Retaining Tacit Knowledge Through Dialogue: The AI Moderator in Work Processes

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Abstract: Tacit knowledge is regarded as a central difficult-to-access resource for organizational learning. Drawing on Michael Polanyi (1985), this kind of knowledge is closely tied to individual action, experience, and contexts, and largely resists documentation capture. In complex work settings, tacit knowledge constitutes a basis for performance and quality assurance. Against the backdrop of demographic change and skills shortages, the challenge of securing, transferring, and making this knowledge usable for subsequent generations is intensifying: around one quarter of the workforce in Germany will reach retirement age within the next ten to fifteen years (Statistisches Bundesamt, 2025). This paper presents an AI-based assistance approach developed at the Fraunhofer Institute for Factory Operation and Automation IFF to support workers when additional guidance is needed, particularly during complex or non-routine tasks. The assistance enables hands-free interaction and goes beyond AI-driven dialogue management by addressing upstream and downstream processes, including preparing existing knowledge for AI use, structured content modelling, and linguistic adaptations. At its core, KIMO (short for AI Moderator) is a dialogue-based AI system that supports employees within their work processes. KIMO facilitates reflection on one's actions and fosters the articulation of experiential knowledge that remains implicit in everyday practice. The approach builds on narrative methods that prompt reflection and the telling of experience-based stories, making implicitly applied heuristics and decision logics more visible (Erlach & Thier, 2004). These methods are complemented by an instructional dialogue design aligned with Bloom's taxonomy of learning objectives (2004). Unlike conventional knowledge management systems, which focus on retrospective documentation and explicit knowledge repositories, KIMO emphasizes AI-based interaction at the moment when knowledge emerges. Through its dialogic mode, person-bound experiential knowledge is externalized, structured, and transformed into organizationally usable knowledge structures. The paper discusses the potential of dialogue-based AI systems for sustainable knowledge transfer and the long-term preservation of organizational memory. It concludes by outlining implications for the design of AI-enabled knowledge management systems, including required information and content infrastructures (e.g., a structured knowledge base).

Keywords: Knowledge transfer, Tacit knowledge, AI-assisted knowledge management, Dialogue-based AI systems, Experiential knowledge

1. Introduction

In the context of an environment characterised by volatility, uncertainty, complexity and ambiguity (VUCA), the management of knowledge is gaining increasing strategic importance, as organisational capability to act depends significantly on the availability and transfer of experience-based decision-making foundations (Weick, 2005). In this regard, the transfer of tacit knowledge represents a central challenge for organisational learning. This implicit form of knowledge—drawing on Michael Polanyi (1985)—is closely tied to individual action and situational contexts and largely resists comprehensive documentation. In complex work environments, it constitutes a key basis for performance and quality assurance.

With increasing automation, tasks are shifting towards monitoring and supervisory activities, while a high level of action competence remains essential in the event of disruptions. At the same time, opportunities for gaining experience within the work process are diminishing. This creates a need to systematically capture implicit knowledge and make it accessible in critical situations. This challenge is further exacerbated by demographic developments: a significant proportion of the workforce will retire in the coming years (Statistisches Bundesamt, 2025). As experiential knowledge is largely developed through practical action, it is particularly at risk of being lost. Without appropriate transfer mechanisms, organisation-specific problem-solving strategies may disappear, thereby impairing organisational performance (Polanyi, 1985). A key issue is the transition from tacit to explicit knowledge. Skilled workers possess extensive experience, yet often lack the means to convey it in a structured manner. Consequently, approaches that not only externalise experiential knowledge but also systematically prepare and integrate it into organisational knowledge bases are gaining importance.

Digital assistance systems already support work processes; however, they are often associated with considerable manual effort in knowledge preparation. Advances in artificial intelligence open up new possibilities to design knowledge transfer in a process-integrated and context-sensitive manner (Stürzebecher et al., 2025). In particular, the combination of work science methods with Industry 4.0 technologies offers potential for the integrated capture, structuring and utilisation of experiential knowledge. Against this background, this paper presents an AI-based assistance approach developed at the Fraunhofer IFF. The focus lies on how experiential knowledge can be systematically elicited, preserved and made usable for organisational learning processes with the help of AI. Following a classification of the state of research, Section 3 introduces the KIMO system, followed by a discussion of dialogue-based AI systems for sustainable knowledge transfer and implications for research and practice.

