Artificial intelligence system reliability and knowledge identity: A model for knowledge workers in knowledge management environments

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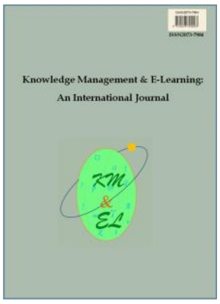

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Artificial intelligence system reliability and knowledge identity: A model for knowledge workers in knowledge management environments

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Abstract: This study examines how perceived AI system reliability shapes knowledge identity (KI) processes in organisations by influencing how knowledge is presented, transferred, and reproduced. Prior work on AI trustworthiness has largely emphasised technical performance, while under-specifying reliability as a socio-cognitive judgement enacted through human–AI interaction. Drawing on socio-technical systems theory and identity-based knowledge management, a mixed-method design was employed in an aviation maintenance context. First, grounded interviews with domain experts identified five human-centred reliability dimensions (accuracy, user trust, explainability, consistency, and responsiveness). Second, the Analytic Hierarchy Process was used to prioritise these dimensions and inform a composite system reliability score (SRS). Third, hypotheses were tested using PLS-SEM on survey data from 116 knowledge workers. Results show that perceived AI reliability positively affects all three KI processes, with accuracy and user trust exerting the strongest influence. The study contributes by (i) conceptualising AI reliability as a socio-cognitive construct central to KI formation, (ii) operationalising a weighted SRS to support evaluation and improvement of AI-enabled knowledge management (KM) systems, and (iii) providing actionable design implications for aligning AI tools with organisational sensemaking and knowledge continuity. Future research should validate the model across industries and integrate objective system metrics with perception-based reliability measures.

Keywords: Artificial intelligence; Knowledge identity; Knowledge workers; AI system reliability; Knowledge management

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1. Introduction

The fourth industrial revolution has driven substantial changes in how knowledge is created, managed, and utilised within organisations, necessitating the redefinition of knowledge management (KM) practices (Anshari et al., 2022). As artificial intelligence (AI) technologies increasingly permeate organisational systems, knowledge acquisition, decision-making, and learning processes are becoming more closely supported and shaped by intelligent systems (Rezaei et al., 2025; Harisankar et al., 2024). Although AI has demonstrated substantial potential to enhance efficiency and analytical capability within KM (Taherdoost & Madanchian, 2023; Chatterjee et al., 2020), current research offers limited understanding of how AI influences the human and identity-related dimensions of organisational knowledge. Recent empirical work has also highlighted the growing synergy between AI-enabled KM practices and sustainable learning outcomes, reinforcing the relevance of AI-supported KM systems for learning-oriented organisational environments (Ranjan et al., 2024).

Because these AI processes underpin how knowledge is learned, retained, and reused over time, the proposed model also informs the design and evaluation of AI-supported learning and knowledge development environments. In this sense, AI system reliability becomes a critical condition for sustaining learning legitimacy and continuity within organisational KM and E-learning infrastructures (Alshammari & Alshammari, 2026). Knowledge has evolved from being an organisation's input or resource to becoming a central aspect of how that organisation defines itself (Van den Berg, 2013). Knowledge identity (KI) is a framework that illustrates how organisations develop, communicate, and maintain a collective understanding regarding the types of knowledge they find important, wish to preserve, and strive to build upon (Intezari et al., 2022). KI involves taking the heritage, current capability (repertoire), and future aspiration of an organisation and formulating a dynamic narrative describing the organisation's identity that will help guide the organisation's efforts, including learning, innovation, and decisions made about future plans (Intezari et al., 2021).

A strong KI allows members to tie together knowledge, information, analytics, and strategic initiatives to support the organisation's established values and knowledge practices (Intezari et al., 2022). Nevertheless, although important from a theoretical perspective, the impact of AI on the development of KI or how an individual perceives AI's influence over the knowledge-based identity processes of an organisation have not received much empirical attention. Most prior research in the field of AI and KM have emphasised the technology's ability to perform tasks such as organising, searching, and processing data (through automation) (Jarrahi et al., 2023), rather than the ways in which AI will affect human perception, understanding, and decision making when adopted by an organisation (Lindgren, 2025). This limitation is particularly important because AI-enabled KM systems are increasingly embedded within learning-oriented organisational contexts. Recent research has also emphasised that KM in educational and learning-oriented institutions requires structured models that support knowledge sharing, retention, and organisational learning continuity (Prodinger et al., 2026).

Therefore, we do not yet understand the potential impact that the introduction of AI into an organisation will have on the organisation's knowledge-based identity. A particularly underexplored issue within this gap concerns the perceived reliability of AI systems. While reliability is largely discussed in the literature through technical indicators such as error rates, level of system output, and degree of transparency (Nguyen et al., 2024b), it is less often examined systematically to understand how perceived reliability affects users' levels of trust and acceptance of AI and how they make sense of that information. This is an area of omission that has important implications; because trust in AI systems by knowledge workers has a direct impact on how AI-generated knowledge is utilised, legitimised, and integrated into the organisation's knowledge structures (Sundaresan & Zhang, 2022). Perceived unreliability of AI outputs will result in users potentially resisting or reinterpreting algorithmically generated knowledge, further eroding the organisation's narrative of shared knowledge and identity (Yang, 2024).

Within KM research, knowledge development is closely associated with efficiency, meaningfulness, and mutual understanding (Basu & Weibull, 2024; Koivisto & Taipalus, 2025), and knowledge is increasingly recognised as both a strategic asset and an identity-defining element of organisations (Suwayd et al., 2024; Sobaih et al., 2025). However, identity-oriented knowledge practices remain marginal in the design and evaluation of AI-enabled KM systems, creating a persistent conceptual and practical gap in KM and AI trust literature (Politis, 2003; Alvesson & Kärreman, 2001; Siong Choy et al., 2006). Despite this recognition, the role of AI system characteristics in shaping these identity-oriented knowledge practices remains theoretically under-developed.

This gap is especially apparent because knowledge workers will increasingly play an active role in assessing and validating AI-sourced information; they will no longer be content to receive it as passive consumers (Reinhardt et al., 2011). Knowledge workers' assessments of the reliability of AI systems will determine whether or not to apply, distribute, and incorporate the results of AI-based algorithms into company-wide knowledge activities (Jarrahi et al., 2023; Marvi et al., 2024; Sokol & Figurska, 2021). Unfavorable perceptions of AI reliability could also prevent companies from implementing outputs from AI sources into their organisational structures, thus diminishing the relevance of identity-based knowledge (Booyse & Scheepers, 2024).

To address a significant gap in the existing literature about knowledge creation and continuity, the present research develops and tests an empirical, user-focused, AI-based model of how the development and maintenance of KI are directly influenced by the perceived reliability of AI systems. As a means of evaluating the level of reliability of an AI system, the present study proposes a system reliability score (SRS), which evaluates AI system reliability on five key dimensions: accuracy, consistency, explainability, trust, and responsiveness. The study also explores the impact that perceived system reliability has on three key processes relating to KI: the presentation of knowledge, the transfer and reproduction of knowledge.

Using an exploratory sequential mixed-methods research design, the present research analyses data obtained through semi-structured interviews, followed by quantitative validation to arrive at a theoretically grounded understanding of the ways in which AI systems (in terms of their reliability) affect the creation and continuity of identity-based knowledge. The research advances the theory of KI by conceptualising AI system reliability as a socio-cognitive mechanism through which technological artefacts are enabled to actively shape the development of organisational identity-based knowledge, rather than being viewed as merely tools or technical instruments, which assist people in performing their work related to knowledge.

