Innovations in Pedagogy and Technology

https://journals.zycentre.com/ipt

ARTICLE

The Missing Link: Knowledge Management in AI-Powered Education Frameworks

Abraham Abby Sen , *Jeen Mariam Joy* , *Murray Jennex* * , *Jeffrey Babb* , *Kareem Dana*

Computer Information Systems, West Texas A&M University, Canyon, TX 79016, USA

ABSTRACT

As Artificial Intelligence (AI) reshapes educational assessment practices, there is a growing need to examine existing frameworks through the lens of Knowledge Management (KM). While models such as TALiP, Assessment for Learning (AfL), Popham's Model, and Stiggins' Five Pillars offer important foundations for assessment literacy, they lack structured mechanisms for systematic knowledge generation, transfer, and alignment with AI-generated insights. This study introduces a novel contribution: a seven-phase KM-AI integration framework designed to support responsible and pedagogically aligned AI adoption in educational assessment. Unlike existing approaches, this framework embeds KM principles into the full lifecycle of AI-supported assessment capturing tacit expertise, contextualizing algorithmic outputs, and enabling iterative learning across instructional settings. The framework is grounded in theoretical analysis and refined through a hypothetical use case and a documented institutional deployment of an AI-powered teaching assistant. Together, these cases illustrate how the framework can enhance teacher agency, support ethical AI use, and improve assessment coherence even in low-resource environments. The outcome is a practical roadmap for educators, policymakers, and developers that ensures AI tools strengthen rather than displace human-centered assessment practices. This study advances both theory and practice by providing an actionable, scalable model for KM-AI alignment in the era of digital transformation.

Keywords: Assessment Literacy; Knowledge Management; Artificial Intelligence; Knowledge Transfer; Teacher Training

*CORRESPONDING AUTHOR:

Murray Jennex, Computer Information Systems, West Texas A&M University, Canyon, TX 79016, USA; Email: mjennex@wtamu.edu

ARTICLE INFO

Received: 26 August 2025 | Revised: 17 October 2025 | Accepted: 24 October 2025 | Published Online: 2 November 2025

DOI: https://doi.org/10.63385/ipt.v1i3.114

CITATION

Sen, A.A., Joy, J.M., Jennex, M, et al., 2025. The Missing Link: Knowledge Management in AI-Powered Education Frameworks. Innovations in Pedagogy and Technology. 1(3): 67–81. DOI: https://doi.org/10.63385/ipt.v1i3.114

1. Introduction

Education depends on structured frameworks to shape teaching, learning, and assessment, promoting consistency, fairness, and effectiveness in classrooms [1]. Although these frameworks aim to enhance educational practices, they inherently draw on knowledge management (KM) principles, particularly those related to knowledge generation and transfer [2]. Knowledge Management (KM) is the process of creating, capturing, organizing, sharing, and applying knowledge to enhance decision-making and innovation. However, many educational frameworks have overlooked KM from their inception and continued to exclude it in subsequent research and applications [2, 3]. Educational frameworks provide educators with a structured approach to curriculum design, instructional strategies, and student evaluation [2]. By offering clear guidelines, they help teachers align their methods with educational goals, fostering a more systematic and evidence-based approach to learning [4, 5]. The impact of these frameworks extends beyond theory; they shape daily classroom practices by helping teachers assess student progress, adjust instruction, and provide meaningful feedback [6]. They also empower students by promoting intrinsic motivation, engagement, self-reflection, and a deeper understanding of their learning [6, 7]. Instructors use these models to create fair assessments, ensuring that evaluations accurately reflect student knowledge and skills [8, 9]. Moreover, these frameworks support professional development by equipping educators with the necessary tools to improve their teaching and evaluating strategies [3, 10]. By fostering consistency across educational institutions, they enhance the quality of education on a broader scale. Ultimately, these structured approaches aim to bridge the gap between education research and practice, ensuring that education remains dynamic and responsive to the needs of both teachers and students [11].

The Assessments For Learning (AFL) and Popham's Model of Assessment Literacy focus on equipping teachers with the knowledge to create valid and reliable assessments that align with learning objectives [12–14]. Similarly, the Stiggins Five Pillars of Assessment Literacy highlight the importance of clear learning targets, quality assessments, and effective communication of results [15]. These frameworks encourage feedback loops and student involvement to ensure assessments guide instructional adjustments and foster learning rather than merely measure performance. Meanwhile, the Teacher Assessment Literacy in Practice (TALiP) framework reconceptualizes assessment literacy by focusing on the practical application of assessment knowledge in real classroom settings [16]. While each framework has a unique perspective, they all contribute to improving the quality of assessments and student learning in education. By guiding teachers in making informed decisions, these models help create more effective and meaningful learning experiences for students. While some assessment literacy frameworks, such as AFL, and TALiP, have institutional backing and are widely used in teacher training, professional development, and policy implementation. There are others, like Stiggins' Five Pillars of Assessments and Popham's Model, function more as conceptual models that provide theoretical insights into assessment literacy rather than structured, empirically validated frameworks [17]. This study chooses to include conceptual frameworks also to ensure comprehensiveness and rigor.

With the rise of AI in education [5, 18], the omission of knowledge management from assessment frameworks poses significant risks. AI-driven tools are reshaping learning assessment, personalized instruction, and feedback [19]. Artificial Intelligence (AI) is the simulation of human intelligence in machines to perform tasks like learning, reasoning, and problem-solving. However, without structured approaches to knowledge generation and transfer, AI's effectiveness can be compromised. AI systems depend on vast data to enhance decision-making [20], but without clear KM, biases and inaccuracies may go unnoticed [21]. Educators without explicit frameworks may misinterpret AI insights, leading to flawed instructional adjustments. Additionally, knowledge transfer ensures consistent AI-enhanced assessment applications across institutions [22–24]. Without structured knowledge sharing, AI adoption may exacerbate assessment literacy gaps, increasing educational disparities [23]. The absence of KM also increases the risk of blind reliance on AI, reducing teacher autonomy and potentially harming student outcomes [24, 25]. Algorithmic opacity may emerge, where students and teachers receive AI-generated scores or recommendations without understanding their derivation [26]. This lack of transparency can lead to disengagement, as students struggle to learn from or challenge results [27]. Without effective knowledge transfer, institutions may implement AI-driven assessments inconsistently, benefiting well-resourced schools while disadvantaging others [28]. Policymakers without integrated knowledge management frameworks may lack the insights needed to regulate AI, leading to misaligned policies that widen educational gaps [26]. Without a clear strategy for managing AI-generated knowledge, trust in AI assessments may erode, undermining education's goal of fostering equitable learning opportunities.

