a dual role. On the one hand, it serves as an instrument for assessing AI maturity. On the other hand, it functions as a guiding mechanism that

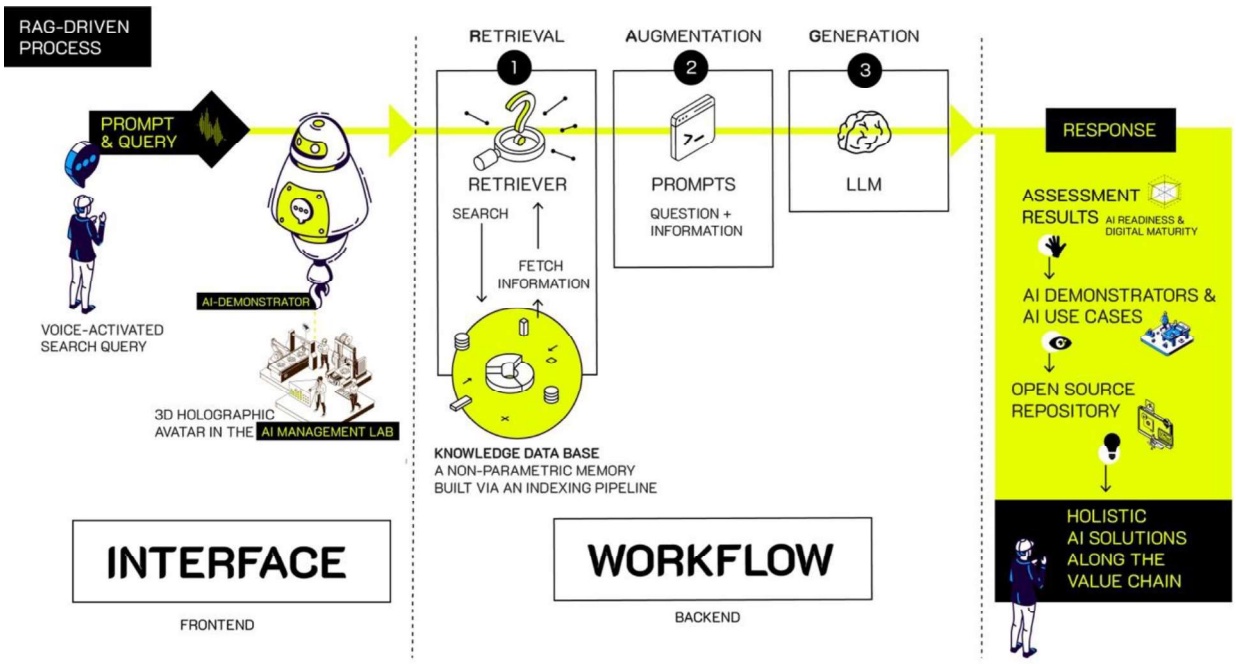

Figure 1: Conceptual framework of Assessment tool and AI UX Lab

raises SMEs' awareness of relevant AI topics and supports the targeted presentation of suitable demonstrators and recommendations. At the beginning of the process, participating companies engage with preparatory information materials addressing the opportunities, risks, and possible fields of application of AI. This initial phase is intended to establish a basic understanding of AI and foster realistic expectations regarding potential implementation. In a subsequent step, the companies use the tool to capture their relevant business processes, existing data structures, competencies, and technical prerequisites. The collected information is auto-matically analyzed and converted into readiness scores, which form the basis of a company-specific profile. This profile then serves as the starting point for selecting suitable demonstrators and designing tailored lab sessions. During the lab session itself, the identified demonstrators are explored together with the participants in a practical environment. This enables the validation of the self-assessment results, the identification of adoption barriers, and the joint development of ideas for improving data structures, competencies, and technical prerequisites. The results are fed back to the companies in the form of structured recommendations for action. Through repeated use of the self-assessment, development progress can be made visible and future implementation measures can be continuously adjusted. Such iterative reassessment is essential for establishing a sustainable improvement process in SMEs (Naheed et al., 2025).

From a didactic perspective, the AI UX Lab draws on findings from digital learning research. Studies show that dialogical support and exploratory learning environments make a substantial con-tribution to competence development, whereas purely instructive forms of metacognitive training are often less effective (Geiger, 2020). These findings are operationalized through the avatar-based guide, which provides a metacognitive scaffold for structured discovery. This includes hypothesis-driven questions, responsive feedback, targeted demonstrator suggestions, and systematic prompts for reflection, for example on how the implementation of an AI solution could be approached. The conceptual design also follows recommendations that identify digital learning environments, AI playgrounds, and practical demonstrators as particularly effective formats for competence development (Stifterverband, 2025).

