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Unlocking Tacit Knowledge in Industrial Production: Exploring Barriers, Practices, and LLM-Driven Potentials for Knowledge Management

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Abstract

In aging societies across western industrialized nations, the loss of expertise due to retiring skilled workers presents a critical challenge for industry. That is especially true on the shop floor, where much of the knowledge is tacitly gained through years of hands-on experience rather than formal documentation. This study explores current knowledge management (KM) challenges and systematically identifies high-potential applications for large language models (LLMs) as part of a broader research initiative aiming to develop human-centered KM solutions supported by generative artificial intelligence (GenAI). We conducted two structured workshops with 23 participants from 14 German manufacturing companies. Three core barriers and two prioritized LLM use cases were identified, contributing specific design recommendations for LLM-supported KM systems for companies. The results advance the understanding of GenAI-assisted knowledge retention in industrial settings and provide a practical foundation for addressing the demographic shift through intelligent, technology-driven solutions.

Keywords: Knowledge Management, Generative Artificial Intelligence, Manufacturing, Shop Floor Management.

1. Introduction

Across industrialized nations, demographic change and the associated retirement of experienced personnel pose serious challenges for knowledge-intensive sectors such as manufacturing (Sumbal et al., 2020). In Germany 16.5 million people are expected to retire by 2036, with only 12.5 million entering the workforce in the same period – intensifying the existing shortage of skilled workers (Deschermeier & Schäfer, 2024). This demographic imbalance is accelerating the loss of expert knowledge, particularly among engineers and technicians (Sumbal et al., 2020). On the shop floor, this knowledge is often tacit, experiential, context-specific, and rarely documented (Nakano et al., 2013). As a result, companies risk losing critical know-how when employees leave. Simultaneously, the manufacturing sector must adapt to increasing changes driven by global crises, technological innovation, new business models, and shifting consumer behavior (Balzer, 2024; Jennex et al., 2024). These pressures result in more complex products and processes, volatile global value chains, and intensifying competition (Balzer, 2024). To manage rising complexity, companies increasingly rely on less experienced or more flexible workers, making effective knowledge transfer essential (Hoerner et al., 2023). KM is widely regarded as a solution, aiming to conserve and transfer employee knowledge within the organization (Rülicke, 2014). Yet, many companies lack structured approaches to managing operational knowledge (Hoerner et al., 2023; Finkel & Wurster, 2025, Manuscript under review). Traditional KM systems often focus on documented or managerial knowledge, neglecting shop-floor expertise (Sumbal et al., 2020). At the same time, advances in GenAI, such as the development of LLMs, offer new opportunities. In this study, we use the term GenAI specifically to refer to LLMs. LLMs are transformer-based systems trained on large-scale text corpora that can generate, retrieve, and contextualize knowledge in natural language interactions (Hadi et al., 2023). These tools can potentially extract, structure, and reuse both explicit and tacit knowledge in novel ways (O'Leary, 2024). However, design principles and validated application contexts for LLMs in industrial KM are still underexplored (Storey, 2025, Just Accepted). Other AI approaches, such as rule-based expert systems or computer vision, are outside the scope of this paper.

This study aims to address this gap by identifying core barriers, current practices, and high-potential use cases for LLM-supported KM in manufacturing. It is embedded within a broader Design Science Research (DSR) initiative that seeks to develop human-centered GenAI systems for capturing and reusing knowledge in manufacturing. The study is guided by the following three research questions (RQ):

RQ1: "What are the key barriers to effective knowledge retention in industrial production environments?"

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RQ2: “Which LLM-supported KM use cases are seen as most valuable by practitioners?”

RQ3: “What implications arise for the design of future GenAI-supported KM systems?”

By addressing these questions, we contribute to developing GenAI-supported KM tools for the industry with a conceptual model. Our paper proceeds with the theoretical background, research approach, findings, design implications, discussion, and conclusion.

2. Theoretical background

2.1. Tacit and explicit knowledge in industry

In academic research, “knowledge” is typically explained with its hierarchy that also includes data and information, each representing increasing levels of abstraction and value (Rowley, 2007; Ackoff, 1989). Within this hierarchy, data refers to raw, unprocessed facts or symbols that describe phenomena. When such data is structured or contextualized through interpretation, it becomes information (Ackoff, 1989). Knowledge emerges when this information is further integrated with experience and understanding, enabling action or decision-making (Ackoff, 1989). This transformation can occur through either personal reflection or learning from individuals who have already acquired the relevant expertise (Alavi & Leidner, 2001).

Knowledge within KM is often distinguished as either explicit or tacit (Schiedermair et al., 2023). Explicit knowledge is codified and documented and for example found in manuals and databases, while tacit knowledge is deeply rooted in personal experience, practices, and intuition, making it difficult to articulate or record (Alavi & Leidner, 2001). In industrial production, tacit knowledge resides often among shop floor workers, who rely on hands-on skills and situational awareness rather than written instructions (Schiedermair et al., 2023). Such experiential knowledge is critical to operational performance but often disappears when employees retire or leave the organization (Sumbal et al., 2020). Without access to the context embedded in tacit knowledge, the explicit documentation may also lack usability (Rowley, 2007).

