Chapter

Knowledge Management in Production: Human-Centered and AI-Supported Approaches for the Shop Floor

Jannis Pfister, Daniela Schmidt, Matthias Jenner, Till Günther and Rainer Müller

Abstract

Knowledge management is a critical enabler for competitiveness in industrial production, especially under demographic change, workforce fluctuation, and digital transformation. Small- and medium-sized enterprises face particular risks, as experiential knowledge is often bound to individuals and easily lost when employees leave. This paper emphasizes the need for systematic approaches to knowledge retention and transfer. While established frameworks such as the knowledge ladder, SECI model, and knowledge balance provide foundations, they remain limited in capturing implicit, action-related expertise essential for production. To address this gap, a model-based approach is proposed that combines cognitive task analysis, methods-time measurement, and AI-assisted tracking technologies, including motion sensors and video analysis, to externalize implicit knowledge. The transformation of human actions and decision-making into structured knowledge objects enables integration into digital assistance and learning systems. The study outlines a research agenda for scalable, technology-enhanced knowledge management systems to safeguard experiential knowledge, reduce training times, and strengthen innovation.

Keywords: knowledge management for SME, human-centered implementation strategies, implicit knowledge, knowledge retention, experiential knowledge, digital assistance systems, best practices, knowledge capture, knowledge preservation, knowledge externalization, artificial intelligence

1. Introduction

In global industry, companies face the challenge of systematically securing experiential knowledge and ensuring its sustainable transfer. Small- and medium-sized enterprises[1] (SMEs) are especially affected, as this knowledge is often bound to individuals and quickly lost when employees leave. In a knowledge-based economy, such loss reduces quality, prolongs training, increases error rates, and weakens innovation capacity. In this chapter, the focus is on experiential knowledge, which in the literature is commonly referred to as implicit knowledge. Both terms are used synonymously, describing practice-based expertise acquired through long-term experience, routines, and situational decision-making.

OECD data show a steady decline in average job tenure. In Germany, it is around 11 years [1]; in the United States, only 4.1 years [2]. In Chinese industrial centers such as Shenzhen and Guangzhou, employees often remain with a company for less than five years, highlighting high labor market mobility [3, 4]. Even moderate attrition on the shop floor can accumulate to significant knowledge loss over time. At the same time, episodes of unusually high turnover demonstrate how disruptive such dynamics can become. A prominent example is the so-called Great Resignation in 2021, when more than 47 million employees voluntarily left their jobs in the United States [5]. In German manufacturing, turnover is lower and more stable. IAB data indicate exporting firms show 2–4% points less turnover than nonexporting ones. Even moderate attrition on the shop floor can erode implicit expertise when knowledge remains undocumented [6].

Younger employees often leave before their knowledge is transferred, while older employees tend to stay longer but keep much of their expertise within established routines. Without deliberate structures for internal exchange, experiential knowledge remains personal rather than organizational. Companies must, therefore, create systematic mechanisms for knowledge sharing and handover.

The economic effects are well documented. A ZEW study shows that a 1% increase in turnover leads to a 0.074% decline in value added. Losing one-third of the workforce results in an average productivity loss of €22,000 per employee, not fully offset even after two years [7]. Replacing a single employee can cost up to €45,529, including lost productivity, training, and recruitment. For an SME with 30 employees and 20% annual turnover, this equates to more than €314,000 annually [8]. According to Wharton, replacing experienced skilled workers costs 100–150% of their salary [9]. The loss is especially harmful when no systematic knowledge management exists, particularly in specialized tasks or roles with customer relationships [10].

When experienced employees leave, training times increase, quality decreases, error rates rise, and project delays occur. Barriers to knowledge transfer include time constraints, knowledge gaps, biases, and missing incentives. Digital tools remain ineffective if not integrated into processes and culture. Existing approaches, such as structured handovers, tandem models, or knowledge maps, illustrate that methods to mitigate knowledge loss are available, yet they are often insufficiently applied or integrated [11].

Compared to large firms, SMEs face particular challenges in digitalization and knowledge management. They are characterized by flat hierarchies, limited resources, and niche expertise [12]. A major barrier to formal structures is the lack of

[1] The EU defines SMEs as companies with fewer than 250 employees and either revenue below €50 million or a balance sheet below €43 million [81, 82]. SMEs account for nine out of 10 companies and create two out of three new jobs [83]. They drive entrepreneurship and innovation and are thus vital to competitiveness.

IT expertise [13]. Specialists are scarce or expensive, preventing sustainable internalization. This leads to inconsistent data and weak database infrastructures. Limited resources and low Research and Development capacity further restrict digitalization and standardization [12–14].

Skills' shortages and expert departures are especially critical for SMEs, as knowledge is highly person-specific [14]. Employees often perform cross-functional tasks requiring broad project knowledge. Expertise is rarely documented; sometimes even process knowledge remains implicit. In many cases, critical know-how is concentrated in a single individual, creating immediate knowledge gaps when that person leaves [15]. Beyond the technical challenge, building a knowledge base requires cultural and organizational change. SMEs' strong face-to-face culture accelerates information flow but reinforces reliance on implicit knowledge. Employees often hesitate to share knowledge if they see little benefit [14].

Modern technologies can help retain knowledge. AI-based tools, semantic models [16], and eye-tracking methods [17] are promising. IT-based measures, such as digital knowledge management systems, mitigate the risk of knowledge loss [18].