2. Theoretical Foundations

This section examines the challenges of explicating tacit knowledge as well as the socio-technical embedding of knowledge processes. Against this background, existing methods and emerging technological developments for supporting the transfer of experiential knowledge are brought into focus in the following section.

2.1 Tacit Knowledge

A central theoretical foundation of knowledge transfer is the distinction between tacit and explicit knowledge. While explicit knowledge is formalised and documented, tacit knowledge—drawing on Michael Polanyi (1985)—is closely tied to individual action, experience and situational contexts, and is hardly articulable. This gives rise to a key challenge for organisational learning: action-relevant experiential knowledge emerges and is applied situationally, yet is rarely transferred into explicit knowledge bases. As a result, a fundamental structural gap arises between knowledge holders and knowledge recipients. Experts possess contextualised experience and implicit decision logics, whereas novices are often not (yet) able to fully reconstruct these relationships. Consequently, the transfer of experiential knowledge should not be understood as a mere transmission of information, but rather as a process of meaning-making in which context, application situations and decision-making processes are conveyed.

Against this background, clear limitations of existing knowledge management systems become apparent: they are primarily designed for the storage and provision of explicit knowledge, enabling structured documentation and efficient access to information. However, in practical application, the embedding in concrete action contexts is often lacking. Documented content rarely includes the underlying decision-making processes or situational problem-solving strategies required for application in complex work settings. Technical documentation and manuals are particularly suited to standardised and repetitive processes, but reach their limits when dealing with variable and non-routine tasks (Kothes, 2010). In such cases, the most relevant portion of knowledge remains tacit and is not accessible to others.

2.2 Socio-technical Perspective

The sustainable design and use of digital knowledge platforms require an understanding of work as a socio-technical system. Work systems can be differentiated into a social and a technical subsystem, which may be analysed separately but must be designed jointly in their interaction (Ulich, 2011). Against this background, knowledge and experiential transfer cannot be understood as a purely technical function, but rather as the result of the interplay between human, organisational and technological factors.

For the analysis of socio-technical systems, the integrative human–technology–organisation approach developed by Sydow (1985) has become established. This approach encompasses design levels ranging from the individual to the organisation and addresses the coordinated design of work systems in the context of technological innovation. The effectiveness of digital tools depends significantly on their alignment with human capabilities, experiential knowledge and organisational conditions (Vuong et al., 2025). A key focus of the socio-technical approach lies in the design of interfaces between subsystems. For the transfer of experiential knowledge, three interfaces are particularly relevant, the design of which substantially influences the effectiveness of digital knowledge systems (Keller et al., 2021):

- the human–technology interface, which describes interaction with digital systems,
- the human–organisation interface, which encompasses the integration of knowledge transfer into roles and organisational structures, and
- the technology–organisation interface, which addresses the integration of digital systems into existing work processes and communication structures.

Effective knowledge transfer can only be achieved through an integrated design approach. Approaches that fail to address all three dimensions are therefore often insufficient.

2.3 Methods for the Explication of Experiential Knowledge

The elicitation of tacit knowledge is particularly supported by the use of narrative methods aimed at externalising experiential knowledge. Approaches such as storytelling enable knowledge to be articulated in the form of narratives, thereby making contextual information and implicit heuristics visible (Erlach & Thier, 2004). The think-aloud method provides a complementary approach to capturing cognitive processes by verbalising actions during their execution (Van Someren et al., 1994). While narration can make tacit knowledge accessible beyond the individual, it is subject to methodological limitations. In particular, narrative methods require targeted facilitation, are time-consuming, and can only be integrated to a limited extent into existing work processes. Their scalability is therefore constrained, especially in dynamic and time-critical work environments.