2. Literature review

2.1. Research background and conceptual gap

Integrating AI in KM systems has been a critical area of conversation around the Fourth Industrial Revolution (Sridevi & Gundoor, 2024). However, although technological advances in the use of AI, the provision of more sophisticated classification, automation and retrieval systems that have received considerable attention (Sarker, 2022), researchers have had little regard for the cognitive and interpretative aspects of AI use in KM. For example, much of the research to date has focused either on the technological performance of algorithms or on the human factors (attack notwithstanding) of knowledge identity (KI) (Intezari et al, 2022), trust (Degachi et al., 2024), and interpretability (Somarathna et al., 2025). This neglect is troubling since AI increasingly affects not only how knowledge is leveraged to facilitate performance, but also (crucially) how it will help define the knowledge edifice is produced, authenticated and reproduced.

Although frameworks linking AI to knowledge performance outcomes exist, they often emphasise measurable outputs over interpretive processes that is, how users experience, validate, and make sense of AI-generated knowledge (Bag et al., 2021; Nylund et al., 2023). Recent research has also highlighted that technology-mediated knowledge sharing platforms play an important role in enabling knowledge dissemination and continuity in practice-based contexts, reinforcing the need to examine how system characteristics shape knowledge processes (Kommey & Fombad, 2024). Similarly, while Intezari et al. (2021) introduced the concept of KI as a multidimensional construct, its interaction with AI technologies remains underexplored. In particular, the construct of AI system reliability has not yet been empirically integrated into KI models, despite its potential influence on how knowledge is perceived and enacted by organisational members.

The study builds on previous research by exploring this conceptual gap. It examines how the level of perceived reliability of the AI system (consisting of technical (functional aspects; accuracy, consistency)) and cognitive determinants (explicability, trust, responsiveness) affects the emergence and continued existence of the KI. To do this, a composite framework is introduced in the form of the System reliability score (SRS) allowing a conversation between technical design and organisational sensemaking. Including reliability in the discussion on knowledge identity leads to a position of AI not merely serving as a computational tool, but as an actor in the meanings produced within organisations.

2.2. Knowledge identity

Knowledge Identity (KI) describes how individuals construct shared understandings of what knowledge they value, preserve, and aspire to develop (Intezari et al., 2021, p. 4896). KI is not only a strategic orientation but a communicative mechanism: it emerges through narrative practices, memory work, and the situated negotiation of expertise within organisational interactions. Through language and shared interpretation, members link past competence, current capability, and future knowledge aspirations into an identity story that guides action and sensemaking (Intezari et al., 2022).

KI has three interrelated dimensions (Intezari et al., 2021, p. 4895):

- Knowledge heritage: how past knowledge is remembered and legitimised
- Knowledge repertoire: how current knowledge resources are defined and enacted
- Knowledge aspiration: how future knowledge priorities and directions are articulated

Existing KI research focuses on human actors. However, as AI systems increasingly mediate access to knowledge, they may participate in reinforcing or challenging these identity dimensions. What remains underexplored is how AI earns epistemic legitimacy to influence this shared identity.

2.3. Knowledge workers and human–AI interaction

Knowledge workers do not passively receive information but actively interpret and validate the insights provided by AI (Sokol & Figurska, 2021; Nylund et al., 2023). Their perception of AI as a reliable source of information, which leads to an internalisation, dissemination and institutionalisation of algorithmic knowledge, i.e. in the sharing of knowledge with other workers, is important. If systems are perceived as reliable, it is also possible to integrate outputs from AI into strategic reasoning and collaborative reasoning and collaboration (Chen et al., 2022; Dell'Acqua et al., 2023). However, the opposite is true, namely distrust or inconsistencies, which would lead to non-integration or selective reliance on, or even a rejection of what is recommended by the system (He et al., 2023).

Creative knowledge workers: the category of workers where expertise in the domain results in critical thinking, are instrumental in refining and contextualising the insights AI offers. It is through the combination of tacit and explicit knowledge that they are able to detect bias, improve interpretability and better align the recommendations provided by AI solutions with the intended outcomes envisioned in the organisation (Jarrahi et al., 2025; Manuti & Monachino, 2020). As such, human–AI co-working would operate via an active feedback loop where reliability of the system itself not only plays a role in inducing user engagement but is also dictated by both the reliability and engagement levels of the user.

2.4. AI system reliability: A multidimensional construct

In contexts where knowledge is of utmost relevance, the proper functioning of an AI system provides criteria for how the knowledge therein can be trusted, interpreted, and applied. By functioning well, we mean that the system generates products that are accurate, consistent, explainable, and relevant to the context within which they are being used (Rausand & Hoyland, 2003, p. 5). More recently researchers have considered reliability in a multidimensional way comprising five dimensions and stating that the dimensions are interrelated, namely, accuracy, consistency, explainability, trust, and responsiveness (Mortaji & Sadeghi, 2024), defining whether users regard AI as an acceptable partner (collaborator) in organisational learning.

2.4.1. Accuracy

Accuracy is concerned with how effectively AI-generated outputs contain relevant and correct information (Duke & Giudici, 2025). This is important in KM design, implies that accurate insights from an AI ensure alignment with organisational goals (rather than other interests) and knowledge bases in knowledge management (Kollar & Alshibli, 2024). Sustained inaccuracies undermine trust and can distort collective sense making knowledge, devaluing the knowledge management system in strategic circumstance.

2.4.2. Consistency

Consistency is indicative of the capacity of AI systems to produce stable and repeatable results in similar operational conditions (Koczkodaj, 1993, p.82). Such consistency of performance engenders trust and contributes to a shared understanding across teams, while inconsistency of outputs raises questions of algorithmic fairness or reliability. Consistency for knowledge workers is a kind of implicit trust builder, thus increasing confidence in AI-supported decision making.

2.4.3. Explainability

Explainability refers to the ability of users to understand how and why specific outputs are generated by AI (Chazette et al., 2021, p.201). Transparent paths of decision-making lend themselves to accountability, and promote conversations between humans and AI, especially in the high-risk environment of knowledge processes (Combi et al., 2022). When explainability is absent, users may disengage from or question the legitimacy of the insights provided by AI.

2.4.4. Trust

Trust forms the cognitive and emotional basis of human–AI interactions (Lukyanenko et al., 2022; Shneiderman, 2020). A system is experienced as trustworthy if it is capable of being fair, reliable and having integrity (Cho et al., 2019). In AI processes, trust is the mediator of how knowledge workers internalise the AI-supported knowledge, while they deliberate on whether the outputs from the system are credible artefacts of the organisation (Vining et al., 2022; Cui et al., 2025). If trust is not continuously retained, even systems showing a certain degree of technical correctness cannot create acceptance or learning (Dodgson, 1993).

2.4.5. Responsiveness

Responsiveness represents how adaptable and timely the system produces relevant results in changeable environments (Chen et al., 2021). A responsive AI system can strengthen user engagement by providing timely feedback and adaptive support, thereby facilitating continuous learning within AI-enabled environments (Vadivel et al., 2025). Low responsiveness, however, leads to user frustration and decreases the integration of AI functionality into the everyday forms of knowledge work (Yigitbas et al., 2019).