With rising process complexity, shorter innovation cycles, and global competition, employee expertise becomes strategically critical. SMEs, in particular, risk losses in quality, efficiency, and costs without knowledge structures. This chapter, therefore, systematically examines the causes, consequences, and countermeasures to experiential knowledge loss. At the core are the externalization, structuring, and dissemination of knowledge across organizations. Technological solutions, digital platforms, and cultural frameworks are discussed. A human-centered perspective emphasizes employees as active knowledge carriers and codesigners of adaptive structures. The goal is to establish pragmatic and cost-effective methods for capturing and applying experiential knowledge.

2. State of the art

This chapter establishes the conceptual and theoretical foundations for a systematic approach to knowledge management in an industrial context. It clarifies the distinctions between data, information, and knowledge, outlines various forms of knowledge, and discusses theoretical concepts relevant to the collection, storage, and utilization of experiential knowledge. These explanations provide the basis for the subsequent analysis of technological, organizational, and cultural design approaches.

2.1 Theoretical and normative foundations

In modern organizations, knowledge is considered a strategic resource and a core element of intangible corporate capital. It is central to innovation, quality assurance, and continuous improvement. In knowledge-intensive production environments, performance depends on the availability, accessibility, and usability of relevant knowledge. Companies can thus be seen as decision-making factories in which information and knowledge are central production factors [19].

A frequently used classification model is the knowledge pyramid, which describes the gradual transition from data to information to knowledge. Data are context-free symbols; information emerges when data are structured and assigned meaning;

knowledge results from context-related interpretation, evaluation, and application [20–22]. North and Maier emphasize that knowledge arises from the active processing of information, manifested in cognitive processes such as thinking, decision-making, and action. These processes are always embedded in individual or social contexts [23].

The pyramid can also be interpreted as a transformation process: Knowledge forms the basis for skills, which are developed through repeated application and experience. The competent application of these skills in specific situations leads to proficiency. Probst et al. argue that value creation depends on translating knowledge into concrete action [24]. According to DIN ISO 30401 and 10015, a distinction is made between knowledge, skill, ability, and competence as different levels of application-oriented utilization. DIN ISO 30401 defines a skill as the learned ability to perform a task according to specified requirements [25]. Competence is the capacity to apply knowledge and skills to achieve desired outcomes. DIN ISO 10015 introduces ability as a prerequisite in cognitive, social, or motor terms, which can be developed through training and experience.

From a theoretical and normative perspective, knowledge is, therefore, understood as an overarching concept that encompasses both content and applicability. It forms the foundation for individual and organizational action, particularly in the digital recording and use of experience-based production knowledge [21, 26, 27].

A detailed understanding of different shapes of knowledge is essential for the design of knowledge management systems. The basic distinction is between implicit and explicit knowledge. As Polanyi already noted in 1966, a significant part of knowledge is not verbalizable [28]. Implicit knowledge is experience-based, action-oriented, and context-sensitive, and is expressed primarily in action. Explicit knowledge, in contrast, can be articulated, documented, and transferred comparatively easily [24, 28]. This distinction remains central in contemporary knowledge management, especially in the identification, transfer, and digitalization of experiential knowledge in production or maintenance.

From a cognitive psychology perspective, knowledge can also be divided into declarative knowledge (knowing that) and procedural knowledge (knowing how). Declarative knowledge refers to consciously retrievable facts and contexts, while procedural knowledge manifests itself in routines, automated skills, and strategies for action. Procedural knowledge is closely linked to implicit components [22]. The dimensions of articulability and proximity to action overlap in practice and cannot be strictly separated.

The anchoring of knowledge carriers is another important aspect. Knowledge may reside at the individual level (in persons), the collective level (in groups), or the organizational level (in processes, routines, systems) [24]. This structure strongly influences how knowledge can be identified, stored, and disseminated, and determines the extent of potential knowledge loss due to demographic change or staff turnover.

Context-specific knowledge forms an additional cross-sectional dimension. It refers to content that can only be clearly interpreted and applied during action. In production, knowledge is effective only when activated in the relevant context. This situational dependency makes both documentation and technological recording difficult, posing a major challenge for digital knowledge management and AI-based solutions [29]. Formalized approaches, such as enterprise models and configurable knowledge services, can mitigate this challenge by dynamically adapting knowledge provision to production roles, product variants, and process stages. This increases the relevance and effectiveness of knowledge usage in distributed manufacturing networks [30].

For targeted implementation in production, it is necessary to differentiate knowledge shapes. According to DIN SPEC 91443 [31], product knowledge, process or action knowledge, technical knowledge, and experiential knowledge are central categories. These shapes differ in structuring, ownership, and digitizability, and thus provide a practical basis for designing knowledge-based systems [22]. Emphasis on these four forms highlights two points: the key role of implicit, action-oriented knowledge in production, and the need to systematically document explicit content and ensure its accessibility across the organization.

These theoretical and normative foundations can be synthesized into an integrated framework. **Figure 1** illustrates the progression from data to information, knowledge, skills, and competences, and links these dimensions with key management models and standards. It thereby provides a visual synthesis of the section and prepares the ground for the following discussion of organizational knowledge management frameworks.

Building on these foundations, several frameworks have become particularly influential. North's knowledge ladder conceptualizes knowledge as part of a transformative process from data to competence, highlighting the interplay of knowledge, motivation, and action. Probst's building block model structures knowledge management into eight interdependent fields, providing a systemic basis for strategic design. Nonaka and Takeuchi's SECI model emphasizes dynamic knowledge conversion between implicit and explicit forms, while other systemic approaches, such as the Munich model, complement this spectrum.