3.3. Theoretical foundation

The theoretical foundation of the AI UX Lab is rooted in connectivism (Siemens, 2005; Downes, 2008). This perspective assumes that learning in the digital age is fundamentally shaped by the ability to establish, maintain, and productively use connections between information sources, technological systems, and human actors. This assumption is reflected in the design of the AI UX Lab, where the avatar-based guide functions as a central node within a broader learning network. It connects organizational challenges with relevant knowledge resources, demonstrators, and interaction formats. The demonstrators and accompanying materials function as information nodes between which participants actively navigate. At the same time, social interaction in the form of discussion, guided exploration, and joint reflection serves as an additional connecting element between participants and facilitators. As a result, the lab provides a learning environment in which knowledge is not conveyed in isolation but explored in relation to practical application

scenarios, technological possibilities, and organizational decision-making situations.

3.4. Evaluation based on SME use cases

To evaluate the AI self-assessment tool and its integration into the AI UX Lab under real-world conditions, three case studies were conducted with three different manufacturing SMEs. Together, these case studies covered the entire process chain, from the assessment of digital maturity and AI readiness to the identification of AI potential and the practical demonstration of a suitable AI solution. The evaluation was carried out in several steps. First, an expert assessment was conducted jointly with each SME in order to produce an initial external assessment of the company's digital maturity and AI readiness. This expert assessment later served as a basis for comparison with the results of the AI-supported self-assessment and provided an initial indication of the extent to which AI support can improve problem diagnosis and the quality of recommendations.

In the second step, the companies carried out the self-assessment through the dialog-based avatar using natural language. Technologically, the tool was implemented as a RAG-based AI framework connected to a vector database and a generative language model. The interaction was embedded in a three-dimensional avatar presented as an interactive light installation. This design aimed to create a low-threshold and engaging conversational interface for the participating companies. Within the dialogue, company representatives provided information on their processes, current challenges, digital infrastructure, competencies, and perceived needs. Based on these inputs, the system generated an individual assessment of digital maturity and AI readiness and proposed suitable AI solutions tailored to the company profile.

In the third step, the proposed AI solution was linked to a corresponding demonstrator in the AI UX Lab. The demonstrator was then either presented by lab staff or explored independently by the participating SME representatives. During this phase, experts observed how users interacted with the lab guide and the demonstrator, paying particular attention to engagement, understanding, transfer to company-specific problems, and the perceived usefulness of the proposed solution. Following the practical exploration, semi-structured interviews were conducted with the participants to capture their user experience, their perception of the avatar-based guidance, and their evaluation of the proposed AI solution. The interviews also served to identify remaining uncertainties, adoption barriers, and possible requirements for implementation in the company context. In a subsequent consulting phase, implementation options for the SME were discussed. Depending on the company's capacities, implementation was either initiated internally or prepared in cooperation with external service providers. Finally, a follow-up phase was envisaged in which experts reassessed the company's digital maturity and AI readiness in order to capture development progress and identify changes resulting from the intervention.

3.5. Results from the case studies

The case studies show that the use of the AI self-assessment tool in combination with a visit to the AI UX Lab triggered substantial learning and knowledge transfer processes in the participating SMEs. During the diagnostic phase alone, deficits relating to data quality, process digitalization, and AI-related competencies became visible. At the same time, the companies generally showed a positive attitude toward innovation, although this was accompanied by uncertainties regarding feasibility, implementation effort, and expected benefits. During the lab sessions, participants demonstrated a high level of engagement. They actively interacted with the lab guide, repeatedly related the presented demonstrators to their own process challenges, and gradually developed a more exploratory and technology-open mindset. The dialogical interaction and guided discovery format frequently led to moments of insight, a deeper understanding of the AI technologies presented, and growing confidence in the applicability of AI to their own operational contexts. On this basis, a concrete use case could be derived for each of the three SMEs. In all cases, internal project teams were formed, data collection activities were initiated, and initial qualification or training measures were discussed or launched. In addition, the use cases identified by experts and highlighted by the avatar could be validated, refined, and made more tangible through the lab environment. This suggests that the combination of expert assessment and AI-supported self-assessment can create a useful triangulation for identifying practically relevant AI opportunities. At the same time, familiar barriers to AI adoption in SMEs became apparent during the implementation phase. These included limited IT resources, insufficiently structured data, a lack of internal AI expertise, and concerns about the additional workload associated with initial implementation. Nevertheless, the pilot efforts were continued in all cases, supported by the assessment that the demonstrators were realistic, understandable, and directly related to operational practice.

