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Organizing Work and Securing Expertise Through AI



Explaining AI in Industrial Production in an Accessible Way

Foundation Models in Industrial Robotics

Interoperable Data Interfaces in Mass Production of Vehicle Bodies

Work Design in the Use of Autonomous Systems

Systematically Planning Vertical Factories

MTM Analyses with AI and Rule-Based Algorithms

Inclusive Work System Design

Audio-Immersive Learning in Continuing Vocational Education

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Editorial

How we can use AI to make industrial work and organizational processes more resilient

The strength of the German economy has always been its excellent education and the application of knowledge to generate high-quality solutions. This applies not only to products and services—Germany has consistently played a leading role, particularly in the development of new technologies. However, when it comes to the development of artificial intelligence (AI), other countries are far ahead. Local companies can currently maintain their position only through the targeted use of AI to optimize processes and implement solutions.

Thanks to its ability to recognize patterns even in highly complex situations, AI takes on knowledge-based tasks, including diagnostics, decision-making, structuring, realignment, optimization, and similar aspects of work that require cognitive abilities. Tasks are increasingly being handled through hybrid intelligence—that is, through the collaboration of skilled professionals and AI. This is a dynamic partnership in which adjustments are continually made to determine which tasks AI can perform autonomously.

The crucial question: What does this development mean for an economy whose strength is based on education and knowledge, but which does not itself develop the technologies that are fundamentally transforming this knowledge work? AI literacy is not a given here, but rather the key lever for turning the application of AI into genuine competitive advantages. Furthermore, AI literacy must not undermine technical expertise, which is the core of economic strength. This balance requires the strategic use of AI in industrial work processes while simultaneously building the knowledge base of both organizations and individuals.

This issue of Industry 4.0 Science highlights solutions that are scientifically rigorous and proven in practice. The authors from the Scientific Society for Work and Business Organization (WGAB) focus on three thematic areas: (1) the far-reaching potential of AI for industrial production and development, (2) the competency requirements associated with AI deployment and pathways for skills development, and (3) implementation options for AI-based knowledge management to enhance the resilience of industrial work and organizational processes.

We hope you find these insights interesting and the suggestions valuable.

Uta Wilkens, Ailina Oelmüller, Bernd Kuhlenkötter

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WGAB Wissenschaftliche Gesellschaft für Arbeits- und Betriebsorganisation

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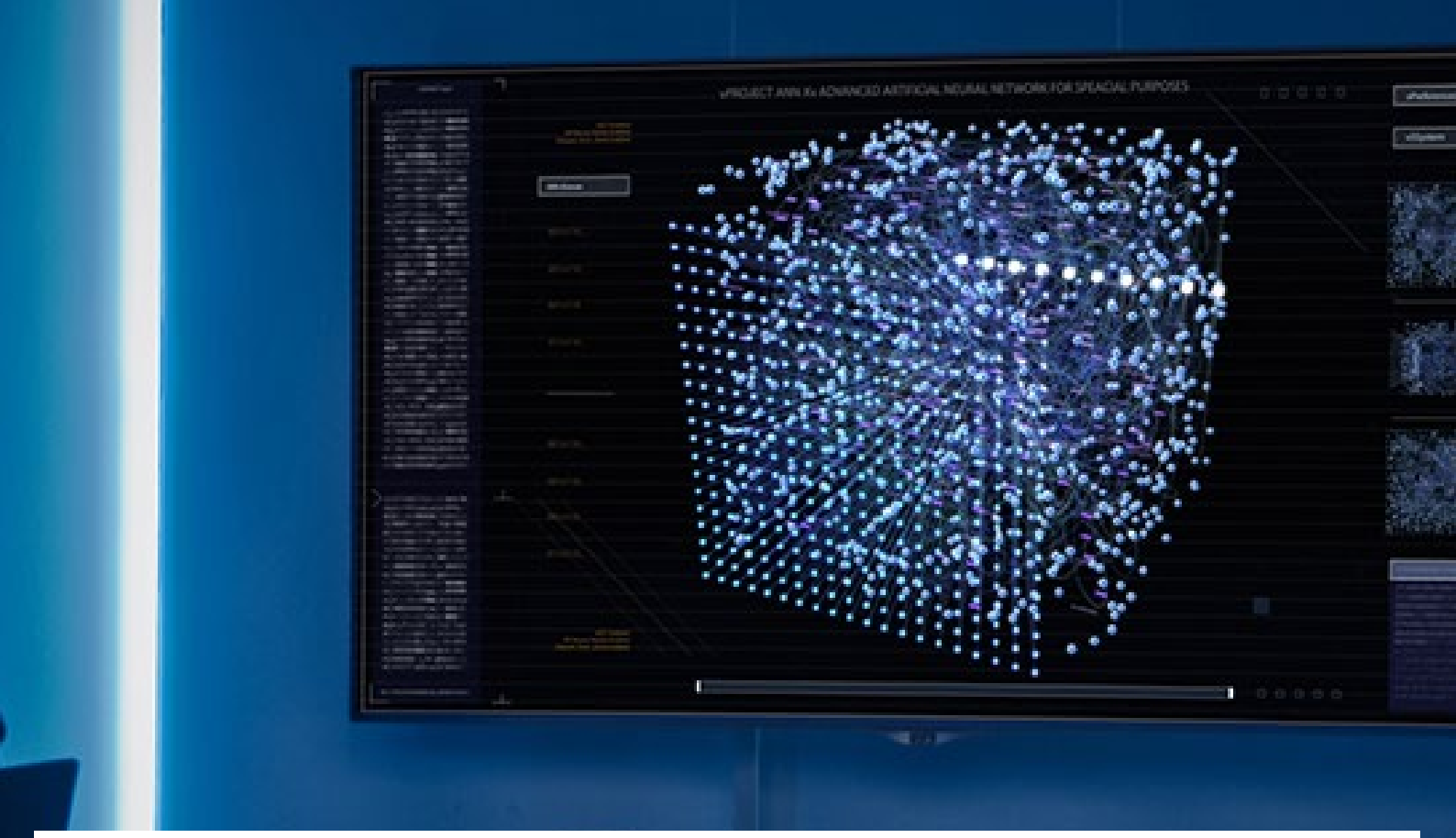
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Explaining AI in Industrial Production in an Accessible Way

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AI is making its way into production, causing uncertainty, skepticism, and concern among many employees. For a successful AI implementation, it is therefore crucial how employees are prepared for the use of AI—in addition to the question of whether and how AI will be used. One option is the use of AI demonstrators, which contribute to greater acceptance, fewer negative emotions, and a better understanding of AI.

Keywords
artificial intelligence, demonstrators, production, acceptance, negative emotions

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Explaining AI in Industrial Production in an Accessible Way

Requirements for AI demonstrators to promote acceptance

Jennifer Link, Markus Harlacher, Colin Srebny and Sascha Stowasser,
ifaa – Institute for Applied Ergonomics

Artificial intelligence (AI) offers a wide range of possibilities in industrial production, but it also presents challenges regarding employee acceptance. AI demonstrators are therefore of central importance, as they enable hands-on experience with AI. However, there has been a lack of systematically identified requirements for demonstrators that specifically promote acceptance and address negative emotions. Using a multi-stage research design, 69 requirements were identified, structured into functional requirements, quality requirements, and boundary conditions.

The increasing use of artificial intelligence (AI) in manufacturing can trigger negative emotions among employees—such as uncertainty, fear, overwhelm, and skepticism—and thus hinder the acceptance of AI in industrial transformation processes [1]. Against this backdrop, competencies in working with AI are becoming increasingly important. An ability to understand, interpret, and critically evaluate AI system is essential for their competent use. A recent study also shows that acceptance of AI increases when individuals have prior experience [2].

AI demonstrators represent a suitable means of imparting these competencies. They serve as interactive artifacts that facilitate practical experience, didactic understanding, and reflective engagement with AI. As boundary objects, they also support communication and exchange among scientific, technical, and application-oriented stakeholders. [3]

Despite their practical relevance, there is currently a lack of systematically derived requirements for AI demonstrators that explicitly aim to reduce negative emotions and promote acceptance. This leads to the following research question: What requirements must AI demonstrators meet to promote acceptance of AI in industrial production and reduce negative emotions?

Method for deriving requirements for AI demonstrators

To answer the research question, a multistage, qualitative research design was chosen that combines empirical data collection with a market and literature analysis **(Fig. 1)**.

The analysis is based on guided interviews with experts, supplemented by market research on existing AI demonstrators as well as (meta)studies. A total of 15 interviews were conducted with experts from academia, industry, and associations (for details, see [7]). The goal of the interviews was to identify relevant design aspects and requirements for AI demonstrators from different perspectives.

In addition to the interviews, an exploratory market and literature analysis was conducted to gain a systematic overview of existing AI demonstrators. Publicly available AI demonstrators were identified, systematically documented, and evaluated both quantitatively and qualitatively. The analysis shows that demonstrators focus on industrial applications such as quality management and process optimization, and that physical and interactive formats are frequently used. Shortcomings in the didactic design are evident, particularly with regard to the transparent presentation of limitations and the tailoring of content to the target audience (for details, see [3]).

(Meta-)studies on changes in work due to AI—with a focus on shifts in job tasks and competence requirements—, areas of industrial AI application and AI acceptance were also taken into account. The findings from these studies served to supplement the empirical results from interviews and market research.

A qualitative content analysis was initially conducted on the interviews and the market and literature analysis at the meta-level using a based on Mayring's method with MAXQDA. The framework from [4], which describes design principles for demonstrators, was used as the analytical framework. Aspects of technology acceptance were incorporated into the analysis using established acceptance models such as the AI-TAM [8] and empirical findings from a meta-analysis [9]. Furthermore, studies investigating changes in work tasks and competency requirements [10-13], as well as meta-analyses on fields of application for AI in industrial practice [14, 15], were considered.

To translate the identified aspects from the meta- to the implementation level, the framework described in [6] was applied, which distinguishes between functional requirements, quality requirements, and constraints. The

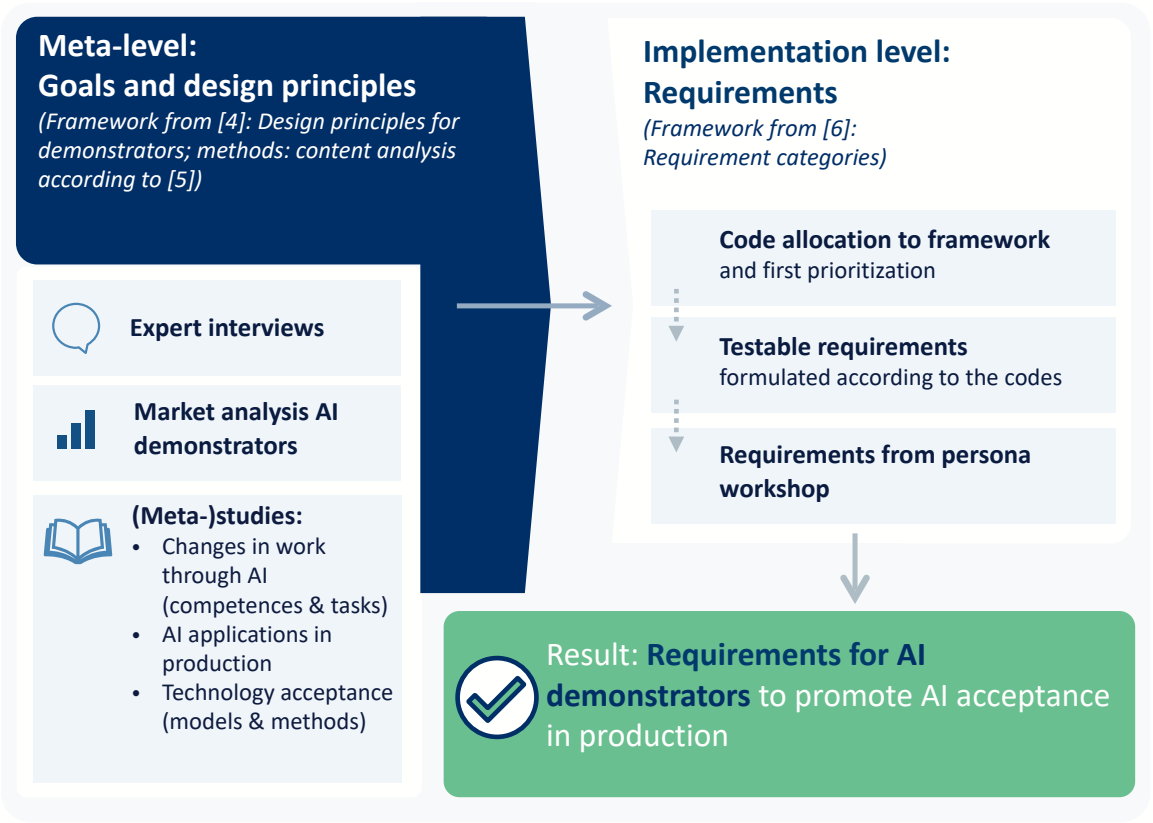


Figure 1: *Method for developing requirements for AI demonstrators to promote acceptance of AI in manufacturing.*

codes and categories formed as part of the content analysis were assigned to the respective requirement types and then selected. The selection criterion was that a code had to be mentioned by at least one-third of the interviewed experts and/or identified in the other analyzed sources (market research and studies). In this way, the number of codes was reduced, and the focus was narrowed to central, repeatedly documented content. Based on the prioritized codes, requirements were finally formulated according to [6].

In a subsequent step, the derived requirements were extended with additional requirements from a user-centered perspective. A persona-based workshop was conducted, building on a prior study investigating the causes of negative emotions toward AI [1]. The underlying personas made it possible to systematically incorporate emotional patterns into the requirements. In an interdisciplinary workshop, user requirements for AI demonstrators were jointly developed, structured, and prioritized (for details, see [16]). Existing requirements from the preliminary analysis were consolidated where content overlapped and newly identified aspects were added to the requirements catalog. While not claiming to be statistically representative, the goal is to develop a structured, practical framework for the design and evaluation of AI demonstrators.

Results: Requirements for AI demonstrators

Based on the analysis, a total of 69 requirements for AI demonstrators were identified, including 42 functional requirements, 22 quality requirements, and five overarching constraints. The functional requirements address content-related and didactic characteristics, while the quality requirements focus on user experience, design, and operation. The constraints describe fundamental prerequisites for the development of AI demonstrators.

The functional requirements were structured according to the goals and design principles outlined in [4] **(Fig. 2)**. These include requirements aimed at transparency, expectation management, and the contextualization of AI systems. Several experts emphasize that demonstrators should also specifically highlight the limitations and errors of AI in order to counteract inflated expectations. A technical expert illustrates this with an example: [One should] make the limitations visible in the demonstrator by showing what was necessary to achieve the result and everything that was done to make it work [...] Then one could take a small and seemingly obvious next step, one

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Goals according to [4]	Design principle according to [4]	Requirements: The AI demonstrator should...	Sources
Communication	Authenticity	promote critical engagement with AI.	[EI, 3]
		demonstrate how change via AI can be shaped.	[EI]
		demonstrate that an AI system can be adapted to own requirements and goals.	[16]
		demonstrate risks that can arise when using AI.	[EI, 10, 16]
		demonstrate measures for the anonymization of user data.	[EI, 11, 12]
		make transparent whether and which personal data can be recorded.	[16]
		demonstrate technical limits of AI systems.	[EI, 3, 10, 11, 16]
		transmit realistic expectations of AI.	[EI]
	Show the invisible	explain fundamental AI concepts.	[EI, 11, 13]
		use an AI method of text and language processing.	[3]
		use an AI method of action planning and optimization.	[3]
		use an AI method of multidimensional pattern recognition.	[3]
		use an AI method of image and sound processing.	[3]
		make the mathematical and statistical character of AI visible and clear up typical misunderstandings.	[EI]
		enable the AI system's programming code to be viewed and changed.	[3]
		demonstrate how AI results can be altered by targeted feedback.	[16]
		demonstrate different ways in which AI learns from data.	[14]
		demonstrate a fault scenario in which human expertise is indispensable.	[16]
		demonstrate why the AI system makes a decision in a concrete case.	[EI, 12]
		demonstrate how the AI fundamentally functions.	[EI, 12]
		depict the AI model's structure.	[EI]
		show which data AI uses and how this influences the result.	[3, 13, 16]
	Context	use real-world examples from everyday work.	[EI, 3, 8, 16]
		demonstrate the general potential of AI for companies.	[EI, 3, 10, 11]

Attraction	Relatedness	depict a scenario in the design and planning of production systems.	[14, 15]
		depict a scenario from process modelling, management, and optimization of production systems.	[15]
		depict a scenario from quality assurance or maintenance of production systems.	[15]
		depict a scenario from automated dis/assembly of production systems.	[14, 15]
		demonstrate the personal benefits of using AI at work.	[EI, 3, 8, 9]
		depict how implementing AI technologies can simplify work.	[EI, 9]
		depict a complex technical system and visualize the value added by AI.	[16]
		demonstrate AI via practical examples in private life.	[EI, 8]
		make the subject area immediately recognizable.	[EI]
Deep engagement	Comparison	show which competences are necessary for AI use.	[10, 11, 13]
		demonstrate that a lack of domain knowledge can lead to a worse AI model.	[11, 13]
		depict a fault scenario where human expertise is indispensable.	[EI, 11, 13]
		demonstrate how automation frees up capacity and enables new tasks to emerge.	[9, 16]
		demonstrate that users retain leadership.	[EI, 10, 13, 16]
		demonstrate how tasks change when AI demands human verification.	[16]
		demonstrate how the tasks fundamentally shift from implementation to control and supervision.	[13, 16]
		show how creative and planning-related tasks emerge in place of monotonous work.	[EI, 13]
		demonstrate which concrete tasks are performed by humans and which by AI.	[EI, 9, 10, 13, 16]

Figure 2: *Functional requirements for AI demonstrators (EI = expert interviews).*

that a human would still be able to understand [...] whereas the AI system [...] would fail completely."

This perspective is supported by both the market and the literature analysis. It underscores the importance of realistic expectation management as a central function of AI demonstrators.

In addition to highlighting technical limitations, illustrating concrete potential benefits is essential. As one company representative explains: "For production workers, the demonstrator needs to highlight the personal benefits much more clearly and at an earlier stage [...]."

Accordingly, functional requirements include practical scenarios, everyday examples, and the visualization of concrete ways in which work is made easier.

The quality requirements were structured according to the categories in [6] as well as supplementary categories derived from the analysis **(Fig. 3)**. In addition to traditional aspects such as reliability and usability, requirements related to design, visual impact, and user experience stand out. As one AI developer puts it: "Something where you can try things out for yourself [...] and not only see the AI's decisions on the screen, but actually experience them physically [...], that's naturally always a crowd-pleaser."

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Category	Requirements: The demonstrator should…	Source
Operation requirements [6]	be accompanied didactically by a trained supervisor during use.	[EI, 16]
	be reviewed to ensure its technical actuality.	[EI]
	ensure uninterrupted, error-free operation.	[EI]
User experience	depict a miniaturized model of a real work environment.	[EI]
	offer a transfer task.	[EI]
	offer further information or opportunities for consolidation.	[EI]
	provide an experience of success together with AI.	[16]
	embrace playful elements.	[EI]
	provide explorative, interactive tasks.	[EI, 16]
Design and presentation	contain surprising or unexpected elements.	[EI]
	contain physically experiential elements.	[EI]
	contain dynamic or animated elements.	[EI]
	combine different media.	[EI]
	have a cohesive and visually appealing design.	[EI]
Performance [6]	use suitable quality metrics for each AI technology.	[EI, 8]
Reliability [6]	be equipped with reliable and easily exchangeable hardware components.	[EI]
Usability [6]	provide step-by-step instructions for system use.	[EI]
	be usable without prior knowledge of AI.	[EI, 16]
	use comprehensible, jargon-free language.	[EI, 16]
	be intuitive and ergonomic.	[EI, 9, 16]
	transmit the function and added value of AI quickly and comprehensibly.	[EI]
	be operational with minor set-up effort.	[EI]

Figure 3: *Quality requirements for AI demonstrators (EI = expert interviews).*

In addition, the following five constraints were identified that pertain to the development and design process of AI demonstrators [EI]:

- The demonstrator's objective must be defined before system development begins.
- The target audience must be clearly defined before system development begins.
- Before implementation, a storyboard must be created that fully describes the application workflow, interactions, and inputs and outputs.
- Development proceeds iteratively, with progress regularly verified with appropriate tests.
- During development, various usage scenarios—including relevant disruptive factors—are taken into account and used in tests to evaluate robustness.

Promoting acceptance is not based on individual design features

The derived requirements make it clear that using demonstrators to promote AI acceptance in production is not based solely on individual design features. Rather, success arises in the interplay of technical implementation, user experience, and didactic integration.

Individual requirements cannot be considered in isolation. There are areas of tension between, e.g., accessibility and technical depth, expectation management and positive portrayal of benefits, and explainability and model complexity. These conflicting goals illustrate that not all requirements can be fulfilled simultaneously; they must

be prioritized depending on the context. The diversity of requirements is also one argument against a singular demonstrator. A multi-demonstrator approach is called for to address different technologies, usage contexts, and emotional reactions in a nuanced way. Specific demonstrators could be provided for specific technologies or applications, for example, allowing users to quickly grasp the benefits before developing a deeper understanding.

The results must be interpreted in light of several limitations. The requirements can only be verified to a limited extent, as they were primarily derived from qualitative analyses and no quantitative thresholds are available. While general formulations facilitate broad application, they make verification more difficult. Furthermore, the requirements were not prioritized, so no conclusions can be drawn regarding the particular importance of certain requirements in practice. Potential end users—that is, production staff—were not directly involved in the empirical study. The requirements are based primarily on expert knowledge, supplemented by by a user-centered extension using personas. While this addresses emotional patterns, it does not capture the direct experience of future users.

These limitations highlight the need for further research, particularly regarding the empirical prioritization of the requirements. A study involving industrial employees and managers is planned to further prioritize the requirements. In addition, the design and development of a multi-demonstrator concept is planned to evaluate the impact of demonstrators on acceptance and emotional perception in real-world applications.

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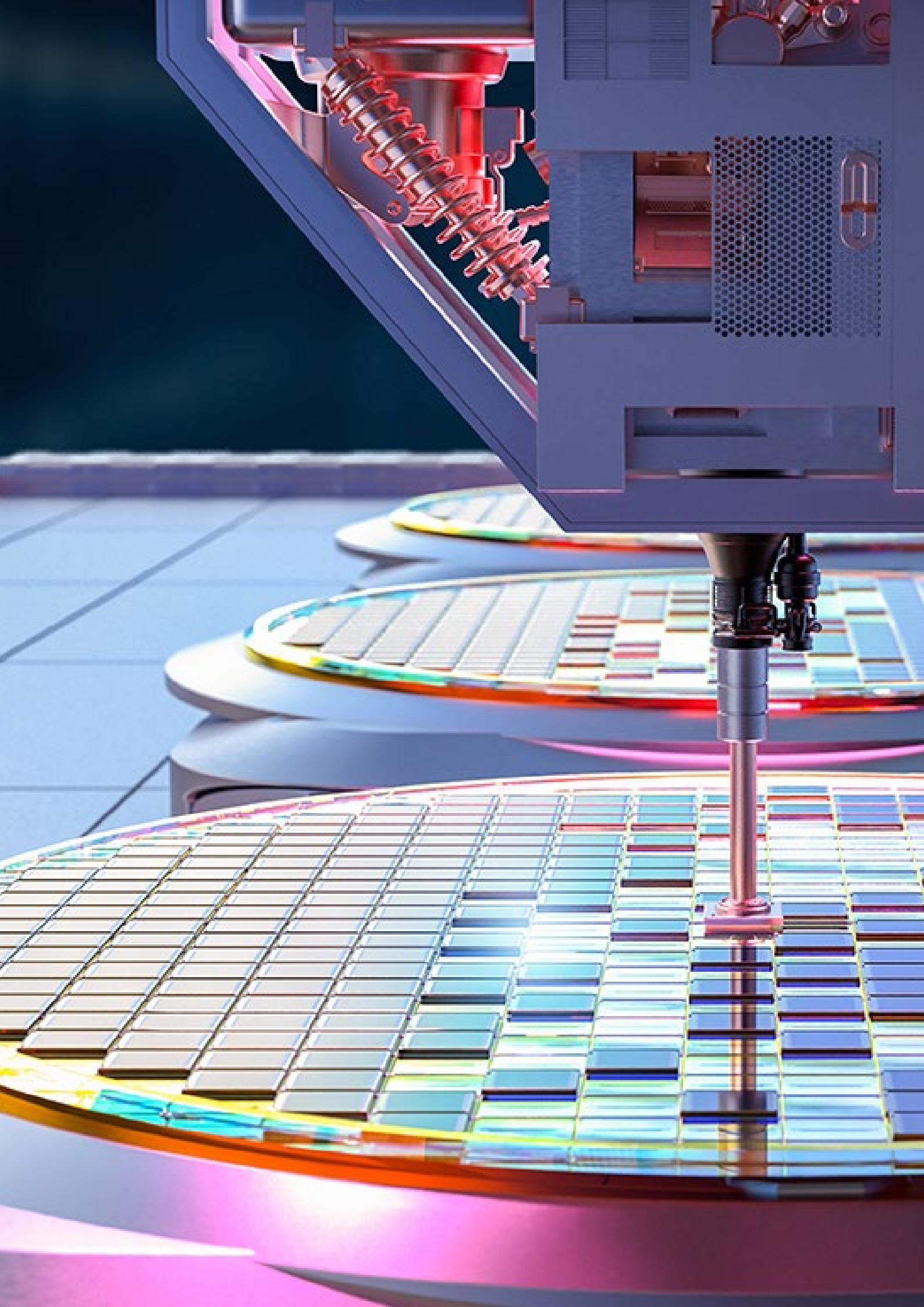
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Foundation Models in Industrial Robotics

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Foundation models are increasingly changing the way robots are used in industry. Instead of writing complex programs line by line, programmers will in the future be able to collaborate more closely with AI systems, describe tasks, and review the generated solutions. This shifts their role from purely generating code to conceptual, supervisory, and validation activities.

Keywords
foundation models, industrial robotics, robot programming, human-AI interaction, competence requirements



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Foundation Models in Industrial Robotics

Potential applications, role change and competence requirements

Bernd Kuhlenkötter and Daniel Syniawa, Ruhr University Bochum

Foundation models, such as large language models (LLMs), open up new possibilities for industrial robot programming. This article builds on the authors' own preliminary work on LLM-based robot programming in switch cabinet assembly. The implications of such an approach for employees and their roles have so far been the subject of very little research. New insights into changing competence requirements are derived here from the development, integration and evaluation of the solution. These are presented as a four-dimensional competence framework comprising application, validation, integration and process design, as well as model understanding and further development.

Industrial robotics has been a key component in automating industrial production processes for decades. Its widespread adoption is due to its ability to implement highly repeatable and efficient process flows in standardized environments [1].

However, the required programming often demands considerable effort. This is particularly true for processes involving frequent product changes, small batch sizes or unstructured working environments. In such scenarios, established programming paradigms are increasingly reaching their limits. Implementation is often reserved for experienced specialists, which prolongs implementation times and limits access, particularly for smaller companies [2].

In parallel, foundation models have led to the development of AI systems that are increasingly relevant to industrial robotics. Foundation models are pre-trained on large datasets that, depending on their design, can process different modalities of information. These include, in particular, LLMs, which process textual input and are capable of interpreting natural-language instructions, structuring tasks and deriving action sequences [3].

Vision-language models (VLMs) link visual and linguistic information. They thus open up new possibilities for the context-aware processing of dynamic environmental and state information [6]. Vision-language-action models (VLAs) extend these capabilities by linking perception, linguistic description and resulting action.

These model classes are particularly relevant to robotics, as they efficiently combine planning, perception and execution [7]. However, these technological developments do not merely hold the promise of greater efficiency and flexibility. Rather, it is reasonable to assume that the wider use of such models will have a significant impact on existing work processes, individual job profiles and competence requirements [4].

Whilst the technical feasibility and application potential of foundation model-based approaches are increasingly being investigated, their implications for skilled workers remain under-researched. This article aims to derive implications for competence requirements based on developments in foundation model-based robot programming for switch cabinet assembly. On this basis, a competence framework is presented that provides a structured summary of the identified tasks and the competence requirements necessary to perform them.

A practical example of LLM-based robot programming

A previous article used switch cabinet assembly with modular clamps as an example of how natural-language work instructions are converted in a two-step process into structured process steps and then into executable C++ code. The technical implementation is based on an architecture consisting of an LLM layer, standardized data storage, and a simulation and execution layer [5].

A key feature of this approach is the high level of abstraction in the programming process. The model-based system does not generate low-level motion instructions but instead relies on a fixed set of predefined high-level functions. These include functions for handling modular clamps and DIN rails. Path planning, collision detection, state management, and scene updating are handled by the underlying software layers. This shifts program generation and system interaction to a semantic level, where tasks are described in the form of understandable process logic and subsequently automatically converted into technically executable programs.

An illustrative test case from this work is the installation of multiple DIN rails in a switch cabinet based on a user instruction. **Figure 1** illustrates the overall process. Depending on the model used, successful program

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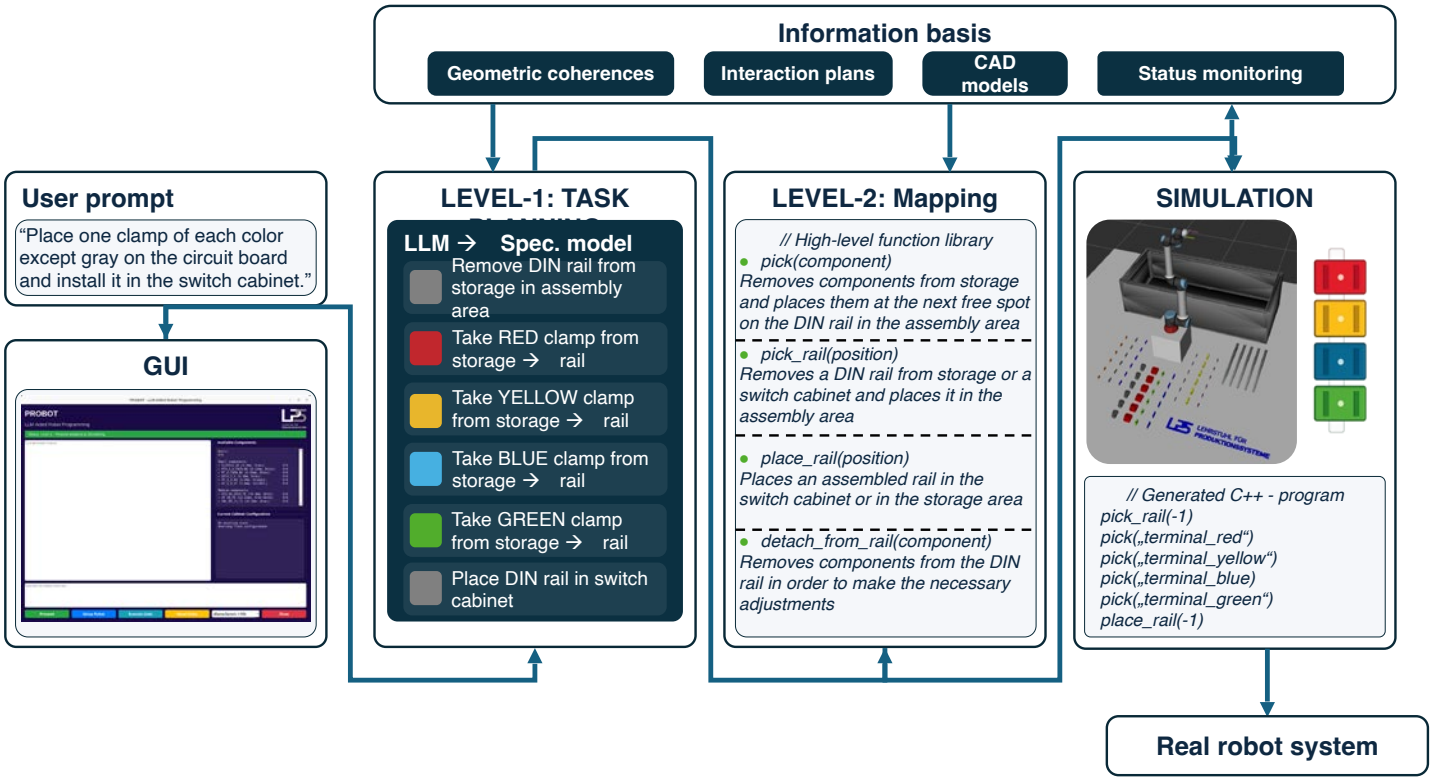


Figure 1: *LLM-assisted robot programming in switch cabinet assembly.*

generation was achieved in up to 57 out of 60 test runs, corresponding to a success rate of 95% [5].

Methodological Approach

The changes in tasks and competence requirements described below were not derived from a separate empirical study but exploratively from the development, integration, and evaluation of the technical system described. Methodologically, this is a qualitative case study based on observations made during the implementation period.

The derivation took place in three steps:

1. Recurring tasks, difficulties, and the need for intervention were documented across the three project phases.

2. These observations were then classified into recurring task categories—goal formulation and prompting, result validation, data provision and integration, and model selection.

3. These categories were abstracted into four overarching competence dimensions and assigned to existing organizational role profiles.

Due to the case-by-case nature of the study, the results cannot be statistically generalized and should be understood as conceptual.

Competence requirements for robot programming

During the development and testing of the solution, both the technical feasibility and the potential of a foundation model-based approach were demonstrated. Changes in job profiles and competence requirements were not the focus of the initial study but can be inferred from accompanying observations. Relevant aspects were identified particularly in the areas of goal formulation, validation, and system integration.

The starting point for all observations is the shift in the level of abstraction in the programming process. Users can program the robot system without familiarizing themselves in detail with proprietary programming languages and system-specific program structures **(Fig. 2)**. This offers significant potential for shortening commissioning times and increasing flexibility in the programming process. At the same time, it lowers the barrier to entry for individuals without in-depth programming knowledge.

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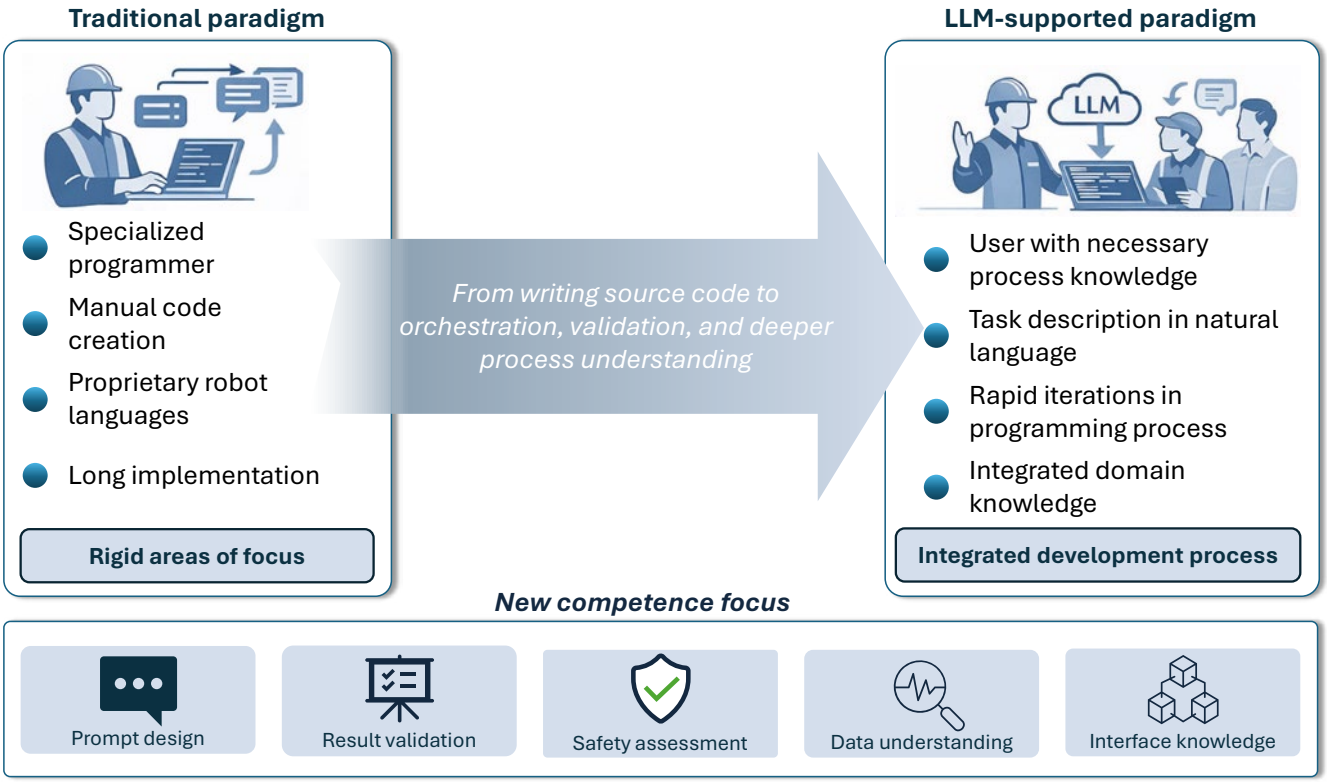


Figure 2: *Changes in the programming process for industrial robots.*

However, this shift is not accompanied by a general reduction in system complexity. Rather, requirements and workloads are redistributed within the overarching programming process. The quality of the results depends largely on the precision, structure, and contextualization of the input. Ambiguities or errors in prompts do not have merely isolated effects. Rather, they can propagate throughout the entire subsequent process and become difficult to trace after numerous processing steps.

Consequently, the design of system prompts and prompt engineering methods are gaining in importance. In particular, structured, context-rich inputs and few-shot examples can significantly improve model performance. At the same time, a single user input is often insufficient. In many cases, iterative refinement is required, in which the model is repeatedly alerted to errors and the task description is gradually refined.

Before transferring the results to real-world systems, the model-generated solutions are always manually evaluated in the simulation environment. This allows for the identification of errors in path planning, implausible process sequences, or collisions before execution on the physical system. The systematic verification of the generated programs currently accounts for a significant portion of the total effort.

Furthermore, model-generated solutions are more difficult to validate than those developed in-house. Since programming is not carried out actively, there is no step-by-step consideration of structure, design, and anomalies. The potential time savings in the overall process are thus largely negated by additional verification and correction work.

Relevant core activities were also identified in the context of system development and integration. The provision of suitable environmental and process information is crucial, since this cannot be fully captured by user prompts, particularly when there is high variant diversity. For the reliable use of foundation model-based systems, existing engineering data and dynamic perception information must therefore be integrated. This requires the availability of suitable communication interfaces, the use of compatible data standards, and the preparation of data in a processable form. As a result, not every application area is suitable for model-based robot programming.

The effective use of foundation model-based methods depends largely on whether these conditions are met and the process requirements favor model-based generation. The business value of such a solution is considered low in areas where programs can be used unchanged for long periods, for example.

Another key activity is the selection and adaptation of the models. The specific strengths, weaknesses, and specializations of the different models must be taken into account on a case-by-case basis. In some cases, fine-tuning may be necessary or at least beneficial, particularly when company- or process-specific data is available. This is precisely where potential lies for foundation model-based approaches, as the performance of the models can be significantly enhanced by incorporating domain-specific information.