The integration of KM into an AI driven assessment framework is not merely a theoretical enhancement but a necessary evolution, given both the successes and failures of AI-driven assessment in real-world educational settings. AI-powered assessments have demonstrated significant potential, such as in adaptive learning platforms like Carnegie Learning and DreamBox, which personalize instruction by analyzing student responses and adjusting difficulty levels in real time [29, 30]. Similarly, AI-driven grading tools, such as those used in standardized tests like the GRE and GMAT, offer efficiency and scalability in evaluating large volumes of student responses [31]. However, AI in assessment has also faced major setbacks, highlighting the risks of improper implementation without a structured KM system. For instance, the UK's 2020 A-Level grading algorithm, which replaced exam-based assessments during the COVID-19 pandemic, resulted in massive grade downgrades for disadvantaged students, leading to widespread backlash and policy reversals [32]. This failure stemmed from opaque decision-making and poor knowledge transfer, demonstrating the urgent need for structured KM principles to ensure AI-driven assessments are transparent, interpretable, and aligned with pedagogical goals. Embedding KM into AI-enhanced assessment frameworks will mitigate these risks while preserving teacher expertise and institutional accountability.

KM provides a natural bridge between AI and Assessment Literacy by addressing how knowledge flows [33] between these domains AI systems generate knowledge through data analysis and pattern recognition, while assessment literacy frameworks guide how this knowledge is interpreted and applied in educational settings [34]. The principles of knowledge generation and transfer in KM are particularly crucial as they explain both how AI systems learn and evolve from educational data, and how educators can effectively understand, validate, and implement AI-driven insights in their assessment practices [33]. Knowledge generation occurs as teachers develop new understanding through data analysis, classroom observations, and student interactions [35]. By engaging in continuous reflection and adaptation, educators refine their assessment methods and instructional techniques. While frameworks emphasize evidence-based practices, they do not explicitly recognize the role of knowledge creation in shaping these strategies. Similarly, knowledge transfer is central to the implementation of these frameworks [36]. Teachers can also share best practices with colleagues, train new educators, and communicate assessment outcomes to students and stakeholders [37]. The dissemination of effective assessment techniques ensures consistency and improves instructional quality [38]. Despite its importance, most frameworks treat knowledge transfer as an implicit process rather than a deliberate mechanism [23]. By recognizing the role of knowledge management, educational frameworks could enhance their effectiveness, ensuring that learning is not just assessed but actively enriched through knowledge creation and exchange.

The objective of this study is to propose a practical, seven-phase framework for integrating Knowledge Management (KM) into AI-enhanced assessment practices in education. While existing assessment literacy frameworks offer valuable foundations, they often lack mechanisms for systematically capturing, sharing, and applying knowledge in contexts where AI plays an active role. This absence can result in fragmented adoption, biased evaluations, and inconsistent application across courses and institutions [22, 39, 40]. The KM-AI integration framework introduced here addresses this gap by embedding KM principles such as knowledge generation, transfer, alignment, and continuous evaluation within the life cycle of AI-supported assessment. To demonstrate its real-world applicability, we present both a hypothetical use case involving a business school professor and a documented institutional example of an AI-powered teaching assistant [41]. Together, these cases illustrate how the framework can support educators in making AI more interpretable, trustworthy, and pedagogically aligned, even in resource-constrained environments. By offering a structured approach grounded in KM, this framework equips educators, developers, and policymakers with a practical guide to ensure AI-driven assessments remain transparent, adaptable, and educationally sound.

2. Literature Review

Assessment frameworks play a crucial role in guiding educators in designing, implementing, and interpreting assessments that inform student learning [18, 41, 42]. However, while these models emphasize assessment literacy, they typically do not incorporate Knowledge Management (KM) principles, particularly in the context of AI-driven education [36]. As Artificial Intelligence (AI) becomes increasingly embedded in classrooms, curriculum design, and evaluation systems, there is a pressing need to integrate KM practices into these frameworks to ensure that AI serves as a pedagogical aid rather than a disruptive force [38, 43]. Based on prior literature [39, 44, 45], this study defines Assessment Literacy (AL) as the integrated knowledge, skills, and dispositions that instructors draw upon to design, select, and implement assessments that support student learning. This includes not only familiarity with the theoretical frameworks and principles of sound assessment design, but also the practical, context-specific decisions instructors make in their day-to-day classroom practice [46–50]. Thus, assessment literacy is understood as both conceptual understanding and instructional application within authentic teaching settings.

The KM literature supporting KM in education can be summarized as providing infrastructure, processes, and strategy for improving knowledge mapping and repositories for supporting class activities including assessment, improved knowledge transfer through the creation of class and topic specific repositories and communities of practice; and improved knowledge sharing through special repositories, and communities of practice [51–54]. In this context, communities of practice refer to the organizational structures that foster knowledge sharing in the educational institution. However, not all institutions are successful using KM to improve educational performance usually due to a lack of a knowledge sharing culture in the educational institution and thus leading to KM being the missing ingredient [55–58]. Integrating KM principles into these frameworks can address gaps in teacher development, institutional knowledge continuity, and responsible AI use [47]. For educators, this integration means access to shared tools and validated practices for interpreting AI feedback. For students, it fosters greater fairness, transparency, and personalization in assessment [52]. For institutions and policymakers, it provides a model for ethical AI deployment grounded in practitioner expertise and sustained by knowledge-sharing systems [53]. This study responds to these needs by proposing a KM-AI integration framework that builds on existing models to support scalable, equitable, and context-sensitive assessment practices in the digital age.

This study reviews four influential frameworks to assess their readiness for AI integration through a KM lens. The Teacher Assessment Literacy in Practice (TALiP) framework [16] highlights how teachers develop assessment expertise through reflection and professional experience. While widely adopted for its emphasis on real-world practice, it lacks formal mechanisms for sharing assessment knowledge or integrating AI into feedback processes. The Assessment for Learning (AfL) model also promotes validity, fairness, and formative assessment strategies [48], but does not account for how knowledge is systematically transferred across institutions or how AI-generated insights can be used to support these principles. Similarly, Popham's model emphasizes assessment fundamentals, interpretation, and instructional application, and is foundational in teacher education [49]. However, it does not address how new knowledge is generated from classroom experience, nor does it consider how AI might inform or complicate teacher judgment. Finally, Stiggins' Five Pillars focus on ethical use, clarity of purpose, and alignment with learning goals [50]. Though conceptually strong, it functions more as a guiding philosophy than a fully operational system, offering no provisions for KM or AI inclusion [51].

Several studies examined teachers' assessment beliefs and practices through the lens of the TALiP framework [35, 38, 59]. While their study offers valuable insights into classroom-based assessment, it does not address the role of emerging technologies such as artificial intelligence or the use of structured knowledge-sharing systems. This omission reflects a broader limitation within the TALiP model itself, which does not explicitly incorporate mechanisms for integrating technology or knowledge management in assessment contexts. Similarly, another study examined the assessment for learning framework to highlight the role of feedback and learner agency in shaping assessment practices [60]. However, since the framework does not address the use of artificial intelligence or structured knowledge-sharing, it restricts its relevance in technology-integrated assessment contexts. The same limitation is evident in studies that adopt Popham's model and Stiggins' Five Pillars framework to conceptualize assessment literacy, as these models similarly do not account for technological integration or systematic knowledge-sharing mechanisms [13, 15, 17]. Recent scholarship has also emphasized the need to expand traditional assessment literacy models to include digital learning environments, particularly those that involve real-time feedback and AI-supported assessment practices [61–64]. While the mode of instruction may vary across online and in-person contexts, the foundation of assessment literacy remains in an instructor's ability to design, implement, and interpret assessments effectively, reinforcing its relevance in both conventional and technology-enhanced classrooms [40, 61].

