Computers & Industrial Engineering 208 (2025) 111363



Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie



# Augmented reality-enabled knowledge management in industrial maintenance: the DILEAF framework

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ARTICLE INFO

*Keywords:*
Augmented reality
Knowledge management
Knowledge transfer
Industrial maintenance
DILEAF framework

ABSTRACT

Effective maintenance in industrial operations relies on efficient management of task-critical knowledge, particularly in dynamic and unpredictable environments. Traditional knowledge management (KM) approaches face challenges in handling fragmented data, delivering procedural guidance, and adapting to evolving operational demands. To address these limitations, this study introduces the Data, Information, Learning, Engagement, Application, Feedback (DILEAF) framework, a structured KM model that integrates augmented reality (AR) as a digital enabler for improving knowledge capture, transfer, and application in industrial maintenance. By leveraging AR's capabilities in real-time visualisation, interactive procedural guidance, and dynamic feedback, the DILEAF framework enhances user engagement and operational adaptability. The effectiveness of the framework is validated through a case study within a rolling stock organisation, where iterative experiments in both laboratory and field environments demonstrated improvements in task accuracy, real-time decision-making, and system adaptability. It was shown that AR overlays play a crucial role in enabling early error detection and correction, directly supporting the overall task success rate. Furthermore, 91 % of participants in the case study expressed satisfaction with the clarity and usefulness of the information presented via AR, underscoring the framework's effectiveness in delivering task-relevant knowledge and supporting robust performance in maintenance scenarios. These findings illustrate that the DILEAF framework provides a system-informed and operationally structured approach to industrial KM, bridging theoretical KM principles with practical AR-driven implementations. This study establishes a scalable and adaptable foundation for integrating AR into industrial workflows, contributing to the advancement of digitalised maintenance strategies in industrial engineering.

## 1. Introduction

The Maintenance, Repair, and Operations (MRO) market was valued at USD 430.98 billion in 2024 and is expected to grow at a compound annual growth rate (CAGR) of 2.28 %, reaching USD 482.40 billion by 2029 (Intelligence, 2023). This market expansion underscores the essential role of maintenance in sustaining industrial efficiency and business continuity. In asset-intensive sectors such as manufacturing, energy, and aerospace, where precision and reliability are paramount, even minor disruptions can lead to significant financial losses and safety risks (Mobley, 2002). Thus, effective maintenance strategies are essential for minimising downtime and extending the lifespan of critical, high-value assets, ensuring that production systems operate at peak performance. Given the complexity of modern maintenance practices, implementing these strategies demands substantial technical expertise, coordination across diverse asset components, and the precise execution of structured workflows (Candell et al., 2009; Cao et al., 2022; Del Amo et al., 2018; Masood et al., 2015). As a result, knowledge management (KM) is central to industrial maintenance, facilitating the systematic capture, transfer, and application of organisational knowledge (McInerney & Koenig, 2011). However, maintenance practices face several KM challenges, including fragmented data stored across multiple platforms, task complexity requiring specialised expertise, and inconsistent records that hinder quick access to accurate information (Roy et al., 2016). Despite the rising importance of digital transformation, most current KM systems fail to offer real-time contextual support or align with the dynamic, task-specific demands of field technicians. Knowledge is often captured and stored post-task, leading to significant time lags and inefficiencies in decision making.

Industrial maintenance contexts demand KM frameworks that

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https://doi.org/10.1016/j.cie.2025.111363
Received 18 February 2025; Received in revised form 16 May 2025; Accepted 1 July 2025
Available online 2 July 2025
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support dynamic knowledge flows and offer real-time adaptability to evolving operational conditions. However, existing models have shown clear limitations in meeting this need, particularly in field settings where adaptability and real-time feedback are crucial (Haddad & Baglee, 2015). For instance, the Data, Information, Knowledge, Wisdom (DIKW) Pyramid (Van Meter, 2020), while providing a hierarchical view of knowledge progression, lacks guidance on how personal knowledge can be managed, transmitted, and applied once it evolves into individual wisdom. On the other hand, the Learnability, Embraceability, Application, Findability (LEAF) framework (Abbas et al., 2022) emphasises usability and accessibility, yet does not sufficiently address the structured processing of raw data into actionable knowledge. These theoretical limitations are compounded by a lack of practical frameworks that integrate knowledge progression with real-time user engagement. As Tuomi (1999)'s notes, knowledge structures data rather than simply emerging from it, a critique that further underscores the need for an adaptive, feedback-driven KM model suited to dynamic industrial conditions.

In response to these theoretical and practical limitations, this study proposes a novel framework, DILEAF (Data, Information, Learning, Engagement, Application, Feedback), which uniquely synthesises the structured knowledge progression of DIKW with the interactive, user-centric principles of LEAF, while addressing prior critiques of linear knowledge flows by incorporating iterative feedback and real-time adaptability. The framework restructures LEAF by replacing Embraceability with Engagement to reflect the necessity of active user participation, and Findability with Feedback to prioritise continuous system refinement and knowledge evolution. These enhancements ensure that KM is not only structured but also adaptive, dynamic, and responsive to real-world maintenance challenges.

The rise of Industry 4.0 and digital transformation has further underscored the need for technology-driven KM solutions, with augmented reality (AR) emerging as a key enabler (Lee et al., 2015). AR's ability to overlay digital information onto real-world environments provides an opportunity to transform KM from passive documentation into an interactive, context-aware process (Azuma et al., 2001). Prior research has demonstrated that AR is able to enhance procedural guidance, reduce cognitive load, and accelerate skill acquisition (Gualtieri et al., 2024). Recent studies have also proposed AR-based frameworks for immersive worker training, object mapping, and task-level automation in industrial assembly and disassembly contexts (Eswaran & Bahubalendruni, 2023; Eswaran et al., 2023, 2024). These works highlight the increasing maturity of AR in supporting operational efficiency and procedural accuracy. Nevertheless, these studies focus primarily on AR as an auxiliary tool rather than as a core mechanism for knowledge creation, contextual learning, and iterative refinement. Additionally, there is limited integration of advanced interactive technologies, such as AR, within KM models in a systematic way. While AR has been studied for isolated task support, it has not yet been embedded into end-to-end knowledge cycles that connect data, learning, and application in industrial maintenance. Despite technological advancements, current KM practices in industrial maintenance remain inadequate for addressing the real-time, context-specific needs of field technicians, key limitations include: (1) disconnected or fragmented use of AR technologies to support holistic KM strategies, (2) static knowledge models that do not adapt to user feedback or evolving operational conditions, and (3) insufficient knowledge between knowledge structuring and interactive guidance. This study's novelty lies in systematically embedding AR within a holistic KM framework that spans the entire knowledge lifecycle, from data capture to feedback, thus enabling intelligent support systems that evolve with user interaction and task complexity. The study has the following key contributions:

- **Introduction of the DILEAF framework:** providing a novel hybrid KM model that unifies data structuring with user-centric interaction and interactive learning.
- **Systematic integration of AR:** enabling immersive, real-time, and adaptive knowledge transfer (KT) across all phases of the KM cycle.
- **Scalable KM framework:** through field experiments, combining laboratory-based and real-world testing, the DILEAF framework ensures practical relevance and bridges the theoretical frameworks and applied innovation, offering a reusable template for KM in other industrial domains.

This study provides both a theoretical and empirical contribution. Beyond proposing the DILEAF framework, it validates its application through a series of iterative experiments conducted in collaboration with a major European railway operator, Nederlandse Spoorwegen (NS). By bridging conceptual insights with applied innovation, this research lays a foundation for future advancements in AR-enabled KM systems and their deployment across varied industrial domains.

The remainder of this paper is structured as follows: Section 2 reviews recent developments in KM and AR, highlighting key research gaps. Section 3 outlines the methodological approach. Section 4 introduces the proposed KM framework, followed by a case study in Section 5 detailing iterative evaluations in both laboratory and field contexts. Section 6 presents a discussion of the findings, limitations, and future directions. Section 7 concludes with a summary of the main contributions.

## 2. State-of-the-art

### 2.1. Knowledge management in maintenance

KM involves systematic processes by which organisations create, capture, share, and utilise knowledge to achieve their objectives (Davenport, 1998). In the maintenance domain, KM is critical due to several persistent challenges (Del Amo et al., 2018; Masood et al., 2015), including:

i) fragmentation of data and information across multiple platforms, which complicates the consolidation and effective utilisation of knowledge.
ii) great diversity of maintenance tasks, ranging from diagnostics to complex repairs, which demands a comprehensive understanding of intricate systems composed of numerous interdependent components and subsystems (Candell et al., 2009).
iii) long service life of high-value assets that introduce variations in quality, standards, and documentation over time, further increasing the complexity of managing and applying maintenance knowledge effectively (Cao et al., 2022); and finally,
iv) substantial costs of maintenance activities in relation to the operational costs, often representing 50 % to 70 % of production expenditures, depending on the industry and operational scale (Dhillon, 2006).

KM systems can address these challenges by enhancing decision-making through digital enrichment, promoting collaboration across organisational levels, supporting strategic objectives such as sustainability and operational excellence, and enabling continuous learning and digital transformation (De Bem Machado et al., 2022). However, current systems are often poorly integrated at the operational level, leading to fragmented KT (Keiser et al., 2023), leading to fragmented KT. Many remain reliant on text-based approaches designed for office contexts (Künkel et al., 2022) and frequently lack automation suited to manual workflows (Abbas & Martinetti, 2023). Moreover, a persistent gap exists between technological deployments and user engagement, often due to inadequate alignment with practical needs and cultural resistance.

