Empowering Teachers for the AI Era: Psychometric Validation of the Instructional AI Literacy Scale

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***Abstract*—The rapid development of Artificial Intelligence (AI) in education has created new expectations for teachers to possess AI literacy, particularly in instructional design. To meet this requirement, this study sought to develop and evaluate a scale to assess in-service teachers' AI literacy in instructional design. The study included 115 Thai in-service teachers. The instrument comprised five dimensions and 30 items, assessing knowledge and understanding of AI, application of AI in teaching, evaluation and creation with AI, the ethical and responsible use of AI, and instructional design with AI integration. Confirmatory Factor Analysis (CFA) was employed to examine construct validity and assess the adequacy of the proposed model. The results indicated that the second-order model was satisfactory and showed fit indices that were highly comparable to those of the correlated-factors model ($\chi^2(368) = 412.535$, $p = 0.054$, $RMSEA = 0.032$, $SRMR = 0.041$, $CFI = 0.985$, $AIC = 4608.183$, $BIC = 4874.441$). All factor loadings were significant at the .05 level. Internal consistency, average variance extracted, and composite reliability of all components were satisfactory. This empirically grounded scale provides a valid psychometric measure for assessing teachers' AI literacy in instructional design, with implications for professional development and educational decision-making.**

***Keywords*—Artificial Intelligence (AI) literacy, instructional design, scale development, teacher competencies, construct validation**

I. Introduction

Artificial Intelligence (AI) has played a transformative role in Thai education over the past decade, not only at the policy and educational system levels, but also at the practical level, particularly in classroom learning design, which is at the heart of education management [1, 2]. AI is no longer just a tool for teachers; it has evolved into a learning assistant with the potential to support the creation of new learning environments. This allows teachers to design personalized learning experiences that meet the unique needs and preferences of individual learners, while also providing immediate feedback, ensuring that students receive appropriate reinforcement and corrections in a timely manner [3, 4]. These developments have significantly influenced the ways teachers think, work, and enact their professional roles.

Given this situation, the role of teachers has changed significantly from the past. Teachers are no longer solely responsible for transmitting knowledge through one-way transfers of information from teacher to learner. Instead, they are expected to act as learning designers skilled in designing activities appropriate for learners, facilitators who create active learning environment and process, and critical technologists capable of using AI critically, while understanding the limitations and potential impacts of AI applications [5, 6]. Being a teacher in this era is therefore not just about using AI superficially or following system instructions. Teachers must have in-depth knowledge and understanding of how AI works, understand its boundaries, and be aware of the ethical issues involved, such as data privacy, equal access to learning opportunities, and preventing AI from creating biases that could impact student development [7, 8].

In teacher practice, these challenges are most evident in the process of "instructional design." Teachers must decide at which stages of instructional design they will use AI for support, from defining clear and measurable learning objectives to selecting teaching strategies that promote higher-order thinking, choosing media and resources relevant to learners, and designing concrete, equitable, and diverse assessments [9, 10]. These design decisions require deeper AI literacy than general digital skills, as they go beyond simply using AI as a tool and instead require integrating it meaningfully and effectively into the structure of lesson plans and learning activities [11, 12].

Globally, there have been some attempts to develop tools and frameworks to describe and measure AI literacy, such as the AI Literacy Scale, which focuses on measuring individuals' perceptions, basic knowledge, and skills in using AI [13], as well as a more comprehensive and systematic competency framework developed by other scholars [14, 15]. However, these tools are limited in that they do not clearly reflect teachers' ability to apply AI in the context of instructional design [16].

Furthermore, in the Thai context, formal AI-related curriculum expectations have been limited and linked mainly to specific content standards at the Grade 12 level [17]. As a developing country, Thailand continues to face constraints related to access to resources, professional training opportunities, and digital literacy, including AI-related literacy, among teachers. Differences in readiness and uneven levels of professional development have further complicated this situation. This has created gaps in teachers' perspectives on and use of AI tools including GenAI in actual educational practice [1, 2]. Empirically, for instance, primary education in Thailand has continued to experience disparities associated with urban–rural location and socioeconomic status in relation to inclusive digital transformation [18, 19]. These problems indirectly reflect the need to develop teachers' AI literacy and to establish a valid instrument for assessing such literacy [20]. However, there has been no systematic development and validation of such measurement tools. This is a significant issue, as the actual state of Thai

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schools presents numerous limitations, including uneven technological infrastructure readiness, limited teacher awareness of AI, and gaps in teacher training and development curricula that do not address emerging challenges [2, 16].

This results in a significant measurement gap, since policymakers and professional development providers currently lack empirical methods to assess teachers' instructional AI literacy and pinpoint areas for improvement. At the regional level, several Asian education systems have begun strengthening teachers' competencies related to AI. Singapore has instituted comprehensive professional development programs and explicit policy frameworks for AI-enhanced pedagogy [21, 22], whereas China has incorporated AI competencies into national teacher standards and initiated extensive strategic plans for AI in education [23, 24]. Vietnam and Malaysia have also piloted AI literacy programs with a view to equipping teachers for AI-assisted learning environments [13, 25–27]. In Thailand, there currently is no validated measurement instrument specifically for teachers' instructional AI literacy; neither is professional training in this area systematically organized or consistent across regions. This brings into sharper relief the urgency of having a contextually grounded measurement tool for Thai teachers [1, 2, 19, 28].

While international studies have suggested several AI literacy frameworks, none of them have been validated in a manner that captures how teachers integrate AI into instructional design processes within the Thai education system. Such frameworks and studies include those reported in Refs. [4, 11, 28, 29].

Therefore, it is imperative to develop and test tools that reflect the realities of Thai teachers. These tools should fully reflect teachers' ability to utilize AI, including using AI in lesson planning, selecting and evaluating the suitability of AI tools, and considering ethical issues and impacts on learners. Such tools would not only be useful for assessing individual teachers' skills and knowledge but would also serve as important empirical data for improving teacher training processes [30]. This research aims to develop and validate an AI literacy measurement tool for instructional design for Thai teachers, focusing on construct validity and reliability [31]. The study is intended to support both scholarly understanding and practical application by providing a contextually relevant instrument that may be useful for teacher development, educational research, and decision-making within similar educational settings.