2.5. Linking system reliability and knowledge identity

The five dimensions of reliability in AI systems- accuracy, consistency, explainability, trust and responsiveness- group together to influence how knowledge workers perceive the credibility of AI systems and accordingly how organisational knowledge identity (KI) changes. Knowledge narratives can be distorted through inaccurate systems while reliable and explainable systems further strengthen shared understanding and enhance collective confidence. A composite measure termed the System Reliability Score (SRS) is introduced here to empirically evaluate how the perception of reliability affects the three KI processes of knowledge presentation, transfer, and reproduction. By integrating a number of these dimensions the framework provides a bridge between technical attributes of the system and socio-cognitive processes, presenting in this way a holistic model of the contribution of AI to KM.

Importantly, while current research treats reliability as a stable performance characteristic, we conceptualise it as both an interpretative and relational phenomena that co-evolves with perceptions of users in the context of organisational identity. This reframing has theoretical implications for KM and AI trust research because it demonstrates that AI reliability is not only a design attribute but also a driver of ongoing knowledge continuity based on identity.

3. Research methods

3.1. Research design

To answer the question "To what extent does the perceived reliability of the AI system affect the formation and reinforcement of organisational Knowledge Identity (KI)?" a mixed methods exploratory sequential design was used. This design was chosen in order to be able to derive inductively the most important factors that influence the reliability of AI systems. Then through a quantitative study, to verify the tendency or non-tendency of these factors to influence KI. The design is that of a tool development study. Thus, the qualitative research informed the quantitative instrument (Leavy, 2022).

In the qualitative phase, grounded theory methodology was implemented with the aim of inductively revealing the core dimensions of AI system reliability in knowledge intensive modes of working (Glaser & Strauss, 1998; Corbin & Strauss, 2014). Grounded theory was chosen as it has been successful in revealing latent cognitive, behavioural and semantic patterns in under-explored domains of human–AI interaction.The quantitative phase integrated PLS-SEM for the statistical validation of the relationships emerging from the qualitative phase and exploiting complex causal paths between latent variables (Hair et al., 2019). This approach facilitated sequential integration of the findings from the qualitative phase, by which qualitative findings directly informed the structure and measurement of quantitative constructs.

3.2. Data collection

Data was collected by performing a two-phase project. The first phase is qualitative, where information was drawn from semi-structured interviews with 15 experts in the aviation maintenance industry who were selected intentionally due to their knowledge management and artificial intelligence experience. The study took place at Pars Aviation Maintenance Company, Tehran, Iran, a leading company active in the aviation maintenance business which has incorporated AI technologies in its maintenance and KM systems. This company was selected as a deliberate choice due the fact that it has a developed KM framework, it is in an ongoing phase of digital transformation and it uses AI-supported diagnostic and decision tools, a rich terrain for studying the perceptions regarding the reliability of the systems.

The aim of the study is analytic rather than statistical generalisation. The goal is to extend theoretical propositions by examining mechanisms such as human–AI interaction, perceived reliability, and identity-based knowledge processes that operate across organisational types and are not unique to this company. Therefore, insights derived from this empirical setting can meaningfully contribute to broader theoretical understanding of AI-supported KM systems in other knowledge-intensive sectors. The ethical guidelines concerning confidentiality, consent, and voluntary participation were adroitly observed. The credibility was assured by the validation of transcripts by participants; the dependability by double-coding of five interview transcripts achieving over 70 per cent agreement between coders (Lincoln & Guba, 1980).

In the quantitative phase, data was collected through a questionnaire applied by the researcher whose contents were derived from the qualitative results and the previous validated models. A total of 116 valid responses were obtained through the application of Cochran's formula for the determination of the sample, thus ensuring the statistical representativeness:

$$n = \frac{N \times Z^2 \times p \times q}{Z^2 \times p \times q + N \times d^2}$$

Where: Confidence level = 95% → z = 1.96; p = q = 0.5;

Population size (N) = 167; Margin of error (d) = 0.05

To enhance contextual clarity, demographic information of the participants (age, gender, job position, experience, and AI exposure) was collected and summarised in Table 1.

3.3. Instrument development and content validity

To ensure the validity and reliability of the measurement instrument, the initial pool of items was adapted from prior validated studies and refined through a multi-stage process. In the qualitative phase, data from 15 domain experts (AI developers, KM specialists, and aviation engineers) were used to identify and confirm key dimensions of AI system reliability. This number is consistent with grounded theory and expert validation standards, which emphasise conceptual saturation rather than statistical generalisation (Guest et al., 2020).

Table 1
Demographic characteristics of participants

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	67	57.8
	Female	49	42.2
Age	Mean (SD)	—	—
Age groups	20–29	14	12.1
	30–39	18	15.5
	40–49	47	40.5
	50+	37	31.9
Education Level	Bachelor's	36	31.0
	Master's	57	49.1
	Doctoral	23	19.8
Work Experience	Mean (SD)	—	—
Experience groups	< 2 years	24	20.7
	2–5 years	33	28.4
	6–10 years	39	33.6
	> 10 years	20	17.2
Job Role	Managerial	27	23.3
	Non-managerial	89	76.7

In the qualitative portion of the study, involving 15 experts is appropriate from a methodological standpoint. In grounded theory studies and development of expert-based instruments, sample adequacy is based on conceptual saturation rather than statistical generalisation (Braun & Clarke, 2021; Francis et al., 2009). Prior research shows saturation is usually reached within 8–12 interviews recommends a sample of 5–25 for grounded theory studies (Guest et al., 2020; Aldiabat & Le Navenec, 2016). The diversity in sample composition of AI developers, KM specialists, and engineers from aviation provided sufficient human variation to capture all relevant cognitive, technical, and organisational aspects of reliability of AI systems. Therefore, the 15 interviews resulted in rich and saturated data for confirming refining the reliability dimensions.

Interviews with experts confirmed that the five dimensions of reliability, i.e. accuracy, consistency, explainability, trust, and responsiveness, had different, non-overlapping conceptions with respect to content. The interview included open questions that guided the participants regarding their experiences with AI-assisted systems (see Appendix I for example questions). In the quantitative phase, the final questionnaire was distributed to 116 knowledge workers from the Pars aviation maintenance sector through organisational communication channels. Although the final sample consisted of 116 respondents, this number is fully adequate for the analytical requirements of the study. In PLS-SEM, sample adequacy is typically assessed using the "10-times rule," which recommends a minimum sample size equivalent to ten times the largest number of structural paths directed at any latent variable (Hair et al., 2019).

In the present model, the most complex construct had no more than three predictors, meaning that a minimum of 30–50 cases would have been sufficient. The sample size of 116 therefore far exceeds this baseline. Furthermore, simulated studies demonstrate that PLS-SEM results in stable parameter estimates and high statistical power at sample sizes of 100 to 150, when factor loadings are above 0.5 and model complexity is moderate, all of which apply to this research (Hair et al., 2021; Kock & Hadaya, 2018). The existing sample also demonstrated acceptable statistical representativeness in its application of Cochran's formula, confirming that 116 cases provide enough variability and precision to estimate the structural relationships examined.

3.4. Data analysis

3.4.1. Qualitative data analysis

The qualitative data were analysed using grounded theory procedures, open, axial, and selective coding (Corbin & Strauss, 2014). MAXQDA software was used for coding and categorisation of interview data, enabling the construction of a conceptual framework linking AI reliability with KI. Emergent categories included algorithmic transparency, user trust, and adaptability, consistent with prior conceptual developments (Dell'Acqua et al., 2023). The full list of measurement items for all constructs, along with their sources, is provided in Appendix II.

3.4.1.1. Analytic hierarchy process (AHP)

In order to prioritise aspects of AI system reliability, we implemented the Analytic Hierarchy Process (AHP) (Saaty & Vargas, 2012). A total of 15 experts in the field participated in a series of pairwise comparisons pertaining to the five main aspects (accuracy, consistency, explainability, trust, and responsiveness) and then we calculated priority vectors based on the eigenvalue method. All pairwise-comparison matrices had an appropriate level of consistency ($CR < 0.10$), providing confidence in the weight-generating process (Feizizadeh et al., 2015).