Within KM, KT plays a central role in onboarding, skill retention, and knowledge continuity (Lopez-Nicolas & Soto-Acosta, 2010). In maintenance contexts, KT is important for introducing new technicians to

processes, teaching existing staff new skills, preserving essential knowledge when experienced personnel depart, and maintaining consistent operational standards (Damgrave et al., 2023; Johnson et al., 2019). A major difficulty lies in conveying tacit knowledge, rooted in experience and context, which is hard to articulate (Nonaka, 1994; Polanyi, 2009). Traditional methods such as mentoring or written instructions often fall short in this regard. Effective KT requires embedding experiential learning into practice, allowing adaptation to dynamic environments (Leonard & Sensiper, 1998). Recent studies also point to problems such as poor documentation and reluctance to share (Klippert et al., 2023), while emerging data-driven approaches propose using artificial intelligence (AI) to support KT in dynamic industrial contexts (Maschler et al., 2022).

### 2.2. AR for knowledge management in maintenance

AR is an innovative technology that overlays digital information onto the physical world, thereby enhancing the user's perception and interaction with their environment (Azuma et al., 2001). This emerging technology has shown considerable promise in addressing some of the limitations of traditional approaches in enhancing KM techniques (Gualtieri et al., 2024). Its capacity to present interactive, context-aware information in real time has been shown to improve performance and reduce errors in tasks such as training, diagnostics, and assembly (Mao et al., 2024; Masood & Egger, 2019).

Within KM practices, AR facilitates the transformation of conventional manuals into interactive, visual formats. By overlaying text, animations, or videos directly onto relevant physical components, AR provides technicians with precise, context-specific information at the exact moment it is needed (Laviola et al., 2025). This reduces the mental effort required to project 2D information onto 3D task settings and also minimises the cognitive workload of attention switching between printed manuals and the task at hand, thereby improving comprehension and efficiency (Wang et al., 2025). Although AR has proved its worth in improving task performance, integrating it for KM in maintenance remains a challenge and is still in the nascent stage.

Palmarini et al. (2023) developed the Fast AR Authoring (FARA) method, which reduced task completion time by an average of 34.7 % and errors by 68.6 % compared to traditional manuals. De Crescenzio et al. (2010) applied AR in aircraft maintenance training, indicating its ability to minimise human errors in high-pressure environments by integrating augmented procedural animations. Marques et al. (2022) showed that AR-based annotation improved both situational awareness and knowledge retention in remote collaboration settings. del Amo et al. (2020) introduced a structured authoring workflow that organises knowledge into ontology-defined AR content elements to improve communication clarity and efficiency in remote maintenance scenarios. Building upon this foundation, del Amo et al. (2022) proposed a hybrid recommendation method that combines ontology-based task modelling with multi-criteria selection logic, considering task hierarchy, spatial context, and frequency of use, to support dynamic AR content retrieval for knowledge reuse in diagnostic applications. Their earlier systematic review (Del Amo et al., 2018) identified three key enabling technologies for AR in KT: authoring (A), context-awareness (CA), and interaction analysis (IA), each contributing to validity, effectiveness, and efficiency.

### 2.3. Related work comparison

Several studies have explored the application of AR in maintenance-related KM (del Amo et al., 2022; Marques et al., 2022; Palmarini et al., 2023). These works focus on specific functionalities (e.g., remote collaboration, authoring, or context-awareness) in isolation. However, they lack an overarching framework that systematically integrates AR into the full cycle of KM processes, spanning from data capture and contextual visualisation to learning feedback loops and long-term knowledge retention. For instance,

- Palmarini et al. (2023) emphasised task authoring and error reduction, but did not address continuous learning or adaptive feedback mechanisms.
- del Amo et al. (2022) proposed ontology-driven content organisation and recommendation mechanisms for diagnostic support, yet their work did not include empirical validation in real-world settings or a structured KM framework applicable across diverse maintenance scenarios.
- Marques et al. (2022) demonstrated improved situational awareness using AR annotations in remote maintenance, but did not align their findings with a structured KM lifecycle or examine user engagement and tacit KT.

In contrast, the DILEAF framework introduces a comprehensive structure that not only integrates these isolated AR functionalities but also ensures that they are purposefully aligned with cognitive, collaborative, and organisational dimensions of KM. While prior works often address specific aspects, such as interface design, content authoring, or contextual visualisation, they lack an integrated framework that links these components to sustained knowledge flows. By comparison, this study offers one of the first validated and user-centred KM models developed for dynamic maintenance environments.

### 2.4. Research gaps

Despite growing interest in the use of AR to enhance KM in maintenance, several key research gaps remain unaddressed. Existing studies often focus on isolated aspects of AR integration, lacking a cohesive framework that systematically aligns AR functionalities with KM processes. This section identifies three major gaps that hinder the effective deployment of AR-driven KM solutions in industrial maintenance:

i. **Absence of a holistic KM framework**

KM in industrial maintenance demands a structured yet adaptive framework that facilitates knowledge capture, transfer, application, and refinement. Current KM approaches often emphasise static knowledge repositories or structured procedural documentation without integrating real-time interactivity and adaptability, which are critical elements for dynamic maintenance environments. While AR offers advanced visualisation and contextualised procedural guidance, its full potential is constrained without a robust KM framework that ensures seamless knowledge flow and aligns with the cognitive and operational demands of maintenance professionals. The lack of such a framework limits the scalability and effectiveness of AR-based KM implementations.

ii. **Limited empirical validation in field environments**

A significant portion of existing research on AR for KM in maintenance is based on controlled laboratory settings or conceptual models, offering limited empirical insights into real-world operational complexities. The dynamic and unpredictable nature of industrial maintenance presents challenges that cannot be fully replicated in experimental environments. Without field-based validation, the applicability and effectiveness of AR in addressing real-world maintenance challenges remain uncertain. This study addresses this gap by conducting iterative experiments in both laboratory and field settings, ensuring that the proposed framework and AR functionalities are rigorously tested under practical industrial conditions.

iii. **Insufficient evaluation of AR's functional impact on KM**

While AR has been widely recognised for its potential in enhancing KM, there is a lack of systematic assessment regarding the impact of specific AR features, such as real-time data visualisation, interactive procedural guidance, and adaptive feedback loops, on task performance

and decision-making. Existing studies often treat AR as a generalised technological enhancement, without analysing how individual functionalities contribute to KM efficiency, user engagement, and operational adaptability. This study aims to fill this gap by evaluating the application of AR-driven KM components within an integrated framework, ensuring that AR tools are optimised for complex, real-world maintenance scenarios.

To address these gaps, this study develops the DILEAF framework, a holistic and structured KM model that integrates AR functionalities to enhance knowledge flow, usability, and adaptability in maintenance practices. By incorporating Data, Information, Learning, Engagement, Application, and Feedback, the framework ensures that AR solutions are not just technological add-ons but are systematically embedded within KM processes to maximise their practical utility. Through empirical validation in real-world maintenance settings, this study provides a rigorous foundation for advancing the integration of AR into industrial KM, bridging the gap between theoretical potential and operational effectiveness.

## 3. Methodology

### 3.1. Methodology overview

This study utilises the Design Science Research Methodology (DSRM) as outlined by Peffers et al. (2007), originally developed for Information Systems but increasingly applied in KM system design (Sarnikar & Deokar, 2017). While DSRM provides a structured process for artefact development and evaluation, its treatment of iteration is relatively implicit. To clarify the iterative design logic applied in this study, principles from user experience (UX) design integrated with agile development cycles have been referenced (Da Silva et al., 2012), emphasising user feedback, interface adjustment, and incremental refinement across development stages. The artefact designed in this study is the DILEAF framework, aimed at improving KM in maintenance contexts through AR integration. By designing, implementing, and evaluating this framework, the study addresses practical challenges in KM within maintenance practices, demonstrating the utility of the DILEAF framework in real-world applications. This study is organised into four main steps (shown in Fig. 1), each addressing a specific research goal:

*Step 1* – Preliminary semi-structured interviews. Conducted with end-users of both the framework and AR solutions to introduce the technology and gather insights into their information needs, usability preferences, and visualisation expectations. This step identifies knowledge gaps between experts and non-experts, captures user requirements, and clarifies preferences in content delivery. Direct engagement ensures the framework aligns with real-world workflows and provides grounded input for its design.

*Step 2* – Literature review and synthesis. A literature review was performed to identify validated methodologies, successful AR applications, and relevant industry benchmarks. Findings from the interviews were synthesised with the literature to ensure the framework reflects both practical demands and current technological directions. A decision matrix was created to evaluate best practices across dimensions. Two key insights emerged: (i) the hierarchical knowledge progression from DIKW, and (ii) the user-centric principles from the LEAF model, both forming the conceptual foundation of the DILEAF framework.

*Step 3* – Framework development. The DILEAF framework was developed as the central artefact to support AR-enabled KM solutions for maintenance technicians. It identifies the key information types and delivery logic needed to guide task execution. Its generalisable structure ensures adaptability across diverse assets and scenarios, offering practical guidance while allowing for contextual refinement.

*Step 4* – Validation through AR prototyping. The framework was validated via three studies: one in a laboratory and two in industrial field settings. All focused on the same fault scenario and maintenance task to ensure consistency. These trials enabled iterative refinement based on real-world feedback, supporting the framework's adaptability, scalability, and practical relevance in maintenance operations.

### 3.2. Proposed framework evaluation

To evaluate the DILEAF framework in a case study, a set of key performance indicators (KPIs) was defined, corresponding to six core elements of the framework: data, information, learning, engagement, application, and feedback. Each KPI was operationalised through specific survey questions, as shown in Table 1, which also served as qualitative evaluation dimensions. These dimensions allow for a structured understanding of how each component functions within the AR-enabled KM platform, which was developed, linking survey questions (SQ) to the six core elements of the framework.