2.2. The strategic role of shop floor KM

In manufacturing, shop floor knowledge directly influences product quality, process efficiency, and the ability to respond to disruptions (Hoerner et al., 2023). It encompasses not only the “how” of operations but also the “why” – often hidden in individual mindsets or learned heuristics (Alavi & Leidner, 2001). Strategic management increasingly recognizes this hands-on knowledge as a source of competitive advantage, especially amid rising complexity, globalization, and demographic change (Schiedermair et al., 2023; Balzer, 2024). The loss of irreplaceable process know-how affects not only continuity but also training, problem-solving, and innovation capacity (Rülicke, 2014).

2.3. Current challenges in industrial KM

Despite a growing awareness of the importance of knowledge retention, many organizations still struggle with fragmented or incomplete KM systems (Fischer, 2025). This is also evident in our preliminary investigations for this study encompassing 19 participants from 11 German industrial companies. The surveys conducted in these investigations show that while the relevance of KM is broadly acknowledged, structured, company-wide implementations do not yet exist (Finkel & Wurster, 2025). We found that in practice, KM efforts often rely on informal exchanges, outdated tools, or personal motivation, lacking the scalability and sustainability needed to address demographic trends. These findings align with Wang et al. (2025), who emphasize the need for integrated KM ecosystems. Overall, there remains a gap between strategic intent and operational execution (Hoerner et al., 2023; Schiedermair et al., 2023; Storey, 2025; zur Heiden & Kaltenpoth, 2024; Finkel & Wurster, 2025).

2.4. GenAI in knowledge-intensive processes

The emergence of GenAI – especially LLMs such as *OpenAI*’s ChatGPT – has unleashed new opportunities for capturing, retrieving, and transferring knowledge (Hadi et al., 2023). LLMs are capable of interpreting and producing human-like text based on extensive training on diverse corpora, enabling context-aware responses and interactive dialogue (Storey, 2025). They can operate in multiple roles relevant to KM, including conversational retrieval (natural language queries across heterogeneous sources), retrieval-augmented generation, where external data is dynamically integrated into responses, and agentic workflows, in which LLMs autonomously coordinate sequences of tasks (Schönfeld, 2025; Wang et al., 2025). With that, LLMs offer potential for capturing tacit knowledge through conversational interfaces, assisting workers in real time, and scaling personalized learning across production environments (Finkel et al. 2024; O’Leary, 2024; Storey, 2025). Initial applications in industry use LLMs to make explicit knowledge accessible to act as adaptive intermediaries between employees and knowledge bases – particularly valuable in training new staff, transferring documented expertise, and augmenting complex tasks on the shop floor (Schönfeld, 2025; zur Heiden & Kaltenpoth, 2024).

Conventional KM tools in industry, such as wikis, spreadsheets, or databases, primarily codify explicit knowledge. They require manual input, structured formats, and user-driven search (Hoerner et al., 2023). In contrast, LLM-based tools can reduce entry barriers by enabling conversational access, contextual retrieval across heterogeneous sources, and low-effort tacit capture through speech (Storey, 2025). This distinction is critical for clarifying the unique value of GenAI-supported KM beyond conventional tools or platforms.

3. Research approach

Given the aim of understanding a practical problem and creating artifacts to address it, this study adopts a DSR approach (Hevner et al., 2004; Peffers et al., 2007). This approach includes six iterative steps: problem identification and motivation, definition of objectives for a solution, design and development, demonstration, evaluation, and communication. DSR provides a structured methodology for addressing complex, real-world problems through iterative cycles of problem identification, artifact design, demonstration, and evaluation (Peffers et al., 2007). The present study is embedded in a broader DSR initiative aimed at developing GenAI-supported tools for KM in industrial settings, with an emphasis on capturing employees' tacit knowledge. By answering the three RQs, its specific objective is to develop a conceptual model that serves as a foundation for future research.

3.1. Initial empirical investigation

The research commenced with a small pre-study phase involving interviews with 13 experts in three German-based companies to assess the potential of LLMs in manufacturing. The interviews revealed specific use case potentials for applying LLMs in KM within industrial companies (Finkel et al. 2024). To validate and extend the initial findings, a follow-up inquiry was conducted with 19 professionals at middle and senior management levels across 11 different German industrial firms, gauging KM importance, existing practices, and best practices. Results showed that KM is widely valued but lacks systematic implementation, with efforts being fragmented and departmental "island solutions." (Finkel & Wurster, 2025) These gaps expose companies to knowledge loss amid workforce transitions. Moreover, none of the companies surveyed reported having a fully structured or organization-wide KM framework in place (Finkel & Wurster, 2025). Despite scattered best practices and growing awareness of the strategic value of KM, these findings highlight a substantial implementation gap that may leave companies vulnerable in the face of ongoing change. A detailed analysis of parts of this pre-study has just been accepted for publication and is expected to be released in fall 2025. Insights from these pre-studies shaped the design of two sequential workshops, serving as input for the design and development phase within the DSR framework. Workshops were chosen because they allow for interactive joint development of results, enabling direct clarification of misunderstandings and ensuring a shared understanding of the multifaceted topic among participants and researchers. This interactive setting helped practitioners see their perspectives reflected in the consolidated outcomes, increasing the practical relevance of the results. Two workshops were conducted to avoid hierarchical influence by separating managerial levels, to maximize sample size by accommodating availability across two dates, and to ensure triangulation of insights. The same 14 firms participated as in the pre-studies.

