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Building Meta-AI Literacy in Construction Education: Evaluating the Impact of a Storytelling-Based Module on Students' Metaknowledge

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Abstract

As emerging artificial intelligence (AI) technologies continue to transform construction processes and work environments, preparing future construction professionals with the competencies required to interact with AI critically, effectively, and ethically has become a pressing priority. Beyond acquiring fundamental and technical knowledge, students must develop metaknowledge of their own AI literacy, referred to as meta-AI literacy, which remains underexplored in construction education and literature. This study develops and presents AIStory, a storytelling-based learning module designed to foster both foundational AI knowledge and meta-AI literacy among construction students. The intervention was implemented with construction students, whose self-perceived AI literacy and objective AI knowledge were measured before and after participation. The discrepancy between the subjective and objective measures was used to quantify meta-AI literacy. Results indicate that the storytelling-based approach positively influences students' metacognitive understanding of their AI competencies. These findings provide actionable insights on how AI literacy integration into construction education curricula can develop students' metaknowledge of AI.

1 Introduction

Artificial Intelligence (AI) is rapidly transforming the construction industry, promising gains in efficiency, safety, and productivity. Projections suggest AI integration could add as much as $0.5 trillion in value to construction by 2035 [1]. A recent survey showed that around 70% of construction firms in the Asia-Pacific region are already using AI/Machine Learning (ML) in 2024 or planning to adopt these technologies in the near future [2]. In light of such trends and the growing potential of AI applications, construction educators increasingly recognize the importance of introducing AI literacy into their classrooms and curricula [3]. However, two persistent questions remain among construction educators and researchers: *What should construction students learn about AI?* and *How should we teach AI in construction education?* [4] These questions continue to fuel ongoing debates and research within construction academia, with several efforts advocating for embedding the concept of AI literacy into construction education.

Early definitions framed AI literacy as *"a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace"* [5]. This concept builds upon earlier literacies (e.g., data, information, digital, and computational literacies) but goes beyond coding proficiency to emphasize a functional understanding of how AI works and how it can be used responsibly [6]. AI literacy, therefore, extends beyond technical knowledge of algorithms and machine learning mechanics to encompass the societal, ethical, and practical implications of AI. Individuals equipped with AI literacy are better prepared to critically evaluate AI's role and relevance, harness its potential ethically and effectively, and anticipate its challenges.

Within construction education, researchers have begun adapting the concept of AI literacy and associated pedagogical strategies from the broader education literature to the construction domain. For instance, Cheng et al. adopted an experiential learning-based methodology to embed AI knowledge into construction safety contexts, thereby facilitating students' AI literacy [7]. Similarly, Okonkwo et al. introduced a hands-on programming laboratory into a construction course to demonstrate how AI can be applied to predict construction material properties, which effectively enhanced students' AI literacy levels [8]. While these pioneering efforts have explored different approaches to foster AI literacy among construction students, many opportunities remain unexplored, one of which involves learners' metaknowledge of their own AI literacy.

Learners' metaknowledge of AI literacy, or meta-AI literacy, refers to individuals' awareness of their own AI literacy levels [9], [10]. Although several AI literacy frameworks have highlighted the importance of understanding learners' metaknowledge [10], this aspect has been largely overlooked in the educational literature [11], particularly in the context of construction education. Yet meta-AI literacy plays a critical role in building AI literacy. Chaudhury et al. emphasized that self-awareness of one's AI literacy level is essential for effectively developing AI literacy, especially during informal and self-directed learning experiences [12]. Other studies also show that a lack of meta-AI literacy can result in ineffective decision-making during human-AI interactions [13].

A critical gap exists in construction education: while research continues to explore pedagogical strategies for fostering AI literacy, meta-AI literacy remains largely overlooked. This deficiency presents a dual risk for future construction professionals. On one hand, a lack of meta-AI literacy can lead to under-confidence, hindering the adoption of beneficial AI tools. Conversely, it can result in over-confidence, where professionals overestimate their AI competency and fall under the risk of over-relying AI-generated data or failing to intervene when AI outputs are flawed. In the high-stakes construction industry, this lack of metacognitive calibration can lead to compromised decision-making, safety risks, and financial loss. Therefore, there is an urgent need to move beyond basic AI literacy education and address the underlying meta-AI literacy of construction students.