In addition to the survey-based KPIs, quantitative task performance was evaluated by observing the success rate of fault resolution in repeated maintenance tasks under both laboratory and real-world conditions. Further qualitative indicators included user perceptions of knowledge sharing effectiveness, trust in system-generated recommendations, and workflow transparency. These indicators served as a basis for iterative design improvements, ensuring that the DILEAF framework

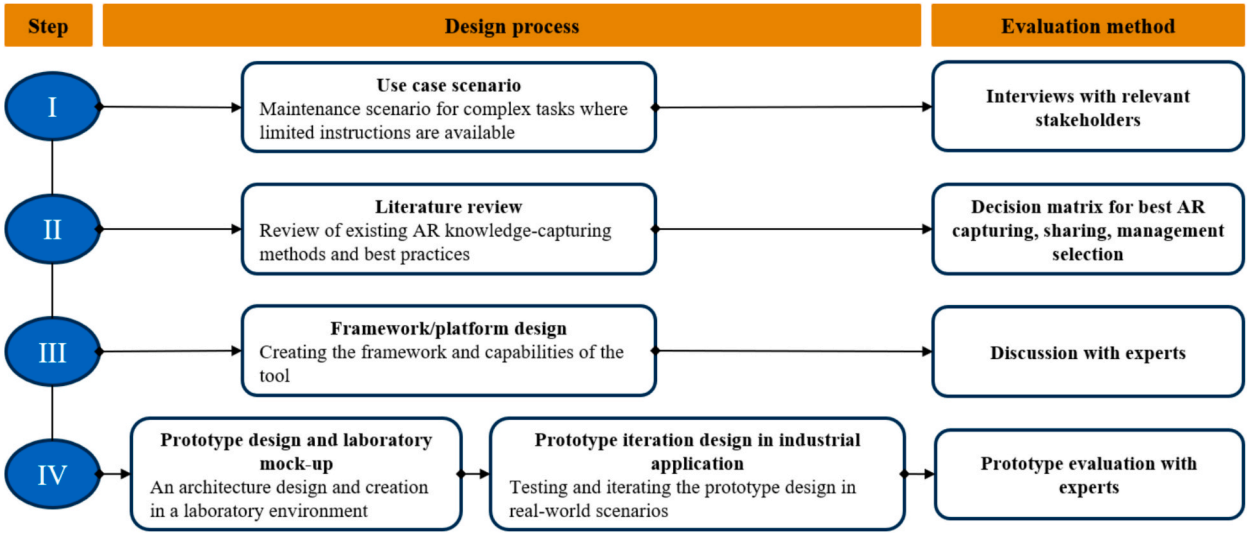



**Fig. 1.** Research methodology of this study.

**Table 1**
Alignment of survey questions (SQ) with the DILEAF framework for evaluation.

| Element | Metric | No. | Question |
|---|---|---|---|
| Data | Data accuracy | SQ1 | Is the pre-filtered data accurate and up-to-date? |
| | Data availability | SQ2 | What data is still missing while executing the experiment? |
| Information | Source findability | SQ3 | Do you always use the problem-solving strategies mentioned in TRIPLO and MAXIMO? |
| | Technological findability | SQ4 | How are current SNT250 failures analysed and solved? |
| Learning | Knowledge sharing at individual level | SQ5 | Do you have experience or knowledge of using AR? What is your opinion about using AR to support your maintenance work? |
| | Knowledge sharing at organisational level | SQ6 | Would you recommend AR to your colleagues? (Why yes/no) |
| Engagement | Contextual knowledge domain status | SQ7 | What is your opinion about the problem-solving process? |
| | Preferred focus of knowledge sharing | SQ8 | What are the advantages of using AR? What are the disadvantages of using AR? |
| Application | Nature of job responsibilities | SQ9 | Do you envision AR being part of troubleshooting? |
| | Level of abstraction | SQ10 | What kind of visualisations would support you more in this AR tool? What is your opinion about the 3D visualisations presented? (e.g., in terms of right timing and correct location) |
| Feedback | Optimal way of knowledge management | SQ11 | What is your opinion about automatically storing this information (e.g., time and maintenance steps)? Would this benefit your problem-solving strategy? |
| | Optimal way of knowledge sharing | SQ12 | How could AR better facilitate the sharing of troubleshooting insights with others? |

met both theoretical and practical requirements for knowledge-driven maintenance.

## 4. The DILEAF framework

### 4.1. Conceptual basis of the DILEAF framework

To address critical challenges in industrial maintenance, such as fragmented knowledge, limited procedural clarity, and inconsistent feedback mechanisms, the DILEAF framework was developed as a structured approach to align KM processes with operational requirements. Key functional priorities included structured knowledge categorisation, centralised data access, interactive guidance, contextual adaptability, and continuous refinement. The theoretical rationale underpinning the DILEAF framework, including critiques of the DIKW model and structural limitations of prior KM approaches, is outlined in Section 4.2.

A critical advancement of DILEAF lies in its ability to dynamically transition knowledge across different conceptual states, drawing from the five perspectives of knowledge (Alavi & Leidner, 2001; Huber, 1991; Nonaka, 1994). Knowledge does not exist in a singular, static form; rather, it shifts between different representations: an object, a process, a capability, a condition for information access, and a state of mind, depending on its role within the KM cycle. The six elements of the DILEAF framework facilitate this dynamic knowledge transformation by ensuring that knowledge continuously evolves rather than being a mere end-product of hierarchical processing. These elements interact cyclically, ensuring that knowledge remains contextually relevant, accessible, and adaptable. The knowledge transitions occurring within DILEAF align with the five perspectives as follows:

- **Data (Knowledge as an Object):** Data forms the foundation of the DILEAF framework, encompassing raw, unprocessed inputs such as sensor readings, historical maintenance records, and real-time operational metrics. In this stage, knowledge is treated as an object, a storable and retrievable entity, that serves as the fundamental building block for subsequent processing. The structured collection of data ensures the availability of essential information required for analysis, decision-making, and future knowledge synthesis.
- **Information (Knowledge as a Condition for Access):** The transformation of raw data into meaningful structures occurs at this stage, ensuring that information is accessible, interpretable, and applicable. By organising data into schematics, procedural guides, and structured documentation, this element enables knowledge users to retrieve relevant insights efficiently. Here, knowledge is understood as a condition for access, its value lies in how effectively it is structured for retrieval and usability. This structured transformation reduces ambiguity, enhances decision-making, and ensures that essential maintenance knowledge is available for operational use.
- **Learning (Knowledge as a Process):** Learning represents the process through which knowledge is internalised and applied to develop expertise. This phase moves beyond static knowledge storage, focusing instead on progressive instruction and skill acquisition. Through structured training, interactive simulations, and contextual examples, this element supports knowledge flow by facilitating the continuous refinement and accumulation of expertise. Knowledge here is understood as a process, where individuals engage in iterative cycles of understanding, applying, and refining their skills in response to dynamic maintenance demands.
- **Engagement (Knowledge as a Capability):** Engagement represents the active participation of users in KM processes, ensuring that knowledge is not passively absorbed but actively shaped through interaction. By integrating task-specific interfaces, collaborative workflows, and knowledge-sharing mechanisms, this element transforms knowledge into a capability, something that enables individuals and teams to act, contribute, and adapt knowledge within real-world settings. Engagement reinforces the sustainability of KM systems by promoting user commitment, fostering collective intelligence, and ensuring that KT is not just an individual activity but an organisational asset.
- **Application (Knowledge as a Process in Action):** Application ensures that structured and engaged knowledge is translated into effective action. It moves beyond knowledge retention, focusing on how insights are implemented in maintenance workflows, troubleshooting tasks, and operational decision-making. Knowledge here is viewed as a process in action, where its effectiveness is determined by how well it is embedded into practical use. By aligning knowledge with operational objectives, this element ensures that KM outputs contribute directly to improving efficiency, reducing downtime, and enhancing task execution in industrial settings.
- **Feedback (Knowledge as an Evolving Entity):** The iterative refinement of knowledge occurs through continuous feedback loops, ensuring that KM processes remain adaptive and responsive to operational demands. Feedback is validated through a combination of technician review and system log analytics, ensuring only relevant insights are integrated into the evolving knowledge base. Here, knowledge is not static but evolves dynamically, shaped by real-world experiences and system refinements. Feedback ensures that emerging challenges, inefficiencies, and user insights are integrated back into the knowledge system, creating a self-improving loop that supports long-term KM effectiveness.

The DILEAF framework brings together hierarchical structuring, user

engagement, and iterative refinement to support KM practices that are both systematic and adaptive (Fig. 2). Unlike conventional models that separate data processing from knowledge application, DILEAF establishes a closed-loop architecture that enables continuous alignment between system feedback and task context.

### 4.2. Designing the framework

The development of the DILEAF framework followed the structured methodology outlined in Section 3.1. Rather than prescribing a predefined model, this approach supported a stepwise refinement of the framework through iterative engagement with functional requirements, theoretical inputs, and stakeholder insights. The process was designed to ensure alignment with the operational realities of industrial maintenance while incorporating key KM principles.

*Step 1: Stakeholder Input.* Stakeholder interviews conducted during the initial phase of the framework design identified several critical functional requirements for effective KM in maintenance practices. Semi-structured interviews revealed recurring challenges, including reliance on fragmented data sources, inconsistent procedural documentation, and the absence of structured troubleshooting processes. Based on these insights, the following prioritised functions were identified and are supported by AR integration to enhance KM processes:

- **Structured Knowledge Categorisation:** To improve retrieval efficiency and reduce fragmentation, this function applies metadata tagging and task-based indexing across knowledge artefacts. Items such as procedures, diagnostics, and sensor data are categorised by equipment type, failure mode, and task phase. This structure enables AR to transfer context-specific content while supporting traceability and reuse across different maintenance scenarios.
- **Centralised Data Integration:** Addressing the challenge of fragmented knowledge sources, this function consolidates real-time and historical data into a unified platform. AR complements this integration by overlaying dynamic, interactive visuals, allowing users to intuitively access and engage with the data.
- **Interactive Procedural Guidance:** To ensure that KT processes are accessible and actionable, AR delivers real-time step-by-step guidance through visual instructions and interactive flowcharts. This ensures non-expert technicians can follow procedures accurately and learn effectively during tasks.
- **Contextual Knowledge Adaptability:** Tackling the need for flexibility in diverse scenarios, this function dynamically adjusts knowledge representations based on specific operational contexts. AR enhances adaptability by tailoring overlays to current environments, ensuring relevance and usability. This is supported by context-aware delivery mechanisms, such as task-phase detection and AI-driven scene recognition, which enable content to adapt dynamically to the user's working conditions.
- **Iterative Feedback Mechanisms:** This requirement ensures that feedback from user interactions and task outcomes is continuously captured and integrated into the KM processes. AR enhances this capability by facilitating real-time feedback capture and performance monitoring, thereby creating a dynamic feedback loop that refines KM workflows and drives ongoing improvements. To ensure consistency and accuracy over time, the framework incorporates lightweight version control, feedback-based flagging of outdated content, and periodic expert validation of high-priority knowledge modules.