3.2. Workshop participants

Two workshops were conducted to address our RQs. The companies were recruited via research partnerships to ensure sectoral diversity. Workshop 1 had 13 senior managers from nine German manufacturers and technology providers (Table 1). Workshop 2 involved ten mid-level managers representing five similar German companies (Table 2). All the manufacturing companies have in common that they rely on the expertise of skilled professionals, such as their shop floor workers and engineers, and all face similar KM challenges. The two technology providers contributed relevant insights into the development of an LLM-enabled KM solution.

Table 1. Overview of companies in workshop 1.

Firm	Short Description and number of participating employees	Size (Employees)
F_1	Manufacturer of tractors and agricultural machinery (3)	5,000 – 10,000
F_2	Rail and mobility technology provider (2)	15,000 – 20,000
F_3	Manufacturer of electrical connectivity solutions for industry (1)	250 - 500
F_4	Manufacturer of electrical protection and safety equipment (1)	2,000 – 2,500
F_5	Technology provider for automation, electrification, and digitalization (1)	250,000 – 350,000
F_6	Manufacturer of electronic connectors and components (1)	1,000 – 1,500
F_7	Hydraulic components and systems manufacturer (1)	2,500 – 3,000
F_8	Digital business services provider (2)	25 – 100
F_9	Manufacturer of precision metal parts and for different industry sectors (1)	2,000 – 2,500

Table 2. Overview of companies in workshop 2.

Firm	Short Description and number of participating employees	Size (Employees)
F_{10}	Manufacturer of electronic connectors and assemblies (4)	100 – 250
F_{11}	Producer of stamping/forming machines and automation systems (2)	1,000 – 1,500
F_{12}	Producer of surface technologies and materials for various industries (1)	5,000 – 15,000
F_{13}	Manufacturer of strip and coil springs, stamped parts, precision components (2)	250 – 600
F_{14}	Producer of dispensing and lubrication systems for automation (1)	50 – 250

All participants gave their consent to the publication of the results. However, a few demanded no direct connections to their person or companies in the publication, so all the companies were codified from F_1 to F_{14} and the participants are not listed separately.

3.3. Workshop design and execution

Each workshop followed the same structure as described in Table 3:

Table 3. Overview of workshop design.

Phase	Workshop Phase Description
W1	Shared KM framing: To ensure consistency, we began each workshop by establishing a common understanding of GenAI and KM in the industrial context, as outlined in section 1 and 2.
W2	Individual questionnaires: Afterwards, the participants were asked to answer five questions (Q) on KM hurdles, tips, tools, LLM usefulness, and use cases: Q1 "What are the most significant current hurdles to making the tacit knowledge of production employees sustainably accessible?"; Q2 "What specific recommendations or practical tips would you offer to other companies for successfully implementing KM in production environments?"; Q3 "Can you describe a particular tool, method, or software solution that you would recommend for supporting KM on the shop floor?"; Q4 "How useful do you consider the application of LLMs for KM in your company? (from 1 *not useful at all* to 10 *very useful*)"; Q5 "In which (up to three) specific areas can you most clearly envision the use of LLM-based solutions for KM? Please briefly describe each use case."
W3	Small group synthesis: Participants then discussed their responses in small groups of three to five people, identifying challenges and promising LLM use cases.
W4	Group-wide consolidation: After discussing the small groups presented their synthesized results to all participants. This collaborative exchange enabled cross-group validation, refinement of identified issues, and a collective understanding of recurring themes.
W5	Collective prioritization: In the end each participant was given two points to allocate toward the LLM use cases they found most valuable for their company. Points could be distributed to one or two use cases. This prioritization step enabled a quantifiable assessment of perceived value across participants.

The first workshop took place on the 6th of May 2025 at the Kempten University of Applied Sciences, Germany. The second workshop took place at the facilities of company F_{11} on the 13th of May 2025.

3.4. Data collection and analysis

To ensure a structured and academically grounded analysis, a clustering process was applied to structure the responses of the individual questionnaires. They were then compared and validated against the results of the group-wide consolidation and the collective prioritization. First, all free-text responses were transcribed and anonymized. Afterwards the responses were screened and thematically clustered. To analyze and group the responses for Q1 meaningfully, the socio-technical systems (STS) model was applied (Bostrom & Heinen, 1977). The model distinguishes between three core system dimensions – social, technical, and organizational – that interact to shape work environments and knowledge processes (Bostrom & Heinen, 1977). Following the barrier analysis, participants were invited to propose specific tips, tools, and methods other companies could adopt to make KM in production successful (Q2, Q3). The responses were initially reviewed to identify recurring themes and categories. Due to the diverse and context-specific answers, an inductive coding approach was applied. All recommendations were qualitative analyzed, open-coded and then inductively grouped into pragmatic clusters that reflect the type of action proposed. Q5 was analyzed in the same way. The results of Q4 were visualized with a bar chart. The following findings then informed the subsequent design requirements for our DSR artifact (Section 5).