KM provides a natural bridge between AI and Assessment Literacy by addressing how knowledge flows [33] between these domains AI systems generate knowledge through data analysis and pattern recognition, while assessment literacy frameworks guide how this knowledge is interpreted and applied in educational settings [34, 35]. The principles of knowledge generation and transfer in KM are particularly crucial as they explain both how AI systems learn and evolve from educational data, and how educators can effectively understand, validate, and implement AI-driven insights in their assessment practices [23, 33, 36]. Knowledge generation occurs as teachers develop new understanding through data analysis, classroom observations, and student interactions [35]. By engaging in continuous reflection and adaptation, educators refine their assessment methods and instructional techniques [26–28]. While frameworks emphasize evidence-based practices, they do not explicitly recognize the role of knowledge creation in shaping these strategies. Similarly, knowledge transfer is central to the implementation of these frameworks [36]. Teachers can also share best practices with colleagues, train new educators, and communicate assessment outcomes to students and stakeholders [37]. The dissemination of effective assessment techniques ensures consistency and improves instructional quality [38]. Despite its importance, most frameworks treat knowledge transfer as an implicit process rather than a deliberate mechanism [23]. By recognizing the role of knowledge management, educational frameworks could enhance their effectiveness, ensuring that learning is not just assessed but actively enriched through knowledge creation and exchange.

3. Methodology

This framework builds on the idea of a comprehensive multi-phase methodology designed to examine the integration of AI and Assessment Literacy (AL) with a KM lens. The selection of KM as a theoretical framework would be particularly significant as its core principles of knowledge generation and knowledge transfer would serve as natural bridges between AI's data-driven insights and assessment literacy's pedagogical applications. While this methodology could be applied to various assessment literacy frameworks, its fundamental focus would remain on understanding how knowledge flows between assessment practices and AI systems, mediated through structured KM processes.

The conceptual grounding for this methodology draws heavily from established Knowledge Management (KM) theories, particularly from the seminal literature that emphasizes KM as a purposeful process aimed at capturing, storing, and applying knowledge to improve organizational effectiveness [6, 29, 34, 45]. These studies highlight the critical role of context, culture, and technology in facilitating meaningful knowledge use factors that are especially pertinent in educational environments integrating artificial intelligence. Researchers also provide a dynamic framework for understanding the conversion between tacit and explicit knowledge through socialization, externalization, combination, and internalization [60]. These models underscore that knowledge in education is not merely content to be delivered, but an active process shaped by interaction and application. The KM cycle further reinforces this by framing knowledge creation, storage, transfer, and utilization as interlinked stages [2]. Against this backdrop, the seven-phase framework operationalizes KM principles, ensuring that AI adoption in educational assessment is not only technologically sound but also epistemologically aligned with how knowledge is generated and used in educational contexts.

3.1. Phase 1: Identifying Types of Knowledge and Their Role in Education

The first phase involves a comprehensive literature review to classify different types of knowledge and analyze how they function in an educational context. Knowledge is broadly categorized into explicit, tacit, procedural, and declarative knowledge, among others. The review in this phase will explore how each type is generated, refined, and transferred within an educational setting, particularly in the chosen assessment literacy framework. This phase is crucial because AI tools in education interact with knowledge in various ways either by encoding explicit knowledge in algorithms, capturing tacit knowledge from educators, or facilitating knowledge transfer among students and teachers. Understanding these dynamics will form the foundation for evaluating AI's role in knowledge-driven assessment.

3.2. Phase 2: Classifying AI Types in Educational Assessment

The second phase focuses on reviewing and categorizing AI technologies based on their strengths, limitations, and applicability to educational assessment. AI tools used in assessment vary significantly ranging from rule-based systems and machine learning models to more advanced natural language processing (NLP) and generative AI applications. This classification will consider the degree of explainability, adaptability, and bias mitigation in different AI models. By systematically organizing AI types, this phase provides a structured understanding of which AI approaches align best with the different knowledge types identified in Phase 1, ensuring that AI applications are integrated effectively within educational frameworks.

3.3. Phase 3: Mapping Knowledge Types to Educational Assessment Frameworks

This phase involves analyzing which types of knowledge (identified in Phase 1) are most relevant to the educational assessment framework under study. For example, if the framework emphasizes formative assessment, tacit knowledge transfer between educators and students might be critical. Conversely, standardized testing may rely more on explicit knowledge encoded in AI-driven scoring models. By linking knowledge types to assessment methodologies, this phase ensures that AI adoption aligns with the specific knowledge processes required for effective assessment, thereby preventing mismatches where AI tools fail to support human decision-making.

3.4. Phase 4: Mapping AI Models to Educational Assessment Frameworks

Building on Phases 2 and 3, this phase involves matching specific AI technologies to the educational assessment framework in question. The goal is to ensure that AI-driven tools complement, rather than replace, human expertise in assessment literacy. For instance, AI models that support automated feedback generation may be better suited for formative assessments, while explainable AI (XAI) models might be preferable for summative assessments where transparency is critical. This mapping process ensures that AI is deployed in ways that enhance assessment accuracy, fairness, and adaptability, fostering a more knowledge-driven assessment approach.

3.5. Phase 5: Surveying Existing AI Tools and Software in Education

This phase entails a systematic survey of existing AI-based educational assessment tools, categorized based on the AI classification from Phase 2. The survey will examine the functionalities, limitations, and effectiveness of these tools in real-world educational settings. Key considerations include whether the tools align with best practices in knowledge management, their level of explainability, and their ability to adapt to diverse learning environments. The findings from this phase will provide empirical insights into AI's current role in knowledge transfer and identify gaps where AI integration could be improved.

3.6. Phase 6: Recommending AI Tools Based on Knowledge Requirements

After identifying AI tools and assessing their effectiveness, this phase will focus on developing structured recommendations for selecting appropriate AI technologies based on knowledge requirements within specific educational frameworks. This involves determining the suitability of AI models for different assessment tasks, ensuring that tools are selected based on their ability to enhance knowledge generation and transfer. These recommendations will serve as practical guidelines for educators, policymakers, and institutions, ensuring that AI adoption in assessment is knowledge-driven and pedagogically sound.

3.7. Phase 7: Evaluating AI Tools and Their Impact on Assessment Literacy

The final phase involves evaluating the AI tools identified in Phase 5 and recommended in Phase 6. This evaluation will occur through multiple approaches:

1. Expert Panel or Delphi Method: A panel of assessment

and AI experts will provide structured feedback on the effectiveness of AI tools in supporting knowledge-based assessment practices. Their insights will be used to refine the integration framework;

2. Empirical Experiments: Real-world trials of selected AI tools in educational environments will be conducted, assessing their impact on assessment literacy and knowledge transfer;
3. Quantitative Verification: Data-driven analysis will validate the theoretical findings, ensuring that AI-driven assessments align with expected outcomes in enhancing student learning, assessment consistency, and educator decision-making.