II. Literature Review

A. Definitions and Core Frameworks

The concept of AI literacy has gained traction and has continued to evolve over the past decade [14]. Definitions are continuously evolving and expanding as new technologies emerge, but one thing is clear: AI literacy is not only about knowing how to use tools. Instead, it is a conceptual framework that includes technological aspects, theoretical comprehension, and moral and ethical consciousness [11, 32]. One widely used framework defines AI literacy as consisting of four dimensions: (1) awareness of AI in everyday life; (2) knowledge and awareness of its fundamentals; (3) use and functioning of AI in appropriate contexts; and (4) reflection and ethical consideration of its implications [13, 33]. This framework is widely regarded as a comprehensive model. Because it connects technical, cognitive, and ethical aspects, it has been widely referenced in academic literature [14].

Some studies show that AI literacy is an important competency for the 21st century. This includes not only knowing how to operate systems or programs, but also knowing how to work with AI, use creativity and critical thinking, and interact effectively with intelligent systems [15, 21]. This viewpoint asserts that AI does not replace people; rather, technology functions as a "thinking partner" with which people must have the skills to engage and interact effectively [34].

Conversely, several conceptual frameworks, particularly those pertaining to education, assert that genuine AI literacy encompasses not just technical competencies but also the capacity for critical thinking and ethical decision-making [7, 32]. This shows that being AI literate means knowing that AI is more than just a tool; it is also a part of society and human life. In this sense, AI literacy also involves a dimension of social responsibility [8].

Table 1. Comparative frameworks of AI literacy

Author (Year)	Focus of AI Literacy	Key Dimensions	Distinct Contribution
Ng *et al.* (2023) [33]	General users, conceptual model	Awareness; Knowledge & Understanding; Usage; Ethics	Clear four-dimension model, widely cited
Long & Magerko (2020) [15]	AI as 21st-century basic skill	Co-design with AI; Ethics	Positions AI literacy as fundamental skill
Markauskaite & Goodyear (2017) [34]	Education-oriented framing	Critical thinking; Ethical decision-making	Broadens scope beyond technical skills

As shown in Table 1, the conceptual frameworks for AI literacy have both similarities and differences. Ng *et al.* [11] laid out a clear foundation through a four-dimensional framework covering awareness, knowledge, use, and ethics, making it a key reference point for this area of study. Meanwhile, Long and Magerko [15] expanded the framework to view AI literacy as an essential 21st-century skill, not limited to use but also encompassing the ability to design with AI and collaborate with it. MacCallum *et al.* [35] focused more on education, emphasizing that AI literacy truly lies in critical thinking and ethical decision-making, rather than solely technical skills.

Although these frameworks have different emphases, they converge on the view that AI literacy is not just technical skills, but rather a set of competencies that include reflection, design, and ethical accountability [8]. This aligns with the current direction of teacher development, which requires not only the ability to use AI, but also the ability to use it meaningfully and sustainably [1, 2]. Analysis of these conceptual frameworks is therefore a key foundation for this research, as it reveals gaps in the field of AI integration in instructional design [16]. This research therefore necessitates the development of an AI literacy measurement tool that not only assesses general literacy but also reflects its practical application in Thai teachers' instructional design processes [12, 28].

B. AI Literacy in the Teaching Profession

When discussing education, a key question that always arises is, "What level of AI literacy should teachers have to effectively manage their teaching?" This issue cannot be overlooked in today's era, as teachers' understanding and application of AI directly influence teaching quality and student learning experiences [1]. Some research has found that teachers with higher levels of AI literacy are better able to evaluate and select technologies that are appropriate for their students [2, 36]. This means that teachers are not choosing AI simply because it's trendy or recommended, but rather because they can decide which AI tools to use based on whether they meet their teaching goals and fit their classroom context [8, 37].

Another important factor is that knowledge of AI can reduce teachers' resistance and apprehension [5, 15]. Teachers who are familiar with technology are more responsive, more likely to experiment, and more willing to adopt new resources [22, 38]. This differs from teachers who have limited familiarity with AI, who are likely to see it as difficult, complex, or even a threat to their professional role, and thus less likely to use it [7, 39].

More recently, the Artificial Intelligence Literacy (AIL) Scale for Teachers [40] was developed to assess teachers' AI literacy levels. The evidence is suggestive that more AI-literate teachers can design AI-integrated lesson plans to support tailored learning. They also understand signs of student engagement and even analyze students' learning outcomes using AI tools, not just for convenience purposes [3, 41].

This empirical evidence is used to show that pedagogy today no longer requires mere practical digital competence or basic operational know-how. What it requires is AI literacy, since it involves not just technical capability but also purpose, judgment, and design. All of these determine how extensively teachers use AI creatively and responsibly [8, 32].

C. Instructional Design and AI

The heart of effective teaching, regardless of the era, lies in "instructional design". Teachers cannot simply rely on new technologies without systematic planning. No matter how advanced AI or media are, if goals, strategies, media, and assessments are not aligned, learning will be weak [9, 42]. Several studies indicate that teachers must understand the importance of integrating these elements and addressing the needs of both learners and the real context of the classroom [42, 43]. The advent of AI has shifted the role of teachers beyond simply being AI users to becoming co-designers of learning experiences [8, 15]. For example, teachers may design lessons in which AI helps generate a variety of activities, provide personalized feedback, or analyze student learning data for targeted instructional improvements [5].