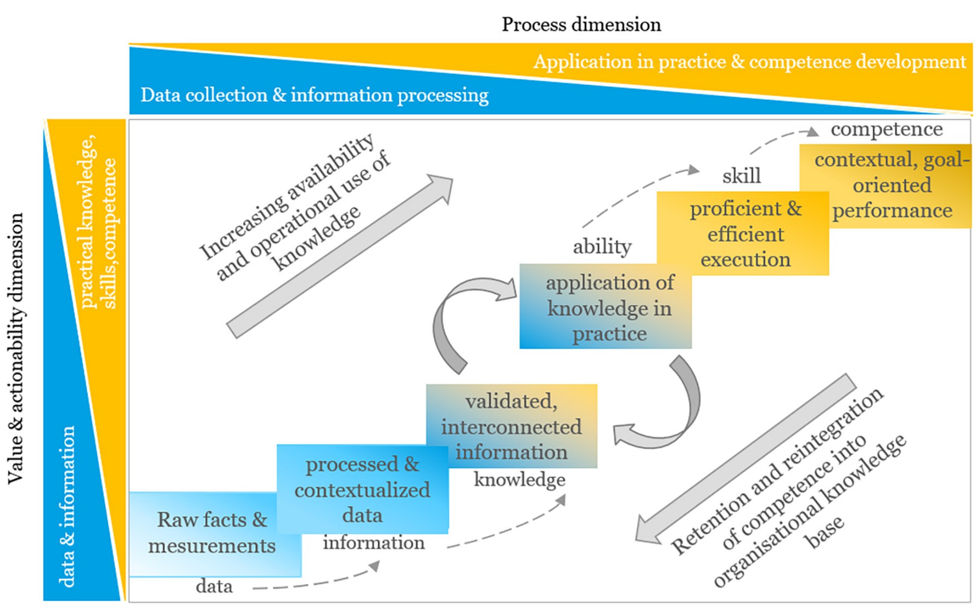

Figure 1.
Integrated framework of knowledge and competence models – own illustration based on Klaus North's knowledge ladder [23].

The knowledge ladder views knowledge as part of a transformative process from data to information, then to skills and competence. Central to this process is the interplay of knowledge, motivation, and the capacity for action, through which individual knowledge evolves into organizational competence [32]. The building block model by Probst et al. conceptualizes knowledge management as the interaction of eight fields: goal definition, knowledge identification, acquisition, development, distribution, use, preservation, and evaluation [24]. This systemic, process-oriented framework provides a basis for the strategic design of knowledge processes.

The SECI model emphasizes the interaction between implicit and explicit knowledge. It distinguishes four modes of knowledge conversion: socialization (implicit to implicit), externalization (implicit to explicit), combination (explicit to explicit), and internalization (explicit to implicit). This cycle illustrates how organizations generate and expand knowledge through interaction, reflection, and application [33].

The figure serves as a link between abstract theoretical models and the subsequent discussion of knowledge management as a socio-technical system.

Beyond these frameworks, knowledge management must be understood as a socio-technical system because its implementation depends on the interplay of people, organization, and technology. While models such as SECI or the building blocks describe knowledge flows, their effectiveness in practice is determined by human-centered design and employee involvement.

Knowledge management rests on three pillars: people, organization, and technology. People are the most important, as they are the knowledge carriers whose expertise and competencies are developed through HR management and training. Organizations provide the framework for the efficient handling of knowledge. Technology supplies tools such as databases that present required information transparently or generate it with AI support. However, a large part of knowledge transfer still occurs through personal communication. This shows that knowledge management is not solely based on databases but also on participation and organizational culture [34].

By applying work-scientific design criteria within a human-centered approach, acceptance and participation can be strengthened [35]. This includes participation, competence development, autonomy, transparency, and sustainable measures. The International Labour Organization addressed these aspects in its concept of “decent work,” known in Germany as “Gute Arbeit” [36]. It emphasizes long-term, sustainable work design and integrates technical and social assessments to ensure transparency and traceability. The aim is an iterative process that evaluates safety, health, data protection, job security, and training while considering legal regulations, work-scientific findings, and employee interests [15].

Building on these principles, various technological approaches now support the acquisition, structuring, and transfer of knowledge, including natural language processing (NLP), large language models (LLMs), data science, computer vision, and semantic knowledge representation.

2.2 Digital and AI-driven technologies for knowledge management

Natural language processing comprises methods that enable machines to interact with, understand (natural language understanding, NLU), and generate (natural language generation, NLG) human language. Positioned at the intersection of computer science, AI, and linguistics, NLP includes functions such as translation, speech recognition, summarization, segmentation, classification, and information extraction [37]. For knowledge management, textual information is key, as much of organizational knowledge is stored in unstructured form, for instance, in reports, technical documentation, or internal protocols. NLP techniques preprocess, normalize, and structure such data, improving accessibility and transfer. Typical applications include automatic classification, extraction of key information, and the summarization of extensive technical documents into concise overviews [38–40]. From a process perspective, NLP follows three fundamental steps: text recognition (e.g., from images, scanned documents, or audio), text understanding (semantic and structural analysis), and text generation (creating or rewriting content). Together, these steps underpin intelligent management of text-based knowledge and form the basis of modern systems for decision support, workplace learning, and systematic knowledge transfer [41, 42].