Furthermore, questions arise regarding technical implementation, namely whether to use local or server-based execution and whether to use open or proprietary models. This involves fundamental decisions regarding information flows, data protection, and integrability.

Overall, the observations suggest that foundation models do not result in an unconditional reduction in workload. If systems, data sources, and verification mechanisms do not interact in a structured manner, it is more likely that the total workload will be merely shifted.

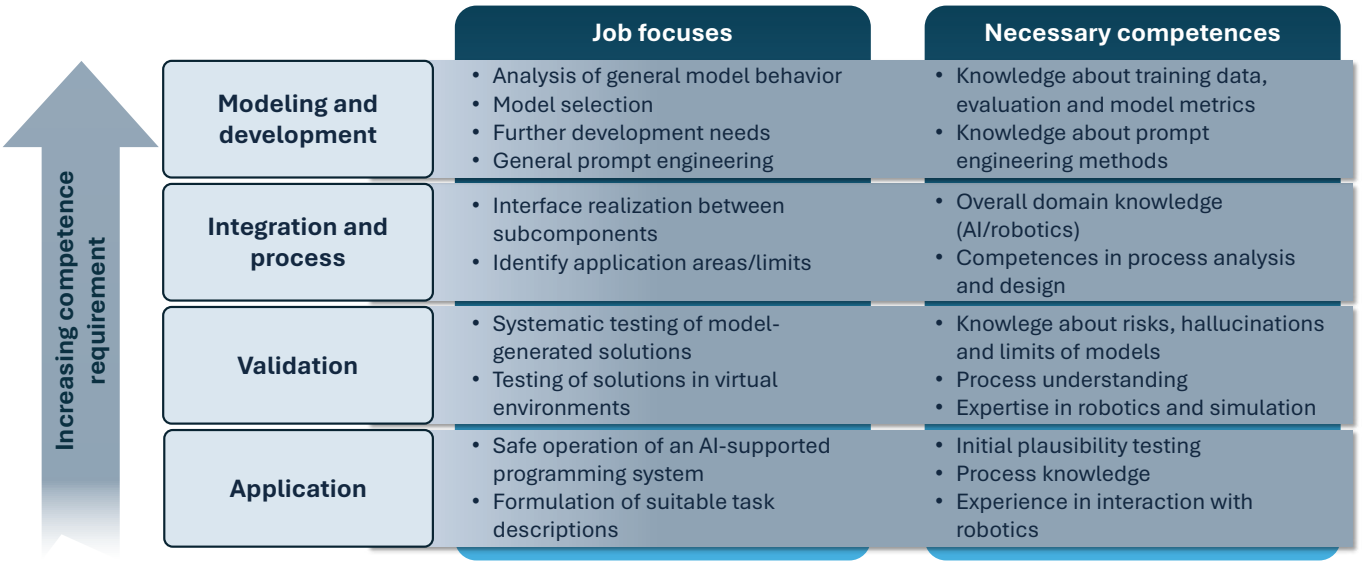
In line with this, the skills required for setting up, using, and maintaining foundation model-based robot programming are also shifting. In addition to traditional programming knowledge, skills in prompt design, result validation, safety assessment, data comprehension, and working with interfaces and integrated software landscapes are becoming particularly important. We have structured the resulting competence requirements into four overarching dimensions, which are summarized in **Figure 3**.

At the application level, the focus is on the use of model-based programming systems. This involves translating implicit experiential and process knowledge into explicit, structured, and model-compatible descriptions. Equally important is the ability to break down complex processes into meaningful subtasks. This builds on the existing roles of specialists in production, robot programming, and application-oriented automation. These individuals already possess the necessary understanding of the processes and of robot kinematics and behavior.

The validation level involves the systematic verification of model-generated solutions prior to their deployment in the physical world. Due to the non-deterministic and context-dependent nature of foundation models, simulation environments, digital twins, and virtual testing methods are increasingly important. The ability to detect malfunctions and validate the generated solutions through simulation is essential. These tasks may fall within the scope of robot programming, commissioning, and quality assurance roles, where simulation testing, fault diagnosis, and safety assessment expertise is already present.

The higher-level integration and process level focuses on embedding model-based programming approaches into existing technical and organizational structures. The central task is to design interfaces between system components and identify areas of application in production and automation processes. This includes connecting data sources, control systems, engineering tools, simulation environments, and user interfaces so that foundation models can be utilized efficiently. At the same time, it requires close coordination with operational domains like production planning, IT, and quality

Figure 3: *Competence framework for the use of foundation models in industrial robot programming.*



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assurance. This level is well-suited to automation and digital engineering professionals, who work at the intersection of technical system integration, process planning, and software integration.

Finally, at the modeling and development level, the focus is on understanding, selecting, adapting, and further developing the models. The central task is to select application-specific models and identify optimization opportunities. This requires expertise in machine learning, data preparation and provision, and the integration of external knowledge sources, e.g. via retrieval-augmented generation (RAG). These tasks correspond to the competence profiles of data scientists and AI specialists. In an industrial context, however, they must be supplemented by an understanding of robotic programming logic, motion sequences, and safety-related constraints.

Overall, the competence requirements described here should be understood less as an indication of entirely new job profiles and more as further developments of existing role profiles. Production and robot programming specialists will likely be more involved in the operational use of model-based systems in the future. Also commissioning and quality assurance are expected to shift toward digital validation. Automation engineers are key players in the technical and organizational integration of such approaches, whereas data scientists and AI specialists perform foundational work at the modeling and development levels.

The proposed framework differs from a large number of existing models in one key respect. Established AI competence models such as AICOMP are typically generic and education-oriented [8]. They describe general skills in work with AI without being tailored to a specific industry or field of activity. This paper operationalizes these general competences for the specific use case of foundation model-based industrial robot programming.

Changing competence requirements due to foundation models

The example presented here suggests that foundation models not only technically expand industrial robot programming but also shift the focus of programming work. As the focus shifts from low-level programming to semantic task description, model-based generation, and simulation-based validation, the required professional skills also change. The competence framework presented here structures these along the dimensions of application, validation, integration, process design, model understanding, and further development.

The insights also led to the hypothesis that using foundation models makes the robot programming process more efficient and accessible only if suitable high-level function libraries, structured engineering data, and simulation-based testing methods are available. If these or comparable peripheral components are missing, the workload simply shifts toward testing, verification, fault diagnosis, and data preparation.

The extent to which the described changes result in operational process change remains unclear. Reliable estimates require extensive empirical studies. Future research should therefore focus on examining changes in work processes, job profiles, and qualification requirements in industrial applications.

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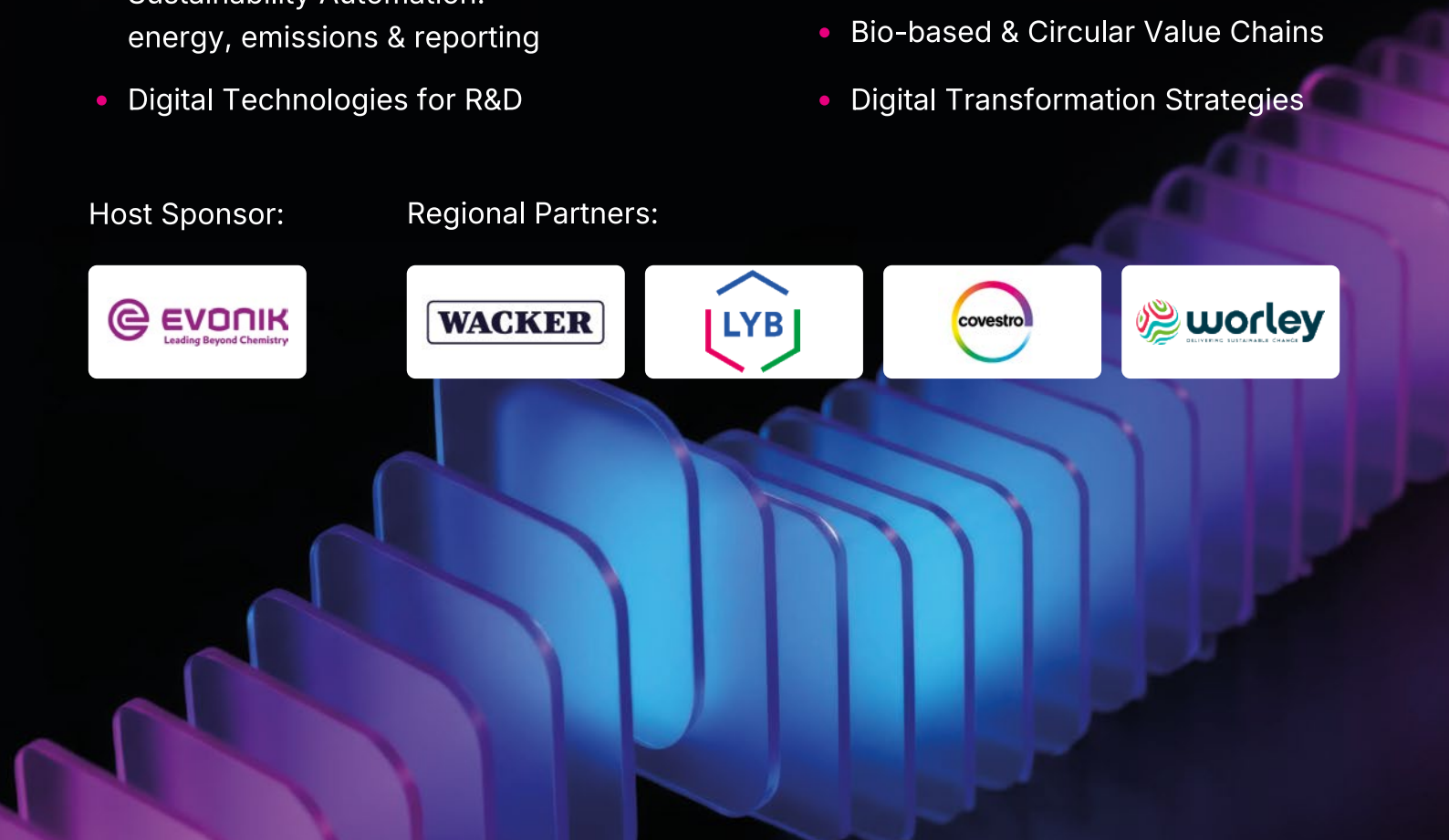
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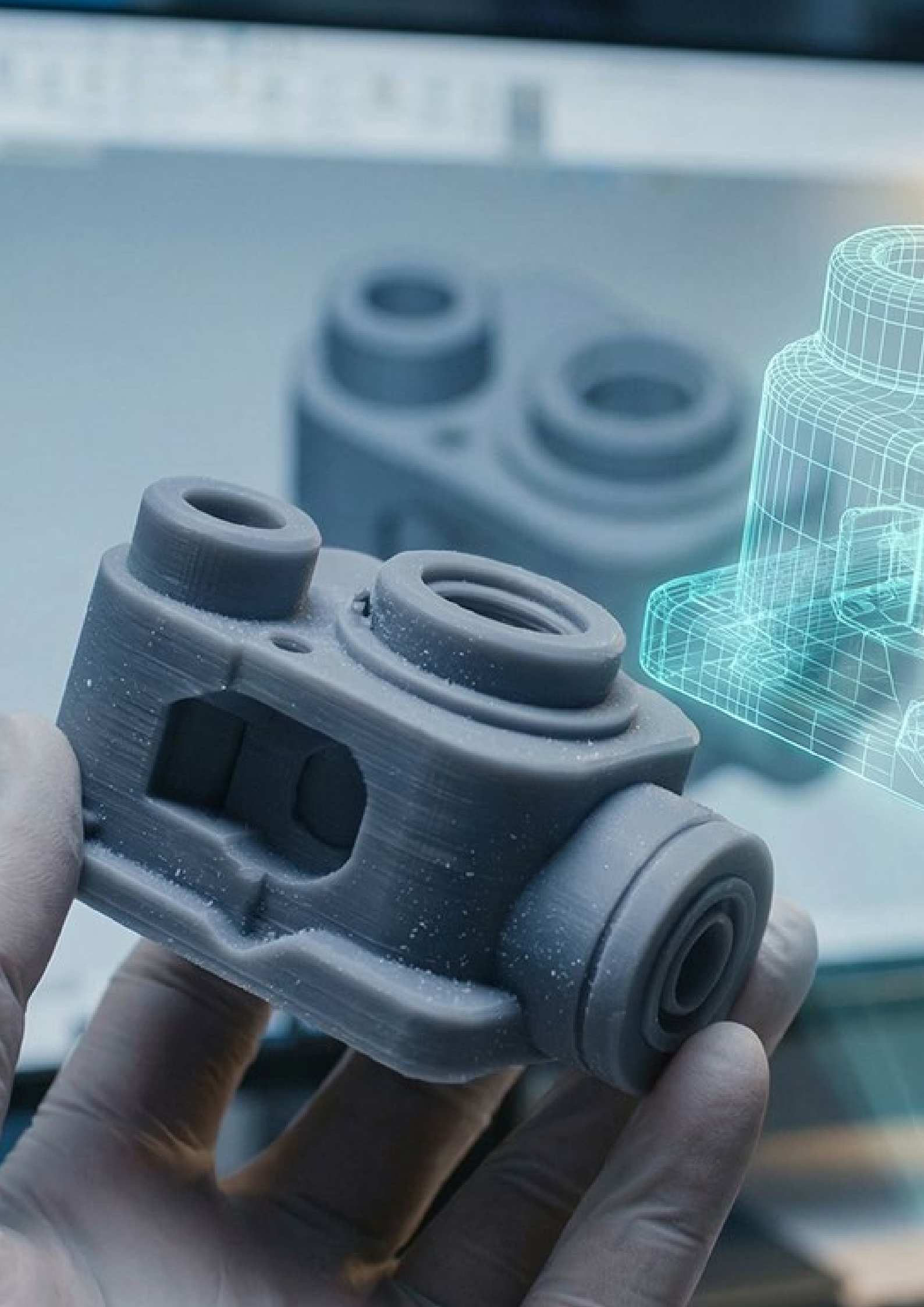
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Competence Assurance for the Verification and Validation of Simulation Models

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Can the validity and credibility of simulation models and data for production and logistics be determined using artificial intelligence? And what requirements must AI assistants meet to support experts in verification and validation while simultaneously safeguarding their expertise? Simulation experts were interviewed in structured interviews about their expectations and wishes.

Keywords
artificial intelligence, competence, discrete-event simulation, production and logistics, verification and validation



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Competence Assurance for the Verification and Validation of Simulation Models

Requirements for AI-supported assistance in production and logistics

Sigrid Wenzel, Felix Özkul and Robin Sutherland, University of Kassel

Discrete-event simulation has proven its worth over the years as a method for analyzing dynamic and stochastic interactions in production and logistics systems; it is therefore currently used across various industries. However, ensuring the validity of the models—including their data—for their respective investigation purpose remains a challenge. To address this issue, this paper analyzes the requirements for an AI-supported assistance designed to ensure competence and support users in the verification and validation of information, data, and models. The results are evaluated by a panel of experts. Underscoring the necessity of such an assistance, this paper also provides a foundation for its implementation.

Simulation-based analysis of production and logistics systems has proven its worth across various industries [1]. To ensure that the use of simulation yields reliable results for the planning and operation of production and logistics systems, it is essential to ensure the validity and credibility of the information, data, and models used. However, a survey [2] conducted by the working group "Simulation in Production and Logistics" of the association for simulation (ASIM – Arbeitsgemeinschaft Simulation) shows that verification and validation (V&V) are typically carried out pragmatically in practice (i.e., only to a limited extent systematically or consistently)—simulation-project-related issues often require rapid insights, so ensuring validity is sometimes viewed as secondary. However, this is risky, as it can result in undetected errors in the simulation models (and thus also in the results), which can lead to incorrect decisions and must be corrected at a later stage.

Nevertheless, it should be noted that the application of discrete-event simulation in production and logistics is also subject to change related to demographic shifts [3] as well as the areas of application within the system life cycle, which drive the development and use of assistive technologies [3]. Wenzel et al. [3] highlight the range of assistance forms (e.g., digital assistance systems) for simulation applications, which not only have the capability of providing operational support in carrying out tasks related to simulation applications but also ensure the competence of simulation experts. The authors demonstrate that the availability of such an assistance in the context of V&V has not yet reached a comparable level to that in, for example, model development or the experimentation phase (see [4] for the phases of a simulation study).

The selection and application of suitable V&V techniques (for an overview of these techniques, see [5]) as well as the assessment of the validity of information, data, and models require comprehensive domain-specific expertise. This paper addresses this issue by analyzing the requirements for an AI-supported assistance for the V&V of simulation models in production and logistics, based on literature-derived and empirically evaluated user stories. It investigates which functions are necessary to provide operational support for the intrinsic V&V of a simulation model (i.e., the verification of the model's internal consistency, completeness, and plausibility) as well as for V&V against the task specification (i.e., the suitability of the model for its intended purpose).

Beyond preserving simulation experts' existing methodological and domain-specific expertise through AI in the context of V&V, this paper also identifies the AI-related framework conditions that serve as fundamental technological prerequisites for practical industrial application.

Terminological classification and scientific delimitation

A systematic simulation procedure model [6] was established for simulation applications in production and logistics. Starting with the sponsor needs, this model encompasses the phases of task definition, system analysis, model formalization, implementation, as well as experiments and analysis. The results of the preceding phases (i.e., the information, data, and models) form the basis for the subsequent phase. V&V involves verifying all results for correctness (the subject of verification: "Is the phase result right?") as well as their suitability for the defined investigation objectives (the subject of validation: "Is it the right phase result?") [7, 8].

V&V can be performed either intrinsically or across phases. Intrinsic check focuses, among other things, on the

plausibility, completeness, and consistency of the result of a single phase without considering the results of other phases. Cross-phase V&V, in contrast, focuses on checking the correct transformation of a phase result derived from a previous phase result. This paper addresses exclusively the intrinsic V&V of the executable model and its V&V against the task specification. For this purpose, various V&V techniques (test methods) are available, which differ in their applicability and objectivity [5].

This paper examines the requirements for AI-supported assistance to faciliate the execution of V&V activities. The aim is to ensure the competence of simulation experts in the field of V&V. While there is no uniform understanding of the term of competence in the relevant literature, it is discussed to some extent in specific works (e.g., in [9]). In the context of this paper, competence is understood as knowledge related to the V&V of simulation models that is extended by a situational readiness for application and internalized by the simulation expert in the form of skills and abilities. Situational readiness for application combines knowledge of V&V techniques with knowledge of how to apply these techniques (experience) in relation to a specific application context (assessability/judgment). While competence development aims at the continuous expansion and systematic acquisition of new skills that were previously unavailable [10, 11], competence assurance (or competence retention) focuses on the preservation and methodical consolidation of existing competencies during ongoing operations.

This form of competence assurance is particularly relevant in automated and digitalized work environments [12]. As operational routine tasks are increasingly taken over by software systems (e.g., automated consistency checks of simulation models), competencies may be applied less frequently and consequently risk being lost over time [12]. To counteract this gradual loss of expertise, this paper explores the conceptualization of an AI-supported assistance. According to Wenzel et al.'s definition [3], assistance includes, among other things, computer-based tools designed to reduce workload. In the context of this paper, an AI-supported assistance system is defined as a computer-based tool that utilizes AI models. Accordingly, the development of such an assistance system can be regarded as a form of software engineering.

Software engineering typically entails a requirements analysis to identify the users' objectives and needs [13]. This process initially includes a stakeholder analysis, which involves identifying the relevant individuals and their objectives. For the identified groups, the relevant functions of the software to be developed are elicited. For this purpose, use cases are defined and formulated in the form of so-called user stories as structured statements following the format: "[Role] requires [function] in order to obtain [benefit]."

These user stories subsequently serve as the foundation for the technical implementation of the software. In this paper, such a requirements analysis is performed for an AI-supported assistance for the V&V of simulation models.

Requirements analysis of AI-supported assistance

For the AI-supported assistance for V&V of simulation models, the primary stakeholders are experts who build, verify, and validate such models. The methodological approach for determining the functional and non-functional requirements of the AI-supported assistance follows a two-step process. In the first stage, the user stories are developed deductively by the authors based on their expertise in the field of V&V.

The functional and methodological basis is the previously defined purpose of the AI-supported assistance, namely to faciliate both the conducting of the intrinsic V&V of the simulation model and its check against the task specification (**Fig. 1:** E1–E6), as well as competence assurance (**Fig. 1:** K1–K7). The primary focus of these requirements is to preserve the V&V competence of simulation experts rather than to promote progressive competence development or the acquisition of entirely new V&V competencies. However, a strict separation between competence assurance and development is considered impractical and is therefore not enforced within the user stories.

The user stories pertain to the application of V&V techniques; however, they are not sufficient on their own, as the use of AI involves inherent system-related requirements. These are represented by so-called user stories describing system-related framework conditions (**Fig. 1:** R1–R3), which include technical and legal requirements necessary for productive use in an industrial environment. To intentionally leave the specific user role open, the user stories are formulated in a modified first-person structure ("I want [function] in order to achieve [benefit]") while preserving the general user story format. In the second stage, the user stories are evaluated by simulation experts. Based on the respondents' self-assessment, different experience groups can be established, which may reveal statistically significant differences in response behavior.

User stories for V&V applications

This area focuses on providing technical and methodological support for conducting V&V. The assistance supports users in selecting a V&V technique suitable for their respective task specification (E1). By automatically checking the

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ID	User Story	Function/Purpose
E1	"I want the AI to recommend the most appropriate V&V techniques based on my task specification, so that I can avoid selecting an unsuitable method."	Recommendation of Suitable V&V Techniques
E2	"I want the AI to automatically assess whether the simulation model is suitable for its intended purpose, so that I can focus on more complex validation tasks."	Assessment of Model Suitability
E3	"I want the AI to automatically assess the internal consistency and plausibility of the simulation model, so that I can focus on more complex validation tasks."	Assessment of Model Consistency and Plausibility
E4	"I want the AI to proactively recommend suitable but rarely used V&V techniques to help me move beyond my habitual methods and continuously expand my expertise."	Recommendation of Rarely Used V&V Techniques
E5	"I want the AI to provide additional information about unfamiliar or rarely used V&V techniques so that I can develop a deeper understanding of them."	Supplementary Information on V&V Techniques
E6	"I want the AI to automatically generate a standards-compliant V&V report based on the results, thereby minimizing documentation effort."	Automated Report Generation
K1	"I want the AI to engage me in an interactive dialogue by asking questions tailored to my current simulation model, so that I can deepen my understanding of modeling and V&V."	Interactive Model Querying
K2	"I want the AI to suggest prompts related to my simulation model to help me get started and improve my analytical capabilities."	Recommendation of Model-Specific Prompts
K3	"I want the AI to involve me in the problem-solving process whenever errors occur, so that I can learn from them and avoid making similar mistakes in the future."	User Involvement in Error Handling
K4	"I want every recommendation made by the AI to be explained and justified in detail so that I can learn from it."	Comprehensive AI Explanations
K5	"I want the AI to recommend corrective actions and implement them automatically after my approval, allowing me to use the time saved more productively."	(Semi-)Automated Corrective Actions
K6	"I want every AI recommendation to be based on an identifiable source (e.g., a standard, guideline, handbook, or the underlying model logic) so that I can easily verify and understand it."	Source-Based Recommendations
K7	"I want the AI's recommendations to be transparent and explainable so that I can develop trust in the AI system."	Explainability of Recommendations
R1	"I want the AI to avoid storing my sensitive model and personal data so that compliance requirements and the protection of proprietary information are always ensured."	Data Protection and Compliance

R2	"I want the AI to be capable of processing large simulation models so that I can still obtain results quickly."	Processing of Large Simulation Models
R3	"I want the AI to process simulation models created with different simulation tools so that I receive support regardless of the software platform."	Tool-Independent Support

Figure 1: *Overview of user stories.*

consistency and plausibility of the simulation model (E3), as well as its suitability for the intended purpose (E2), the system reduces the likelihood of errors and relieves experts of routine tasks. The relevance of this category lies in improving the execution of simulation studies and extending the methodological application of V&V by recommending rarely used techniques (E4 and E5) and by providing automated, standards-compliant documentation (E6).

User stories for competence assurance

User stories in this category focus on the didactic interaction between humans and AI. The aim is to ensure that simulation experts remain actively involved in the problem-solving process (K3) rather than accepting AI recommendations without critical reflection. Sustainable competence assurance is promoted through interactive, model-specific questioning (K1), suggested simulation-model-related prompts (K2), and corrective measures (K5), as well as the provision of explanations based on standards and manuals (K4, K6, and K7). The relevance of this category stems from the need to prevent blind trust in AI systems and to preserve the judgment of simulation experts in the long term by ensuring the explainability of AI-generated recommendations.

User Stories for system-related framework conditions

This category defines the necessary technical and legal prerequisites for the productive use of AI assistance in industrial environments. It focuses on the protection of trade secrets and adherence to compliance guidelines through strict data protection for sensitive model-related and personal data (R1). In addition, the user stories address requirements for scalability (i.e., maintaining responsive performance even when processing large simulation models; R2) and tool independence (R3). These framework conditions are essential for user acceptance, as only a high-performing, secure, and tool-independent system is likely to be successfully adopted in practice.

Evaluation of the user stories

The aim of the evaluation is to ensure the theoretically derived user stories in terms of their technical accuracy and their relevance in an industrial context. To this end, an anonymous expert survey is conducted online using LimeSurvey among members of the ASIM working group "Simulation in Production and Logistics" [2].

The survey consists of four parts. In the first part, respondents characterizes themselves based on their professional experience and their current field of work (i.e., services, research, or industry). They are also asked to assess whether V&V is typically performed in a pragmatic manner in practice and whether the use of AI-supported assistance for the V&V of simulation models in production and logistics would be beneficial. Responses are collected using a four-point Likert scale ("strongly agree," "agree," "disagree," and "strongly disagree"), supplemented by a "don't know" option.

The second part consists of a dual matrix question designed to evaluate the 16 user stories in terms of both the suitability of the proposed functionality and its benefit for maintaining the respondents' own V&V competence. Each user story is assessed using the same four-point Likert scale, with an additional "don't know" response option available for every item. This design enables the identification of potential discrepancies between theoretically desirable functionalities and those perceived as practically valuable.

In addition to the matrix questions, an open-ended text field is provided at the end of this part for qualitative feedback. In the third part, respondents are asked to select the five user stories they considered most relevant. Finally, participants are invited to suggest additional user stories for an AI-supported assistance for the V&V of simulation models.

Discussion of the user stories

The survey results (see [2]) indicate that the respondents (N = 27) are predominantly highly experienced, with 52%

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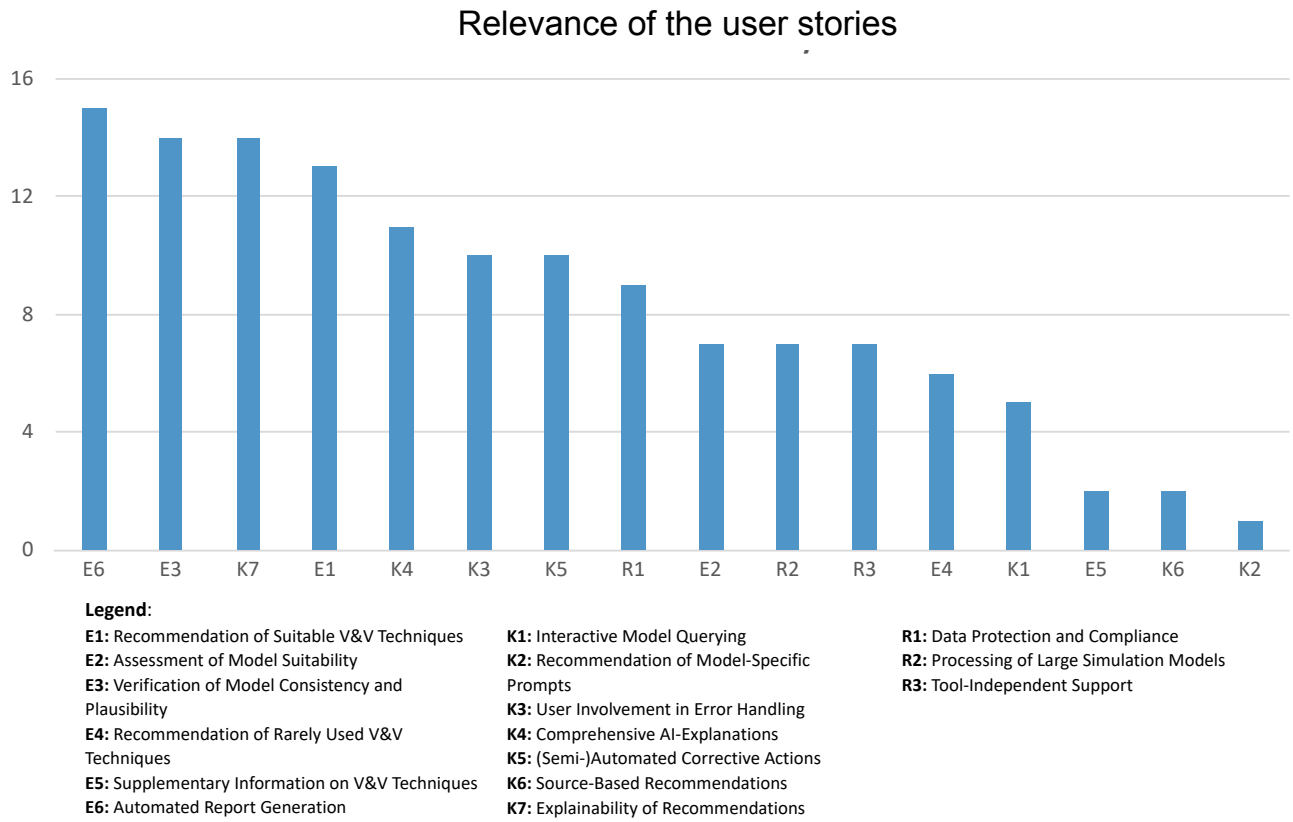


Figure 2: *Frequency distribution of user story selections (five mentions; N = 27).*

reporting more than ten years of professional experience. Most participants work in research (51.9%), followed by industry (29.6%) and services (18.5%). Overall, the experts confirm that V&V is typically carried out pragmatically in practice and regarded AI-supported assistance for the V&V of simulation models as beneficial. The following discussion is organized according to the prioritized relevance of the user stories **(Fig. 2)** and the three functional categories (E, K, and R), complemented by the evaluation of each user story regarding the suitability of its functionality and its benefit for competence assurance **(Fig. 3)**.

Within the V&V application category (E1–E6), respondents express strong support for AI-assisted operational functions **(Fig. 3)**. The user story describing the AI-based generation of a standards-compliant report (E6) receives the highest priority **(Fig. 2)** and is also rated highly in terms of functional suitability, with approximately 70% of respondents selecting "strongly agree." Similarly, the automated assessment of model consistency and plausibility (E3) and the recommendation of appropriate V&V techniques based on the task specification (E1) are considered highly relevant.

These findings indicate that respondents view AI-supported assistance not only as a means of preventing errors and selecting suitable V&V techniques but also as valuable support for methodological decision-making. This is also evident when considering the benefit for competence assurance. In particular, user stories E2 (assessment of model suitability) and E6 (automated report generation) receive substantially lower ratings in this regard. Although automated report generation (E6) is regarded as highly suitable, only approximately 26% of respondents strongly agree that it contributes to maintaining their own competence. For the automated assessment of model suitability (E2), negative responses even outweigh the positive ones **(Fig. 3)**. These findings empirically demonstrate that respondents primarily seek relief from time-consuming V&V activities, whereas their own learning is considered secondary. Consistent with this interpretation, providing supplementary information on unfamiliar or rarely used V&V techniques (E5) is among the least frequently selected user stories.

Interestingly, for the learning-oriented functions E4 (recommendation of rarely used V&V techniques) and E5 (supplementary information on V&V techniques), the value attributed to them in terms of competence assurance is significantly higher than their purely operational utility **(Fig. 3)**. The experts thus clearly recognize the didactic potential of these functions.

When examining the specific user stories in the context of competence assurance (K1 through K7), the high relevance of detailed explanations and explainability (K4 and K7) is noteworthy. Explainability of AI recommendations (K7) receives approximately 70% "strongly agree" responses regarding functional suitability and about 67% regarding competence assurance. Likewise, detailed explanations of AI recommendations (K4) achieve approximately 63% overall agreement concerning their benefit for competence assurance. These findings suggest that respondents are generally unwilling to invest substantial additional learning time—for example, by consulting standards or technical manuals—but nevertheless have a strong desire to understand the rationale behind AI-generated recommendations. Their primary motivation appears to be building trust in the AI-supported assistance while maintaining ultimate responsibility for decision-making.

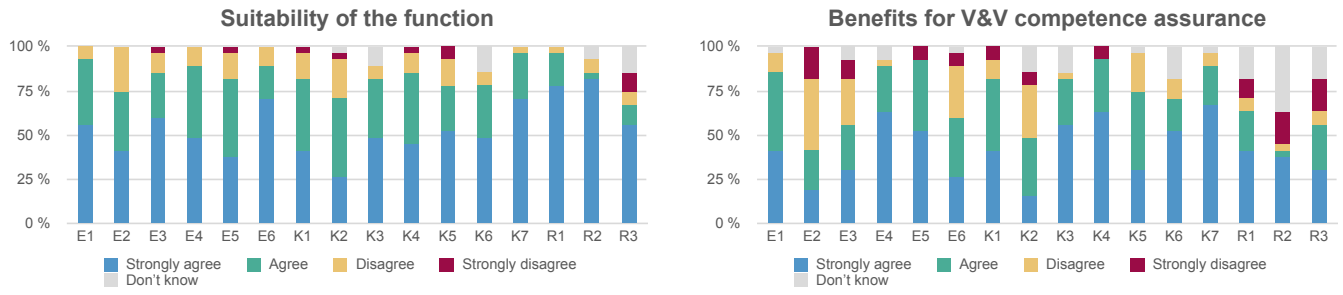
Functions supporting error handling (K3 and K5) are also perceived as highly relevant. In particular, involving users in the problem-solving process when errors occur (K3) is considered by more than 55% of respondents to make a substantial benefit for maintaining professional competence. In contrast, user stories describing AI-generated simulation model-specific prompts (K2) and those featuring recommendations explicitly linked to identifiable sources such as standards, guidelines, manuals, or model logic (K6) are among the least frequently prioritized. The recommendation of simulation model-specific prompts (K2) receives the lowest rating for competence assurance, with only 15% of respondents selecting "strongly agree." Instead, respondents express a clear preference for remaining actively involved in problem solving and for receiving suggestions for corrective actions. Overall, these findings reinforce the importance of transparent and explainable AI over fully automated execution of V&V activities. Rather than delegating responsibility to AI, respondents wish to learn from errors and avoid repeating them in the future.

Furthermore, the fundamental role of system-related framework conditions (R1–R3) is confirmed by the predominantly positive assessment of the functions' practicality **(Fig. 3)**. In addition, the importance of data protection (R1) is prioritized **(Fig. 2)**. Thus, adherence to compliance guidelines and the protection of sensitive model data represent an absolute prerequisite for the acceptance of AI-supported assistance in industrial environments. Accordingly, the protection of sensitive data (R1) and the processing of large simulation models (R2) receive the highest number of "strongly agree" responses regarding their practicality across all user stories **(Fig. 3)**.

This demonstrates that data protection and model-based scalability are not optional requirements but essential in practice. As expected, the ratings regarding competence assurance are lower across all three system-related framework conditions, since these represent a fundamental prerequisite for the implementation of AI-supported assistance. While they are necessary for the physical deployment and acceptance in industrial practice, their benefit for maintaining simulation experts' competence is largely indirect.

In addition to the 16 evaluated user stories, respondents formulate further relevant user stories that address the technological, methodological, and organizational

Figure 3: *Evaluation of the 16 user stories regarding the suitability of their functionality and their benefit for competence assurance (percentages; N = 27).*



Legend:

E1: Recommendation of Suitable V&V Techniques
E2: Assessment of Model Suitability
E3: Verification of Model Consistency and Plausibility
E4: Recommendation of Rarely Used V&V Techniques
E5: Supplementary Information on V&V Techniques
E6: Automated Report Generation

K1: Interactive Model Querying
K2: Recommendation of Model-Specific Prompts
K3: User Involvement in Error Handling
K4: Comprehensive AI-Explanations
K5: (Semi-)Automated Corrective Actions
K6: Source-Based Recommendations
K7: Explainability of Recommendations

R1: Data Protection and Compliance
R2: Processing of Large Simulation Models
R3: Tool-Independent Support

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capabilities of AI-supported assistance. Among the technological and methodological functions, respondents emphasize AI-supported parameter selection and parameter variation within task-specific constraints to ensure an adequate testing range. To facilitate interdisciplinary collaboration, participants also propose generating different views of the model logic to provide target group specific discussion material during V&V—for example, for process owners or management.

In this context, the configurability of AI-powered assistance could be suitable. For example, a flexible filtering mechanism for different user groups could dynamically switch between "verified knowledge" (based on standards, guidelines, and manuals) and "open exploratory search." While the former minimizes potential errors for less experienced users, the latter allows experienced users to expand the solution space and utilize innovative V&V techniques. From an infrastructure perspective, the necessity of on-premise hosting is highlighted as a critical requirement to ensure control over sensitive corporate data. Respondents also propose functionality for capturing users' reasoning during the V&V process and for automatically comparing the simulation model documentation with its actual implementation.

Summary and open research topics

Based on a methodological requirements analysis and a subsequent expert survey, this paper demonstrates that AI-supported assistance holds significant potential for ensuring competence in the V&V of simulation models in production and logistics. The evaluation confirms broad acceptance of AI-supported functionalities, particularly those that provide decision support, explainable recommendations, and robust data protection. In addition, respondents identify valuable requirements and practical needs that provide important directions for future research.

Further analysis of the user stories is necessary to support software engineering process. In addition to taking other stakeholders and their needs into account, the goal is to prioritize requirements—for example, using the MoSCoW method ("Must-have," "Should-have," "Could-have," "Won't-have"). This should be combined with a detailed cost-benefit analysis. Thus, for each user story, it must be assessed whether the benefits achieved justify the development effort. Further research is needed to incorporate the knowledge of simulation experts into AI-supported assistance and to determine the objective information requirements for the AI models—in addition to the actual simulation model—in order to achieve satisfactory support. Furthermore, it is necessary to investigate which AI approaches can be used for the various V&V activities, for example, in parameter selection and automated testing.

The requirements analysis presented in this contribution forms the foundation for the development of an AI-assistance that is explicitly intended not to replace humans but to empower them in performing complex V&V activities. In this context, the successful implementation of an AI-supported assistance in simulation-based applications therefore depends not only on technological feasibility but, more importantly, on sound methodological implementation, transparent and explainable decision-making, and careful consideration of industrial requirements and constraints.

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Announcement

Announcement

Industry 4.0 SCIENCE

Lean Product Life Cycle Management

In the era of Industry 4.0, Product Life Cycle Management (PLM) is evolving beyond its traditional role as a data backbone. Increasing product complexity, shorter development cycles, and sustainability demands call for a more integrated, value-driven approach. Lean Product Life Cycle Management (Lean PLM) addresses this by combining lean principles with digital technologies and modern engineering practices.

At its core, Lean PLM focuses on eliminating waste while maximizing value across the entire lifecycle. By connecting data, processes and stakeholders through a digital thread, it enables transparency, faster decisions and effective cross-functional collaboration. Methods such as value stream mapping, agile development, and concurrent engineering help streamline processes and improve coordination from design to production.

