Assessing AI for Sustainability in SME Value Creation

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Abstract
Small and medium-sized manufacturing enterprises (SMEs) are under increasing pressure in the wake of sustainable and digital transformation to prioritize transformation measures in a targeted manner with limited resources. Artificial intelligence (AI) can act as an enabler of the twin transition here, especially when it comes to achieving sustainability goals in value-adding processes. However, there is currently a lack of SME-specific approaches that evaluate AI for Sustainability (AI4S) use cases prior to implementation, while also taking feasibility into account. This article provides a concise overview of the overarching research project. It begins by presenting the current state of research. It also highlights the typical challenges faced by SMEs in the EU manufacturing sector despite the promising prospects of AI, and defines key terms. On this basis, research deficits are presented and requirements for the evaluation logic are then derived. The result is an initial generic, deliberately unvalidated phase model that structures the selection process. Finally, limitations and approaches for further research are discussed.

1. Introduction

1.1. Motivation
Manufacturing companies are currently facing a convergence of various challenges that are particularly affecting small and medium-sized enterprises (SMEs). Typical drivers include stricter sustainability and transparency requirements in the wake of the European Green Deal (EGD) and the increasing globalization of value creation networks (Brinken et al., 2023; Europäische Kommission, 2025; Milewska & Milewski, 2025; Shen et al., 2020). This results in cascade effects, whereby regulatory obligations are often passed along the supply chain, placing SMEs as upstream suppliers under particular pressure to act and comply with regulations. At the same time, limited financial and human resources make it difficult for SMEs to systematically address transformation requirements and prioritize appropriate measures. In the SME context in particular, the sustainability transformation is therefore associated with ambivalence. On the one hand, investments in sustainability are a burden in the short term, but on the other hand, they can generate a medium to long-term competitive advantage (Bella et al., 2024; Fontana et al., 2024; Leu et al., 2021; Schmitt et al., 2025; Steidle et al., 2025).

In addition to growing regulatory pressure due to sustainability, there is also increasing pressure to digitize. The increasing globalization of value creation networks and higher transparency requirements are intensifying the pressure to use digital technologies for efficient, value-adding processes (Bella et al., 2024). Although digital technologies offer considerable potential for efficiency gains, cost reductions, transparency, and innovation along the value chain, this is countered by limited financial resources, a lack of strategic orientation and corporate culture, and a lack of expertise (Behrendt et al., 2023). In addition, digital initiatives are often implemented in isolation, which makes it difficult to fully exploit their potential. Against this backdrop, the concept of twin transition (TT) addresses the need to take an integrated view of sustainability and digitalization transformation (Bella et al., 2024; Schmitt et al., 2025).

Artificial intelligence (AI) can play a key role here, as it offers considerable potential for addressing these trends through data-driven analysis functions, for example, by increasing efficiency, improving quality, or developing new data-driven business models. This presents SMEs with the challenge of jointly and systematically tapping into the potential of AI as an enabler of both digitalization and sustainability. Although many SMEs recognize the relevance and potential of AI, concrete AI projects have rarely been implemented to date due to a lack of AI strategies and expertise (FZI Forschungszentrum Informatik, 2025; Iyelolu et al., 2024).

Existing research therefore lacks SME-specific approaches that systematically evaluate the potential of AI for environmental sustainability (AI4S) prior to implementation and embed it in the TT. Particularly in view of the aforementioned ambivalence between short-term financial burdens and medium- to long-term strategic advantages, an ex-ante assessment appears particularly relevant in order to prioritize measures not only according to their ecological potential, but also according to their feasibility and expected benefits.

The entire research project therefore pursues the following overarching research question: **Under what structural and organizational conditions do AI4S applications develop an assessable sustainability potential in value-adding processes of manufacturing SMEs?**

However, this question cannot be answered in this article alone. Rather, the question pursued is what challenges SMEs face and what requirements are therefore placed on an evaluation logic within the framework of the research project.

The aim of this article is therefore to develop an initial, deliberately unvalidated structuring logic that manufacturing SMEs can use to classify AI4S use cases along the value chain, taking feasibility into account before implementation. To this end, key concepts are first presented and defined, and typical SME challenges are analyzed. This will identify key gaps in existing research and describe requirements for the model. On this basis, a generic structuring logic for evaluation will be presented and requirements derived from the structuring logic will be identified for further research. Finally, potential for subsequent research and, in particular, empirical validation will be highlighted. The article follows a design science-oriented approach.