Large language models are advanced AI systems designed to process, understand, and generate human language [43, 44]. They analyze and comprehend text and generate context-appropriate responses. Unlike systems based on predefined modules, LLMs interact through natural written language in full complexity [45]. Technically, they are neural networks with self-attention mechanisms that assign weights to input elements, enabling contextual interpretation and prediction of subsequent content. Through deep learning, this capability extends to generating entire sections of text [46, 47]. In industrial and business settings, LLMs are increasingly used for conversational agents, automated text generation, machine translation, literature analysis, content summarization, and sentiment analysis of customer feedback [44, 48, 49]. Retrieval-augmented generation (RAG) further extends their functionality by supplying external knowledge sources at query time. This reduces hallucinations and improves factual reliability [50–52]. Compared to fine-tuning, RAG is more flexible, though fine-tuning remains useful for style adaptation and structured output, especially when domain-specific or output format constraints are stringent [53, 54].

In environments with strict data protection requirements, deployment architecture is crucial: Local/offline deployment of LLMs with RAG-based pipelines can offer maximal administrative control and minimize reliance on external providers, while still enabling retrieval of up-to-date domain data [55–57]. Recent advances in hardware efficiency allow large models to run on standard- or high-performance workstations. Open-source LLMs provide transparency, adaptability, and independence [46, 53]. Self-hosted models enable tailored solutions, including fine-tuning for specialized tasks. From an engineering and knowledge management perspective, the combination of LLM and RAG offers a robust architecture for integrating human expertise with computational processing, supporting structured preservation, dissemination, and targeted application of organizational knowledge [44, 51, 52].

Data science and machine learning represent another core pillar of knowledge-oriented systems. Data are among the most valuable assets of organizations, as it enables evidence-based decisions that improve efficiency. Data science aims to identify patterns and extract meaning from large datasets, whether structured or unstructured, by means of analytics, AI, machine, and deep learning. Its aim is to identify patterns and extract meaning from large datasets, whether structured or unstructured [58, 59]. Methods draw on mathematics, statistics, programming, data engineering, pattern recognition, visualization, and high-performance computing [38]. Machine learning focuses on systems that learn from examples rather than explicit programming, using approaches such as supervised, unsupervised, reinforcement, and self-supervised learning [60, 61]. Applied to knowledge management, data science and machine learning support knowledge capture and analysis, the development of intelligent training and guidance systems, the creation of structured repositories, and the prediction or prevention of errors during training. These applications significantly optimize knowledge transfer in industrial environments [62, 63].

Computer vision is another central field. Inspired by human vision, it processes and analyzes images and videos to extract information for actions or recommendations. Methods include image processing, pattern recognition, and geometric modeling, aiming at machine-based image understanding [64]. For knowledge capture, two- and three-dimensional images and videos are essential. Computer vision tools support image segmentation, object detection, classification, human activity recognition, quality inspection, robotic perception, and immersive AR/VR applications [65]. Advanced models such as YOLOv12 enable data collection, classification, and workflow analysis, turning raw data into structured information for training, documentation, and process improvement [66].

Knowledge representation and modeling are prerequisites for structuring, transferring, and systematically applying organizational knowledge. Semantic technologies provide declarative descriptions and formal relationships between concepts [67]. Glossaries, taxonomies, and thesauri represent increasingly detailed structures, while ontologies provide comprehensive, formally defined models. Ontologies enable machine-readable representations that support logical reasoning and automated processing [67]. Knowledge graphs (KGs) build on this principle by representing entities and relations as nodes and edges, integrating heterogeneous data sources, providing context-sensitive access, and forming the basis for reasoning.

Combining KGs with AI is a major research focus. Ontologies supply the semantic backbone, KGs contain the structure of the knowledge, and LLMs provide natural language access. This interplay enhances contextual relevance and reliability by grounding AI outputs in structured and validated knowledge bases. For SMEs, structuring and modeling knowledge is especially challenging due to missing governance, reluctance to adopt new technologies, and difficulties in formalizing implicit or procedural expertise [68]. KGs can mitigate these challenges by consolidating diverse knowledge, improving efficiency, reducing risks, and facilitating systematic transfer, though issues of scalability, quality, and usability remain [69].

LLMs also support KG construction and maintenance by extracting entities and relations from documents, modeling procedural knowledge, and updating ontologies. KGs, in turn, improve LLM performance in RAG applications by providing domain-specific grounding. Human expertise remains essential to ensure AI supports rather than replaces human roles. In practice, pipelines for named entity recognition and relation extraction often combine pretrained models with domain expert input [70]. Human-in-the-loop (HIL) approaches allow experts to intervene in each cycle, for instance, in interactive Q&A dialogs [70]. This reduces manual effort [71], ensures validity, and supports continuous curation as knowledge bases evolve [72, 73]. When these requirements are met, KGs provide a foundation for structuring explicit and procedural knowledge and can support transfer, for example, through KG-enhanced RAG chatbots that deliver context-specific recommendations and explanations.

Taken together, these technological approaches, combined with theoretical foundations and human-centered design, constitute the current state of the art in knowledge management. They show how conceptual models, socio-technical frameworks, and emerging technologies interact to capture, structure, and transfer knowledge in industrial contexts. The convergence of these elements underlines both the complexity of knowledge as a resource and the potential of integrated, interdisciplinary approaches to ensure its effective and sustainable use in production.

3. Concepts

This section builds on the fundamentals and state-of-the-art by presenting three complementary concepts for systematically recording, structuring, and digitally utilizing experiential knowledge in industrial assembly. These concepts were developed for settings with a high degree of manual work, where procedural knowledge has largely remained implicit. The first concept focuses on visual recording and standardized motion modeling; the second on language- and cognition-oriented methodologies. Together, they capture both the physical execution of actions and the decision-making logic behind them. A third concept integrates these perspectives into AI-supported modeling linked to enterprise systems. **Figure 2** illustrates how the three concepts complement and converge, combining methods for capturing experiential knowledge with approaches for its modeling and digital representation. This integration enables systematic utilization in assembly contexts.