From a Design Science Research perspective, the case studies confirm several relevant aspects of the artifact. First, they substantiate the practical relevance of the identified problem. Second, they provide initial evidence that the theoretical foundations of the artifact can be translated into a usable intervention format. Third, they show that the artifact offers practical utility by supporting SMEs in diagnosing their current status, identifying suitable AI opportunities, and initiating concrete implementation steps. A comparison of the

situation before and after the intervention also indicates an increase in AI-related knowledge and in readiness to implement AI-based solutions. Although these effects should be interpreted with caution due to the exploratory nature of the case studies, they nevertheless point to a positive change in organizational AI readiness.

4. Validation, limitations, and generalizability

The evaluation of the developed artifact aims to examine both the methodological robustness and the practical applicability of the AI self-assessment tool in combination with the AI UX Lab. In line with Design Science Research, a distinction can be made between verification and validation. Whereas verification examines whether the artifact functions as intended in conceptual and technical terms, validation addresses its usefulness in real-world application contexts for small and medium-sized enterprises (SMEs). Verification is first carried out at the conceptual and methodological level through the theory-driven derivation of the assessment dimensions from the current state of research. The dimensions integrated into the tool, processes, data, competencies, and technical prerequisites, were derived from existing approaches to AI maturity, maturity models, research on AI adoption in SMEs, and requirements for AI-ready data. In addition, verification is supported by comparing expert-based assessments with AI-supported self-assessments. This comparison serves to examine the extent to which the results generated by the AI self-assessment tool correspond to expert-informed evaluations and whether AI-supported diagnosis leads to plausible and comprehensible results. Functional verification is further ensured through the technical implementation of the dialogical assessment, the consistency of result generation, and the alignment between the generated profiles and the demonstrators selected in the AI UX Lab.

Validation of the approach is conducted through three case studies involving SMEs from the manufacturing sector in a real-world application context. The aim is to examine the practical utility of the artifact under actual organizational conditions. For this purpose, several levels of data collection and observation are combined. First, the maturity and readiness profiles generated by the tool are analyzed. Second, observations are made of how representatives of the participating companies interact with the avatar-based lab guide and the proposed demonstrators. Third, semi-structured interviews are used to capture perceptions regarding the comprehensibility, usefulness, and feasibility of the proposed AI solutions. Fourth, implementation-related impulses within the companies are taken into account, such as the formation of internal project teams, the initiation of data collection activities, or the planning of further qualification measures. Validation is therefore not limited to subjective satisfaction measures but is based on multiple indicators that make learning processes, initial transfer effects, and organizational acceptance visible.

The central indicators used to evaluate the artifact include the degree of correspondence between expert judgment and AI-supported diagnosis, the comprehensibility of the recommendations, participant engagement in the lab, the perceived relevance of the demonstrators, the increase in AI-related understanding, and the willingness to continue implementation. In addition, initial transfer effects can be considered, for example when concrete use cases are derived from the lab intervention, internal responsibilities are defined, or next implementation steps are prepared. Although these indicators do not yet allow for a comprehensive impact analysis in terms of long-term business outcomes, they provide solid initial evidence of the usability and immediate value of the approach.

The evaluation results obtained so far indicate that the artifact is fundamentally suitable for supporting SMEs in the structured reflection on their initial situation as well as in the identification and contextualization of AI potential. In particular, the combination of dialogical self-assessment, visualized interaction, demonstrator-based exploration, and subsequent reflection appears capable of triggering learning and transfer processes. At the same time, it becomes clear that the quality of the results depends not only on the technical capabilities of the system, but also on the openness of the participants, the quality of the information provided, the existing data situation, and the organization's ability to translate insights into action. The interpretive value of the evaluation results must therefore always be considered in light of the specific organizational context. Despite these promising findings, several limitations must be acknowledged. First, the present analysis is based on a small number of exploratory case studies. The empirical basis is therefore limited and does not allow for statistical generalization. Second, only SMEs from the manufacturing sector were included, leaving open the question of the extent to which the findings can be transferred to other sectors, such as services or public organizations. Third, part of the data is based on self-reports by the participants. Such assessments may be influenced by social desirability, incomplete information, or subjective misperceptions. Fourth, the evaluation currently focuses primarily on short-term effects, such as gains in knowledge, changes in attitudes, and initial implementation impulses. Whether these impulses actually lead to sustainable AI adoption, measurable process improvements, or economic effects cannot yet be conclusively assessed on the basis of the current state of investigation.