1.2. Methodological Approach

This research project follows the overarching framework of the Design Science Research (DSR) methodology. DSR deliberately addresses the interface between theory and practice. This iterative research method is particularly suitable for the development of artifacts and is characterized by its strong application orientation. The term artifact is initially abstract and can be understood as the result of the research process (Hevner et al., 2004; Peffers et al., 2007). In the context of the research project, the assessment methodology is to be understood as such an artifact.

In an iterative process, the DSR process follows these five phases (Peffers et al., 2007):

- **Problem identification and motivation:** Defines the practical problem and justifies the scientific necessity of the research.
- **Definition of objectives for a solution:** Requirements for the artifact to be developed are derived from the problem identification. These can be both qualitative and quantitative.
- **Design and development of the artifact:** Based on existing scientific knowledge, the artifact is constructed by defining the desired functionalities.
- **Evaluation and validation of the artifact:** The developed artifact is evaluated using suitable test procedures. Iterations back to the design are possible here. Validation can be carried out against the identified research gap or against the real world. If the artifact solves the problem, the next step can be started.
- **Communication and summary:** The results are documented and published in a suitable forum in order to expand the current state of knowledge.

This article focuses primarily on problem identification and motivation. In this early phase of the research project, the focus is less on the development and evaluation of a fully elaborated artifact and more on consolidating existing theoretical findings into clearly formulated research deficits and design requirements that form the basis for later design and evaluation cycles. Since the article initially focuses on problem identification at the contextual level, no specific use cases for AI are yet identified or examined.

In this article, requirements are derived deductively on the basis of the research gaps identified. To translate these requirements into a procedural logic, the article uses Simon's generic decision-making process as the conceptual reference frame. This choice is made because the SME context discussed in the literature is characterized by limited information, restricted financial and human resources, heterogeneous data availability, and bounded managerial attention. Under such conditions, decision-making cannot be assumed to be fully rational or optimization-based. Simon's concept of bounded rationality therefore provides an appropriate theoretical foundation for a sequential and resource-sensitive ex-ante assessment logic. In contrast to more data-intensive optimization or maturity-based approaches, Simon's process is particularly suitable for the early project stage because it allows a problem structuring that starts with incomplete information and gradually narrows down feasible alternatives. To ensure broad coverage of the knowledge needed to generate the research gaps, the holistic research (Trojahn et al., 2024) model is also used (Fig. 1). Due to the early stage of the research project, only the pillars "expert surveys" and "own data" are not included in this article.

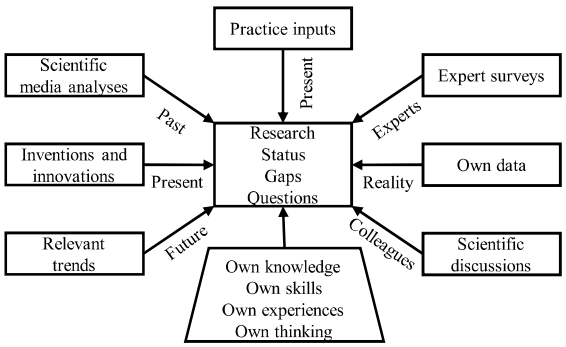

Figure 1: Holistic research model (Trojahn et al. 2024)

This chapter covers important preparatory steps. First, AI function classes in value creation are identified. Next, the AI4S concept is concisely defined and existing research on the TT is presented. Finally, typical SME challenges are analyzed.

2.1. AI in Value-Adding Processes

AI has been a subject of scientific and practical interest for several decades and has rapidly gained in importance as a result of increasing computing power and the availability of large amounts of data (Buxmann & Schmidt, 2021). Moderate scenarios assume that AI alone will increase Germany's gross domestic product by 0.8% annually over the next 15 years (Zika et al., 2025). In this article, AI is defined as a machine-supported system that derives patterns from input data, generates predictions, recommendations, or decisions, and thus influences value-adding processes autonomously or semi-autonomously, with learning and adaptation capabilities playing a central role (EU AI Act, 2025; Goudz & Erdogan, 2024).