To address this notable research gap, this study aims to propose the use of a storytelling-based methodology to enhance construction students' meta-AI literacy. In doing so, this study contributes not only to a deeper understanding of how AI literacy can be fostered in construction education but also to advancing an important yet underexplored dimension within the broader AI literacy field. Furthermore, this study adopts a systematic approach and corresponding indexes to evaluate learners' meta-AI literacy, offering a valuable resource for future research that seeks to assess this competency.

2 Research Methodology

To achieve the aim of this research, a three-step process was undertaken to evaluate the impact of the storytelling-based learning module on construction students' meta-AI literacy. First, storytelling was adopted as the pedagogical strategy for designing the AI literacy learning module, with story plots and learning objectives carefully mapped. Second, a AI literacy learning module was developed, where a set of educational resources was created to support and advance the story plots. Finally, a learner-centered study with a pretest-posttest design was conducted to assess students' subjective and objective AI literacy levels, with the discrepancies between these measures used as indicators of students' meta-AI literacy. The following sections elaborate on each step in detail.

2.1 Selection of Pedagogical Strategy: The Power of Storytelling

Storytelling is an interactive pedagogical approach that utilizes narratives and visual aids to communicate complex events [14], [15], [16]. As one of the oldest forms of instruction, it was selected for this research because it provides a memorable structure that captures student interest and fosters meaning-making through contextualized examples [17], [18], [19].

While often viewed as distinct from scientific domains, storytelling is a powerful tool for communicating technology to non-expert audiences [20], [21]. Given the interdisciplinary nature of AI and the non-computer science backgrounds of construction students, storytelling provides the accessible and contextualized experience necessary for effective learning [10], [20], [22]. Supported by Cognitive Load Theory, this narrative framework reduces the reliance on trial-and-error problem solving for novice learners, thereby sustaining engagement [23], [24]. Moreover, storytelling fosters meta-AI literacy by providing a situated context for applied judgment. As students navigate narrative-based AI challenges, they are forced to calibrate their own knowledge against the story's outcomes, transforming abstract concepts into observable professional consequences.

In construction education, the efficacy of storytelling for knowledge transfer is well-documented. It has been successfully used to preserve project experiences [26] and, when paired with immersive technologies, has delivered effective safety training in less time than traditional methods [27]. Thus, storytelling serves as a highly suitable strategy for integrating AI literacy into existing construction curricula.

To guide the design of the learning module in this research, the plot-based storytelling design model proposed by Mangione et al. [28] was adopted. This model embeds diverse learning objectives within narrative structures using Bloom's Taxonomy [29] to form Storytelling Complex Learning Objects. Narrative plots typically follow a structure of beginning, call to adventure, problem, solution, and closure. In this study, construction safety served as the context of the story narrative. This context was selected because safety remains a cornerstone of the construction curriculum and a prerequisite skill for all industry professionals. Furthermore, construction safety is a field where AI tools are extensively leveraged [30], providing a wealth of practical examples for the learning module.

The learning outcomes were tailored to the construction-specific AI literacy framework proposed by Cheng et al. [31] under safety context, ensuring that essential AI competencies were adequately covered. Fig 1 shows how different learning outcomes are mapped to each story progress. Notably, the module emphasizes the critical importance of AI literacy, encouraging students to reflect on their own proficiency and thereby fostering their metaknowledge. The module was designed for a two-hour duration, assuming continuous progress; however, the actual time may vary as the self-directed nature of the module allows students to adjust the pace to their individual learning needs.