An additional limitation concerns the role of AI support itself. While the use of a RAG-based system with a generative language model can facilitate interaction and support individualized recommendations, the quality of the results still depends on the quality of the knowledge base, the structure of the queries, and the consistency of the underlying assessment logic. Even if responses appear technically plausible, it cannot automatically be assumed that every recommendation is optimal or complete for the respective organizational context. It follows that AI-based assessment and recommendation systems should currently be understood as supportive rather than autonomous decision-making instruments. Human expertise remains indispensable, particularly when prioritizing measures, considering organizational contingencies, and planning concrete implementation steps.

A differentiated view is therefore required with regard to the generalizability of the findings. In a statistical sense, the present results are not generalizable, since neither the sample size nor the research design was intended to achieve representativeness. However, analytical generalization appears possible. This means that the patterns, barriers, and enabling factors identified in the case studies may be transferable to similar contexts, especially to SMEs facing comparable challenges in relation to digitalization, resource scarcity, data structures, and competence development. Generalizability therefore relates less to the precise manifestation of individual findings than to the broader mechanisms of the artifact, such as the linkage between assessment, reflection, demonstration, and the initiation of implementation. At the same time, the use of the artifact opens up considerable opportunities. The AI self-assessment tool can help lower the threshold for engaging with AI-related topics in SMEs, translate abstract technological potential into concrete business problems, and bridge the gap between maturity assessment and practical implementation. Its potential to stimulate organizational learning processes and make implementation barriers visible at an early stage is particularly promising. In addition, integration into the AI UX Lab creates the opportunity not only to convey knowledge about AI, but also to test this knowledge in an experience-oriented environment and relate it directly to the company-specific context. This represents a significant added value compared with purely diagnostic maturity models.

For future research, this implies that the evaluation should be extended to a broader empirical basis in the next step. Additional case studies in other industries, comparisons across company sizes, and longitudinal studies capturing medium- and long-term effects appear particularly valuable. Furthermore, future research should examine which assessment dimensions and interaction formats prove especially relevant in different application contexts and to what extent the artifact can be adapted modularly. In this way, not only the generalizability but also the robustness and scalability of the developed approach could be systematically advanced.

References

Aström, J., Reim, W., & Parida, V. (2022). Value creation and value capture for AI business model innovation: A three-phase process framework. Review of Managerial Science, 16(7), 2111–2133. https://doi.org/10.1007/s11846-022-00521-z

Béchard, P., & Marquez Ayala, O. (2024). Reducing hallucination in structured outputs via retrieval-augmented generation. https://doi.org/10.48550/arXiv.2404.08189

Becker, J., Knackstedt, R., & Pöppelbuß, J. (2009). Developing maturity models for IT management: A procedure model and its application. Business & Information Systems Engineering, 1(3), 213–222. https://doi.org/10.1007/s12599-009-0044-5

Bettoni, A., Matteri, D., Montini, E., Gładysz, B., & Carpanzano, E. (2021). An AI adoption model for SMEs: A conceptual framework. IFAC PapersOnLine, 54(1), 702–708. https://doi.org/10.1016/j.ifacol.2021.08.082

Bitkom e. V. (2025). Generative KI im Unternehmen: Rechtliche Fragen zum Einsatz generativer Künstlicher Intelligenz im Unternehmen. Bitkom. https://www.bitkom.org/sites/main/files/2024-02/Bitkom-Leitfaden-Generative-KI-im-Unternehmen.pdf

Bitkom Research. (2023). Künstliche Intelligenz - Wo steht die deutsche Wirtschaft? Bitkom e. V. https://www.bitkom.org/sites/main/files/2023-09/bitkom-charts-ki-im-unternehmen.pdf