As Goudz and Erdogan (2024) show, AI is already being used in many parts of the value chain. The value chain is defined as those processes that take an input, add value to it, and deliver an output for internal or external customers (Harrington, 1991). In this context, value creation should not be seen as a corporate goal, but rather as a means of securing long-term existence (Sucky, 2019).

A function-oriented classification that structures AI according to typical task types rather than individual algorithms is useful for categorizing it in the context of value-adding processes in SMEs. Based on Goudz and Erdogan (2024), AI can be classified in industrial value-adding processes according to the following function classes:

- **Recognition tasks:** Based on the external appearance of products, objects, or systems, AI is able to locate, identify, and count them (Goudz & Erdogan, 2024).
- **Analysis tasks:** AI can evaluate large amounts of data and patterns, thereby identifying unknown correlations (Goudz & Erdogan, 2024).
- **Planning and decision-making tasks:** AI can improve the use and quality of data by providing an additional basis for decision-making, automation, and error reduction (Goudz & Erdogan, 2024).
- **Execution tasks:** AI supports execution tasks by, for example, making logistical processes more efficient through language- and sensor-based learning systems (Goudz & Erdogan, 2024).

These functional classes can in turn be linked to established technology and product families, such as computer vision-based quality assurance systems, ML-supported forecasting and optimization software, AI-based energy management systems, or dialogue-oriented assistance solutions (e.g., chatbots, voice assistants) for operational decision support (Ayyat et al., 2025; Chen & Lin, 2025; Vamvakas et al., 2025).

Schönberger (2023) examines the use of AI in German SMEs in an empirical survey. Based on a quantitative survey, it appears that applications such as chatbots, recommendation systems, and machine learning methods dominate. However, these applications are only implemented selectively and in low-threshold fields of application. In addition, more complex, value-added AI solutions are less frequently implemented. The main obstacles cited are a lack of expertise, strategies, investment costs, and cultural aspects such as data protection concerns (Schönberger, 2023).

2.2. AI for Sustainability

In addition to its pure technical capabilities, the role of AI in an ecological context is also increasingly coming into focus. This is reflected in an exponential increase in scientific publications on sustainable AI between 2000 and 2022 (Falk & van Wynsberghe, 2024). In this context, sustainability in relation to AI must be considered from two perspectives. In the literature, two perspectives are considered under the umbrella term “sustainable AI” and distinguished from each other as “AI for sustainability” and “sustainability of AI.” The umbrella term “sustainable AI” refers to a movement to promote changes throughout the entire life cycle of AI products toward greater ecological integrity. On the one hand, AI can be used to actively support sustainability goals. The use of AI as a tool for achieving sustainability is being investigated. On the other hand, the development and use of AI itself must also be designed to be sustainable. This perspective focuses, for example, on the resource consumption of AI, in particular energy requirements, computing power, emissions, data usage, and, in recent research, water consumption for cooling data centers (Hoffmann et al., 2025; van Wynsberghe, 2021).

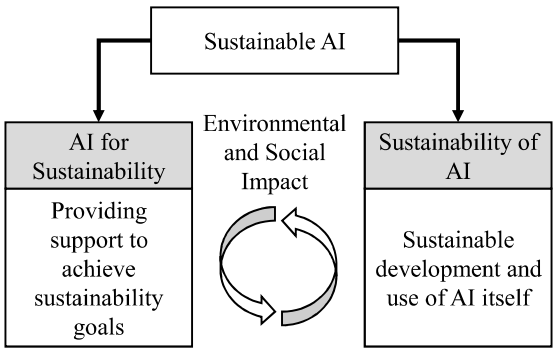

Figure 2: Structuring the concept of sustainable AI

In the normative sense according to van Wynsberghe (2021), it is not enough to consider just one perspective in order to describe AI as truly sustainable. For example, it is emphasized that AI4S is not achieved solely through prediction or monitoring functions, but only when an AI system contributes to an ecological sustainability goal through concrete action while simultaneously reflecting on its own environmental impact (Falk & van Wynsberghe, 2024). Nevertheless, the focus of this research project will be on AI4S, as the emphasis is on the sustainability potential that AI can generate in value-adding SME processes. The sustainability of AI itself, on the other hand, will merely be contextualized, as it can hardly be influenced by everyday business operations.