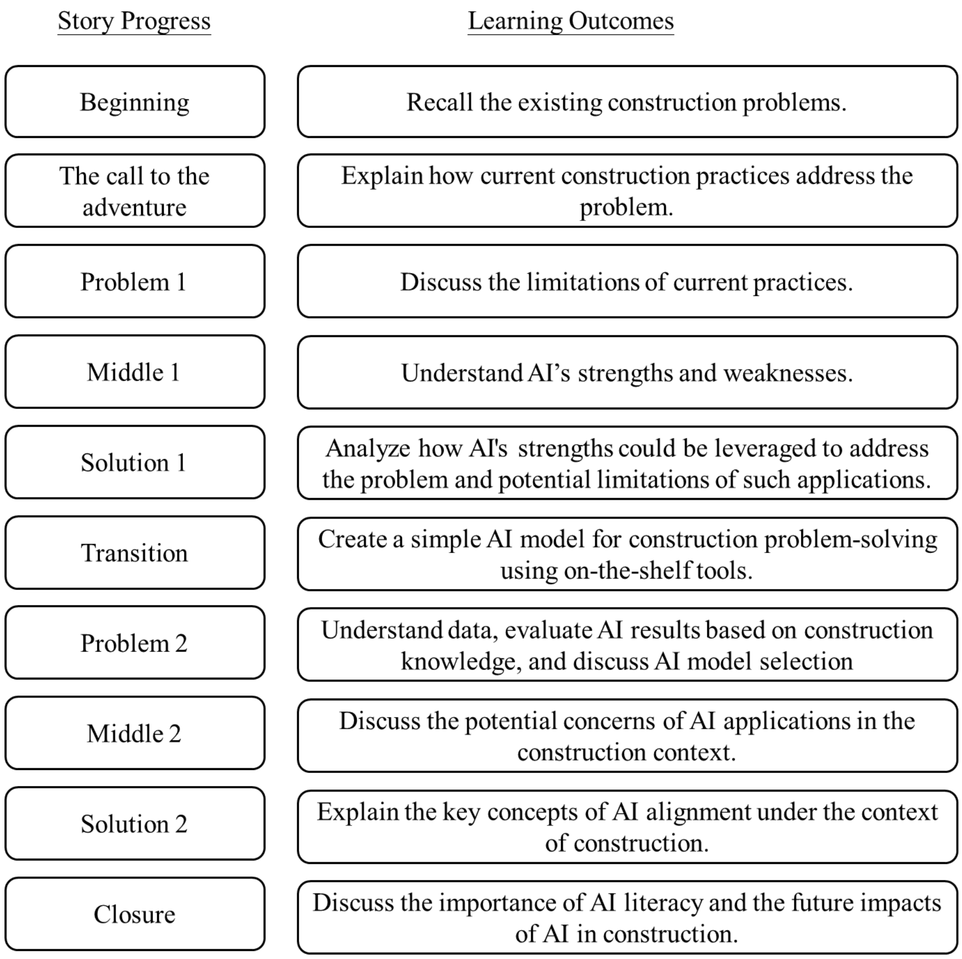

Fig 1. Story plot design and mapped learning outcomes

2.2 Development of AI Literacy Learning Module

This step of developing the AI literacy learning module involved creating a variety of educational resources, such as narratives, figures, videos, hands-on activities, quizzes, and reflections, and integrating them into the story plots designed in the previous stage. These resources were developed not only to advance the storyline but also to enhance learner engagement and interactivity within the module. The interactive e-learning authoring tool *Articulate® Storyline* [32] was employed to generate and integrate these resources.