3.4.2. Quantitative data analysis

The survey instrument was developed on the basis of the qualitative results obtained from the studies and was refined through research by an expert panel of three academics and two practitioners in the field of AI. A pilot test of the instrument with 10 participants confirmed its clarity of meaning and the construct validity. The reliability of the measures, and the convergent validity were examined by Cronbach's alpha, Composite Reliability (CR) and Average Variance Extracted (AVE) and were all shown to exceed 0.70 (Fornell & Larcker, 1981; Tavakol & Dennick, 2011). We used PLS-SEM (SmartPLS 4.0) for evaluating the measurement models and the structural models, where we established the discriminant validity with the Fornell–Larcker criterion. To evaluate model fit, the Standardised Root Mean Square Residual (SRMR) was examined.

3.5. Research hypotheses

Based on the conceptual framework derived from the qualitative phase and supported by the literature, the following hypotheses are proposed for empirical testing:

H1: AI system reliability has a positive effect on the presentation of KI.

H2: AI system reliability has a positive effect on the transfer of KI.

H3: AI system reliability has a positive effect on the reproduction of KI.

4. Findings

4.1. Interview results

Since the aim of this study is to evaluate the reliability of AI systems in presenting KI to knowledge workers, the data analysis in this chapter is focused on qualitative findings. The variables required for the research model were extracted from interviews, and the relationships between them were determined. For the data analysis process, the research validity was assessed using the Lincoln and Guba (1980) method, and reliability was checked through internal agreement. Descriptive statistics of the interviewees were then presented, followed by data analysis aimed at extracting codes, categories, and their relationships using MAXQDA software.

In the present study, the validation was done with the help of the method suggested by Lincoln and Guba (1980), (Table 2) which is based on four elements: transferability, credibility, dependability, and confirmability. This method confirms the reliability of the instrument used for the study.

Table 2
Research validity according to Lincoln and Guba's Method (1980)

Index	Process
Transferability	Survey of experts who did not participate in the current study.
Credibility	Allocating sufficient time for research and confirmation of interview data by participants.
Confirmability	Documentation and adherence to all steps taken in the research process.
Dependability	Recording all details and taking notes during the interview phase.

To evaluate the reliability of the research, two individuals outside the scope of the study were asked after receiving the necessary explanations and training, in order to code five interviews in order to measure and compare reliability.

Table 3
Research reliability using the internal consistency method

Interview	Number of Codes Extracted	Number of Agreements	Agreement Percentage (Reliability)
Interview 1	43	37	86.05%
Interview 4	51	42	82.4%
Interview 5	37	30	81.1%
Interview 9	34	25	73.53%
Interview 11	28	23	82.1%

According to Lincoln and Guba (1980), as shown in the Table 3, the intercoder agreement for the five interviews exceeds 70%, indicating an acceptable level of reliability for the conducted interviews and the extracted codes by the researcher. To identify the necessary variables for the research model related to solving expert domain issues, various methods are employed. These methods can be categorised in different ways. One common approach is to classify them based on how knowledge is obtained from experts. Accordingly, two types of knowledge extraction are proposed: direct and indirect extraction.

Direct methods involve asking the expert to explain how these tasks are done. Obviously, the success of these methods depends on the expert having both the ability and willingness to communicate his knowledge. These are generally very simple methods except in cases where the knowledge has been so frequently applied that it is rendered implicit or automatic. Indirect methods are utilised for the purpose of getting at facts which the expert is not apt to state readily.

Furthermore, methods can also be categorised based on the type of information they provide, which will be discussed in this section. In the current study, the direct method was used. As shown in Table 4, after the interviews, the concepts required for the research were first open-coded, then categorised, and finally axial coding was performed to extract the research model. The extraction of other concepts from interview data followed the same process, which is fully presented in the following Table.

Table 4
Open coding process of expert interviews

Main Component	Sub-Component	Sub-Sub-Components
Accuracy	Information Accuracy	- Absence of errors in knowledge - Alignment with credible sources - Content neutrality - Conceptual coherence
	Timeliness of Information	- Content freshness - Consistency with scientific changes - Regular updates - Use of new resources - Relevance to user needs
	Relevance of Content	- Coverage of relevant specialised topics - Consistency with the application context - Lack of ambiguity in information
Consistency	Repeatability of Outputs	- Similar outputs in similar situations - Consistency across different levels of complexity
	Resistance to Errors	- Testability of performance - Robustness to variations in input data - Maintaining functionality with data errors - Ability to detect system errors - Minimal output errors - Correct response to incomplete data
	Long-Term Performance	- Maintaining quality in continuous use - No performance degradation over time - Continuous learning capability - Memory and resource management
Explainability	Algorithmic Transparency	- Comprehensibility of decision-making logic - Access to the analysis pathway - Complete documentation of outputs - Traceability of the process
	User Comprehensibility	- Use of simple language, diagrams, and supplementary data - Adaptation to the user's expertise level - Expressibility of results by users
	Output Causality	- Explanation of the reasons behind decisions - Logical justifications for suggestions - Displaying the weight of influencing factors - Access to the explanatory model
User Trust	Positive User Experience	- Simple user interface - Easy access to information - Fast response times - Interactive system
	Transparency in	- Information about data sources - Display of the

	Performance	analysis process - Warnings about uncertainties - Absence of systemic bias
	Reliability of Knowledge Produced	- Relevance to user expertise - Comparability with human resources - Acceptance by experts - Referencing of information
Responsiveness	Response Speed	- Short processing time - Quick response to queries - Maintaining quality with increasing data volume
	Real-World Stability	- Real-world effectiveness - Resistance to network disruptions - Stable operation under high load - No performance degradation in specific conditions - Maintaining reliability
Flexibility in Adaptation	Adaptability	- Customisation capability - Learning from previous interactions - Compatibility with organisational culture - Support for various input types

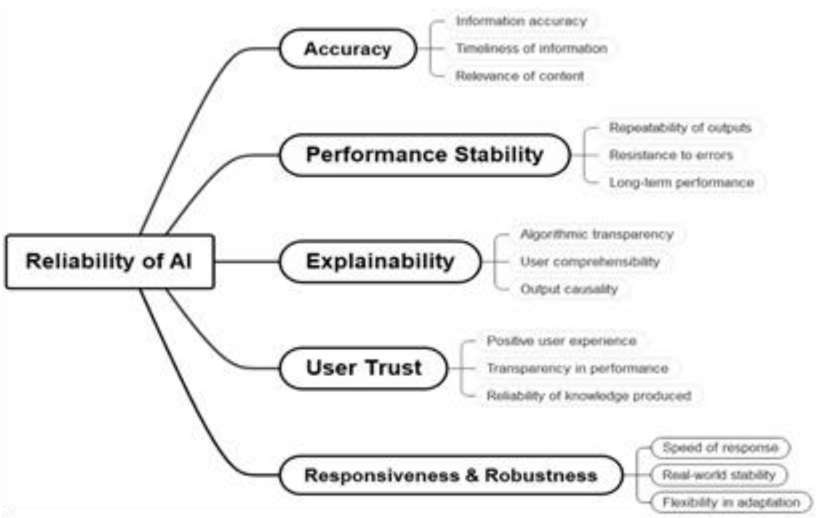

Fig. 1. Thematic conceptual framework linking AI system reliability to KI

At this stage, based on levels of variables, the final access matrix of the proposed research model is provided (Fig. 1). In this conceptual model, reliability of the information system as an AI will be treated as a second-order latent construct consisting of five core perceptual constructs as stated by knowledge workers of the model: precision, consistency, explainability, trustworthiness and responsiveness. These constructs are to be considered basic inputs to the overall perceived reliability of the system.