Current systematic literature reviews (SLR) identify three key sustainable mechanisms of action of AI4S in particular. It should be noted that these should not be viewed in isolation from one another, but rather as mutually influencing each other. (Sah et al., 2024):

- **Energy consumption reduction:** AI can act as a key lever for reducing energy consumption in value-adding manufacturing processes by continuously analyzing machine, sensor, and environmental data. Energy flows can thus be optimized in real time based on predictions of energy requirements. This could result in significant CO2 savings (Sah et al., 2024). Studies show a reduction of up to 20% in energy consumption (Kumar & Shahin, 2025).
- **Resource optimization:** AI also enables precise control of material usage through the use of production and planning data, thereby increasing resource efficiency. For example, AI is able to optimize cutting patterns and machining processes and reduce material losses (Sah et al., 2024). Optimized production control can reduce CO2 emissions by 4.4%, for example (Kumar & Shahin, 2025).
- **Waste prevention/reduction:** Another key contribution lies in reducing scrap, rework, and process waste in manufacturing. AI-supported systems can be used here for preventive error detection, anomaly detection, and quality assurance (Sah et al., 2024). For example, an accuracy of 98% in error detection in additive manufacturing has been proven (Zhang et al., 2023), which offers considerable potential for related areas in the value chain.

2.3. Twin Transition

There is no uniform definition of the concept of TT. Rather, TT is interpreted differently in the literature depending on the context of application. Nevertheless, the basic idea of the simultaneous digital and sustainable transformation of companies remains the same, within which organizations combine technological innovation with ecological objectives. It is assumed that digital technologies, such as the Internet of Things and AI, act as key enablers to increase transparency, efficiency, and sustainability. The basic principles of TT are climate neutrality, resilience and inclusivity, circular economy, and synergistic integration (Schallmo & Jehle, 2025). In recent literature, TT is increasingly seen as a strategic necessity for simultaneously addressing environmental requirements, regulatory developments, and economic efficiency. In an integrated approach, TT comprises five sequential phases (Schallmo & Jehle, 2025). The approach presented by Schallmo and Jehle (2025) shows that TT goes beyond structural changes and also encompasses cultural aspects. What is required is an organization-wide, strategically embedded transformation.

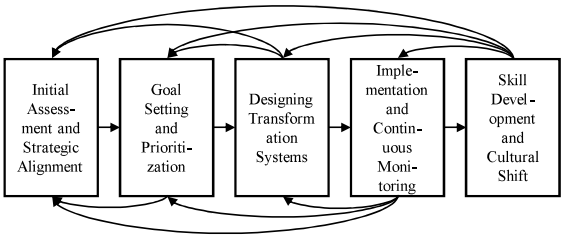

Figure 3: Integrated approach to TT (Schallmo & Jehle, 2025)

Based on this approach, it can be argued that TT is already firmly established at a fundamental theoretical level. However, empirical research reveals significant deficits in its practical implementation in manufacturing companies. Spaltini et al. (2024) analyze barriers to TT and, based on an SLR, identify a total of 39 different obstacles that affect the categories of "process, technology, economy, regulation, and culture" as well as the respective macro, meso, and micro levels. Although the authors propose a roadmapping model that structures the strategic path to TT in manufacturing companies, specific SME restrictions and AI-based sustainability approaches are not taken into account in the model. Instead, the focus here is limited to large companies and the application of technical solutions for process optimization (Spaltini et al., 2024).
With regard to SMEs, various studies show that they are confronted with significantly greater resource scarcity, a lack of skills, and strategic uncertainties. In a bibliometric analysis,

Burinskienė and Nalivaikė (2024) collected data from 27 SMEs within the European Union (EU) and showed that they lag significantly behind large companies in both digital and sustainable transformation. In addition, there are hardly any systematic evaluation models that can adequately reflect the progress of TT in SMEs or their respective degree of maturity. It is also emphasized that there are considerable gaps in research linking the two dimensions of transformation (Burinskienė & Nalivaikė, 2024). The study does not make any specific reference to manufacturing SMEs. Rather, the analysis remains generic in its focus on SMEs.

Bella et al. (2024) offer a perspective specific to the German context, showing that German SMEs recognize the strategic importance of both sustainability and digitalization practices, but predominantly address them separately. This means that potential synergy effects remain untapped. In addition, it is emphasized that limited financial and human resources, limited expertise, and a low level of strategic orientation are key factors in SMEs' reluctance to invest in transformation projects (Bella et al., 2024). However, here too there is no specific reference to manufacturing SMEs.