Furthermore, the usability of experiential knowledge depends significantly on its structured preparation. Didactic models provide suitable reference frameworks in this regard. Bloom's taxonomy (2004) enables a systematic structuring of knowledge across different cognitive levels of employees and thus supports target group-oriented preparation for various usage contexts. Clearly structured and reduced information presentation can support learning processes by taking into account the limited cognitive processing capacity of humans (Wood et al., 1976; Sweller et al., 2011). Overall, it becomes evident that the effectiveness of knowledge provision largely depends on how content is didactically prepared and adapted to the cognitive prerequisites of users. At the same time, such concepts have so far been insufficiently integrated into technical systems and have therefore not yet fully realised their potential for organisational knowledge transfer.

2.4 Artificial Intelligence Approaches for Experiential Knowledge Transfer

With the increasing use of artificial intelligence in assistance systems, new potential for experiential knowledge transfer is emerging. However, current applications primarily focus on the processing and provision of explicit knowledge, for example through document-based knowledge management systems. In this context, Retrieval Augmented Generation (RAG) is frequently applied, whereby large language models generate responses based on previously retrieved information from documents or web sources. While such systems enable efficient access to explicit knowledge, they do not adequately address the elicitation of experiential knowledge (Böhm & Durst, 2025). The focus remains on information retrieval, whereas the generation and structuring of tacit knowledge within the work process are still underrepresented.

Recent approaches therefore emphasise process-integrated and context-sensitive knowledge integration. In particular, combining continuous documentation with feedback mechanisms shows potential to gradually externalise tacit knowledge and transform it into structured knowledge bases (Stürzebecher et al., 2025). However, the challenge remains to design these processes so that they are integrated into everyday work, scalable, and didactically sound.

Overall, existing approaches to the elicitation, structuring and provision of knowledge are often considered in isolation. Knowledge management systems focus on explicit knowledge, narrative methods enable the externalisation of tacit knowledge, and didactic models support the structuring of learning content. AI-based systems offer new potential but are mainly used to access existing knowledge. This highlights the need for a holistic perspective that integrates these approaches within the work process while considering socio-technical requirements. Section 3 therefore introduces a dialogue-based AI-based assistance system that enables context-sensitive elicitation, didactic preparation and broader organisational use of experiential knowledge.

3. The AI-based Moderator KIMO

The following section introduces KIMO (named after the German term KI-Moderator, which translates to AI moderator in English), developed at the Fraunhofer Institute for Factory Operation and Automation IFF in Magdeburg. KIMO is a dialogue-based, AI-based assistance system designed to support knowledge retention by:

- providing situational guidance to employees during work processes,
- capturing tacit knowledge not retrospectively but directly within the work process,
- structuring and preparing this knowledge, and
- making it available for organisational learning processes.

KIMO addresses the challenges identified in Section 2 by integrating the elicitation, structuring and provision of experiential knowledge into a unified, process-oriented system. The development of KIMO was guided by Design Science Research principles, with the aim of designing, implementing and exploratively evaluating an AI-based artefact for tacit knowledge retention. Following an agile and iterative development process, early prototypes were progressively refined through technical testing and feedback from potential users. The crane commissioning use case served as the primary application context in which successive cycles of problem identification, artefact development and evaluation informed the evolution of the system. KIMO is used by crane commissioning personnel during commissioning activities to provide hands-free procedural guidance and to capture expert knowledge for future reuse. While novice workers benefit from step-by-step support and access to expert knowledge, experienced workers can use the system to document and transfer their experiential knowledge.

The system was developed in the context of crane commissioning, a safety-critical industrial application characterised by complex procedures and a high dependence on experiential knowledge (Figure 1). In this use case, the knowledge base is particularly diverse, as key processes are often highly dependent on the specific situation of the crane installation. The knowledge base was initially derived from existing crane commissioning documentation and procedural instructions. To complement these formal sources, tacit knowledge was elicited from domain experts through semi-structured interviews and translated into structured process descriptions and action sequences. The resulting knowledge structures were reviewed and validated by experts to ensure their technical correctness and practical applicability. This scenario serves as a reference framework for the subsequent discussion of the system. Within this context, KIMO is used directly by crane commissioning personnel during the execution of commissioning tasks. Its purpose is to provide process guidance, support decision-making in complex situations, and preserve experiential knowledge that would otherwise remain undocumented. A further particularity arises at the human–technology interface: operators require both hands to control the crane, meaning that only hands-free assistance systems can be employed. Within this application context, KIMO functions as a rule-based support system designed to ensure safe and transparent assistance for actions performed during the work process. In contrast to generative dialogue systems, the approach is based on a clearly structured dialogue design with a limited knowledge base in the sense of a closed-world assumption (Jurafsky & Martin, 2026). This enables controlled and robust interaction, which is of particular importance in safety-critical environments.