Key enablers include product data management, model-based systems engineering and simulation-driven design, allowing earlier validation and fewer costly iterations. Continuous feedback loops and integrated product development further support adaptability, better change management, and data-driven portfolio decisions.

This issue of Industry 4.0 Science (www.industry-science.com) explores how Lean PLM transforms product development into a faster, more collaborative, and sustainable process—reducing time-to-market while enabling integrated collaboration across business functions and heterogeneous software systems.

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Interoperable Data Access in Automotive Body Manufacturing

OPEN ACCESS

While AI has long been capable of analyzing production processes, why is it so difficult to feed its insights directly back into production? In the automotive industry's mass production of car bodies, the issue is less a lack of data than a lack of holistic integration concepts involving the machines. The key question is: What design principles are necessary to effectively integrate AI results into the production process in the future?

Keywords
IIoT, digital manufacturing, automotive industry, interoperability



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Interoperable Data Access in Automotive Body Manufacturing

Deterministic integration of structured target parameters into tact-time production

Tim Richter, Mercedes Benz AG, Robert Weidner, TU Freiberg

For the use of artificial intelligence (AI)-based systems in automotive body-in-white mass production, the bidirectional integration of development and production data is becoming increasingly important. While existing approaches have already extensively investigated the analysis of machine and process data, robust concepts for the secure, standardized, and scalable feedback of structured target parameters into operational production are still lacking. This paper examines the architectural principles required for the bidirectional integration of production equipment with central data platforms in body-in-white manufacturing. A comparison of existing solutions against the requirements of body-in-white manufacturing shows that the deterministic and state-dependent adoption of structured parameters into cycle-time-driven production processes represents a key challenge.

Fundamentals of AI-supported production processes

With the increasing digitalization of the automotive industry, the structure and dynamics of industrial value creation are undergoing fundamental changes. Shorter product life cycles, increasing product variety, and globally distributed production networks require a closer integration of previously separate information spaces to implement production-relevant changes consistently, promptly, and across different factories [1]. Concepts such as the Digital Thread and the Digital Twin pursue the goal of maintaining continuous and traceable data throughout the entire product life cycle. This paper applies the fundamental principles of these concepts to automotive series production. This sector in particular, requires information systems (IS) that link product information documented at the development stage with process data derived from the shop floor. Changes from development departments must be seamlessly transferred to production systems (downstream)—for example, adjustments to welding parameters based on new strength requirements—while, conversely, changes arising in production must be systematically fed back to the relevant departments (upstream). This bidirectional integration is particularly relevant in the context of AI-based applications, whose effectiveness depends directly on the availability and quality of the underlying data [2]. Welding parameters for example, can already be optimized using AI. However, implementing these optimized parameters in production largely remains a manual process [3]. This article addresses this gap by establishing the conceptual foundation for a generic information system (IS) that enables AI-modified process parameters to be transferred deterministically to production equipment following human approval. The IS serves as an enabling platform that existing AI applications can build upon, allowing their results to be transferred directly to the operational level of production. At the same time, such an IS can help preserve expertise long term by permanently archiving automatically transferred parameters, whereas documentation has traditionally depended on the diligence and consistency of individual personnel. The automotive body-in-white production department serves as application context for the design of such an IS in this study. The objective of this paper is to derive fundamental principles of an IS for the bidirectional transfer of structured parameters—both downstream and upstream—within the cycle-time-driven production processes of the automotive industry. This paper is part of an ongoing research series in this field and follows the Design Science Research (DSR) paradigm. It represents the first building block of an nascent design theory and draws on established solution patterns from the Industrial Internet of Things (IIoT) to develop architectural approaches for the transfer described above (exaptation according to [4]).

For the purposes of this paper, it is important to distinguish between different types of data. A distinction is made between three types of parameters:

- Runtime variables that are read or modified during operation (e.g., the pressure in a vessel),
- structured setpoint parameter sets in the form of programs or recipes that define the process logic (e.g., a welding program with specified setpoints/targets for current, voltage, and time), and
- configuration data with long-term relevance (e.g., the network configuration of a production machine).

This article focuses on structured parameter sets, as they directly specify and determine the execution of production processes.

Criteria	Opacin [5]	Ungurean [6]	Jeng [7]	Parant [3]	Sanz [8]	Schramm [9]	Geplante Forschungsreihe
Instantiation in automotive series production	×	×	×	✓	✓	×†	✓
Structured setpoint parameters	×	×	×	×	×	✓	✓
Upstream	✓	✓	(✓)	✓	✓	(✓)	✓
Downstream	✓	✓	(✓)	×	×	✓	✓
Downstream: deterministic integration in cycle-time operation	×	×	×	×	×	✓	✓
Downstream: applicable in large scale series production	×	×	×	×	×	×	✓

Figure 1: *Distinction between related studies based on criteria defining the subject of investigation (✓ met, (✓) partially met, × not met; † automotive context without implementation in series production).*

Current state of research

The bidirectional integration of industrial systems has been the subject of numerous research studies in the context of the Industrial Internet of Things (IIoT). Opačin et al. [5] and Ungurean and Gaitan [6], for example, demonstrate that industrial controllers can be connected bidirectionally to higher-level systems using Message Queuing Telemetry Transport (MQTT)- and fog-based architectures, respectively. However, these approaches focus primarily on runtime variables, with IoT capabilities largely limited to the sensor and actuator levels. Web-based Human–Machine Interface (HMI) approaches, such as those presented by Jeng and Chieng [7], primarily expand operator interaction and visualization capabilities without addressing the structured and process-safe transfer of setpoint parameter sets to the operational production environment.

In contrast, cloud- and platform-centric architectural approaches within the automotive industry demonstrate a high degree of maturity in the upstream integration of machine data, as shown in [3] and [8]. Both studies highlight the potential of centralized platforms for aggregating and analyzing production data. However, these studies do not address the automated downstream transfer of structured setpoint parameters into production.

The closest match to the topic addressed in this paper is the Digital Process Chain proposed by Schramm et al. [9]. Their approach describes a bidirectional IIoT architecture in which production-relevant parameters are managed through a central IS and transmitted to machine controllers in a standardized manner via middleware. This demonstrates the fundamental feasibility of transferring setpoint parameters within a production environment. At the same time, the authors themselves point to open questions regarding the scalability of the approach to high-volume series production systems. The present paper, together with subsequent studies in this research series, builds on the work presented in [9] as a conceptual foundation and aims to address these open issues.

Based on criteria relevant to this research, all reviewed studies are compared in **Figure 1**.

The comparison presented in **Figure 1** reveals a clear asymmetry: while the upstream of state and process data has already reached a high level of maturity, the downstream transfer of structured setpoint parameter setswithin cycle-time-driven execution has so far been addressed only to a limited extent and has not been comprehensively solved for high-volume series production in any of the reviewed studies. Recent literature reviews confirm that Digital Manufacturing architectures largely remain at the prototype level, while bidirectional approaches are still rare [10, 11].

The resulting research gap therefore lies in the development of a concept that consistently transfers structured setpoint parameter setsto the operational

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execution level in a technology-independent manner while meeting the requirements for robustness, availability, and process safety in high-volume body-in-white series production.

Methodology and meta requirements

This paper adopts the DSR paradigm [12] and structures the research according to the DSR phases outlined by Peffers et al. [13]. Hevner et al. [12] describe DSR as a problem-solving-oriented paradigm that generates knowledge by creating and evaluating innovative artifacts to solve relevant problems.

As a problem-centered study following [13], this article covers the first two activities of the Peffers model: problem identification and the derivation of solution objectives. The development, demonstration, and evaluation of the overall artifact will be addressed in subsequent papers within this research series. The problem is identified through the introduction and state-of-the-art review and is further specified below using so-called Meta-Requirements (MRs) [13], while the solution objectives are formulated as architectural design principles. According to the "Knowledge Contribution Framework" of Gregor and Hevner [4], this work represents a Level 2 knowledge contribution, namely a nascent design theory in the form of an exaptation that transfers established solution patterns from the IIoT to the previously described problem context.

For the bidirectional target architecture, the meta-requirements (MR) are derived from the problem context. Building on these, architectural design principles for the body in white domain are developed.

The first MR concerns robustness. In body-in-white production, any equipment downtime directly affects the entire line and results in significant opportunity costs. An IS whose failure interrupts production would therefore not be suitable for practical use. This leads to **MR-1**: Ongoing production must be able to continue without disruption in the event of an IS failure or a loss of connectivity to the IS (non-production-critical).

The second MR concerns the timing of parameter adoption. Uncontrolled adoption of parameters during an ongoing production step can lead to inconsistencies: a weld spot whose current is changed during the process is neither reproducible nor quality-assured. In extreme cases, this can result in product defects or equipment failure. This leads to **MR-2**: Structured setpoint parameter sets must be adopted deterministically and in a process-compatible manner during ongoing production.

The automotive body-in-white production process typically involves several thousand IIoT assets capable of communication. In this environment, an IS must thus be designed to scale effectively even with a high amount of assets. This leads to **MR-3**: The IS must be designed to be cost-effective and communicatively scalable when handling a vast number of assets, with minimal additional effort per asset.

The control landscape in the body in white production is heterogeneous across manufacturers. Production equipment is gradually renewed over long lifecycles. Therefore, the architecture must be able to uniformly integrate equipment from different manufacturers and generations. Hence, **MR-4**: Data access and parameter descriptions must be standardized and semantically unambiguous across heterogeneous equipment.

An unauthorized change of setpoint parameters can destroy both the product and the manufacturing system. Consequently, controlled Operational Technology (OT)/ Information Technology (IT) interfaces and means of authorized parameterization are required. This leads to **MR-5**: Changes to setpoint parameter setsin the downstream process must be authorized and protected against unauthorized access.

Architectural principles of the target architecture

Principle 1 (fulfills MR-3, MR-2, MR-1): Target parameters are distributed centrally and event-driven in the downstream. They are activated by the controller based on its system state.

This distinction builds on the overarching communication logic (pull vs. push). In a pull-based approach, the production equipment actively retrieves the setpoint parameters from a central instance **(Fig. 2)**, enabling state-dependent and therefore deterministic parameter adoption (see [9]). However, in body-in-white production, a pull-based approach presents significant scalability challenges: to detect changes in a timely manner, each of the N assets within a given technology must periodically retrieve its complete set of x setpoint parameter sets, regardless of whether any parameter has changed. Thus, each polling cycle generates a load of $N \cdot x$ requests per technology, resulting in a total of $Q = N \cdot k \cdot x$ requests across k technologies. For example, in spot welding, a controller can execute multiple weld spots p per cycle (e.g., $p = 5$), which might be programmed differently for different vehicle variants (e.g., $v = 20$ *variants*). The number of programs that must be maintained would be $x = v \cdot p = 100$ per asset. With $N = 1{,}000$ assets, spot welding alone would generate 10^5 requests per cycle; across multiple technologies, Q can quickly reach the millions. Because target parameters are changed relatively infrequently compared to the amount of polls during steady-state series production, this data traffic is almost entirely redundant.

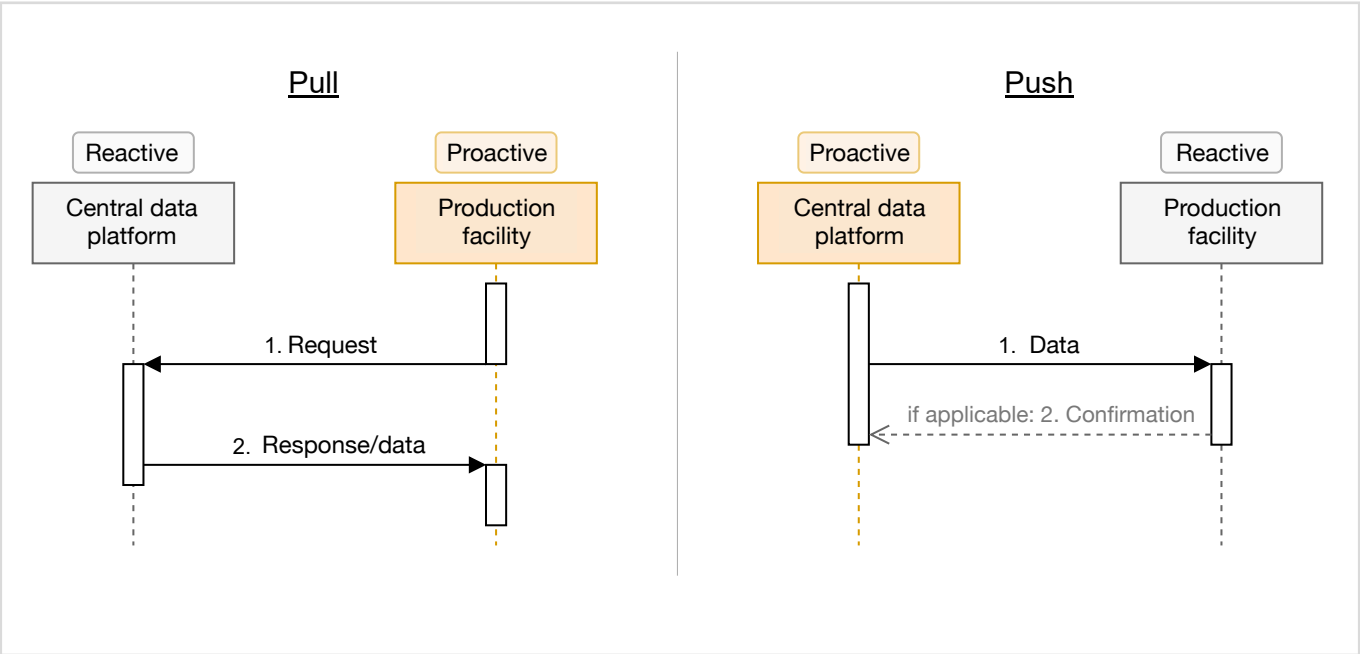


Figure 2: *Schematic comparison of pull- and push-based communication in the downstream process.*

The problem is further highlighted by the fact that requests are not uniformly distributed over time. Since many stations operate with similar cycle times, requests can become concentrated in certain time windows, requiring the central IS to be dimensioned for load peaks that provide no additional information. The pull approach therefore scales poorly with the number of production assets and fails to satisfy MR-3.

In contrast, a push-based IS distributes the target parameters as needed and only when actual changes occur. The load (on the order of $N \cdot fp$ with a change rate of fp per asset) is several orders of magnitude lower and is not cycle-correlated. To comply with MR-2, the IS must be supplemented with a buffer and a transfer mechanism within the asset. The setpoint parameter sets are pushed to the buffer and transferred to the production programs by the controller only when the relevant state conditions are met, ensuring that the ongoing production process is not affected in an uncontrolled manner. Since the most recently distributed parameter set is available locally, this also decouples the controller from the platform's availability (MR-1).

Principle 2 (meets MR-3): IIoT communication capabilities should be ensured device-natively wherever possible; dedicated hardware should be avoided.

Today, production systems are often connected to central data platforms via dedicated hardware in the form of edge or IIoT gateways [14] (Fig. 3), which convert fieldbus-based communication into standardized IIoT protocols.

Given the several hundred to thousand assets N typical in the body-in-white domain, this approach does not scale economically or operationally (MR-3). Each gateway entails acquisition costs CHW and, in most cases, an annual, device-specific management license CLic. Over n years, the total cost $C(N) = N(CHW + n \cdot CLic)$ grows linearly with N.For N = 1,000 and n = 10, the licensing costs alone quickly reach several million euros. Operationally, each gateway also introduces an additional node with its own deployment and lifecycle management effort, creating a second prerequisite for commissioning that must be fulfilled for each asset.

Modern assets, by contrast, increasingly incorporate native IIoT interfaces [15, 16], thereby becoming IIoT participants themselves. Additional procurement, licensing, and maintenance costs are largely eliminated, as connectivity and updates occur within the assets' lifecycle. A prerequisite for this approach is a standardized interface and data model (MR-4). The adoption of device-native connectivity should therefore be pursued as a long-term objective, while edge gateways should remain reserved for legacy assets without native IIoT capabilities.

Principle 3 (fulfills MR-3, MR-5, MR-1): Security and coordination functions should be consolidated in decentralized on-premises fog nodes.

A fog node refers to a decentralized computing unit within the IIoT architecture that is positioned between shop-floor-based systems and central cloud services and acts

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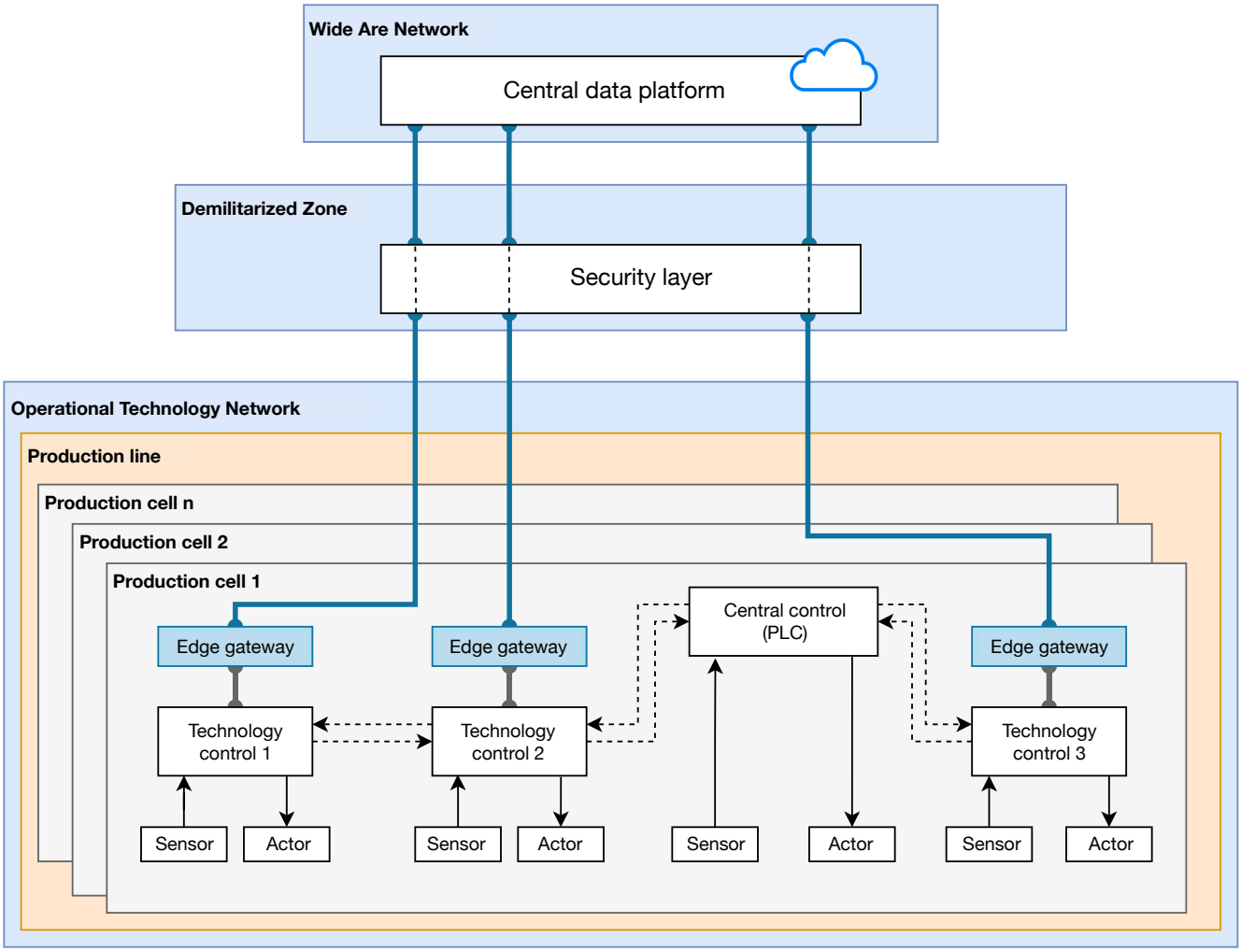


Figure 3: *Schematic illustration of the use of edge devices to connect production equipment to centralized data platforms.*

as an intermediary. In the context of automotive body-in-white manufacturing, the fog node can assume coordination and security functions for defined areas, such as production lines or sites. Figure 4 schematically illustrates how fog nodes can be integrated into an IIoT architecture. Instead of N direct shop-floor-to-cloud connections, each fog node maintains local connections with the assets, with only one outward cloud-connection per area (MR-3). For downstream communication, incoming setpoints parameter sets can be pre-validated, e.g., regarding semantic correctness and version consistency. At the same time, the fog node can act as a security enforcement point, providing a clear separation between OT networks and wide-area networks (MR-5).

Principle 4 (fulfills MR-3, MR-4): Parameter distribution is performed using a widely adopted IIoT communication standard (preferably MQTT) and is based on a standardized information model.

Two communication standards dominate the IIoT landscape: Open Platform Communications Unified Architecture (OPC UA) and MQTT. OPC UA provides structured information through an object-oriented information model implemented on the machine side [3, 9], thereby ensuring unambiguous semantic representation of setpoint parameters (MR-4). However, large parameter sets entail considerable modeling effort, while the fine-grained read/write communication of OPCUA results in a large number of individual accesses: A set of P parameters may require up to P individual accesses (contradicting MR-3).

In contrast, MQTT takes a lightweight, broker-based publish/subscribe approach using topics, thereby enabling efficient, scalable distribution to many subscribers (meets MR-3), but does not specify any message semantics. For downstream communication, the semantics of the messages must therefore be standardized outside the protocol, for example through Asset Administration Shells [17], to ensure correct machine-side processing (MR-4).

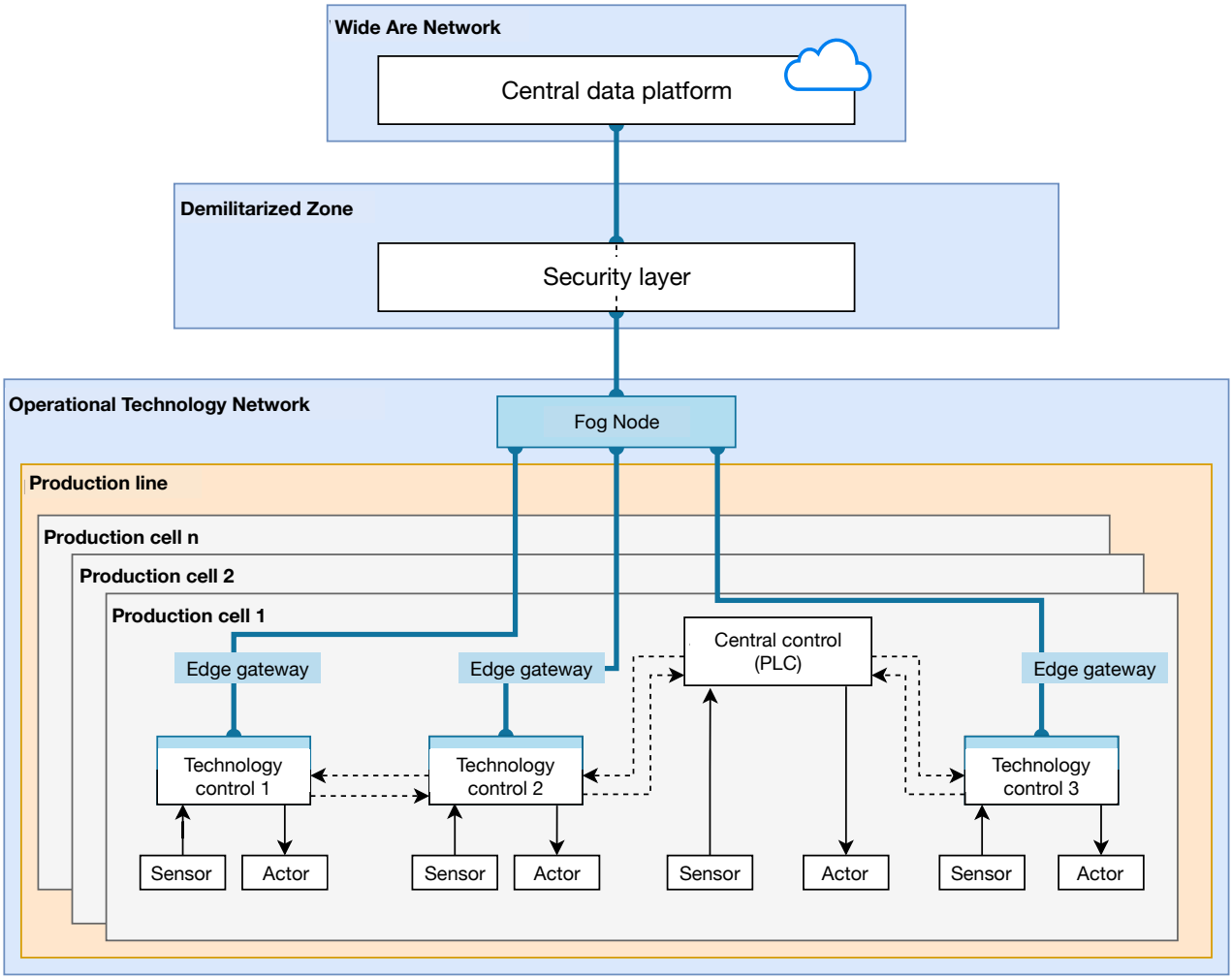


Figure 4: *Schematic illustration of the use of fog nodes to connect IIoT-enabled production assets to centralized data platforms*.

Due to its better scalability, MQTT should preferably be used in body-in-white manufacturing.

Evaluation of the principles

The evaluation of the derived principles is conducted ex ante in an artificial-formative manner, in accordance with [18]. The principles formulated above are evaluated analytically against the meta-requirements and validated using a representative scenario.

Completeness: Each of the five meta-requirements is addressed by at least one principle (MR-1: P1, P3), (MR-2: P1), (MR-3: P1–P4), (MR-4: P4), (MR-5: P3). Conversely, each principle can be traced back to at least one meta-requirement. Thus, neither an unaddressed requirement nor an unsubstantiated principle without a corresponding requirement remains.

Consistency: The principles are mutually consistent and interrelated: Push-based, event-driven distribution (P1) is compatible with device-based connectivity (P2) and asynchronous, broker-based transport (P4). Buffering the parameters on the asset (P1) resolves the apparent contradiction between the asynchronous broker and the cycle time-driven production by shifting determinism to the asset (MR-2).

Scenario walkthrough: A set of welding parameters—approved by the development team and optimized by AI—is distributed in an event-driven, broker-based manner along with a supplementary information model (P1, P4). Along the path to the asset, communication is secured and pre-validated by a fog node (P3). The welding parameter set is buffered in within the production assets (P2) until the controller activates it in a defined state outside an active production cycle. The path complies with all principles without contradiction and culminates in a deterministic, cycle-accurate implementation.

A naturalistic, summative validation through quantitative studies requires a system instantiated in the field and will

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therefore be addressed in subsequent contributions of this research series.

Implications for architecture development

This article demonstrates that the bidirectional connection of production systems in body-in-white manufacturing is not merely an integration problem but raises fundamental questions regarding architectural design. While existing IIoT approaches largely address the upstream of machine state data, significant deficits remain in the downstream of setpoint parameter setssinto cycle-bound processes in a deterministic and state-dependent manner. These deficits become increasingly relevant with the adoption of AI-based applications. To address them, four key architectural principles were derived.

Further research is should focus on developing and validating a corresponding architecture under real-world production conditions: While the fundamental feasibility of bidirectional communication is established, the central challenge lies in its process-reliable, scalable, and standardized implementation.

In this paper, the generative AI tool ChatGPT (provider: OpenAI, version: GPT-4/5, period: February–June 2026) was used for the linguistic revision of text passages. All substantive statements, assessments, and scientific arguments were formulated independently.

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Work Design in the Use of Autonomous Systems

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Demographic change is reducing the available workforce and thus exacerbating the shortage of skilled workers. Companies can offset this shortage by leveraging the potential of digitalization and artificial intelligence. Autonomous systems, in particular, can help ensure operational continuity and increase productivity. What changes are needed, and what economic potential do they hold?

Keywords
skills shortage, industrial engineering, autonomous systems, challenges, success factors, work design

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Work Design in the Use of Autonomous Systems

Addressing the shortage of skilled workers

Tim Jeske, Sascha Stowasser, Nicole Ottersböck and Sebastian Terstegen, ifaa, Düsseldorf, Rasmus Adler, Fraunhofer IESE, Kaiserslautern

Companies are increasingly challenged to address shortages of skilled workers while meeting rising demands for productivity, flexibility, and innovation. Because labor supply can only be expanded to a limited extent, there is a growing focus on designing work systems with productivity in mind. Autonomous systems offer significant potential in this regard. Their implementation requires not only technical adjustments but, above all, changes in organization, skills, and work design. This article analyzes empirically grounded change requirements in existing work systems as well as associated economic potential.

Germany's labor force is declining as a result of demographic change. This is becoming increasingly evident as the baby boomer generation begins to retire. The resulting shortage of skilled workers is felt more acutely during economic booms whilst, conversely, economic downturns provide temporary alleviation. **Figure 1** illustrates this trend.

The metal and electrical industries have been hit particularly hard by the shortage. Between July 2021 and June 2022, approximately 110,000 skilled workers were lacking nationwide in this sector, including just under 57,000 in mechatronics, energy, and electrical trades [1].

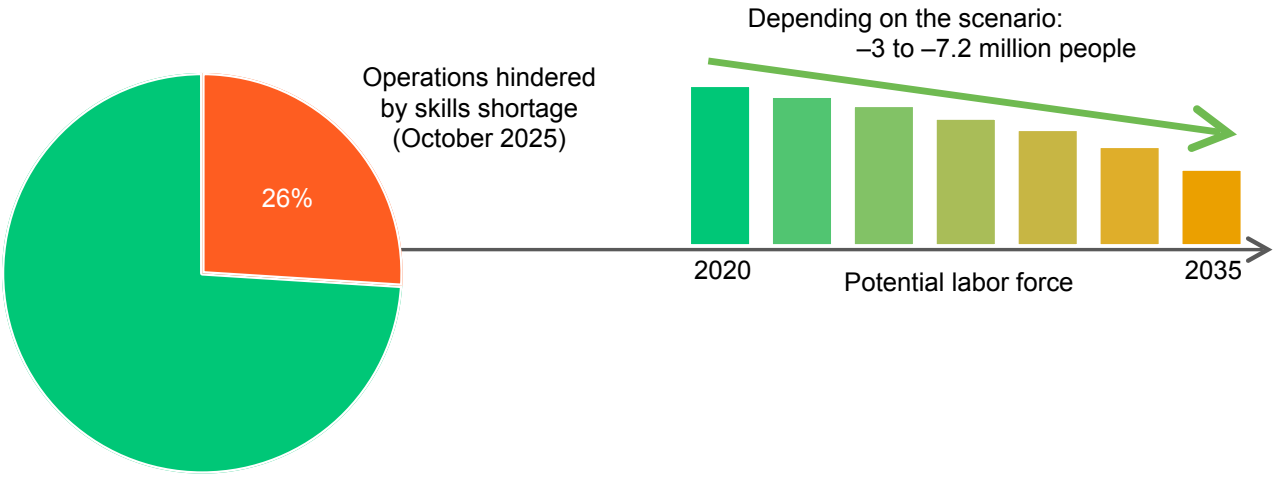
In October 2025, approximately 26% of German companies reported that their business operations were constrained by a shortage of skilled workers [2].

Framework conditions for the deployment of autonomous systems

For a long time, policy-makers and businesses focused on expanding the labor supply. This involved tapping into untapped labor capacity, extending working lives [3], recruiting foreign workers [4], and making employers more attractive [5]. Monetary and non-monetary incentives should also help increase the labor supply. However, measures to expand the labor supply are not sufficient to successfully offset the growing shortage of skilled workers and labor. This is also because they do not help increase productivity.

In addition to measures expanding supply, reducing labor demand is therefore becoming increasingly important. For example, business processes and workflows can be made more efficient using methods from industrial engineering and lean management [6]. Furthermore, digitalization and automation offer extensive opportunities for further developing processes [6]. Thanks to artificial intelligence (AI) and robotics, for instance, production

Figure 1: *Impact of the skilled labor shortage and trends in labor force potential based on the KfW-ifo skilled labor barometer (German: Fachkräftebarometer).*



can be maintained with fewer staff, counteracting the lack of experienced workers while also increasing productivity.

Furthermore, these approaches make it possible to relieve employees of repetitive or physically demanding tasks [7]. Flexible processes are key, as they enable companies not only to respond to changing market requirements but also to compensate temporary staffing shortages (such as absences due to illness). Autonomous systems can take on increasingly complex tasks, respond flexibly to disruptions [8], and collaborate with humans or other systems [9]. Examples range from driverless transport systems to collaborative robotics (cobots) and self-optimizing production systems.

Autonomous systems are complex; they are designed to act independently (without human control) and perform demanding tasks. Due to this complexity, their behavior cannot be programmed in advance for all possible situations, causing some unpredictability. Nevertheless, they are expected to function reliably and safely even with limited human supervision [10]. The design of autonomous systems requires a balanced interplay between autonomy and coordination. Other key challenges include investment costs, integration into existing production systems, employee acceptance, and compliance with safety and legal requirements [7, 11].

Applied work research addresses these challenges to promote productive work organization. The autoWert project (FKZ: 02J24B000) analyzes prerequisites for the successful deployment of autonomous systems as well as the risks involved. The focus is on technical, organizational, and personnel requirements for sustainable and profitable deployment. The project's results provide companies with practical approaches to addressing current and future challenges, thereby helping to strengthen Germany as an industrial hub.

Methodological approach

The project objectives were developed empirically, drawing on individual expertise related to the challenges posed by skilled labor shortage as well as the design and implementation of automation solutions. On this basis, key hypotheses and research approaches were derived and presented for discussion **(Fig. 2)** [12].

First, a structured approach was developed for gathering and analyzing subject expertise and semi-structured interviews were planned for data collection. To develop an interview guide, scientific studies and forecasts were researched and analyzed. This process took into account demographic and socioeconomic trends as well as economic growth rates, innovation trends, and the

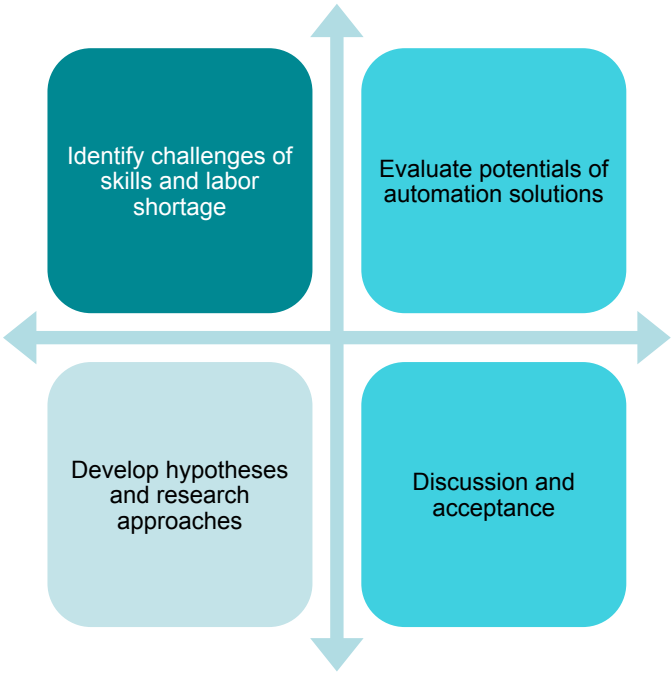


Figure 2: *Key areas for action and analysis in the autoWert project.*

characteristics of autonomous systems. The interview guide addressed key questions regarding the impacts of both the shortage of technical expertise and labor and the use of autonomous systems on organizational work systems. Experts from industrial companies, associations, research institutions, and a network of project partners were selected for the interviews. The goal was to capture a broad and diverse range of perspectives. The semi-structured interviews were primarily conducted online and transcribed.

After ten of the fifteen planned interviews, an interim evaluation of the results was conducted. The aim was to validate initial findings and identify thematic priorities for the remaining interviews in order to specifically address existing knowledge gaps. To this end, the available interviews were systematically analyzed using qualitative content analysis [13] to identify key statements, recurring patterns, and relevant correlations. The results were clustered by topic, documented, and validated in a workshop with eight engineers. The participating engineers come from various employer associations and thus work with a range of different companies. They therefore possess comprehensive knowledge of operational conditions as well as the implementation and use of digital and autonomous systems. During the workshop, the results across all thematic areas and clusters were systematically discussed to establish a shared understanding. This allowed the findings to be validated and additional perspectives to be integrated.

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Metacategory	Example skill deficits
1) Automation and integration	• Programming • Commissioning • Learning • AI/robotics integration
2) Data and AI literacy	• Data expertise • Data flows • Data management and quality • Structured implementation
3) Comprehensive understanding of the system	• Systems engineering/system-of-systems • Mechatronic, software-integrated roles
4) Governance, security and cost-effectiveness	• Safety/norms/certification • Monitoring and fault detection • Use case identification • Cost-benefit analysis (ROI)
5) People, organization und transformation	• HR and qualification • Mindset/transformation • Transfer of research results into practice • Future orientation and prediction

Figure 3: *Examples of commonly missing skills for integrating autonomous systems.*

Why autonomous systems often fail in practice

The experts generally believe that autonomous systems have the potential to alleviate labor and skilled worker shortages in industry, but they still see a need for further development. Company representatives, academic experts in robotics and AI, and association staff point out that there are significant challenges involved in integrating these systems.

In nearly all expert interviews, it became clear that a lack of know-how regarding the integration of autonomous systems is a major obstacle to deploying these systems profitably. Companies face the challenge of selecting suitable systems, integrating them into existing processes, and operating them safely. The experts' statements regarding current competency gaps in the industry were structured into five meta-categories, which are described below and summarized in **Figure 3**.

1) Automation and integration

Within companies, shortcomings in automation expertise are particularly evident at the foreman and team lead levels. While traditional manufacturing skills are present, advanced qualifications necessary for implementing automated processes and transitioning to a mechatronics- and software-oriented job profile are lacking. Employees with skills in mechanics, electronics, and software are in particularly high demand.

2) Data and AI literacy

According to experts, there is a lack of data literacy. The ability to collect and process machine-relevant data and to understand its significance for digital production must be fostered. In addition, there is often a lack of knowledge about how to ensure adequate data quality. This hinders the efficient use of AI and the further development of data-driven processes in the workplace.

3) Comprehensive understanding of the system

This meta-category addresses the need for holistic systems thinking, particularly in light of the increasing autonomy and interconnectivity of subsystems. Companies lack functions and specialists who can take a big-picture view and identify cross-system interdependencies. In addition, methods for fault diagnosis, monitoring, and training of autonomous systems are needed. The absence of these methods can lead to uncertainty and instability, especially in early stages of development.

4) Governance, security, and cost-effectiveness

There are shortcomings in assessment and decision-making capabilities, particularly in small and medium-sized enterprises. Often, there is an inability to make

informed decisions regarding software investments, training initiatives, or the deployment of technical solutions such as cobots. When deploying autonomous systems, there is a lack of expertise for independently assessing safety requirements, conducting risk assessments, and ensuring compliance with standards. This is especially true for dynamic environments involving collaborative robotics, where complex safety issues arise. To comply with safety requirements, cobots are sometimes fenced off, for example, and used for purposes other than their intended function—namely, to perform tasks on their own rather than collaboratively.