However, the implementation of AI is not always smooth or problem-free. Researchers have clearly warned against several caveats, particularly regarding bias, equity, and data privacy. These are key issues that teachers must understand and address [7, 39]. For example, if an AI system is trained on a biased database or does not reflect the diversity of learners, this can unknowingly lead to injustices in the learning process [9]. Furthermore, if teachers are inattentive to student privacy, they risk violating their privacy rights [7, 8]. When these issues are not adequately addressed, teachers' AI literacy becomes merely a "technical checklist" indicating their ability to use various tools, rather than a set of professional competencies enabling them to purposefully and responsibly design and use AI [8]. This is a key reason why many researchers emphasize that teachers' AI literacy should not end with basic knowledge or skills, but must also be integrated into application, design, and ethics [11, 34].

D. Present Tools for Measuring and Their Constraints

Although there have been some attempts to develop tools for measuring AI literacy in recent years, such tools remain limited and do not systematically capture the depth or practical application of AI in the context of teachers and teaching [14, 15]. Some research has proposed a theoretical framework for AI literacy that includes four main dimensions: awareness, knowledge, use, and ethics [11]. This framework lays the foundation for a comprehensive understanding of the topic. However, a major weakness of this framework is that it is not designed for direct use in the context of teachers' teaching, making it ineffective for measuring or assessing teachers' abilities in terms of instructional design [8, 12].

There is also research using the Delphi technique to identify indicators of AI literacy for policy use [35], which provides a useful starting point because it confirms the need for and importance of such indicators in the education system [44, 45]. However, it has not yet developed into a questionnaire or actual tool capable of collecting field data. Simply put, it remains more of a "concept" than a "real-world tool" [46].

In terms of tools tailored to instructors, there are very few. For example, Younis's [47] tool was explicitly created to assess teachers' AI literacy. However, its major shortcomings are that it does not adequately address instructional design or the aspect of being a "co-designer" of AI, thereby limiting its usefulness in actual learning environments [15]. Another tool, developed by Chenqi *et al*. [48], also has methodological limitations, as the model was not validated through confirmatory testing (e.g., CFA) and its psychometric evidence is insufficient to support large-scale use [30, 31, 49].

As can be observed in Table 2, even when efforts to build AI literacy tools have been made, none of them have fully captured how AI literacy should be measured in relation to instructional design [8, 12]. Some tools remain at the level of conceptual proposals or policy guidance and have not been pilot-tested in real classrooms [31, 35]. Some tools, although initially developed specifically for teachers, remain methodologically weak, with limited evidence of validity or reliability. In particular, Confirmatory Factor Analysis (CFA) plays a vital role in the development of reliable instruments [30, 31, 49].

Table 2. Strengths and limitations of AI literacy instruments

Instrument	Strengths	Limitations
Ng *et al*. (2021) [11]	Clear framework (Awareness, Knowledge, Usage, Ethics)	Lacks teaching/instructional design focus
MacCallum *et al*. (2023) [35]	Expert-validated, policy relevance	Not operationalized into a questionnaire
Younis (2024) [47]	Teacher-specific (TAIL) instrument	Does not capture co-design or pedagogy
Chenqi *et al*. (2023) [48]	Tailored to Singaporean teachers	CFA not validated; limited psychometric rigor

This issue also highlights the regional gap in Southeast Asia, including Thailand, in the availability of empirically grounded tools for systematically measuring teachers' AI literacy in relation to instructional design [28, 44]. This is a strong reason why this topic remains an important area for further research and tool development that responds realistically to Thai teachers' needs [1, 2].

E. Emerging Trends

The last few years have witnessed the advent of Generative AI and Large Language Models, which have substantially reshaped the debate around AI literacy. Previously, AI literacy was broadly defined as understanding and using AI. Today, the focus has shifted much deeper. Experts are recommending that AI literacy in this new age should include the ability to critically analyze AI-generated content, collaborate with AI to co-create new knowledge and content, and address ethical dilemmas in real-world and real-time contexts [4].

This is a very different approach from previous conceptual frameworks, since AI is no longer a tool that one has to be trained to use, but an "intellectual collaborator" with which users must interact thoughtfully and critically [14, 32]. Teachers therefore require adaptive decision-making and human-AI collaboration competencies that are much more advanced than those associated with earlier forms of educational technology [8, 12].

In the Thai context, this issue intersects with ongoing challenges, including the readiness of technological infrastructure and the adequacy of teacher development. Multiple reports indicate that while access to digital technology in Thailand has increased, there remains a significant gap between urban and rural schools [18, 19]. For example, urban schools have broadband connectivity, adequate hardware, and more opportunities to participate in AI teacher training, whereas rural schools lack even basic equipment. Most teachers lack continuous training, thereby creating substantial disparities in technology usage [1, 2].

Furthermore, some research has found that while most Thai teachers have positive attitudes toward AI and are open to using AI in teaching, they lack confidence when it comes to using it in real-world instructional contexts, such as lesson plans or designing complex activities [37, 47]. Many are familiar with basic AI tools, including popular generative AI tools, but are unsure how to apply them in more sophisticated ways to align with learning indicators and outcomes [10, 42].

These facts clearly demonstrate that if AI literacy measurement tools are to be developed for Thai teachers, they must be contextually valid and relevant to the Thai context, not directly copied from other countries [1, 2]. Crucially, such tools should serve more than just measurement; they should also provide feedback that contributes to teacher professional development [22, 44]. Such tools should help identify strengths, weaknesses, and skill gaps, while also informing systematic development efforts appropriate to the contexts of Thai teachers across different affiliations and regions [19].

F. Conceptual Rationale for the Present Study

A review of the literature and previous research suggests at least three key reasons for conducting this study.

First, existing conceptual models of AI literacy, though they address important dimensions such as awareness, knowledge, use, and ethics, fail to adequately address instructional design. This gap is particularly evident in relation to "how instructors can incorporate AI into the lesson planning and learning activity design process" [8, 12]. This is essential because teachers are not only using AI to help students access answers more quickly, but they must also be capable of designing learning processes with AI [10, 15].