Böhme, C., Graf-Pfohl, C., & Meusinger, K. (2024). Human-centered implementation process of AI in SMEs – Conditions for success. AI Tomorrow, 83–99. https://doi.org/10.1007/978-3-658-43705-3_7

Bucher, T., Klesse, M., Kurpjuweit, S., & Winter, R. (2007). Situational method engineering. In J. Ralyté, S. Brinkkemper, & B. Henderson-Sellers (Eds.), Situational method engineering: Fundamentals and experiences (pp. 33–48). Springer. https://doi.org/10.1007/978-0-387-73947-2_5

Dahlin, G. (2020). What can we learn from process maturity models? A literature review of models addressing process maturity. International Journal of Process Management and Benchmarking, 10(4), 495–519. https://doi.org/10.1504/IJPMB.2020.110285

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 67–84.

https://hbr.org/2018/01/artificial-intelligence-for-the-real-world

De Bruin, T., Freeze, R., Kulkarni, U., & Rosemann, M., (2005). Understanding the main phases of developing a maturity assessment model. In D. Bunker, B. Campbell, & J. Underwood (Eds.), Australasian Conference on Information Systems (ACIS) (pp. 8–19). https://aisel.aisnet.org/acis2005/109

Downes, S. (2008). An introduction to connective knowledge. In T. Hug (Ed.), Media, knowledge & education: Exploring new spaces, relations and dynamics in digital media ecologies (pp. 77–102). Innsbruck University Press. https://doi.org/10.25969/mediarep/19789

European Commission. (2019). The European Green Deal (COM(2019) 640 final). EUR-Lex. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52019DC0640

European Union (2016). Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). Official Journal of the European Union, L 119, 1–88. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R0679

European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence. Official Journal of the European Union. https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=OJ:L_202401689

Gausemeier, J., Bensiek, T., Kühn, A., & Grafe, M. (2012). Maturity-based improvement of product development processes in small and medium-sized enterprises. In DS 70: Proceedings of DESIGN 2012, the 12th International Design Conference, Dubrovnik, Croatia (pp. 41–50).

Geiger, M. (2020). Digitale Lernräume und kognitive Unterstützung in der Weiterbildung (Kap. 4–5). Springer.

González-Pérez, C. (2007). Supporting situational method engineering with ISO/IEC 24744 and the work product pool approach. In J. Ralyté, S. Brinkkemper, & B. Henderson-Sellers (Eds.), Situational method engineering: Fundamentals and experiences (pp. 7–18). Springer. https://doi.org/10.1007/978-0-387-73947-2_3

Govori, A., & Sejdija, Q. (2023). Future prospects and challenges of integrating artificial intelligence within the business practices of small and medium enterprises. Journal of Governance and Regulation, 12(2), 176–183. https://doi.org/10.22495/jgrv12i2art16

Häberer, S., Behrendt, F., & Seidel, H. (2020). Train-the-Trainer concept for the "Industrie 4.0-CheckUp." In Proceedings of the 53rd Hawaii International Conference on System Sciences (HICSS). https://doi.org/10.24251/hicss.2020.562

Hammer, M. (2007, April 1). The process audit. Harvard Business Review. https://hbr.org/2007/04/the-process-audit

Hellmann, M. (2023). Das Konzept des soziotechnischen Systems – Vorschlag eines Rahmenmodells zur Analyse von Digitalisierungsprozessen. https://doi.org/10.13140/RG.2.2.16919.79527

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75–105. https://doi.org/10.2307/25148625

Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. Business Horizons, 65(3), 329–339. https://doi.org/10.1016/j.bushor.2021.03.006

Institut für Mittelstandsforschung (IfM) Bonn. (2025, 22. Januar). Mittelstandsdefinition des IfM Bonn. https://www.ifm-bonn.org/definitionen/mittelstandsdefinition-des-ifm-bonn

Iyelolu, T. V., Agu, E. E., Idemudia, C., & Ijomah, T. I. (2024). Driving SME innovation with AI solutions: Overcoming adoption barriers and future growth opportunities. International Journal of Science and Technology Research Archive, 7(1), 36–54. https://doi.org/10.53771/ijstra.2024.7.1.0055

Jalil, M. F., Lynch, P., Marikan, D. A. B. A., & Isa, A. H. B. M. (2024). The influential role of artificial intelligence (AI) adoption in digital value creation for small and medium enterprises (SMEs): Does technological orientation mediate this relationship? AI & Society, 40(3), 1875–1896. https://doi.org/10.1007/s00146-024-01969-1