4. Findings

4.1. Identified barriers to sustained access to tacit shop-floor knowledge

To answer RQ1, we first clustered the total of 71 qualitative responses to Q1 collected across the two workshop sessions. The conducted STS clustering revealed that social factors were mentioned most frequently, comprising 30 of the 71 responses (42%). These included issues related to employee motivation ($F_{1,2,3,4,5,6,8,9}$), the ability to communicate ($F_{1,2,6,8,9,10,11}$), fear of losing job relevance ($F_{2,8,13}$), or unwillingness to share expertise (F_7) – driven by a lack of recognition (F_{10}) or psychological ownership of one's knowledge (F_8). One participant, for example, stated, "People keep their knowledge to stay indispensable" (F_6), highlighting the fear of losing perceived job security as a key motivational barrier.

Technical barriers were the second most prominent category, cited in 27 responses (38%), referencing the absence of adequate platforms ($F_{1,5,6,10,13}$), tools ($F_{1,2,3,8,9,10}$), or digital infrastructure ($F_{1,2,5,12,13}$) for capturing and distributing tacit knowledge. Multiple participants described how existing systems were inaccessible ($F_{7,8}$), fragmented ($F_{3,7}$), or ill-suited for production environments ($F_{1,4,8,10}$). For instance, one participant noted, “There is no easy system to capture and retrieve know-how” (F_{2}), pointing to the lack of intuitive documentation tools on the shop floor.

Organizational issues accounted for the remaining 14 responses (20%) and included challenges such as missing strategic guidance ($F_{1,3,5,7}$), lack of leadership support ($F_{1,8}$), or insufficiently institutionalized processes ($F_{2,3,9,10,14}$) for knowledge transfer. A recurring theme in this category was the absence of a structured KM approach across company departments ($F_{10,11,13}$). For example, a participant remarked that “under production pressure no one has time to write things down” (F_{7}), illustrating how knowledge retention efforts are often deprioritized in the face of daily operational demands. Taken together, motivational barriers, technical hurdles, and missing organizational guidance, support, and structures emerge as the core challenges to effective KM in industrial settings. These findings are consistent with Wang et al. (2025), on the need for coordinated, responsible AI-augmented KM.

4.2. Practical recommendations for shop-floor KM

In all, 34 actionable suggestions were gathered in response to Q2. They were analyzed separately from the barrier data because the intent was prescriptive rather than diagnostic. Each entry was qualitatively coded and assigned to one of six thematic clusters (A1-A6) that emerged inductively from the data, as described in Table 4 and discussed afterwards.

Table 4. Main clusters of Q2 responses.

Cluster	Description	Count
A1, Tool-specific / documentation practices	Specific advice on databases, error logs, visual handbooks, instant data capture	8
A2, Motivation & incentives	Formal or gamified rewards, public recognition, team-based bonuses	8
A3, Collaboration & mentorship	Tandems, pairing juniors with veterans, cross-generational projects	7
A4, Simplicity & accessibility	Low effort capture interfaces, mobile apps, minimal bureaucracy	6
A5, Formal processes	Structured transfer pathways, rotation plans, retirement handovers	4
A6, Engagement in design	Early involvement of workers in tool selection or use case definition	2

A1, Tool-specific / documentation practices: One of the most frequently cited clusters highlighted specific practices for documentation – including maintaining detailed error logs ($F_{10,13}$), custom manuals for project-specific features (F_{10}), and user-friendly idea management platforms (F_{4}). One participant mentioned, “carefully maintaining tool databases is key in maintenance” (F_{10}), while another emphasized the importance of having “immediate data collection (temporarily in *Excel*)” (F_{13}).

A2, Motivation & incentives: The second most common cluster addressed motivational structures. Respondents suggested gamification (F_{8}), visible recognition (F_{8}), and collective reward systems to make knowledge sharing attractive (F_{8}). One participant noted that “tying rewards to team contributions increases engagement” (F_{8}), while others suggested configurable incentives (F_{1}) or highlighting the benefit to individual workers, such as “making the job easier and more secure” (F_{7}).

A3, Collaboration & mentorship: Several participants focused also on the social aspects of knowledge transfer. They advocated mentoring structures such as “experienced workers partnering with new employees” ($F_{5,6,10,11}$) and fostering intergenerational collaboration (F_{3}). One mentioned using apprentices to collect and document expert knowledge as a bottom-up strategy (F_{9}).