*Step 2: Theoretical Foundations.* KM frameworks provide structured methodologies for organising, processing, and utilising knowledge within industrial environments. One of the most widely recognised models in this domain is the DIKW Pyramid, which conceptualises knowledge transformation as a hierarchical process. For instance, Conger and Probst (2014) illustrated its effectiveness in IT service management, where the DIKW model improved incident resolution by enabling the transition from raw data to institutionalised knowledge. Similarly, Grieves (2024) extended the DIKW framework to digital twin systems, showcasing its utility in integrating data and knowledge for complex technical environments.

While DIKW provides a well-defined structure for knowledge processing, it has been critically examined for its foundational assumptions about the nature of data and knowledge. Tuomi (1999) challenged the conventional bottom-up progression from data to knowledge, arguing that knowledge does not necessarily emerge from data, but rather precedes and influences how data is recognised, structured, and interpreted. According to Tuomi, data is not an objective entity that exists independently; instead, it is shaped by pre-existing knowledge frameworks, meaning that individuals identify, categorise, and process data based on what they already know. This inversion of the DIKW hierarchy suggests that knowledge is not merely an outcome of structured data aggregation but an active agent that defines how information is

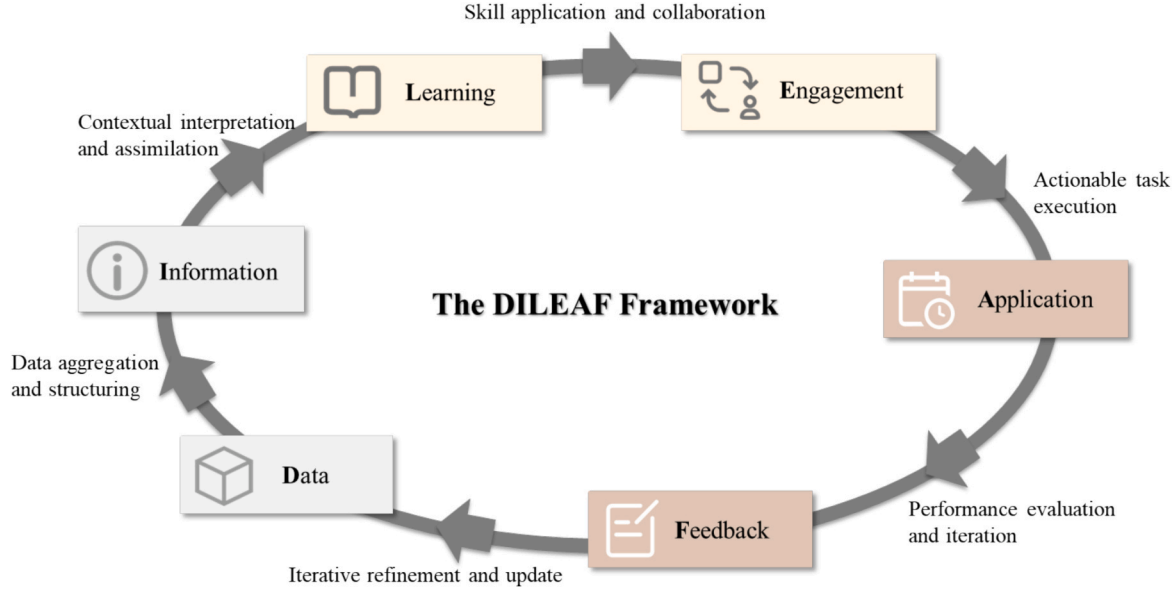



**Fig. 2.** Interrelations and Workflow of the DILEAF Framework.

extracted and understood. Consequently, traditional DIKW-based KM approaches may struggle in contexts where tacit, experience-based, and contextual knowledge play a dominant role in decision-making and problem-solving.

Beyond this epistemological critique, the practical limitations of DIKW have also been noted, particularly in its inflexibility in dynamic and complex environments. Cepeda and Vera (2007) highlighted the necessity of iterative feedback mechanisms and real-time adaptability, emphasising that knowledge processes should be fluid rather than rigidly hierarchical. This underscores a fundamental limitation of DIKW: its linear structure does not account for the interactive and evolving nature of knowledge exchange in industrial settings.

To address these challenges, alternative KM frameworks have introduced more dynamic and user-centric approaches. One such model is the LEAF framework, which departs from DIKW's rigid hierarchy by emphasising modular knowledge structuring, stakeholder engagement, and accessibility. Unlike DIKW, which assumes a static transformation from data to knowledge, LEAF enables bidirectional interactions, allowing knowledge to be dynamically refined, adapted, and expanded based on real-time inputs. However, LEAF design does not sufficiently integrate hierarchical knowledge transformation or iterative refinement. Recognising this gap, DILEAF modifies two core elements of LEAF:

- "E" (Embraceability) is replaced with "Engagement": This reflects a shift in epistemological stance, from system adoption to active knowledge involvement. While Embraceability concerns whether users are willing to accept a system, Engagement highlights the extent to which individuals participate in the formation, adaptation, and contextualisation of knowledge. In industrial maintenance, knowledge is not static content to be passively retrieved, but a situated resource that requires users to continuously interpret, apply, and respond to it. Engagement, in this framework, underscores the dynamic relation between users and knowledge processes, where the act of using knowledge simultaneously contributes to its development and refinement.
- "F" (Findability) is replaced with "Feedback": Findability in LEAF primarily concerns information retrieval, but this does not sufficiently address the need for real-time adaptation and continuous improvement in industrial settings. Instead, Feedback ensures that knowledge is not only accessible but also dynamically updated based on evolving operational conditions and user input. This modification ensures that knowledge is validated, refined, and improved over time, rather than remaining static (Kotranza et al., 2011; Martins et al., 2022; Wierinck et al., 2005).

Moreover, LEAF lacks structured mechanisms for managing hierarchical knowledge flows, embedding advanced digital tools, and ensuring procedural standardisation in industrial contexts. Thus, a more comprehensive KM framework is needed, one that bridges structured knowledge processing with real-time adaptability, facilitates interactive engagement, and integrates digital tools for enhanced KM (Salman & Ahmad, 2023). These theoretical developments inform the architectural design of the DILEAF framework, which adopts a modular, closed-loop structure to support dynamic transitions across evolving knowledge states.

*Step 3: Framework Design.* Using the insights gained from stakeholders and the literature, a decision matrix was developed to evaluate and prioritise the functional requirements essential for the proposed framework. Table 2 summarises the outcomes of this prioritisation, highlighting four key functions deemed vital for the framework's design.

By prioritising these functions, the identified requirements establish a clear foundation for a KM framework that can address the complexities of modern maintenance environments. These needs set the stage for the development of a structured framework that integrates KM principles with AR-driven enhancements.

### 4.3. AR solution guided by the DILEAF framework

The AR solution was developed in direct correspondence with the six stages of the DILEAF framework, each mapped to a specific module in the system architecture. The AR system is deployed on the Microsoft HoloLens 2, selected for its support of spatial mapping, voice commands, gaze-based targeting, and hands-free operation, all of which are essential for industrial maintenance environments. The AR interface was built using Unity 3D, with Microsoft's Mixed Reality Toolkit (MRTK) providing key interaction capabilities, including spatial anchors, hand tracking, and scene understanding. The backend knowledge engine is hosted on Microsoft Azure, where a cloud-based repository stores structured knowledge objects defined by a domain ontology. Real-time communication between the frontend and backend is achieved via RESTful APIs, enabling the system to retrieve procedures, update status logs, and record user feedback.

Through integration with AR, the six DILEAF elements are realised via concrete system functions, interaction logic, and data flows across the platform architecture (Fig. 3). Each stage is supported by mechanisms such as backend retrieval, holographic guidance, multimodal input capture, task performance logging, and feedback-based content refinement, as detailed below:

- **Data:** The system begins with the collection of operational and historical data that form the basis for initiating maintenance tasks. Real-time data was captured directly from IoT-enabled sensors, such as temperature fluctuations and vibration anomalies, reflecting actual equipment conditions in operational environments. Historical maintenance records were manually uploaded into the backend knowledge base in structured JSON format, including component IDs, timestamps, and fault descriptions. These datasets were stored in a cloud database (Azure Cosmos DB), where they could be retrieved by the AR system via API calls. This setup ensured that all knowledge retrieval and task execution began with data grounded in realistic fault conditions and equipment history.