Jalowski, M., Roth, A., Oks, S. J., & Wilga, M. (2021). Innovation KI-basierter Dienstleistungen für die industrielle Wertschöpfung – Ein artefaktzentrierter Ansatz. In M. Bruhn & K. Hadwich (Eds.), Künstliche Intelligenz im Dienstleistungsmanagement (pp. 158–183). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-34324-8_7

Kagermann, H., Süssenguth, F., Körner, J., Liepold, A., & Behrens, J. H. (2021). Resilienz als wirtschafts- und innovationspolitisches Gestaltungsziel (acatech IMPULS). acatech – Deutsche Akademie der Technikwissenschaften. https://www.acatech.de/publikation/resilienz-als-wirtschafts-und-innovationspolitisches-gestaltungsziel/

Kirste, M. (2019). Augmented intelligence – Wie Menschen mit KI zusammen arbeiten. In V. Wittpahl (Ed.), Künstliche Intelligenz: Technologie | Anwendung | Gesellschaft (pp. 58–71). Springer Vieweg. https://doi.org/10.1007/978-3-662-58042-4_4

Kühn, A., Bensiek, T., & Gausemeier, J. (2013). Framework for the development of maturity-based self-assessments for process improvement. In ICED13, Proceedings of the 19th International Conference on Engineering Design. Volume 1: Design Processes (pp. 119–128).

Lopez, M., Khan, A., & Wei, L. (2023). Artificial intelligence in intelligent transport systems: Challenges and opportunities. In D. Watzenig (Ed.), The future of intelligent transport systems (Chapter 4). Elsevier. https://doi.org/10.1016/B978-0-323-99135-3.00004-X

Majithia, N., Carey-Wilson, T., & Simperl, E. (2025). *A framework for AI-ready data*. Open Data Institute. https://doi.org/10.61557/ODEX6433

Mayer, R. J., Keen, A., & Wells, M. (1992). Information integration for concurrent engineering (IICE): IDEF4 object-oriented design method report (Report No. AL-TR-1992-0056). Armstrong Laboratory, Air Force Systems Command. https://www.researchgate.net/publication/235082262_Information_Integration_for_Concurrent_Engineering_IICE_IDEF4_Object-Oriented_Design_Method_Report

Mittelstand-Digital. (2024). KI-Readiness. In Wissenschaft trifft Praxis (Issue 22, pp. 12–17). https://www.mittelstand-digital.de/MD/Redaktion/DE/Publikationen/Wissenschaft-trifft-Praxis/magazin-wissenschaft-trifft-praxis-ausgabe-22.pdf

Naheed, S., Pinto, R., & Pirola, F. (2025). A preliminary multidimensional AI readiness assessment model for SME's. Procedia Computer Science, 253, 774–783. https://doi.org/10.1016/j.procs.2025.01.139

Niewöhner, N., Lang, N., Asmar, L., Röltgen, D., Kühn, A., & Dumitrescu, R. (2021). Towards an ambidextrous innovation management maturity model. Procedia CIRP, 100, 289–294. https://doi.org/10.1016/j.procir.2021.05.068

Oldemeyer, L., Jede, A., & Teuteberg, F. (2024). Investigation of artificial intelligence in SMEs: A systematic review of the state of the art and the main implementation challenges. Management Review Quarterly, 74(1), 1–43. https://doi.org/10.1007/s11301-024-00405-4

Olivan, P. (2019). Methode zur organisatorischen Gestaltung radikaler Technologieentwicklungen unter Berücksichtigung der Ambidextrie (Dissertation, Universität Stuttgart). Fraunhofer Verlag. https://doi.org/10.18419/opus-10639

OpenAI. (2022, November 30). Introducing ChatGPT. https://openai.com/index/chatgpt/

Patel, C., de Cesare, S., Iacovelli, N., & Merico, A. (2004). A framework for method tailoring: A case study. In M. Serour (Ed.), Proceedings of the 2nd OOPSLA Workshop on Method Engineering for Object-Oriented and Component-Based Development (pp. 23–37). Centre for Object Technology Applications and Research. https://www.academia.edu/2405699/A_Framework_for_Method_Tailoring_A_Case_Study