A4, Simplicity & accessibility: Another cluster was the importance of designing KM processes to be low-threshold (F_{1}) and easily integrated into daily routines (F_{1}). Participants emphasized the need for intuitive tools and minimal entry barriers ($F_{1,7,8}$). One respondent recommended that knowledge capture systems should be “as simple as a mobile app” (F_{1}), while another stressed that “it must be truly low-barrier” (F_{8}). Multiple contributions pointed to the necessity of short feedback loops and quick turnaround times (F_{8}) to encourage ongoing engagement.

A5, Formal processes: Structured approaches such as formal knowledge transfer programs (F_{12}) or retirement transition planning (F_{3}) were also recommended. For example, one participant advocated “introducing a process for institutional transfer of knowledge from employees nearing retirement” (F_{3}). Others proposed defining KM as part of the tasks at lowest management level, e.g., team leader (F_{1}).

A6, Engagement in design: Finally, a few participants stressed the importance of involving workers in designing KM solutions themselves. This cluster includes responses suggesting co-creation of use cases (F_{8}) and ensuring that team leaders at the shop-floor level take ownership of KM integration (F_{4}).

This thematic structure illustrates the breadth of practical advice shared by participants and highlights that effective KM in production settings is rarely dependent on a single factor. Instead, successful implementation appears to require a balanced interplay of intuitive tooling, motivational structures, interpersonal knowledge sharing, and processual formality – tailored to the specific work context.

4.3. Tools and methods recommended for KM on the shop floor

Q3 in the workshop aimed to gather practitioner insights into effective tools, methods, or software solutions either currently used or considered promising for supporting KM in industrial production environments. A variety of tool categories and implementation practices were mentioned, reflecting diverse organizational maturity levels and technology adoption strategies. Twenty-four discrete suggestions were assigned to the clusters (B1-B3) shown in Table 5.

Table 5. Main clusters of Q3 responses.

Cluster	Description	Count
B1, Non-AI Workarounds & process-centric methods	Practical, often informal KM approaches including spreadsheets and checklists augmented by cultural or procedural practices	11
B2, GenAI-enhanced & low-code solutions	Emerging technologies such as GenAI, voice capture, and low-code apps	7
B3, Structured KM platforms (Non-AI)	Centralized enterprise tools such as wikis and databases as foundational infrastructures	6

B1, Workarounds & process-centric methods: A persistent reliance on spreadsheets ($F_{6,13}$), quick guides ($F_{6,13}$), and evaluation check-sheets (F_1) demonstrates the pragmatic culture of shop-floor KM. While these workarounds are low-cost and familiar, respondents acknowledged their limitations in scalability and searchability. Some emphasized that fostering a "living error culture" ($F_{3,1}$) can inject much-needed structure and transparency into such informal systems. This cluster highlights the continued use of spreadsheets and quick guides, thus successful GenAI or platform deployments should integrate, not replace, these habitual tools.

B2, GenAI-enhanced & low-code solutions: Seven answers referred to technologies like LLM-based chatbots ($F_{4,8,9}$), agentic workflow engines (F_8), or voice-to-text capture (F_8) (e.g., *Whisper*, *AudioPen*). These suggestions echo recent literature arguing that LLM interfaces can lower documentation friction and improve contextual retrieval (Storey, 2025; Finkel, 2024); and they indicate growing interest in LLM-driven capture and retrieval, supporting earlier findings on low-threshold documentation needs (Section 4.2.).

B3, Structured KM platforms (non-AI): Respondents suggested learning-management systems, e.g., *TalentSoft* (F_7), or corporate wikis such as *Confluence* (F_8) as backbones for codifying and disseminating explicit knowledge. However, two respondents warned of high licensing costs (F_{10}) or legacy complexity (F_6), underscoring the need for cost–benefit alignment when selecting enterprise tools.

4.4. Usefulness ratings for LLM-enabled KM

Participants were asked in Q4 to rate the overall perceived usefulness of LLMs for KM on a ten-point Likert scale. Figure 1 visualizes the distribution.

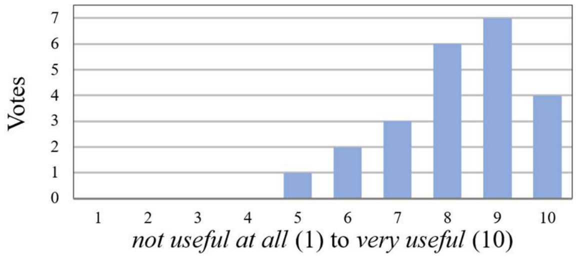

Figure 1: Perceived usefulness of LLMs for KM.

The mean score of the responses is 8.2, indicating a generally positive perception of LLMs' usefulness in the KM of companies. In fact, 86% of respondents (20 of 23) selected 7 or higher, suggesting that most managers view LLMs as a promising lever for KM. No ratings below 5 were recorded, underscoring the absence of outright skepticism. These results echo recent surveys in industrial GenAI adoption, which report growing confidence in LLM-based assistance despite limited large-scale deployments (Storey, 2025; Finkel et al., 2024).