By systematically following these phases, the research will offer both theoretical and practical insights into integrating AI and Knowledge Management into assessment literacy. The findings will help bridge the gap between AI-driven assessment practices and human expertise, ensuring that AI tools enhance rather than diminish the role of educators in fostering knowledge-driven education.

3.8. Bias Elimination and Quality Assurance

Throughout all phases, the research proposes to implement systematic bias elimination strategies. Following prior literature, researcher bias would be addressed through clear documentation of assumptions and regular reflexivity exercises [4]. Selection bias would be minimized through comprehensive inclusion criteria and systematic sampling approaches [43]. Similarly, measurement bias would be controlled through standardized evaluation tools and regular calibration checks, while analysis bias would be addressed through multiple analytical approaches and independent verification. Credibility would be established through member checking and prolonged engagement with the data. Transferability would be ensured through detailed contextual description, while dependability would be maintained through comprehensive audit trails. Confirmability would be achieved through the systematic documentation of research processes.

Another essential dimension of this methodology involves recognizing and accounting for the real-world biases and limitations inherent in AI systems. AI models used in educational assessment are trained on datasets that may reflect cultural, linguistic, and socioeconomic biases, which can inadvertently perpetuate inequity when deployed at scale. For example, generative or scoring AI systems may underperform with students from underrepresented linguistic or regional backgrounds due to underexposure in training data. Furthermore, institutional disparities in digital infrastructure and educator preparedness can create uneven implementation outcomes, particularly in regions with limited technical capacity or bandwidth. These concerns underscore the need for a context-aware approach when applying AI tools. The KM-AI framework thus emphasizes not only the technical alignment of AI with educational knowledge but also a critical awareness of cultural appropriateness, fairness, and infrastructural readiness, ensuring that AI integration supports rather than undermines equity in assessment practices.

However, since this research is exploratory and designed to be broadly applicable across various educational assessment frameworks, we provide a comprehensive guideline that can be adapted to multiple contexts while maintaining scientific rigor. By generalizing across frameworks, our approach ensures flexibility in KM-AI integration, allowing researchers to apply these principles to diverse educational settings. However, to maintain the integrity and validity of implementation, researchers must contextualize each phase by incorporating the necessary steps specific to their chosen framework. This includes refining knowledge classification, tailoring AI selection, and establishing appropriate evaluation metrics. Additionally, researchers should implement rigorous checks and balances at every stage to ensure methodological soundness, mitigate biases, and align AI-driven assessment practices with pedagogical and ethical standards.

4. Applied Scenarios: Illustrating the KM-AI Framework in Practice

Given the conceptual nature of our study, there is a limited availability of data points we can use to ground our suggestions in data. However, to support our posits, we present a hypothetical scenario to demonstrate how the phases can be implemented.

4.1. Scenario 1: Bridging the AI Assessment Literacy Gap for a Business School Professor Using the KM-AI Framework

Dr. J is an associate professor of Information Systems at a mid-sized business school, known for his expertise in systems analysis and enterprise design. In his senior-level capstone course, students submit technical artifacts such as system design documents, UML diagrams, and business process models. These are evaluated for accuracy, completeness, and alignment with business goals. Recently, the university adopted an AI-supported assessment platform that automates aspects of feedback and scoring using natural language processing and pattern recognition. While Dr. J is open to innovation, he expresses uncertainty in interpreting the AI's outputs, particularly when flagged issues seem valid to the algorithm but pedagogically acceptable to him. His grading process becomes fragmented as he alternates between ignoring and deferring to the AI without confidence. This scenario illustrates a practical gap in AI-related assessment literacy, where expert judgment and machine-generated evaluations are misaligned. The objective in analyzing Dr. J's case is to explore how the KM-AI framework can support small teams of faculty in low-resource environments to improve the interpretability, alignment, and integration of AI-assisted assessment practices.

4.2. Scenario 2: Applying the KM-AI Framework to an AI-Powered Teaching Assistant Initiative

At a leading North American university, an AI-powered teaching assistant, built on a large language model and fine-tuned with course materials, was deployed in undergraduate business courses to handle routine student inquiries [53]. Over the course of a semester, the assistant responded to thousands of questions related to assignment instructions, course content, and conceptual clarifications. While the system demonstrated impressive scalability and responsiveness, faculty raised concerns about over-reliance, misalignment with pedagogical intent, and the uneven development of students' assessment literacy. The AI often provided technically accurate answers that lacked contextual nuance or inadvertently encouraged superficial engagement. This scenario represents a real-world institutional case where AI was successfully implemented at scale but without a structured approach to managing how knowledge was generated, interpreted, or transferred. The objective in analyzing this case is to show how the KM-AI framework can guide institutions in capturing faculty knowledge, aligning AI behavior with educational goals, and establishing sustainable practices for transparent, ethical, and pedagogically coherent AI integration.

4.3. Operationalizing the KM-AI Model

To apply the KM-AI integration framework effectively, both Dr. J and the AI-TA faculty team can follow a seven-phase process that is grounded in practical, low-cost strategies. In Phase 1 (Identifying Types of Knowledge and Their Role in Education), the first step is to map out the explicit, tacit, and procedural knowledge that supports assessment activities. Dr. J and his small faculty team can do this through structured peer interviews and collaborative reflection sessions using Google Docs. These discussions can surface assessment heuristics that are typically internalized but not articulated. The AI-TA team, working at a larger scale, can extract knowledge types by reviewing anonymized logs of AI-student interactions, identifying gaps between what students ask and what instructors consider pedagogically meaningful. Tools like NVivo may assist in coding qualitative inputs, while LMS data, rubrics, and syllabi provide the explicit baseline for a shared knowledge map.

In Phase 2 (Classifying the AI Tools and Assessing Their Capabilities), both teams should conduct practical audits of their AI systems to determine what tasks the tools can perform, where they are likely to fail, and how explainable their logic is. Dr. J's team can test the AI by feeding it example assignments and noting cases of agreement or conflict in a shared spreadsheet. The AI-TA team can use prompt engineering and real-time student queries to map the AI's response types. Tools such as Google's What-If Tool, LIME, or ELI5 can help assess the transparency and interpretability of AI outputs without requiring advanced technical expertise. This classification step reduces over-reliance and improves human-AI role clarity.

Phase 3 (Mapping Knowledge Types to Assessment Frameworks) involves aligning those knowledge types with established assessment tasks to define optimal human-AI workflows. Dr. J can use concept mapping platforms like Lucidchart or Miro to visualize where AI can assist, such as detecting formatting errors and where human judgment remains critical, such as assessing logical coherence in system designs. The AI-TA team, faced with high student volume, can define functional boundaries, e.g., assigning procedural queries to AI while directing interpretive or ethical questions to instructors. These mappings serve as a blueprint for integrating AI without compromising pedagogical nuance.