5) People, organization, and transformation

This meta-category concerns the holistic integration of autonomous systems into operations. A proactive strategy for identifying and addressing future training needs in a timely manner is currently lacking. In addition, a lack of understanding among the workforce regarding the potential of AI and robotics hinders the necessary willingness to embrace change. Finally, the rapid translation of research findings into commercially viable innovations remains a major challenge.

Recommendations for companies

To address the identified skills gaps sustainably, various measures were discussed in the expert interviews, and an competency-based approach was favored. This does not involve one-time training sessions. Rather, a learning-oriented implementation process is created based on real-world use cases and experimental environments for AI implementation within company operations.

To empower companies—and SMEs in particular—low-threshold access to proven solutions is essential. Numerous research initiatives, projects, digital centers, and AI competence centers are already addressing this need: Companies can systematically—and often free of charge—take advantage of these offerings to learn about best-practice examples from comparable or other industries (including cost-benefit metrics) and to try out AI through "hands-on" demonstrators.

Regional Competence Centers for Work Research (ReKodA) such as the WIRKsam Competence Center, which focus on the design of AI-supported work, offer interactive learning environments. These lower barriers to entry and highlight requirements for data quality, interfaces, and occupational safety based on best practices in real work environments at partner companies. In addition, their extensive networks provide access to development partners and innovative startups, who in turn can serve as an information pool.

Internal advocates—so-called AI scouts or AI enthusiasts—help promote and sustainably integrate AI within the company. In small steps, this approach can build capabilities combining technology adoption, secure implementation, and organizational change. This lays the foundation for the productive, compliant, and cost-effective deployment of autonomous systems.

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Systematically Planning Vertical Factories

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Space is becoming a scarce resource, forcing the industry to rethink its approach. Vertical factories utilize height to combine production and logistics within a small footprint. However, as the third dimension is added, the complexity of planning also increases. A morphological analysis makes the design space visible, and clearly defined factory types help identify the appropriate approach quickly.

Keywords
vertical factories, morphological analysis, factory types, factory planning, layout optimization, sustainable factory



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Systematically Planning Vertical Factories

Developing factory types as a foundation for intelligent planning support

Nikolaus Kremslehner, Sebastian Schlund and Wilfried Sihn, Fraunhofer Austria

Vertical factories reduce land use and harness the advantages of urban production. However, their multi-story structure significantly increases planning complexity. To counter such effects, this paper presents a typology that combines proven solutions for recurring challenges in the planning and operation of vertical factories. Relevant characteristics were examined using real-world case studies and structured within a morphological framework. This framework was consolidated into factory types that provide guidance for conceptual planning and serve as the foundation for intelligent planning support.

New land use and soil sealing lead to a loss of vital ecosystem functions, including groundwater recharge, carbon sequestration, and soil fertility, while also exacerbating flood risk and biodiversity loss [1]. Accordingly, the European Union aims to reduce net land take to zero by 2050 [2]. Countries such as Germany and Austria have consequently set national targets to reduce land take by 2030. However, current rates in both countries remain several times higher than the respective targets [3, 4]. As a result, available land is becoming a scarce production factor for industrial enterprises.

Vertical factories are therefore offering an attractive alternative, as they integrate production and logistics processes across multiple floors. Particularly in urban areas, this concept proved successful during the early stages of industrialization by enabling manufacturing in close proximity to both skilled workers and customers [5]. However, the advent of more affordable transportation systems and prefabricated concrete construction shifted industrial development toward peripheral locations [6]. Today, modern in-plant material handling technology makes it possible to efficiently manage vertical material flows as well.

Nevertheless, planning a vertical factory presents additional challenges compared with designing single-story buildings. On the one hand, planning methods and tools are not designed to address the complexity of multi-story factories [7]. On the other hand, planning is complicated by the lack of reference solutions and design guidelines. This article addresses these challenges by defining factory types that reflect the challenges, potential benefits, and contextual conditions of real-world vertical factories. These factory types provide guidance for human planners while also serving as the foundation for transparent and intelligent decision support. The proposed typology considers not only physical layout aspects but also the design of communication and personnel flows, thereby capturing essential prerequisites for work organization in multi-story production environments.

State-of-the-Art: Factory planning and factory types

Factory planning describes the systematic process from defining objectives to ramping up of production, both for new designs and the redesign of existing facilities [8]. This process is divided into several phases that reflect increasing levels of planning detail. During the conceptual planning phase, rough factory layouts designed, including the decision of whether to implement a vertical or a single-story factory [9].

Extensive research has been conducted on mathematical optimization approaches, including methods for multi-story layouts [10]. However, the practical application of these approaches is often limited by the specialized expertise required to formulate and solve mathematical optimization models, as well as by the lack of user-friendly software tools that can be used without programming knowledge [11]. Accordingly, expert systems that combine human expertise with quantitative methods have emerged as a promising alternative [10]. In current practice, factory planning is primarily based on material flow-oriented layout structures [12].

However, these two-dimensional structures cannot be directly applied to multi-story layouts. Model types for vertical factories have already been described from an urban planning perspective [13]. However, these models provide little guidance for the internal layout design of the buildings. [14] and [15] propose structures for multi-story assembly factories characterized by flexible openings in the ceiling structure. Nevertheless, no typology of vertical factories was identified that provides various approaches for arranging manufacturing, assembly, and logistics areas.

From characteristics to factory types

The central artifacts presented in this paper are a morphological framework which describes the design space of vertical factories, and a typology of vertical factories, which reduces the design space to a manageable set of example solutions.

No.	Characteristic	Layout Relevance	User Relevance	Mentions	Result
1	Structural reinforcement	No	No	6	Variant
2	Site densification	Yes	Yes	6	Type
3	Vertical material handling systems	No	Yes	10	Variant
4	Elevator failure mitigation	No	No	8	Variant
5	Building services	No	Yes	4	Variant
6	Floor allocation	Yes	Yes	10	Type
7	Location of storage/ logistics areas	Yes	Yes	10	Type
8	Fire protection	No	No	3	Variant
9	Personnel flow	Yes	Yes	9	Type
10	Floor plan	Yes	Yes	7	Type

Figure 1: *Feature space of vertical factories.*

Morphological approaches are well suited for structuring complex, multidimensional problem spaces, particularly when these cannot be fully quantified. A morphological analysis describes such a space through features and their discrete values. The objective is to systematically define the solution space while restricting it to plausible configurations through a consistency assessment. A central element is the cross-consistency assessment, which eliminates incompatible combinations [16]. Morphological frameworks are therefore particularly useful during the early planning phases, when design options are made transparent.

Typologies serve to classify empirical objects according to relevant characteristics and to condense them into a limited number of analytically meaningful types. The selected characteristics must correspond to the purpose of the artifact and meaningfully distinguish among the objects under investigation. At the same time, a typology should be concise, robust, and explanatory [17].

The development of the two artifacts is based on guided expert interviews covering ten vertical factories located in German-speaking countries. The interviewees were experts in production, logistics, or facility management from large and medium-sized companies producing machinery, electrical equipment, food, metal products, or pharmaceuticals.

The interviews examined both the motivation for implementing vertical factories and the resulting benefits, as well as the operational challenges and their solutions. Key topics included production, material flow, layout design, and structural requirements. The objective was to identify recurring problems across different cases and to determine which design variants had been used to solve them. Despite differences in industry sectors, company size, and planning scenarios, the data collection process reached thematic saturation with respect to the challenges encountered and the corresponding solutions.

The morphological framework was developed in a problem-oriented manner. The starting point consisted of the solutions observed in the case studies. These were then grouped according to the planning task or challenge they addressed. From this analysis, recurring tasksassociated with the design of vertical factories were derived. These tasks constitute the characteristics of the morphological framework, while the solution approaches observed in the case studies constitute its corresponding attributes.

To define factory types, the initial set of characteristics was reduced. Only characteristics that have a significant influence on both the conceptual layout and at least one of the utility dimensions of vertical factories were considered. Characteristics primarily relevant to detailed design remain part of the morphological framework as alternative design options but are not considered for type

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I: Floor allocation	a) Product characteristics	b) Machine weight	c) Process sequence	
II: Location of storage/ logistics areas	a) Ground floor	b) Top floor	c) Along the building perimeter	d) Central
III: Floor plan	a) Atrium	b) Hall	c) Comb	
IV: Site densification	a) Courtyard	b) Expansion	c) Basement expansion	d) New construction
V: Personnel flow	a) Central	b) Perimeter		

Figure 2: *Morphology of vertical factories.*

definition. A cross-consistency assessment was then conducted to eliminate invalid or impractical combinations of characteristics. This limited the morphological space to consistent and practically feasible configurations.

The factory types were derived based on the identified functional dimensions and their underlying mechanisms. For each functional dimension, the attributes that consistently contributed to achieving the respective benefit across the case studies were combined into representative configurations. A new type was defined whenever variation in one or more characteristics resulted in a significantly different objective or application context. This approach ensures that the types are clearly distinguishable from one another in terms of their functional purpose and their conditions of application

Each type is described by a representative configuration, the benefit dimension it addressed, and the appropriate contextual conditions. This resulting artifact not only structures the configuration space but also supports the selection of suitable solution approaches.

Morphological framework: Five characteristics of vertical factories

Initially, a total of ten different challenges facing vertical factories were identified from the expert interviews. **Figure 1** shows the characteristics derived from these challenges and indicates whether they were incorporated into the typology or included in the morphology solely as details for variant formation.

Thus, there are five characteristics of vertical factories that can have a significant influence on the overall layout and the intended benefits. **Figure 2** illustrates each characteristic and its 3–5 variations, resulting in 288 possible configurations. After excluding invalid or impractical combinations, 66 configurations remain and act as foundation for defining the factory types.

Factory types: Dimensions of benefit defined through expert interviews

Factory types were derived from the morphological framework based on the benefits that can be achieved through a vertical factory. To this end, the expert interviews explored both the initial motivations for implementing a vertical factory and the advantages observed during operation. Based on this, the benefits of a vertical factory can be summarized using the operating principles listed in **Figure 3**.

To classify the factory types, contextual conditions that are particularly relevant to the defining characteristics were analyzed. These include the production system (hereinafter abbreviated as PS), the production segmentation strategy (SG), the product size (PR), machine foundation requirements (MF), and the planning scenario (PL). **Figure 4** shows the resulting factory types with their benefits and associated operating principles **(Fig 3)**, configurations of the type-defining characteristics **(Fig. 4)**, and suitable framework conditions.

Rapid development of a customized layout

The developed types of vertical factories are validated using the case study of a medium-sized company that manufactures large electrical systems. The overall aim is to demonstrate the practical applicability and potential impact of the approach. Components are manufactured in a cellular production system and subsequently

Benefit	Description	Underlying Mechanisms
1) Land-use efficiency	The ratio of production output to the required land area is increased.	a) Increasing the number of stories reduces the required building footprint.
		b) A centralized storage area serving multiple stories reduces buffer space requirements on individual floors.
2) Site utilization	Continued use of the existing site is made possible.	a) The existing building can be expanded through the addition of extra stories.
		b) The existing building can be expanded through a horizontal extension.
		c) The existing building can be expanded by adding a basement level.
3) Energy efficiency	Factory operation requires less energy.	a) Transportation and/or production processes require less energy by taking advantage of gravity.
		b) Heat loss during winter and/or solar heat gain during summer are reduced because of the building's more compact envelope
4) Communication	Communication among employees is enhanced.	a) Shorter travel distances increase communication between departments.
		b) Centrally located shared areas promote communication between departments.
		c) Floor-specific competence centers promote communication within departments.
5) Material handling efficiency	The effort required for internal material handling is reduced.	a) Shorter distances between sources and destinations reduce material handling effort.
		b) Storage levels simultaneously serve as material transport routes.

Figure 3: *Dimensions of benefit of vertical factories.*

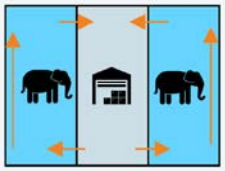
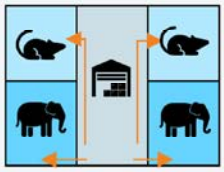
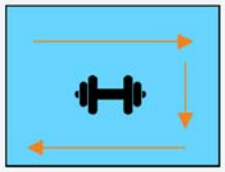
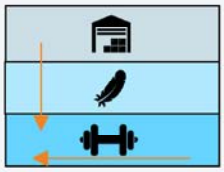
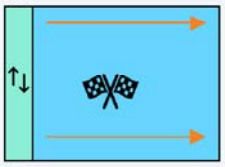
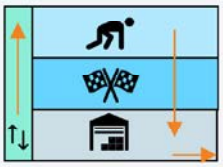
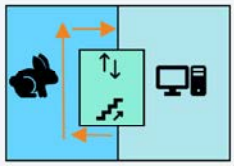
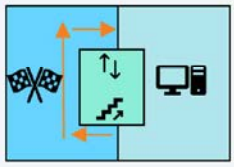
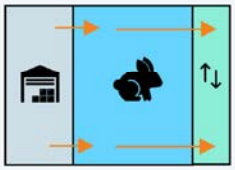
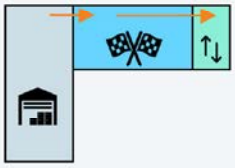
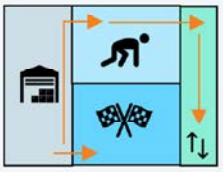
assembled into the final product at fixed assembly stations. To expand its production capacity, the company intends to add an additional story to the existing building while maintaining its current location in order to continue benefiting from access to a highly skilled workforce. It thus becomes apparent that the factory type 5.2 is fully suitable for these conditions. Consequently, this type is used as a template for a two-story factory layout, which is compared with a single-story, horizontal expansion. **Figure 5** shows the floor plans of the two expansion variants.

An evaluation of both variants reveals that the two-story layout requires 39.8% less floor space compared to the single-story layout while simultaneously reducing manual material flow effort by 7.1%. The validation demonstrates the usefulness of this approach, as it enabled the rapid development of a customized rough layout that leverages the advantages of vertical factories for this specific application.

Intelligent layout planning based on factory types

Intelligent planning support can help identify an optimal layout, particularly for use cases involving a large number of areas and complex material flows. Existing approaches such as metaheuristics or reinforcement learning can be used to generate layouts that align well with quantitative criteria but neglect qualitative factors [11]. The developed factory types capture the factors particularly relevant to vertical factories through their associated benefit

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No.	Benefit	Context	Production Floor Plan	Section	Config.
1	1)a) 1)b)	PS: Series production SG: By product PR: Small to Medium MF: No PL: Greenfield			I. a) II. d) III. b) IV. d) V. a)
2	2)a)	PS: Series production SG: By product PR: Medium to Large MF: Yes PL: Brownfield			I. b) II. b) III. b) IV. b) V. b)
3	3)a) 3)b)	PS: Flow production SG: By process PR: Small MF: No PL: Greenfield			I. c) II. a) III. b) IV. a) V. b)
4.1	4)a) 4)b)	PS: Series production SG: By product PR: Small to Medium MF: No PL: Greenfield			I. a) II. a) III. a) IV. d) V. a)
4.2	4)a) 4)b) 4)c)	PS: Cell production SG: By process PR: Small to Medium MF: No PL: Greenfield			I. c) II. a) III. a) IV. d) V. a)
5.1	5)a) 5)b)	PS: Series production SG: By product PR: Small to Medium MF: No PL: Greenfield			I. a) II. a) III. c) IV. d) V. b)
5.2	5)a) 5)b)	PS: Cell production SG: By process PR: Medium to Large MF: No PL: Brownfield			I. a) II. a) III. c) IV. d) V. b)

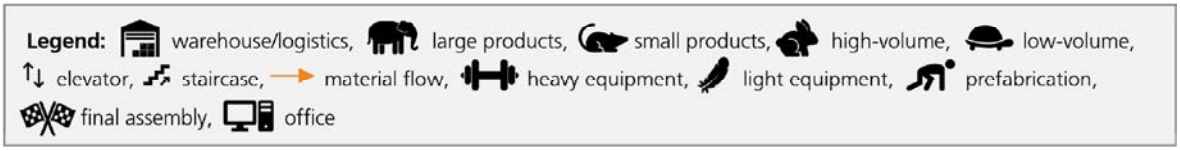


Figure 4: *Overview of vertical factory types.*

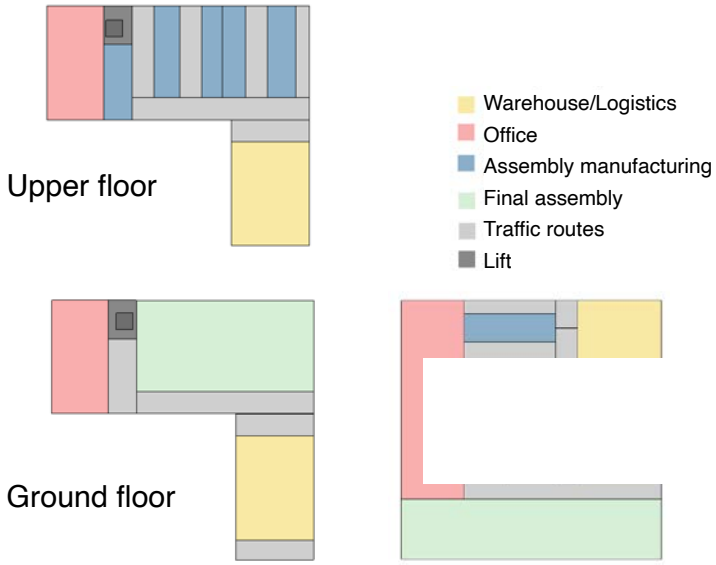


Figure 5: *Floor plans of the vertical expansion (left) and the horizontal expansion (right).*

dimensions. Therefore, the following procedure for developing an optimized factory layout is proposed:

1. The most suitable factory type is selected as described above.

2. The characteristics of the selected factory type are defined as constraints for the optimization algorithm.

3. The optimization algorithm delivers an optimal configuration with respect to quantifiable criteria such as material flow effort.

Factory types as a foundation for intelligent layout planning

This paper presents the first problem-oriented morphological framework for vertical factories and derives a corresponding typology of factory types as planning-oriented archetypes. They establish a clear link between empirically observed solution approaches and practical layout design, providing planners with a streamlined, substantively robust framework within the otherwise highly complex three-dimensional solution space.

Their particular benefit lies in intelligent layout planning. Since the factory types already explicitly capture the qualitative factors relevant to vertical factories, they can be used as constraints for optimization procedures. This allows both qualitative aspects and quantitative metrics to be considered simultaneously, while the reduced solution space enables faster convergence.

Furthermore, digital assistance systems can simplify the application of factory types. The morphological framework and the derived factory types have already been implemented in the “Morpheus” tool [18]. Building on this, a promising direction for future research is the development of an AI-assisted digital configurator capable of selecting appropriate factory types and adapting them to contextual requirements described in natural language.

Further case studies could reveal additional variations. This also highlights a key strength of the proposed approach: the morphological framework can readily be expanded to include additional features, variants, or contextual references.

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In the age of Industry 4.0, resource efficiency is becoming a critical competitive factor. Rising energy and material costs, geopolitical uncertainties, stricter regulatory requirements, and the transition to a circular economy call for new approaches to use resources more intelligently and make industrial value creation more sustainable. Digital technologies lay the foundation for this by enabling transparency regarding energy, material, and data flows and by unlocking optimization potential throughout the entire product life cycle.

Key enablers include artificial intelligence, digital twins, Industrial IoT, data spaces, and simulation-based optimization. They help companies reduce consumption, make production processes more efficient, lower emissions, and keep resources in the value chain longer in line with the principles of a circular economy. At the same time, new data-driven business models are emerging that combine environmental and economic goals and strengthen the resilience of industrial systems.

This issue of Industry 4.0 Science (www.industry-science.com) is dedicated to the technological, organizational, and economic foundations of Resource Efficiency 4.0. The focus is on scientific and practice-oriented articles that demonstrate how digitalization and intelligent production systems pave the way for a resource-efficient, competitive, and sustainable industry.

Industry 4.0 Science, Issue 1/2027
Publication **February 11, 2027**

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MTM Analyses with AI and Rule-Based Algorithms

OPEN ACCESS

MTM methods are a proven standard for the precise analysis of manual work processes. However, applying MTM involves significant methodological effort. A hybrid approach—in which LLMs are used to extract relevant information, which is then further processed by a rule-based algorithm—significantly simplifies the application. This allows workflows to be supplemented, validated, and translated into MTM-UAS® analyses in compliance with regulations.

Keywords
hybrid AI approach, large language models, MTM-UAS®, MTMmotion®, work instructions, process analysis



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MTM Analyses with AI and Rule-Based Algorithms

An approach to interpreting textual process descriptions

Constantin Eckart, Martin Benter and Peter Kuhlang, MTM ASSOCIATION e. V.

MTM methods are a proven standard for analyzing and designing human work processes. However, work planners continue to face challenges in applying these methods correctly and efficiently. Artificial intelligence — particularly in the case of large language models — holds significant potential for combatting these challenges. However, the use of AI raises legitimate questions regarding the reliability and traceability of the results. The approach presented here combines LLMs with a rule-based algorithm to extract the information required for MTM analyses from textual process descriptions such as work instructions. This information is then translated into MTM analyses in accordance with the MTM methodology. This approach ensures that the resulting analyses can be transparently traced back to the original input data by the user.

MTM process language and artificial intelligence

The MTM process language (Methods-Time Measurement) is a proven and internationally established standard for the analysis and design of human work processes. Particularly in times of increasing global competition and digitalization, it serves as a key tool for industrial companies to systematically plan, evaluate, and optimize their processes [1].

Recent developments in the digital design of human work, such as human simulation (HS) [2], virtual reality (VR) [3, 4], and motion capture (MoCap) [5], have helped partially automate the creation of MTM analyses. However, these technologies are often technically complex and costly, resulting in a lack of widespread adoption, especially by smaller companies.

This is why there is growing interest in technologies that are simple and intuitive to use. Chief among these are large language models (LLMs), a branch of artificial intelligence (AI). These models can capture semantic relationships and contextual dependencies in natural-language texts, thereby unlocking new potential for interpreting and analyzing text-based process descriptions [6]. In industrial settings, LLMs are already used to evaluate technical documents, interpret process descriptions, and support planning and decision-making processes [7]. In human work design, they make it possible to translate textual process descriptions into MTM analyses.

At the same time, the use of AI raises questions surrounding reliability and traceability. Since AI systems often engage in complex and opaque decision-making processes, it can be difficult for users to know how results are derived [8]. This also makes quality, including compliance with formal requirements such as the MTM methodology, difficult to assess.

To address these challenges, this article presents a hybrid approach that combines LLMs with a deterministic, rule-based algorithm. The goal is to extract MTM-relevant information from textual process descriptions (e.g., work instructions) and to translate it into rule-compliant MTM analyses. This procedure ensures that the results are traceably derived from the input data and that compliance with the MTM methodology is guaranteed.

The focus of this article is on presenting the methodological approach. An empirical evaluation as well as tests and comparisons with reference analyses are currently carried out and are the subject of further work.

Work process analysis with MTM-UAS®

Various MTM process building block systems exist. Each has its own syntax and semantics to standardize description of work processes [1, 9].

MTM-UAS® is the most widely used MTM process building block system in industrial practice and is characterized by a comparatively low analysis effort while maintaining a high level of detail. The process building blocks used in MTM-UAS are referred to as “basic operations”. They describe the components of human work, each of which has specific influencing factors. Depending on the nature of these influencing factors, each basic operation is assigned a basic time, more precisely, a manual time.

One example is the basic operation “handle tool,” which models the use of a tool (e.g., a cordless screwdriver). Relevant influencing factors here are the case of placing, which describes the control effort required when applying the tool, and the distance range, which represents the movement lengths during handling. The basic operations, their corresponding influencing factors, and the resulting basic times are shown on the MTM-UAS data card [10].

To analyze a workflow, the sequence is broken down into individual process steps, which are then modeled using the appropriate MTM process building blocks. This results in a complete description from which the basic time for the workflow can be determined [1]. The detailed representation also makes it possible to identify optimization potential and to carry out targeted improvements and actual/target comparisons.

Connecting MTM and digital technologies with MTMmotion®

The systematic description of work processes via the MTM process language provides a suitable basis for connecting with digital technologies, for the planning and design of human work. Relevant technologies include HS, VR, and MoCap, which digitally capture or generate motion data [3–5].

To facilitate the coupling between these technologies and the MTM process language, the MTMmotion service (MTMmotion®) was developed [11]. Its aim is to connect these two areas while ensuring the correct application of the MTM methodology. To this end, MTMmotion® provides a defined interface through which motion data, object data, body movements, and body postures are transmitted. Another key component of MTMmotion® is a deterministic translation algorithm. It checks the transmitted data for content consistency and supplements missing information as needed using stored default values. The validated data are then converted, on a rule-based basis, into the corresponding MTM process building blocks, resulting in a traceable and rule-compliant MTM analysis [12].

Thanks to its modular architecture, MTMmotion® can be connected to a wide variety of digital tools while ensuring the correct application of the MTM process language [3–5].

Previous AI developments in the MTM context

Alongside digital technologies for capturing and processing human motions (HS, VR, MoCap), LLMs are increasingly coming into focus. These are based on the transformer architecture, which enables the semantic processing of natural language texts as well as the modeling of contextual dependencies [6]. LLMs are used, among other things, to derive structured information from unstructured text input, which is particularly relevant for knowledge-intensive industrial tasks such as planning, document analysis, and process interpretation [7, 13].

A first systematic contribution to the application of LLMs in the MTM context is provided by Ceylan et al., who investigate the extent to which MTM-UAS® analyses can be generated from textual work descriptions. The results show that, for scenarios that are described in detail and completely and with explicitly provided MTM rule knowledge, a high level of alignment with manually created MTM analyses is archived. At the same time, however, deficits arise with implicit work steps and nuanced rule applications [14].

This reveals a central weakness of LLM-based approaches: When information is incomplete or contexts unclear, not only does the quality of the results decline, but it often also remains unclear which assumptions the models make and which domain rules were actually applied. Particularly for rule-based methods such as MTM, it is therefore impossible to determine whether a result stems from a rule-compliant derivation or from statistical inference. This problem of a lack of transparency and explainability is further exacerbated by so-called automation bias, as users tend to increasingly adopt AI-generated results without verification [8, 15].

Combined translation of texts into MTM-UAS®

To leverage the interpretive capability of LLMs for natural-language texts while ensuring the rule-compliant application of the MTM process language, a hybrid approach was developed. It combines AI-based text interpretation with deterministic, rule-based algorithms and integrates MTMmotion® as the translation engine. The goal is to translate textually described into MTM-UAS® analyses in a traceable and rule-compliant manner.

Figure 1 illustrates this process: First, the input text (such as a work description) is converted into structured data using an LLM. The structured information is then compared with a process database and adapted using a combination of AI and rule-based algorithms to generate a complete, valid process description. The resulting process description is translated via MTMmotion® into a rule compliant MTM-UAS® analysis . The following section provides an example of this process.

Input: text (work description)

The developed method is designed to automatically process various forms of text-based work descriptions. Informal process descriptions can be used in addition to formal work instructions. The method is fundamentally flexible and adaptable, allowing for the use of any text sources that contain relevant information about work processes. The example used is a short textual description of a typical

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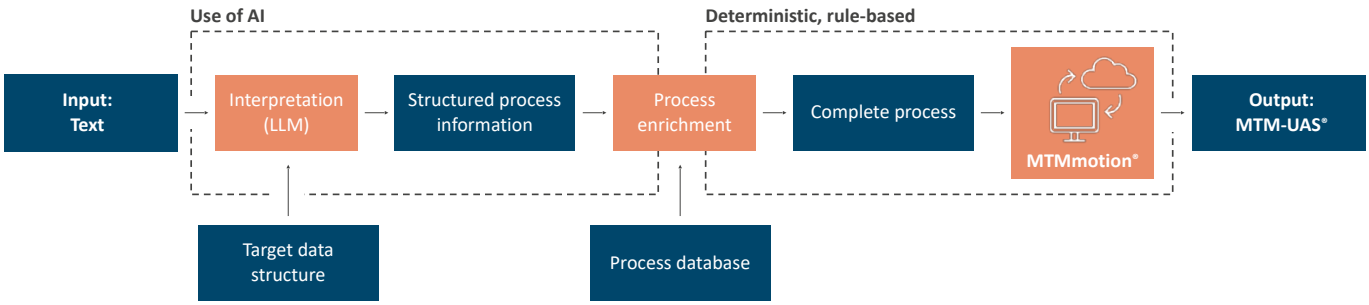


Figure 1: *Combined translation of texts into MTM-UAS®.*

manual work process, as frequently found in industrial practice:

"Walk 3 meters. Take a box (5 kg) from the shelf. Walk 4 meters and place the box on the workbench. Then take one wing screw from the box with each hand and insert each screw into a hole."

Interpretation (LLM)

In the first processing step, the input text is analyzed by an LLM, namely the GPT-5.2 Chat language model, which is used for the semantic interpretation of natural-language process descriptions. The goal is to identify and extract relevant information for an MTM analysis, such as the objects handled and the actions performed, as well as their sequence and contextual information.

The interpretation is guided by specially developed prompts and a predefined target data structure (**Fig. 2**, table header), which maps the information required for an MTM analysis. The selection of the LLM and the prompt strategy was carried out exploratively, with a focus on high-quality results. A systematic evaluation of various models in terms of precision, stability, or computational effort is not the subject of this article. The prompts, data structures, and knowledge bases used are part of the system implementation and are not disclosed in full detail here.

Structured process information

The result of the LLM-based interpretation is a structured process description that consolidates the key information extracted from the text. **Figure 2** depicts the result of this step for our example. It demonstrates the LLM's ability to identify relevant objects and actions from the source text and assign additional attributes such as quantity, side, or frequency. The structure generated provides a suitable basis for subsequent processing.

Process enrichment

In the next step, the structured description is converted into a complete and valid process. To do this, objects and actions are matched against a domain-specific object and action catalog—the process database—and translated into a formally consistent sequence of sub-steps. The underlying knowledge base is derived from object and action catalogs for industrial assembly processes, which are continuously maintained and expanded.

Object & action recognition: The names of recognized objects and actions are matched against the process

Figure 2: *Structured process information identified by the LLM.*

No.	Object	Count	Action	Page	Frequency	Additional information
1	-	-	walk	-	1	3 m
2	box	1	take	right	1	5 kg
3	-	-	walk	-	1	4 m
4	box	1	place	right	1	-
5	wing screw	2	take	left/right	1	-
6	wing screw	2	insert	left/right	1	-

No.	Object	Object type	Action	Page	MTMmotion®
1	-	-	walk	-	walk
2	box	carton	take	right	obtain object
3	-	-	walk	-	walk
4	box	carton	place	right	put object down
5	wing screw	metric screw	take	left	obtain object
	wing screw	metric screw	take	right	obtain object
6	wing screw	metric screw	bring	left	move object to point of use
	wing screw	metric screw	bring	right	move object to point of use
7	wing screw	metric screw	Insert	left	use object (insert)
	wing screw	metric screw	Insert	right	use object (insert)

Figure 3: *Completed process description.*

database comprising object and action types relevant to industrial assembly. The comparison is initially performed via string-based data matching, using similarity measures. If a suitable type cannot be identified in this way, supplementary semantic data matching is performed using LLM-based embeddings. This allows object and action descriptions to be unambiguously mapped even in cases of linguistic variation or vague formulation.

Process completion: Finally, the process is checked for completeness. If any sub-steps required for a rule-compliant mapping are missing, they are added. For example, if a cordless screwdriver is mentioned only in connection with the screwing operation itself, the steps “obtain the cordless screwdriver,” “move the cordless screwdriver to the point of use,” and “put down the cordless screwdriver” are automatically added. This results in a valid sequence that can be meaningfully converted into an MTM analysis using MTMmotion®.

Complete process

The process identified by the LLM **(Fig. 2)** has been refined into a more detailed process **(Fig. 3)**. Thus, concrete object types are assigned to the objects identified in the text, for example the classification of the "wing screw" as a "metric screw." In addition, the movements necessary for a complete description are added. For example, the steps "object to point of use" are inserted between picking up and screwing in the wing screw.

Translation into a valid MTM analysis using MTMmotion®

The complete process is then transferred to MTMmotion® in JSON format, where the rule-based translation of the interface data into a valid MTM analysis takes place. MTMmotion® supports various MTM process building block systems. This article describes the translation into MTM-UAS®.

MTMmotion® reads the transmitted process information and uses it to generate corresponding MTM-UAS® process building blocks. If information is missing from the file—e.g., distance traveled or an object’s dimensions or weight—the service falls back on transparent default values stored in the MTMmotion® object catalog [4, 8].

Output: MTM-UAS® analysis

The result of this hybrid approach is a rule-compliant MTM-UAS® analysis derived entirely from text-based input data **(Fig. 4)**.

In this example, a weight of 5 kg was specified for the box, but no dimensions were provided. Therefore, the standard dimensions of 600 × 400 × 400 mm stored in the object catalog were used, classifying the box as a bulky object in accordance with the MTM rule set. Since walking occurs both before picking up and after setting down the box, the residual distance rule means that distance range 1—and thus the MTM process building block AL1—is applied. The walking movements are accounted for as KA using distances of three and four meters respectively, as specified in the text. No information on movement length is available for the screws. In this case, MTMmotion® applies a standardized movement length of 40 cm (distance range 2). Weight and dimensions are also taken from the object catalog. For simultaneous actions involving two screws, an additional basic interaction operation for the second screw with distance range 1 is added in accordance with MTM-UAS® rule set. Based on all of this, the example results in a rule-compliant MTM-UAS® analysis with a total basic time (tb total) of 340 TMU (approx. 12.2 seconds).

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No.	Description	Code	t_b [TMU]	Q * F	T_{btotal} [TMU]
1	walk	KA	25	3 * 1.0	75
2	place object, box	AL1	80	1 * 1.0	80
3	walk	KA	25	4 * 1.0	100
4	insert, wing screw	AE2	55	1 * 1.0	55
5	interaction for insertion/mounting, wing screw	AE1	80	1 * 1.0	30
				Total basic time:	**340**

Figure 4: *Derived MTM-UAS® analysis.*

Evaluation of the method and further development activities

With the developed combined approach, an initial trial demonstrated that textual descriptions of work processes can be translated into rule-compliant MTM analyses that correspond to the described work process. This makes clear that the automated translation of process descriptions can be implemented in a rule-compliant and traceable manner, allowing industrial companies to efficiently analyze and optimize existing workflows.

However, the development and testing phases have also revealed numerous challenges and open questions. In particular, the LLM's interpretation of the input text can lead to fluctuating output quality, which may result in varying process interpretations. In addition, not all relevant process data is always recognized, which can affect the reliability of the MTM analysis. Moreover, the process database with the catalog of objects and actions must be developed further.

In the future, the focus will be on extensive testing and comparison with manual MTM analyses to ensure quality and practical applicability. Furthermore, a systematic comparison with existing LLM-based approaches, like that of Ceylan et al., is useful for identifying differences in traceability, regulatory compliance, and result stability. It is also necessary to investigate at which points targeted human review of intermediate and final results is advisable to further enhance the traceability and correctness of the analyses.

From the perspective of the MTM ASSOCIATION e. V., the developed approach is to be understood as support for all those who wish to use a correct MTM analysis. The result is always an MTM simulation analysis that should be subjected to a final review and approval by qualified MTM practitioners to be converted into an MTM planning analysis.

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Derivation of MTM Analyses from Motion Capture Data

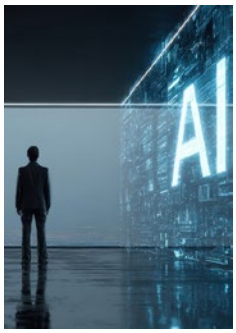
Evaluation of the procedure and comparison with a manual MTM analysis

Silas Pöttker, Maria Neumann, Martin Benter, Constantin Eckart, Ulrike Wolf, Peter Kuhlang and Hermann Lödding

Digitalization is commonly believed to have significantly increased labor productivity. However, between 2007 and 2023, labor productivity rose by less than one percent per year. Making productivity analyses, such as MTM analyses, less complex and reliant on expert knowledge, could harbor great potential.

In: I4S 5/2025, *Artificial Intelligence and Digital Assistance*, pp. 108–115

DOI: 10.30844/I4SE.25.5.108



Frameworks for the Structural Integration of Artificial Intelligence

Comparing organizational approaches

Sascha Stowasser

Artificial intelligence is finding its way into all areas of business. However, one key question remains unanswered: Who actually controls the use of AI? Too often, roles remain unclear and structures diffuse. This article uses four specific models to show how companies can embed AI into their organization. Without thorough coordination, AI remains fragmented; with the right structure, it can be integrated into everyday business life.

In: I4S 5/2025, *Artificial Intelligence and Digital Assistance*, pp. 138–144

DOI: 10.30844/I4SE.25.5.138



Large Language Models in Production

An analysis of the potential for transforming production processes in modern factories

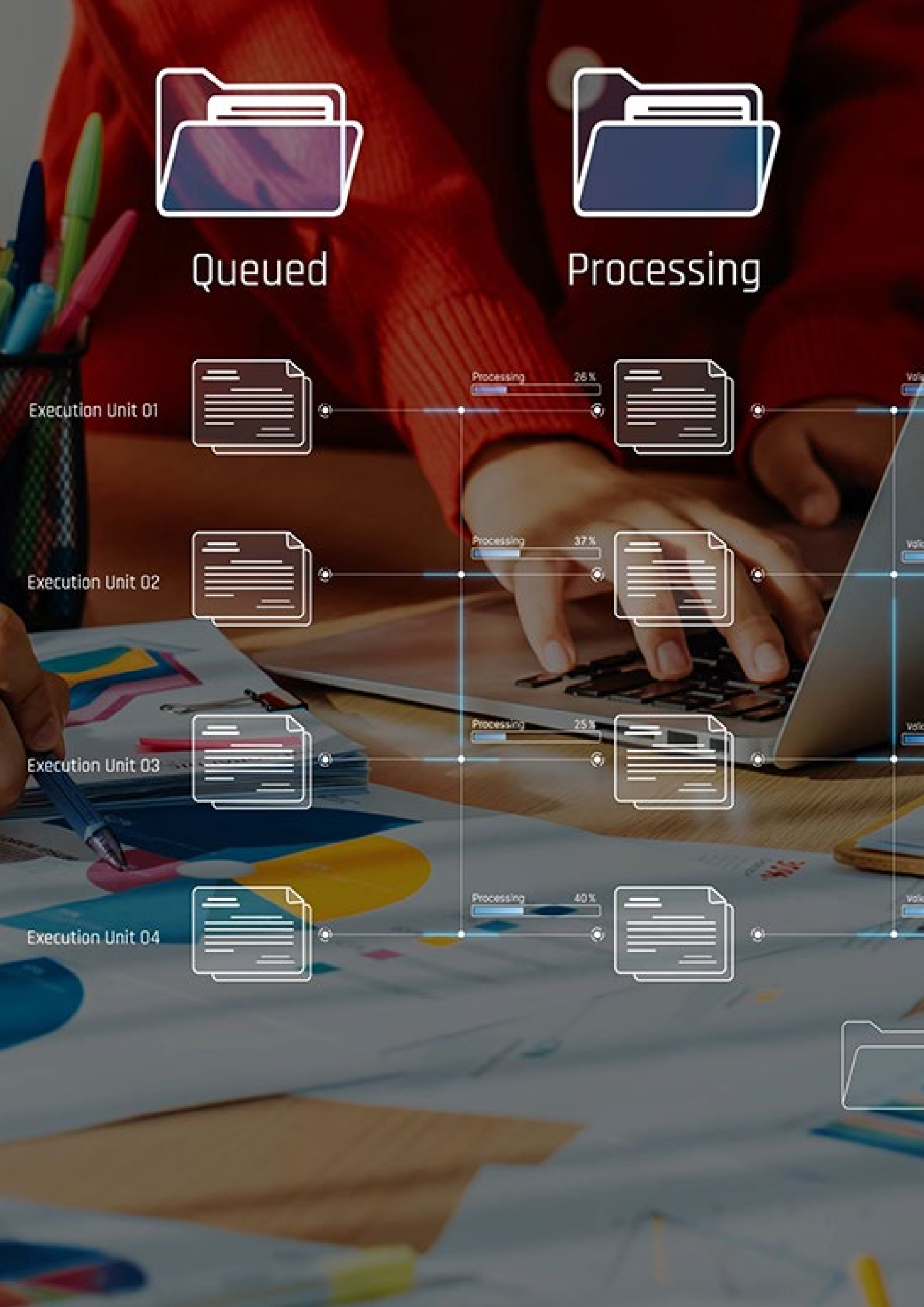
Pius Finkel, Peter Wurster and Robin Radler

The rapid development of generative AI is opening up new avenues for the manufacturing industry amid a shortage of skilled workers. Large language models can potentially make production processes in medium-sized businesses more efficient. But how exactly is this potential measured? Key areas of application such as communication, training and knowledge management show why a lot depends on employee acceptance.