4.5. Identified LLM-supported KM-use cases

To assess how participants envision applying LLMs in industrial KM and to address RQ2, Q5 asked for the specific areas in which respondents could most clearly imagine using LLM-based solutions in KM, encouraging them to describe their envisioned use cases in free-text form. Across 14 companies, a total of 71 responses were collected and thematically clustered into five application domains (C1-C5), as shown in Table 6.

C1, Training, on-boarding & cross-skilling: The most frequently cited cluster involved GenAI applications for transferring knowledge to new or rotating employees ($F_{1,2,3,4,5,7,8,10,11,13,14}$). Participants suggested GenAI-generated work instructions ($F_{5,13}$) or safety instructions (F_7), categorization of required knowledge ($F_{6,14}$), and video/audio-based onboarding aids (F_{13}). Several companies proposed using LLMs to "monitor the success of training concepts" ($F_{1,3,6,10}$), e.g. by auto-generating quizzes from work instructions, tracking completion, and summarizing skill gaps for supervisors. The strong emphasis on digital training support indicates an increasing demand for scalable, personalized learning formats in industry.

C2, On-demand knowledge retrieval: The second most frequently stated LLM use case was to serve as conversational search engines ($F_{1,2,3,4,5,6,8,9,10,12,13}$) for retrieving distributed content such as fault logs (F_6), work instructions (F_{10}), or best practices (F_{10}). Participants frequently referred to the idea of interfaces to simplify querying across diverse sources ($F_{2,4,5,9}$). For example, one senior manager from Company F_2 described the desired capability as "querying across various sources (videos, PDFs, ERP systems…) using simple prompting" (F_2). Others highlighted structured document searching, with one describing the need to "automatically contextualize and retrieve explicit knowledge" using tools such as automated tagging or GenAI-enhanced searches (F_8). Another innovative idea was to use human-machine interaction to identify knowledge gaps in KM and automatically solve them. (F_{12}) These responses underline a pain point in manufacturing KM with fragmented information demands and tedious manual searches.

C3, Tacit capture & documentation: This domain covers LLM applications that support the conversion of unspoken or experiential knowledge into accessible digital formats ($F_{1,2,4,8,9,10,12}$). Techniques include voice-to-text ($F_{8,9}$) and systems that assist with transcribing and summarizing interviews (F_{12}). Participants described using a voice assistant for "capturing implicit knowledge on the shop floor" (F_4) throughout the entire hierarchy ($F_{4,10,12}$), reflecting current efforts to make intangible know-how recordable and retrievable. Such cases align closely with research highlighting the challenge of externalizing tacit knowledge in industry. The underlying assumptions were that conversational or voice-first capture lowers documentation barriers for busy shop-floor staff, provided that the captured snippets later resurface in human-machine dialogs.

C4, Quality & troubleshooting support: This cluster covers use cases where LLMs help operators resolve issues or assess deviations ($F_{7,10,11,13}$). Examples include accessing historic quality data ($F_{10,11}$), detecting patterns in recurring errors (F_{11}), and supporting tool maintenance ($F_{7,10}$). One participant described how LLMs could "automatically retrieve past solutions to fix recurring machine faults" (F_{10}). These cases reflect a broader trend toward GenAI-supported root-cause analysis and predictive quality management in smart manufacturing.

C5, Process optimization & continuous improvement: Although less frequent, this cluster identifies use cases in which LLMs support organizational learning and operational efficiency ($F_{1,7,8,10,11}$). Participants proposed using GenAI to suggest improvements to workflows ($F_{1,7}$), identify inefficiencies (F_8), and track performance over time (F_{13}). Such use cases suggest that, while the application of LLMs in continuous improvement is still nascent, practitioners recognize their strategic potential to move from reactive to proactive knowledge utilization.

Table 6. Main clusters of Q5 responses.

Cluster	Description	Count
C1, Training, on-boarding & cross-skilling	GenAI-generated work instructions, quiz-based success checks, or video/AR learning aids for new or rotating staff	24
C2, On-demand knowledge retrieval	LLM chat or search functions that deliver solutions, fault logs, or best practices	21
C3, Tacit capture & documentation	Voice-to-text or speech-to-text utilities to externalize and document implicit know-how	9
C4, Quality & troubleshooting support	Contextual recommendations for fault diagnosis, maintenance, tool-life tracking, or quality assessment	9
C5, Process optimization & continuous improvement	Agents that derive new workflow suggestions, monitor spare-parts usage, or support structured improvement programs	7

The results reveal training, onboarding, and cross-skilling (C1) as the most frequently cited LLM application domains in KM. This indicates that practitioners primarily view GenAI as a means of accelerating workforce development and reducing onboarding effort via self-paced, automated support. On-demand knowledge retrieval (C2) also ranked highly, underscoring the value of frictionless access to dispersed organizational knowledge for day-to-day problem-solving. Tacit capture (C3), although less frequently mentioned, continues to represent a critical yet underdeveloped frontier in KM. Several participants noted the potential of voice-to-text and GenAI-supported transcription tools for documenting experiential know-how without disrupting operational flow. Quality and troubleshooting support (C4), process optimization, and continuous improvement (C5) were less frequently mentioned but highlight more advanced, system-integrated use cases aligned with long-term KM exploration strategies. Taken together, the findings suggest that industrial stakeholders currently prioritize LLM-enabled solutions that (a) support scalable, self-directed learning, (b) simplify access to heterogeneous knowledge sources, and (c) offer low-friction ways to externalize tacit knowledge.