3.1 AI-supported motion modeling for capturing implicit assembly knowledge

The first concept addresses the challenge of capturing procedural knowledge from manual assembly and transforming it into a measurable, digitally usable form. It combines AI-based object recognition with standardized motion modeling to

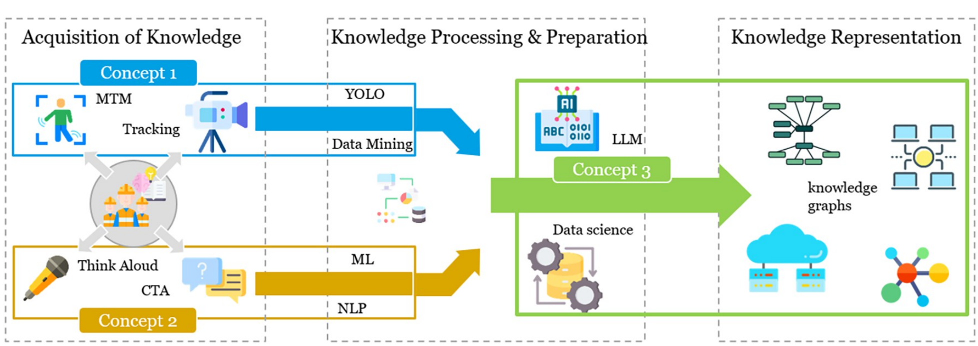

Figure 2.
AI-supported concepts for acquisition, processing, and representation of experiential knowledge in assembly – own illustration.

create structured representations of action sequences. Applications include process evaluation, derivation of best practice sequences, context-sensitive assistance, and model-based training.

In a prototype environment, interactions between operators, tools, and parts are captured via camera-based object recognition and converted into a formal structure. High-resolution RGB video sequences serve as input for a YOLO-based object recognition model, fine-tuned to the assembly domain using annotated datasets of typical objects (e.g., tools, parts, hand positions). Data augmentation techniques, such as perspective distortion, contrast variation, or background noise, improve robustness under real workshop conditions. The trained model detects relevant objects in real time, outputs confidence values per frame, and enables downstream motion analysis.

For structured analysis, the methods-time measurement (MTM) system is applied. Recent studies demonstrate how MTM can be digitized and automated, for example, through VR-based transcription using digital twins [74] or the integration of Industry 4.0 technologies into MTM-1 analysis for automotive applications [75]. Converting visually recognized actions into MTM elements produces a structured movement plan that allows systematic recording, comparison with best practices, and alignment with specifications.

To connect visual recognition with MTM analysis, mappings between object states and movement patterns must be defined. A rule base interprets sequences such as "hand approaches tool → hand covers tool → hand moves away with tool" as a grasping event. This logic can be refined with additional sensors or classifiers. The resulting profiles can then be stored in a structured form and compared with target sequences, process descriptions, or experience profiles.

These data can later inform training requirements, error analysis, or digital assistance services. Examples include context-sensitive assistance based on actual best practices or simulation-based learning tailored to individual weaknesses. Aggregated data can be integrated into semantically structured knowledge bases, supporting standardization and broad availability of experiential knowledge. Crucially, the concept follows a human-centered paradigm: Technologies are not used to monitor or evaluate workers but to document and make explicit skills previously embedded in the practice of experienced specialists. The combination of AI-based vision, ergonomic structuring, and semantic analysis thus opens new potential for digitalizing implicit assembly knowledge.

3.2 AI-supported speech processing and semantic modeling for capturing implicit assembly knowledge

The second concept targets the capture and structuring of procedural and strategic knowledge in complex manual assembly, for example, fixed-position assembly in special-purpose machinery. In such contexts, process knowledge, adaptation to unforeseen events, and optimal sequencing of work steps are highly dependent on individual expertise. The goal is to record this knowledge during real work, analyze and formalize it, and make it digitally accessible.

Methodologically, the approach builds on the think-aloud method and cognitive task analysis (CTA). In think-aloud, specialists verbalize thoughts, decisions, and perceptions while working, directly documenting cognitive processes. CTA complements this through structured post-hoc interviews, particularly using the critical decision method, which captures critical events, decision alternatives, and reference points, and makes action variants explicit. Primary data sources include audio recordings from think-aloud sessions and CTA interviews, optionally supported by video for complex or safety-critical cases. Audio is transcribed with speech-to-text systems enriched with domain-specific terminology to ensure recognition accuracy.

Transcripts are processed with NLP and LLMs, which filter irrelevant content, segment text into knowledge units, recognize entities (tools, components, test criteria), and map them to process steps. They also extract causal relations and decision logic, linking reasons to actions. LLMs further enrich vague passages with known process details, ensuring completeness.

The enriched content is linked with contextual parameters such as environment, resources, time constraints, or disruptions. This produces process-related knowledge objects that combine activity with decision logic. Ontologies or KGs then provide semantic representation and interlinking. This allows context-based searches, automated connection derivation, pattern recognition, and recommendations.

The approach aims to produce a consistent, machine-readable knowledge base supporting digital assistance, targeted training, and process analysis. Knowledge remains anchored in its original context of action and thus retains situational relevance. By combining human-centered data collection with AI-supported processing and semantic modeling, implicit knowledge is sustainably externalized and made available across the organization.

3.3 AI-supported knowledge modeling with human validation for reliability

The third concept extends these perspectives toward scalable integration into enterprise systems (e.g., ERP). Its objective is to structure experiential knowledge so it becomes machine-processable, context-sensitive, and expandable. Input sources include visually recorded actions, linguistically captured decision-making logic, and process data. These heterogeneous sources are integrated into a uniform semantic model, enabling adaptive, AI-assisted application.