Second, existing tools lack proper psychometric validation. Many tools lack both systematic model validation CFA and reliability testing. Hence, the results are not sufficiently validated to ensure accuracy and precision [30, 31]. Moreover, if such tools are applied in contexts other than those in which they were originally developed, particularly in Thailand, the precision of the results may be reduced [28].

Third, Thailand lacks assessments tools that can accurately evaluate and support the development of teachers' AI literacy. Most instruments currently used are adapted or reconstructed from foreign sources and are typically not sufficiently contextualized to reflect Thai conditions in terms of resources, technology, infrastructure, and teachers' pedagogical practices. Thus, they may not adequately reflect the Thai education system [19, 44]. To address these three gaps, this research has developed a new conceptual framework and defined AI literacy as a second-order construct with five overall dimensions:

(1) Knowledge and Understanding of AI
(2) Application of AI in Teaching
(3) Evaluation and Creation with AI
(4) Ethical and Responsible Use of AI
(5) Instructional Design with AI Integration

This framework not only addresses the requirements of measuring competence but also provides a important foundation for long-term teacher competency improvement and development [22, 44]. Confirmatory Factor Analysis (CFA) and other supporting analyses are used to test the tools' robustness and to ensure that it is theoretically and practically dependable [49].

The developed tool not only enable the assessment of individual teachers' AI literacy competencies, but also provides crucial data to support:

- Individual teacher development [22]
- Training and professional learning program design [22, 44]
- School-level planning and broader policy discussion [44, 45]

In other words, this research aims not only to develop a measurement model but also to produce a tool that connects global trends with local needs and contexts in Thailand. Such a tool may help support more contextually grounded and sustainable teacher development in relation to AI within the Thai education system [2, 28].

III. Materials and Methods

This research was a quantitative study aimed at developing and validating the Instructional AI Literacy Scale for teachers. Samples, instruments, and data analysis were as follows.

A. Samples

The 115 participants were recruited through formal invitation letters sent to both public and private schools in Mukdahan and Yasothon provinces, Thailand. Teachers were recruited through a request to schools to nominate 1 or 2 teachers who were willing to participate in a professional learning activity on the integration of AI into teaching practices. This sample of teachers, therefore, was not a random sample but consisted of teachers who expressed an interest in AI integration. Most participants were female (88.7%), had an average age of 37.43 years (SD = 10.17), held a bachelor's degree (95.7%), and had 5–10 years of teaching experience (43.5%). Most of them taught at the elementary level (44.3%) and had experience using one AI tool (44.3%). The sample size exceeded the minimum required sample size calculated using the "semPower" package in R [50]. According to an a priori power analysis with RMSEA set at .05, degrees of freedom at 400, significance level at .05, and statistical power at 0.95, the minimum required sample size was 105 teachers. In addition, after analyzing the data, a post hoc power analysis was conducted by specifying RMSEA as 0.054, the significance level as 0.05, degrees of freedom as 368, and the actual sample size as 115. The actual statistical power was 0.99, which exceeded the pre-determined power [6].

B. Instrument

The Instructional AI Literacy Scale was developed through a multi-stage process to ensure content validity, clarity, and contextual appropriateness for Thai in-service teachers [49]. First, an initial pool of items was generated based on existing AI literacy frameworks, instructional design theories, and literature on AI integration in Thai educational settings [2, 17]. The preliminary version consisted of five dimensions—(1) Knowledge and Understanding of AI, (2) Application of AI in Teaching, (3) Evaluation and Creation with AI, (4) Ethical and Responsible Use of AI, and (5) Instructional Design with AI Integration—each containing six items rated on a 5-point Likert scale [31].

Next, content validation was conducted by three experts representing the fields of curriculum and instruction, educational technology, and measurement and evaluation. Experts evaluated each item for relevance, clarity, and adherence to conceptual definitions. Item-Objective Congruence (IOC) ratings varied from 0.50 to 1.00, indicating satisfactory content validity. Expert feedback was incorporated, resulting in various enhancements, such as rectifying minor linguistic inconsistencies and incorporating specific examples to improve item specificity and aid respondent understanding [2].

Following the expert review, a small-scale study was conducted with in-service teachers (n = 81) from one public school in Kanchanaburi province. This small-scale pilot test examined clarity, usability, and response patterns [51]. Respondents completed the questionnaire without raising concerns or requesting clarifications, suggesting that the instrument was understandable and appropriate for field administration. No structural modifications were required after the pilot study.

The finalized instrument was subsequently administered to the main study sample (N = 115) for confirmatory factor analysis and psychometric validation.

C. Analysis

Data preparation involved multiple imputation to handle missing data [46, 52, 53]. The proportion of missing data ranged from 0.00% to 1.74% across items. Examination of the missing data revealed ten missing-data patterns and 103 complete cases. According to Little's MCAR test (p = 0.003), the missing data were not MCAR. Further examination suggested that missingness in some items was associated with responses on other observed items, which was consistent with a missing at random (MAR) mechanism. Hence, predictive mean matching with 50 iterations and five imputations was used to handle missing data. All items were included in the imputation model. Parameter estimates from the imputed datasets were pooled following Rubin's rules. Descriptive statistics, including Mean (M), Standard Deviation (SD), Skewness (Sk), and Kurtosis (Ku) for all components and items were reported. Competing confirmatory factor analysis models, namely a correlated-factors model and a second-order model, were examined using absolute fit indices to evaluate construct validity [49, 51]. Maximum Likelihood with Mean-adjusted Chi-square (MLM) estimator was utilized to handle non-normality in the data [54, 55]. Because the overall fit of the two models was highly similar, model selection was based on theoretical interpretability, parsimony, and the magnitude of inter-factor correlations, rather than on fit superiority alone. Lastly, further validity and reliability analyses were conducted for the retained model [37]. Discriminant validity was also examined using inter-factor correlations, the square root of AVE, and the Heterotrait-Monotrait ratio (HTMT). Data were analyzed using the R program through the missR [53], mice [52], lavaan [55], semTools [56], and psych [57] packages.