In Phase 4 (Aligning AI Models with Assessment Needs), both teams begin limited, low-risk pilot deployments of the AI in real classroom settings. Dr. J may use AI to generate formative feedback on student drafts and compare results to human grading, capturing reflections on alignment and friction points. The AI-TA team can monitor how the assistant responds to various question types and flag recurring issues. Platforms like Turnitin's AI-assisted feedback tools and survey software like Qualtrics or Google Forms can be used to collect performance and perception data. Ideally, 100–150 interactions provide a robust sample, but even 70–120 can yield meaningful trends when analyzed in context.

In Phase 5 (Surveying Existing Tools and Knowledge Flows), both teams begin documenting how the AI is used, what judgment calls are made, and how knowledge flows between team members. Dr. J's group might maintain a faculty-facing log where AI misinterpretations are cataloged with a rationale for override, which can help new instructors align grading decisions. In the TA scenario, log reviews can reveal patterns in student misunderstanding or highlight repetitive queries that suggest AI prompt tuning. LMS platforms like Canvas or Moodle provide built-in usage logs, while collaborative notes, diary studies, and focus groups help capture the qualitative side of tool adoption.

Phase 6 (Recommending AI Tools and KM Strategies Based on Gaps) synthesizes insights from earlier phases into structured guidance. For Dr. J, this might mean drafting a short departmental memo that outlines approved AI usage scenarios and warning signs for overreach. In the TA initiative, this phase might result in a faculty-facing AI response protocol or a student guide outlining how and when to consult the assistant. Notion or Confluence can serve as repositories where guidelines are iteratively updated by the instructional team, creating a living knowledge base accessible to all stakeholders.

Finally, in Phase 7 (Evaluating the Impact of Integration), both teams assess whether AI integration has improved outcomes such as grading consistency, student satisfaction, or instructional workload. Dr. J can analyze feedback clarity using rubric comparisons and faculty reflections, while the AI-TA team may use pre/post-course analytics or student surveys to measure engagement and satisfaction. Mixed methods, combining performance metrics with interviews or open-response surveys allow for a comprehensive view. A single semester of data collection is sufficient to draw actionable insights and set the stage for iterative refinement.

These two scenarios, one hypothetical and one based on a publicly documented initiative demonstrate the versatility and relevance of the KM-AI integration framework across both individual and institutional settings. The AI-powered assistant model explored in the real-world example highlights how innovative educational technologies can expand instructional capacity and improve responsiveness to student needs. Our intention is not to critique such efforts but to build upon them by offering a structured approach to managing the underlying knowledge dynamics they inevitably surface. By systematically aligning knowledge types, clarifying AI capabilities, and supporting faculty through explainable systems and institutional learning loops, the KM-AI framework enhances the transparency, interpretability, and pedagogical integrity of AI-supported assessment. In doing so, it adds value to existing initiatives by fostering responsible, sustainable, and educator-empowered AI integration in higher education.

While the KM-AI integration framework is not implemented through a single turnkey solution, it is highly accessible using a collection of free or institutionally available tools. Most phases can be operationalized with common platforms such as Google Forms, shared documents, LMS analytics, and openly available explainability tools like LIME or ELI5. Other activities, such as knowledge mapping or feedback gathering, can be carried out with minimal coordination among 2–3 faculty members and do not require extensive IT support. Surveys, reflection logs, and small-scale pilots can be seamlessly integrated into coursework, potentially even as extra credit opportunities for students, thereby increasing participation without adding administrative overhead. Importantly, the structured application of this framework can generate rich, publishable insights. Faculty involved in piloting KM-AI alignment can contribute to conference presentations, practitioner journals, or education research through case studies and design-based research. For students, the process encourages metacognitive awareness and agency, as they are invited to reflect on feedback, understand AI's role in their assessment, and participate in shaping responsible technology use in education. Moreover, institutions that apply the framework even on a small scale can gain clarity on AI tool deployment, reduce faculty resistance, and foster a culture of ethical innovation. In sum, operationalizing this model is not only feasible, but can also become a catalyst for pedagogical renewal, scholarly output, and deeper engagement with AI across the academic community.

5. Discussion: Theoretical and Practical Benefits of Integrating Knowledge Management and AI into Assessment Frameworks

This study proposes a comprehensive framework for integrating KM and AI into multiple assessment literacy frameworks. The potential impact of this work spans both theoretical advancements and practical applications, addressing critical gaps in how assessment knowledge is generated, transferred, and applied in educational settings. As explained in this paper, while existing assessment frameworks provide structured methodologies for improving assessment literacy, they do not account for the evolving role of AI in assessment practices or the systematic management of assessment-related knowledge. By embedding KM principles and AI-driven insights, this study has the potential to modernize assessment literacy, enhance knowledge accessibility, and ensure that AI serves as a supportive tool rather than a dictating force.

5.1. Theoretical Contributions

A key theoretical contribution of this research is the redefinition of assessment literacy as a dynamic, knowledge-driven process [5, 7, 22]. Traditional assessment frameworks emphasize competency development in assessment design, implementation, and interpretation but often neglect the mechanisms through which assessment knowledge is generated, refined, and transferred over time [12, 13, 15, 16]. This study introduces KM as a foundational element in assessment literacy, positioning it as a critical framework for sustainable assessment practices. By embedding KM principles into assessment structures, this research offers a systematic approach to institutionalizing, documenting, and disseminating assessment expertise across educators and institutions. This perspective broadens educational assessment theory by framing assessment literacy not only as a skillset but as an evolving knowledge ecosystem that supports continuous learning and adaptation.

Furthermore, this study enhances the theoretical understanding of AI's role in assessment literacy by addressing its conceptual integration into assessment frameworks. While AI-driven tools have been widely adopted for automated scoring, predictive analytics, and feedback generation, their role in knowledge transfer and teacher decision-making remains under-theorized [19]. Existing AI applications often function in isolation, lacking structured mechanisms for aligning AI-generated insights with pedagogical best practices [3, 11, 22]. This research advances a KM-based AI integration model, ensuring AI-driven assessments are interpretable, contextually relevant, and supportive of human expertise rather than replacing it [54]. By linking KM processes to AI within assessment literacy, this study contributes to both KM and AI research, emphasizing the need for structured knowledge-sharing mechanisms in educational contexts. While KM has been extensively explored in corporate and technological fields, its application to teacher assessment practices remains limited [19]. This research extends KM theory by illustrating how explicit and tacit knowledge in assessment literacy can be systematically documented, analyzed, and transferred through AI-driven systems. Additionally, by bridging KM, AI and assessment literacy, this study lays the foundation for new theoretical frameworks that explore the co-evolution of human and AI-driven knowledge generation in educational settings.