Modeling begins with NLP and LLMs for entity recognition, relation extraction, and context assignment. Semantic normalization ensures consistency, while rule- and confidence-based checks, combined with expert validation, guarantee sufficient reliability. Human experts play a central role in validating outputs, contributing situational knowledge, and providing feedback [76, 77]. Versioning mechanisms ensure traceability and currency.

Structured content is represented in KG, enabling scalable analysis of relations and dependencies. Combined with RAG, this allows LLMs to deliver context-specific answers, recommendations, and process descriptions [70, 78]. Outputs follow a human-centered paradigm, tailored to user roles, expertise, and situational needs.

Integration potentials include ERP, MES, and PLM systems, creating continuous information chains across enterprise levels. This links operational data, experiential knowledge, and digital infrastructures. For example, motion data and decision rules from assembly can be connected with MES process records and ERP production orders, ensuring that experiential knowledge directly informs scheduling, resource planning, and quality documentation. Embedded validation, feedback, and continuous updating ensure that the approach combines AI efficiency with human expertise, producing reliable, up-to-date, and expandable knowledge models for sustainable use in production.

Together, the three concepts complement one another. The first provides objective, visually based representations of actions; the second captures cognitive processes and decision logic; and the third integrates both into semantically structured knowledge bases connected to enterprise systems. This results in a holistic digital knowledge base covering both execution and decision-making, forming a foundation for analysis, optimization, assistance, and training in assembly environments.

To operationalize these concepts in practice, **Figure 3** illustrates the core pipeline that summarizes the steps from elicitation to continuous improvement.

All data collection (video, audio, sensor) was conducted with the informed consent of participants. Recordings were securely stored, anonymized where possible, and retained only for the duration required for analysis. Access to raw data was strictly role-based and limited to authorized researchers. HIL validation ensured that data were used exclusively for knowledge elicitation and transfer, preventing surveillance drift or misuse for performance monitoring.

4. Best practices

Beyond conceptual approaches, current research projects already show how AI methods can be applied in practice. The following best-practice cases illustrate different ways of using such technologies in knowledge-intensive processes, ranging from structured learning and competence development to operational decision-making.

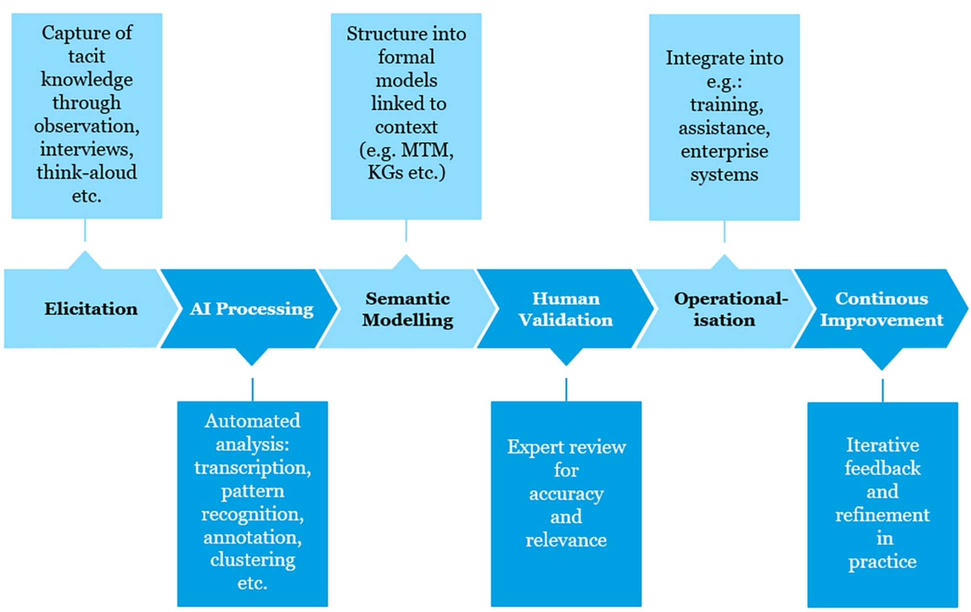

Figure 3.
Summarized pipeline for knowledge elicitation and operationalization – own illustration.

4.1 Customizable digital learning environments for AI-enhanced knowledge management

Within the KOMATRA project, the focus is on supporting sustainable and value-oriented transformation in SMEs. One central theme is learning and competence development as a prerequisite for long-term organizational change. In this context, digital learning platforms were explored as a means of structuring knowledge transfer and skill acquisition. The open-source learning management system (LMS) Moodle was evaluated as a best-practice example for integrating AI-based methods into corporate learning.

Moodle can be adapted to specific organizational needs, including the integration of locally hosted AI solutions. While the current version supports the OpenAI and Azure APIs, on-premises deployment of an LLM allows companies to maintain full control over data and infrastructure. Such integration enables AI-assisted content creation, image generation where models are available, and summarization tools that help learners condense and understand materials more effectively. Beyond AI functions, Moodle can be customized through user interface adjustments, additional plugins, and workflow-specific modifications. Structured guidelines further support the creation of interactive content, such as exercises and drag-and-drop activities, enhancing learner engagement.