2.4. SME as Design Constraints for AI4S within TT

This article focuses on SMEs in the manufacturing sector within the European Union. The choice of an EU-wide scope ensures conceptual alignment with standardized definitions and, in particular, political framework conditions (e.g., EU AI Act). The focus on SMEs is justified by their macroeconomic relevance and their particular constraints when introducing new technologies.

The distinction from large companies is deliberate, as they generally have specialized departments, larger data and IT resources, established governance structures, and higher budgets for transformation and technology testing. This means that decision-making processes in large companies differ fundamentally from those in manufacturing SMEs. A generic assessment approach is therefore often insufficient for SMEs or requires conditions that do not exist in the SME context.

The following section provides a neutral summary of the key challenges facing SMEs within the defined scope and in the context of digital and sustainability-related transformation.

SMEs are particularly affected by **economic** challenges. Limited financial resources and uncertainties about economic benefits restrict their ability to systematically evaluate new technologies and scale successful solutions. SMEs also lack clear strategies and operationalized implementation routines. In current transformation literature, economic barriers are therefore often described as frequent triggers that particularly exacerbate technological, personnel, and environmental challenges (Abilakimova et al., 2025; Zare et al., 2025).

Another key area concerns the **technological** challenges mentioned above. When it comes to advanced digital solutions, recurring deficits in IT infrastructure, digitalization maturity, heterogeneous data landscapes, and security aspects are frequently cited (Abilakimova et al., 2025; Zare et al., 2025). In addition, there are issues with poor data quality and, in some cases, a lack of data availability (Oldemeyer et al., 2025).

Closely related to this are **organizational** restrictions, particularly those caused by gaps in employee qualifications. Internal resistance to change and the immense amount of learning required in everyday work are also cited. Limited time budgets and a lack of training environments in SMEs reinforce this effect (Zare et al., 2025). In reviews related to AI, the qualification factor is even identified as one of the biggest implementation hurdles, addressing both the shortage of skilled workers and the lack of procedural knowledge (Oldemeyer et al., 2025).

In addition to internal factors, **environmental** challenges are also mentioned. These include a lack of advice/guidance, limited visibility of suitable support services, and the observation that many solutions on the market tend to be tailored to the structures and needs of large companies. This creates a further hurdle for SMEs if the available solutions require a great deal of adaptation or offer an unclear ROI (Oldemeyer et al., 2025).

Finally, particularly in the context of transformation, there are challenges relating to the **community** that are closely linked to current politics, governance, and stakeholder dynamics. Here, a lack of transparency, legislation, and ethical concerns have a negative impact on successful transformation. It should also be noted that European SMEs in the manufacturing sector in particular are more likely to focus on regulation-oriented sustainability initiatives (Abilakimova et al., 2025; Zare et al., 2025).

It follows that the challenges facing manufacturing SMEs are multidimensional and interdependent. Table 1 summarizes typical challenges that are relevant in the context of the TT and AI4S.

Table 1: Challenges facing manufacturing SMEs (Zare et al. 2025; Abilakimova et al. 2025)

Category	Typical challenges
Organization	Lack of awareness
	Lack of strategy
	Lack of qualifications
	Lack of mindset change
	Lack of self-assessment tools
	Deficits in communication
Economic	High investment costs
	Resource allocation problem
	Uncertain benefit assessment
	Risk of failure
Technological	IT infrastructure (maturity level)
	Data protection concerns
	Unclear benefits
	Lack of standardization
	Long implementation time
Environmental	Lack of advice/guidance
	Limited visibility
	Lack of tailor-made solutions
Regulatory	Cybersecurity compliance
	National and international agreements

3. Results of the conceptual work

This chapter derives deficits in existing research from the theoretical foundations presented. Requirements for the model are defined based on the existing deficits and, in general, the typical challenges faced by SMEs. An initial outline of the model is then presented and explained, showing how individual phases address the requirements.

3.1. Deficits

From the functional classes identified by Goudz and Erdogan (2024), questions are central for SMEs as to which of these areas are associated with low implementation barriers and/or which areas require specialized technological infrastructure. (Schönberger, 2023). Furthermore, the question arises as to what extent the aforementioned functional potential of AI along the value chain can also be used to achieve ecological sustainability potential.

