The Development of a Critical Intelligence Inventory for Teachers in the Use of Generative Artificial Intelligence

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Abstract

The development of Generative Artificial Intelligence (Gen AI) has transformed how teachers access information and make professional decisions. However, overreliance on AI-generated outputs without critical evaluation may reduce cognitive effort and increase the risk of using inaccurate information. This study aimed to (1) examine the components of teacher' critical intelligence skills in using Gen AI and (2) develop and validate a scale to assess these skills. This study employed a developmental research design using both qualitative and quantitative approaches. The sample consisted of 538 teachers from private schools in Thailand with at least one year of teaching experience, selected through multistage sampling. The research instrument was the self-report Likert-scale questionnaire, namely the Critical Intelligence Inventory for Teachers in the Use of Generative Artificial Intelligence (CI-GAI), developed from the synthesis of the concepts of critical thinking, intelligence, and critical intelligence. Content validity was verified by five experts, and the instrument was pilot-tested before the main data collection. Data were analyzed using descriptive statistics and confirmatory factor analysis (CFA) with LISREL. The results indicated that the construct comprises six components with 41 indicators: Analytical reasoning, Metacognition, Cognitive adaptability, Ethical decision-making, Epistemic awareness, and Cultural intelligence. The scale demonstrated acceptable psychometric properties, and the second-order CFA showed a good model fit with the empirical data, confirming the validity of the developed scale.

Keywords: critical thinking, intelligence, critical intelligence, generative artificial intelligence

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Introduction

Generative artificial intelligence (Gen AI) technologies, such as ChatGPT, Google Gemini, and DeepL, have become important tools in learning processes, communication, and decision-making in everyday life. These technologies increasingly influence multiple dimensions of human work, ranging from individual practices to organizational operations and policy development. However, a critical issue that has received growing scholarly attention is users' tendency to accept AI-generated outputs without thorough evaluation (Holmes et al., 2022; Lee et al., 2025). Such reliance poses risks related to information inaccuracies, flawed decision-making, and unethical communication (Lee et al., 2025; UNESCO, 2023; Weidinger et al., 2021).

Users who lack higher-order thinking skills such as analytical thinking, inhibitory control, and the ability to update information based on new evidence are more likely to accept AI-generated information without proper scrutiny. This condition may lead to what Lee et al. (2025) describe as "mechanized convergence," in which individuals become constrained by AI-generated response patterns rather than engaging in independent cognitive processing. Furthermore, Lee et al. (2025) found that continuous use of Gen AI is associated with reduced cognitive effort, particularly among individuals with limitations in Executive functions (EFs). The widespread adoption of generative conversational systems powered by Large language models (LLMs), such as ChatGPT, has contributed to increasing levels of over-reliance since 2023. This trend may reduce users' cognitive engagement and affect their analytical thinking and decision-making processes (Lee et al., 2025; Zhai et al., 2024).

This risk is especially pronounced when Gen AI systems do not provide references, fail to explain their reasoning processes, or are trained on biased datasets, resulting in responses that may appear plausible but are actually incorrect, a phenomenon with significant cognitive and ethical implications (Weidinger et al., 2021). Studies in higher education similarly report that although Gen AI may improve short-term writing performance, it can also reduce cognitive engagement and increase reliance on unverified information (Gerlich, 2025; Jose et al., 2025).

Within the teaching profession, these challenges become even more complex. Research indicates that many teachers remain hesitant, uncertain, or unprepared to integrate generative AI into instructional design, assessment, and feedback practices. These concerns are associated with issues such as misinformation, limited understanding of digital ethics, and uncertainty about managing students' use of AI technologies (Kohnke et al., 2023; OECD, 2023; Rajapakse et al., 2024; Van Brummelen & Lin, 2021). This challenge does not necessarily reflect resistance to technology but rather highlights the evolving role of teachers in the Gen AI era—from technology users to "orchestrators of thinking." In this role, teachers function both as information-quality gatekeepers and trust calibrators, helping students critically evaluate AI-generated outputs (Katsaounidou et al., 2025; Müller et al., 2025). Consequently, teachers must develop a solid understanding of AI literacy, including the limitations of LLMs that rely on historical data and lack human-like cognition (Holmes & Porayska-Pomsta, 2023; UNESCO, 2023). They must also be able to recognize potential errors and algorithmic bias, while employing EFs such as inhibition and updating to regulate responses, evaluate evidence, and make ethical decisions (Brochard, 2025; Diamond, 2013; Miyake et al., 2000).