The open-source Adapt authoring tool complements Moodle by creating SCORM-compliant learning packages for any LMS. With JavaScript expertise, the Adapt tool can be customized and extended with additional functions, enabling content creation beyond the standard framework. Possible customizations include UI modifications and integration of locally hosted LLMs. Generated outputs can be transferred to the web interface or stored directly in the database via API. Workflows may include direct prompt-based generation, guided content creation from predefined topics, or RAG integration with external context. Relevant corporate documents can be indexed to increase contextual awareness, with configurations defined at individual, departmental, or organizational levels. API keys provide a means of access control, ensuring that only authorized roles can interact with the system. However, secure handling of sensitive data additionally requires encryption, secret management, and strict access policies.

AI integration also extends to automated assessment. LLMs can generate quizzes based on selected course content, with parameters such as question type, number, and focus configurable. Communication between the LMS and AI can be set up for the automatic transfer of grading results. To comply with data minimization, any RAG-generated content is deleted from the LLM after use, preventing unnecessary accumulation. **Figure 4** illustrates how these elements converge in a customizable digital learning framework: Moodle as the core LMS, complemented by the Adapt tool for SCORM-compliant content, with AI functionalities such as LLM and RAG integrated through modular connections.

From a knowledge management perspective, the combined use of Moodle and Adapt with LLM and RAG enhances the capture, organization, and delivery of knowledge. Automated content creation, context-aware enrichment, and adaptive assessment improve efficiency while systematically preserving and disseminating organizational knowledge. For SMEs, such solutions are valuable as accessible, customizable and secure tools for building long-term knowledge infrastructures aligned with transformation objectives. In comparison, annual costs of unmanaged

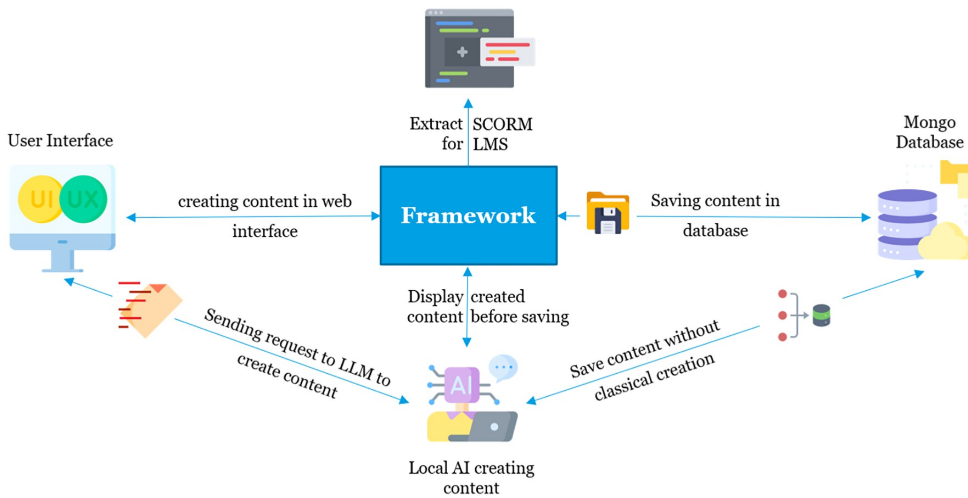

Figure 4.
Framework for customizable digital learning environments with integrated AI functionalities – own illustration.

loss of knowledge in SMEs can exceed €80,000 [8]. By contrast, implementing a self-hosted, AI-enhanced learning system involves one-time investments of around €12,500 and annual operating costs of approximately €8,000, making the system a clearly more cost-efficient option for sustainable knowledge management.

4.2 Human-centered AI for order allocation

As part of the ViSAAR research project, an application-oriented study explored the use of AI in knowledge-intensive logistics operations. The scenario focused on manual order picking, a process marked by short-term orders, high product variety, and fluctuating workloads. Under such conditions, allocation decisions typically rely on the implicit expertise of shift supervisors. Conventional systems and static algorithms often reach their limits, especially when rapid rescheduling or balanced workload distribution is required.

The project aimed to develop an adaptive, human-centered decision-support system for order allocation, as illustrated in **Figure 5**.

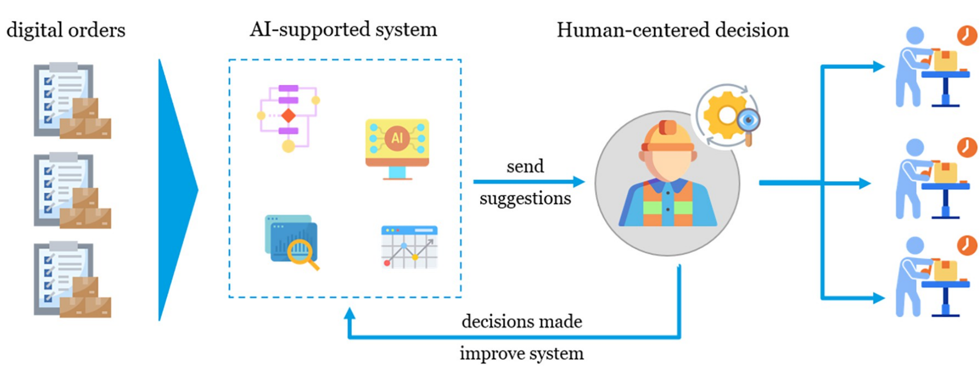

Figure 5.
Human-centered AI system for order allocation – own illustration.

A key challenge lies in formalizing decision-making processes previously driven by implicit knowledge. By combining human expertise with AI-based optimization, the system automated routine tasks while reducing cognitive load. As a result, process efficiency improved, idle time decreased, and workloads were distributed more evenly, enhancing both performance and employee satisfaction.