For manufacturing SMEs, therefore, it is not so much the specific algorithm that is decisive as the question of which of these function classes can be used in which process steps of value creation with a reasonable amount of resources and which sustainability effects they can have. Currently existing frameworks for TT do not allow for holistic coverage of SME challenges, AI in value-adding processes, and AI4S.
Analysis of current research therefore reveals three key shortcomings:

1. **Lack of process- and SME-specific structuring of AI4S mechanisms of action along the value chain:** Despite extensive research on AI in industrial value creation and on AI4S, there is a lack of process- and SME-specific structuring approaches that systematically map AI4S impact mechanisms to value-adding processes in manufacturing SMEs. AI applications are often considered in isolation, without a structured assignment of sustainability impacts to process steps under SME constraints.
2. **Lack of ex-ante assessment approaches that integrate sustainability impacts with feasibility requirements for SMEs:** In addition, there are currently few ex-ante assessment approaches that systematically integrate feasibility criteria alongside sustainability impacts, thereby allowing prioritization prior to actual implementation.
3. **Lack of an integrated, SME-specific TT framework with AI relevance:** Existing frameworks for TT are predominantly theoretical, unspecific in terms of technology, and designed for large companies. Integrated, practice-validated frameworks that consider AI as an enabler for digitalization and sustainability are currently lacking, especially for manufacturing SMEs.

3.2. Requirement Derivation

The derivation of requirements follows a deductive approach, based on the previously identified deficits, generally the analyzed SME challenges. To ensure traceability, the following derivation rules (R) are applied:

- **R1:** If the literature identifies a research gap X that reinforces challenge Y faced by SMEs, a requirement is formulated that addresses this.
- **R2:** The recurring emphasis on resource constraints in the literature implies the need for a lean, early-stage assessment approach.
- **R3:** If a theoretical framework is described as necessary but not specific to SMEs, a context-specific embedding is created.

These shortcomings and the challenges facing SMEs outlined in Table 1 can be used to derive requirements for the procedural model to be developed. The model must be able to function with early, incomplete data and minimal effort in order to meet the challenges facing SMEs (A1). In addition, the model needs clear scope parameters, such as process area, country, or regulations, so that requirements and results do not become arbitrary (A3). The AI4S potentials must also be structured along the value-adding processes and the relevant AI function classes in order to establish a connection to real use cases and available technology building blocks (A4). In addition to the pure sustainability and efficiency potentials that could be associated with AI4S, the technical and organizational feasibility must also be explicitly evaluated (A2). In addition to this dual perspective,

the digital and sustainability transformations must also be considered together within the framework of the TT and not in isolation from each other (A5). Since the overarching goal of the model is to compare potentials transparently and prioritize them before implementation, it must also be based on a multi-criteria evaluation logic in order to enable robust decision support and make prioritization comprehensible (A6).

Table 2: Derived requirements for the model

Number	Requirement	Rule
A1	Ex-ante suitability under SME restrictions	R2
A2	Dual perspective (potential and feasibility)	R1, R2
A3	Context parameters	R3
A4	Process and function class reference	R1
A5	Embedding in the TT	R3
A6	Multi-criteria evaluation logic	R1, R2

3.3. Initial Sketch of the Phase Logic

The phase model is based on the generic decision-making process according to Simon (2000), which is supported by the theory of bounded rationality. According to this theory, completely rational decisions in organizations are not realistic due to limited time, information availability, and cognitive and organizational resources (Simon, 2000). Since SMEs are repeatedly characterized in the literature by precisely such resource constraints, the adaptation of a decision-making process that is selective, sequential, and heuristic appears particularly suitable for the context under consideration.

The phases are structured according to the previously derived design requirements for an SME-compatible preliminary assessment of AI4S along value-adding processes. The operationalized four-phase model, which translates these requirements into a sequential decision-making process, is explained below.

Intelligence phase: In the context of this paper, the first phase involves identifying potential starting points for AI4S in value-adding processes in manufacturing SMEs and, at the same time, clarifying the objectives that would justify its use. Accordingly, the decision-making context and scope must first be defined (see A3). This establishes the process and value creation reference as a regulatory framework and prepares the target system for later evaluation.