D. Ethical Considerations

This study adhered to established ethical standards for educational research. Prior to data collection, institutional permission was obtained from Mahasarakham University, and permission to access participants was granted by the participating school. All participants received an informed consent statement explaining the study objectives, voluntary participation, confidentiality safeguards, and their right to withdraw at any time without penalty [16].

The study did not include sensitive personal information or methods that could present physical, psychological, or professional risks to participants. The study involved anonymous, voluntary survey responses only. All responses were anonymized, and no identifiable data were retained. Data were securely maintained, objectively assessed, and clearly reported to ensure integrity and protect participant rights.

IV. RESULT AND DISCUSSION

A. Results

The results of the competing models are presented in Table 3. The second-order model and the correlated factors model provided highly similar global fit indices, including relative chi-square, p-value, RMSEA, SRMR, and comparative fit indices such as CFI. However, when considering information criteria, namely AIC and BIC, the second-order model provided lower values than the correlated factors model [51, 58, 59].

Table 3. Measurement model comparison

Model	χ^2	*df*	χ^2/df	*p*	*RMSEA*	*SRMR*	*CFI*	*AIC*	*BIC*
1. Correlated factors model	416.633	373	1.117	0.059	0.032	0.039	0.985	4632.883	4885.417
2. Second-order model	412.535	368	1.121	0.054	0.032	0.041	0.985	4608.183	4874.441

Because the overall fit of the two models was highly similar, and because the second-order model showed lower AIC and BIC values while also aligning with the theoretical assumption of a broader higher-order construct, it was selected for further analysis of component- and item-level psychometric properties in Table 4 and Fig. 1, as well as validity and reliability analyses in Table 5.

Table 4. Descriptive statistics, component and item psychological properties for the second-order model

Item	*M*	*SD*	*Sk*	*Ku*	*b*	*Beta*	*SE*	*p*	R^2
Component 1 Knowledge and Understanding of AI									
1.1) Understanding differences between ML, DL, and Generative AI	3.49	0.87	−0.55	0.69	1.000	0.644	-	-	0.414
1.2) Explaining how AI works	3.47	0.80	−0.62	0.95	1.228	0.863	0.166	< 0.001	0.745
1.3) Identifying limitations of AI	3.44	0.85	−0.63	0.77	1.293	0.853	0.190	< 0.001	0.728
1.4) Identifying AI tools that can be used for instructional purposes	3.70	0.91	−0.55	0.12	1.361	0.836	0.224	< 0.001	0.699
1.5) Understanding how AI differs from typical digital tools	3.52	0.76	−0.48	0.26	1.149	0.839	0.176	< 0.001	0.703
1.6) Explaining the role of AI in education clearly	3.40	0.85	−0.16	0.07	1.361	0.906	0.216	< 0.001	0.821
Component 2 Application of AI in Teaching									
2.1) Using AI tools to generate analytical or open-ended questions	3.55	0.95	−0.41	−0.09	1.000	0.812	-	-	0.660
2.2) Using AI tools to develop engaging instructional materials or lesson content	3.90	0.95	−0.65	−0.19	0.933	0.768	0.075	< 0.001	0.590
2.3) Selecting AI tools appropriate for content and student level	3.63	0.89	−0.48	−0.22	1.044	0.901	0.090	< 0.001	0.812
2.4) Teaching students to use AI for searching or summarizing lessons	3.57	0.87	−0.32	−0.26	1.031	0.910	0.087	< 0.001	0.827
2.5) Using AI to create worksheets or exercises	3.49	1.01	−0.42	−0.34	1.199	0.913	0.098	< 0.001	0.833
2.6) Using AI to support the preparation of classroom learning activities	3.55	0.98	−0.38	−0.31	1.177	0.933	0.090	< 0.001	0.870
Component 3 Evaluation and Creation with AI									
3.1) Verifying the accuracy and credibility of AI-generated information	3.49	0.91	−0.27	−0.24	1.000	0.886	-	-	0.784
3.2) Adapting AI output for student contexts	3.34	0.92	−0.24	−0.22	1.034	0.908	0.052	< 0.001	0.824
3.3) Evaluating AI tools for potential bias	3.33	0.85	−0.07	−0.38	0.939	0.895	0.065	< 0.001	0.802
3.4) Using AI to create assessments aligned with learning objectives	3.43	0.89	−0.26	−0.20	0.988	0.895	0.065	< 0.001	0.800
3.5) Using AI to analyze student work and refine subsequent instruction	3.37	0.96	−0.50	−0.06	1.037	0.857	0.073	< 0.001	0.735
3.6) Creating original teaching materials based on AI-generated ideas	3.42	0.97	−0.45	−0.26	1.025	0.839	0.078	< 0.001	0.705
Component 4 Ethical and Responsible Use of AI									
4.1) Recognizing ethical implications of using AI in the classroom	3.59	0.86	−0.20	−0.61	1.000	0.851	-	-	0.725
4.2) Avoiding student misuse of AI for cheating	3.55	0.84	−0.33	−0.13	1.004	0.866	0.065	< 0.001	0.749
4.3) Explaining privacy and data security issues related to AI	3.46	0.91	−0.40	−0.30	1.156	0.920	0.075	< 0.001	0.845
4.4) Encouraging students to use AI responsibly and respectfully	3.58	0.89	−0.29	−0.35	1.063	0.877	0.089	< 0.001	0.769
4.5) Providing examples of ethical issues from AI in education	3.49	0.87	−0.31	−0.01	1.082	0.897	0.096	< 0.001	0.805
4.6) Guiding students in the responsible use of AI in school contexts	3.66	0.95	−0.61	0.12	1.067	0.819	0.077	< 0.001	0.671
Component 5 Instructional Design with AI Integration									
5.1) Writing lesson plans that integrate AI in different stages	3.41	0.93	−0.42	0.06	1.000	0.922	-	-	0.851
5.2) Choosing AI tools to support each stage of a lesson appropriately	3.46	0.99	−0.69	0.10	1.086	0.929	0.040	< 0.001	0.862
5.3) Designing activities where students engage with AI	3.46	1.01	−0.60	−0.02	1.121	0.942	0.046	< 0.001	0.887
5.4) Considering AI's pros and cons before integration	3.52	0.93	−0.68	0.29	1.001	0.928	0.049	< 0.001	0.861
5.5) Using AI to co-design lesson plans with other teachers	3.33	0.95	−0.51	−0.15	1.002	0.900	0.034	< 0.001	0.811
5.6) Planning lessons that systematically integrate AI	3.43	0.95	−0.77	0.39	0.993	0.892	0.058	< 0.001	0.795
Overall Instructional AI Literacy									
Component 1 Knowledge and Understanding of AI	3.50	0.72	−0.60	0.92	1.000	0.920	-	-	0.846
Component 2 Application of AI in Teaching	3.61	0.85	−0.60	0.00	1.419	0.950	0.260	< 0.001	0.903
Component 3 Evaluation and Creation with AI	3.40	0.83	−0.25	−0.37	1.510	0.966	0.249	< 0.001	0.934
Component 4 Ethical and Responsible Use of AI	3.56	0.80	−0.45	−0.07	1.346	0.958	0.206	< 0.001	0.918
Component 5 Instructional Design with AI Integration	3.44	0.90	−0.67	0.18	1.570	0.953	0.231	< 0.001	0.909