5.2. Practical Benefits

The practical implications of this research span educators, policymakers, and technology developers. A central contribution is the integration of Knowledge Management (KM) into assessment frameworks, offering systematic methods for capturing and sharing the tacit expertise teachers develop through experience. By embedding KM principles, the framework supports collaborative refinement of assessment practices and reduces redundancy across classrooms and institutions. It also positions AI not as a replacement but as a complement to teacher expertise, ensuring that AI-driven tools used for grading, feedback, and analytics are transparent, explainable, and aligned with pedagogical goals. For policymakers, the KM-AI model offers guidance for ethical AI adoption, balancing innovation with fairness and teacher autonomy. It enables the development of standardized practices that mitigate risks such as bias and inconsistent implementation. At the institutional level, KM-AI integration promotes coherence in assessment practices, enabling equitable access to high-quality assessment tools and insights. From a development standpoint, the framework informs the creation of AI systems that prioritize human-AI collaboration, preserving educator agency and interpretability. Finally, this integration has the potential to improve student outcomes. More consistent, transparent assessments enhance trust and engagement, while personalized AI support fosters motivation and retention. By grounding AI tools in KM principles, institutions can cultivate learning environments that are adaptive, inclusive, and academically rigorous strengthening the connection between instructional innovation and educational equity.

6. Limitation & Future Consideration

While this study offers a structured framework for integrating Knowledge Management (KM) and Artificial Intelligence (AI) into assessment literacy, several practical and contextual limitations remain. First, although the proposed KM-AI integration model emphasizes low-cost and scalable strategies, implementation still requires a baseline level of digital infrastructure and faculty engagement. Instructors must be willing to experiment with AI-assisted tools and commit time to knowledge-sharing practices, which may be challenging in high-workload or under-resourced environments. While this study demonstrates feasibility with as few as two to three faculty members, broader institutional adoption may still be uneven without supportive leadership or policy alignment. Second, while the framework encourages ethical safeguards, the risk of algorithmic bias in AI models cannot be entirely eliminated. Future adopters must remain vigilant by auditing training data sources, integrating diverse input, and applying human-in-the-loop oversight. This is especially crucial in contexts where historical assessment practices may reflect entrenched inequities. Finally, although this study grounds the framework in both conceptual and applied examples, further empirical validation is needed. Future researchers should evaluate the KM-AI framework through pilot studies, cross-course applications, and longitudinal assessments to measure sustained pedagogical impact, assessment coherence, and faculty adoption. These research efforts will help build a more robust, evidence-based foundation for scalable and ethical AI integration in assessment literacy practices.

7. Conclusions

This study introduces a practical framework for integrating Knowledge Management (KM) into AI-enhanced educational assessment, addressing critical gaps in how assessment knowledge is captured, transferred, and aligned with pedagogical intent. While existing models focus on developing assessment literacy, they rarely provide mechanisms for navigating AI-driven tools or managing institutional knowledge over time. The KM-AI framework fills this void by offering a structured, seven-phase model grounded in both theory and practice. By embedding KM principles and AI applications into these frameworks, this study aims to modernize assessment literacy, improve knowledge accessibility, and ensure that AI serves as a collaborative tool that complements pedagogical expertise. Through two applied cases, one hypothetical and the other documented, we demonstrate how small teams can use accessible tools and reflective practices to implement the framework without requiring external support. These cases illustrate how KM principles help clarify the boundaries between human and machine judgment, improve feedback quality, and support faculty trust in AI systems.

The potential impact of this research extends across theoretical and practical domains, offering a new conceptualization of assessment literacy as a knowledge-driven process while also providing practical guidelines for AI adoption in educational assessment. By structuring how assessment-related knowledge is captured, analyzed, and shared, the proposed integration of KM ensures that best practices do not remain isolated within individual educators or institutions but instead contribute to a collective, continuously evolving understanding of effective assessment strategies. Simultaneously, the incorporation of AI-driven tools can support real-time data interpretation, automate feedback processes, and enhance knowledge-sharing mechanisms, provided that such implementations are transparent, ethically sound, and aligned with teacher agency.

The framework also addresses potential challenges associated with AI adoption, including concerns over algorithmic bias, teacher trust in AI-generated insights, and disparities in access to AI-powered educational tools. By proposing a structured KM-AI integration model, this study emphasizes the need for explainable AI, fair assessment practices, and institution-wide strategies for equitable implementation. Additionally, the study highlights the importance of expert validation and empirical testing, ensuring that the proposed AI-enhanced assessment literacy models remain grounded in educational best practices and real-world applicability. By ensuring that knowledge transfer remains systematic and teacher-driven, the integration of KM and AI can empower educators with better tools, enhance student learning outcomes, and create more informed, transparent, and adaptable assessment systems. While the full realization of these benefits requires further empirical testing, the framework established here serves as a foundational step toward transforming assessment literacy in the era of AI-enhanced education.

Author Contributions

Conceptualization, A.A.S., J.M.J., M.J., J.B. and K.D.; methodology, A.A.S., J.M.J., M.J., J.B. and K.D.; formal analysis, A.A.S., J.M.J., M.J., J.B. and K.D.; investigation, A.A.S., J.M.J., M.J., J.B. and K.D.; writing—original draft preparation, A.A.S.; writing—review and editing, J.M.J.; visualization, A.A.S., J.M.J.; supervision, M.J., J.B.; All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Atjonen, P., Pöntinen, S., Kontkanen, S., et al., 2022. In Enhancing Preservice Teachers' Assessment Literacy: Focus on Knowledge Base, Conceptions of Assessment, and Teacher Learning. Frontiers in Education. 7, 891391. DOI: https://doi.org/10.3389/feduc.2022.891391

[2] Alavi, M., Leidner, D.E., 2001. Review: Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. MIS Quarterly. 25(1), 107. DOI: https://doi.org/10.2307/3250961

[3] Sancar, R., Atal, D., Deryakulu, D., 2021. A new framework for teachers' professional development. Teaching and Teacher Education. 101, 103305. DOI: https://doi.org/10.1016/j.tate.2021.103305

[4] Lee, J., Hicke, Y., Yu, R., et al., 2024. The life cycle of large language models in education: A framework for understanding sources of bias. British Journal of Educational Technology. 55(5), 1982–2002. DOI: https://doi.org/10.1111/bjet.13505

[5] Xue, M., Cao, X., Feng, X., et al., 2022. Is College Education Less Necessary with AI? Evidence from Firm-Level Labor Structure Changes. Journal of Management Information Systems. 39(3), 865–905. DOI: https://doi.org/10.1080/07421222.2022.2096542

[6] Huang, K., Ge, X., Law, V., 2017. Deep and Surface Processing of Instructor's Feedback in an Online Course. Educational Technology & Society. 20(4), 247–260.

[7] Ng, P.M.L., Chan, J.K.Y., Lit, K.K., 2022. Student learning performance in online collaborative learning. Education and Information Technologies. 27(6), 8129–8145. DOI: https://doi.org/10.1007/s10639-022-10923-x

[8] Walji, S., Deacon, A., Small, J., et al., 2016. Learning through engagement: MOOCs as an emergent form of provision. Distance Education. 37(2), 208–223. DOI: https://doi.org/10.1080/01587919.2016.1184400

[9] Zaneldin, E., Kabbani, S., 2021. Online Education: Lessons Learned from Teaching Undergraduate Courses. Turkish Online Journal of Qualitative Inquiry. 12(6), 9727–9736.