**Table 2**
Prioritisation of Functional Requirements for the KM Framework Design.

| Requirement | Stakeholder Need | Theoretical Evidence | Priority Justification | Overall Priority |
|---|---|---|---|---|
| Structured Knowledge Categorisation | Yes | N/A | Supports operational continuity by enabling task-aligned knowledge access through structured metadata tagging. | Medium |
| Centralised Data Integration | Yes | Yes | Resolves fragmented data issues and enables real-time decision-making through dynamic KM flow integration. | High |
| Interactive Procedural Guidance | Yes | Yes | Provides actionable, step-by-step guidance, crucial for non-expert users to reduce errors and enhance task learning. | High |
| Contextual Knowledge Adaptability | Yes | N/A | Essential for scalability and relevance in varying scenarios. | Medium |
| Iterative Feedback Mechanisms | Yes | Yes | Ensures continuous improvement via real-time feedback capture and integration, optimising adaptive KM workflows. | High |

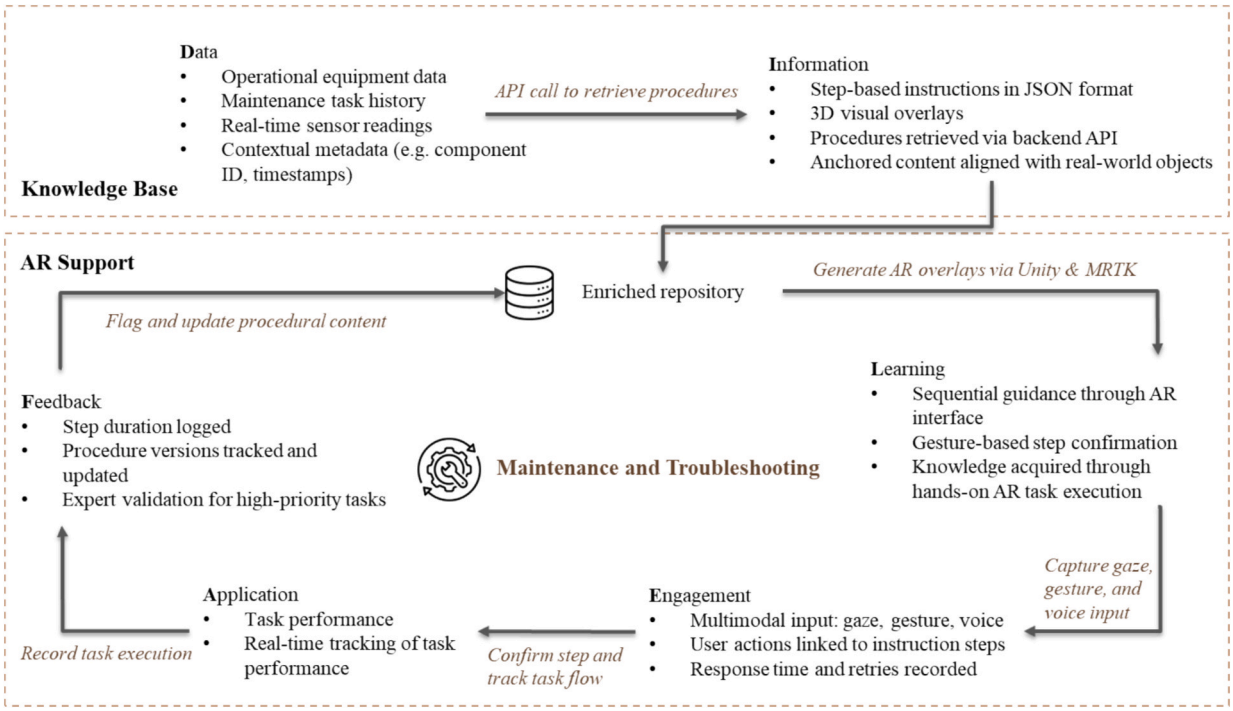



**Fig. 3.** AR System implementation guided by the DILEAF framework.

- **Information:** Once retrieved, raw data was processed into actionable task guidance. For each fault trigger or component reference, the system called a corresponding maintenance procedure via API requests to the backend knowledge base. The procedures were stored in structured JSON format and included stepwise instructions, visual highlights, and simple schematic diagrams. The AR interface parsed this information and displayed relevant instructions using Unity and MRTK, with holographic overlays anchored to real equipment through spatial mapping. These overlays ensured that information was delivered at the precise point of use, allowing technicians to follow accurate, location-specific procedures directly within their field of view.
- **Learning:** Procedural knowledge was delivered incrementally through interactive step-by-step guidance embedded in the AR interface. Each instruction remained active until the technician confirmed completion using gesture-based input, after which the system advanced to the next step. This structure enabled technicians to learn procedures through live execution, without diverting attention to printed manuals or external screens. The alignment between physical components and instructional overlays allowed users to internalise both spatial and functional knowledge during real-time task performance, reinforcing experiential learning under realistic operational conditions.
- **Engagement:** The system facilitates multimodal technician interaction by supporting a combination of voice commands, hand gestures, and gaze input, all processed through MRTK's built-in capabilities. Technicians can progress through tasks by tapping in-air, using simple voice prompts, or focusing on gaze-anchored buttons within the AR field. This multimodal setup reduces reliance on a single input mode and supports hands-free engagement during complex maintenance actions. Also, the system records behavioural metrics such as step duration and retries, allowing analysis of user engagement across procedures.
- **Application:** The AR system was deployed in real maintenance-like scenarios, supporting technicians as they performed a defined sequence of troubleshooting and repair tasks. As users progressed through each instruction, the system tracked execution consistency by logging the order, duration, and completion of steps. Instructional overlays remained anchored throughout the task and were designed to reduce ambiguity in tool identification, component location, and action sequence. This ensured that task execution followed standardised procedures while providing hands-free, spatially aligned support. All system outputs were automatically recorded and stored for post-task analysis.
- **Feedback:** Upon task completion, the system generates structured logs capturing interaction data, flagged steps, and technician comments. Each procedure is versioned, with change history maintained in the backend. Frequently flagged steps are marked for review using a simple classification scheme (e.g., "unclear" or "outdated"), triggering content updates by designated maintainers. For high-priority tasks, procedural content undergoes periodic expert validation to ensure critical instructions remain accurate. This lightweight review cycle links field-level use with content improvement, maintaining procedural consistency over time.

The integration of DILEAF into the AR system provides not only a structured mapping of KM processes but also a practical mechanism for continuous refinement through feedback and task interaction. Rather than treating AR as a static interface, the framework embeds it within a dynamic knowledge cycle, supporting adaptability across changing maintenance contexts.

## 5. Case study

In the Netherlands, Nederlandse Spoorwegen (NS) operates one of the busiest rail networks in Europe, serving millions of passengers annually (International Union of Railways Annual Report, 2015; Netherlands Railways Guide – Dutch Train Travel Tips, 2023). Effective maintenance is essential for NS to ensure operational reliability, for the high capacity Verlengd InterRegio Materieel (VIRM) trains, which are double-decker intercity trains designed to handle high passenger volumes on busy routes. On such trains, the sanitary system is critical to ensuring hygiene and environmental control on board, as it is responsible for waste collection, processing, and subsequent safe disposal. At

the core of this system is the bioreactor, which facilitates waste processing and helps maintain sanitary conditions throughout the journey. Effective temperature regulation is paramount, as extreme conditions, particularly freezing temperatures, can disrupt the functionality of the system and lead to service interruptions. The SNT250 code specifically refers to a recurring failure in the temperature management of the sanitary system's components, such as the bioreactor and associated pipework. During cold conditions, such temperature regulation is essential to prevent freezing, which could otherwise impede the waste processing function.

Internal research within NS has identified the SNT250 as one of the top twenty most frequently failing systems in trains, highlighting how critical the reliability of this system is for maintaining operational continuity and passenger satisfaction. Effective troubleshooting and maintenance of any SNT250 failure is thus vital for NS to uphold the operational reliability of the VIRM trains and ensure uninterrupted sanitary services, even under challenging weather conditions.

To enhance KM within maintenance practices for complex systems such as the sanitary system, the DILEAF framework was applied as a guiding tool to both address key challenges and improve KM processes. This case study began with semi-structured interviews to gather insights from NS technicians, followed by a series of experiments (shown in Fig. 1). These included an initial laboratory-based experiment and two subsequent field iterations, which provided opportunities to refine and validate the framework under real-world conditions. After completing each experiment, participants were required to respond to an open-ended survey.

### 5.1. Current maintenance knowledge management

Semi-structured interviews were conducted with four experienced technicians, each with over a decade of experience in troubleshooting complex systems at an NS maintenance facility. The interviews followed established guidelines for conducting semi-structured interviews, which balance a structured framework whilst affording sufficient flexibility to explore the experiences of the participants in depth (Kallio et al., 2016). Focusing on understanding the current state of KM, a predefined set of open-ended questions guided the discussion, addressing topics such as current maintenance procedures, the use of data platforms and knowledge gaps, while follow-up questions provided opportunities for clarification and deeper insights. Each interview was approximately one hour in duration, during which detailed notes were taken, and the summaries were later shared with participants for verification. Thematic analysis was applied to the validated interview data to identify recurring themes and patterns (Braun & Clarke, 2006). This analysis revealed critical insights into existing challenges, such as limitations in the use of current data platforms for troubleshooting and gaps in KM practice, discussed.

In NS, the diagnostic and maintenance procedure begins when a train driver identifies an error, typically flagged by the train's central board computer. The train driver then contacts the 'Materieel Besturingscentrum' (MBN), a remote maintenance service platform, that provides support to resolve the issue. If remote support is unable to resolve the issue, the MBN records a status report and, if required, arranges for the train to undergo maintenance. After the train is scheduled for maintenance, a technical maintenance manager (TMM) develops a comprehensive plan outlining time estimates and resource requirements. At the maintenance facility, technicians utilise a data platform that consolidates historical reports and MBN registrations to support diagnostics and repair activities.

The following four primary data platforms are utilised in the organisation for registering and retrieving data during diagnostics and maintenance practices:

- MAXIMO: This is the main source for logging and reviewing maintenance work orders and failure reports. While technicians can view previous maintenance records, they cannot modify existing records or procedures and can only document new maintenance actions. However, MAXIMO presents challenges in its use; notably, it is difficult for technicians to navigate, and the retrieval of useful information often requires a series of complex steps better suited for analysts or users with advanced knowledge. Consequently, technicians can struggle to rapidly access the necessary data during fault diagnosis.
- DINO: This contains essential technical resources, such as electrical and pneumatic diagrams, equipment documentation, and specifications. However, technicians report difficulty in accessing these materials due to the complexity of two-dimensional (2D) diagrams and the platform's limitations when used on tablets. To gather sufficient information from the diagrams, technicians sometimes must piece together information from multiple screens, thereby further complicating the process.
- TRIPLO: This serves as a repository for work descriptions, but it has limited functionality on the tablet devices used by technicians. This, in turn, reduces its value as a support tool, particularly when handling detailed maintenance tasks, as technicians struggle to access work descriptions effectively on site.
- SharePoint: This is a collaborative data platform where technicians document and share descriptions of failures and resolutions. Others can access and build upon this information, enabling continuity in KM. However, each maintenance facility manages SharePoint independently, leading to inconsistencies in how information is documented and shared. This lack of a unified system restricts knowledge sharing across facilities, limiting the technicians' ability to learn from experiences at other locations.