Table 4 presents the descriptive statistics for all items. Overall, the mean scores across components ranged from 3.40 to 3.61. Skewness values ranged from −0.67 to −0.25. Kurtosis values ranged from −0.37 to 0.92.

As shown in Table 4 and Fig. 1, all factor loadings were statistically significant at the.05 level. When considering the second-order factor structure, Component 3—Evaluation and Creation with AI—demonstrated the highest standardized factor loading, with explained variance of 93.4% (*Beta* = 0.966, R^2 = 0.934).

At the first-order factor level, the results were as follows. In Component 1—Knowledge and Understanding of AI—item 1.6, *explaining the role of AI in education clearly*, demonstrated the highest standardized factor loading, with explained variance of 82.1% (*Beta* = 0.906, R^2 = 0.821). In Component 2—*Application of AI in Teaching*—item 2.6, *Using AI to support the preparation of classroom learning activities*, demonstrated the highest standardized factor loading, with explained variance of 87.0% (*Beta* = 0.933, R^2 = 0.870). In Component 3 – *Evaluation and Creation with AI*—item 3.2, *adapting AI output for student contexts*, demonstrated the highest standardized factor loading, with explained variance of 82.4% (*Beta* = 0.908, R^2 = 0.824). In Component 4—*Ethical and Responsible Use of AI*—item 4.3, *explaining privacy and data security issues related to AI*, demonstrated the highest standardized factor loading, with explained variance of 84.5% (*Beta* = 0.920, R^2 = 0.845). Lastly, in Component 5—*Instructional Design with AI Integration*—item 5.3, *designing activities where students engage with AI*, demonstrated the highest standardized factor loading, with explained variance of 88.7% (*Beta* = 0.942, R^2 = 0.887).