Paulk, M. C. (2009). A history of the Capability Maturity Model for software. ASQ Software Quality Professional, 12(1), 5–19. https://personal.utdallas.edu/~mcp130030/papers/p2009c.pdf

Paulk, M. C., Curtis, B., & Chrissis, M. B. (1991). Capability maturity model for software. Carnegie Mellon University, Software Engineering Institute. https://apps.dtic.mil/sti/citations/ADA240603

Paulk, M. C., Curtis, B., Chrissis, M. B., & Weber, C. V. (1993). Capability maturity model, version 1.1. IEEE Software, 10(4), 18–27. https://doi.org/10.1109/52.219617

Petzolt, S., Hölzle, K., Kullik, O., Gergeleit, W., & Radunski, A. (2022). Organisational digital transformation of SMEs—Development and application of a digital transformation maturity model for business model transformation. International Journal of Innovation Management, 26(3), Article 2240017. https://doi.org/10.1142/S1363919622400175

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. Journal of Management Information Systems, 24(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Plattform Lernende Systeme. (2024). Mit KI Wert(e) schaffen: Eine Orientierung zum erfolgreichen KI-Einsatz in Unternehmen (Whitepaper). acatech – Deutsche Akademie der Technikwissenschaften. https://doi.org/10.48669/pls_2024-8

Rosemann, M., & de Bruin, T. (2005). Towards a business process management maturity model. In D. Bartmann, F. Rajola, J. Kallinikos, D. E. Avison, R. Winter, P. Ein-Dor, J. Becker, F. Bodendorf, & C. Weinhardt (Eds.), Proceedings of the 13th European Conference on Information Systems: Information systems in a rapidly changing economy (ECIS 2005) (pp. 521–532). University of Regensburg. https://aisel.aisnet.org/ecis2005/37

Schönmann, A., Lodes, L., & Schiendorfer, A. (2023). KI-Augmentation der Reifegradbewertung von Technologien: Können KI-Sprachmodelle Expertenwissen ersetzen? In R. Dumitrescu & K. Hölzle (Ed.), Vorausschau und Technologie-planung: 17. Symposium für Vorausschau und Technologieplanung, 14. und 15. September 2023, Berlin (pp. 371–387). Universität Paderborn. https://doi.org/10.17619/UNIPB/1-1821

Schuster, T., Waidelich, L., & Volz, R. (2021). Reifegradmodelle zur Bewertung Künstlicher Intelligenz in kleinen und mittleren

Unternehmen. In INFORMATIK 2021 – Computer Science & Sustainability. Proceedings der 51. Jahrestagung der Gesellschaft für Informatik (pp. 1237–1246). Gesellschaft für Informatik e. V. https://doi.org/10.18420/informatik2021-102

Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. (2024). The new normal: The status quo of AI adoption in SMEs. Journal of Small Business Management, 1–35. https://doi.org/10.1080/00472778.2024.2379999

Siemens, G. (2005). Connectivism: A learning theory for the digital age. International Journal of Instructional Technology and Distance Learning, 2(1), 3–10. https://www.itdl.org/Journal/Jan_05/article01.htm

Stifterverband. (2025). KI-Kompetenzen in deutschen Unternehmen. https://www.stifterverband.org/sites/default/files/2025-01/ki-kompetenzen_in_deutschen_unternehmen.pdf

Tarhan, A., Turetken, O., & Reijers, H. A. (2016). Business process maturity models: A systematic literature review. Information and Software Technology, 75, 122–134. https://doi.org/10.1016/j.infsof.2016.01.010

von Garrel, J., & Jahn, C. (2023). Design framework for the implementation of AI-based (service) business models for small and medium-sized manufacturing enterprises. Journal of the Knowledge Economy, 14(3), 3551–3569. https://doi.org/10.1007/s13132-022-01003-z

Wendler, R. (2012). The maturity of maturity model research: A systematic mapping study. Information and Software Technology, 54, 1317-1339. https://doi.org/10.1016/j.infsof.2012.07.007

Yams, N., Richardson, V., Shubina, G., Albrecht, S., & Gillblad, D. (2020). Integrated AI and innovation management: The beginning of a beautiful friendship. Technology Innovation Management Review, 10(11), 5 -18. https://doi.org/10.22215/timreview/1399

Zukunftsinstitut GmbH. (2025). Megatrend-Dokumentation 2025. https://shop.zukunftsinstitut.de/Megatrend-Dokumentation-2025-p722369654