Every maintenance facility in NS operates with unique processes, and hence, knowledge sharing between facilities is minimal. This organisational structure contributes to differences in data availability and access across facilities. While technicians have access to these data sources, in the absence of the ability of such sources to communicate with each other, technicians must consult each source individually. This often results in fragmented information and workflow inefficiencies.

Despite the existing information supply from various data platforms, technicians face challenges due to inconsistencies, data silos, and gaps across platforms. Information is often poorly aligned, with one interviewee noting that, "…half the time, the reports do not match reality." This lack of coherence between reported issues and actual faults hampers the diagnostic process and reduces efficiency. Furthermore, the absence of historical data on prior maintenance actions can hinder diagnostic continuity, as technicians are often unable to verify whether similar repairs were previously attempted. The lack of synergy between data sources also adds to the workload, as technicians must access each platform individually, further complicating the diagnostic process and reducing efficiency.

When information is missing, technicians often need to manually request access to certain systems, leading to further delays. For specific faults, details such as the environmental conditions or prior diagnostic actions, are frequently unavailable, thereby not only adding complexity to the analysis but also extending the time needed to complete diagnostics. On average, a basic analysis of failures typically takes one to one and a half hours, while preparation, information review, and preliminary tasks generally add an extra half hour. However, the duration of the troubleshooting process remains unpredictable and can extend to more than five hours, especially in complex cases requiring expert intervention.

In summary, the current data platforms provide a foundation but lack both integration and completeness. MAXIMO's usability challenges, DINO's complex diagram navigation, and TRIPLO's limited functionality on technicians' devices reduce their effectiveness in facilitating efficient maintenance. While SharePoint offers basic support for collaboration, its separation from other platforms contributes to the

overall fragmentation and inconsistency across the data ecosystem.

### 5.2. AR-based validation of the DILEAF framework

#### 5.2.1. Participants

In this study, eleven technicians (N = 11) from the Onnen and Maastricht maintenance facilities participated in the AR-based SNT250 calibration experiments. The selection of the technicians was based on the following criteria: i) eleven were required to be specialised in troubleshooting system failures of the sanitary system, and ii) none were to have any prior experience with AR technology. Before the experiments, all the participants provided informed consent to take part in the study and were given a tutorial on the AR device, which covered the following: basic functionality of the AR system, navigation through the AR interface, and specific instructions for using the calibration tool. This tutorial ensured that the participants were comfortable with the AR device before the official validation phases.

#### 5.2.2. Pre-experiment survey

To establish a baseline, a pre-experiment survey was conducted to understand current troubleshooting methods and problem-solving strategies for the SNT250 system. The responses revealed that technicians primarily rely on experience-based, iterative methods to address system failures, often employing trial-and-error techniques. They begin by determining if the reported issue represents a genuine fault prior to proceeding to isolate and locate the specific problem. This process frequently involves consulting temperature readings, analysing failure codes, or seeking out core indicators of malfunction within the bioreactor. Technicians typically refer to work descriptions or consult colleagues for further guidance as needed.

When questioned about the use of MAXIMO and TRIPLO in supporting their troubleshooting tasks, most technicians indicated their considerable reliance on personal expertise and on-the-job experience over these systems. MAXIMO and TRIPLO were used as supplementary tools rather than primary resources. While MAXIMO offers essential work descriptions, technicians found its information too generic for effective troubleshooting, often requiring additional, situation-specific insights. TRIPLO was consulted sporadically, while DINO, a platform with technical drawings and specifications, was occasionally accessed for its detailed schematics. Some technicians noted that fault trees, despite being available, were underutilised, and most troubleshooting tasks were completed based on personal knowledge and, when necessary, support from colleagues.

Before the experiments, the technicians generally expressed a positive attitude toward AR as a potential support tool, suggesting an openness to its possible advantages in enhancing their diagnostic and maintenance tasks.

#### 5.2.3. Troubleshooting produce

The specific steps of the SNT250 calibration process are shown in Fig. 4, with detailed descriptions in Appendix A. The participants were divided across three rounds of experiments, as illustrated in Figs. 5 and 6. The initial laboratory-based experiment involved five technicians and focused on establishing baseline calibration steps and testing the accuracy of the flowchart. Real-time data from Arduino was integrated to simulate operational conditions. In the first field iteration, three participants worked with real-time data to fine-tune visual settings and cursor positions. The second field iteration introduced three technicians who independently gathered tools and troubleshoot actual faults, adding realism to the troubleshooting process. A detailed summary of each testing phase is presented in Table 3. To ensure clarity and effective communication, all instructions and prompts within the AR tool were provided in Dutch, as all technicians were Dutch-speaking.

After each experiment, participants completed SQ (seen in Section 3.2) to provide feedback on their experience with the AR system. This feedback was integrated into specific elements of the DILEAF framework, which subsequently guided iterative adjustments to the AR system. This process facilitated the continuous refinement of the functionality of the AR platform to ensure its suitability for real-world applications.

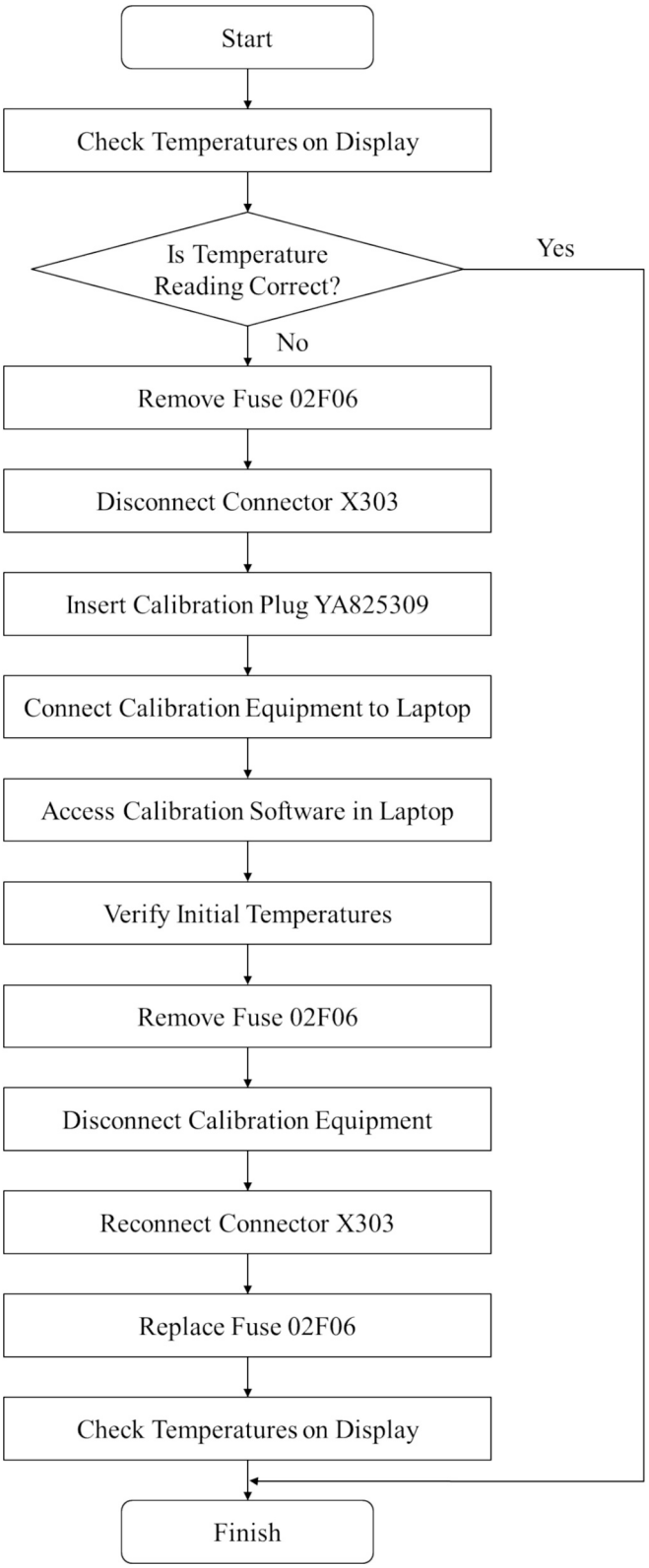



**Fig. 4.** SNT250 Temperature Sensor Calibration Detailed Flowchart.

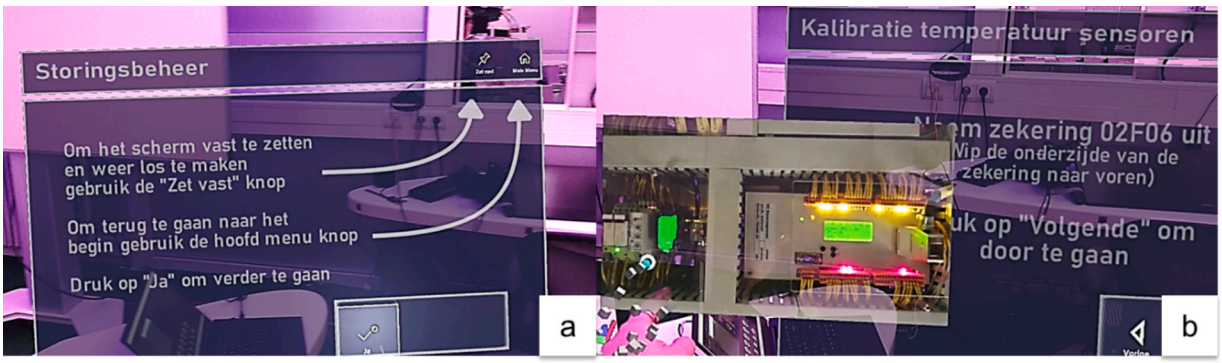



**Fig. 5.** Lab Experiment: AR-Guided Calibration Instructions: (a) Screen Lock and Navigation: Use the "Set Lock" button to lock/unlock the screen. Press the main menu button to return to the beginning. Press "Yes" to proceed; (b) Remove fuse 02F06: Flip the underside of the fuse forward, then press "Next" to continue.