In: I4S 6/2024, *Machine Learning*, pp. 48–55

DOI: 10.30844/I4SE.24.6.48

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Queued
Processing
Execution Unit 01
Execution Unit 02
Execution Unit 03
Execution Unit 04
Processing 26%
Processing 37%
Processing 25%
Processing 40%



Inclusive Work System Design

OPEN ACCESS

Against the backdrop of demographic imperatives, the imperative of equal opportunity and accessibility—for example, for people with disabilities—and by leveraging the technical capabilities of AI-based automation, current basic assumptions and paradigms of work design must be reexamined with a view toward designing an inclusive work system.

Keywords
inclusive design, adaptive work systems, accessibility, artificial intelligence, automation, standardization, adaptability



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Inclusive Work System Design

Automation, standardization, and adaptability

Sebastian Schlund, TU Wien, Fraunhofer Austria

The design of inclusive work systems is gaining importance due to demographic change and the increasing digital penetration of value creation processes. While traditional ergonomic approaches are based primarily on percentile logic and thus address only a portion of the user population, the integration of digital technologies opens up new possibilities for the dynamic and individualized adaptation of work systems. This article presents a conceptual framework for inclusive work system design that integrates standardization, automation, and adaptability. Methodologically, the article is based on a conceptual analysis of existing approaches from ergonomics and human-centered design. The article makes a theoretical contribution to the systematization of inclusive work system design and identifies areas of focus for further research and industrial practice.

A central goal of work system design is to consistently take into account future users and their individual characteristics, abilities, and needs. This is essential for developing human-centered and high-performance work systems that contribute not only to increased productivity and quality but also to well-being and user acceptance [1]. Nevertheless, current work design practice is constrained by a fundamental paradigm: work systems are not tailored to the individual requirements of specific people but are designed around aggregated user groups.

This approach is evident in so-called "percentile logic," which seeks to cover the largest possible proportion of potential users by taking into account statistical distributions of human characteristics [2]. As a result, however, individuals whose characteristics fall outside defined percentile ranges are systematically overlooked. Inclusive design concepts challenge this paradigm by orienting the design of technical systems so that, in principle, they can be used by all people [3].

The aim of this article is therefore to present a conceptual framework for inclusive work system design. This framework should react to current challenges and encompass the essential strategies for inclusive work system design. The short-term goal is to stimulate discussion within the industrial and organizational engineering community, while the medium-term goal is to specify design patterns, examples, and evaluations of inclusive work systems.

This article is structured as a conceptual paper based on the current state of research and implementation in ergonomics, human-centered design, adaptive systems, and industrial production. The author's experiences in analyzing existing work systems form the basis for the discussion.

Dynamic adaptation through artificial intelligence is already possible

The term "inclusive design" was originally coined in the context of design and later applied to ergonomics [3]. Inclusive work system design aims to systematically integrate the full range of human variability into the design process. Products, systems, and work environments designed in this way should be accessible to as broad a user group as possible without additional adaptation.

In practice, this means explicitly taking into account various dimensions of human diversity – such as age, gender, cultural background, and physical or cognitive limitations. Related concepts include Design for All [4], Human-Centered Design [5], and Universal Design [6]. Although they differ in their focus, these concepts all share the goal of comprehensively addressing human differences, ensuring that no potential user group is excluded.

The term has been in use in the fields of industrial and organizational engineering since 1995 [7]. Although its conceptual roots lie in a different disciplinary domain, inclusive design aligns with industrial engineering's traditional core principle: adapting work systems to people.

The goal of inclusive work system design is to design and implement work systems in such a way that they can be used productively by everyone. For a long time, this could only be achieved by adapting workplaces to specific groups of people with reduced ability. For example, "Silver Lines"—workstations separated from the production cycle for employees with altered abilities—were implemented under the banner of "age-appropriate" work design. The goal was to separate productive, cycle-based work systems from non-cycle-based pre-assembly tasks. Today, this approach holds negative connotations: Exclusion from the production cycle often meant exclusion from the larger organization and an implicit devaluation of the work itself. The concept of age-appropriate work design has also evolved from a focus on the differences between older and younger employees to a consideration of the increasing

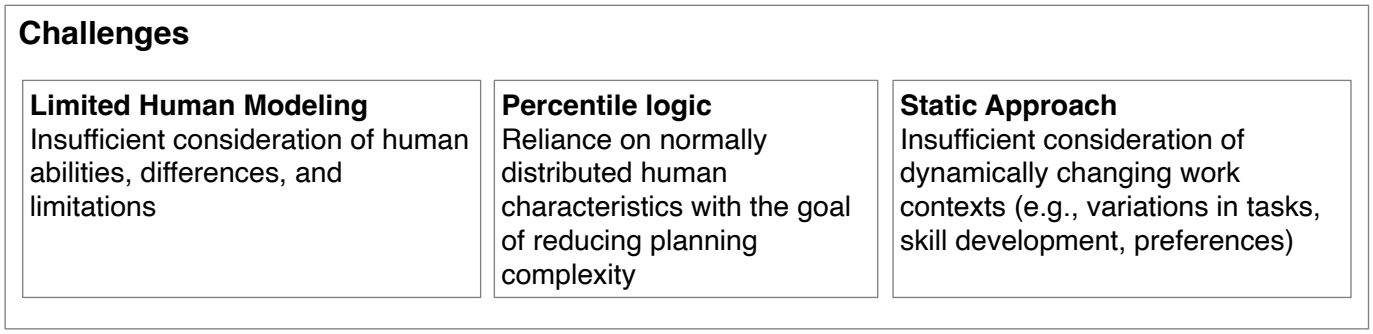


Figure 1: *Current challenges in inclusive work system design.*

variance in abilities that comes with age. Today, the more popular term is aging-adaptive work design.

New, increasingly cost-effective sensor and actuator technologies now make it possible to dynamically adapt work systems using artificial intelligence. This allows the variability of human ability to be continuously taken into account within a practical context. Such developments not only mitigate performance deficits, for example through the individual adjustment of grip ranges and ability enhancers. The accompanying digitalization also enables optimizations in production control.

Current challenges and prospects

Despite the growing importance of human-centered approaches, significant challenges remain when implementing inclusive work system design **(Fig. 1)**. A central problem lies in the highly simplified modeling of humans in technical systems. In much current research, the variability of human abilities, differences, and limitations is not adequately taken into account.

In production engineering, an increasing number of studies have appeared in recent years that use terms such as "human-centric" [8] or "symbiotic" [9]. These approaches often focus either on the automation of so-called DDD tasks (dirty, dull, dangerous) or on supporting human work through sensory, digital, or physical systems.

However, the evaluation of such approaches is usually limited to productivity metrics and simple indicators of user workload (e.g., NASA-TLX or SUS). A nuanced modeling of human diversity generally does not take place and differences between potential user groups are rarely taken into account systematically.

Since its inception, ergonomics has applied human parameters to the design of work systems. Over time, the percentile approach has established itself as the dominant method. This method aims to cover as wide a range as possible of normally distributed human characteristics, for example in anthropometry.

Though widespread, this approach, by definition, excludes individuals outside the selected percentile ranges. Although variance is acknowledged, it is rarely accounted for in practice due to largely static implementations. A clear example is height-adjustable work tables. Although they allow for individual adaptation, they are often not used in practice because they require active adjustment.

Another problem lies in the predominantly static view on work systems. In reality, work contexts are dynamic: tasks vary, requirements change, and human ability is subject to continuous development in line with the stress-strain model. These changes can be both negative (e.g., overload) and positive (e.g., training effects).

Framework for inclusive work system design

The following section presents fundamental strategies for designing inclusive work systems. Three central design dimensions come together to form a framework for action: standardization, automation, and adaptability.

Standardization

An established approach to promoting inclusion is the development and application of standards, particularly with regard to accessibility. EU Directive 2019/882 (the European Accessibility Act) and its national implementations dictate accessible design for a range of products and services [10].

One key example is the Web content accessibility guidelines (WCAG) [11], which are based on the principles of recognizability, operability, intelligibility, and robustness. These guidelines provide empirically grounded design recommendations and contribute to

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the standardization of information provision. Standardization thus creates an important foundation for inclusion by defining minimum requirements and systematically improving accessibility.

Automation

A second key approach is the automation of work tasks. In addition to productivity and quality benefits, automation can help make tasks accessible to broader user groups.

A distinction must be made between substitution and augmentation: While traditional automation replaces human labor, modern technologies increasingly serve to expand human capabilities. Examples include active assistance systems and exoskeletons.

At the same time, potential negative effects such as a loss of skills, monotony, or reduced learning opportunities do arise. Inclusive design must therefore draw a deliberate balance between technological support and the preservation of human agency.

Adaptability

The third central dimension is adaptability, which describes the ability of work systems to dynamically adapt to individual users, work tasks, and conditions. Unlike static adjustment, adaptability allows for the continuous consideration of individual differences. This includes, in particular:

- Adapting to different physical and cognitive abilities
- Accounting for experience and skill development
- Responding to changing tasks and conditions

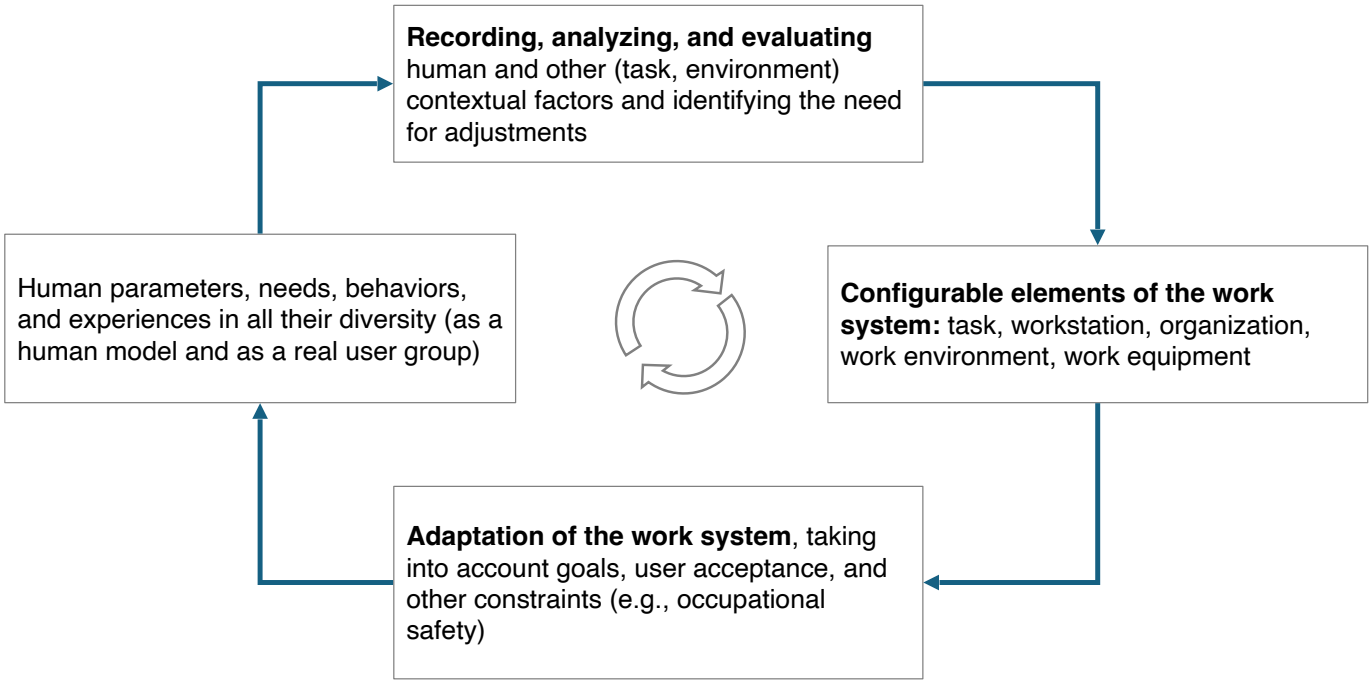
In a technical sense, adaptability relies on the integration of sensor technology, data analysis, and adaptive control mechanisms. Both the perception of the context and the processing of time series, images, and text, as well as the adaptation itself, are handled by machine learning algorithms. It is only through developments in the field of artificial intelligence that high-resolution tracking of human poses and movements [12] and accurate assessments of cognitive load are possible [13]. Equally, artificial intelligence allows for better analysis of adaptations and thus continuous dynamic adaptation during operation **(Fig. 2)**.

The overarching goal is to design work systems that can flexibly adapt to different usage situations without active user intervention. Only via the interplay of standardization, automation, and adaptability does a coherent design framework for inclusive work systems emerge **(Fig. 3)**.

The effects of individual and dynamic adaptations remain largely unexplored

This article serves as a catalyst for the further development of inclusive work system design. It focuses on the systematic integration of standardization,

Figure 2: *Adaptability as a central principle.*



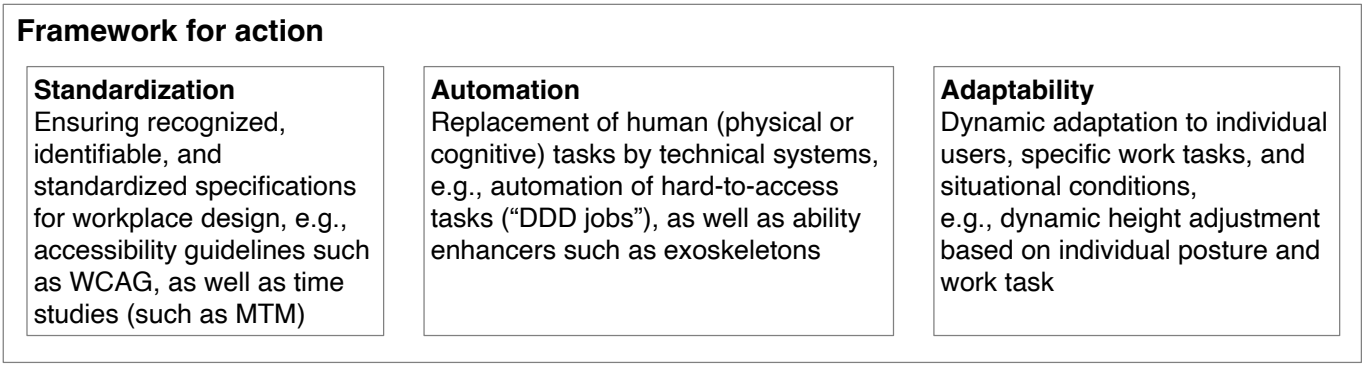


Figure 3: *Framework for the design of inclusive work systems.*

automation, and adaptability as complementary design dimensions.

For the first time, thanks to artificial intelligence, it is possible to adapt work systems individually and dynamically rather than relying on systems designed with average user groups in mind. This can significantly improve accessibility for people with varying abilities.

At the same time, however, the complexity and potential cost of design are increasing. The effects on productivity have not yet been conclusively clarified. The potential benefits of better utilizing individual abilities could be offset by the effects of increased performance variability.

Since existing implementations are limited and the evaluation of adaptive systems presents methodological challenges, there remains a significant need for further research. However, against the backdrop of demographic change, there is growing pressure to make industrial work systems accessible to new user groups. It is important, therefore, for future research to systematically analyze and empirically evaluate the potential and risks of inclusive work system design.

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AI-Based Building Inspection for Large Structures

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How can construction status on large-scale sites—such as in shipbuilding—be assessed more quickly and objectively? A sensor-based AI approach allows multiple inspection criteria to be recorded and analyzed simultaneously. Combined with an automated comparison of planned versus actual schedules, this enables objective and efficient monitoring of construction progress. The resources saved can then be specifically allocated to developing corrective measures.

Keywords
artificial neural networks, construction progress monitoring, quality assurance, industrial AI, shipbuilding

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AI-Based Building Inspection for Large Structures

A new approach to construction progress monitoring

Jan Sender, University of Rostock, Konrad Jagusch, Michael Geist, David Jericho and Christian Scharr, Fraunhofer IGP

Monitoring construction progress, as required in the one-off production of large structures, is very time- and labor-intensive due to a high level of complexity and individuality. The goal of this article is to develop a sensor-based approach for capturing and evaluating multiple inspection characteristics. The use of machine learning models to detect objects and derive relevant information forms the basis for linking current condition to construction schedule. This enables a significant increase in efficiency during construction progress monitoring and a well-founded assessment of progress.

The construction of complex large structures such as buildings, production facilities, or ships requires continuous monitoring to detect deviations early and respond in a targeted manner. Construction progress monitoring (CPM) involves the systematic documentation of processes, planning and work steps during production to ensure compliance with technical specifications, quality standards, and legal requirements. This includes data collection and comparison with a defined reference entity [1]. Interpretation, evaluation, and derivation of corrective actions then takes place on this basis.

CPM encompasses several inspection dimensions:

- the geometric dimension (presence and position of components),
- the temporal dimension (deadlines and sequences), and
- the qualitative dimension (condition).

Depending on the timing of the inspection, the process may serve to verify a completed work step, prompt acceptance of a component, or document overall progress. Across all industries, CPM faces key challenges: manual data collection, subjective assessment, and heterogeneous data sources. To address these, intensive research is being conducted into automated digital data collection, analysis, and evaluation, including digital models such as building information modeling (BIM) [2].

In shipbuilding, CPM is of particular importance. Ships are manufactured as one-of-a-kind vessels in a shipyard environment where numerous trades work in parallel on a stationary structure [3]. High product complexity, combined with strict regulatory requirements (e.g., from classification societies), makes it challenging to maintain an overview of current construction status. Systematic inspections identify missing components and work steps at an early stage, thereby reducing costly rework and delays. At the same time, however, they require a significant amount of manual effort for documentation and comparison with the target model and deadlines.

The aim of this article is therefore to support data collection with machine learning models and to automate comparison with the production plan to significantly increase efficiency in CPM. The methodological approach follows the design science research model as described in [4]. In the first step, the limitations of conventional methods are analyzed, and research needs are identified. Building on this, the requirements for objective CPM are formulated. In the third step, a system architecture comprising sensor-based data collection, machine-learning-based data analysis, and automated plan comparison is developed. Prototype testing of the architecture is conducted in a shipbuilding context. Finally, the results are evaluated, and further research needs are identified.

Limitations of conventional construction progress monitoring

Conventional construction progress monitoring relies primarily on manual visual inspections with photographic documentation. Particularly at shipyards, inspections take place under varying spatial and organizational conditions. Consequently, condition assessments are not standardized but depend largely on the experiential knowledge of the specialists involved [5]. To provide an objective digital database for assessment, artificial intelligence methods are increasingly being used alongside optical measurement techniques. Techniques such as 3D laser scanning or digital image processing can be used to map construction progress [1].

At the same time, augmented reality (AR) approaches are becoming more common. They project planning information into the user's field of view and allow for a visual comparison of target versus actual on-site conditions. AR approaches have proven effective for simple inspection tasks but reach their limits in complex construction

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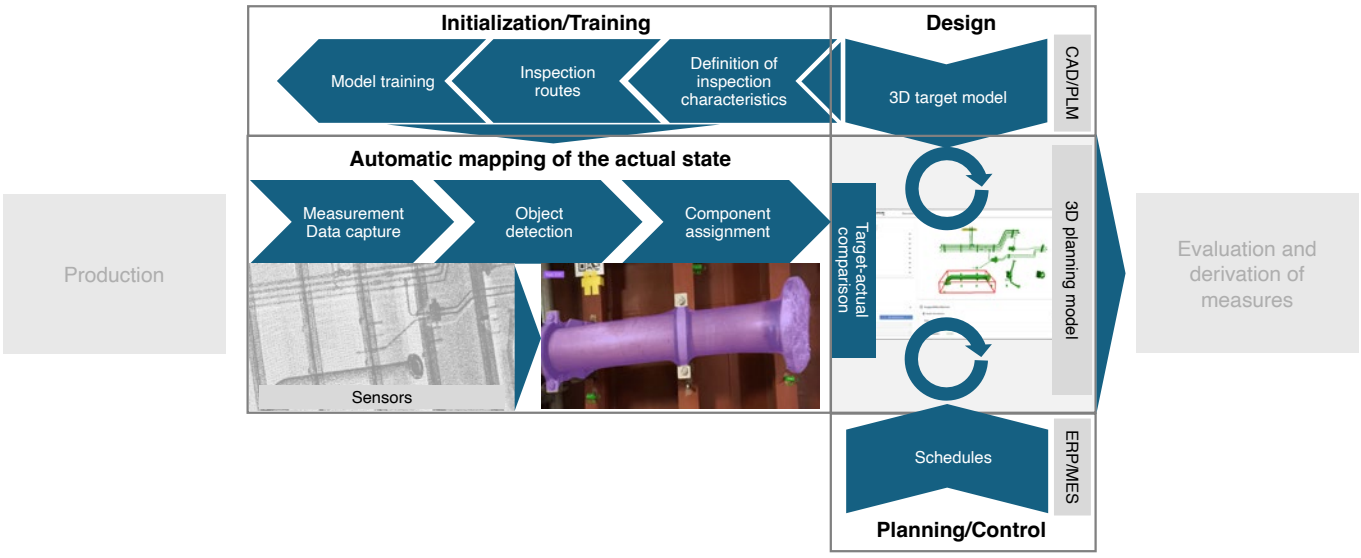


Figure 1: *Process flow of AI-supported construction progress monitoring.*

situations, as the assessment is performed manually and therefore remains subjective [6]. The operation of 3D laser scanners also requires qualified specialists, which brings about higher costs [7]. The approach presented here stands out due to its automated, learning-based detection and algorithmic comparison with design data, which enables evaluation independent of human intervention.

The integration of 3D scanning into planning models—such as BIM—for schedule coordination is already taking place on a case-by-case basis. In one-off production, however, this process remains largely manual. Reference models often lack the necessary level of detail or flexibility [8, 9]. The integration of data from enterprise resource planning (ERP) and product lifecycle management (PLM) systems is not sufficiently guaranteed.

The large number of components—and thus inspection characteristics—also complicates the automation of the process. These include, for example, geometric characteristics such as the position, orientation, or completeness of pipes, brackets, or fittings. In particular, components whose installation location and timing vary ("soft features") require flexibility in data capture, unlike precisely quantifiable variables.

Likewise, the dynamic environment of construction sites poses a hurdle for digital CPM documentation. Custom construction is characterized by continuous changes in the construction process. Existing methods are not sufficiently robust when applied in such real-world conditions [10]. Organizational and economic challenges, such as training needs and high investment costs, complicate implementation further. All these shortcomings clearly point to a need for more research.

Objective of objective condition assessment

The goal is to develop an efficient approach to objective and reproducible condition assessment in shipbuilding. An objective digital database is to be made available for the evaluation process. The following requirements can be derived from the research needs outlined above:

- The system must be able to simultaneously and reproducibly record and evaluate various test characteristics.
- Regular data collection must not result in any additional effort compared to existing procedures.
- The evaluation must function reliably under real-world construction site conditions and be possible without an external network connection.
- The recorded actual data must be linkable to existing design information to enable a comparison of target versus actual values over time.
- The results must be presented in a way that is traceable and interpretable.

The following section presents a system architecture that addresses these requirements.

AI-supported construction progress tracking

The system architecture is based on three core components:

- a mobile multisensor system
- a local computing unit for data analysis

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- a verification logic for the algorithmic comparison of detected objects with the digital planning model

Only the interaction of these three components enables the transition from pure data collection to an evaluative CPM. A continuous data flow accompanies the process, spanning all construction phases from planning to evaluation. **Figure 1** shows the methodological workflow. In the initial planning phase, building components and their relevant inspection characteristics (primarily presence and position) are first defined based on a 3D target model. In addition, inspection routes and schedules are established to ensure structured and reproducible data collection.

Measurements are taken regularly throughout the construction process. To this end, visual and geometric sensor data reflecting the current state of construction are recorded along the inspection routes. The local computing unit processes and segments the sensor data and detects building components using a residual network (ResNet) for image data [11] and the deep learning network (PointNet) for point clouds [12]. For building components with soft features, 2D and 3D information is merged to enable context-based alignment with the 3D target model. 2D information includes features from images—color, texture, contour—while 3D information consists of geometric properties from point clouds, such as shape and position.

A 3D planning model serves as a foundation. It is based on established BIM methods and links the 3D target model with the schedule. Due to sometimes limited detail, the comparison is performed at the type level within spatial contexts. In this process, component types—such as a pipe in a defined area—are considered rather than individual component instances. This goes beyond existing approaches by ensuring that it remains applicable even for models with limited detail [13]. Work packages and schedule deadlines are integrated via an ERP interface.

The key added value of this approach lies in the fact that it is only by linking actual status with the schedule—based on a static status assessment—that progress can be reliably monitored. To this end, the components identified during data collection are assigned to corresponding elements in the 3D planning model. For the target-actual comparison, the identified object types—and their quantities—are assigned to the components specified in the model. Components not identified before the target deadline are marked as overdue, thereby systematically highlighting deviations from the construction schedule. Missing components whose target deadlines have been exceeded are also visually highlighted in the digital model.

In addition, status reports are generated that compare target and actual dates. This provides a sound basis for decision-making by the construction management team regarding subsequent process steps.

Practical implementation in a shipbuilding context

A robust, mobile handheld system was developed for use at a shipyard: a compact action camera and a wireless 3D handheld laser scanner enable continuous data capture along the inspection route. Image and video data, as well as point clouds for the CPM, are captured. This data is processed on a standalone computer as part of an edge computing approach. Using appropriate machine learning models, the data is segmented and objects are detected. By comparing the data to the 3D planning model and the object IDs, a precise comparison between target and actual states can be performed **(Fig. 2)**.

To this end, a software prototype with an object database was developed that merges the target data locally and evaluates and visualizes the actual data. Interfaces to ERP and PLM systems are implemented to integrate the required information. The central foundation is the 3D model with component structure from the PLM system. The ERP system provides data on work packages and schedule deadlines. The assignment of assembly work packages to components is based on the respective component and the associated space.

The object IDs detected during measurement are algorithmically assigned to the target model. The defining factor here is the location where the data was captured. The type-level comparison described earlier is implemented here. In this way, a reliable assessment of current status is also made possible in cases where component identification is ambiguous. Through this linkage, the installation status and the capture date for each component can be updated automatically. Based on the capture time, the actual due date for identified components is set simultaneously.

A 3D-model-based user interface visually represents the target-actual comparison using color coding. A traffic-light system evaluates schedule deviations based on the degree of completion and delay (time of capture relative to the target date). “Green” indicates installed components, “Yellow” indicates uninstalled components with an upcoming deadline, and “Red” indicates a missed deadline. This allows for a quick assessment of the construction status and provides more time for evaluation and the identification of appropriate measures between data entry cycles. **Figure 2** shows the schematic process.

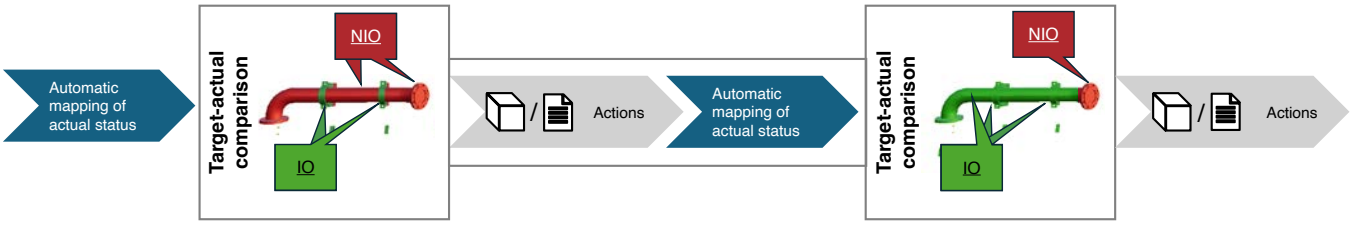


Figure 2: *Visualization of the target-actual comparison across multiple data collection cycles.*

Increased efficiency in one-off production

The system developed here offers clear advantages for the complex and dynamic shipbuilding and plant construction industries, as it captures components with variable installation locations. Its ease of use allows for an increase in inspection frequency, enabling deviations to be detected earlier. A mobile handheld scanner also enables intuitive operation independent of specialized personnel, allowing measurements to be performed in less time and with a 50% reduction in rework. At the same time, objective evaluation ensures a more consistent CPM. The characteristics formalized during the initial planning phase are stored and thus remain permanently available.

Another advantage is the combination of 2D and 3D data. This improves the robustness of object recognition and alignment with the 3D planning model. The decentralized system architecture also offers the advantage of low dependence on external network infrastructures. Since all processing steps take place locally, the system remains operational even in environments with limited connectivity. At the same time, this ensures a high level of data security.

A current limitation of the system is its initial integration. Although employee training effort is minimal, training the model itself for inspection involves a certain amount of organizational effort. Nevertheless, significant efficiency gains can be expected.

To date, the system has only been trialed in test environments. In these tests, all components were successfully detected. To reliably demonstrate the system's performance, quantifiable tests in an industrial setting will be required in the future.

For now, the research presented here serves as a proof of concept for linking current state and schedule via a time-contextualized assessment. The traffic-light system provides an objective basis for evaluation. Future studies will also take dependencies and cascade effects into account to enable the automatic suggestion of countermeasures. With this transition from pure status monitoring to a decision support system, further efficiency gains can be expected.

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AI



Designing Effective AI Certification

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Certifications for the human-centered use of AI are gaining importance—as a competitive differentiator, as a response to regulatory expectations, and as a tool for creating a people-centered work environment. But how can we tell if their requirements are truly being met? It is not audits and certificates that are decisive here, but rather the willingness of leadership and the organization to seriously engage with the process.

Keywords
certification, human-centered AI, norm embedding, standardization, symbolic compliance



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Designing Effective AI Certification

Insights from established certification domains for the standardization of human-centered AI

Katharina Morsch, Ruhr University Bochum

Certification can institutionalize normative requirements, but the degree to which this is achieved varies considerably. Drawing on expert interviews from established certification domains, this paper identifies indicators and conditions for the effective embedding of standards and transfers these insights to the context of AI. Substantial embedding is not evident in the certification event itself, but rather across audit cycles. Leadership commitment, the role of the internal representative, and practically applicable indicators emerge as key enabling factors. The paper derives three areas of action for the process certification of human-centered AI deployed in workplace processes.

Certification as a response to normative requirements for AI

How organizations use artificial intelligence (AI) in a human-centered manner [1] while ensuring its positive impact constitutes one of the central design questions regarding new forms of work organization. Certifications offer a concrete solution: They operationalize normative requirements, make human-centered AI use visible to external stakeholders, and can serve as an internal framework for organizational design [2,3]. This paper focuses on the process certification of AI use in organizations—that is, the assessment of whether a documented AI-supported work process is designed with a human-centered approach.

Relevant approaches are beginning to emerge. Since 2023, ISO/IEC 42001 has provided the first international standard for AI management systems [4], addressing governance requirements at the organizational level. In addition, process-oriented approaches are being developed that build on human-centered work design criteria [1] to assess whether the use of AI in work processes is human-centered in practice.

A credible certification label can become a significant differentiator, provided it is more than just a certificate displayed on the wall. However, formal structures and day-to-day practice do not necessarily align [5], and the degree of implementation varies considerably [6,7]. Although established certification domains have generated substantial knowledge about the conditions and indicators associated with different levels of organizational institutionalization, these insights have not yet been systematically applied to the emerging field of AI certification. This article addresses this gap by examining the following research questions:

Which indicators characterize the effective embedding of normative requirements within organizations, and how can this be identified through certification processes?

What enabling and inhibiting conditions influence this process, and what specific characteristics emerge in the context of AI?

Research design

The research sample comprises six experts from certification consulting, auditing, IT consulting in certified companies, and AI-specific standardization. Participants were purposively selected to cover perspectives across the entire certification process. The interview guide was divided into three sections: experiential knowledge from established standardization domains, transferability to the AI context, and reflection. The interviews were transcribed and analyzed using qualitative structured content analysis according to Kuckartz [8] with MAXQDA. Deductive categories were derived from the research questions and the guide, while inductive categories were added whenever recurring themes in the data were not adequately captured by the initial coding framework. The coding scheme is illustrated in **Figure 1**. The presentation of results follows its main categories and synthesizes conceptually related results.

Indicators of effective norm embedding

A key finding from the interviews is that the substantive embedding of normative requirements is not evident in the certification process itself but becomes apparent only in day-to-day organizational practice beyond the audit. Whether normative requirements have truly been embedded can be reliably determined over the course of surveillance audits. This finding provides a more specific understanding of the decoupling between formal structures and organizational practice [5] described in the research.

Category	Description (paraphrased from interview material)
K1 – Indicators of effective norm embedding	Characteristics that indicate the embedding of normative requirements in the certification process
K1a – Substantive embedding	System activity increases continuously between audits; evident in document management, management review, and key performance indicators; modified interface processes and responsibilities with a real mandate.
K1b – Symbolic compliance	Organizational activity follows the audit cycle, increasing before audits and declining afterward. Normative requirements are maintained administratively but are not translated into everyday work practices—often because of gaps in understanding rather than deliberate deception.
K2 – Contextual conditions	Structural and procedural factors that facilitate or inhibit substantive institutionalization
K2a – Enabling conditions	Leadership commitment: Senior management views regulatory requirements as a tool for shaping the organization and demonstrates this commitment in practice; the internal management representative has a clear mandate and direct access to senior leadership.
K2b – Inhibiting conditions	Resistance to the distribution of responsibility; poor audit quality focuses primarily on documentary compliance and creates incentives for superficial compliance.
K2c – Standards inflation	Simultaneous compliance with multiple, sometimes conflicting standards reduces organizations' willingness to engage substantively with any individual standard; organizations may select the certification option requiring the least effort.
K3 – Certification motivation	Organizations driven by external pressure pursue certification primarily to satisfy customer requirements, whereas intrinsically motivated organizations seek certification to support organizational improvement. Motivation may evolve over time, with certification acting as a catalyst for changes that would otherwise be difficult to implement.
K4 – AI-specific characteristics	AI-specific challenges for the substantive institutionalization of normative requirements in work processes
K4a – Operationalization complexity	Human-centered criteria (e.g., transparency and the promotion of human potential) are more difficult to translate into auditable requirements than traditional quality concepts, increasing the risk of decoupling between leadership commitment and operational practice.
K4b – Development dynamics	AI applications evolve more rapidly than conventional certification cycles, creating a trade-off between certification requirements that are overly specific and quickly become obsolete, and those that are overly generic.
K4c – Informal AI use	AI tools are easily accessible for personal use; certified processes can effectively be undermined by the use of unauthorized systems.

Figure 1: *Deductive-inductive coding framework for analyzing the effective institutionalization of normative requirements.*

The respondents unanimously described a characteristic pattern associated with a low degree of institutionalization: organizational activity increases shortly before an audit and declines again afterward. Symbolic compliance is therefore characterized not by complete nonimplementation but by recurring cycles of heightened and diminished system activity. Organizations with a high degree of institutionalization, by contrast, exhibit a different pattern. The intensity of management system activities increases from one audit cycle to the next because the organization regards the management system as an integral management tool rather than merely a certification requirement.

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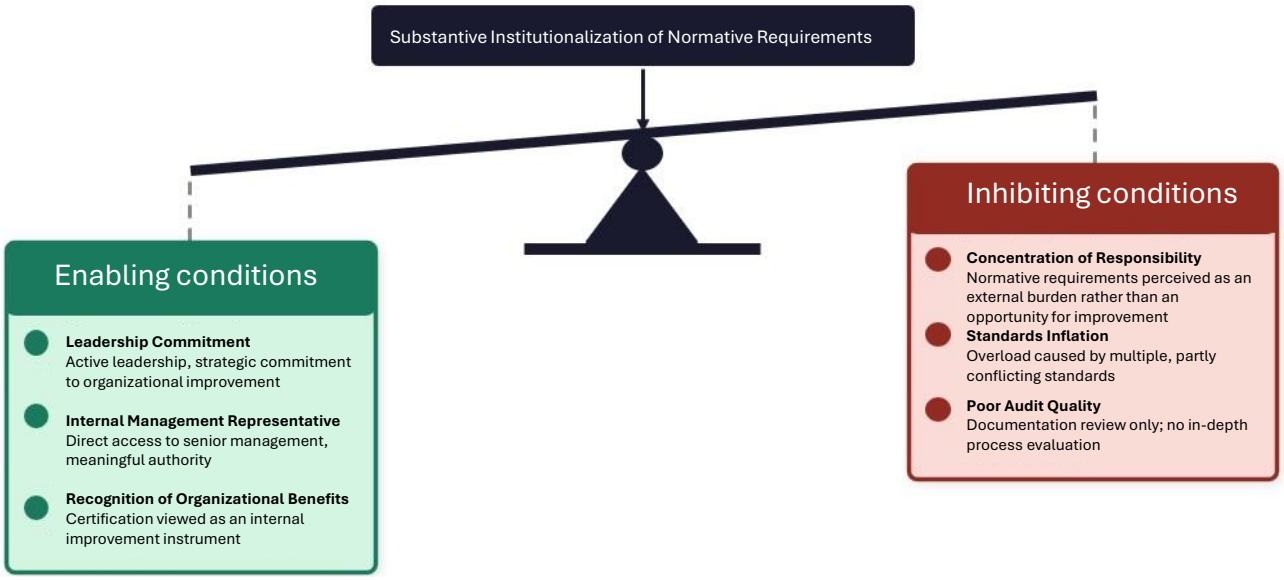


Figure 2: *Enabling and inhibiting conditions for the institutionalization of normative requirements.*

This pattern can be observed empirically using document management data, the development of internal audit reports, and trends in key performance indicators. At the process level, substantive integration is evident in modified interface workflows as well as in responsibilities accompanied by genuine decision-making authority. At the leadership level, it is evidenced by managers' willingness to participate in internal audits themselves and by management reviews that are conducted as meaningful organizational self-assessments, resulting in the definition of concrete objectives for the following year.

The interviews further suggest that a low degree of institutionalization is often not the result of deliberate deception but rather of a lack of perceived meaning. When employees do not experience normative requirements as meaningful for their own work, or when the relationship between quality requirements and their daily activities remains unclear, these requirements remain abstract rules administered by a small group rather than being translated into routine organizational practice. This observation adds a process-oriented dimension to the decoupling mechanisms described in the literature [6, 7]. Decoupling is not solely the result of strategic exploitation but also of gaps in understanding and insufficient organizational translation efforts.