An overview of the AI literacy learning module development is illustrated in Fig 2. The technical development of the AI literacy learning module involves 4 major aspects: (1) Narratives and Animations; (2) Visual Aids; (3) Hands-on Experience; and (4) Quizzes and Reflections. The technical development process of the interactive e-learning module is described as follows:

1. **Narratives and Animations:** The audio-based narratives were first generated using the built-in text-to-speech function in *Articulate® Storyline*. These narratives serve as the primary story drivers, while 2D characters were animated to align with the scripts to enhance learner engagement.
2. **Visual Aids:** To enrich the learning experience, visual resources such as images and videos were embedded within the 2D canvas. These aids were specifically mapped to the narrative content to help learners visualize and grasp abstract AI concepts.
3. **Hands-on Experience:** Hands-on experience was embedded in the module, as prior research has demonstrated that experiential tasks can effectively facilitate students' understanding of AI concepts [7]. Specifically, Google Teachable Machine was integrated as a web-based activity. Characters provided step-by-step guidance and prompted learners to critically reflect on the machine learning results.
4. **Quizzes and Reflections:** Quizzes and reflections were integrated to encourage learners to continually monitor and evaluate their progress. These activities not only reinforced content retention but also supported the development of learners' meta-AI literacy as they are required to frequently reflect on what they have learnt throughout the module.

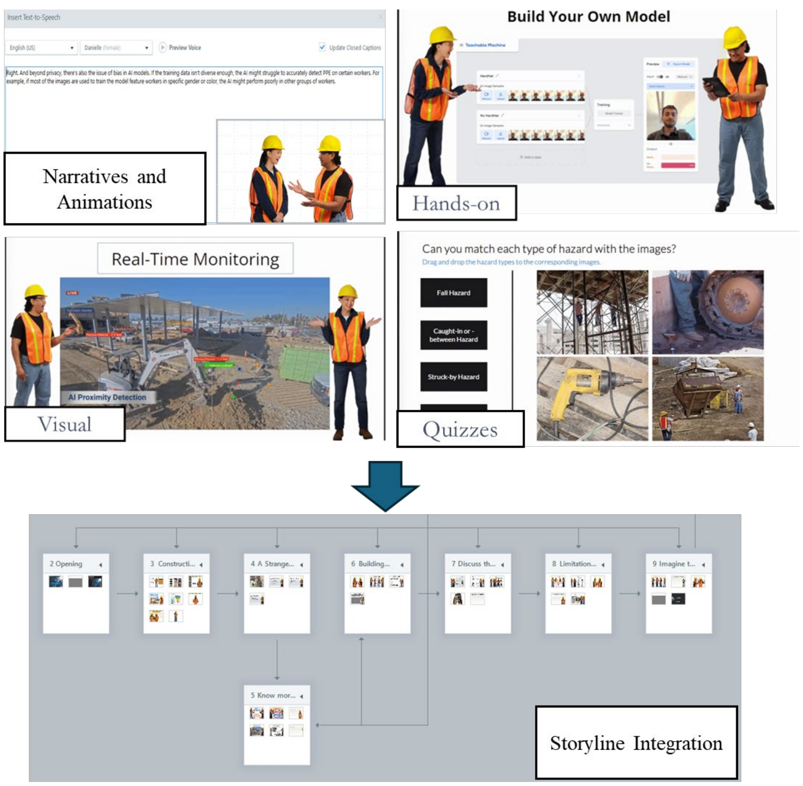

Fig 2. Generation and Integration of Educational Resources

2.3 Assessment of Learners' Meta-AI Literacy

The assessment of learners' meta-AI literacy involves 14 objective knowledge test questions and 1 subjective question. This measure was developed based on the construction domain specific AI literacy framework proposed by Cheng et al. [31], which informed the learning objectives of the AI literacy learning module. For example, one question was designed to ask students to differentiate the difference between AI-driven solution and non-AI application, which aligns with the competency of "*Explain how AI technologies are different from non-AI technologies*" (as shown in Fig 3). The 14 objectives questions reflect different competencies and learning objectives defined in the framework. The development of this assessment is based on the principle of performance-based assessment, where scenario-based multiple-choice questions were adopted to approximate learners' behavioral performance. Moreover, the final self-reported question requires learners to evaluate their understanding of their own AI literacy level. This design allows the study to calculate learners' meta-AI literacy, which by definition refer to one's knowledge of their own AI literacy.