At the same time, ecological targets are systematically linked to digital goals such as transparency or increased efficiency in order to embed AI4S in the logic of the TT from the outset (A5).

Building on this, an initial checkpoint is defined that serves to limit resource consumption (see A1). If there is no reliable sustainability or value creation reference and AI appears to be merely an end in itself, the AI4S approach is classified as not worth pursuing.

Subsequently, an actual analysis of the value-adding process under consideration is carried out during the information gathering phase. In addition, existing data sets of the respective SME must be recorded. Maturity models can be used here to help collect data and organizational requirements (see A1). The result of this core activity is a value stream and data map, including key restrictions (A4).

Design phase: In this phase, alternative courses of action are to be developed and structured in such a way that they are comparable. Here, use case portfolios, a set of criteria, and the impact logic are developed as artifacts. In the search for alternatives, specific use cases are first generated along the value-adding process under consideration, and impact mechanisms are formulated in order to consistently continue the process reference (see A4). In order to support realistic connectivity, use cases can also be described at the level of AI function classes in order to ground the subsequent feasibility discussion (see A2).

A catalog of criteria is then created, consisting of the overarching categories of sustainability potential, value-adding benefits, and feasibility (A2). This prepares the ground for the subsequent evaluation of the alternatives. Factors that cannot be influenced, uncertainties, and conflicting objectives must also be taken into account. This is also reflected in the definition of multi-criteria measurement logic (A6).

Choice: In this phase, the generated alternatives are evaluated and prioritized. In line with bounded rationality, this is done using a transparent method that makes use of data available at an early stage and limits the evaluation effort (A1). The dual perspective of sustainability potential and feasibility is implemented by evaluating all use cases along the categories of the criteria catalog and incorporating both dimensions into the decision, so that purely technology-driven approaches that are difficult to implement in practice are systematically deferred (A2). Methodologically, simple scoring procedures such as MCDM methods are applied (A6). The final decision is made taking into account key risk considerations, such as regulatory, reputational, or technical risks related to the TT framework (A5).

Implementation: The aim of the final phase is to translate the decision made into an implementable pilot plan. To this end, the prioritized AI4S use cases are assigned specific implementation steps, responsibilities, and resource allocations, with explicit consideration given to the feasibility restrictions identified previously (A2). The pilot plan serves as a bridge to subsequent development and evaluation cycles, linking the conceptual ex ante assessment with later empirical validations and TT-related transformation paths.

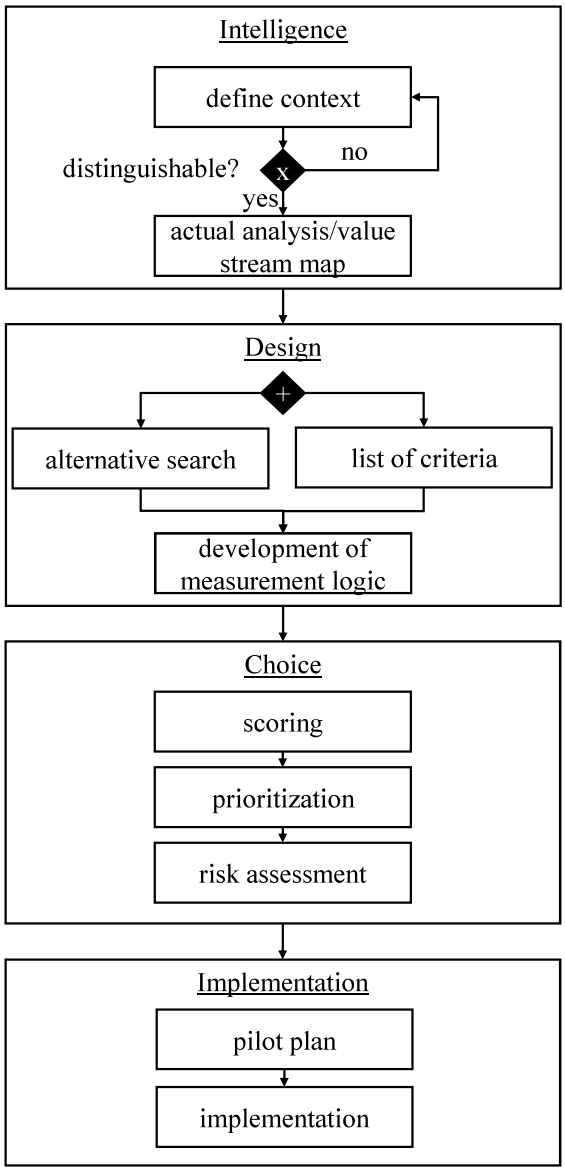

Figure 4: Phase model

Table 3 summarizes how the requirements are addressed in the model. It can be seen that most requirements are represented in several phases at the same time. Only A3 is represented in the intelligence phase only.