Reinforcement learning formed the methodological core. Here, an artificial agent developed decision strategies in a simulated environment. Training combined historical data with synthetic scenarios to establish a baseline, which was refined continuously using real-time inputs and structured human feedback. Crucially, final decision authority remained with operational staff, ensuring that domain knowledge and situational judgment stayed decisive.

To simulate realistic conditions, the environment modeled key logistics parameters such as order arrivals, workstation capacities, workload variability, and time-critical priorities. Continuous feedback in the form of reward signals guided the agent whenever its allocation strategies improved measurable performance. Through iterative learning, the system adapted progressively, improving allocation quality by integrating both operational outcomes and human input. For example, when urgent orders arrived on top of existing workloads, traditional allocation rules tended to overload one station. The RL-based system instead redistributed tasks dynamically across all workstations, balancing urgency and capacity. This reduced delays and idle time while improving on-time performance.

A distinctive element of the approach was the integration of workplace-specific experiential knowledge. Qualitative feedback and structured assessments from staff informed the design of the reward function, allowing the AI to internalize human expertise over time. This enabled systematic digitalization and targeted reuse of implicit knowledge within the optimization process.

The resulting system proved flexible, transparent, and adaptive. Decision-making capabilities were enhanced, while supervisors were relieved of routine tasks, enabling them to focus on complex cases where human judgment is essential. The study shows that AI can not only increase efficiency but also formalize, preserve, and apply experiential knowledge in a human-centered manner. Initial simulations indicated that the optimized allocation system could reduce overall working time by around 17% per shift, while subsequent pilot tests in real operations confirmed a sustained reduction of approximately 11% compared to the baseline. These findings demonstrate that measurable efficiency gains can be achieved both under controlled conditions and in practice. The system is currently undergoing further testing and refinement in operational environments to continuously improve robustness, accuracy, and integration into existing workflows, while keeping human expertise at the core [79, 80].

The two cases demonstrate complementary ways AI contributes to systematic knowledge management. The KOMATRA case highlights how LLM- and RAG-supported learning environments structure and disseminate knowledge, while the ViSAAR case shows how AI can capture and operationalize implicit expertise in dynamic logistics environments. Both follow a human-centered paradigm, ensuring AI supports rather than replaces expertise, and thus contribute to sustainable, adaptive knowledge infrastructures in SMEs.

5. Outlook and future developments

The best-practice examples show that AI-based technologies are no longer confined to theory but are already applied successfully in knowledge-intensive environments. They demonstrate how experiential knowledge can be externalized, structured, and utilized through digital systems while ensuring that human expertise remains central. Building on the presented concepts and implementations, several research directions and technological developments will shape the future of knowledge management in industrial contexts.

A major trend is the growing integration of multimodal data sources. Current solutions mostly combine text, structured data, and video, but future developments are expected to focus on vision language models capable of processing visual and linguistic information jointly. These models could support a more holistic representation of experiential knowledge by linking recorded actions with verbal explanations or contextual annotations in real time. In assembly, video data could be enriched with reasoning or procedural descriptions, creating semantically structured multimodal knowledge objects. For SMEs, this approach may simplify entry into knowledge management by reducing reliance on complex documentation or written records.

Scalability and interoperability of knowledge models form another key perspective. Ontologies and KGs already provide a strong foundation, yet seamless integration with enterprise systems such as MES, ERP, or PLM remains challenging. Advances in standardization and semantic web technologies are likely to be crucial in enabling cross-organizational knowledge exchange, especially for SMEs that require flexible but reliable infrastructures.

Human-centered design principles must continue to guide these developments. The examples from KOMATRA and ViSAAR have shown that acceptance, transparency, and employee participation are essential for successful implementation. Future systems must, therefore, focus not only on technical performance but also on governance structures, validation mechanisms, and participatory processes that safeguard trust and ensure responsible use of AI in operations.

The convergence of AI subfields – ranging from NLP and LLMs to reinforcement learning, computer vision, and multimodal modeling – will likely produce increasingly adaptive and autonomous systems. Rather than replacing human expertise, these systems will extend it, providing targeted support for decision-making, training, and process optimization. The long-term vision is the creation of sustainable knowledge ecosystems in which experiential, procedural, and contextual knowledge is continuously captured, structured, and made available across organizational boundaries.

In summary, the state of the art, together with the presented concepts and applications, underlines the transformative potential of AI for knowledge management in industrial production. Future research must refine methods for multimodal knowledge capture, strengthen human-centered integration, and advance scalable, interoperable infrastructures. These efforts will pave the way toward resilient knowledge systems that preserve and expand experiential expertise, ensuring its long-term availability for innovation, efficiency, and sustainable value creation.

Acknowledgments

This research was carried out within the framework of the ViSAAR project, "Virtual Work Design and Technologies for Innovation in Structural Change" (funding number 02L20B088), funded by the German Federal Ministry of Education and Research (BMBF), and the KOMATRA project, "Competence Center for Work Research: Shaping Transformation in the Saar-Palatinate Corridor – Value-Oriented Work and Learning in the Circular Economy" (funding number 02L22C005), supported by the German Federal Ministry for Research, Technology, and Space (BMFTR). The authors gratefully acknowledge this support.

The authors also thank Felix Weber and Abbas Nouri for their support and contributions to the implementation of this book chapter.

Author details

Jannis Pfister[1]*, Daniela Schmidt[1], Matthias Jenner[1], Till Günther[1] and Rainer Müller[2]

1 ZeMA – Centre for Mechatronics and Automation Technology gGmbH, Saarbrücken, Germany

2 University of Saarland – Chair of Assembly Systems, Saarbrücken, Germany

*Address all correspondence to: jannis.pfister@zema.de

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