Enabling and inhibiting conditions

A particularly consistent finding across all interviews is the paramount importance of leadership commitment. Substantial embedding is most likely to succeed when senior management views normative requirements not as external impositions but as tools for organizational improvement and actively models this approach. Organizations whose leadership uses certifications to advance their own improvement objectives achieve long-term and more sustainable effects compared to those that act primarily in response to external pressure.

The respondents consistently distinguished between organizations that pursue certification due to external pressure and those that recognize an intrinsic need for improvement. This distinction reflects the logic of institutional isomorphism described in the literature [5, 9] and the legitimation paradoxes of standards [10]: Certifications are adopted without this necessarily being linked to a change in internal practices. However, motivation is not a fixed characteristic. Certification can act as a catalyst for changes that would otherwise be difficult to implement.

Another enabling condition is the design of the internal representative's role: With hierarchical access to senior management and the mandate to communicate uncomfortable findings, this role makes a significant structural difference. Conversely, when organizations deliberately fill this role without providing sufficient organizational support—a practice repeatedly described in the interviews— they implicitly signal that implementation of the standard is not an organizational priority.

Among the most significant obstacles is the rejection of shared responsibility. When decision-making authority is concentrated among only a few and compliance requirements are perceived as a constraint, substantive embedding is unlikely to occur. A further challenge is

standards inflation. When companies are required to comply simultaneously with multiple, sometimes contradictory requirements, their willingness to engage substantively with individual standards declines. Finally, according to the respondents, poor audit quality creates incentives for superficial compliance—a connection confirmed by research [7]. Effective auditing therefore requires in-depth process understanding and domain-specific expertise.

The enabling and inhibiting factors identified in this study are summarized in **Figure 2**.

Characteristics specific to the AI Context

Respondents generally consider it possible to transfer the identified patterns to the process certification of human-centered AI use but note that this involves specific challenges. Three specific characteristics were identified in this context. First, the respondents described the operationalization of certification requirements as more difficult compared to traditional management system certification. While ISO 9001 builds on a long-established and operationalized concept of quality, concepts of human-centered work design—such as transparency, traceability, and the promotion of human potential [1]—must first be translated into organizational practice. The risk of decoupling [6] is particularly pronounced here: human-centered principles may be endorsed by senior management as organizational values without actually guiding day-to-day decision-making.

Second, the respondents pointed to the rapid evolution of AI systems as a fundamental challenge for traditional certification approaches. When AI systems and their effects on work processes evolve faster than recertification cycles, certificates risk becoming snapshots of past conditions or hindering the organization's adaptability. This creates a fundamental trade-off: certification requirements that are highly specific may become obsolete as the technology evolves, whereas requirements that are too generic may fail to capture the characteristics of individual AI applications.

Third, the interviewees identified the general availability of AI tools as a structural challenge without a direct counterpart in other certification domains: Since AI tools are easily accessible to employees on a personal basis, certified processes can effectively be undermined through the parallel use of unauthorized systems without this becoming visible to external auditors.

Taken together, these three points point to a fundamental shift: The primary challenge is not the establishment of a management system but the continuous monitoring and evaluation of dynamic human-AI interactions within the work process.

Paths to effective implementation: Implications for practice

Three areas of action can be derived from the identified findings **(Fig. 1)**. They address complementary dimensions of effective certification and build on the key findings of the analysis: the importance of continuous audit cycles, the role of leadership commitment and internal representatives, and the challenges of operationalizing human-centered criteria in an AI context.

Design certification as a learning process rather than a compliance event. The findings suggest that the effectiveness of certification lies less in the certificate itself than in the organizational learning and reflection it stimulates. Certification for human-centered AI should therefore be conceived not as a one-time assessment of compliance but as a continuous process of organizational reflection that regularly encourages organizations to critically evaluate their use of AI. Because AI systems evolve more rapidly than conventional certification cycles, surveillance audits become more important than the initial certification itself. In practical terms, organizations should invest not only in achieving initial certification but also in establishing robust and continuous surveillance processes.

Leadership must lead the way. Substantive embedding stands or falls with the commitment of senior management. Leaders who subject themselves to audits, empower internal representatives with genuine authority, and use management reviews to define and monitor meaningful organizational objectives create the organizational conditions necessary to ensure that human-centered requirements extend beyond the executive level into day-to-day work. Substantial integration also requires a basic level of organizational awareness: Without an understanding of the risks associated with unauthorized AI tools, even certified processes remain vulnerable to informal workarounds. Organizations seeking certification for human-centered AI should therefore appoint an internal management representative with a clear mandate and direct access to executive management, integrate AI governance into existing management systems, and raise employee awareness of the responsible use of AI tools, including those used outside formally certified processes.

Develop practically applicable indicators. Human-centered requirements become embedded in organizational practice only when they are translated into operational indicators that can be applied in everyday work without sacrificing their normative intent. Requirements that remain overly abstract encourage superficial implementation rather than meaningful organizational change [6,7]. Frameworks such as the requirement structure of ISO/IEC 42001 [4] provide an important starting point. However, because they primarily address

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organizational governance, they must be extended to assess the human-centered impact of AI at the process level. Initial practical support may be provided through professional training programs, such as certification courses for AI management representatives.

The patterns identified should be further examined and refined using real-world AI certification processes. Several methodological limitations should be acknowledged. Because the sample consisted of experts from established certification domains rather than AI-specific certification, the direct transferability of the findings is necessarily limited. Furthermore, profession-specific perspectives and potential biases among the interviewees were not systematically controlled. The proposed fields of action should therefore be regarded as an initial framework that requires further empirical validation.

Overall, the results suggest that the challenges of human-centered AI certification [1] do not lie in the certification event itself but in developing mechanisms capable of continuously monitoring, evaluating, and shaping the effects of AI on work over time. Current standardization initiatives [4] provide an important foundation for this objective. Their effectiveness, however, will depend largely on whether they succeed in integrating continuous organizational learning, leadership responsibility, and robust operational indicators into a coherent certification approach.

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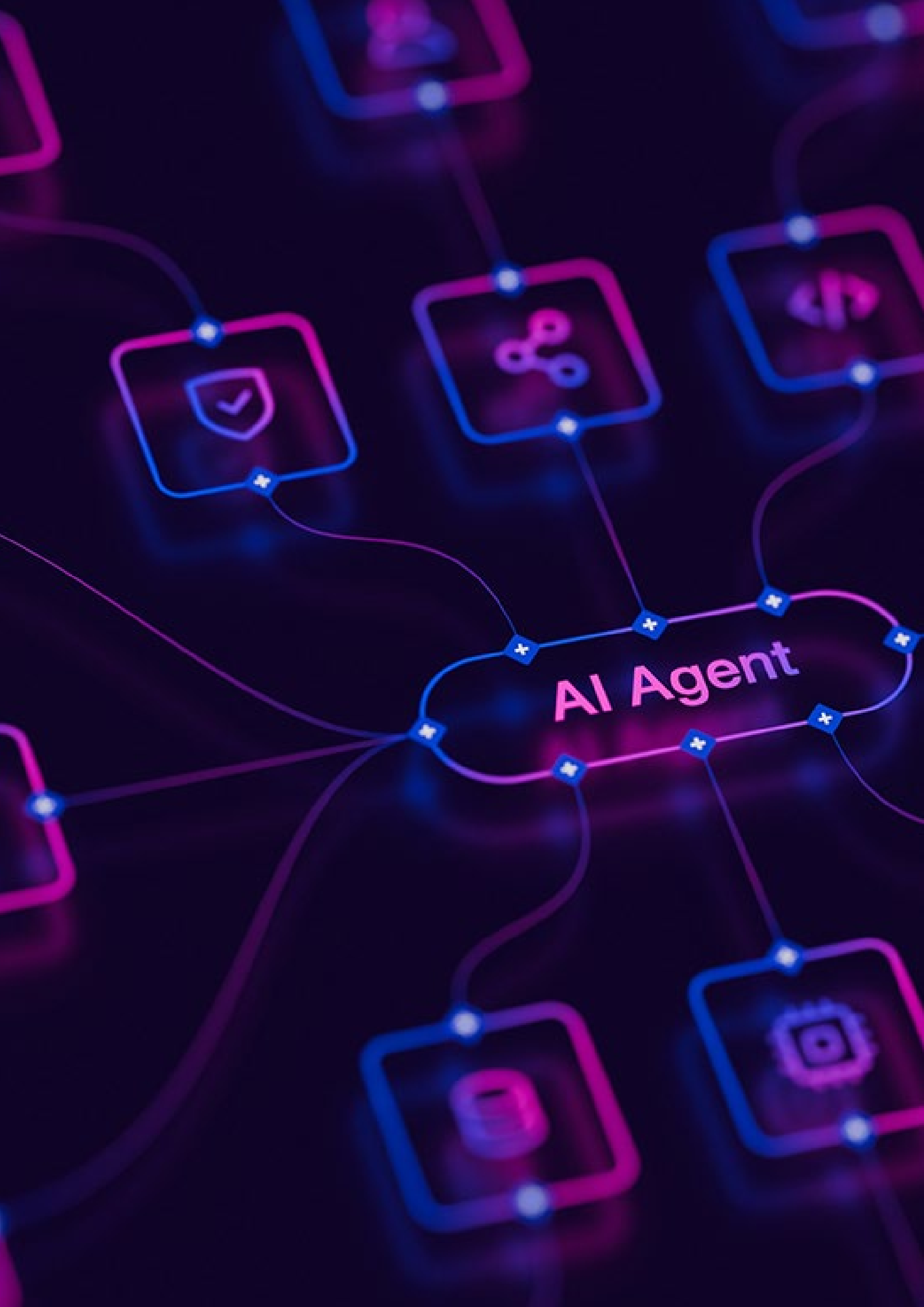
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AI Agent

AI-Driven Organization as a New Work Paradigm

The rapid evolution of generative AI from a mere tool to an organizational framework in which agent-based AI systems are embedded as actors within roles, routines, and processes requires profound changes in organizational design as well as in employee empowerment. In this context, the focus of work shifts from “task execution” to “task stewardship”: employees manage AI-supported process chains, review results, and are responsible for defining operational limits.

Keywords
agent-based AI, AI organization, upskilling, competence development, digital enablement

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AI-Driven Organization as a New Work Paradigm

Implications for individual and organizational change

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The rapid evolution of (generative) artificial intelligence (AI) from a tool that merely assists humans to an organization in which agentic AI systems are embedded as organizational actors within roles, routines, and processes requires profound changes in organizational design and workforce development. In this context, work is shifting from task execution to task stewardship: employees manage AI-supported process chains, review AI-generated outputs, and are responsible for defining operational limits. This paper develops a digital enablement model with three competency dimensions: AI tool proficiency, methodological and process competence, and critical judgment and accountability. Building on this framework, it presents an AI upskilling program developed as a work-integrated learning initiative at the Fraunhofer Institute for Industrial Engineering IAO, incorporating insights gained from a pilot implementation.

The AI organization: Definition and requirements

The advent of agent-based artificial intelligence (AI) in the workplace marks a paradigm shift: AI is evolving from a passive tool designed to support human activities—that is, an object of work organization—into a functional subject or organizational actor within defined domains that performs tasks autonomously [1, 2]. The focus of human work is shifting from AI-supported tasks within a process toward the active orchestration of AI-supported process chains, management, and exception handling [3, 4].

The effect of this transformation on work organization and competence development is still unclear. This paper addresses this gap by developing a concept of the AI organization as an analytical framework for the systematic integration of AI into work processes. Based on this framework, it derives a digital enablement model that is being evaluated at the Fraunhofer Institute for Industrial Engineering IAO through a multi-stage AI upskilling program.

While AI tools are developing rapidly today, the organization's roles, processes, governance, and competencies often fail to keep pace—resulting in a growing adoption gap, known as the AI Adoption Gap **(Fig. 1)**.

Jarrahi et al. [5] emphasize that neither full automation nor absolute human control yields optimal results in complex knowledge domains. Instead, hybrid intelligence approaches aim for a complementary division of tasks between humans and AI. Ideally, this requires a systematic co-configuration of defined role contracts, in which the division of roles between human and AI actors is dynamically configured throughout the different stages of the work process [2]. AI acts autonomously within defined domains with humans intervening where contextual knowledge, moral judgment, or strategic judgment are required. Dell'Acqua et al. [6] illustrate this distinction using the concept of the "jagged frontier"—an irregular line between tasks that AI handles excellently and those at which it fails, even when both task types appear to be similarly complex, underscoring the need to reallocate existing tasks. Based on this, this paper adopts the following working definition:

An AI organization is a work organization in which AI systems with their own capacity for action are designed as regular organizational elements and are thus an autonomous part of the organization's collective and adaptive capacity. Humans retain final normative and strategic responsibility.

Digital enablement as an empowerment strategy

Productivity effects and shifts in tasks resulting from the use of AI are already visible today. For example, Schmidt et al. [7] show that the benefits of using Microsoft Copilot are highly context-dependent, indicating high efficiency when used for structured text tasks, low efficiency when used for learning or networking activities, although evaluations converge over time. The key development is the qualitative shift in tasks: through interaction with AI, human work shifts from operational, step-by-step execution—i.e., "task execution" (e.g., information gathering, summarization, and text creation)—through control (setting the framework for AI) toward responsible

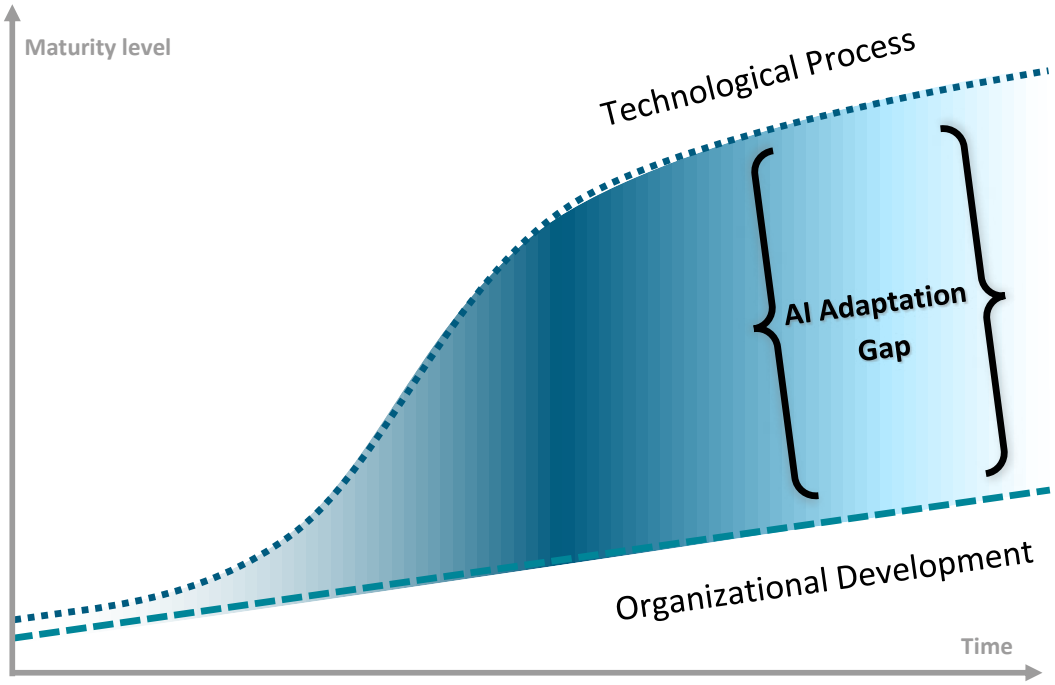


Figure 1: *AI adoption gap.*

decision-making regarding the use of AI-generated outputs, which can be understood as "task stewardship" [8, 9].

In this process, AI takes on specific functional roles such as structuring or pattern recognition [5, 10]. This suggests that training employees for an AI-driven organization must include context-sensitive use of AI as well as a cultural shift. Upskilling therefore requires not only learning to use new tools, but above all a shift in skills and mindset, as well as the ability to continuously adapta. At the same time, the latent risk of deskilling must be prevented.

Previous research has addressed various facets of human-AI interaction but converges on three central requirements for competency development:

1. Dell'Acqua et al. [6] and Schmidt et al. [7] show that AI tools generate productivity benefits only when employees understand their operating principles and use them appropriately in context. This underscores the need for sound AI **tool proficiency**: employees require a foundational technical understanding of agentic and generative AI systems and their integration into existing work environments. This includes confident operation, an understanding of key operating principles, and basic prompting skills.

2. The concept of the "jagged frontier"[6] illustrates that blindly delegating tasks to AI leads to quality losses. employees must therefore be able to specifically identify tasks suitable for AI, deconstruct processes in granular detail, and consciously design the division of labor between humans and AI. This requires **methodological and process expertise**, including the ability to design AI-supported process chains, specify roles and permissions, and iteratively optimize workflows. Human value creation consequently shifts from step-by-step execution toward the design and orchestration of hybrid processes.

3. Lee et al. [8] and Simkute et al. [9] show that the use of generative AI reduces the cognitive effort required and promotes systematic substitution effects. Counteracting this tendency requires the ability to critically examine AI outputs for factual accuracy, bias, and normative compatibility—that is, **critical judgment and accountability** as a core mindset. When AI is embedded in an organization as an agent with implicit assumptions and potential biases, the need for context-sensitive evaluation and normative control increases. In addition, the scope of action and permissible decisions that agents are authorized to make must be defined. Employees thus assume "task stewardship", meaning that they remain responsible for deciding where and how AI is deployed and where human judgment remains irreplaceable [5].

These three dimensions form the basis of the Digital Enablement Model **(Fig. 2)**. It operationalizes the three pillars of competence described above for workforce development in the AI organization and follows the empirically derived logic that effective upskilling must

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	Basic Literacy	Advanced Literacy	Strategic Literacy
Toolset	Develop a foundational understanding of AI and learn to use AI tools	Deepen prompting skills and develop AI use cases	Design and orchestrate AI-enabled workflows
Skillset	Integrate AI into work processes and apply it effectively	Deconstruct tasks and design end-to-end process workflows	Design and manage processes and organizational roles
Mindset	Understand legal and ethical principles and ensure data privacy	Reflect on and shape human–AI collaboration	Exercise ultimate human accountability and reflect on the risks of deskilling

Figure 2: *Digital enablement model.*

include not only a toolset but, above all, a skillset and mindset.

The model distinguishes between three progressive levels of competence: Basic Literacy targets employees with little or no AI experience. It establishes the foundation for tool proficiency and an initial understanding of responsibility by providing legal and ethical guidelines for AI implementation. Employees are empowered to integrate AI into their own work processes.

Advanced Literacy targets employees with basic or advanced AI proficiency. This level deepens tool proficiency and addresses methodological and process competence. Employees learn to consciously divide tasks between humans and AI, design process chains, and establish iterative improvement cycles.

Strategic Literacy targets employees with extensive AI experience and promotes their methodological and process competence as well as their critical judgment and accountability. It empowers employees to shape AI use at both the process and organizational levels.

The Digital Enablement Model aims to strengthen cognitive agency in working with agentic AI: AI should be deployed as an organizational actor without eroding human judgment, willingness to take responsibility, and methodological design capabilities. Reflective tasks are crucial for maintaining and developing these competencies.

The digital enablement model was translated into an AI upskilling program at the Fraunhofer Institute for Industrial Engineering IAO. The program builds on a pilot project and addresses the practical requirements of an AI-driven organization. The AI upskilling program targets over 500 employees working in research or administration. Approximately 40 employees participated in the pilot project. The AI upskilling program was designed as a work and learning project (WLP).

Work and Learning Projects (WLP) represent an established format of work-integrated continuing education in which real world work tasks are transformed into learning tasks and addressed through structured learning steps [11,12]. Learning thus does not take place separatlyly from value creation but rather within the work process itself, enabling the targeted use of diverse prior knowledge, as participants select tasks based on their skill level and job profile [12, 13]. Peer-to-peer learning and the joint reflection on challenges, edge cases, and deviations serve as central mechanisms for developing complex, context-sensitive competencies [14]. Against the backdrop of the paradigm shift toward AI-driven organization outlined above, WLPs thus function as organizational living laboratories.

In the pilot project, learners independently select real-world work tasks, process them according to a standardized, AI-supported learning process, and document the prompts they develop in a shared library. Peer-to-peer learning sessions facilitate colleagues to exchange experiences about challenges, edge cases, and best practices in the context of task stewardship. Initial findings suggest that the approach is particularly effective in productively leveraging heterogeneous prior knowledge, promoting context-specific learning, and strengthening the transferability of acquired competencies across different domains [15].

Building on the experiences gained in the pilot project, the AI upskilling program is deliberately not designed as a rigid, mandatory track. Employees enter at the competency level that corresponds to their individual level of knowledge: the more relevant experience they have with AI tools and with designing human-AI processes, the higher their entry point. The required self-assessment of individual competencies fosters the ability to reflect and exercise critical judgment. This differentiated approach considers the diverse starting points of the workforce and supports tailored development across the three pillars: toolset, skillset, and mindset.

To acquire basic AI skills, the Basic Literacy level offers a module designed to build a general understanding of AI, as well as a module introducing Microsoft Copilot and FhGenie, an internal LLM platform of the Fraunhofer Society. Binding usage and data privacy guidelines are reinforced throughout all sessions. At the Advanced Literacy level, the program supplements so-called Promptathons with a module on the systematic identification and development of cross-process use cases.

While the free selection of tasks in the pilot project promoted exploratory learning processes , the expanded program provides a structured methodology that enables employees to systematically identify AI-suitable tasks within their area of work along the jagged frontier and integrate them into process workflows. This supports the deliberate configuration of roles in the context of hybrid intelligence.

AI masterclasses are offered to employees at the Strategic Literacy level. These classes develop competencies for designing more complex workflows and structuring tasks at the process level. Participants learn to design agentic AI systems as regular organizational elements (roles, routines, information flows, rules) while consciously assuming ultimate normative and strategic responsibility. In addition, specific leadership modules address the unique role of managers within the AI organization. Topics include raising awareness of systemic risks such as deskilling, enabling managers to foster AI competencies within their teams, and developing strategic process and role architectures based on hybrid intelligence.

In addition, an institutionalized AI community is being established as a structured forum for continuous exchange of experience, the presentation of new use cases, and targeted knowledge transfer through internal multipliers. Advanced community members are responsible for maintaining the prompt library: they add new prompts and provide feedback in terms of application areas and quality criteria. This measure ensures the quality of shared resources and establishes a sustainable internal knowledge structure.

The impact of the program is evaluated continuously at three levels: output and reach (completed modules, templates created, prompts maintained), outcome (time savings, usage rates, perceived self-efficacy, and changes in usage patterns), and impact (demonstrable process improvements and quality gains in pilot areas). Following completion of each program module, anonymized short surveys are conducted.

In addition, a company-wide online survey is conducted halfway through the overall program to assess the usability and transferability of the content and to gather more detailed feedback on components that are still missing. The survey also includes an assessment of relevant tools and technology trends in the field of AI. The AI upskilling program is currently being piloted, and evaluation results are not yet available. Impact measures such as productivity effects and transferability are assessed using standardized scales that capture individual experiences and are systematically analyzed across all respondents.

Next steps toward an AI Organization

In this paper, we derived a Digital Enablement Model comprising three competency dimensions based on theoretical considerations of the AI organization and translated it into a three-level upskilling program that is currently being piloted as a Work and Learning Project at the Fraunhofer Institute for Industrial Engineering IAO. This represents both a strength and a limitation of the approach: the model currently draws on experience from a single research organization with a highly qualified workforce, and its transferability to other types of organizations has yet to be examined. In addition, the evidence gathered so far is based primarily on qualitative observations; systematic evaluation of the program's impact remains outstanding.

The next step is to implement and empirically validate the Digital Enablement Model in additional organizations and establish connections with existing frameworks such as DigComp 2.2. For practitioners, the paper demonstrates that effective AI upskilling must address tool proficiency, process design competence, and critical judgment equally and must do so within the work process rather than separately from it.

From the traditional perspective, AI is a digital assistant: an intelligent helper that takes over specific tasks—more cheaply, quickly, and consistently. Yet the organization itself essentially remains unchanged. Overcoming the AI adoption gap requires new structures, processes, and competencies. Tasks, responsibilities, and decision-making authority are distributed between humans and machines. The AI organization, by contrast, is not understood as a collection of individuals but as a hybrid sociotechnical system in which humans and AI are intertwined: AI is no longer an object within the organization but becomes part of the organization itself—a subject rather than a tool. Tasks and processes must therefore be decomposed at a granular level and reallocated between humans and AI.

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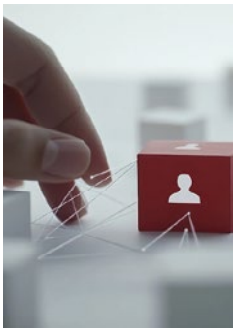
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Human-Centered AI-Paired Work Systems

Integrating GenAI and the human factor in work system theory

Katharina Hölzle and Udo-Ernst Haner

The advent of generative AI is fundamentally changing work systems: for the first time, an intelligent, autonomous actor with social skills is entering the work context alongside humans. This development requires new models that take into account the interaction between humans, AI agents, and collaborative robots. A human-centered work system model shows how this expanded potential can be integrated responsibly.

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Human-Centered AI in Companies with Employee Representation

Using the HUMAINE model for a company-specific works agreement

Alexander Ranft, Fabian Hoose, Claudia Niewerth, Mathias Preuß and Manfred Wannöffel

AI systems place new demands on regulation. The 2025 EU AI Act brought binding requirements into force, which must be linked nationally with the Works Constitution Act. The regional competence center HUMAINE has developed a model AI works agreement in accordance with Section 77 BetrVG, which strengthens co-determination rights in the workplace and implements European regulatory practice in a practical way.

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Audio-Immersive Learning in Continuing Vocational Education

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Artificial intelligence is increasingly becoming a focus of professional development to personalize learning journeys. At the same time, audio formats are a popular learning medium that is gaining increasing interest. However, a concept for an AI-supported audio format—as well as the potential of combining AI and audio—has not yet been explored and therefore requires a conceptual examination of the possible design options.

Keywords
audio, skills transformation, learning formats, learning facilitators, continuing vocational education

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Audio-Immersive Learning in Continuing Vocational Education

From linear audio playback to AI-supported conversational learning companions

Tim Beichter and Vanessa Hartmann, Fraunhofer IAO, Stuttgart, Katharina Hölzle, University of Stuttgart, Fraunhofer IAO, Stuttgart, Manuel Kaiser, Fraunhofer IAO, Stuttgart

Recent studies on continuing vocational education and training show that audio formats are gaining increasing interest among learners. Audio makes learning suitable for everyday use, is a central component of microlearning, and can be flexibly integrated into daily work routines, enabling on-the-job training. However, one area that has previously received little attention in both academia and practice is the interaction between audio training and artificial intelligence (AI). AI enables the transformation of a linear learning format into a dialogic one. As a result, audio evolves from a one-size-fits-all format into a personalized learning companion. Against this backdrop, this article addresses the interplay between audio-based learning and AI in continuing education by outlining a concept for an AI-supported audio format and explores the potential of AI-supported conversational learning companions.

Continuing professional development has gained significant importance in recent years, and both research and practice are focusing on the question of how to structure skills development for current or future jobs. Accordingly, this issue is continually driven by trends and technological advances and, as such, gives rise to new debates [1]. Artificial intelligence (AI) is particularly noteworthy in this context [2, 3], as it influences future competency requirements ("future skills") within organizations [4, 5]. In particular, digital competencies and the ability to use AI applications are increasingly prioritized in their portrayal as key topics for the future [5]. Furthermore, AI is also changing the requirements for continuing education formats and strategies [3] and is thus becoming an important companion and coach in the learning process, with whom one can discuss questions and topics [5, 6]. This, in turn, has implications for the future role of human instructors, who are being somewhat forced to address this technological shift in the learning process and adapt their offerings accordingly.

In addition to AI, the field of continuing vocational education is showing growing interest in audio-based microlearning formats [5, 7, 8]. Audio-based learning is particularly well-suited to work-integrated learning, enabling training on-the-job. Since it is screen-, hands-, and eyes-free, learners can engage with audio content while performing manual tasks—for example, in production—without interrupting the work process itself. In this way, learning becomes readily integrated into everyday work and can be seamlessly integrated in professional practice, thereby creating new opportunities for acquiring skills in the workplace [7, 8].

Empirical findings from the e-learning study reported in [8] also demonstrate that audio-supported learning formats outperform text-based formats, resulting in better knowledge retention, faster task completion, and greater transfer of acquired knowledge to the workplace [8]. Furthermore, audio narratives activate emotional and linguistic processing mechanisms that foster deeper mental representations, which are associated with enhanced long-term retention [9].

Discussing informal learning, [10] also show that, depending on the target group, setting, and design, audio can support comprehension and knowledge retention as effectively as—or even more effectively than—text. Furthermore, exploratory interview studies involving employees performing routine tasks indicate that speech- and audio-based learning formats are particularly well-received when they are embedded in work processes, can be accessed through voice interaction, and support different listening and learning modes, such as background listening and focused listening [7]. Against this backdrop, the use of generative AI—particularly in voice-controlled, conversational audio formats—appears to hold considerable potential for enabling an immersive yet work-integrated approach to competence development.

This article explores this interplay between audio-based learning and AI in vocational continuing education, presenting audio-immersive learning as a key future technology for work-integrated competency development.

The traditional linear approach to audio playback

The current standard for audio-based continuing education is based primarily on linear approaches to audio playback. Within this traditional linear framework,

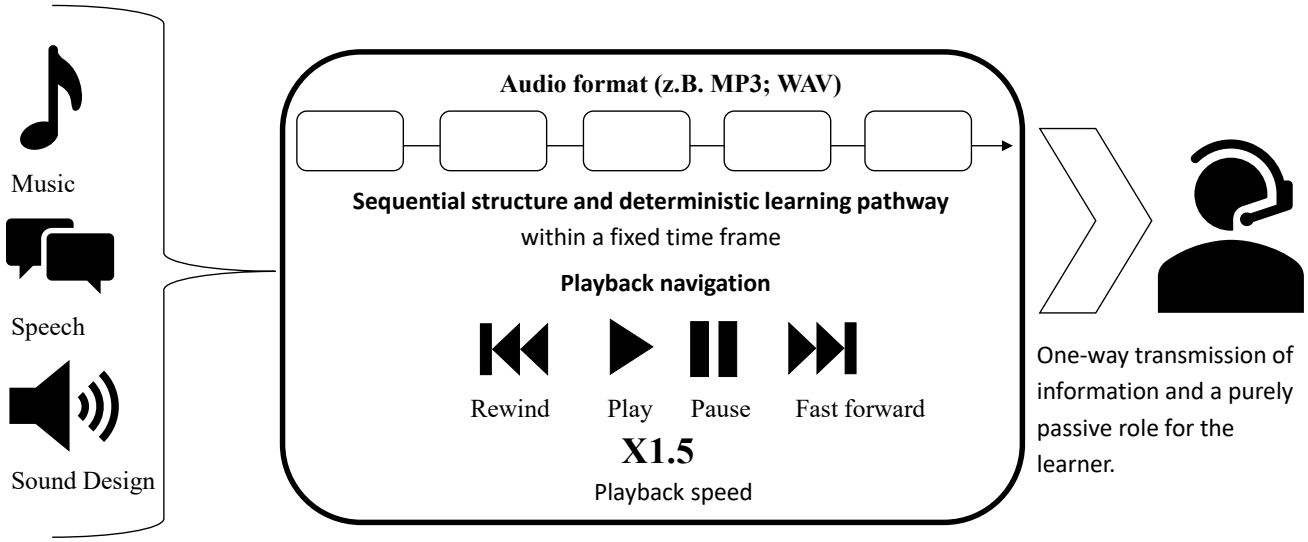


Figure 1: *Classical linear approach to audio-supported learning.*

audio content (speech, music, sound design) is compiled into a static audio file (e.g., MP3 or WAV format) within a fixed time frame—ranging from a few minutes for microlearning modules to hours for audiobooks [11].

The learner's interaction with this traditional format is primarily limited to controlling the playback timeline. Users interact with the content through conventional playback controls, such as play, pause, and fast-forward or rewind navigation within the audio track. Additionally, adjusting the playback speed using time-stretching allows for individual regulation of the listening pace without affecting the pitch, thereby adapting information processing to the learner's individual pace [12].

A key feature of this classical linear approach is the sequential chaining of learning units [13, 14]. The content is arranged in a fixed hierarchy (e.g., Chapter 1 follows the introduction, Chapter 2 follows Chapter 1, etc.). The learning path is thus deterministically predetermined. The structure of the information itself is therefore rigidly linked to the medium [14]. In this model, the audio format functions as a one-way information channel. The medium cannot respond to the user's specific questions or level of knowledge, which leaves the learner with a largely receptive role [11]. The audio file remains unchanged throughout its entire usage period without any adaptation of the content taking place beyond the selection of the file.

Artificial Intelligence as a conversational learning companion

AI is evolving from a supportive tool into an active, conversational learning companion. In particular, the use of conversational agents, adaptive learning systems, and generative AI is enabling new forms of interaction in which learning is no longer merely one-sided but is continuously accompanied, reflected upon, and individually guided.

A key driver for this development is the ability of AI systems to personalize learning processes and respond in real time to individual needs. A qualitative literature review in [15] shows that AI-supported learning environments lead to improved learning outcomes among adults, particularly due to individualized learning pace and immediate feedback [15]. This form of responsive support is further enhanced by conversational AI: learners can ask questions at any time, delve deeper into content, and adapt their learning speed as needed.

The conversational nature of AI is particularly evident in the use of chatbots and intelligent tutoring systems. A scoping review by [16] demonstrates that conversational agents are primarily used as tutors and support learning processes through rapid access to information and increased interactivity [16]. These systems enable continuous, low-threshold interaction that integrates learning more effectively into everyday work life.

Furthermore, experimental studies show that conversational AI not only supports learning but can also significantly improve learning outcomes. In a randomized

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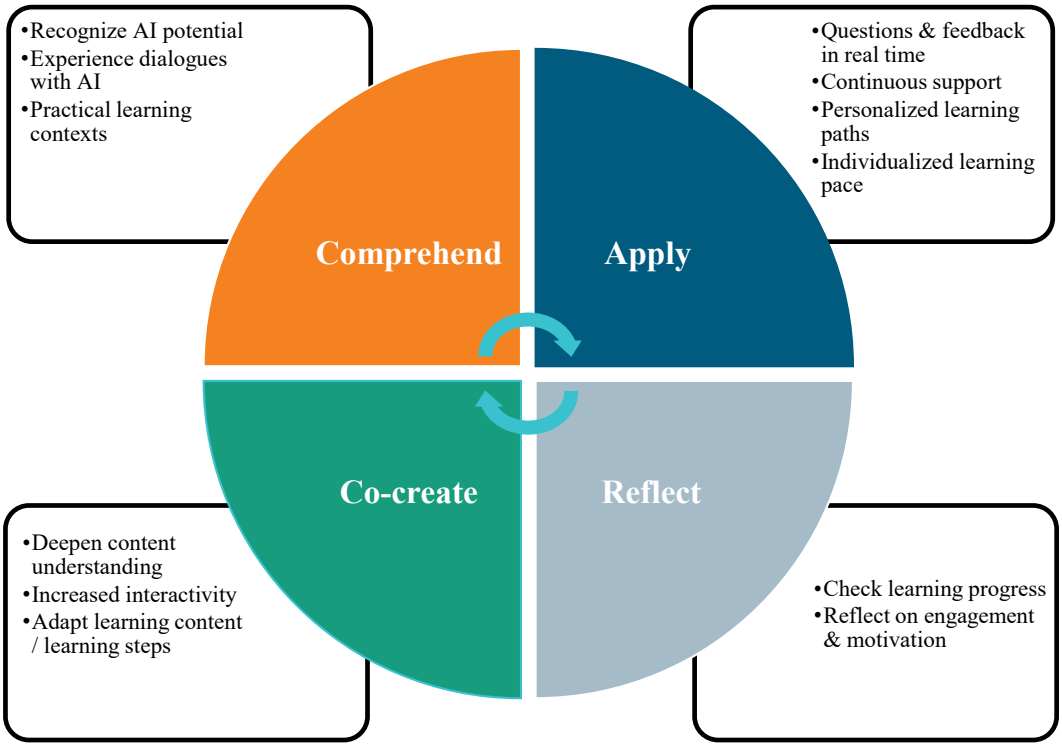


Figure 2: *AI as a conversational learning companion.*

controlled trial, [17] evaluated an AI-supported tutor based on generative AI and evidence-based principles from educational and learning sciences, which offers personalized support and immediate feedback. Compared to an in-person course, the students achieved significantly greater learning gains in less time and reported higher engagement and stronger motivation. The authors mainly attribute these effects to personalized feedback and individual learning pace—key features of conversational learning assistants [17].

In addition to cognitive effects, conversational interaction with AI systems also influences affective factors in learning. A comprehensive meta-analysis by [18] demonstrates a strong positive effect of AI on learners' self-confidence (Cohen's d ≈ 1.24). AI systems promote self-efficacy, particularly through individualized scaffolding, continuous feedback, and the ability to autonomously manage learning processes [18]. At the same time, they create psychological safety by allowing learners to ask questions without fear of social judgment. This conversational interaction reduces anxiety, while also promoting active engagement with learning content.

In the context of vocational education and training, it is also evident that AI acts as a systemic driver of transformation. An international analysis by [19] identifies key areas of application such as personalized training delivery, automated competency assessment, and AI-supported learning guidance [19]. Evidence is particularly compelling in authentic learning contexts: learners who work with AI tools achieve significantly higher competence in performing complex tasks and benefit from improved transitions into the labor market.

In summary, the studies presented illustrate that AI, as a conversational learning companion—particularly through personalization, immediate feedback, adaptive support, and continuous interaction—has the potential to positively influence both cognitive and affective learning processes [14, 16, 17]. Particularly in the field of continuing vocational education, AI has the potential to create new opportunities for self-directed, work-integrated, and needs-based learning [15, 18].

As **Figure 2** shows, AI as a conversational learning companion can support learners throughout the entire learning process—from understanding and applying knowledge, through reflection, to actively shaping learning content. The potential lies primarily in the individual adaptation of learning processes, the promotion of engagement and motivation, and the continuous support of learning through conversational interaction.