Table 3: Requirement implementation in the model

Requirement	Implementation in the model
A1	**Intelligence**: formerly "stop-or-go" checkpoint; focus on existing data
	Choice: simple scoring methods
	Implementation: planning from the perspective of SME restrictions
A2	**Design:** development of a catalog of criteria with categories such as "sustainability potential", "value-adding benefits" and "feasibility"
	Choice: linking the criteria catalog with scoring
A3	**Intelligence:** narrow down the scope
A4	**Intelligence:** creation of a value stream map
	Design: generation of use cases along the process under consideration
A5	**Intelligence:** linking environmental goals with digital transparency/efficiency goals
	Choice: consideration of risk factors linked to the TT framework
A6	**Design:** development of multi-criteria measurement logic based on the criteria catalog (see A2)
	Choice: use of simple MCDM methods

4. Limitations and Discussion

This article deliberately addresses only the early phase of DSR, without empirically evaluating the outlined phase model. The theoretical foundations are based on a broad but not entirely systematic review of the literature. As a result, other relevant technical work may not have been taken into account. In addition, the requirements are deduced without systematically comparing alternative frameworks. Explicitly established rules ensure a certain degree of traceability. Nevertheless, complete determinism cannot be achieved with deductive derivation, which must be taken into account. The deductively derived requirements must therefore be empirically confirmed in future research and thus validated, supplemented, or relativized.

The derived requirements mean that the model is explicitly tailored to manufacturing SMEs in the EU. However, the limitations to date still encompass a high degree of heterogeneity in terms of industry or process characteristics. It is therefore conceivable that an evaluation logic based on the

current scope could lead to differing priorities in different subdomains. In addition, the AI4S perspective dominates, while sustainability of AI is only mentioned in passing. Potential conflicts of interest within the framework of TT thus remain unresolved. Consequently, the model in its current state should be understood as a conceptual framework that also represents further steps in the research process. Parameterization and evaluation logic must be adapted to the specific context in the future. In addition, meta-decisions are pending in the model that have not yet been objectified in the early phase of the project.

Furthermore, in the choice phase, the model relies on heuristic scoring methods that have to make do with early, often incomplete data. This can negatively affect objectivity, accuracy, and robustness. This effect of uncertainties must be taken into account in future research. At the same time, the impact of individual AI use cases is often difficult to attribute clearly in practice, as effects typically arise as a bundle of measures and cannot be attributed exclusively to AI. Within the current scope of this article, potential rebound effects that could significantly alter the net sustainability impact of a use case are also not taken into account.

Finally, the phase model should currently be understood as an ideal-typical structure, whereas real decision-making processes are iterative.

5. Conclusion

In the context of TT, manufacturing SMEs face the challenge of prioritizing transformation measures in a targeted manner with limited financial and human resources. AI can act as an enabler here, especially in terms of AI4S in value-adding processes. However, there is currently no SME-specific approach that structurally evaluates potential AI4S use cases prior to implementation and takes into account not only sustainability potential but also feasibility.

Against this background, this article presents the state of research at the interface of AI in value-adding processes, AI4S, TT, and the challenges facing manufacturing SMEs. From this, deficits and requirements for an SME-compatible evaluation are deduced. As a conceptual result, a generic phase model is proposed, which is based on bounded rationality and the classic decision-making process according to Simon (2000). This initial outline shows how the derived requirements are addressed in the individual phases. This creates an initial basis for identifying and prioritizing AI4S use cases not purely opportunistically, but along a transparent decision-making process.

The article is deliberately intended as an early phase in the DSR framework and primarily provides a structuring frame of reference rather than an empirically validated methodology. Future research will therefore initially focus on an in-depth and systematic literature analysis in order to obtain a consolidated overview of the state of research and thus further develop the phase model.

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