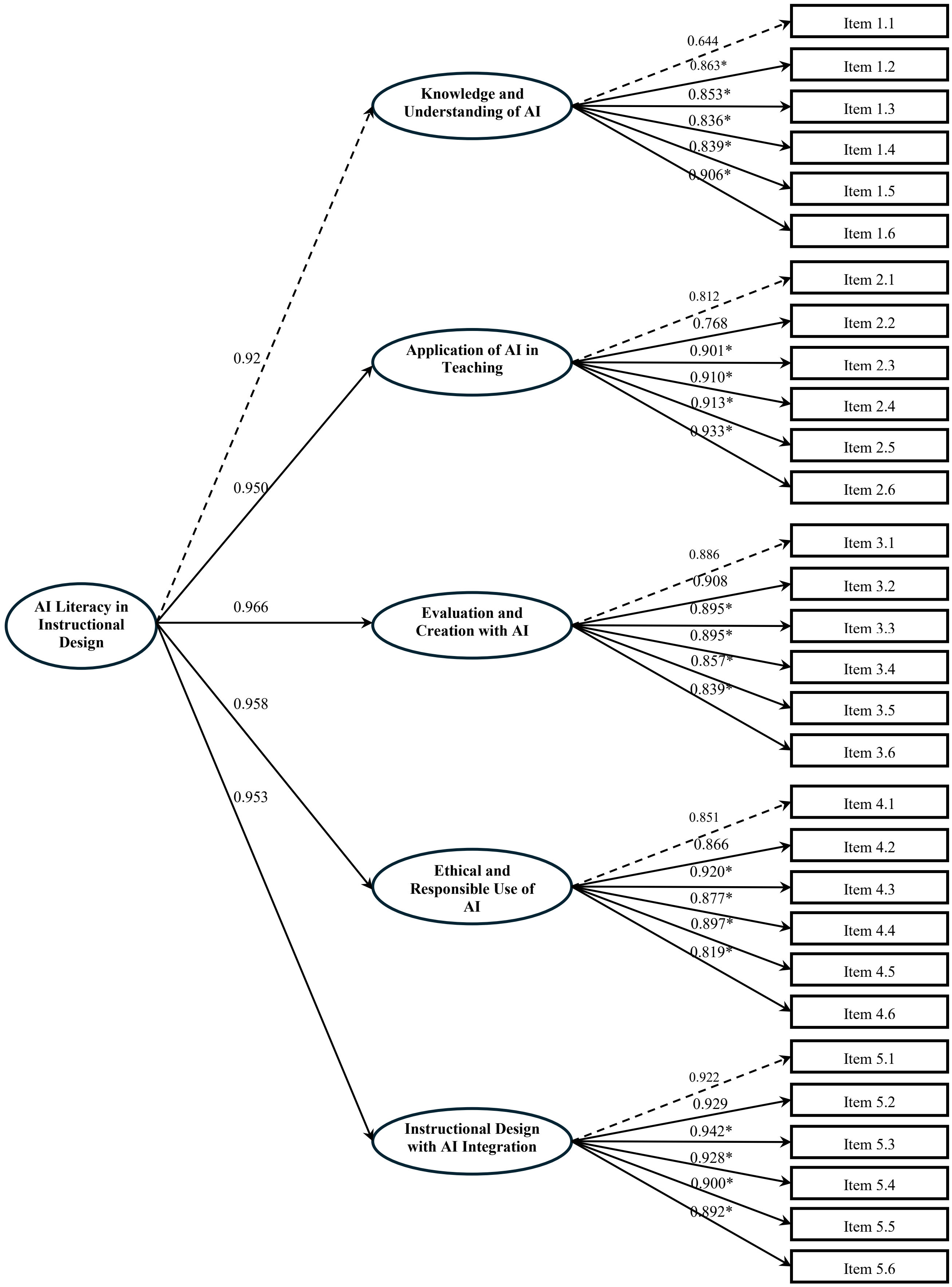

Fig. 1. Second-order model with standardized factor loading (*p < 0.0).

According to Table 5, Cronbach's alpha, AVE, and CR of all components were at satisfactory levels [31, 49, 58]. Component 5—*Instructional Design with AI Integration*—showed the highest values of Cronbach's alpha and Average Variance Extracted (AVE). However, Component 3—*Evaluation and Creation with AI*—provided the highest value of Construct Reliability (CR).

Table 5. Validity and reliability analysis for second-order model

Component	Cronbach's alpha	AVE	CR
Component 1 Knowledge and Understanding of AI	0.924	0.681	0.931
Component 2 Application of AI in Teaching	0.953	0.760	0.930
Component 3 Evaluation and Creation with AI	0.955	0.780	0.954
Component 4 Ethical and Responsible Use of AI	0.953	0.753	0.926
Component 5 Instructional Design with AI Integration	0.973	0.838	0.950

In addition to the validity and reliability analyses for the second-order model, discriminant validity was inspected and presented in Table 6.

According to Table 6, relatively high correlations between factors were observed, resulting in HTMT values exceeding the recommended cutoff. The Fornell-Larcker criteria for discriminant validity were not fully satisfied. However, due to the higher-order structure of the measurement model, the first-order factors reflected closely related dimensions of the same broader construct. Hence, relatively high correlations among factors can be expected in a hierarchical measurement model.

Table 6. Discriminant validity examination

Component	1	2	3	4	5
Component 1	0.826	0.874	0.899	0.881	0.877
Component 2	0.904	0.872	0.918	0.910	0.906
Component 3	0.901	0.925	0.883	0.926	0.921
Component 4	0.862	0.842	0.891	0.868	0.913
Component 5	0.825	0.849	0.902	0.946	0.915

diagonal values = square roots of AVE, upper triangle = factor correlations, lower triangle = HTMT

B. *Discussion*

Results showed that this second-order model provided fit indices that were highly comparable to the correlated-factor model. This suggests that the five components of instructional AI literacy function coherently under a higher-order latent construct rather than as entirely independent domains. Such a structure is consistent with prior research that has conceptualized AI literacy as a unified yet multidimensional capability [11]. Similarly, other measurement studies have also reported satisfactory fit indices when modeling AI literacy as a second-order construct [60], which further supports the robustness of the current approach. The second-order model was preferred due to parsimony [59]. Moreover, the structure of the second-order model allowed for the comparison of factor loadings between the higher-order construct and its subcomponents. In addition, results from this model provide evidence for calculating factor scores for both the main construct and the subcomponents. Additionally, high correlations among factors implied that the content of all components may share conceptual similarity. Consequently, shared variances between factors could be explained through the higher-order latent construct of AI literacy. Therefore, based on theoretical, practical, and empirical considerations, the second-order model was preferred. After examining discriminant validity, relatively high correlations between factors were observed. This can be explained by the fact that the first-order factors represent closely connected dimensions of the broader construct of AI literacy.

Confirmatory factor analysis indicated that, within the internal structure of the model, the standardized factor loading of the Evaluation and Creation with AI dimension was higher than those of other dimensions. It can thus be inferred that instructional AI literacy might best be expressed through teachers' competencies to critique, refine, and generate instructional outputs using AI tools. The lowest loading was observed for the Knowledge and Understanding of AI dimension. This can be explained by the different cognitive demands associated with each domain. Evaluation and creation require higher cognitive processes than remembering or understanding, according to the literature on learning taxonomies [40, 44].

Further, according to both the classic and revised taxonomies of learning, evaluation and creation tasks represent the highest levels of cognitive processing. The knowledge base involved in being able to evaluate and create with AI already entails other foundational competencies—understanding AI concepts, applying AI tools, and integrating them into pedagogical contexts—meaning that the overarching construct is better captured. On the other hand, knowledge or conceptual understanding of AI does not necessarily translate into the ability to apply it in more extensive, instructional ways. This reflects an idea that has long been theoretically assumed in cognitive process hierarchies [43] and extends to views on creativity as a kind of advanced reasoning and problem solving [61]. Thus, the high loading of the evaluation and creation dimension and the lower loading of knowledge and understanding are consistent with the cognitive progression found in previous literature [28, 43].

Beyond considerations of model fit and factor loadings, the results can be understood through several influential educational frameworks. First, the substantial contributions of all elements of instructional AI literacy align with key elements of the TPACK model [17]. Teachers who exhibit instructional AI literacy inherently blend technological, pedagogical, and content knowledge when designing AI-supported learning experiences. Knowledge and understanding of AI strongly overlap with technological and content knowledge, while application, evaluation, and ethical use reflect interactions between technological and pedagogical knowledge. The strong loading for evaluation and creation suggests that teachers who use AI in sophisticated ways might be approaching the ideal TPACK intersection in which technology, pedagogy, and content are fully integrated.