This model expands upon previous work by introducing perceptual dimensions of AI reliability as a second order construct which influences knowledge presentation, transfer and reproduction (Nguyen et al., 2024b; Valente et al., 2022). It goes beyond the conventional performance based approach by incorporating how users' cognitive evaluations affect the sustainability of the KI. These dimensions reflect how organisational knowledge is expressed, communicated, and regenerated through interaction with intelligent systems. As illustrated in the diagram, the right-side components are grouped under "KI Dimensions" to emphasise their role as output factors shaped by the integrity and dependability of the system. Accordingly, knowledge workers' perception of system-level attributes forms the infrastructure for building a strong and sustainable KI in AI-supported organisational environments.

In the conceptual model, the five dimensions of AI System Reliability namely accuracy, consistency, explainability, trust, and responsiveness are placed under the category of Knowledge Workers to reflect the subjective and perceptual nature of these dimensions. They are not intrinsic attributes of the system itself, but arise out of human interaction and in the indirect evaluation and cognitive assessment of AI performance in knowledge-working processes, therefore being a reflection of how knowledge workers perceive, validate and respond to the behaviour of the AI system itself in decision-making and knowledge-related tasks.

Fig. 2 shows the conceptual model of the study. In this model, knowledge workers are regarded neither as statistical moderators, but perceptual agents, whose subjective evaluations enact the five dimensions of AI system reliability. This framing draws emphasis to the interpretive role of humans in negotiating the relationship between AI, reliability and knowledge identity formation.

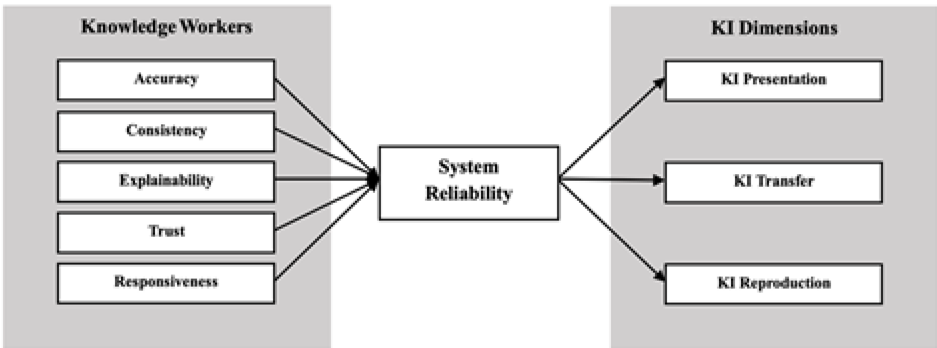

Fig. 2. Conceptual model

In this model, the reliability of AI systems is defined as a second order latent construct composed of 5 dimensions which refer to how knowledge workers perceive the quality and effectiveness of AI applications in their knowledge work. These 5 dimensions (accuracy, consistency (reliability), explainability, trust and responsiveness) follow the qualitative interviews, and were verified in the quantitative phase with confirmatory factor analysis.

- Accuracy refers to the extent to which the output from the systems is accurate, correct without errors and specific results.
- Consistency relates to the systems' ability to provide stable and reproducible results under different conditions.
- Explainability is used to refer to the capacity of the user to understand the reason for the output results from an AI system and hence the interpretability dimension.
- Trust refers to the faith that knowledge workers have in AI systems. This is based on previous interactions which they have recourse to and the perceived fairness of the systems.
- Responsiveness refers to the efficiency of the systems in responding to user inputs and the feedback timeliness and relevance of results obtained.

In addition, the qualitative phase identified two contextual dimensions, performance stability and adaptability which were conceptually subsumed under the broader construct of System Reliability during the quantitative modelling stage to ensure theoretical parsimony and measurement coherence. These dimensions collectively shape the overall perception of AI system reliability, which in turn influences the three core processes of KI: Presentation, Transfer, and Reproduction.

4.2. Results from PLS-SEM

At this stage, the proposed conceptual model was tested using PLS-SEM, which is appropriate for exploratory models involving latent constructs that mention in Fig. 3 and Fig. 4. The model evaluation included both measurement and structural components, and the results are depicted in the corresponding diagram.

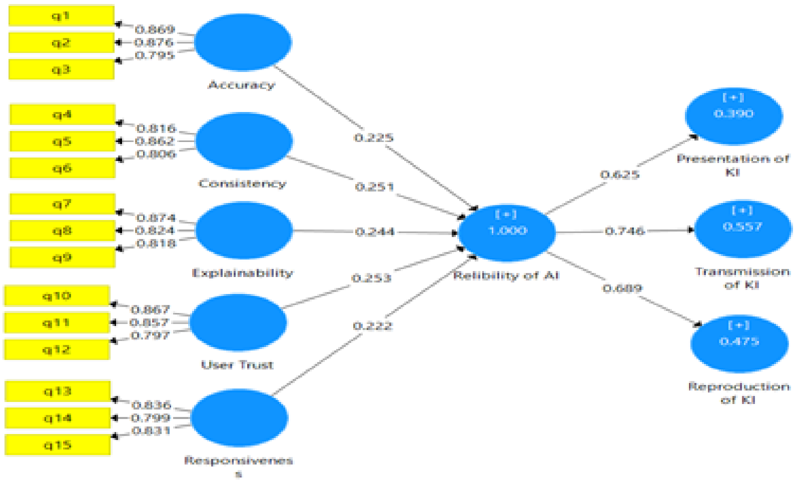

Fig. 3. Overall model measurement in standardised form

The structural paths in the model mirror socio-technical perspectives that position system reliability as a cognitive enabler in human–AI interaction (Bostrom & Heinen, 1977).

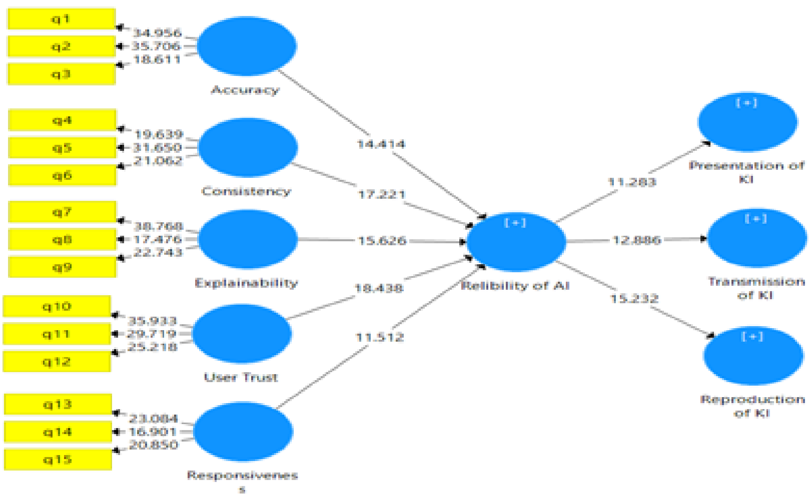

Fig. 4. Overall model measurement in significance mode

To assess the model's validity, indices of validity, reliability, and goodness-of-fit were used. The results are presented in the Table 5.