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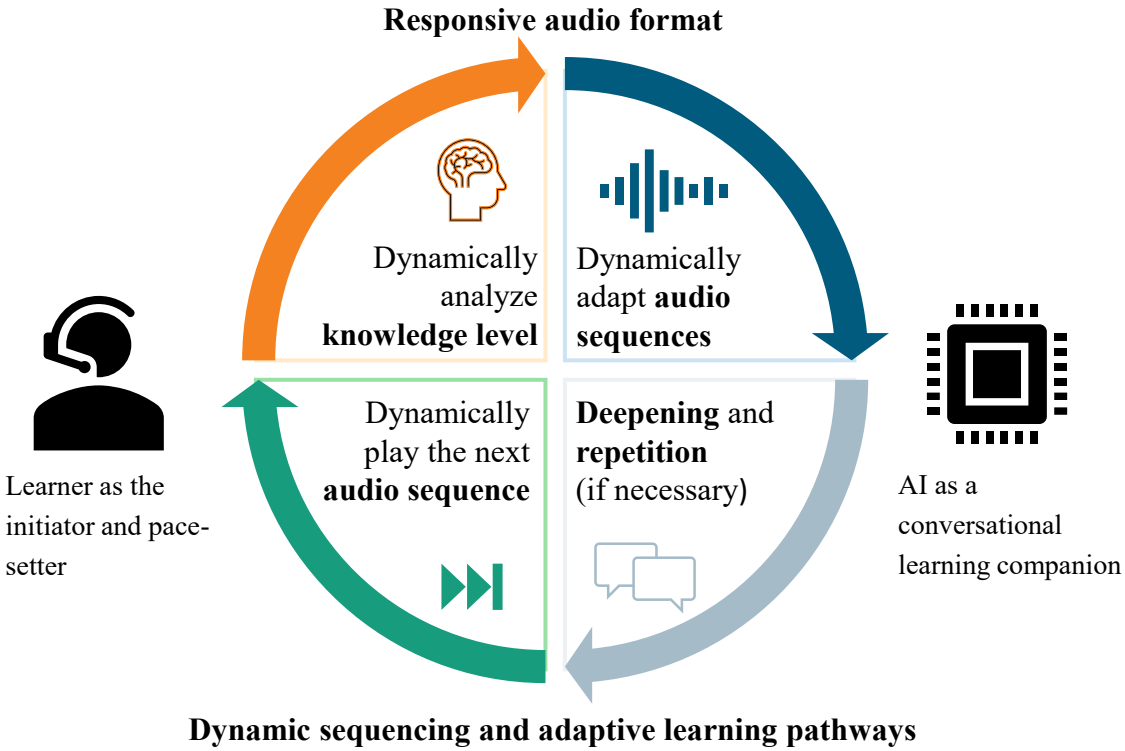


Figure 3: *AI-supported audio learning.*

AI-supported audio learning in continuing vocational education

A comparison of the traditional linear audio approach and conversational AI learning highlights a paradigm shift in continuing vocational education. While the conventional audio format is characterized by its linear structure and narrative coherence, AI learning guides offer the adaptability and interactivity necessary to overcome individual learning barriers.

The synthesis of both approaches gives rise to the concept of AI-supported audio learning, illustrated in **Figure 3**. In this model, passive reception is thereby transformed into an active, adaptive, and interactive learning process. The primarily receptive role of the listener in the traditional linear model is expanded to include active participation in shaping their individual auditory learning path. Instead of a fixed, sequential arrangement of learning units and chapters, AI-supported audio formats enable dynamic sequencing.

Figure 4: *Dimensions of potential for AI-supported audio learning.*

Potential Dimension	Benefits of AI-Supported Audio Learning
Instructional Design	Personalized learning content, individualized feedback, self-paced learning, adaptive content elaboration
Self-Efficacy	Increased learner engagement, enhanced psychological safety, improved long-term knowledge retention
Work Organization	Training-on-the-job, authentic workplace exercises, microlearning, hands-free, screen-free, eyes-free learning
Competence Management	Development of future skills, transfer of learning to practice, AI literacy, voice interaction skills

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Based on the user's level of knowledge or questions, the system can adjust the sequence of audio nuggets in real time or generate in-depth explanations that were not originally included in the source file. This transforms audio from a static repository of content into a dynamic, responsive ecosystem that not only makes professional learning more efficient but also more accessible by reducing barriers to participation and technological complexity. Building on this conceptual framework, **Figure 4** illustrates exemplary dimensions of the potential of AI-supported learning companions in the context of audio-based learning.

In summary, the convergence of audio training and artificial intelligence marks a turning point for work-integrated competency development. While conventional audio formats have long supported the flexibility required for training-on-the-job, integrating AI overcomes the remaining limitation of static content. As a result, audio evolves from a passive medium for information delivery into a proactive conversational learning companion

In a working world increasingly shaped by future skills and the confident use of AI systems, dialog-based audio learning offers low-threshold access to complex content. It transforms microlearning from an isolated episode into continuous, voice-guided support that can be integrated into the workflow. This makes the vision of immersive, personalized learning a reality—one that not only enhances knowledge retention but also empowers learners to retrieve knowledge in context and deepen their understanding through direct conversational interaction. Ultimately, AI-supported audio learning is emerging as a key enabling technology capable of meeting the growing demands for dynamic, efficient, and learner-centered continuing vocational education and training.

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AI-Based Identification of Knowledge Transfer Situations

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When knowledge is lost in product development, it is usually not due to a lack of expertise, but rather to complex situations in which information, experience, and artifacts are not effectively integrated. Daily scrums, in particular, reveal how quickly misunderstandings can arise or important details can be overlooked. An AI-based real-time multi-agent system is designed to recognize typical patterns in knowledge transfer and provide targeted support.

Keywords
knowledge transfer, product development, scrum, multi-agent system, multimodal AI, reinforcement learning



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AI-Based Identification of Knowledge Transfer Situations

An adaptive multi-agent system for agile product development in engineering

Georg David Ritterbusch, Ravil Goetzke and Norbert Gronau, University of Potsdam

Although it has been demonstrated that organizational knowledge transfer can be improved in principle, there is still no automated approach for identifying patterns in complex, context-dependent, and domain-specific knowledge transfer situations. This conceptual article therefore examines and characterizes knowledge transfer situations using the real-world example of product development in engineering. Furthermore, a concept for an adaptive, AI-based, real-time multi-agent system uses data to recognize recurring patterns in knowledge transfer situations and enables context-sensitive interventions. Finally, an outlook is provided on AI-based learning mechanisms (reinforcement learning) that can be used to adapt interventions for higher effectiveness in the long term.

Agile product development in engineering is characterized by a high rate of change, cross-disciplinary collaboration, and continuous alignment between product, process, and organization. Particularly in the development of mechatronic systems, it is therefore not sufficient to view product development as a linear sequence of technical steps. Rather, short cycles give rise to knowledge transfer situations in which, for example, task and artifact status, uncertainties, or even courses of action are exchanged [1, 2].

The daily scrum is particularly well-suited for this purpose because, according to the scrum methodology, it reviews daily progress toward the sprint goal and adjusts the plan accordingly. Furthermore, the daily scrum is limited to 15 minutes, making it a formally recurring and comparable process [3]. In mechatronics, however, this coordination becomes more complex, as knowledge transfer involves not only language but also CAD models, prototypes, drawings, test reports, photos, or experiential knowledge. As a result, the daily scrum evolves from a purely status-based meeting into a condensed knowledge transfer situation [3, 4].

To analyze such situations, it is essential to differentiate between various forms of knowledge [5, 6]. In **Figure 1**, building on the SECI model developed by Nonaka and Takeuchi, Grum and Gronau distinguish between tacit, explicit, and embedded knowledge.

In product development, tacit knowledge manifests in routine problem-solving behaviors, judgments based on experience, or intuitive anomaly identification based on motor or sensory skills. Explicit knowledge, on the other hand, can be described and conveyed using a wide variety of communication tools including graphics, images, text, or speech. Embedded knowledge is embodied in artifacts such as models, components, or experimental setups.

The intertwining of these forms of knowledge is a defining characteristic of knowledge transfer within product development teams. This knowledge transfer occurs in a multimodal and situation-dependent manner, which often makes it difficult to reconstruct from individual documents or transcripts alone [4, 7].

Extending the SECI model is important for classifying knowledge transfer situations in engineering, as it accounts not only for knowledge conversions like socialization, externalization, combination, and internalization, but also extraction, codification, decodification, intraction, and transformation. It highlights that knowledge transfer occurs not only in conversation but also in the interpretation of

Figure 1: *Conversions according to the extended SECI model and its application in product development [5].*

Source Goal	Tacit knowledge	Explicit knowledge	Embedded knowledge
Tacit knowledge	Socialization	Externalization	Intraction
Explicit knowledge	Internalization	Combination	Decodification
Embedded knowledge	Extraction	Codification	Transformation

Key Knowledge form | Knowledge-based activities | Knowledge-intensive tasks

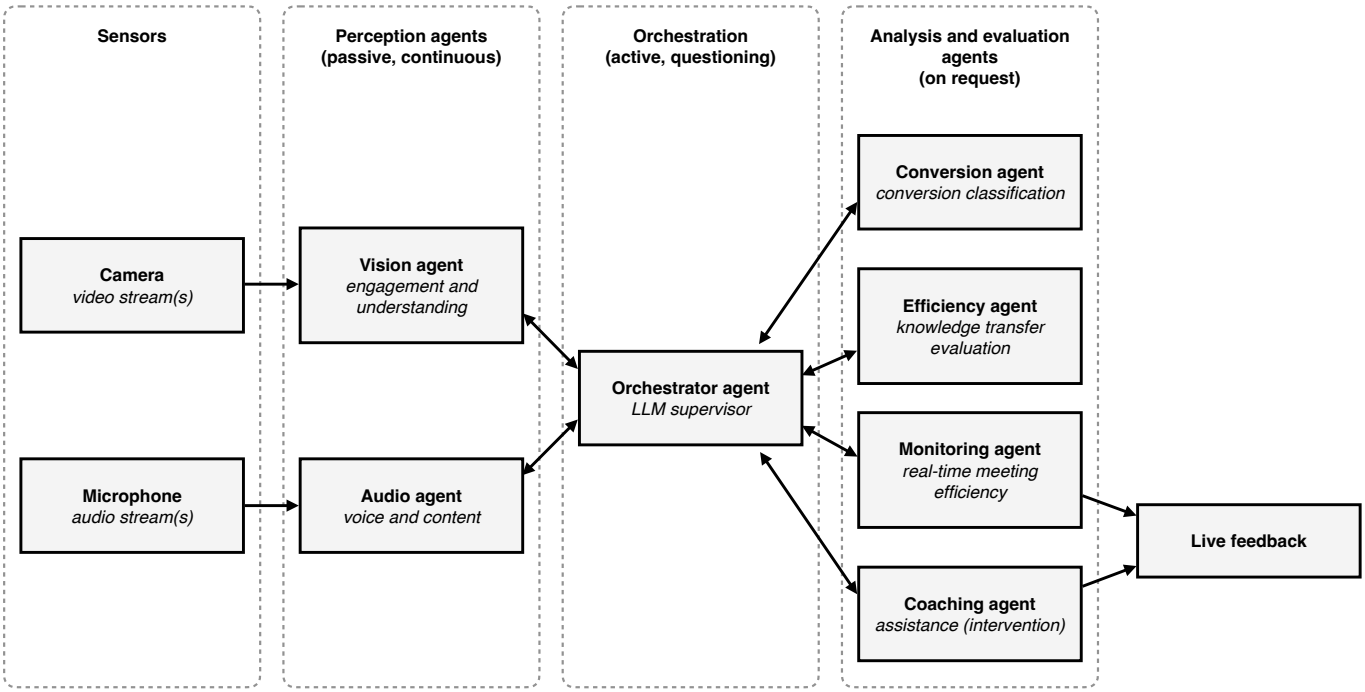


Figure 2: *Architecture of an adaptive, AI-based, real-time multi-agent system for intervention in knowledge transfer situations.*

documents, the derivation of insights from artifacts, or the creation of new designs.

In addition, there are influencing factors that significantly shape the quality and speed of knowledge transfer. Preliminary studies show that the competence of team members, the complexity or novelty of the knowledge, time pressure, and team composition are particularly relevant. Furthermore, "stickiness"—that is, the difficulty of the transfer in terms of duration or the need for follow-up questions—is a decisive influencing factor [8–10]. In more advanced conceptualizations, distinctions can also be made between sender-receiver relationships, confidentiality, organizational culture, communication culture, language proficiency, the richness of media content, the degree of media synchrony, and error-prone process dynamics [9, 11, 12].

In a real-world product development situation, however, these factors cannot be observed as isolated variables. They manifest in patterns such as follow-up questions, stalling conversation, repeated externalization, a lack of connection to prior knowledge, frequent references to documents, or shifts between conversation and collaborative work on artifacts. It has been empirically demonstrated that targeted intervention can improve knowledge transfer. However, no approach has yet recognized such patterns in on-site situations in a domain-specific and automated manner for real-time intervention [1, 13, 14].

Daily scrums in product development are particularly suitable as a use case, as they occur regularly but differ in terms of their tasks, artifacts, team configurations, and problem statuses. They can thus be understood as microprocessual knowledge transfer situations in which purpose, content, actors, media, timing, artifact references, and progression shape the situational context. For AI-supported identification, therefore, pure semantic analysis of spoken language is no longer sufficient. Rather, conversion patterns, artifact references, and other forms of interaction must be captured in a multimodal and process-sensitive manner.

While generic meeting summarization systems can extract decisions, consensus, or action items from conversation, they often treat meetings as linear transcripts and capture negotiation processes, temporal structures, and nonverbal signals only to a limited extent [15, 16]. For knowledge transfer in product development, an architecture is required that combines linguistic, audiovisual, and contextual information with an intervention-based situation assessment.

Adaptive AI-based real-time multi-agent system

This problem highlights the need for a distributed, context-sensitive system architecture. A monolithic approach

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would be unsuitable for this use case for two reasons. Firstly, data sources such as audio, video, documents, role information, or prototype images are heterogeneous. Secondly, partial decisions must be made across different time horizons. Real-time analysis during a meeting requires different methods than those used for downstream verification, labeling, or the adjustment of interventions. Therefore, an adaptive multi-agent system is proposed that builds on existing process and activity layers [7, 17–19]. In **Figure 2**, the architecture of the adaptive AI-based real-time multi-agent system is divided into five functional levels.

In this architecture, the course of the meeting is primarily captured via camera and microphone. The first layer consists of the sensor system. This is followed by two perception agents that operate passively and continuously. The vision agent processes the video stream into observable features such as attention, agreement, irritation, and understanding conveyed through facial expressions or gestures [20, 21]. In the future, the goal is to visually capture not only the participants but also the artifacts used in the meeting. The audio agent processes the audio stream into transcripts, detects speaker changes (diarization), and extracts prosodic features such as stress, uncertainty, or questioning intonation [22]. It is crucial that these agents initially only collect evidence and do not yet trigger any interventions. This separation is important because nonverbal and paralinguistic signals can only be reliably interpreted in conjunction with the situational context.

The orchestrator agent forms the operational core of the architecture. It assumes the role of a context-aware decision-making module that places observations from the perception agents into a situational context. Unlike a purely data-driven processing chain, the orchestrator agent does not operate continuously at the same level of abstraction. Rather, it invokes specialized analysis and evaluation agents only when the perception data indicate a need for clarification. This may be the case when an explanatory pattern repeats itself, follow-up questions increase, agreement is lacking, or an agenda item takes up a disproportionate amount of time. The orchestrator agent thus assumes the role of context control and task distribution [18, 23].

The four analysis and evaluation agents become active upon request. The conversion agent assigns a sequence of interactions to a presumed knowledge conversion, asking which form of knowledge is being converted into another form in a specific situation. The efficiency agent synthesizes linguistic, temporal, and interactive features to assess the quality of the knowledge transfer. The monitoring agent continuously synthesizes these evaluations into a concise overview of the meeting's current status, in the form of a traffic light system that updates in real time. Only when a reliable potential for improvement becomes apparent (the light turns red or yellow) is the coaching agent called upon to generate a specific intervention or recommendation for action. In this way, the continuously recorded analysis and evaluation results are transformed into situation-specific live feedback. The architecture does not focus on communication in general but asks whether an intervention is necessary in each specific knowledge transfer situation to improve the knowledge transfer.

Reinforcement learning for the adaptive control of interventions

The architecture is only fully adaptive if it can also continuously adjust the selection of interventions based on their observed effects. Reinforcement learning is particularly well-suited for this task, since recurring knowledge transfer situations can be described as sequences of states, decisions, and feedback. In reinforcement learning, an AI system gradually learns an appropriate action strategy based on feedback regarding the effects of its decisions. For example, the system not only recognizes a communication difficulty but also learns which intervention is more likely to lead to an improvement in knowledge transfer in that context. In human-AI interaction, reinforcement learning is particularly useful for adapting to human behavior or new interaction partners, and for coordinating highly dynamic environments [24].

For the use case considered here, the state is derived from the situation description aggregated by the orchestrator agent. This includes the presumed knowledge conversion, follow-up questions, indications of understanding or lack thereof, speaking shares, duration, and intervention history to date. The agent-based AI system has only a few predefined intervention options, such as a clarification request, a suggestion for visualization, a recommendation to delegate, or deliberate non-intervention.

The learning signal (reward function) for reinforcement learning should not be based solely on a shortened meeting duration. Qualitative aspects of collaboration can also be decisive, such as perceived fairness, transparency, or the opportunity for personal participation [25]. For this reason, both objective effects—such as faster clarification or fewer follow-up questions—and subjective assessments of usefulness should be incorporated [24, 25]. Methodologically, this calls for a phased approach in which the agent-based AI system is first trained offline using annotated meeting data and then adapted online within a limited decision space. Adaptive query processing methods enable the timing and form of feedback to be specifically controlled [26]. For example, approving,

rejecting, ignoring, or correcting an intervention can also be used as learning signals for reinforcement learning.

Such a learning mechanism requires clear boundaries, as feedback on interventions is not neutral but shaped by roles, expectations, and values. The system should therefore not decide independently on the appropriateness of an intervention but rather gradually adapt its suggestions based on observed effects. The human remains part of the decision-making loop and the system learns from recurring knowledge transfer situations which interventions are appropriate under which conditions [24, 27].

From pattern recognition to effective intervention

It is difficult to capture knowledge transfer situations based solely on transcribed speech. In agile product development, knowledge transfer arises in the interplay of verbal interaction, technical artifacts, nonverbal cues, and situational process dynamics. The example of the daily scrum illustrates that, while these knowledge transfer situations recur in form, their content is shaped by changing tasks, team configurations, and problem statuses. A multimodal and context-sensitive architecture is therefore required for situational classification. The proposed real-time multi-agent system functionally separates recording, evaluation, and coaching, and focuses analysis on patterns in knowledge transfer that are relevant for intervention.

The conceptual framework of this article forms the basis for further empirical investigations. The proposed architecture is to be implemented as a prototype and adapted using appropriate data collection and evaluation routines. Recurring knowledge transfer situations in daily scrums will be recorded, processed, and annotated (data labeling) to create training data for the detection of knowledge conversions and intervention needs. Building on this, the system will be tested in live-lab studies and, in the future, in field studies. In addition to data quality, real-time capability, and context-sensitive interpretation of multimodal signals, quantitative potential should also be considered. This can be measured based on transfer duration, follow-up questions, subsequent coordination needs, the quality of work outcomes, and the AI system's performance. In addition, feedback from participants regarding usefulness and acceptance should be incorporated to evaluate the impact of AI-generated interventions on knowledge transfer.

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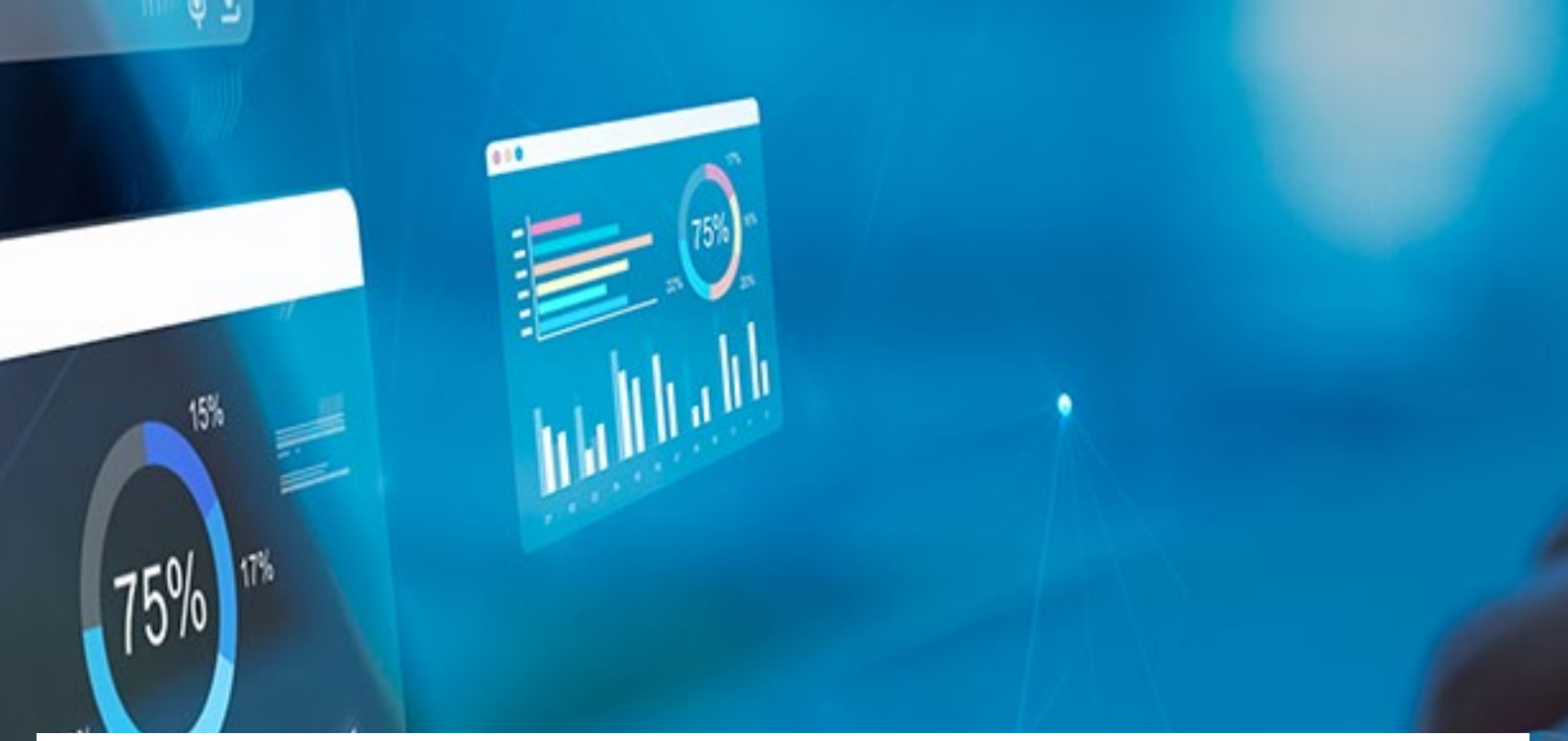
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Generative AI in Organizational Knowledge Management

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Generative AI can support organizational knowledge management—especially when explicit, organization-specific, and implicit knowledge is required. Process optimization that enhances human capabilities is achieved when users integrate their domain expertise with their AI proficiency. This results in augmentation at both the individual and organizational levels.

Keywords
firm-specific knowledge, generative artificial intelligence, tacit knowledge, AI competence, AI user behavior, maintenance, knowledge management



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Generative AI in Organizational Knowledge Management

AI literacy as a prerequisite for augmentation

Uta Wilkens, Valentin Langholf and Niklas Obermann, Ruhr University Bochum

Generative Artificial Intelligence (GenAI) offers new opportunities for organizational knowledge management, particularly when it comes to learning processes at the interface between explicit, firm-specific, and tacit knowledge. Its use is therefore of particular interest for application areas such as industrial maintenance. Based on a mechanical engineering case study, this article demonstrates that augmenting both processes and employees with GenAI requires AI literacy combined with professional skills.

The use of generative artificial intelligence (GenAI) ideally leads to augmentation—both of the workforce and of the organizational processes in which it is deployed [1]. In general terms, augmentation means that something grows in size or develops positively. According to a meta-analysis by Bear et al. [1, p. 760], this applies to four distinct areas: "body, cognition, work, and performance."

In industrial applications—such as customer service or maintenance work—these four areas should not be considered in isolation. The augmentation of the individual, work output, and organizational performance are interrelated. From a sociotechnical perspective, the use of AI serves the joint optimization of both people and the organization [2].

However, areas of tension may arise. For example, an increase in organizational output can come at the expense of employee skills because AI-based automation means that they no longer apply their expertise in task completion. A user study by Lee et al. [3] suggests that individuals tend to limit their critical thinking when collaborating with GenAI.

With regard to organizational performance, Pereira et al. [4] show that the productivity potential of AI in operational applications often remains unrealized at U.S. companies. They note that this is not due to the technology itself but rather a failure to align the technology with the organizational context.

Organizational knowledge management is one fruitful area for GenAI optimization [5]. The primary aims are:

1. to ensure that the knowledge critical to organizational performance and problem-solving is available at all times and
2. to continuously develop the relevant knowledge base.

This includes knowledge about (technological) artifacts, organizational routines, and processes, as well as the individual, person-specific knowledge of employees **(Fig. 1)**. The goal is to make this knowledge available independently of the individual knowledge holders and to ensure it is accessible at all times to employees involved in the organizational performance process [6].

When GenAI is deployed, it provides codified knowledge but also facilitates internal knowledge exchange—from problem identification to problem-solving—for the mutual benefit of both the organization and the individual. GenAI-based knowledge management systems can strengthen an organization's resilience against critical influences, protect against the loss of knowledge holders, and at least partially compensate for the shortage of skilled workers [7, 8]. It can also enhance the capacity of available employees to act by reducing their dependence on other individual knowledge holders and, ideally, enabling them to gain new knowledge and experience.

This is where our article can contribute. We aim to specify the conditions under which GenAI contributes to an augmentation that strengthens system resilience while simultaneously developing the capabilities of human experts [1]. To this end, we focus on organizational knowledge management and specify the challenges for typical application areas such as industrial maintenance. We also identify the necessary prerequisites with regard to employees' AI literacy. A qualitative empirical study carried out at a medium-sized pump manufacturer illustrates approaches to the joint optimization of GenAI, revealing that the use of GenAI leads to the augmentation both of processes and members of the workforce. Whether this succeeds depends on whether professional skills and AI literacy are developed interdependently.

Augmentation of processes through GenAI: Knowledge management in industrial maintenance

Industrial maintenance can be corrective—that is, focused on repairing machines when malfunctions occur—or preventive, preventing malfunctions in the sense of predictive maintenance [9]. The unique potential of GenAI for optimizing industrial maintenance is seen in the

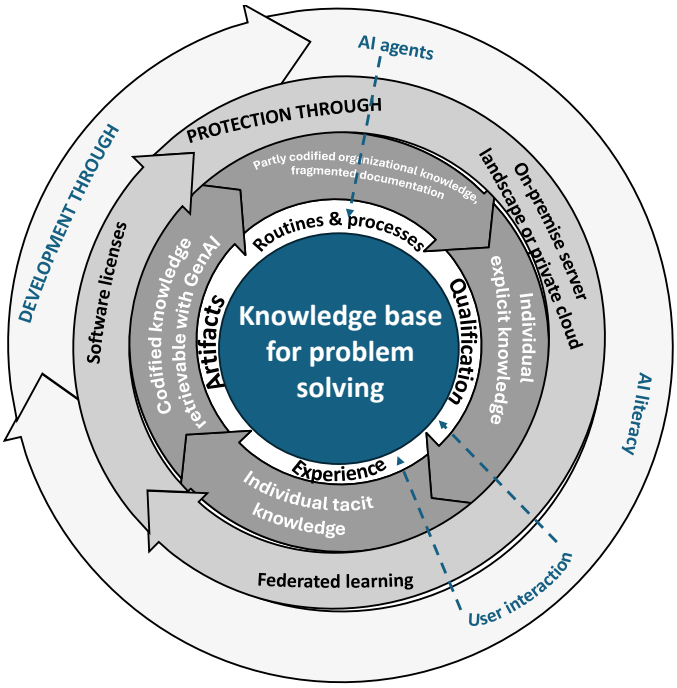


Figure 1: *Prerequisites for the development and protection of a company's knowledge base.*

predictive function [10, 11]. Using large language models (LLMs), AI agents can be generated to take on prospective maintenance roles [12] requiring access to libraries of codified maintenance-related knowledge. Key performance indicators for AI-based augmentation range from reduced downtime to increased resilience [13]. First of all, a knowledge management system must be established.

With regard to establishing a knowledge management system for the field of industrial maintenance, it should be noted that operational work processes require both explicit and tacit knowledge [14]. Explicit knowledge refers to original blueprints, subsequent modifications, limit values, functionalities, or other characteristics of machines and systems—that is, artifacts in the broadest sense. This knowledge is usually documented, although the quality of the documentation varies.

Tacit knowledge is associated with human expertise and experience. It is rarely codified, more ephemeral and has a procedural or episodic character as it is developed informally in the course of work. Experienced employees recall critical incidents and the ways in which these were resolved, including using unconventional methods.

Explicit and tacit knowledge are not distinct but interconnected to varying degrees [15], both in the case of organizational and individual knowledge. The latter comprises both explicit components—i.e., those reflected in qualifications—and tacit components—i.e., those built on experience. In industrial maintenance, all components of knowledge are required. Procedural knowledge about system environments goes hand in hand with knowledge about the technical artifact. Due to the lack of documentation, tacit knowledge appears to be a greater bottleneck than explicit knowledge and is particularly critical to success: "Tacit knowledge is fundamental in maintenance due to the diverse and often non-routine nature of tasks, the involvement of multiple disciplines, and the constant evolution of technology" [7, p. 1].

If a GenAI-supported knowledge management system is to be established, it must include all knowledge components **(Fig. 1)**:

1. Bibliographic knowledge about the machines and systems (artifacts) already mapped in GenAI and

2. supplementary firm-specific knowledge about artifacts and organizational routines and processes. This is documented in some places but is mostly unstructured.

3. Person-specific knowledge, which includes the skills and knowledge acquired by employees in training, as well as

4. their tacit knowledge built up through experience, which is often difficult to make explicit.

The GenAI system provides the first knowledge component and prioritizes it over other types of knowledge when it

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comes to problem-solving. The second component requires operational data preparation, a process in which GenAI can also provide support. To do this, LLMs must be able to access knowledge codified within the organization. This can be achieved by defining distinct roles for AI agents to handle this task [16]. Qualifications, as the third component, come into play through personnel deployment, whereby staff members are assigned tasks that match their skills and apply these skills beyond their own workstations to broader organizational operations. Dealing with AI can present an additional challenge here. For tacit knowledge—the fourth component—ways are being sought to make it available independently of individual experts [7, 17]. This can occur through the use of and interaction with AI [5].

Even in his early writings, Nonaka [14, 18] addresses how to make tacit knowledge accessible and identifies various learning processes. A key focus is the specific contribution of tacit knowledge for gaining and sustaining competitive advantages. To make tacit knowledge accessible independently of specific individuals, it must either be externalized through documentation or learned from one tacit source to another through socialization, whereby a task domain is intuitively understood within a shared experiential space and internalized by other experienced individuals [18]. Externalization increases reach while potentially diminishing the specific advantages that tacit knowledge offers. Socialization better preserves the knowledge but is limited in its scope.

GenAI-based organizational knowledge management can support both learning approaches [5]. GenAI makes it possible to extract previously inadequately documented organizational and individual knowledge from a wide variety of available sources (email threads, voice messages, brief minutes, digital notes, etc.) and keep it readily accessible for critical problem-solving situations. User queries reveal the task areas in which additional knowledge is needed, so that the social system becomes recognizable and visible through the digital system [19]. This interaction also leads to system development that, in the future, will enable LLM-based preventive condition monitoring using operational documents.

When it comes to learning from tacit to tacit, federated learning [20] provides a useful security measure, as it allows for the structured use of data without prior externalization. Questions related to what, where and how knowledge is required is specified from the user logic. This is a considerable advancement compared to early knowledge management systems, which were heavily oriented toward the perspective of the knowledge holder [5]. GenAI instead mediates from the perspective of users. It should be noted that an LLM continuously modifies the knowledge base in this process, which poses challenges for reliability. For this reason, augmentation through GenAI always requires a high level of user competence.

Augmentation of individuals through GenAI: AI literacy and user behavior

Augmentation aims to enable employees to expand their capability in performing tasks and solving problems, rather than gradually losing expertise or ceding it to technology [21]. The set of skills required to effectively utilize AI for problem-solving while simultaneously developing one's own skill set is referred to as AI literacy. This encompasses not only the competent use of GenAI tools but also the background knowledge of large language models (LLMs) necessary to anticipate how the technology operates. Another dimension is the critical reflection on AI-generated suggestions, supplemented by an ethical assessment of the impacts of AI use. Promma et al. [22] were able to identify four AI literacy dimensions of working with GenAI through factor analysis:

1. User competence to consistently leverage GenAI for problem-solving processes (also described, in simplified terms, as prompt engineering);

2. basic knowledge of how GenAI works [23];

3. analytical skills for critically reflecting on AI-generated propositions and the underlying data. This capacity for reflection requires the domain expertise to make judgments independently [24];

4. ethical responsibility regarding both the origin of the data and the overall consequences of AI use [3, 25].

GenAI user studies show that individuals' critical reflection is changing. The critical evaluation of a proposition is no longer primarily driven by domain knowledge but has shifted to the question of AI trustworthiness [3]. This could imply that augmentation on the system level goes along with a negative impact on employees in the long run, as their contribution is successively based less on their own expertise but increasingly on their situated trust in the AI.

In the context of industrial maintenance, this would mean that employees who draw on AI support and expand their GenAI-specific competence would less frequently activate their professional maintenance skills. As a result, their individual explicit and tacit knowledge would gradually decline.

User behavior is therefore decisive in determining how AI literacy is developed in combination with professional, domain-specific expertise. The conditions under which simultaneous augmentation at both the organizational

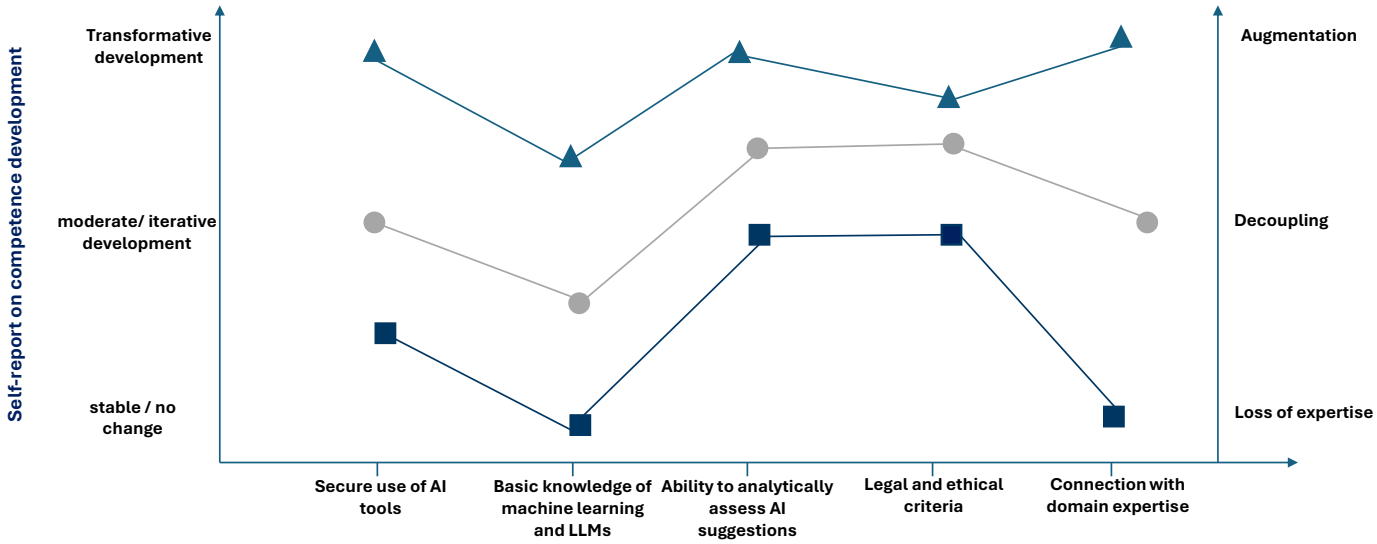


Figure 2: *Case study on the development of AI literacy in combination with domain expertise (author's own representation of the data processing from [26]).*

and individual levels—or joint optimization—is achieved, and the conditions under which it fails, require empirical validation.

Case study on AI interaction at a pump manufacturer

Between February and October 2025, Langholf et al. [26] conducted a case study at a medium-sized pump manufacturer that is part of a larger American corporation. There, GenAI (Copilot) was introduced for all employees with desktop workstations, following instructions from the American parent company. This applies to all positions in technical service and maintenance, though it is not limited to these departments. Overall, the goal was to optimize work processes while establishing a knowledge management system.

The case study involves monitoring the implementation phase to observe changes in processes, including the augmentation of both processes and individuals. Qualitative user interviews were conducted at two points of measurement, each with twelve employees, first during the implementation period and then six months later. Information about the user interaction with GenAI was captured from self-reports. The collected data was then analyzed using longitudinal thematic analysis [27, 28].

Overall, it can be observed that employees develop AI agents to optimize operational processes and mutually train each other in prompt engineering with the help of a so-called champion program.

Process optimization, process innovation and organizational learning

On the organizational level, two issues of augmentation could be observed: the enhancement of efficiency in existing processes and the advancement of organizational learning processes for innovation. For optimization, AI agents are used to translate recurring prompts and workflows into automated processes that can be systematically reproduced. Entire process chains can be automated in this way, with AI agents reducing multi-step workflows (e.g., data search, enrichment, and verification) by eliminating manual intermediate steps (e.g., searching for specific pieces of information). AI agents lead to significant time savings, particularly for repetitive tasks, both in terms of individual task completion and overall process times.

For process innovation, an internal database of frequently used documents is further developed towards an organizational knowledge management system, systematically utilized by AI agents to extract support for individual requests. This facilitates the onboarding and training of employees regardless of the availability of individual experts, while avoiding delays in the work process caused by searches for knowledge. Based on the positive experiences in individual use cases and as an expression of internal organizational learning, each department develops AI agents for specific problems. This fosters organization-wide, experimental process innovation.

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Workforce augmentation

Ideally, process augmentation goes hand in hand with workforce augmentation. The qualitative interviews reveal that this requires a specific type of user, which can currently only be observed among a sub-group of employees. Workforce augmentation occurs when the affected workers combine their AI literacy with domain expertise across the four aforementioned AI literacy dimensions **(Fig. 2)**. Three distinct user types were identified. They differ in how AI literacy is developed according to Promma et al.'s dimensions [22] and how it is linked to—or decoupled from—professional expertise, i.e. in customer service or maintenance.

The "augmented type" experiences competence development while enhancing cognitive skills beyond GenAI usage by also including creative outcomes and extended contextual domain knowledge. This goes along with process optimization activities in terms of improved depth of solutions, uninterrupted workflow, etc.

The "decoupled type" uses AI only for peripheral tasks that do not—or hardly—touch upon their own core professional qualifications (domain expertise). This decoupling is a strategy consciously pursued by the individual to protect their expertise. The user's knowledge of prompt engineering and their background knowledge of LLMs is less extensively developed compared to the first type. While protecting their expertise the employees do not experience additional development or expansion, meaning that the protected aspect may gradually become outdated.

The "loss of expertise type" comes about as a result of fear that human competence may decline due to AI usage. Here, the ethical and reflective dimensions of AI literacy are developed slightly but remain separated from other dimensions of AI literacy or professional domain-specific skills.

The results of the case study show that the joint optimization of processes and employees is ensured when AI users undergo a transformative development across all dimensions of AI literacy—user competence, foundational knowledge, analytical and critical-reflective skills, and ethical judgment—and combine them with their domain expertise when performing tasks. Only with these prerequisites does individual explicit and tacit knowledge expand. In this scenario, prompting skills continuously grow, routines for comprehensive critical review are established, and new workflows emerge based on increasing individual competences. In this case, individual and organizational knowledge provided by the organization's process landscape continuously co-evolve **(Fig. 1)**.