This also aligns with the revised taxonomy of learning, placing knowledge and understanding at the "understand" level; application, ethical use, and instructional design at the "apply" level; and evaluation and creation at the top levels of "evaluate" and "create." The empirical hierarchy identified here shares this theoretical structure, providing further evidence that the development of instructional AI literacy proceeds from foundational knowledge toward higher-order levels of instructional capacity. The findings align with the domains of AI literacy identified by Ng *et al*. [11], including knowing and understanding AI, applying AI, evaluating and creating AI, and ethical engagement. However, the present study contributes additional conceptual clarity by extending these domains to the context of instructional design. Specifically, the dimension "Instructional Design with AI Integration" represents a unique contribution, addressing teachers' ability to strategically embed AI tools into lesson planning—a capability not explicitly included in earlier AI literacy frameworks [2, 28]. These findings also suggest that there may be connections with more general teacher professional development frameworks involving pedagogical, personal, social, and professional competencies. All major domains of instructional AI literacy reflect teachers' personally competent use of AI tools, pedagogically competent integration of AI in practice, and professionally competent management of the instructional role. Instructional AI literacy is less directly related to social competence. However, the instructional design dimension that involves AI integration does have implications for collaborative lesson planning and thus connects to co-design and PLC practices that are increasingly used within schools' professional learning processes.

C. Recommendation

1) Recommendation for applying research results

Results from this research indicated that the developed Instructional AI Literacy Scale possessed acceptable reliability and construct validity indices. Moreover, results from model comparison indicated that the second-order measurement model was retained because it offered a more parsimonious representation of the construct. Therefore, teachers, school administrators, and educators could use this scale to assess teachers' AI literacy in instructional design, both at the overall level and across subdimensions, in order to identify strengths and areas for further development [47].

In application, the scale could be used to diagnose teachers' professional development needs, inform the development of AI-related professional development programs, and provide evidence-based decision making at schools. The instrument may also be used by institutions to track changes in AI competencies over time and assess the effectiveness of AI-integrated instructional programs.

At the policy level, the scale may additionally contribute to broader discussions about teacher AI competency frameworks and provide empirical data that may inform professional development planning and educational decision-making in similar contexts [19, 44].

Although the psychometric properties of this AI literacy scale were examined, there were some considerations for teachers or educators who needed to apply this scale. Due to the self-reported nature of this scale, teachers or educators using it should be aware that the resulting scores reflect perceived AI literacy rather than actual demonstrated competence. In addition, some dimensions were conceptually close to each other, specifically the dimensions of Application of AI in Teaching, Evaluation and Creation with AI, and Instructional Design with AI Integration. The core emphases of these dimensions, as reflected in the items, are described as follows. The Application of AI in Teaching component focuses on the practical use of AI to support instruction, such as generating learning resources and assisting classroom activities. In contrast, Evaluation and Creation with AI emphasizes the ability to critically examine AI-generated outputs, adapt them to student needs, and use AI to develop assessment and instructional materials. Instructional Design with AI Integration specifically reflects the ability to use AI systematically across stages of lesson planning, integrate AI into instructional design decisions, and support collaboration with others during the design process. Moreover, the findings should be interpreted in light of the sample characteristics, as the participants were teachers who had already expressed interest in AI-related practices. As a result, the scale may have been validated with a group that was more open to or motivated toward AI integration than the broader teacher population.

2) Recommendations for future studies

Confirmatory factor analysis results indicated that the standardized factor loading of the Evaluation and Creation with AI dimension was higher than those of other dimensions. Therefore, future studies may consider developing complementary assessment formats—such as situational judgment tasks, classroom scenarios, or authentic performance assessments—that emphasize teachers' capacity to evaluate and create instructional artifacts using AI tools [37, 40]. Such assessments could then be validated through concurrent or convergent validity analyses against this scale [51, 62].

The limitations of the present study include a small sample size for certain subgroups, which was insufficient for conducting multi-group analysis, particularly for male teachers. Future studies, therefore, should increase sample diversity in order to test measurement invariance across gender, educational levels, regions, and school types. The establishment of invariance would strengthen the interpretability and generalizability of the scale.

Cross-cultural validation is also recommended. Considering the increasing recognition of AI literacy in international educational systems, more research should examine the scale's structure with samples from other ASEAN or Asian countries to evaluate cross-national stability [19, 63]. Such comparisons may also help clarify contextual variations in educators' conceptualizations and use of AI in instructional design.

Finally, the measurement model could be further applied to other constructs, such as instructional innovation or technology integration self-efficacy, to investigate their relationships to AI literacy. Longitudinal or mixed-methods studies could provide deeper insights into how teachers' AI literacy develops over time and how this in turn shapes classroom practice. To establish additional validity evidence for the scale, future studies may examine other forms of validity, such as criterion-related validity.

V. Conclusion

The results revealed that the second-order model was retained as the preferred model because it showed highly comparable global fit and lower AIC and BIC values than the correlated factor models (2(368) = 412.535, p = 0.054, $RMSEA$ = 0.032, $SRMR$ = 0.041, CFI = 0.985, AIC = 4608.183, BIC = 4874.441). All factor loadings were statistically significant at the level of .05. Cronbach's alpha, AVE, and CR of all components were at satisfactory levels.

The developed AI literacy scale incorporates ethics into the framework of Ng *et al*. [11], stresses the importance of instructional design with AI integration by extending the work of Younis [47], and provides more specific labels for AI literacy components compared with the broader dimension names presented in the framework of Chenqi *et al*. [48]. In addition, the study provides evidence regarding an appropriate measurement model for AI literacy with sufficient information about the validity and reliability of the scale. Additionally, the findings contributed a context-specific scale for measuring AI literacy among Thai teachers.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

C.I. conceptualized the research idea, designed the study, collected and analyzed the data, and drafted the manuscript. C.S. contributed to the development of the research methodology, assisted in instrument validation, and critically revised the manuscript for academic quality. Both authors approved the final version of the paper and agreed to its submission.

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