Table 5
Reliability and validity of outer models

Variable	CR	AVE	SRMR	MSV	Fornell & Larcker Matrix 1	2	3	4
Reliability of AI	0.787	0.552		0.193	0.743			
Presentation of KI	0.844	0.644	0.061	0.478	0.342	0.803		
Reproduction of KI	0.918	0.651		0.423	0.331	0.47	0.807	
Transfer of KI	0.885	0.720		0.478	0.440	0.692	0.65	0.849

According to the Table 5, in order to measure the reliability and validity of the measurement model, some key indicators were evaluated. Firstly, it was demonstrated that there was sufficient internal consistency according to Cronbach's alpha and Composite Reliability (CR) > 0.70 and secondly, that there was sufficient convergent validity according to average variance extracted (AVE) > 0.50. The model achieved an SRMR value of 0.061, below the recommended threshold of 0.08 (Hu & Bentler, 1999), indicating satisfactory model fit and supporting the adequacy of the measurement model. All of these results support the fact that the measurement model which has been used in this study is deemed sufficient.

Table 6
Hypotheses testing results

Hypotheses	Standard Coefficient	Significance (t-value)	Result
Reliability has a positive and significant effect on the presentation of KI to knowledge workers.	0.62	11.28	Confirmed
Reliability has a positive and significant effect on the transfer of KI to knowledge workers.	0.74	12.88	Confirmed
Reliability has a positive and significant effect on the reproduction of KI to knowledge workers.	0.68	15.23	Confirmed

In Table 6, the findings demonstrate that the reliability of the AI system has a significant and positive effect on the three dimensions of KI, namely presentation, transfer, and reproduction of knowledge. Where perception of accuracy and trust is high, the legitimacy and acceptance of the organisation's knowledge derived from AI-generated results are enhanced. Explainability in the AI systems provides consideration for the users in their interpretive capability on the value of the outputs of the systems. On the other hand, a lower reliability increases uncertainty, leads to lower knowledge continuity and resistance to knowledge-sharing processes.

Similar results were discovered in previous studies highlighting the factors of accuracy and trust in users' endorsement of AI-supported knowledge (Lee & See, 2004; Nguyen et al., 2024b). Path coefficients for all three KI dimensions are strong and correspond to identity-based knowledge arguments that reliable technological agents strengthen knowledge legitimacy and anchor sensemaking in organisations (Intezari et al., 2021).

4.3. Results of ranking the main indicators

Table 7 presents the prioritisation of key indicators influencing the perceived reliability of AI systems in relation to KI. These priorities were derived using the AHP, based on expert comparisons of each dimension's relative importance.

Table 7
Priority ranking of main indicators

Weight	Criterion	Rank
0.264	Accuracy	1
0.210	User Trust	2
0.192	Explainability	3
0.130	Consistency	4
0.106	Responsiveness	5

In AHP-based analyses, priority weights are often reported either as raw local priorities or as normalised weights, depending on the intended analytical application. While the initial AHP results provide relative importance rankings, composite index construction requires the weights to sum to one to ensure comparability and mathematical consistency (Saaty & Vargas, 2012). Therefore, the initial AHP-derived weights were subsequently normalised by dividing each weight by the total sum of all criteria weights. This normalisation step does not alter the relative ranking of the criteria but enables the computation of the system reliability score (SRS) as a weighted composite index.

Table 8
Normalised weights for system reliability score (SRS)

Weight (Normalised)	Criterion	Rank
0.293	Accuracy	1
0.233	User Trust	2
0.213	Explainability	3
0.144	Consistency	4
0.117	Responsiveness	5
1.000	Total	

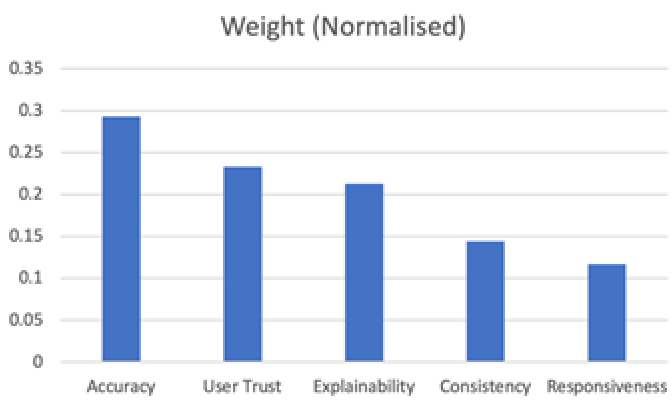

Fig. 5. Priority ranking of main indicators

According to Fig. 5 and Table 8, accuracy (0.293) was top priority, signalling that participants see truthfulness as the primary condition for trusting an AI-enabled knowledge process. This is consistent with established work showing that user trust of intelligent systems is very sensitive to their correctness (Tavakol & Dennick, 2011). User trust (0.233) ranked second, indicating that relational and psychological assurance is an important part of human–AI interaction, similar to Sokol and Figurska's (2021) assertion that trust is foundational to users engaging with intelligent technologies.

Explainability (0.213) also came third, continuing to support previous indications that transparent and interpretable system behaviour strengthens interpretive confidence and contributes to system credibility (Sundaresan & Zhang, 2022). The relatively lower weights for consistency and responsiveness (0.144 and 0.117, respectively) reflect the observation that users assume a baseline of technical stability and are more attuned to cognitive and relational aspects of reliable AI (Novalin et al., 2024). Totally, this ranking reinforces our main thesis, which is that there are cognitive, affective, and interpretive features of AI reliability that is, dimensions that are not exclusively technical that are more important for knowledge workers. This strengthens our central claim that human-centred reliability indicators provide valuable support for knowledge workers' formation and use of KI. Fig. 6 shows the final conceptual model of KI.

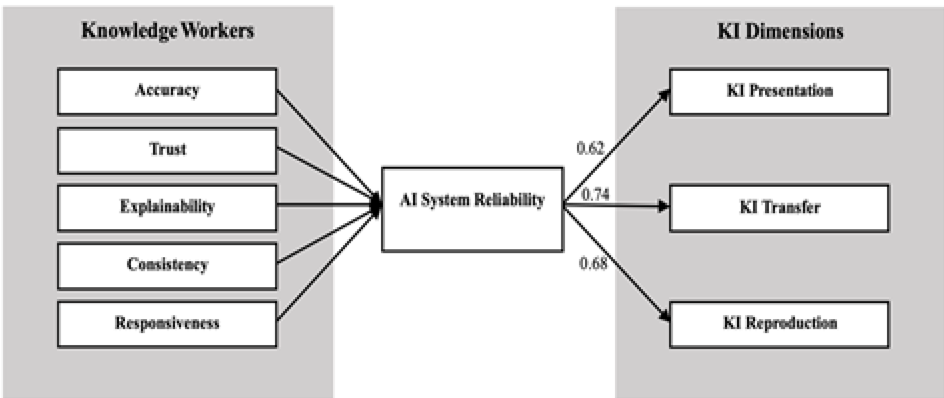

Fig. 6. Final structural model of KI

4.4. Proposed system reliability score formula

The SRS is a composite index designed to quantify the perceived reliability of AI systems based on key human-centered indicators identified through empirical research. The formula is expressed as follows:

SRS = (0.293× Accuracy) + (0.233× User Trust) +
(0.213× Explainability) + (0.144× Consistency) + (0.117× Responsiveness)

These coefficients indicate the normalised weights from AHP, which synthesised expert opinions on how critical each dimension is. As suggested, accuracy had the most weight (0.293), and was, therefore, the most important driver of perceived reliability, followed by user trust, explainability, consistency, and responsiveness.