1. A construction company wants to build a safety chatbot to handle common safety inquiries. They can choose between an AI-driven chatbot that uses machine learning models or a traditional, rules-based chatbot. Which of the following options best illustrates a primary difference between the AI-driven solution and the rules-based chatbot?

A. The AI-driven chatbot can learn from past interactions and refine its answers automatically, while the rules-based chatbot will strictly follow programmed rules and need manual updates to handle new or changing inquiries.

B. The AI-driven chatbot will only use pre-defined scripts to handle user questions, while the rules-based chatbot can gather user behavior data to adjust its responses over time.

C. The AI-driven chatbot will rely on a fixed set of scenario trees, while the rules-based chatbot can automatically generate new conversation paths for unexpected questions.

D. Both the AI-driven and rules-based chatbots can continuously adapt to new user questions without any input from human developers.

Correct Answer: A

Competency: Explain how AI technologies are different from non-AI technologies

Fig 3. Generation and Integration of Educational Resources

Specifically, this study employed two widely recognized indices from metacognitive research to assess students' meta-AI literacy levels [33], [34]. The first index, the *Meta-Literacy Bias Score*, is calculated as the signed difference between the average self-perceived AI literacy score and the average objective knowledge test score. This index measures learners' degree of over- or under-confidence in their own AI literacy [34], with positive values indicating over-confidence and negative values indicating under-confidence (equation 1).

$$\textit{Meta Literacy Bias Score} = \textit{Self-perceived AI Literacy score} - \textit{Objective Knowledge Test Score} \quad (1)$$

The second index, *Meta-Literacy Absolute Accuracy* [33], is calculated as the absolute value of this difference and reflects the degree of misalignment between self-perceived and actual AI literacy, irrespective of direction (Equation 2).

$$\textit{Meta-Literacy Absolute Accuracy} = \textit{ABS}|\ \textit{Self-perceived AI Literacy score} - \textit{Objective Knowledge Test Score}| \quad (2)$$

To evaluate the proposed AI literacy learning module in a controlled environment, an in-person workshop was conducted. This setting ensured that immediate technical support was available, thereby minimizing potential disruptions to the learning experience. A total of 32 students participated in the study. The following section presents the collected data, analysis results, and the discussions of the research implications of the results.

3 Results and Discussion

Participants' demographics are shown in Table 1.

Table 1. Demographics of Participants

Variable	Category	Number	Percentage
Gender	Male	24	75%
	Female	7	22%
	Prefer not to tell	1	3%
Undergraduate level	Junior	26	81%
	Senior	6	19%
Feelings about the increased use of AI in the construction industry	More excited than concerned	16	50%
	Equally concerned and excited	16	50%
	More concerned than excited	0	0%

To evaluate the impact of the intervention, a paired sample t-test was performed for normally distributed variables, and a Wilcoxon signed-rank test was performed for non-normal data (Self-perceived AI Literacy) to determine if the differences in means were statistically significant. Along with p-values, Cohen's d (effect size) was reported to quantify the magnitude of these improvements, providing a measure of the module's practical educational impact.

Table 2 summarizes participants' objective knowledge test scores, self-perceived AI literacy, meta-AI literacy, and the changes observed before and after the intervention of the AI literacy learning module. The results show that learners' objective knowledge test scores improved moderately, from 69 ± 22% to 75 ± 20% after the intervention (effect size = 0.489, p = 0.009), demonstrating the module's effectiveness in enhancing AI knowledge and literacy. In addition, self-perceived AI literacy increased significantly (effect size = 1.771, p < 0.001), echoing the gains shown on the objective scale.

To determine whether the increase in self-perception reflected over-confidence or mitigated under-confidence, meta-AI literacy was assessed using the bias and absolute accuracy indices. Prior to the intervention, there was a clear mismatch between students perceived and actual AI literacy levels, with an absolute difference of 26%. Specifically, students exhibited under-confidence in their AI literacy, as reflected by a −19% difference. After the intervention, results indicated that the proposed learning module helped students better align their perceived competence with their actual AI literacy, significantly reducing under-confidence with a large effect size (effect size = 1.115, $p < 0.001$). However, the intervention did not significantly improve the precision of their metacognitive self-assessments ($p = 0.108$). In other words, while the module corrected the directional bias (moving students from under-confidence toward a balanced mean), it did not enhance their metacognitive precision (the consistency of individual self-assessments).