**Fig. 6.** Field Experiments: Technicians Using AR System for SNT250 Calibration: (a) Technician preparing wiring connections for calibration; (b) Technician monitoring real-time data on a service laptop.

*5.2.4. DILEAF framework evaluation*

The DILEAF framework was evaluated within the NS case study by aligning its six core elements with real-world data and the processes associated with maintaining the SNT250 sanitary system. This mapping demonstrated the practical application of the DILEAF framework and its potential to enhance KM through AR solutions, as summarised in Table 4. To validate the framework, KPIs were defined for each core element and measured using a combination of post-experiment survey questions (linked to each KPI), task observation, and technician feedback. The KPIs include: data accuracy and availability, information findability, knowledge sharing effectiveness, user engagement, application relevance, and feedback usefulness. A thematic analysis of the technician feedback across lab and field iterations supported the evaluation.

*Data Accuracy and Availability*. The accuracy and availability of data were consistently verified across all the experimental phases, though distinctions emerged between controlled and real-world settings. In the controlled laboratory setting, data was considered accurate and complete, with participants noting that "All [of the] information is complete." During the first field iteration, technicians highlighted the need to verify data across sources, stating, "Yes, [we] but need to check sources." In the second field iteration, data availability was generally affirmed, though minor gaps were reported, particularly in procedural steps such as connecting to the computer. These findings suggest that while DILEAF ensures high data accuracy under controlled conditions, improvements are needed to maintain data completeness and accessibility in more dynamic field contexts.

*Information Findability*. The ability to find the appropriate information varied across the experimental phases, with participants identifying key areas for improvement in practical contexts. In the laboratory setting, information was generally accessible, though participants recommended richer visualisation, such as a full 3D system view ("having the entire system visualised in 3D"). In the first field iteration, technical issues, especially with sensor calibration, hampered access to key data ("We couldn't connect the laptop to calibrate sensors"). By the second field iteration, findability improved, but further refinements were suggested, including the addition of component images to better support localisation. These results suggest that while the framework supports information retrieval, practical deployment requires iterative adjustment to address task-specific navigation needs.

*Knowledge Sharing*. The experiments demonstrated AR's potential to enhance knowledge sharing, both at the individual level and within broader organisational structures. In the lab experiment, participants primarily focused on individual task execution, with limited

**Table 3**
Summary of Iterative Testing Phases for SNT250 Temperature Sensor Calibration.

| Setting | Data Source | System Adjustments | Technician Tasks | Goals |
|---|---|---|---|---|
| Lab environment | Real-time data from Arduino | Initial setup, verifying calibration steps; basic 3D visualisation without individual adjustments. | Follow the SNT250 calibration steps. | Verify the feasibility of the SNT250 calibration flowchart and identify baseline adjustments for real settings. |
| Field test (on train) | Real-time data | Added 3D visualisation with adjustable cursor and screen calibration for each technician; simultaneous real-time data extraction. | Complete calibration and troubleshooting based on real-time data. | Test real-time data visualisation; confirm AR usability in a real train setting. |
| Field test (on train) | Real-time data | Continued 3D visualisation with adjustable settings; introduced tool/equipment collection for realism; explored feedback system for manual update. | Gather all necessary tools independently and solve the failure. | Increase scenario realism by simulating real troubleshooting; assess the feasibility of real-time. manual updates. |

**Table 4**
Mapping the DILEAF Framework Elements to the SNT250 Maintenance Case.

| Element | NS Case Study Application |
|---|---|
| Data | Technical documentation includes temperature sensor logs, failure frequency reports, and specific maintenance order histories. Real-time data (e.g. sensor calibration status and live operational temperature readings) is captured via IoT devices. Historical data includes patterns of failures in cold weather conditions. KPI: Data accuracy (SQ1), Data availability (SQ2) |
| Information | Maintenance information is visualised using 3D interactive models. AR overlays identify key components directly in the technician's field of view. KPI: Information findability (SQ3, SQ4). |
| Learning | AR enables real-time guidance, including inexperienced workers. Instructions assist with tasks like sensor calibration or replacing pipe components. KPI: Knowledge sharing (SQ5, SQ6) |
| Engagement | AR supports multimodal inputs (e.g. voice commands, hand gestures, and gaze-based controls). Behavioural data (task duration, gesture retries) is logged to track engagement. KPI: User engagement (SQ7, SQ8) |
| Application | AR supports real-time task execution, tracking completion, and guiding technicians via spatial overlays. KPI: Application relevance (SQ9, SQ10) |
| Feedback | Structured logs record technician actions, flagged issues, and improvement suggestions. Revised steps are validated and versioned. KPI: Feedback usefulness (SQ11, SQ12). |

opportunities for organisational knowledge sharing. However, in the first field iteration, participants highlighted the importance of documenting steps for future use, reflecting a shift towards collective learning. One participant noted, "Problem-solving steps should be documented." The second field iteration further emphasised the value of storing and sharing task logs, enabling continuity in collaborative maintenance efforts. Feedback such as "[the] Storing tasks performed supports team collaboration" reinforces the utility of the DILEAF framework in fostering a culture of shared learning and knowledge retention within maintenance environments.

*User Engagement*. User engagement with the AR system improved significantly as the experiments progressed, particularly in field scenarios. In the laboratory experiment, participants were cautious about the long-term utility of AR, with comments such as "Difficult to look into the future; useful for educational purposes." However, engagement increased during the first field iteration, as participants began to appreciate the practical applications of AR. One technician remarked, "It's useful and supportive." In the second field iteration, engagement reached its peak, with participants recognising the potential of the AR system for addressing complex troubleshooting tasks. "Especially useful for supporting highly complex systems" was a common sentiment, demonstrating that the framework effectively incorporates contextual knowledge to enhance user interaction.

*Application Relevance*. The experiments highlighted the evolving nature of AR in supporting job responsibilities, particularly in handling complex tasks. In the laboratory experiment, AR was viewed as a supplementary tool, with limited immediate impact on job performance. One participant noted, "Nice but cannot yet see [the] added value [when] compared to [an] iPad." During the first field iteration, the structured guidance of the AR system proved beneficial for tasks requiring precision, although some questioned its necessity for simpler tasks. By the second field iteration, AR was widely regarded as indispensable for managing complex scenarios. Feedback such as "You cannot make a wrong step" underscores AR's alignment with task-specific requirements, validating the applicability of the framework in dynamic work environments. Compared to iPad-based manuals or videos, the AR system was seen to offer more consistent support during task execution, particularly in environments where hands-free operation, precision, and step validation were critical.

*Feedback Usefulness*. The feedback mechanisms integrated into the AR system were increasingly appreciated across the experiments. Logging mechanisms were initially appreciated for their potential to

improve traceability, though some participants raised concerns about surveillance. One participant commented, "Recording steps is useful, but [does] raises privacy issues." In the first field iteration, feedback emphasised that recorded steps facilitated learning from past errors, as noted in feedback like "You can see how others solved the failure." By the second iteration, task logs were widely recognised as essential for supporting task continuity and collaboration, with participants advocating for their constructive use. However, caution was advised to prevent punitive applications of recorded data, as reflected in the comment, "Task logs help, but avoid [any] blame culture." These insights demonstrate the capacity of the framework to promote adaptive feedback mechanisms while highlighting areas for ethical and practical refinement.

Across all experimental phases, task completion was systematically monitored. All participants, regardless of prior experience with AR, successfully completed the assigned maintenance procedures on the SNT250 system. This consistent task success demonstrates the practical viability and usability of the DILEAF framework within both laboratory and real-world settings. While this outcome provides a solid qualitative indicator of effectiveness, the current evaluation primarily emphasises thematic and perception-based feedback. Error rates remained low, and 45 % of the participants needed information on related subcomponents for task completion. Notably, AR overlays helped users detect and correct errors early, contributing to the overall high task success rate. In total, 91 % of participants were satisfied with the information presented in AR, demonstrating the framework's robustness.

An evaluation of AR system adaptability was conducted across the three experimental stages. Adaptability was observed through the system's responsiveness to different task complexities, user behaviours, and operational conditions. Key challenges included visual misalignment due to lighting variation, anchor drift in complex environments, and inconsistent interaction patterns. These were addressed through incremental interface calibration, user-informed adjustments, and flexible visual overlays tailored to each task phase.

## 6. Discussion

The application of AR within the DILEAF framework supports a more dynamic and situated form of KM. Unlike traditional KM systems that often remain static and document-driven, AR enhances the dynamic flow of knowledge, ensuring both real-time accessibility and usability in high-pressure environments. The limitations of traditional KM systems, which often fail to capture and transfer knowledge effectively in fast-paced industrial environments, have been highlighted in previous studies (Shidende et al., 2023). Our findings align with the prior research that emphasises the potential of AR in improving knowledge accessibility and transfer, particularly in complex and time-sensitive scenarios (Funk & Schmidt, 2021; Gualtieri et al., 2024). By providing real-time, context-specific information, AR facilitates seamless knowledge flow, ensuring that technicians are well-equipped to handle intricate, complex maintenance tasks.