Summary of GenAI-based knowledge management in industrial maintenance

The aim of our study was to better understand the conditions under which the use of GenAI can support operational knowledge management in industrial maintenance by simultaneously augmenting both processes and human expertise [1]. A necessary condition is the ability to handle the diverse and interlinked knowledge components required for operational maintenance. Accordingly, the approach encompassed explicit knowledge about artifacts, firm-specific knowledge about routines and processes, as well as the explicit and tacit knowledge of the maintenance employees.

If GenAI-based augmentation goes along with company-specific and individual knowledge as critical sources of competitive advantage, a commercially available GenAI solution must be combined with an on-premises approach or a private cloud solution hosted in Europe. This means that the technology is either hosted and operated on the organization's own, secure server infrastructure [29] or that a high level of security is ensured in a cloud environment. Under these safety conditions, an organizational knowledge base can be developed and accessed by AI agents. Moreover, the users' interaction with the GenAI fosters the sharing of personal explicit and tacit knowledge within an organization while protecting it from access through potential external users. To enable this process, AI agents must be programmed with different roles for knowledge processing and structuring **(Fig. 1)**.

According to the case study results, achieving an augmentative effect—in which employees expand their expertise and tasks while contributing to workflow optimization—requires a high level of AI literacy combined with domain expertise [24]. Comprehensive AI literacy training tailored to specific operational application areas is therefore a key practice for organizations. Core outcomes include efficiency gains and enhanced resilience [13] on both the process and individual levels.

The case study analysis is an example of an in-depth exploration of organizational knowledge management for a specific GenAI application area, which takes into account both the process and individual levels. Statements regarding the frequency of augmentation and GenAI user types require a quantitative research approach, which may be the subject of future studies.

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Experiential Knowledge Powered by AI

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How can companies preserve and effectively utilize their valuable experiential knowledge? Whether in assembly, document retrieval, or field service, the success of AI-based solutions depends crucially on a strategically maintained knowledge base, system settings tailored to the specific use case, and acceptance by employees.

Keywords
experiential knowledge, RAG system, knowledge utilization, AI, knowledge management, organizational development

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Experiential Knowledge Powered by AI

Practical insights from industry

Martin Schmauder, Gritt Ott and Bianca Windisch, Dresden University of Technology

The use of experiential knowledge is a key success factor for companies. Based on four corporate case studies, this article analyzes the technical, organizational, and personnel challenges associated with the use of retrieval-augmented generation (RAG) systems. The results show that the success of such systems depends on the strategic development and maintenance of the knowledge base, as well as on employee engagement.

Preserving and utilizing experiential knowledge continues to pose significant challenges for companies [7]. This article focuses specifically on experiential knowledge that is relevant for making decisions not guided by formalized policy, reducing task complexity, or optimizing time and resource consumption [1, 4]. Currently, there is a risk of losing experiential knowledge due to the retirement of employees, workforce reductions, or changes in job responsibilities resulting from automation and digitization [7]. As our research over the past 15 years shows, companies must respond by implementing solutions for identifying, preserving, and making experiential knowledge available [5, 8]. At the same time, however, effective strategies are needed to continuously identify and integrate newly emerging knowledge into the corporate knowledge base [3].

With the development of generative AI, particularly retrieval-augmented generation (RAG), high expectations are placed on technical support for capturing experiential knowledge [9]. RAG systems combine language models with intelligent retrieval mechanisms for local corporate knowledge bases, enabling context-sensitive access [6].

Although RAG systems hold great potential for capturing experiential knowledge, their practical implementation—especially in small and medium-sized enterprises—poses significant technical, organizational, and personnel challenges. In addition to building suitable knowledge bases, issues related to data preparation, system integration, and operational implementation must be addressed. The PAL project (PerspektiveArbeit Lausitz, funded by the German Federal Ministry of Research, Technology and Space 2021–2027) developed a RAG tool addressing these requirements. The tool has been tested in various business contexts since 2022 [9].

Research objective: Identify framework conditions for the deployment of RAG systems

This research aims to analyze the framework conditions for the successful use of RAG to capture experiential knowledge. It also derives recommendations for the successful implementation of AI-powered solutions.

The study uses an action research approach [2], combining scientific knowledge acquisition with the collaborative development and testing of practical

Figure 1: *Characterization of the business cases.*

Case	Company	Deployment scenario	Company size
Company 1 / Case A	Manufacturing company in the mechanical engineering sector	Stationary assembly and commissioning processes	Approx. 360 employees
Company 1 / Case B		Locating documents in file archives (approx. 10 years)	
Company 1 / Case C		Subassembly processes	
Company 2 / Case D	Maintenance and service activities for equipment at the customer's site		Approx. 60 employees
Laboratory testing	Comparative testing of various RAG systems based on the knowledge gained from Case D **(Fig. 4)**		

	Supported file formats	Output	Feedback option
RAG system developed in-house (WINI – Knowledge and Information Interface)	PDF	List of search results as links to the document (10 results by default) Average response time: approx. 1.6s	Feedback for each document in the chat; verbal feedback possible; option to manually analyze the log file
Microsoft 365: Copilot Pro in combination with SharePoint (paid)	Office formats	Full-text response + (list of) relevant documents	Feedback in chat is possible; manual evaluation and processing are administrator's responsibility

Figure 2: *Characteristics of the examined systems (as of March 2026).*

solutions with corporate partners. It encompasses four corporate case studies. Project teams were formed within the companies and a co-creation process was established. Regular project status meetings served to document ideas, decisions, and identified deviations. The data set consists of this project documentation, as well as workshop results and guided feedback sessions with employees.

To address each business case, a pilot solution was implemented within the company and RAG systems were tested in-house.

- **Case A:** To streamline assembly processes, the existing, very extensive (> 150 pages) assembly instructions can be searched by employees via the RAG system in order to obtain answers to assembly problems. In parallel, interviews are conducted with experienced employees to document tips for work performance—supplementing the instructions—and to integrate them into the knowledge base.

- **Case B**: An RAG system supports the searching of existing document collections that are over 10 years old. The technical challenge lies in processing different file formats.

- **Case C:** In an assembly area, the RAG system is used to determine how employees can be supported with assembly tasks that have not been performed in a long time. As a supplement, a self-produced video is integrated to provide hands-on insight into specific processes.

- **Case D:** The RAG system supports field employees with maintenance and commissioning tasks, relieving back-office staff of recurring technical inquiries. All relevant user manuals and work instructions are provided as PDF files. In addition, one-on-one discussions are held between departing employees with extensive experience and less experienced colleagues regarding specific work tasks. This knowledge source, alongside a video created by another employee, is integrated into the RAG system.

Technical challenges and solutions

The literature describes a number of technical challenges associated with the use of RAG systems [6]:

- The selection of appropriate strategies and parameters for processing digital information (chunking, embedding) is crucial for providing relevant and accurate information on demand. This is particularly important given the small datasets in an RAG system.

- Despite the retrieval component, RAG systems can generate erroneous or fabricated content (so-called hallucinations).

- Processing large, heterogeneous corporate datasets requires sufficient computing power.

- Corporate data is often available in various formats. Integration requires specialized interfaces or preprocessing.

- The limited context length of large language models (LLMs) makes it difficult to process complex queries that aggregate information from multiple documents.

- Outdated, incomplete, or inconsistent data leads to errors in retrieval and increases the risk of hallucinations.

These aspects are reflected in the corporate use cases. The technical framework and design decisions identified in the case studies are presented below.

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Both systems run on a high-performance PC equipped with a GeForce RTX graphics card. The latter is a prerequisite for an acceptably fast search process; however, given the currently low number of concurrent users, no wait times occurred.

In all the cases examined, the focus is on information retrieval, not on AI-assisted text generation. Copilot Pro, for example, formulates short answers to questions by evaluating several relevant, ranked documents or passages and combining them into a concise response. To reduce the risk of hallucinations and promote acceptance, the focus—in consultation with users—is placed on displaying relevant documents rather than formulating full answers.

Organizational and personnel requirements

The case studies represent different use cases for the deployment of RAG systems. Scientific monitoring of the trials shows that there is often a gap between expectations for these systems and the prerequisites for their successful deployment. Key challenges lie in the availability of suitable digital knowledge sources and the willingness to allocate resources to ongoing development and maintenance. Several concrete findings were derived:

In Case B, it became apparent that RAG systems could be usefully deployed, particularly with large document collections that have grown over an extended period. The ability to find information independently of exact search terms is especially beneficial for new employees. The list view of references to the sought-after information provides a quick and comprehensive overview of past specifications. While there is a specific need for information in Case D, the clearly structured and well-known work instructions available in Case C eliminate the need for additional information-based support.

Dealing with different file formats is technically challenging but solvable. WINI was equipped with additional functionality to automatically convert text documents into PDFs. However, graphic- and number-based formats, such as Excel, cannot be processed by language-model-based systems unless they contain analyzable text as metadata. For the employee videos documenting work processes (Case C, Case D), transcripts of the commentary were therefore created and integrated into the system. This makes the videos accessible for information retrieval based on the "image description."

In Cases A, B, and C, the system could not be integrated into the company's IT infrastructure for cybersecurity reasons, which is why a separate computer was required in each case. This both negatively affects acceptance and hinders use in the work process. In Case D, the browser-based WINI system was made available to field service employees on tablets for order processing. It is evident that involving the relevant IT department to establish individual requirements is of immense importance.

Overall, employee acceptance plays a central role in the provision and use of experiential knowledge. The employees in Cases B through D tested WINI and provided positive feedback on its functionality and usability. In Case A, the use of RAG failed, in part, due to a lack of willingness on the part of employees to make their experiential knowledge explicit. Without discernible benefits for work performance or targeted incentives, the willingness to make tacit knowledge explicit is low. After all, the continuous collection, review, and maintenance of information from various sources involves significant effort. In Case D, high appreciation from management led to an increased number of video files created independently in the knowledge base.

Another key finding concerns the time it takes for the RAG system to be put to productive use. Cases C and D show that employees who have previously worked without digital support do not immediately or automatically develop a need for these new forms of information retrieval. In Case D, it took seven months for employees to begin systematic testing. It is therefore sensible to select one initial use case, such as a new product or process for which there is still little experiential knowledge and thus a high need for knowledge exchange. A sufficiently long trial period, including an initial rollout and repeated encouragement by management, is necessary to assess usage across the workforce and, consequently, the solution's effectiveness.

The knowledge base is the priority

However, as the case studies show, the priority for AI-supported knowledge provision clearly lies with the knowledge base and is therefore the responsibility of the user companies. The well-known large language models reach their limits when dealing with domain-specific and knowledge-intensive queries [6]. RAG systems therefore utilize company-specific know-how, which must be sufficiently complex and comprehensive to generate added value.

To investigate the influence of the knowledge base on the performance of RAG systems, these were evaluated comparatively in Case D.

To this end, identical queries were posed to the respective RAG systems. The evaluation focused on the number of correctly identified documents or passages, as well as the

	Case C	Case D	Test environment
Number of documents	1	33	110
Document types	Video clips with PDF transcripts	PDF, video clips with PDF transcripts	PDF
Scope of topic coverage	Single assembly process	Job-specific operating instructions, tips and tricks	Occupational safety regulations and design recommendations
Timeliness of data	Up-to-date	Up-to-date, formalized and non-formalized documents	Up-to-date, formalized and verified documents
Qualitative assessment of the usability and quality of the output	No meaningful use of a RAG system is possible	Only for a limited set of questions; relevant documents are displayed; high sensitivity to prompt wording due to small number of documents	Only for a limited set of questions; relevant documents are displayed

Figure 3: *Characterization of the knowledge bases and their suitability for use with WINI.*

usability of the generated output for answering the queries. In addition, a qualitative assessment was conducted regarding the manner in which answers were provided and their suitability for practical use **(Fig. 4)**.

Questions:

1. How should the office chair be adjusted?
2. How should the monitor be positioned? What angles should be observed?
3. Which distances should be maintained at the desk and in the surrounding area?
4. What should be considered when using LED light sources?
5. Who is responsible for designing computer workstations?

The tests reveal a correlation between system functionality, knowledge base, query type, and user expectations regarding the output of the RAG system. For example, while Copilot's fully formulated responses initially provide a high level of convenience, their practical usefulness depends on users' willingness to read and verify them. Company-specific alignment of system functionality, knowledge base, and user expectations is therefore central to a successful implementation strategy.

The definition and continuous development of the knowledge base should be closely linked to corporate strategy, e.g., through regular workshops with employees, as carried out in Case D. New key topics can be derived from these workshops, for which experiential knowledge should be jointly documented either retrospectively or

Figure 4: *Excerpt from the manual test: number of relevant documents per question.*

	Number of correctly identified documents per query					Overall assessment
Questions	1	2	3	4	5	
WINI: out of 10 documents correct …	2	3	4	1	2	Provides specific sources with answers to the question
Copilot Pro (AI answer)	3	2	2	1	2	Provides a fully formulated, AI-generated response and lists relevant documents
Copilot Pro (document list)	3	3	2	4	4	Lists only the relevant documents, without page numbers

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as part of the ongoing process. In addition, the knowledge base's timeliness and quality must be maintained, for example by analyzing usage frequency, user feedback, and frequently requested knowledge content.

Conclusion and further recommendations

The case studies confirm that the successful deployment of RAG systems depends on the quality of the knowledge base and appropriate organizational and personnel conditions [6]. The long-term benefits of such systems stem less from the choice of a specific technical solution than from the continuous development, maintenance, and use of the knowledge base.

To integrate a user perspective, testing and evaluation tools must be developed to assess the functionality, acceptance, and benefits of RAG systems under real-world conditions. Further research and development regarding employees' ability to make knowledge explicit is also required [8]. This involves fostering individual reflection and articulation skills, as well as implementing documentation principles that support automated processing.

The focus in implementation should be on process design and knowledge base development, independent of the specific technical solution, as technologies are evolving rapidly [6, 9]. Acceptance can be supported by transparent communication of mutual benefits for all affected employee groups.

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Ad

Announcement

Announcement

Industry 4.0 SCIENCE

Hybrid Decision Support in Product Development

Industry 4.0 opens up new possibilities for overcoming the performance limitations of product development using data-driven methods. The central question is how extreme volumes of data and artificial intelligence can be used to support development and production decisions more intelligently while simultaneously closing material loops. Hybrid decision support, which combines human experiential knowledge with data science methods, plays a central role here.

The focus is on the early phases of the product life cycle, during which the course is already set for resource efficiency, circularity, and sustainability. Digital twins, data science, and AI can help better understand complex decision-making situations, improve predictions, and optimize development processes in a targeted manner. At the same time, new requirements are emerging regarding data quality, metadata, interoperable datasets, and the shared use of research and industrial data.

This issue of Industry 4.0 Science (www.industry-science.com) highlights current approaches at the intersection of data science, artificial intelligence, product development, and the circular economy. The focus is on technologies and methods that enable hybrid decision-making processes and thus open new paths toward a more sustainable and data-driven Industry 4.0.

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Tacit Talk

When experienced technicians leave a company, more is lost than just a job—decades of practical expertise. Yet most knowledge management tools require precisely what production workers cannot provide: time, a keyboard, and structured input. Tacit-TALK takes a different approach. This speech-based AI system captures tacit maintenance knowledge through natural conversations.

Keywords
tacit knowledge, knowledge management, speech-based interaction, large language models, knowledge graph, industrial maintenance

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Tacit Talk

A speech-based hybrid AI system for capturing tacit maintenance knowledge

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The tacit expertise required for industrial maintenance is increasingly at risk due to demographic change and system complexity. This article presents Tacit-TALK, a speech-based system that externalizes tacit knowledge through AI-guided conversation. Spoken input is transcribed, analyzed by large language models (LLMs), and persisted in a knowledge graph, linking new insights to existing organizational data. Using a design science research process grounded in sociotechnical theory and instantiated for semiconductor maintenance, the article contributes design principles for AI-supported tacit knowledge capture derived from value-based stakeholder engagement, a reference architecture combining LLMs with knowledge graphs, and preliminary prototyping insights into user acceptance and organizational implications.

Much of the expertise that keeps industrial maintenance running is never written down. Experienced technicians rely on intuition, sensory cues, and improvised workarounds—knowledge that is deeply personal and context-dependent. Whether as a result of retirement, turnover, or increasing specialization, organizations face a compounding risk: critical know-how disappears when the people who hold it do. Beyond demographic change, rising system complexity means that even stable teams struggle to document expertise that resists formalization [1]. Conventional approaches such as wikis, static documentation, or informal mentoring have shown limited success in capturing this experiential knowledge [2].

Existing AI-assisted knowledge management approaches presuppose that knowledge already exists in a structured form; systematically capturing new tacit knowledge from workers without disrupting operational workflows remains largely unaddressed. Speech-based interaction, however, offers a promising path, lowering the documentation threshold for hands-occupied workers and enabling knowledge capture at the moment of greatest relevance.

Building on prior work on AI-assisted knowledge management in maintenance [3], this article presents Tacit-TALK, a speech-based system that enables technicians to externalize tacit knowledge through natural, AI-guided conversation. Recognizing that knowledge capture in operational settings is as much an organizational challenge as a technical one, the system design adopts a sociotechnical lens throughout, balancing automation with human agency and individual contribution with collective benefit. The system was designed following a design science research methodology and is instantiated as a proof-of-concept in semiconductor maintenance.

The article's primary contributions are:

1. sociotechnical design principles for AI-supported tacit knowledge capture,
2. a reference architecture combining LLMs with a persistent knowledge graph for operational maintenance settings, and
3. preliminary prototyping insights into user acceptance and organizational implications.

Tacit knowledge and knowledge loss in organizations

The distinction between tacit and explicit knowledge, rooted in Polanyi's observation that "we can know more than we can tell," remains foundational to knowledge management research [4, 5]. Knowledge loss through employee exit leads to measurable declines in productivity and organizational capability [6].

Knowledge Management 4.0 reframes this challenge, making it a strategic function of smart factories to balance knowledge generation and utilization across human-machine collectives [7]. While behavioral approaches such as gamification and nudging have been explored to incentivize knowledge sharing [8], they do not address the fundamental difficulty of externalizing embodied, context-specific expertise in operational maintenance environments.

Recent advances in large language models (LLMs) and retrieval-augmented generation (RAG) have opened new avenues for knowledge management (KM) in industrial

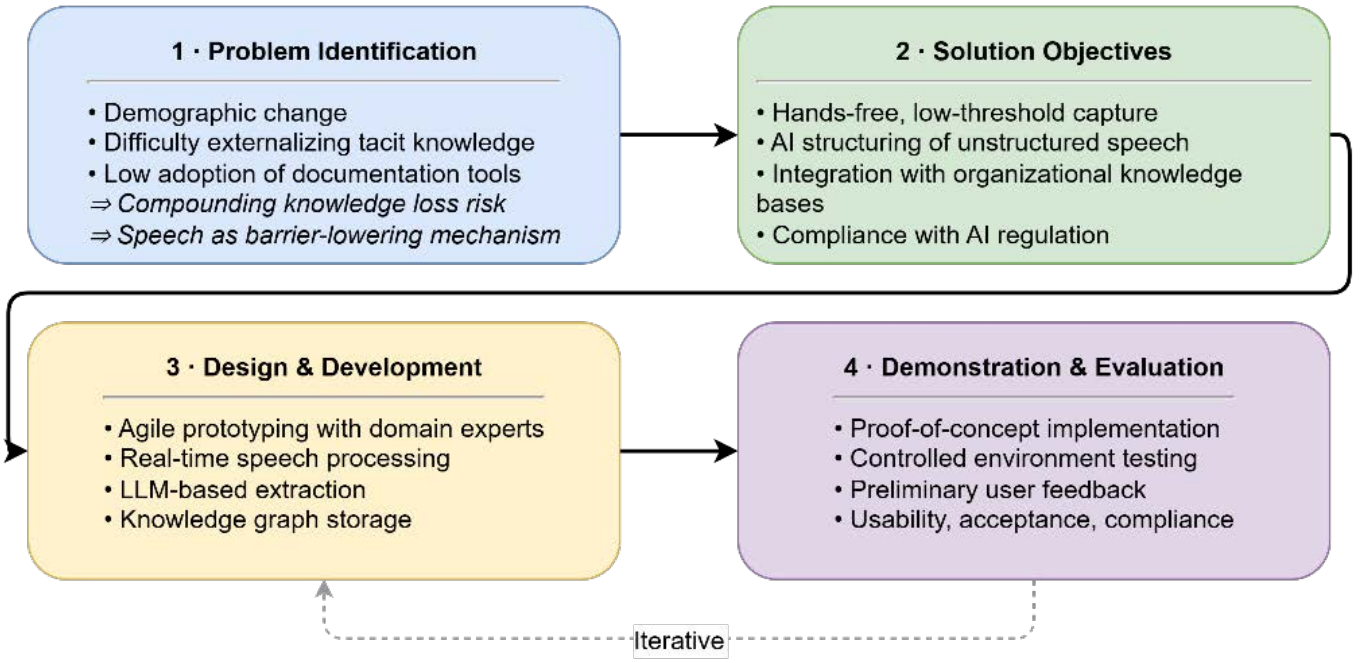


Figure 1: *Phases of the design science research process.*

maintenance. RAG-grounded generation reduces hallucination in maintenance instructions and actions, and domain-specific LLMs have been developed for semiconductor applications [9, 10]. However, all these approaches presuppose that knowledge already exists in a structured form—none address the capture of new tacit knowledge through natural interaction. Our prior work laid the groundwork by identifying requirements for integrating LLM-based extraction into organizational knowledge bases [3].

Most KM systems rely on text-based input, posing a barrier for technicians whose hands are occupied. Prior work on voice annotation in CAD environments has shown that speech provides a more natural, low-barrier modality [11], but the concrete extraction of structured tacit knowledge from unstructured speech is yet to be addressed. This is the gap that Tacit-TALK aims to fill.

Design science research methodology

This research follows the design science research (DSR) paradigm [12, 13], chosen because an artifact that must function within a complex sociotechnical work system requires iterative cycles of design, demonstration, and evaluation rather than purely explanatory research. The process comprises four iterative phases **(Fig. 1)**.

We adopted a value-based engineering approach to prioritize stakeholder values and business objectives in the requirements elicitation process [14].

The mapping **(Fig. 2)** revealed three inherent tensions:

1. ease of use versus data quality (simplified input may reduce granularity),
2. automation versus control (AI structuring may introduce errors), and
3. openness versus privacy (sharing must respect data concerns).

Applying a value-weighted prioritization, we identified four critical requirements in descending priority:

1. speech-based input with real-time transcription feedback,
2. human-in-the-loop verification before knowledge becomes official,
3. transparent AI processing with explainable outputs, and
4. role-based access control with clear data ownership.

To translate identified values into concrete design decisions, we constructed four representative personas based on role profiles identified during structured workshops with maintenance managers and team leads at the semiconductor partner site. Each persona synthesizes observed characteristics, constraints, and motivations of actual user groups:

1. a maintenance worker with limited documentation time and concerns about surveillance,
2. a generic user wishing to record spontaneous insights,

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Stakeholder Group	Core Values	Derived Requirements
Maintenance Workers	Minimal workflow disruption, recognition of expertise	Hands-free capture, acknowledgment of contributions
Knowledge Managers	Quality assurance, traceability	Verification workflows, audit trails
Organization	Knowledge preservation, operational continuity	Structured storage, searchable knowledge base

Figure 2: *Stakeholder identification and value mapping.*

3. a verifier responsible for validating entries against consistent standards, and
4. a new user focused on confident onboarding.

Using these personas, we conducted user journey mapping sessions to identify interaction touchpoints and design requirements across five journey phases. Goals, pain points, and design responses are summarized in **Figure 3**.

Three cross-cutting insights shaped the subsequent design. Users require immediate visual feedback during speech capture to trust that the system is working. The distinction between unverified and verified status must be communicated transparently to prevent anxiety about lost or rejected contributions. Finally, the retrieval phase must provide transparent reasoning for suggested connections so that users understand why certain entries are surfaced. These design choices are described in more detail later on.

System design

The system extends existing maintenance ontologies to accommodate tacit knowledge artifacts captured through conversational interaction. The data model is implemented as a labeled property graph, enabling both structured queries and semantic similarity search. The traditional maintenance ontology is extended with concepts specifically designed to capture implicit, experience-based knowledge:

```
Insight
   ├── problem_context      # Trigger
   ├── action_taken         # Response
   └── lesson_learned       # Takeaway

TacitCategory
   ├── Deviation            # Differs from SOP
   ├── Intuition            # Gut feeling
   ├── Hack                 # Workaround
   ├── Info_Gap             # Undocumented
   └── Hot_Fix              # Emergency solution
```

The architecture integrates three subsystems (see **Fig. 4**):

1. a speech processing pipeline for real-time transcription and voice dialogue;
2. an LLM orchestration layer managing dialogue state, elicitation technique selection, and structured extraction;
3. a knowledge graph persistence layer linking new insights to existing organizational data through embedding-based entity matching.

Figure 3: *User journey map.*

Phase	User Goal	Critical Pain Points	Design Response
Initiation	Decide to capture knowledge	Recording effort, fear of monitoring	Clear value proposition, privacy assurance
Capture	Speak freely	Unclear recording status	Pulse animation, live transcription
Review & Save	Refine and confirm entry	Information overload, storage uncertainty	Editable summaries, explicit success feedback with status tag
Verification	Validate entries	Inconsistent standards	Clear criteria, audit trail
Retrieval	Reuse stored knowledge	Opaque search results	Explainable retrieval with context

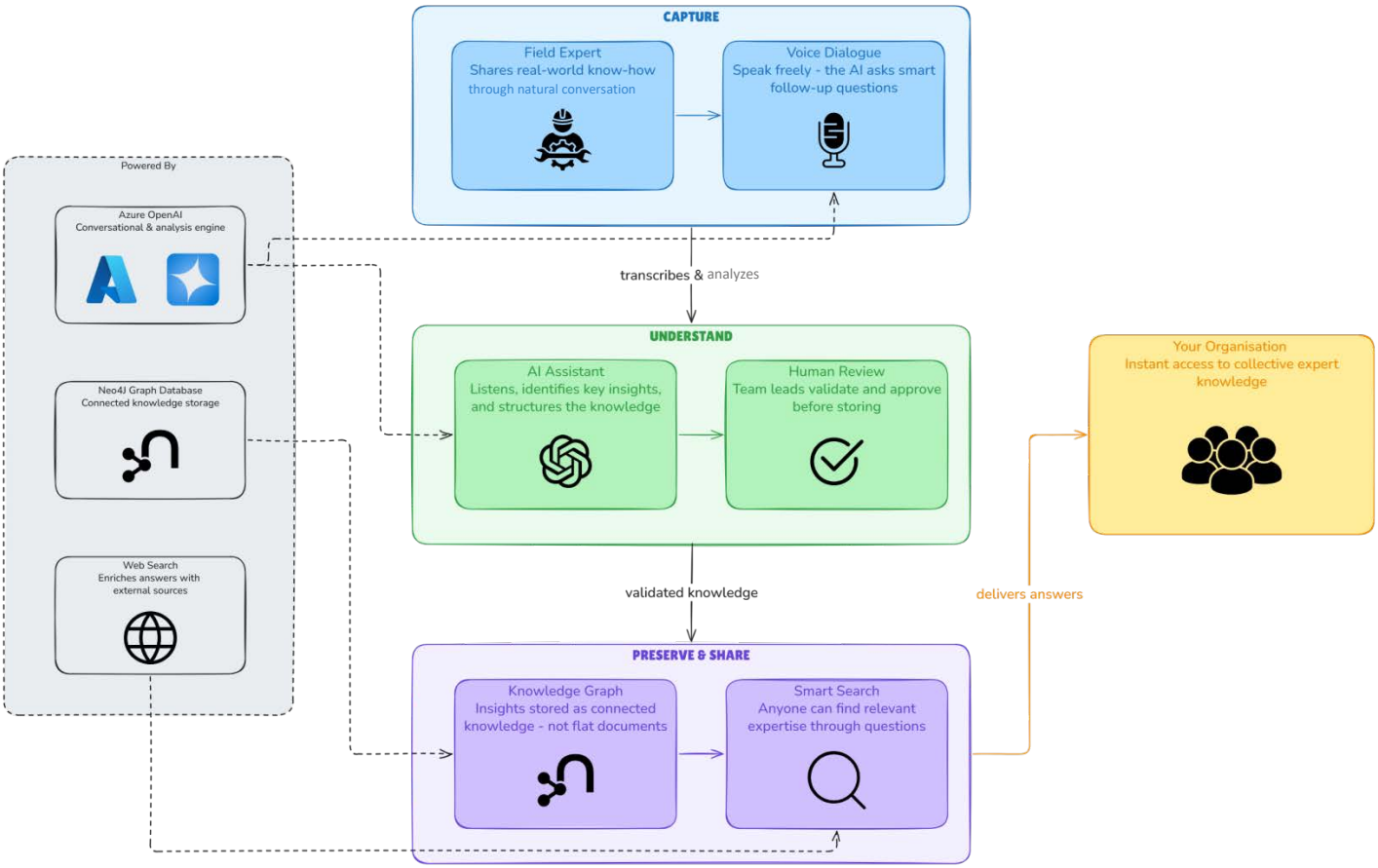


Figure 4: *Architecture overview showing the speech processing pipeline, large language model orchestration layer, and knowledge graph persistence with interactions.*

All nodes carry vector embeddings, enabling Graph RAG retrieval: query-matched nodes and their graph neighborhoods are fused as contextually enriched input for answer generation.

Proof of concept

The proof-of-concept implementation of Tacit-TALK is deployed as a web application **(Fig. 5)**.

A typical capture session begins when a technician initiates a new recording after completing a maintenance task. The system greets the user by voice with an open-ended prompt. As the technician speaks, live transcription is displayed on screen, providing continuous feedback. The conversational agent then guides the dialogue as described in the remainder of this section. Upon completion, the system generates a structured summary for review and editing, reinforcing the human-in-the-loop principle. The resulting Insight node is stored with the status Unverified. For example, a captured entry might document an emergency bearing replacement, classified as an Intuition-type insight, containing the triggering condition (e.g., sensor flag), the action taken, and a transferable lesson about lubrication alignment.

Tacit-TALK's AI-guided conversation systematically elicits tacit knowledge while preserving the natural feel of a spoken exchange. The dialogue design follows four principles:

1. posing one question at a time to prevent cognitive overload,
2. adapting follow-ups based on conversation state and knowledge gaps,
3. intervening only when genuinely needed to avoid the feeling of an interrogation, and
4. allowing graceful termination at any point so that partial captures remain valuable.

A prompt sequencer operationalizes these principles by rotating through empirically grounded elicitation techniques spanning situational recall, reasoning and decision-making, and knowledge transfer. The sequencer selects techniques based on which dimensions—problem context, action rationale, transferable lesson—remain sparse. A state machine transitions the dialogue from an open-ended narrative phase through a follow-up loop,

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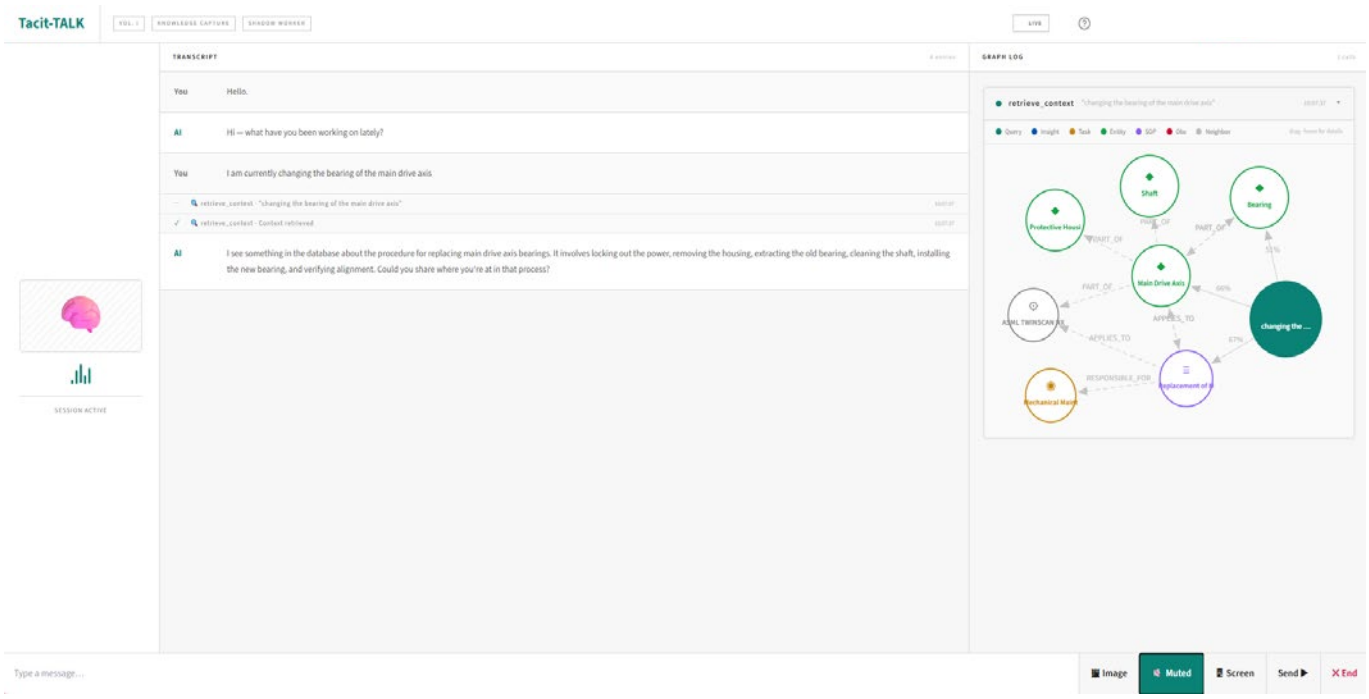


Figure 5: *Tacit-TALK interface.*

including clarification and graph-based context retrieval, to summary generation and user confirmation.

The proof of concept demonstrates how captured insights are woven into the organization's existing knowledge graph. The extraction module identifies references to machines, components, and tools and matches them against existing graph nodes using embedding-based cosine similarity, accounting for the inherent imprecision of spoken language. A new entity node is created only when no match exceeds a high confidence threshold, preventing both duplicate proliferation and erroneous merges. Every entry is linked to its authenticated creator, enabling expertise discovery while restricting worker-identifying details to appropriate access roles.

Each new Task is automatically compared to embeddings of existing SOP documents. When similarity is sufficiently high, a RELATED_SOP relationship is created, subject to verifier confirmation. Over time, this produces an SOP enrichment effect: formal procedures are progressively augmented with experiential annotations, capturing what documentation alone does not convey.

Discussion, limitations, and conclusion

Tacit-TALK demonstrates that speech-based, AI-guided interaction is viable for tacit knowledge capture in industrial maintenance. This gap was identified but unaddressed in existing AI-assisted KM research, which presupposes already-structured input [9, 10]. Unlike prior voice annotation work, which was limited to explicit design artifacts [11], our system employs LLM-guided elicitation to surface knowledge that workers themselves may not recognize as documentable.

The value-based requirements engineering process revealed that the central design challenge is not technical feasibility but sociotechnical balance: users are willing to share knowledge when the system is perceived as a tool for recognition rather than surveillance, and when documentation effort remains below the threshold of workflow disruption. This aligns with Knowledge Management 4.0 principles that position knowledge processes as collaborative human-machine functions [7].

Deploying speech-based capture in semiconductor maintenance introduces domain-specific challenges that extend beyond standard speech recognition. Technicians routinely mix languages—German syntax interspersed with English technical terms produces utterances such as "Fehler am Platen behoben" or "Crash nach Aligner Error"—requiring robust multilingual and code-switching capabilities in the transcription pipeline. High ambient noise levels on the factory floor and the use of clean room suits, which muffle speech and obscure facial cues, further degrade recognition accuracy. Addressing these constraints will likely require targeted evaluation and architectural adaptations such as noise-robust speech models and domain-specific vocabulary fine-tuning.

Several additional limitations must be acknowledged. The current proof of concept has not yet undergone structured empirical evaluation; findings regarding user acceptance and knowledge quality remain preliminary. Furthermore, the system's graph integration presupposes existing structured organizational data such as equipment registers, SOPs, and work orders; organizations with sparse knowledge bases may see limited benefit. Future work will address empirical evaluation with technicians, multimodal input combining speech with sensor data, and an ontology refinement based on field experience.

To conclude the findings of this article for now, it can be argued that effective externalization of tacit maintenance knowledge requires not only technical capability but deliberate sociotechnical design. Tacit-TALK offers a replicable, DSR-grounded approach for organizations seeking to preserve operational expertise amid demographic change and increasing system complexity.

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Improving Documentation Quality and Creating Time for Core Activities

Success factors for implementing AI-based documentation systems in nursing care

Sophie Berretta, Elisabeth Liedmann, Paul-Fiete Kramer, Anja Gerlmaier and Christopher Schmidt

In the nursing sector, increasing documentation burdens are compounded by an acute shortage of skilled workers, while AI is seen as a promising solution to alleviate the workload and improve quality. This article shows how AI-based documentation systems can strengthen care overall. It focuses on the experiences and perspectives of stakeholders in the nursing sector, as well as key requirements for a human-centered implementation.

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Industry SCIENCE 4.0

Preview 6/2026

Lean Product Lifecycle Management

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December 9, 2026

Issue 1/2027, focusing on "Resource Efficiency 4.0," will be published in February 2027.

SMED-Based Setup Time Reduction in Corrugated Cardboard Production

In the corrugated cardboard production industry, long setup times have a significant impact on productivity, equipment availability, and competitiveness. The aim of this article is to investigate the potential of the Single-Minute Exchange of Die (SMED) method for reducing setup times. An empirical case study was conducted at a company in the corrugated cardboard production industry. Analysis of the setup process identified significant potential for optimization through the implementation of SMED in conjunction with Yamazumi. Separating internal and external setup activities and optimizing task allocation resulted in a significant reduction in setup times and improved resource utilization.

Tamer Abdulghani, Moritz Heyne and Herwig Winkler (Brandenburg University of Technology Cottbus-Senftenberg)

Maturity Model for System Integrators in the Production Equipment Sector

System integrators designing manufacturing lines face inefficiencies due to one-off, build-to-order processes. Transitioning to mass customization is essential, yet many lack a clear roadmap. By applying the Grounded Theory Approach to industry interviews, this study identifies 27 key actions and constructs a novel Capability Maturity Model. Empirically validated with 20 companies, this framework bridges theoretical mass customization concepts with practical application, providing a robust self-assessment tool to systematically guide organizational modernization.

Masahito Komiya (Hosei University, Japan), Shinichiro Haruyama and Seiko Shirasaka (Keio University, Japan)

Toward Lean Product Lifecycle Management

Many PLM implementations strengthen the forward flow of information from development to manufacturing. Yet it remains difficult to institutionalize the feedback mechanism from actual values to design decisions. This paper proposes a Lean PLM framework that positions cost information as a cross-functional communication medium linking development, manufacturing, and cost management. Based on the bill of materials (BOM) and the bill of processes (BOP), the framework integrates planning and actual data using four context-related dimensions—where, when, how, and what—and introduces a maturity model ranging from static master data to learning master data. It also defines indicators such as learning frequency, scope of alignment, feedback rate, and feedback delay. A case study from the Japanese manufacturing industry illustrates how reduced latency in cost feedback supports organizational learning through the operation of feedback loops.

Ken Wakabayashi and Katsuhiro Iyoda (Business Engineering Corp.), Masanari Ukai (Zuken PreSight Inc.)

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