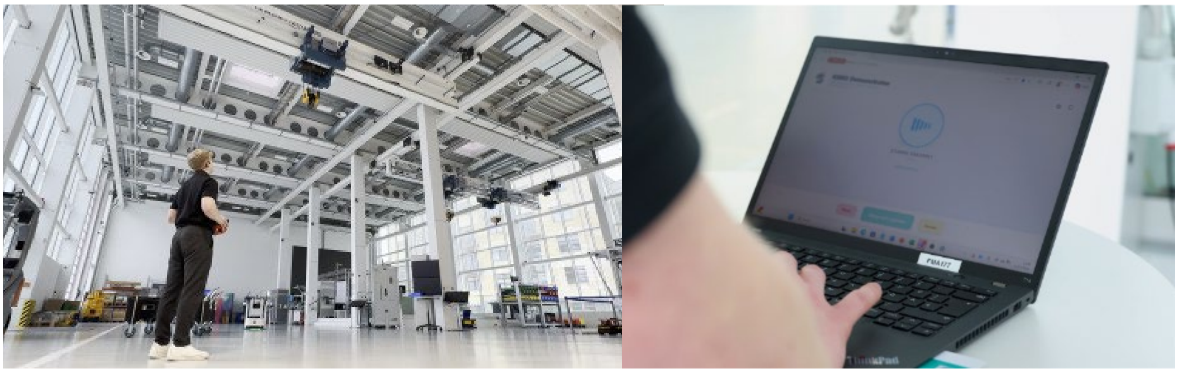

Figure 1: Use case "crane commissioning"

From a socio-technical perspective (section 2.2), KIMO assumes a structuring function at the interface between humans, technology and organisation. It supports the interaction between operators and technical systems, integrates into existing work processes, and enables the systematic transfer of experiential knowledge into organisational knowledge structures. Through this approach, KIMO addresses the shortcomings of isolated approaches identified in Section 2 by pursuing an integrated design of knowledge transfer in line with the human–technology–organisation approach. It not only considers the socio-technical integration outlined in Section 2.2 at a conceptual level, but also implements it concretely within the system architecture and usage context.

From a technical perspective, KIMO is realised as a dialogue-based, AI-based assistance system (Colabianchi et al., 2023) that enables interaction with users via natural language. The underlying system process is illustrated schematically in Figure 2. Spoken input is automatically converted into text by a speech-to-text system and processed by a central dialogue manager. This dialogue manager takes the current request as well as the previous course of the interaction into account and determines which information or functions are needed to provide an appropriate response. The system is built upon a knowledge base containing validated, domain-specific information such as work instructions and process descriptions. This knowledge is organised into structured sequences of work steps that represent the logical flow of a task. When a user asks a question or requests support, KIMO searches the knowledge base for relevant information and provides the most suitable content for the situation. In this way, the system can access existing organisational knowledge and make it available to users directly within their work process.