Ensuring the accuracy and timely availability of data is fundamental to the success of maintenance operations, especially in dynamic environments. This study demonstrates that the AR platform can enhance fault diagnosis by seamlessly presenting real-time and historical data. Existing research highlights that AR has great potential to support complicated tasks when supported by robust backend systems capable of dynamic data synchronisation (Masood & Egger, 2019). However, field experiments revealed that despite improvements in data accessibility, inconsistencies remain in real-world contexts, calling for enhanced interoperability between AR systems and enterprise databases.

This study highlights the role of AR tools in fostering active learning and engagement among technicians. By providing technicians with step-by-step, immersive guidance, AR encourages active participation and deeper procedural understanding. The results support earlier findings that AR enhances skill acquisition by providing immediate, context-aware feedback (Gabbard et al., 2018; Padmaja & Mukul, 2021). Beyond simply replicating procedural instructions, AR enhances a hands-on learning environment that bridges the gap between theoretical knowledge and its practical application. By providing real-time feedback and simulations, AR tools ensure that users gain the confidence and competence needed to perform complex tasks efficiently (Vidal-Balea et al., 2020; Webel et al., 2013). This capability is particularly advantageous in sectors undergoing rapid technological advancements, where continuous learning and adaptation are essential (Dawarka, 2024).

A key strength of this study lies in its emphasis on real-world applicability, effectively bridging the gap between controlled experimentation and practical deployment. While many AR studies are limited to solely laboratory settings, our field iterations demonstrated the system's robustness in dynamic and unpredictable environments, highlighting its potential as a scalable solution for industrial maintenance (Palmarini et al., 2018). In such contexts, variability in task complexity, environmental conditions, and technician expertise often presents significant challenges (Erkoyuncu et al., 2017). The adaptability of AR to these diverse conditions ensures its effectiveness across a broad spectrum of maintenance tasks and user profiles. The customisability of AR interfaces, such as adjustable visual displays and integrated user feedback, further enhances its usability, particularly in environments with fluctuating light, noise, or space constraints (Webel et al., 2013). This aligns with Palmarini et al. (2018), who highlighted the technology's value in operational contexts for improving both efficiency and accuracy. Our findings extend this perspective by demonstrating AR's role in facilitating KT and supporting decision-making in real-world scenarios, ultimately contributing to more resilient and responsive maintenance workflows (Lee et al., 2008). This positions AR not merely as a tool for enhancing immediate task performance but as a strategic asset for driving long-term operational improvements (Zhu et al., 2015).

Feedback loops are essential for evolving maintenance practices and refining KM systems. By incorporating user inputs and real-time task logs, the AR platform supports a cycle of continuous procedural improvement (Palmarini et al., 2018). This reflects modern KM principles, which emphasise iterative learning and system adaptability (Davari-Najafabadi, 2024; Siew et al., 2021). The findings from the railway industry revealed a lack of consistent feedback mechanisms in existing systems, which often leads to incomplete or outdated maintenance records. For instance, technicians noted discrepancies in historical documentation and expressed the need for more streamlined processes to capture their real-time insights during field operations. The AR platform addressed this gap by enabling immediate feedback capture, which not only improved procedural accuracy but also ensured that field-level insights were systematically integrated into the KM framework (Geng et al., 2020). Moreover, the research demonstrates how AR can act as a catalyst for developing more resilient and user-informed maintenance protocols, bridging the gap between static documentation and dynamic operational feedback (Sarhan et al., 2024). By facilitating real-time learning and adaptation, AR tools can support organisations in building a more agile and knowledge-rich maintenance ecosystem.

This study contributes to the growing body of research on AR in industrial maintenance by introducing the DILEAF framework, which integrates the DIKW Pyramid and LEAF principles. This framework provides a structured yet flexible approach to enhancing KM practices, offering practical guidelines for AR platform design and deployment. Unlike previous models that focus primarily on static KM (Del Amo et al., 2018), DILEAF emphasises dynamic, user-centred interactions, bridging the gap between theoretical knowledge and practical application. The iterative experimental design further underscores the importance of real-world validation, demonstrating AR's capacity to drive innovation in maintenance practices.

This study has several limitations that should be considered in interpreting its findings. The sample size was relatively small, and the experiments were conducted within a specific industrial context, which

may limit the generic nature of the findings. Future research should explore the scalability of the DILEAF framework across different industries and maintenance environments, including its adaptation to larger teams and enterprise-level AR infrastructures. Also, further investigation into the long-term impact of AR on KM, KT and organisational learning is warranted. Expanding the scope of feedback integration to include AI-driven analytics, predictive modelling, and interoperability with digital twins could further enhance the adaptability and responsiveness of the DILEAF framework to evolving knowledge contexts. Future research may explore adaptive AR interfaces that respond to user experience levels and task complexity, alongside the application of cognitive design principles to reduce perceptual load and optimise information flow. Finally, as AR-enabled KM systems increasingly interface with cloud platforms and enterprise data systems, the implementation of appropriate cybersecurity and data protection mechanisms will be essential to ensure the safe handling of sensitive knowledge.

## 7. Conclusion

This study introduced the DILEAF framework, a novel conceptual model designed to advance KM in industrial maintenance. By integrating the structured knowledge progression of the DIKW Pyramid with the interactive, user-driven principles of the LEAF framework, DILEAF establishes a comprehensive, adaptable, and technologically enhanced approach to KM. The framework addresses two fundamental limitations in existing models: (1) the rigid, linear progression of knowledge in DIKW, which fails to accommodate iterative learning and feedback-driven improvements, and (2) the lack of structured knowledge transformation processes in LEAF, which restricts its applicability to complex industrial settings. By embedding dynamic feedback loops and restructuring user interaction mechanisms, DILEAF ensures that knowledge is not merely stored but continuously refined and applied.

Empirical validation of the DILEAF framework was conducted through iterative experiments in both laboratory and real-world maintenance environments. The findings demonstrate that AR-enabled KM significantly enhances procedural accuracy, decision-making efficiency, and user engagement, addressing practical challenges such as fragmented information access and inconsistent procedural adherence. The integration of real-time feedback mechanisms within AR interfaces further enables continuous system adaptation, ensuring that KM processes remain aligned with evolving operational requirements.

This study validates the DILEAF framework as a robust KM solution tailored for dynamic maintenance operations. By redesigning the role of Engagement and Feedback, the framework ensures that knowledge acquisition is an active, iterative, and context-driven process. This reconfiguration bridges the gap between static knowledge repositories and real-time knowledge application, offering a pragmatic and scalable approach to KM in high-stakes industrial settings. Future research can explore cross-industry applications, integrating emerging technologies such as AI-driven knowledge synthesis, predictive analytics, and cognitive computing to further enhance KM performance. By addressing both conceptual and practical challenges, this study offers a rigorously validated, future-oriented model for KM in industrial maintenance, establishing a foundation for next-generation AR-enabled knowledge systems.

## CRediT authorship contribution statement

**Wanting Mao:** Writing – original draft, Software, Formal analysis, Conceptualization, Writing – review & editing, Visualization, Methodology, Data curation. **Sara Scheffer:** Conceptualization, Supervision, Project administration, Writing – review & editing, Resources, Investigation. **Arnab Majumdar:** Writing – review & editing, Project administration, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgement

The authors would like to thank Nederlandse Spoorwegen for their support during this research, and appreciate the valuable feedback provided by the editor and anonymous reviewers. This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

## Appendix A

**Table 5**
SNT250 Temperature Sensor Calibration Steps.

| No. | Step | Description |
|---|---|---|
| 1 | Remove Fuse 02F06 | Flip the bottom of fuse 02F06 forward to remove it. |
| 2 | Disconnect Connector X303 | Disconnect the X303 connector. |
| 3 | Insert Calibration Plug YA825309 | Insert the calibration plug (YA825309) specifically designed for the VIRMm1 toilet calibration check. |
| 4 | Connect RS232 Cable to Toilet Module | Insert the RS232 cable into the toilet module using the specified adapters and cable (9p Sub-D female-female, Null-modem adapter, and D-sub 9p male–female 3m cable). |
| 5 | Connect RS232 Cable to Laptop | Connect the other end of the RS232 cable to the service laptop (MAT00089). |
| 6 | Replace Fuse 02F06 | Reinsert fuse 02F06, ensuring the bottom clicks into place. |
| 7 | Access VIRM/Toilet Directory | Go to the VIRM/Toilet directory on the laptop. |
| 8 | Click on “DDT.x.x.xx” | Click on “DDT.x.x.xx” to initiate the process. |
| 9 | Select COM Port Block (Green) | Click on the COM port block when it turns green, indicating a connection. |
| 10 | Click on “Terminal” | Click on “Terminal” to access the command input screen. |
| 11 | Enter Code 2633 | Enter code “2633″ and press ”Enter“. |
| 12 | Verify Baud Rate | Ensure the baud rate is set to 115200.n.8.1. |
| 13 | Select “File” and “Execute Script/File” | Click on “File”, then “Execute Script/File”. |
| 14 | Navigate to the Calibration File | Go to “D:/firmware/VIRM/23R2/VIRMm1/Toilet/Toiletcontroller x.xx Virm/237_Toiletcontroller_x.xx_Virm_v2″ and select ”Calibration temperature sensors.par“. |
| 15 | Confirm Selection | Click “OK” four times to confirm the selection. |

(*continued on next page*)

**Table 5** (*continued*)

| No. | Step | Description |
|---|---|---|
| 16 | Verify Initial Temperatures | Check that initial temperature values Tw and Tr are set to 0. |
| 17 | Remove Fuse 02F06 | Remove fuse 02F06 by flipping the bottom forward. |
| 18 | Disconnect RS232 | Disconnect the RS232 cable from the toilet module. |
| 19 | Remove Calibration Plug | Remove the calibration plug from the system. |
| 20 | Reconnect Connector X303 | Reconnect the X303 connector to restore the sensor connection. |
| 21 | Replace Fuse 02F06 | Reinsert fuse 02F06, ensuring it clicks into place. |
| 22 | Check Temperatures on Display | Verify that the temperatures Tw and Tr on the display match the actual room temperature. |

## Data availability

The data that has been used is confidential.

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