From a cognitive perspective, this suggests that the module functioned as an "anchor," preventing students from underselling their skills, but that the fine-grained calibration required for high precision is a complex skill that may require multiple exposures or more intensive feedback loops than a single-session intervention can provide. Thus, while the module effectively "rebalanced" perceptions, achieving high-precision meta-AI literacy is likely to remain a longitudinal developmental process.

Table 2. Knowledge test and meta-AI literacy results

Variables	Pre-intervention Mean (SD)	Post-intervention Mean (SD)	p-value*	Effect size
Objective Knowledge Test Score	69% (22%)	75% (20%)	**0.009**	0.489
Self-perceived AI Literacy	49% (22%)	73% (18%)	**<0.001**	1.771
Meta Literacy Bias	-19% (27%)	-3% (27%)	**<0.001**	1.115
Meta Literacy Absolute Accuracy	26% (21%)	20% (19%)	0.108	0.292

* *Normality assumption is rejected for Self-perceived AI Literacy* [35]*, therefore, the Wilcoxon signed-rank test* [36] *is applied. All other items retain normality assumption* [35]*, so the paired sample t-test* [37] *is applied.*

As literature increasingly focuses on AI literacy, it is imperative that students' self-awareness of their competency is also researched to ensure their perceptions align with their actual capabilities post-intervention. As an early effort in construction engineering education focused on meta-AI literacy, this study suggests that educators should look beyond technical proficiency and consider metacognitive alignment in curriculum design. The findings underscore the importance of deliberately addressing meta-AI literacy through structured curriculum design. Specifically, instructional strategies can incorporate specific contents on the importance of AI literacy or iterative feedback loops. Such calibration informs students of their specific strengths and weaknesses, which could encourage them to pursue further knowledge rather than resisting AI due to under-confidence or neglecting critical oversight due to over-confidence. Overall, these results offer critical insights for the integration of AI into construction curricula.

4 Conclusion

AI literacy is increasingly regarded as an essential set of competencies for modern citizens living in an era where AI applications are rapidly permeating daily life. Within this context, scholars have emphasized that construction students and professionals should also develop AI literacy competencies that enable them to critically and effectively apply AI solutions to construction challenges, while simultaneously managing the ethical and practical risks associated with these technologies. Among the competencies identified in literature, meta-AI literacy, the ability to recognize and understand one's own AI literacy, has been acknowledged as equally important but has received comparatively little attention.

This study's primary novelty lies in its focus on metacognitive alignment in AI literacy curriculum design in construction education. It is among the first efforts in construction engineering education to specifically explore students' metaknowledge and examine the impact of a storytelling-based learning module on this dimension. A repeated-measures, learner-centered study was designed, employing two indexes to assess changes in students' meta-AI literacy before and after the intervention. Results indicate that both students' objective AI knowledge and their self-perceived AI literacy improved significantly following the intervention. More importantly, their meta-AI literacy also improved: under-confidence was significantly reduced, and students' self-perceptions became better aligned with their actual AI literacy.

This research builds upon the foundation of AI literacy in construction engineering education and metacognitive learning theory, offering both a systematic approach to integrating meta-AI literacy into curriculum design and empirical evidence regarding the potential of storytelling as a pedagogical strategy. However, this study did not explicitly isolate the connection between context-specific narrative learning and the development of students' metaknowledge. Future research could benefit from collecting qualitative data to understand which specific characteristics of narrative learning best facilitate the development of meta-AI literacy. Furthermore, future studies should compare the effectiveness of various pedagogical strategies and investigate the underlying mechanisms through which these approaches influence learners' self-awareness and the calibration of their AI literacy.

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