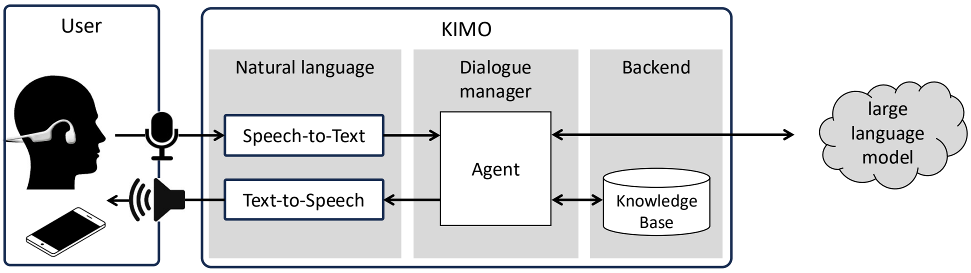

Figure 2: The technical architecture of the AI-based moderator

For response generation, an external large language model is used which formulates a comprehensible and context-specific answer on the basis of a structured prompt consisting of the user query and the previously identified content. The determination of the current processing state as well as the next appropriate action steps is not based on an explicit system-controlled state model; instead, it is implicitly handled by the language model on the basis of the dialogue context. Thereby, the model does not independently access unverified knowledge sources but operates exclusively within the provided information base. The response is initially generated in text form and subsequently converted into spoken output via a text-to-speech system, thereby enabling hands-free use within the work process.

The interaction with the AI-based moderator can be described as a multidimensional state model. At a fundamental level, KIMO distinguishes between listening and non-listening states. In the non-listening state, the system may either be completely inactive or passively await an activation keyword (“KIMO”), thereby enabling event-based reactivation. In the listening state, user speech input is continuously transmitted to the back end and processed accordingly. A distinction is made between situations in which no speech input is detected and those in which user activity is recognised, the latter typically triggering a system response. Independently of these states, KIMO operates along three functional dimensions: listening, thinking and speaking. During the “thinking” phase, the underlying language model generates a response, which is subsequently transformed into an auditory output (“speaking”). These processes can, in principle, occur in parallel, thereby enabling smooth and context-adaptive interaction. At the same time, the system is designed to immediately interrupt its output processes as soon as new speech input is detected, ensuring that interaction remains user-centred at all times.

3.1 Conceptual Development of the AI-based Moderator

KIMO fulfils two closely interrelated core functions: (1) assistance within the work process and (2) knowledge capture.

Within its *assistance function*, KIMO supports both inexperienced users in carrying out work processes and experts in performing infrequent or less routinised tasks. This goes beyond dialogue management and includes the preparation of existing knowledge for AI use, structured content modelling, and linguistic adaptation. Interaction takes place hands-free via an ergonomic headset (bone conduction headphones) using natural language, enabling flexible use across work contexts. The design follows the principle of instructional scaffolding (Wood et al., 1976): the system provides sequential action steps and proceeds only after user confirmation. This enables context-adaptive, step-by-step support, reduces cognitive load, and ensures the safe execution of complex tasks. In this way, KIMO assumes a tutorial role and supports learning within the work process by making contextualised decision-making foundations accessible, thereby helping to bridge the gap between experts and novices described in Section 2.

In addition, KIMO enables process-integrated *capture of experiential knowledge* directly within the work process. Experienced employees are encouraged to verbalise their actions and decision-making processes in line with the think-aloud method (Van Someren et al., 1994). These verbal inputs are recorded continuously without interrupting task execution. Knowledge capture and structuring take place in a subsequent processing step, in which dialogue data are analysed and transformed into structured knowledge units, such as revised or newly created instructions. Based on a predefined knowledge categorisation, KIMO evaluates whether relevant information should be added or outdated or incorrect content removed. This includes not only procedural knowledge but also underlying reasoning (conditional knowledge), ensuring deeper understanding and transferability. By capturing these reasoning processes, the system makes the “why” behind actions visible—an aspect often missing in conventional documentation (Section 2.1). In this way, KIMO supports the development of continuously evolving instructions and addresses the challenge of explicating tacit knowledge (Polanyi, 1985).

The subsequent processing step is implemented as a separate review process to ensure quality assurance and continuous development of the knowledge base (Figure 3). During this phase, interaction is paused and no speech processing or output occurs. KIMO analyses the recorded dialogue data and generates proposals for updating knowledge content. These results are presented to users, distinguishing between unchanged and revised instructions. In both cases, users are informed visually (via a pop-up window) and can confirm or reject the proposed changes.