4.6. Workshop on conversation-based barriers and LLM-supported KM use cases

To validate and supplement the consolidated answers to RQ2 in section 4.5, this section synthesizes the group-level discussions (W4) in the two workshops, including the prioritization votes (W5) for promising LLM-supported use cases for industrial KM.

Barriers to making tacit knowledge accessible: Across both workshops, the most prominent challenges centered on motivational, technical, and structural barriers. Participants in all groups highlighted a lack of motivation and incentives to share knowledge. One group framed the issue directly as: “Why should I share my knowledge – what do I gain from it?”, which became the most discussed barrier. This aligns with earlier questionnaire findings, where employee motivation was the most frequently mentioned obstacle. Another barrier discussed in detail was the lack of suitable digital tools for capturing and disseminating knowledge, reinforcing earlier statements that current systems are often too complex or inaccessible for use on the shop floor. Other groups emphasized the absence of a company-wide KM strategy, reporting no comprehensive concept, no responsibility assigned, and a widespread difficulty among employees with recognizing or articulating valuable knowledge. This last issue reflects a deeper cognitive hurdle to tacit KM. Interestingly, many technical and process-related challenges – such as high documentation effort or low acceptance of digital tools – received fewer or no attention, suggesting that participants view human and organizational factors as more critical to address first.

Identified and prioritized use cases: Participants then collaboratively discussed and formulated specific LLM-based KM use cases, based on their individual questionnaires. These were subsequently prioritized by vote to gauge perceived relevance and value.

The use-case category “on-demand knowledge retrieval” received the highest overall score in Workshop 1 (12 points) and was also prioritized in Workshop 2 (6 points). This suggests broad consensus on the utility of LLMs for enabling contextual, fast, and user-friendly access to organizational knowledge. Capturing tacit knowledge emerged as the second most critical category in both workshops (10 and 7 points respectively). Participants proposed multiple methods, including recording voice/video, GenAI-supported dialog systems, and automated transcription tools to facilitate simple documentation of experiential knowledge. Use cases related to new employee training and onboarding received moderate attention, particularly in the form of video-based learning aids or instruction workflows (2 points in each workshop). Broader workforce development was explicitly mentioned in Workshop 2 and received three votes, indicating its growing relevance in the context of aging workforces and increasing skill volatility. Less prioritized, but still mentioned, were more complex scenarios such as guided root-cause analysis, reduction of engineering change loops, and process optimization – suggesting that, while these use cases are recognized, their perceived readiness or feasibility may still lag behind simpler LLM applications.

Taken together, the group-level consolidation and prioritization steps confirm the main patterns identified in the questionnaires: Industrial KM stakeholders are most urgently seeking low-barrier solutions for retrieving and externalizing knowledge. Motivation remains a deeply rooted challenge, but participants recognize the role of LLMs in reducing friction and making KM more accessible. These workshop outcomes directly informed the design criteria and feature scoping in the subsequent DSR artifact development.

5. Design artifact for LLM-supported KM

Drawing upon the workshop findings, and consistent with DSR principles (Hevner et al., 2004; Peffers et al., 2007), this section synthesizes actionable system-level implications for developing LLM-based KM tools tailored to industrial production environments to derive an artifact that addresses these requirements in order to answer RQ3.

The STS-clustered barriers (Section 4.1) define a clear design problem: KM in industrial environments is hindered by motivational issues (e.g., lack of recognition, job security concerns), technical limitations (e.g., poor tooling, fragmented systems), and organizational weaknesses (e.g., lack of ownership or process structure). Complementing this, Sections 4.2–4.6 provide prescriptive input – pointing to a need for intuitive, embedded tools (A1, A4), motivational mechanisms (A2), flexible integration with existing processes (B1-B3), and explicit use case domains (C1-C5) – resulting in the following five design objectives (DO) in Table 7 with the respective clusters.

Table 7. Synthesized design objectives.

DO	Description
DO_1	Simplify access to fragmented knowledge (A1,A2,A4,C2)
DO_2	Enable low-effort, voice-driven tacit capture (C3,A3,A4)
DO_3	Automate training & onboarding processes (A5,C1)
DO_4	Embed informal/formal legacy systems (B1,B2,B3)
DO_5	Support learning from past issues and evolving improvements (A2,A6,C4,C5)

These objectives directly shape the artifact features proposed next. Each of the seven features (FT) highlighted in Table 8 supports one or more of the above design objectives, translating needs into actionable system components.

Table 8. Synthesized artifact features.