The SRS actualises this 'AHP' result in a single evaluative measure. This composite score provides several advantages. For instance, organisations can compare AI systems, prioritise them for improvement, and see how different user types perceive that systems reliability. With an SRS we can use that subjective measure and feed it through a funnel to that weighted measure and say "here's a number we have to aim for". Thus, guiding evidence-based decision considerations regarding drivers of AI development and KM implementation.

5. Discussion

This study examined how the perceived reliability of an AI impacts the identity-based construction of knowledge in the context of organisations. The findings show that constructs such as accuracy, trust, explainability, consistency, and responsiveness described KSR and impact the presentation, transfer, and reproduction of KI. The results confirm their conceptual model using grounded interviews with experts at Pars Aviation Company and eliciting the components of reliability SRS to be used as weights with AHP. They confirmed their model in a PLS-SEM analysis of 116 knowledge workers' responses.

Accuracy and trust were the most important factors altogether; consistent with other work that identifies the importance of precision and trustworthiness for adopting and relying on different types of systems (Nguyen et al., 2024b; Dell'Acqua et al., 2023). While explainability was less important, it appears to enhance trust indirectly consistent with work showing the effect of increased transparency on AI-user trust (Sundaresan & Zhang, 2022). In total, the results suggest that in order for AI reliability to be established, users have to perceive AI as a socio-cognitive construct shaped by user interpretation and organisation rather than just a technical attribute. The more semantically responsive and transparent AI was, the more it aided internalisation of AI-provided knowledge and users' KI (Intezari et al., 2021). Unlike studies focused on automation efficiency (Thakuri et al., 2024), this research frames AI reliability as central to identity-based KM, offering a practical framework for KM practitioners and system designers seeking to build trustworthy and context-aware AI tools.

5.1. Hypothesis testing summary

Our findings indicate that AI system reliability (accuracy, trust, explainability, consistency, and responsiveness), is important for enabling meaningful KI processes within organisations. Rather than existing merely as a technical property, reliability is a perceptual and socio-cognitive property dependent upon how users experience and interpret intelligent systems. The results corroborate and build upon theorising (Intezari et al., 2021; Nguyen et al., 2024b) that perceived reliability directly promotes the presentation, transfer and reproduction of KI. Here, accuracy and trust were the strongest perceived reliability drivers, further supporting claims that effective knowledge use requires confidence both that content is true, and that the tools used are reliable.

The potential influence of explainability thus further suggest that people weigh the value of transparency in terms of its importance for understanding, as well as in terms of belief in knowledge processes as corroborated by findings on the mediating role of XAI in similar settings (Sundaresan & Zhang, 2022). These findings contribute to a larger body of socio-technical research that conceptualises AI as a cognitive collaborator rather than just a neutral tool. By exhibiting the mutual dependence between the attributes of the system and the perceptions of users, this research grounds the reliability of the AI systems as a means to sustain knowledge identity in dynamic organisations where knowledge is situated.

5.2. Theoretical and practical implications

5.2.1. Theoretical implication

This research extends the theoretical understanding of knowledge identity (KI) by elucidating the processes through which the reliability of an AI system influences the development and change of KI. Whereas much of the previous research has defined KI primarily as an amalgam of knowledge connectedness, knowledge repertoire, and knowledge aspiration (Intezari et al., 2021, 2022), the studies did not identify mechanisms regarding how technology agents affect knowledge processes in the context of identity. Expanding upon this gap, the current study illustrates that reliability, operationalised through accuracy, trust, explainability, consistency, and responsiveness, functions as a cognitive filter through which members of an organisation legitimise, internalise, and reproduce knowledge.

The study thus reconceptualises KI as not merely a stable organisational characteristic, but as a fluid socio-technical construct that is co-produced through human□AI interaction. This theoretical extension to the KI literature provides a mechanism-based account of the relationship between system reliability and identity-based sensemaking and, ultimately, the persistence of knowledge in organisations. This contribution addresses an under-theorised intersection of system trustworthiness, identity-based knowledge structures, and AI system characteristics. The proposed SRS (using AHP and validated through PLS-SEM) provides a replicable, multidimensional measure of AI in knowledge-intensive contexts. The model further draws on and contributes to three theoretical streams: (1) socio-technical systems theory (Bostrom & Heinen, 1977), (2) trust in automation literature (Lee & See, 2004), and (3) the knowledge-based view (KBV) of the firm (Grant, 1996). These linkages encourage future interdisciplinary research on how AI-enabled systems can simultaneously advance organisational learning, trust, and KI.

5.2.2. Practical implication

The results show that the reliability of AI systems not only affects technical acceptance but also organisational knowledge continuity. This shows the strategic importance of accuracy, trust-based design principles, and explainability to influence user interaction with AI-supported knowledge processes. These implications highlight the importance of human-centered AI design. From a practical perspective, the findings suggest that AI system reliability should be treated as a core design principle rather than a purely technical performance criterion in AI-enabled KM and E-learning systems.

Designers of organisational knowledge repositories, AI-supported training platforms, and digital learning environments can utilise the proposed system reliability score (SRS) as a diagnostic tool to evaluate whether AI-generated knowledge is likely to be perceived as legitimate, trustworthy, and learnable by users. Embedding reliability dimensions such as explainability and consistency into system design can enhance users' willingness to engage with, internalise, and reuse AI-supported knowledge.

5.3. Managerial practical recommendations

Based on the results of the study, managers, AI system designers, and KM professionals working with AI-enabled KM and E-Learning technologies receive tangible and practical recommendations on how to apply AI in their workplaces. First, companies need to take the concept of AI system reliability and treat it as a measurable and manageable business competency rather than an intangible technological quality. By creating systematic metrics for evaluating the five essential AI system reliability dimensions (i.e., accuracy, consistency, explainability, trustworthiness, and response time), businesses will be able to measure the epistemic value of AI-generated knowledge and identify warning signs of declining user confidence or knowledge misalignment.

Second, the outcomes of this study indicate that whether users trust AI-assisted knowledge systems is dependent both on the quality of the products and also on transparency and the users' ability to understand them. Therefore, organisations need to develop specific training programmes to train knowledge workers to help them understand how artificial intelligence, including its logic, limitations, and the way it develops its conclusions. These types of training are especially important for knowledge-intensive and learning organisations because users will need to use that AI-based instructional material to make decisions based on their own professional judgement.

Third, the explainability of AI is a key area of concern for managers. Businesses are advised to utilise explainable AI as a means for their users to be able to not only follow, but also understand and verify any AI recommendations that are generated. The ability of users to better interpret explainable AI influences their opinions on fairness and reliability, primarily in high-value operational environments such as aviation maintenance, continuing care, and industrial engineering, where wrong or ambiguous information can have dire consequences.

Fourth, the results demonstrate that having a consistent method of receiving feedback about the relevancy, accuracy, and transparency of the information in AI-based knowledge systems is essential for maintaining the reliability of those systems. Establishing structured feedback loops for receiving user feedback allows organisations to systematically improve their algorithms and user interfaces over time. In addition, by designing certain features of high-resilience AI-based systems, including redundancy, recoverability, and self-diagnostic capacity, organisations will have greater success in ensuring knowledge continuity when faced with uncertainty or interruptions in business operations.

Lastly, the research illustrates that when organisations embed AI-based knowledge systems within a larger framework, including their human resources and KM strategies, the instances of linking AI-generated knowledge to training, succession planning, performance evaluation, and knowledge retention are valued as an integral part of an organisation's knowledge identity and thus classified as an asset. Integrating ai into a cohesive socio-technical environment will better facilitate the long-term learning processes, preserve institutional knowledge, and ensure a greater degree of continuity between identity-focused knowledge and holding places within an increasingly digital and volatile marketplace.