[10] Romijn, B.R., Slot, P.L., Leseman, P.P.M., 2021. Increasing teachers' intercultural competences in teacher preparation programs and through professional development: A review. Teaching and Teacher Education. 98, 103236. DOI: https://doi.org/10.1016/j.tate.2020.103236

[11] Kim, J., Lee, H., Cho, Y.H., 2022. Learning design to support student-AI collaboration: Perspectives of leading teachers for AI in education. Education and information technologies. 27(5), 6069–6104.

[12] Laxton, D., Cooper, L., Younie, S., 2021. Translational research in action: The use of technology to disseminate information to parents during the COVID-19 pandemic. British Journal of Educational Technology. 52(4), 1538–1553. DOI: https://doi.org/10.1111/bjet.13100

[13] Black, P., Wiliam, D., 1998. Inside the black box: Raising standards through classroom assessment. Phi Delta Kappan. 80(2), 139–148.

[14] Popham, W.J., 2009. Assessment Literacy for Teachers: Faddish or Fundamental? Theory Into Practice. 48(1), 4–11. DOI: https://doi.org/10.1080/00405840802577536

[15] Pastore, S., 2023. Teacher assessment literacy: a systematic review. Frontiers in Education. 8, 1217167. DOI: https://doi.org/10.3389/feduc.2023.1217167

[16] Stiggins, R., Chappuis, J., 2005. Using Student-Involved Classroom Assessment to Close Achievement Gaps. Theory Into Practice. 44(1), 11–18. DOI: https://doi.org/10.1207/s15430421tip4401_3

[17] Xu, Y., Brown, G.T.L., 2016. Teacher assessment literacy in practice: A reconceptualization. Teaching and Teacher Education. 58, 149–162. DOI: https://doi.org/10.1016/j.tate.2016.05.010

[18] Popham, W.J., 2018. Assessment literacy for educators in a hurry. ASCD: Alexandria, VA, USA.

[19] Gotch, C.M., McLean, C., 2019. Teacher outcomes from a statewide initiative to build assessment literacy. Studies in Educational Evaluation. 62, 30–36. DOI: https://doi.org/10.1016/j.stueduc.2019.04.003

[20] Sein Minn, 2022. AI-assisted knowledge assessment techniques for adaptive learning environments. Computers and Education: Artificial Intelligence. 3, 100050. DOI: https://doi.org/10.1016/j.caeai.2022.100050

[21] Twomey, B., Johnson, A., Estes, C., 2024. It Takes a Village: A Distributed Training Model for AI-Based Chatbots. Information Technology and Libraries. 43(3). DOI: https://doi.org/10.5860/ital.v43i3.17243

[22] Yim, I.H.Y., Su, J., 2024. Artificial intelligence (AI) learning tools in K-12 education: A scoping review. Journal of Computers in Education. DOI: https://doi.org/10.1007/s40692-023-00304-9

[23] Wilson, H.J., Daugherty, P.R., 2024. Embracing Gen AI at Work. Harvard Business Review. 102(5), 151–155.

[24] Muhisn, Z.A.A., Almansouri, S., Muhisn, S., et al., 2022. The Effectiveness of Knowledge Combination in e-Learning Management System (eLMS). International Journal of Emerging Technologies in Learning (iJET). 17(16), 33–42. DOI: https://doi.org/10.3991/ijet.v17i16.31873

[25] Benbya, H., Davenport, T.H., Pachidi, S., 2020. Artificial Intelligence in Organizations: Current State and Future Opportunities. SSRN Electronic Journal. DOI: https://doi.org/10.2139/ssrn.3741983

[26] Ercikan, K., McCaffrey, D.F., 2022. Optimizing Implementation of Artificial-Intelligence-Based Automated Scoring: An Evidence Centered Design Approach for Designing Assessments for AI-based Scoring. Journal of Educational Measurement. 59(3), 272–287. DOI: https://doi.org/10.1111/jedm.12332

[27] Teodorescu, M.H.M., Morse, L., Awwad, Y., et al., 2021. Failures of Fairness in Automation Require a Deeper Understanding of Human-ML Augmentation. MIS Quarterly. 45(3), 1483–1500. DOI: https://doi.org/10.25300/MISQ/2021/16535

[28] Jackson, S., Panteli, N., 2023. Trust or mistrust in algorithmic grading? An embedded agency perspective. International Journal of Information Management. 69, 102555. DOI: https://doi.org/10.1016/j.ijinfomgt.2022.102555

[29] Berry, R., 2008. Assessment for learning (Vol. 1). Hong Kong University Press: Hong Kong, China.

[30] Romi, I.M., 2023. Adaptive E-Learning Systems Success Model. International Journal of Emerging Technologies in Learning (iJET). 18(18), 177–191. DOI: https://doi.org/10.3991/ijet.v18i18.42929

[31] Siddique, A., Durrani, Q.S., Naqvi, H.A., 2019. Developing Adaptive E-Learning Environment Using Cognitive and Noncognitive Parameters. Journal of Educational Computing Research. 57(4), 811–845. DOI: https://doi.org/10.1177/0735633118769433

[32] Dianova, V.G., Schultz, M.D., 2023. Discussing ChatGPT's implications for industry and higher education: The case for transdisciplinarity and digital humanities. Industry and Higher Education. 37(5), 593–600. DOI: https://doi.org/10.1177/09504222231199989

[33] Major, L.E., 2024. End predicted grade system to make universities fairer. Available from: https://www.thetimes.com/comment/columnists/article/ending-predicted-grade-system-would-make-universities-fairer-kkgq8bjgn (cited 18 July 2024).

[34] Vendrell-Herrero, F., Darko, C.K., Ghauri, P., 2019. Knowledge management competences, exporting and productivity: uncovering African paradoxes. Journal of Knowledge Management. 24(1), 81–104. DOI: https://doi.org/10.1108/JKM-07-2018-0433

[35] Russo, G., Manzari, A., Cuozzo, B., et al., 2023. Learning and knowledge transfer by humans and digital platforms: which tools best support the decision-making process? Journal of Knowledge Management. 27(11), 310–329. DOI: https://doi.org/10.1108/JKM-07-2022-0597

[36] Ramdass, K.R., 2023. Knowledge building through academic development. European Conference on e-Learning. 22(1), 261–269. DOI: https://doi.org/10.34190/ecel.22.1.1884

[37] Auth, G., Jokisch, O., 2023. A systematic mapping study of standards and frameworks for information management in the digital era. Online Journal of Applied Knowledge Management. 11(1), 1–13. DOI: https://doi.org/10.36965/OJAKM.2023.11(1)1-13