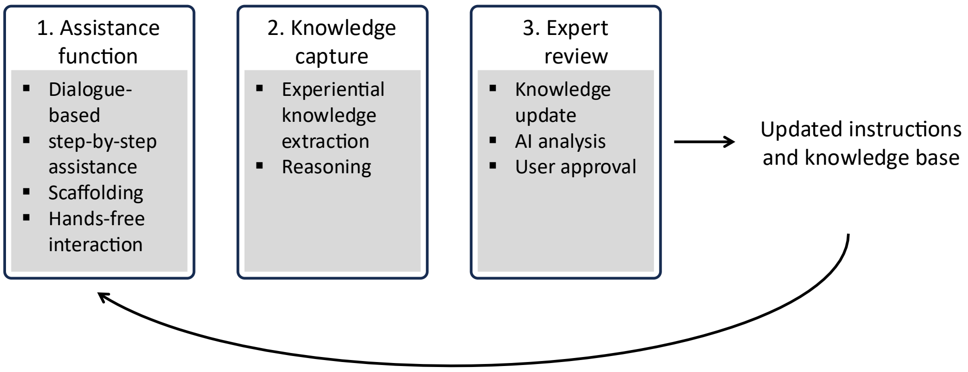

Figure 3: Knowledge capture with KIMO

3.2 Methodological Design of the Dialogue

The dialogue design of the AI-based moderator combines didactic and narrative approaches to support the explication of tacit knowledge. The content structure follows Bloom's taxonomy (2004), with targeted follow-up questions encouraging experts to articulate not only procedural knowledge in the form of action steps, but also underlying reasoning and experience-based narratives. Initial dialogue sequences and prompts were derived from crane commissioning procedures and expert interviews and were iteratively refined through technical testing, user interactions and feedback from the exploratory evaluation. Particular attention was given to eliciting both procedural and conditional knowledge while ensuring clarity, brevity and suitability for industrial practice. Guided by the concept of action competence (Erpenbeck & Heyse, 2015), the dialogue structure supports users in carrying out work processes while preserving their autonomy and systematically capturing knowledge in terms of both application and rationale.

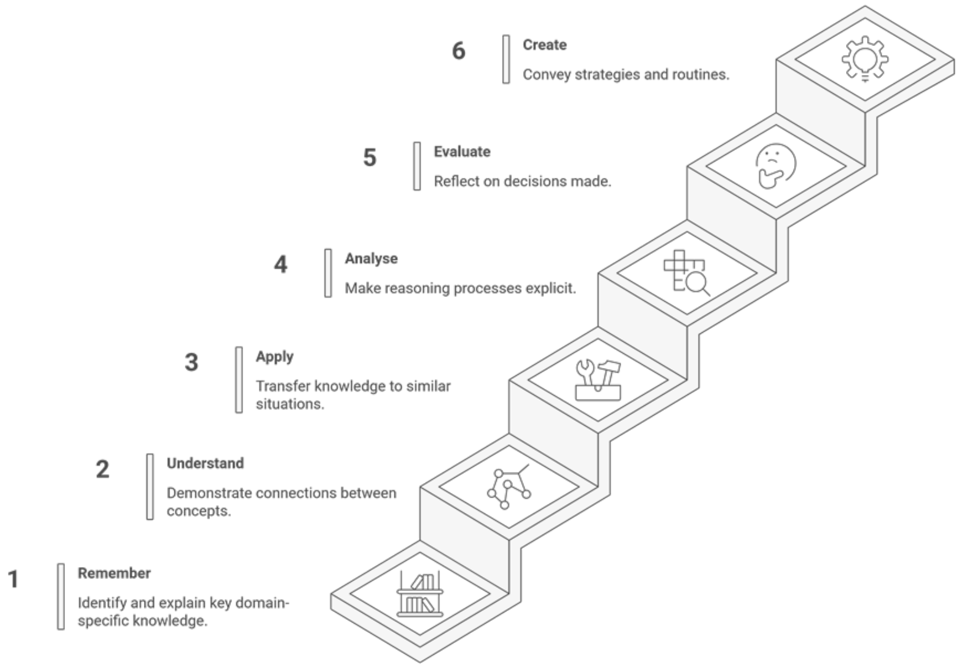

Figure 4: Bloom's taxonomy of learning objectives (2004)

To reduce cognitive load, the interaction follows the principles of Cognitive Load Theory as proposed by John Sweller et al. (2011): by focusing on individual action steps and providing clearly structured and reduced information, cognitive demands are minimised. This is particularly important in complex and safety-critical work environments in order to prevent errors caused by overload.