6. Conclusion

This research furthers the discussion of embedding artificial intelligence (AI) into knowledge management (KM), specifically by empirically validating the important connection between the belief that an AI system can be relied upon and important aspects of the iterative process of establishing knowledge identity (KI). Through a mixed-methods design consisting of grounded theory interviews with PLS-SEM modelling, the research identified five interrelated dimensions of AI reliability (accuracy, consistency, explainability, trust, and responsiveness) related not to technical characteristics per se, but rather to socio-cognitive characteristics developed through knowledge workers' perceptions and interactions with AI systems.

The findings suggest perceived AI reliability has substantial influences on the three KI processes including presentation, transfer and reproduction, with high perceived reliability leading to legitimacy, acceptance and continuity, and low perceived reliability encouraging resistance, uncertainty and fragmentation. Of the five dimensions, accuracy and trust had the most significant effects, suggesting that AI systems need to provide outputs that are both accurate and contextually valuable. In spite of explainability being rated slightly lower, it served as a mediating factor for enhancing trust and interpretability for users.

The new System Reliability Score (SRS) offers a weighted, experiential measure for evaluating perceived AI reliability in the five human-centric dimensions. Organisations can use SRS to evaluate and improve the reliability of AI-assisted KM systems in accordance with their strategic objective and identity based knowledge practices. The study also operationalises the developmental link between system design and organisational sensemaking, indicating AI is more than a functional technology, it also acts as a cognitive collaborator that sustains institutional KI.

From a theoretical standpoint, this research bridges socio-technical systems theory, the trust-in-automation literature, and the knowledge-based view (KBV) of the firm. Practically, it offers actionable guidance for the design, evaluation, and alignment of AI systems with HR and KM strategies. With the rapid acceleration of AI adoption, future research should further explore how trust and reliability dimensions evolve across diverse organisational contexts, and how AI systems can be ethically and culturally aligned to reinforce (rather than disrupt) organisational knowledge identity.

6.1. Limitations of the study

Although this research contributes valuable understanding regarding AI system reliability in shaping knowledge identity (KI), there are some limitations to note. To begin with, the study was primarily perception-based. Generally, perceptions are reasonable for the study of socio-cognitive constructs such as trust, explainability, and perceived reliability, future research could balance this work with objective metrics (i.e., system log data, number and rates of errors, or response time) to enhance the precision of the measurement.

Second, the recommended model emphasises on five critical dimensions of AI trustworthiness: accuracy, consistency, explainability, trust, and responsiveness. These traits are noted in the literature and are otherwise well developed. Related influential characteristics, such as fairness, ethical transparency, safety, and portability were not specified in the proposed model. These attributes may have implications in other domains where an ethical and regulatory constraint is high, such as healthcare, education, or public governance.

Third, the research was undertaken within a solitary organisation, which may have an effect on the findings due to the organisation's culture, organisational structure, and the organisations level of digital maturity. Aviation maintenance is a high-reliability, knowledge-based context which is likely to influence how users may interpret and prioritise certain system reliability attributes. Future research should seek to explore multi-organisations with case sampling from a range of industries and levels of AI maturity to improve the generalisability of empirical work.

Though the study focuses on this context, it makes a contribution in analytic generalisation (not statistical generalisation). As Halkier (2011) observed analytic generalisation is appropriate for case evidence to extend, refine, or corroborate theoretical propositions. The mechanisms under examination here in human–AI interaction, perceived reliability, and identity-based knowledge processes which are relational socio-cognitive dynamics that operate in a variety of knowledge-intensive settings. And because the five dimensions of reliability (accuracy, consistency, explainability, trust, and responsiveness) are core elements of AI-supported KM systems, the implications of this case can contribute to understanding in a greater context in other high-reliability systems or knowledge-driven work realms such as engineering, public safety, and healthcare.

Finally, this research focused on individual-level perceptions of AI reliability and trust. Organisational learning processes also occur at team and collective levels. Future research could examine team-based knowledge identity, hybrid human–AI collaboration models, and the role of group-level trust to develop a deeper understanding of how socio-technical interactions shape organisational identity.

6.2. Future research directions

Future research may build on this study by exploring the model in additional organisational and cultural contexts such as multinationals, public institutions, or start-up organisations. Longitudinal studies may consider examining how users' perceptions of trust in AI systems change over time as they continue to use the AI system. Future research may also consider exploring additional constructs such as fairness, ethical transparency, and adaptability features of AI systems which may impact users' engagement behaviours and longer-term knowledge retention and the development of organisational identity.

Author Statement

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Appendix I

Example interview questions

1. How would you describe your general experience with the AI system used in your organisation?

2. When the AI system provides a result or recommendation, how do you decide whether to use or act on it?

3. Can you describe a time when the AI system gave you an unexpected or unclear response? What did you do?

4. To what extent do you rely on the AI system when making decisions in your role?

5. Have you ever found the AI system to be wrong or misleading? How did that affect your work?

6. Does the AI system behave consistently when you repeat the same task or input? Can you give an example?

7. How easy or difficult is it for you to understand how the AI system reaches its conclusions?

8. How well does the system respond to your information needs in real time?

9. Have you ever tried to correct or improve the AI's output? How did the system respond, if at all?

10. What makes you feel confident (or doubtful) about the AI system in your work?

Appendix II

Measurement scales

Construct	Code	Measurement Item	Source
Accuracy	A1	The AI system provides results that are free from errors.	Wang & Chung, 2022; Bag et al., 2021
	A2	The system's outputs are precise and factually correct.	
	A3	The information generated by the AI is dependable for decision-making.	
Consistency	C1	The AI system performs reliably under similar conditions.	Novalin et al., 2024; Lee & See, 2004
	C2	The system delivers stable results across repeated tasks.	
	C3	The output quality does not fluctuate unexpectedly.	
Explainability	E1	The system provides clear reasoning for its recommendations.	Sundaresan & Zhang, 2022; Bansal et al., 2021
	E2	I can understand why the system produces a specific output.	
	E3	The AI's decision process is transparent and	

		interpretable.	
Trust	T1	I can rely on the AI system's outputs for my work tasks.	Lee & See, 2004; Sokol & Figurska, 2021
	T2	The system operates in a fair and unbiased manner.	
	T3	I have confidence in the AI system's decision logic.	
	T4	The AI system behaves consistently with organisational norms.	
Responsiveness	R1	The system responds quickly to my queries.	Bag et al., 2021; Novalin et al., 2024
	R2	The system provides timely feedback relevant to my needs.	
	R3	The system adapts effectively to changes in task requirements.	
KI Presentation	KIP1	AI systems help express organisational knowledge clearly.	Intezari et al., 2021
	KIP2	AI outputs enhance how knowledge is communicated within the organisation.	
	KIP3	The use of AI makes organisational knowledge more visible and structured.	
KI Transfer	KIT1	AI facilitates smooth exchange of knowledge among employees.	Nguyen et al., 2024a
	KIT2	The system supports knowledge sharing across different departments.	
	KIT3	AI tools reduce barriers to knowledge dissemination.	
KI Reproduction	KIR1	AI contributes to renewing and updating organisational knowledge.	Intezari et al., 2021; Grant, 1996
	KIR2	The system supports the reuse of prior knowledge in new contexts.	
	KIR3	AI helps sustain the organisation's knowledge over time.	

Note. All items were rated on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree