Measuring AI Literacy of Future Knowledge Workers: A Mediated Model of AI Experience and AI Knowledge

Research Paper

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Abstract. AI Literacy is crucial for knowledge workers, yet existing models fail to capture theoretical and practical evolvement and its predictors. This study extends the AI Literacy framework by Pinski and Benlian (2023), conceptualizing AI Knowledge as a second-order construct and using this as a mediator linking AI Experience and AI Literacy. Using Experiential Learning and Information Processing Theory, we examine AI Experience (Usage and Design) and its impact on AI Literacy via PLS-SEM. A survey of 352 master's students at a French business school reveals that AI Knowledge mediates the relationship between AI Experience and AI Literacy, challenging prior models. We contribute to IS by developing a new mediation model, extending the existing AI Literacy framework, and testing this in a new context. These results highlight the practical importance of hands-on AI Experience and AI Knowledge to enhance AI Literacy.

Keywords: knowledge worker, AI literacy, digital intelligence, digital literacy, AI knowledge.

1 Introduction

Artificial intelligence (AI) increasingly permeates professional environments, and AI Literacy has become a critical competency for effectively interacting with AI-based systems. While prior research has conceptualized AI Literacy (e.g., Long & Magerko, 2020, Pinski & Benlian, 2023), existing frameworks largely focus on general users or technical experts, overlooking the specific needs of knowledge workers[1] - individuals whose primary tasks involve cognitive, analytical, and creative work rather than manual or purely technical labor (Davenport, 2018). Since they largely perform non-repetitive

[1] The concept of "knowledge work" describes professions focused on generating, distributing, or utilizing specialized knowledge. These roles are typically filled by individuals who possess significant expertise, advanced education, or substantial experience. Examples include engineers, scientists, legal professionals, consultants, and academics (Benbya et al., 2024; Benbya, 2008; Davenport, 2005).

work, AI's generative capabilities fundamentally alter how tasks are approached, requiring a critical understanding of AI-generated outputs rather than mere tool usage. Generative AI (GenAI), a subtype of AI, focuses on generating new content based on existing data, producing results that closely resemble real-world data (Feuerriegel et al., 2024; Dwivedi et al., 2023). Unlike traditional AI systems that automate structured tasks, GenAI tools - such as ChatGPT, DALL·E, and Copilot - enable dynamic, co-creative processes, requiring knowledge workers to critically assess, interpret, and refine AI-generated outputs (Mollick & Mollick, 2023). Integrating GenAI with human expertise is a valuable approach to freeing up time and resources for higher-value tasks, such as creative problem-solving and critical thinking (Benbya et al., 2024; Dwivedi et al., 2023). However, without sufficient AI Literacy, knowledge workers risk falling behind, either replaced by more AI-savvy peers or by AI systems themselves (Chamorro & Frankiewicz, 2019). This growing dependence on AI-infused tools raises an urgent need to understand how AI Literacy develops and what factors drive it, particularly for knowledge workers expected to collaborate effectively with increasingly sophisticated systems. This understanding can inform targeted educational and organizational interventions. For instance, knowing how different types of experience contribute to AI Literacy allows educators and employers to design learning pathways that combine conceptual understanding with practical exposure, both essential for preparing the workforce for AI-integrated environments.

A recent contribution to AI Literacy research is the work by Pinski and Benlian (2023), which introduces an AI Literacy framework comprising AI Experience and diverse types of AI Knowledge. However, their model was developed before the widespread adoption of GenAI and was not tested specifically in the context of future knowledge workers. GenAI differs significantly from earlier AI systems in terms of accessibility, interactivity, and adaptability (Banh and Strobel, 2023). Additionally, this earlier model treats AI Experience and AI Knowledge as direct antecedents of AI Literacy, overlooking how AI Knowledge may act as a mediator in this relationship. Based on this, we ask the following research question (RQ):

RQ: How does AI Experience contribute to AI Literacy among knowledge workers, and what role does AI Knowledge play in this relationship?

Building on the AI Literacy model by Pinski and Benlian (2023), this study examines its adequacy in the era of GenAI and knowledge work. We conceptualize AI Knowledge as a second-order construct (comprising AI Technology Knowledge, Human Actors in AI Knowledge, and AI Steps Knowledge) and test its role as a mediator between AI Experience (Usage and Design) and AI Literacy. Thereby, our hypotheses are drawn on the Experiential Learning Theory (Kolb, 1984) and the Information Processing Theory (Atkinson & Shiffrin, 1968) to explain how AI Literacy develops through hands-on experience, cognitive processing, and knowledge integration. To test the proposed model, we surveyed 352 master's students representing future knowledge workers at a business school. Our PLS-SEM analysis indicates that AI Knowledge mediates the relationship between AI Experience and AI Literacy. Thereby, we contribute to IS knowledge by developing a new mediation model, extending the existing AI Literacy framework, and testing this model in a new context, i.e., future knowledge workers. This model can guide educators and organizations in structuring GenAI learning experiences that balance applied exposure with theoretical understanding - two pillars essential for developing AI-literate knowledge workers.

2 Theoretical Background and Hypotheses Development

2.1 Foundations of AI and AI Literacy as the Study Context

The context of this research is AI, while its theoretical foundation is grounded in Experiential Learning Theory (Kolb, 1984) and Information Processing Theory (Atkinson & Shiffrin, 1968). Building on these foundations, our study also draws from the work of Pinski and Benlian (2023), who conceptualized AI Literacy.

First, AI refers to computational systems that simulate human intelligence by performing tasks such as problem-solving, decision-making, and language processing (Ågerfalk et al., 2022; Feuerriegel et al., 2024). AI spans rule-based automation, machine learning, and GenAI, the latter of which creates new content from existing data (Dwivedi et al., 2023). As AI transforms workplaces, knowledge workers, engaged in cognitive, analytical, and creative tasks (Davenport, 2018), must develop AI Literacy to effectively interpret and apply AI-generated insights (Benbya et al., 2024). Without AI Literacy, they risk making decisions without fully grasping the ramifications of AI systems (Berente et al., 2021). The black-box nature of AI further exacerbates these risks, as inscrutable decision-making processes often lead to ethical blind spots, unintended biases, and accountability gaps (Faraj et al., 2018; Martin, 2019).

Second, AI Literacy refers to the overall proficiency of an individual in understanding and engaging with AI systems (Fleischmann et al., 2024). It reflects the ability to recognize unique characteristics, comprehend AI decision-making processes, and assess AI outputs critically (Southworth et al., 2023). AI literacy develops through prior knowledge of AI technologies, human–AI collaboration, and AI processes, as well as practical experience in using and designing AI systems (Pinski & Benlian, 2023; Honigsberg et al., 2025). AI Literacy helps knowledge workers move beyond passive AI usage to informed decision-making and responsible AI integration.

We conceptualize AI Literacy as an emergent outcome influenced by both AI Experience and AI Knowledge. While literacies are often described as holistic and socio-cognitive in nature, we argue that a mediation model allows us to analytically disentangle the internal dynamics that contribute to literacy development. This does not imply a strict linear causality or fragmentation of the construct, but rather offers a structured approach to examining how different components interact within the literacy formation process (Ng, 2012). Our model aligns with prior frameworks by acknowledging the integrated nature of literacies while extending them by modeling underlying mechanisms (e.g., Hatlevik et al., 2015). This approach serves as an initial step toward understanding the developmental process of AI Literacy and encourages future research to explore more socio-cognitive and holistic conceptualizations (Southworth et al., 2023; Pinksi and Benlian, 2023).

2.2 Relationship between AI Experience and AI Literacy

To explain our hypothesis development, and specifically how individuals develop AI Literacy, we draw on Experiential Learning Theory (Kolb, 1984) and Information Processing Theory (Atkinson & Shiffrin, 1968). Experiential Learning Theory posits that learning occurs through an iterative cycle of four stages: (1) concrete experience, (2) reflective observation, (3) abstract conceptualization, and (4) active experimentation. Applied to AI Literacy, individuals gain firsthand AI experience (e.g., usage and design), reflect on AI interactions, develop structured knowledge, and integrate AI skills into practice (Kolb & Kolb, 2005; Konak et al., 2014). In this framework, knowledge serves as a mediating factor, enabling individuals to process AI experiences, critically evaluate outputs, and refine their literacy skills. Prior research in IS has leveraged these theories to understand technological adaptation and learning (Becker & Wambsganss, 2024; Kamis & Khan, 2009; Galliers & Huang, 2012).

AI Literacy, like other literacies, develops as individuals engage with AI systems, gaining hands-on experience that forms the foundation for understanding and applying AI-generated insights (Kolb, 1984; Konak et al., 2014). One primary form of this engagement is AI Usage Experience, which refers to the direct interaction with AI tools, such as chatbots, machine learning applications, and decision-support systems (Pinski & Benlian, 2023; Heyder & Posegga, 2021). Through problem-solving, task execution, and AI-driven feedback mechanisms, users progressively refine their AI Literacy by observing outputs, reflecting on interactions, and integrating insights into their cognitive processes.

Beyond usage, some individuals actively engage in designing and modifying AI systems, a process that can be defined as AI Design Experience. This includes training AI models, configuring system behaviors, and integrating AI into workflows (Pinski & Benlian, 2023; Long & Magerko, 2020). Engaging in AI design fosters a deeper understanding of AI's inner workings, allowing individuals to conceptualize AI capabilities and constraints through direct experimentation. Based on Experiential Learning Theory, we propose the following hypotheses:
H1: AI Usage Experience positively influences AI Literacy.

H2: AI Design Experience positively influences AI Literacy.

Individuals interact with AI in various contexts, such as using GenAI tools and decision-support applications (Berente et al., 2021). These engagements constitute AI Usage Experience, which provides exposure to AI-driven functionalities. However, without a structured knowledge base, users may lack the ability to critically assess AI outputs, recognize biases, or effectively integrate AI into their workflows.

2.3 Mediating Role of AI Knowledge

Both hypotheses, H3a and H3b, follow the idea that existing AI Knowledge supports individuals in processing information and developing more specific knowledge through interpretation and critical understanding coming from its application and leading to improved AI Literacy. The Information Processing Theory (Atkinson & Shiffrin, 1968)

suggests that learning occurs through encoding, storage, and retrieval of information, emphasizing how individuals process and structure knowledge from experiences. Drawing from Experiential Learning Theory (Kolb, 1984), knowledge acquisition occurs when individuals actively interpret their AI experiences, reflecting on capabilities, to develop a conceptual understanding. Pinski & Benlian (2023) define AI Literacy as consisting of both explicit and tacit knowledge, where AI Experience primarily contributes to explicit literacy, while AI Knowledge accounts for tacit literacy. By equipping individuals with a structured understanding of AI, knowledge facilitates their ability to critique and apply AI outputs in informed ways. Thus, AI Knowledge acts as a filter to make sense of the experiences. We, therefore, propose the following hypothesis:
H3a: AI Knowledge mediates the relationship between AI Usage Experience and AI Literacy.

Beyond usage, some individuals engage in AI-related activities at a deeper level, involving the design, fine-tuning, and evaluation of AI models (Ng et al., 2021). This AI Design Experience allows individuals to experiment with AI's inner workings, such as algorithm training, prompt engineering, and bias mitigation (Long & Magerko, 2020; Sundberg et al., 2024). However, experience alone does not ensure literacy as users must be able to conceptualize and systematize their learnings. In line with Experiential Learning Theory (Kolb, 1984) and Information Processing Theory (Atkinson & Shiffrin, 1968), active experimentation in AI design must be followed by cognitive structuring, allowing individuals to organize new insights, connect them with prior knowledge, and retrieve them when needed. AI Knowledge acts as an intermediary cognitive mechanism that helps individuals interpret the design process, understand AI's underlying logic, and critically assess the societal and ethical implications of AI applications (Van Slyke et al., 2023).
H3b: AI Knowledge mediates the relationship between AI Design Experience and AI Literacy.

3 Method

3.1 Data Collection

A quantitative, cross-sectional survey research design was selected for two primary reasons. First, it provides a structured and generalizable approach to measuring AI Literacy among future knowledge workers, who are increasingly exposed to AI-driven tools in professional and academic settings (Rindfleisch et al., 2008). This design offers a timely and cost-effective method for capturing AI Experience, Knowledge, and Literacy at a single point in time. Second, this study explores the relationships between AI Experience, AI Knowledge, and AI Literacy, a critical yet under-examined area in the context of future knowledge workers' readiness for AI-integrated workplaces. To analyze these relationships, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed. PLS-SEM is particularly appropriate for exploratory research, theory extension, and early-stage model development, especially when prediction, model complexity, and the inclusion of second-order constructs are central concerns (Hair et al., 2021). It is well-suited for variance-based modeling with reflective indicators and performs robustly with moderate-to-large sample sizes. In this study, PLS-SEM enabled the identification of underlying patterns and the estimation of direct and mediated effects among latent constructs, serving as a foundation for future in-depth theoretical and empirical work.

Table 1. Sample Description

Variable	Category	N	Proportion (%)
Age	Under 20	3	0.85
	20-25	341	96.87
	26-30	7	1.98
	31-35	1	0.28
Gender	Female	179	50.85
	Male	167	47.44
	Non-binary	1	0.28
	Prefer not to say	5	1.42
Domain	Marketing & Business Development	159	45.17
	Finance	82	23.29
	Organization Management & Strategy	111	31.54
Years of Experience	Less than 1 year	90	25.56
	1-3 years	225	63.92
	4-6 years	32	9.09
	7-10 years	3	0.85
	More than 10 years	2	0.56

The data for this study was collected from six French-speaking student groups enrolled in the second year of the Programme Grande École at a French business school. These students were taking a common core module in Management Information Systems (MIS). They participate in an alternating study format, meaning they simultaneously hold professional roles in companies as part of their academic curriculum. This dual engagement allows them to apply theoretical knowledge to real-world business contexts. This makes them an ideal population for studying AI Literacy among future knowledge workers. Data collection took place between September and October 2024 as part of regular coursework, ensuring a natural and relevant context for participants. One of the authors, who was the instructor for these groups, facilitated the data collection process. Participation in the study was voluntary, and students provided informed consent before completing the survey. The survey was administered online during class sessions, maximizing response rates and ensuring clarity in case of participant queries. To preserve data integrity, responses were anonymized and securely stored. To determine the required minimum sample size, we conducted a statistical power analysis using G*Power 3.1.9.7 software (Faul et al., 2009). With parameters set to a medium effect size ($f^2 = 0.15$), a statistical power of 0.95, nine predictors, and a significance level of 0.05, the analysis recommended a minimum of 166 respondents to maintain statistical rigor and generalizability. As our dataset consists of 352 participants, it surpasses this requirement, ensuring adequate power for our study (Nitzl, 2016). Table 1 describes our sample.

3.2 Sample

The sample consists of students specializing in Marketing & Business Development (45.17%), Finance (23.29%), and Organization Management & Strategy (31.54%). Most participants are aged 20-25 (96.87%), with a nearly equal gender distribution (50.85% female, 47.44% male, and 1.7% non-binary or undisclosed). Regarding professional experience, 63.92% have 1-3 years, 25.65% have less than a year, 9.09% have 4-6 years, and 1.41% have over 7 years.

3.3 Measures

By integrating a validated scale, multi-item reflective measures, and relevant controls, our instrument ensures conceptual rigor and empirical precision in evaluating AI Literacy development. First, to measure the constructs (see Table 2) in our research model, we adopted validated scales from Pinski & Benlian (2023) (see Appendix), ensuring theoretical alignment and empirical robustness. In selecting our measurement instruments, we relied on the multidimensional framework developed by Pinski and Benlian (2023), which conceptualizes AI Literacy as a construct composed of both experiential and knowledge-based dimensions. This framework aligns with our research objective of theory extension and supports variance-based structural modeling using PLS-SEM. While recent contributions have introduced objective, performance-based assessments of AI Literacy (e.g., Weber et al., 2023), these instruments are primarily suited for evaluating competency rather than modeling latent relationships between constructs. Our study focuses on explaining how AI Literacy develops through the interaction of experience and knowledge, for which the reflective, survey-based approach by Pinski and Benlian (2023) provides a conceptually and methodologically appropriate foundation.

Our measurement instrument captures AI Usage Experience, AI Design Experience, AI Knowledge (a second-order construct), and AI Literacy, using multi-item reflective scales. Second, AI Usage Experience assesses individuals' practical interaction with AI tools (e.g., chatbots, machine learning applications), while AI Design Experience measures hands-on engagement in developing or configuring AI systems (e.g., training models). AI Knowledge, conceptualized as a second-order construct, comprises AI Technology Knowledge (understanding AI fundamentals, applications, and underlying technologies), Human Actors in AI Knowledge (awareness of human roles, ethical AI use, and decision-making dynamics), and AI Steps Knowledge (comprehension of AI processing mechanisms, decision-making, and interpretability concerns) (Pinski & Benlian, 2023; Long & Magerko, 2020; Southworth et al., 2023; Heyder & Posegga, 2021; Bansal et al., 2024; Van Slyke et al., 2023). Finally, AI Literacy reflects individuals' overall proficiency in interpreting and engaging with AI-generated insights (Southworth et al., 2023). The survey included 28 items (see Appendix), with all constructs measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). To enhance measurement validity, we controlled for Age, Gender, Work Experience, Field of Study, AI Training, and AI Comfort. Age, Gender, and Work Experience help account for demographic variations in AI familiarity, while Field of Study captures disciplinary differences in AI exposure. AI Training assesses formal AI education, and AI Comfort reflects self-perceived ease of interacting with AI, controlling for individual confidence biases.

Table 2. Construct Overview

Const.	Conceptualization	Sources
AI Usage Experience	The degree of hands-on interaction with AI tools for tasks like problem-solving, execution, and feedback-based improvement.	Pinski & Benlian, 2023; Heyder & Posegga, 2021; Ng et al., 2021; Rudolph et al., 2023
AI Design Experience	Practical involvement in creating or configuring AI systems, including model training, behavior adjustment, and integration into workflows.	Pinski & Benlian, 2023; Long & Magerko, 2020
AI Technology Knowledge	Understanding the fundamental principles of AI, including its core technologies, applications, infrastructure, distinction from non-AI systems, and algorithmic foundations.	Pinski & Benlian, 2023; Long & Magerko, 2020; Ng et al., 2021; Southworth et al., 2023; Sundberg et al., 2024
Human Actors in AI Knowledge	Understanding human roles in AI use and implementation, such as collaboration, oversight, ethics, tasks where humans outperform AI, human-AI collaboration strategies, and critical thinking skills.	Pinski & Benlian, 2023; Bansal et al., 2024; Heyder & Posegga, 2021; Strzelecki & El Arabawy, 2024
AI Steps Knowledge	Understanding how AI processes inputs, analyzes data, and generates outputs, with attention to transparency, ethics, and data handling.	Pinski & Benlian, 2023; Long & Magerko, 2020; Southworth et al., 2023; Van Slyke et al., 2023
2nd-order Construct: AI Knowledge	A combination of AI Technology Knowledge, Human Actors in AI Knowledge, and AI Steps Knowledge, forming a comprehensive understanding of AI aspects.	Aler Tubella et al., 2024; Bansal et al., 2024; Strzelecki & El Arabawy, 2024; Honigsberg et al., 2025
AI Literacy	AI Literacy refers to an individual's overall proficiency in understanding and engaging with AI systems. It is developed through prior knowledge and practical experience with AI usage and design.	Pinski & Benlian, 2023; Fleischmann et al., 2024; Southworth et al., 2023; Honigsberg et al., 2025

4 Empirical Analysis and Results

4.1 Measurement Model Evaluation

First, we checked the external validity of our composite constructs by performing a confirmatory composite analysis to evaluate the fit of the saturated model before testing the actual model (Henseler, 2020). A confirmatory composite analysis compares the empirical and the model-implied correlation matrices to analyze whether the data support the structure of the composite measures (Benitez et al., 2020). We calculated the saturated and estimated SRMR (0.045 and 0.053), unweighted least squares (dULS = 0.312 and 0.425), and geodesic discrepancies (dG = 0.257 and 0.293). We validate our model based on an alpha level of 0.01, which states that the structure of the measures is correct and should not be rejected. Moreover, we evaluated the internal validity (i.e., content and discriminant), multicollinearity, and significance of weights and loadings for items and dimensions (Hair et al., 2020). First, the HTMT ratios of the first-order latent constructs are below the suggested critical threshold of 0.90, with the highest being Design Experience and AI Literacy (0.815), so discriminant validity can be ensured. Further, multicollinearity was evaluated at first- and second-order levels. The values of the variance inflation factor (VIF) are below 3.182 (Benitez et al., 2020; Hair et al., 2020), so multicollinearity is not a problem. Lastly, we evaluated the level of significance of the weights and loadings at first- and second-order levels, which are all significant. In sum, the measurement model results are appropriate, and we can proceed with testing the hypotheses of the proposed research model.

4.2 Structural Model Evaluation

To test the model empirically, we estimated path coefficients, direct and indirect effects, their significance level, and R2 values. The results suggest that AI Usage Experience is positively related to AI Literacy (Hypothesis 1) (β = 0.163, pone-tailed < 0.001). Further, AI Design Experience is positively linked to AI Literacy (Hypothesis 2) (β = 0.510, pone-tailed < 0.001). Moreover, AI Knowledge serves as a mediator in relationships. The results indicate an indirect effect between AI Usage Experience (β = 0.549) and AI Design Experience (β = 0.244) toward AI Literacy. The R2 values are 0.708 for AI Literacy and 0.464 for AI Knowledge, indicating good explanatory power of the endogenous variables. Finally, for the control variables, only age is significant on AI Literacy (β = -0.049). The results indicate that AI Usage Experience and AI Design Experience (Hypotheses 1 and 2) and AI Literacy are positively related. AI Knowledge (Hypotheses 3a and 3b) mediates the relationship.

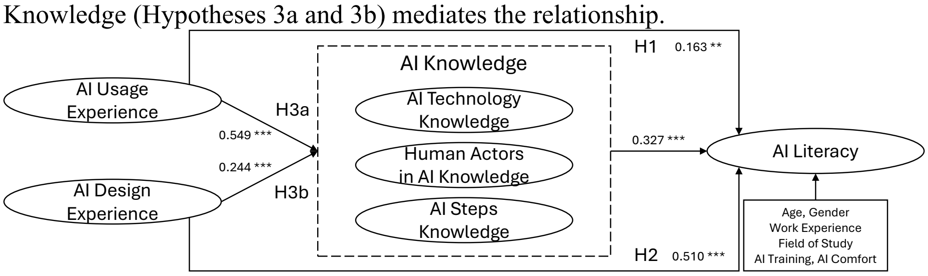

Figure 1. Theoretical Model

5 Discussion and Conclusion

5.1 Theoretical Contribution

This study examines how AI Experience (Usage and Design) contributes to AI Literacy and the mediating role of AI Knowledge, conceptualized as a second-order construct. Our findings refine existing models by demonstrating that AI Knowledge is a critical cognitive bridge between AI Experience and AI Literacy, rather than merely a direct antecedent. These insights refine existing models and highlight the importance of structured knowledge acquisition and hands-on AI interaction in the education of knowledge workers (Heyder & Posegga, 2021; Long & Magerko, 2020). Next, we discuss theoretical contributions, managerial implications, and future research. With that, our study makes several key contributions to the field of AI Literacy measurement and its implications for knowledge workers in the AI-driven workplace.

First, drawing from Experiential Learning Theory (Kolb, 1984), we propose a new mediation model, where AI Experience links to AI Literacy through AI Knowledge. Prior studies, like Pinski and Benlian (2023), treated AI Knowledge and AI Experience as direct antecedents of AI Literacy. Our study challenges and refines this perspective by showing that AI Experience (Usage and Design) impacts AI Literacy indirectly, partially mediated by AI Knowledge. Thus, AI Knowledge acts as a cognitive intermediary that structures and refines learning. This new model better explains the learning process, where experience in using and designing AI systems enhances AI Knowledge, which in turn drives AI Literacy. Our model demonstrates that AI Knowledge consolidates experiences into structures and retrievable literacy, helping individuals filter, critique, and apply AI insights effectively. With this theory in mind, we consider that learning is not linear but follows a multi-step process and that the learning mechanism behind AI Literacy is a multi-step learning approach where experience strengthens knowledge acquisition, and both are essential for literacy.

Second, building on Information Processing Theory (Atkinson & Shiffrin, 1968), we extend the existing AI Literacy framework by Pinski and Benlian (2023) by introducing a second-order construct for AI Knowledge. This integrates AI Technology Knowledge, Human Actors in AI Knowledge, and AI Steps Knowledge into a single higher-order concept. This conceptualization more accurately reflects how individuals internalize AI-related knowledge holistically rather than as separate, disconnected categories. This advancement enables a more structured and theoretically sound measurement approach, which provides a stronger foundation for future research and applications in AI Literacy assessment.

Although not a key motivation and contribution of our work, we tested AI Literacy in a new context with business students as future knowledge workers. While the original scale was developed before the GenAI breakthrough and focused on general AI Literacy across roles, we apply it in a highly relevant, emerging context (Benbya et al., 2020). Our findings reinforce that AI Literacy has evolved as it is no longer just a technical skill but a fundamental competency for future knowledge workers across industries (Fleischmann et al., 2024, Honigsberg et al., 2025). This validates the need for AI Literacy beyond IT specialists and supports calls for integrating AI Literacy into business and management education (Gimpel et al., 2024; Dwivedi et al., 2023).

5.2 Managerial Implications

Our lessons learned are threefold, offering insights for universities, organizations, and knowledge workers themselves. These practical contributions to AI Literacy refer mostly to education and upskilling. First, at knowledge institutions, AI Literacy should be integrated across disciplines, not just in IT programs. Business and management curricula should include AI decision-making and hands-on AI design activities (Honigsberg et al., 2025). Moreover, interactive learning (e.g., low-code AI modeling and simulations) could better prepare students for AI-driven workplaces (Heyder & Posegga, 2021). Second, companies should assess AI Literacy levels and address competency gaps (Fleischmann et al., 2024). Training should combine AI usage experience with structured AI knowledge acquisition. As hands-on AI design experience significantly improves AI Literacy, this should be part of corporate training programs if AI Literacy is desired. Third, AI Literacy is a core skill for all professionals, not just technical experts (Chamorro & Frankiewicz, 2019). Actively engaging with AI tools and participating in AI-related training enhances career readiness and develops AI design experience, even at a basic level, and thus strengthens AI Literacy.

5.3 Limitations and Future Research

As with any empirical study, this research has limitations that also offer directions for future investigation. First, the sample consists of master's students in a business school context. While relevant as a proxy for future knowledge workers, findings may not generalize to other professions, industries, or cultural contexts. This study should thus be viewed as a theoretically informed starting point for understanding AI Literacy among emerging knowledge workers. Future research should investigate broader populations across different career stages, disciplines, and regions.

Second, the cross-sectional design captures AI Literacy at a single time point, limiting insight into its development over time. Longitudinal studies could examine how AI Literacy evolves and how the roles of experience and knowledge shift in response to changing technologies and work environments.

Third, AI Literacy, Knowledge, and Experience were assessed through self-reported data. While useful, such measures are subject to bias and may not fully capture actual competencies. Future work should combine self-reports with objective, performance-based assessments (e.g., Weber et al., 2023) to enhance validity.

Methodologically, the use of PLS-SEM is appropriate given the study's aim to develop theory and model second-order constructs. This variance-based approach suits exploratory research focused on prediction and complexity. Nonetheless, future studies might consider covariance-based SEM or hierarchical regression for theory testing or model fit analysis.

Finally, results show AI Design Experience exerts the strongest influence on AI Literacy, suggesting hands-on engagement, such as model training or customization, may accelerate learning, even for non-technical users. This opens new avenues for research into how usage, design, and reflection contribute to literacy, and how they can be embedded in education and workplace training. The present model offers a conceptual starting point, framing AI Literacy as shaped by both experience and knowledge. Future work may expand on this by developing integrated frameworks and examining literacy as part of broader socio-technical learning ecosystems.

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APPENDIX

Table 3. Used Items

Construct	Dimension	ID	Item
			I have experience in…
AI Usage Experience	**AI Usage**	UE1	…in interaction with different types of AI, like chatbots, visual recognition agents, etc.
		UE2	…in the usage of AI through frequent interactions in my everyday life
AI Design Experience	**AI Design**	DE1	…in designing AI models, for example, a neural network
		DE2	…in development of AI products
			I have knowledge of…
AI Knowledge	**AI Technology**	TK1	…of the types of technology that AI is built on
		TK2	…of how AI technology and non-AI technology are distinct
		TK3	…of use cases for AI technology
		TK4	…of the roles that AI technology can have in human-AI interaction
	Human Actors in AI	HK1	…of which human actors beyond programmers are involved to enable human-AI collaboration
		HK2	…of the aspects human actors handle worse than AI
		HK3	…of the aspects human actors handle better than AI
		HK4	…of the human actors involved to set up and manage human-AI collaborations
		HK5	…of the tasks that human actors can assume in human-AI collaboration
	AI Steps - Input	SK1	…of the input data requirements for AI
		SK2	…of how input data is perceived by AI
		SK3	…of potential impacts that input data has on AI
		SK4	…of which input data types AI can use
	AI Steps - AI Processing	SK5	…of AI processing methods and models
		SK6	…of how information is represented for AI processing
		SK7	…of the risks AI processing poses
		SK8	…of why AI processing can be described as a learning process
	AI Steps - AI Output	SK9	…of using AI output and interpreting it
		SK10	…of AI output limitations
		SK11	…of how to handle AI output
		SK12	…of which AI outputs are obtainable with current methods
AI Literacy	**Overall AI Competency**	AIL1	In general, I know the unique facets of AI and humans and their potential roles in human-AI collaboration
		AIL2	I am knowledgeable about the steps involved in AI decision-making
		AIL3	Considering all my experience, I am relatively proficient in the field of AI

Items from Pinski & Benlian, (2023)