[38] Fernández-Toro, M., Duensing, A., 2021. Repositioning peer marking for feedback literacy in higher education. Assessment & Evaluation in Higher Education. 46(8), 1202–1220. DOI: https://doi.org/10.1080/02602938.2020.1863911

[39] Midigo, J., 2025. Integrating Multiple Teaching Strategies in Language Learning for Teacher Training in the Digital Era. Innovations in Pedagogy and Technology. 1(1), 1–15. DOI: https://doi.org/10.63385/ipt.v1i1.26

[40] Abdellatif, H., Al Mushaiqri, M., Albalushi, H., et al., 2022. Teaching, Learning and Assessing Anatomy with Artificial Intelligence: The Road to a Better Future. International Journal of Environmental Research and Public Health. 19(21), 14209. DOI: https://doi.org/10.3390/ijerph192114209

[41] Abdel-Karim, B., Pfeuffer, N., Carl, K.V., et al., 2023. How AI-Based Systems Can Induce Reflections: The Case of AI-Augmented Diagnostic Work. MIS Quarterly. 47(4), 1395–1424. DOI: https://doi.org/10.25300/MISQ/2022/16773

[42] Mohammadkhah, E., Kiany, G.R., Tajeddin, Z., et al., 2022. EFL Teachers' Assessment Literacy: A Contextualized Measure of Assessment Theories and Skills. Language Teaching Research Quarterly. 29, 102–119. DOI: https://doi.org/10.32038/ltrq.2022.29.07

[43] Zlatović, M., Balaban, I., Kermek, D., 2015. Using online assessments to stimulate learning strategies and achievement of learning goals. Computers & Education. 91, 32–45. DOI: https://doi.org/10.1016/j.compedu.2015.09.012

[44] Ahmad, K., Iqbal, W., El-Hassan, A., et al., 2024. Data-Driven Artificial Intelligence in Education: A Comprehensive Review. IEEE Transactions on Learning Technologies. 17, 12–31. DOI: https://doi.org/10.1109/TLT.2023.3314610

[45] Bijsterbosch, E., Béneker, T., Kuiper, W., et al., 2019. Teacher Professional Growth on Assessment Literacy: A Case Study of Prevocational Geography Education in the Netherlands. The Teacher Educator. 54(4), 420–445. DOI: https://doi.org/10.1080/08878730.2019.1606373

[46] Brown, S., 2005. Assessment for learning. Learning and teaching in higher education. 1, 81–89.

[47] Gotch, C.M., French, B.F., 2014. A Systematic Review of Assessment Literacy Measures. Educational Measurement: Issues and Practice. 33(2), 14–18. DOI: https://doi.org/10.1111/emip.12030

[48] Jennex, M.E., 2009. Knowledge Management in Support of Education. Journal of Administration and Development, Mahasarakham University. 1(2), 15–28.

[49] Rudolph, J., Mohamed Ismail, F.M., Popenici, S., 2024. Higher Education's Generative Artificial Intelligence Paradox: The Meaning of Chatbot Mania. Journal of University Teaching and Learning Practice. 21(06). DOI: https://doi.org/10.53761/54fs5e77

[50] Yan, Z., Pastore, S., 2022. Are teachers literate in formative assessment? The development and validation of the Teacher Formative Assessment Literacy Scale. Studies in Educational Evaluation. 74, 101183. DOI: https://doi.org/10.1016/j.stueduc.2022.101183

[51] Estaji, M., Banitalebi, Z., Brown, G.T.L., 2024. The key competencies and components of teacher assessment literacy in digital environments: A scoping review. Teaching and Teacher Education. 141, 104497. DOI: https://doi.org/10.1016/j.tate.2024.104497

[52] Fischer, B., Guerrero, M., Guimón, J., et al., 2021. Knowledge transfer for frugal innovation: where do entrepreneurial universities stand? Journal of Knowledge Management. 25(2), 360–379. DOI: https://doi.org/10.1108/JKM-01-2020-0040

[53] Hosen, M., Ogbeibu, S., Lim, W.M., et al., 2023. Knowledge sharing behavior among academics: Insights from theory of planned behavior, perceived trust and organizational climate. Journal of Knowledge Management. 27(6), 1740–1764. DOI: https://doi.org/10.1108/JKM-02-2022-0140

[54] Li, S., Martins, J.T., Vasconcelos, A.C., et al., 2023. Knowledge sharing in project work: the dynamic interplay of knowledge domains and skills. Journal of Knowledge Management. 27(2), 328–355. DOI: https://doi.org/10.1108/JKM-06-2021-0455

[55] McGuffin, K., 2024. Rotman Professors Launch Revolutionary AI Teaching Assistant for Higher Education. Available from: https://www.rotman.utoronto.ca/news-events-and-ideas/news-and-stories/2024/december-2024/20241216/ (cited 16 December 2024).

[56] Dörfler, V., Cuthbert, G., 2024. Dubito Ergo Sum: Exploring AI Ethics. In Proceedings of the 57th Hawaii International Conference on System Sciences, Hawaii, HI, USA, 3–6 January 2024. DOI: https://doi.org/10.24251/HICSS.2024.671

[57] Omona, W., Van der Weide, T., Lubega, J., 2010. Using ICT to enhance knowledge management in higher education: A conceptual framework and research agenda. International Journal of Education and Development using ICT. 6(4), 83–101.

[58] Dhamdhere, S.N., 2015. Importance of Knowledge Management in the Higher Educational Institutes. Turkish Online Journal of Distance Education. 16(1).

[59] Santos, E., Carvalho, M., Martins, S., 2024. Sustainable Enablers of Knowledge Management Strategies in a Higher Education Institution. Sustainability. 16(12), 5078. DOI: https://doi.org/10.3390/su16125078

[60] Adhikari, D.R., Shrestha, P., 2023. Knowledge management initiatives for achieving sustainable develop-

ment goal 4.7: higher education institutions' stakeholder perspectives. Journal of Knowledge Management. 27(4), 1109–1139. DOI: https://doi.org/10.1108/JKM-03-2022-0172

[61] Yeşilçınar, S., Kartal, G., 2020. EFL teachers' assessment literacy of young learners: Findings from a small-scale study. Journal of Theoretical Educational Science. 13(3), 548–563.

[62] Dann, R., 2014. Assessment as learning: blurring the boundaries of assessment and learning for theory, policy and practice. Assessment in Education: Principles, Policy & Practice. 21(2), 149–166. DOI: https://doi.org/10.1080/0969594X.2014.898128

[63] Nyimbili, F., Nyimbili, L., 2024. Types of Purposive Sampling Techniques with Their Examples and Application in Qualitative Research Studies. British Journal of Multidisciplinary and Advanced Studies. 5(1), 90–99. DOI: https://doi.org/10.37745/bjmas.2022.0419

[64] Zahedi, M.R., 2024. Nonaka and Takeuchi knowledge management model based on institutional and infrastructure factors. VINE Journal of Information and Knowledge Management Systems. DOI: https://doi.org/10.1108/VJIKMS-02-2023-0033