Through the open prompts used during knowledge capture, which encourage users to describe new knowledge in their own words, reflection on individual actions is stimulated while also supporting the articulation of experiential knowledge that would otherwise remain implicit in everyday work (Erlach & Thier, 2004). In line with the think-aloud method, experts describe their actions during task execution, while the AI-based moderator structures these descriptions through targeted follow-up questions and prepares them for subsequent use (Van Someren et al., 1994). In contrast to traditional narrative elicitation methods, which are often time-consuming and only limited in scalability (Section 2.3), KIMO enables continuous knowledge capture that is directly integrated into the work process.

3.3 Exploratory Evaluation

To obtain initial insights into the usability and practical applicability of the AI-based moderator, an exploratory evaluation was conducted. The evaluation pursued two objectives: to assess the usability of the dialogue-based assistance system and investigate its suitability for knowledge transfer in an industrial context. The evaluation was carried out in two phases involving different participant groups. In the first phase, nine students interacted with the demonstrator to assess fundamental interaction patterns and general usability. In the second phase, two crane commissioning experts representing the intended target group evaluated the system from a domain-specific perspective. Participants were introduced to the demonstrator and its role within the crane commissioning process before interacting with KIMO in a demonstration setting. Participants first completed a questionnaire created using LIME that collected socio-demographic data, expectations regarding the system, and prior experience with artificial intelligence. Subsequently, the crane commissioning procedure was carried out in pairs using KIMO. One participant performed the tasks while the second documented observations and issues. Following the practical testing phase, participants took part in a guided group discussion addressing perceived effectiveness, user satisfaction, and Responsible AI aspects. This qualitative exchange provided additional insights into user experiences and recommendations for future improvements. The evaluation provided initial evidence regarding the practical applicability of the approach. Participants reported a positive sense of safety and perceived the dialogue-based guidance as supportive during the execution of complex tasks. Particularly noteworthy was the reported feeling of remaining “in command” throughout the interaction. This perception of control is especially relevant in safety-critical industrial environments, where users must remain responsible for operational decisions despite receiving AI-based assistance. Furthermore, participants reported a high level of trust in the system. The guidance provided by KIMO was perceived as reliable, and the suggested process flow was evaluated as logical and comprehensible. The dialogue structure, which was designed on the basis of instructional scaffolding and informed by Bloom’s taxonomy (Bloom, 2004), was perceived as beneficial for supporting users during task execution.

The evaluation also indicated a high level of acceptance of KIMO for training-on-the-job scenarios. Participants highlighted the potential of the system to support inexperienced employees by providing contextual guidance directly within the work process while simultaneously facilitating the transfer of experiential knowledge. One participant described the system as “very practical for inexperienced users” and particularly valuable “for the new generation” of employees. The evaluation also revealed several limitations of the current approach. Industrial noise environments remain challenging for speech recognition, as standard microphone solutions quickly reach their limits. In addition, participants highlighted a fundamental limitation of the system architecture. As one expert noted, “KIMO listens, but does not see.” The system relies on verbal user input and cannot independently verify whether actions are performed correctly. Future versions could therefore benefit from the integration of complementary visual sensing technologies. Another challenge concerns the maintenance of the knowledge base. While KIMO can capture new insights from user interactions, knowledge updates derived from dialogue data still require expert validation before integration to ensure correctness and relevance.

Furthermore, the findings should be interpreted with caution due to the exploratory nature of the study and the limited number of participants. Since the evaluation was conducted exclusively in the context of crane commissioning, the transferability of the results to other industrial domains remains to be investigated in future research.

4. Implications for Research and Practice

Dialogue-based AI systems should be conceptualised more explicitly as socio-technical systems (Ulich, 2011; Sydow, 1985). Rather than deriving value from isolated components such as speech processing, their effectiveness emerges from the interaction of human–AI communication, knowledge structuring, and organisational integration. Future research should therefore examine how these dimensions can be jointly designed and aligned (Keller et al., 2021). A central challenge concerns the representation of procedural and conditional knowledge, which is often tacit and context-dependent (Erlach & Thier, 2004). This highlights the potential of hybrid approaches that combine data-driven methods with structured knowledge models. At the same time, continuously evolving knowledge bases require mechanisms for versioning, updating, and contextual adaptation. Closely related are issues of quality assurance: transforming dialogue data into organisational knowledge structures demands processes that ensure reliability, traceability, and transparency while balancing automated suggestions with human validation (Böhm & Durst, 2025). Beyond technical considerations, the increasing use of AI-based assistance systems raises questions about their long-term effects on learning and competence development (Dehnbostel, 2021). Future studies should investigate under which conditions such systems foster learning, which competences users require, and how AI can support rather than replace expertise development. Several limitations of this study should be acknowledged. The evaluation was exploratory and involved a small number of participants, providing initial insights rather than generalisable findings. Furthermore, the study focused exclusively on crane commissioning, leaving the transferability of the approach to other industrial contexts open. The current system relies solely on speech-based interaction and therefore depends entirely on verbal user input. Integrating complementary sensing technologies could improve contextual awareness and robustness. In addition, the evaluation focused on user perceptions and practical applicability; objective measures such as task completion time, error rates, cognitive load, knowledge retention, and learning outcomes were not assessed.

From a practical perspective, the successful implementation of dialogue-based AI systems requires a holistic organisational approach. User acceptance is critical, as interaction with a speech-based and largely invisible system depends on trust, familiarisation, and training. Equally important is the integration of knowledge capture into existing work processes. Although knowledge can be captured during task execution, organisations must establish structures for reviewing and validating content without impairing operational performance. Maintaining the knowledge base also remains a key challenge, as experiential knowledge evolves through technological change, new workflows, and personnel turnover (Stürzebecher et al., 2025). Finally, organisations must address the risk of de-qualification. While AI-based assistance can facilitate complex tasks, excessive reliance on automated support may reduce opportunities for developing problem-solving competences. Complementary learning and reflection activities therefore remain essential.

5. Conclusion and Outlook

This paper demonstrates that AI systems represent a promising approach to addressing the gap between explicit and tacit knowledge in organisational contexts. At the core of this approach is the shift from retrospective documentation towards a process-integrated, interactive elicitation and utilisation of experiential knowledge. By combining narrative methods with didactically structured dialogue design and AI-based processing, it becomes possible to systematically access and utilise even those elements of knowledge that are difficult to articulate. A key contribution of the approach lies in the integration of perspectives that have previously been considered in isolation: while traditional knowledge management systems primarily focus on explicit content and narrative methods are often applied only selectively, KIMO brings both approaches together within a single system—thereby conceptualising knowledge provision as situational support within the context of action. At the same time, the approach highlights the importance of a didactically grounded design of human–AI interaction, using dialogue specifically to structure, reflect upon and further develop knowledge bases.

The findings indicate that the effectiveness of such systems does not depend solely on technological progress, but is significantly shaped by the interplay between knowledge structures, interaction design and organisational embedding. In this sense, KIMO can be understood as a prototype for a new generation of knowledge systems that are more strongly oriented towards context sensitivity, interaction and continuous learning. Several directions for future development emerge: these include adaptive systems that are more closely tailored to individual users and specific work situations, as well as integration into broader digital infrastructures, for example in the context of digital twins. Furthermore, ongoing advances in AI create opportunities to support reflection and learning processes more explicitly by making underlying rationales and alternative courses of action visible. Overall, dialogue-based AI systems such as KIMO have the potential to make a significant contribution to the sustainable retention and transfer of experiential knowledge by systematically transforming individual experience into explicit structures, thereby strengthening organisational capability to act.

Ethics Declaration: No ethical clearance was required for the research presented in this paper. Since the study did not involve human or animal subjects or the collection of sensitive or personal data, approval from an ethics committee was not needed.

AI Declaration: An AI tool (Fraunhofer Gesellschaft's FhGenie) was used during the development of this paper for minor tasks related to structure and translation. Specifically, the tool helped the author rephrase and organize certain sections more clearly and translate select passages from German to English. All content generated or revised with the help of the AI was carefully reviewed and edited by the author to ensure accuracy, coherence and academic integrity.

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