FT	Description
FT1	Conversational knowledge interface (DO_1): A semantic search and retrieval chatbot enabling multi-source queries across manuals, logs, ERP systems, and other legacy systems
FT2	Voice-to-text tacit capture (DO_2): Workers dictate insights in real time, reducing entry barriers for tacit knowledge, especially valuable in fast-paced shop-floor settings.
FT3	Expert dialogue templates (DO_2): Adaptive LLM prompts guide structured interviews or debriefs, making tacit expert knowledge transcribable and searchable.
FT4	Personalized GenAI onboarding paths (DO_3): Automatically generated learning journeys combining checklists, videos, and quizzes
FT5	Knowledge checks & feedback (DO_3): Dashboards visualizing learning outcomes and identifying skill gaps
FT6	Legacy tool integration (DO_4): Connectors to *Excel*, *SharePoint*, or others allow organizations to layer GenAI over familiar tools rather than disrupt workflows.
FT7	Root-cause memory and recall (DO_5): LLM-based similarity matching helps resolve recurring issues by surfacing relevant historic fixes and storing new learnings.

A conceptual model of the artifact for the LLM-supported KM tool could consist of five modular layers in order to fulfill the named features: an interaction layer (Chat UI, dashboards, voice capture), a capture Layer (speech-to-text, dialog-based input, manual ingestion), a knowledge layer (unified store linking tacit and explicit sources), a retrieval layer (semantic search, prompt enhancement), and an analytics layer (usage tracking, learning validation, feedback loops). This layered architecture ensures adaptability across maturity levels – supporting both low-tech environments and advanced deployments.

The proposed artifact addresses the top-ranked use cases: training and onboarding (C1), followed by retrieval (C2), and tacit capture (C3), as prioritized in both the survey and workshop votes (Section 4.6). It also accommodates advanced yet less prioritized functions such as quality recall (C4), reflecting a full range of practitioner maturity and readiness.

Therefore, this section answered RQ3 by applying the DSR method to derive an LLM-enabled KM artifact from stakeholder-informed requirements. By integrating voice capture, GenAI-enhanced retrieval, and embedded training, the artifact aligns with practitioner needs while accommodating future growth.

6. Discussion

This study set out to answer three RQs on barriers (RQ1), use cases (RQ2), and design implications (RQ3) for LLM-supported KM in production environments. The results offer actionable contributions while revealing important limitations.

The key barriers to sustainable knowledge retention (RQ1) addressed in Section 4.1 confirm known barriers, such as motivational reluctance, poor tooling, and organizational neglect (cf. Sumbal et al., 2020; Hoerner et al., 2023; Wang et al., 2025), but beyond that highlighted the dominance of social factors (e.g. fear of redundancy, lack of recognition). This nuance reinforces prior findings (Schiedermair et al., 2023) but also adds clarity to the psychological dimension of hoarding tacit knowledge.

RQ2 explored valuable LLM use cases and was answered via a combined analysis of questionnaire responses and group discussions (Sections 4.5 and 4.6). The top-ranked application domains (training, on-demand retrieval, and tacit capture) indicate a practitioner preference for low-threshold, user-centric tools. While these findings align with O'Leary (2024) and Storey (2025), who emphasize dialog-based GenAI for improving access to fragmented knowledge, our study goes further. We extend the state of the art by addressing the active extraction and preservation of tacit knowledge by designing a dedicated artifact.

RQ3, addressed in section 5, synthesizes a DSR-driven conceptual artifact emphasizing modularity, informal and formal integration, and user motivation – a perspective also advocated in prior studies (Finkel et al., 2024; Jennex et al. 2024), but here empirically grounded in workshop data. While the artifact reflects current readiness levels, more complex applications (C5) remain aspirational. Through the developed objectives and features, our work advances traditional KM research with a specific, production-focused concept for a GenAI-supported KM. Implementing such a LLM-supported KM requires clear roles (ownership for content quality and model curation), responsibilities (updating sources, monitoring drift), and incentives aligned with HR policies to address motivational barriers. These governance aspects will be specifically addressed in future work.

Methodologically, the dual-workshop format enabled a participatory, practice-informed derivation of needs. However, limitations remain. The sample size, while diverse, was limited to German companies and mid-to-senior management levels. Including frontline shop-floor workers could have enriched the perspective on tacit knowledge practices. In terms of the DSR cycle, this study reports on the stages of problem identification, objective definition, and partially artifact design. The subsequent steps of demonstration and evaluation have not yet been conducted.

7. Conclusion

This study explored how GenAI, specifically LLMs, can support KM in industrial production. We conducted two practitioner workshops to identify key barriers, prioritize use cases, and derive actionable design implications. The resulting artifact design outlines a modular, low-threshold solution aligned with industry's needs. While the findings provide a strong foundation, future work will pilot the artifact, evaluate the designed artifact in real-world settings and refine governance mechanisms. Future work should also involve frontline workers more directly and consider broader organizational and cultural dynamics. As GenAI technologies evolve, their role in operational KM will require continuous reassessment – not only as a tool but as a catalyst for rethinking how tacit knowledge can be captured, shared, and applied.

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