Despite the growing importance of these competencies, a clear knowledge gap remains. Currently, there is no validated measurement instrument specifically designed to assess the Critical Intelligence Inventory for Teachers in the Use of Generative Artificial Intelligence (hereafter referred to as CI-GAI). This absence is particularly problematic given teachers' central role in guiding learning processes, supporting decision-making, and promoting ethical technology use. Without standardized assessment tools, it becomes difficult to systematically evaluate and develop these competencies.

Therefore, the development of a CI-GAI is both academically and practically significant. Such a scale can help address this knowledge gap by translating the concept of critical intelligence into measurable constructs and by providing empirical data to inform teacher professional development programs and educational policies. Ultimately, this effort aims to enable Thai teachers to act as intellectual leaders who use technology critically and make ethically responsible decisions in a rapidly evolving AI-driven society.

Accordingly, this study aims to examine the components and operational definitions of CI-GAI, and to develop and validate a measurement instrument based on the synthesized components. The resulting instrument is intended to support the assessment and development of teachers' critical intelligence competencies in Gen AI mediated educational contexts.

Literature Review

This study is grounded in three major conceptual domains: critical thinking, intelligence, and critical intelligence, which collectively inform the development of the CI-GAI.

First, critical thinking provides the foundation for systematic analysis and evaluation in decision-making. Facione (1990) defined critical thinking as a reasoned process aimed at reaching well-supported conclusions based on evidence, involving interpretation, analysis, evaluation, and self-regulation. Similarly, Ennis (2011) emphasized the ability to determine what to believe and what actions to take through the examination of information and the credibility of sources, while Paul and Elder (2014) highlighted intellectual standards such as clarity, accuracy, and logical consistency. In the context of generative AI, these competencies are essential for evaluating AI-generated information, which may contain inaccuracies or biases (Holmes et al., 2022; Lee et al., 2025). Therefore, critical thinking serves as a key foundation for analytical reasoning, reflective thinking, and ethical decision-making.

Second, intelligence is conceptualized as a multidimensional capability involving adaptation, reasoning, and the management of complex information. Sternberg (1986, 2012) proposed the triarchic theory of intelligence, which includes analytical, creative, and practical intelligence, emphasizing the ability to apply cognitive strategies to solve real-world problems. Likewise, the American Psychological Association (1996) defined intelligence as the ability to reason, plan, learn, and manage novel situations, while Wechsler (2025) conceptualized intelligence as purposeful and adaptive thinking. These perspectives highlight the role of higher-order cognitive processes, particularly those related to executive functions, in enabling individuals to adapt to changing contexts. In this study, intelligence theories provide a foundation for understanding cognitive adaptability and metacognitive processes in the use of Gen AI.

Third, the concept of critical intelligence integrates analytical reasoning, reflective thinking, and value-based judgment in response to complex and uncertain information environments. Bean et al. (2021) described critical intelligence as the ability to question, analyze, and evaluate information while regulating one's thinking. Goldewijk (2021) emphasized epistemic awareness, which enables individuals to recognize the limitations and contextual nature of knowledge. In addition, Brochard (2025) linked critical intelligence to EFs, highlighting the importance of cognitive control processes such as inhibition, working memory, and cognitive flexibility in evaluating information. Newbery and Kaunert (2023) further emphasized the ethical dimension of decision-making in complex contexts.

Based on the synthesis of these theoretical perspectives, this study conceptualizes critical intelligence as comprising six core components: analytical reasoning, metacognition, cognitive adaptability, ethical decision-making, epistemic awareness, and cultural intelligence. These components represent an integration of cognitive, ethical, and socio-cultural competencies required for critically engaging with Gen AI in educational contexts.

Research Methodology

The development of the CI-GAI followed a research process consisting of 3 phases.

Phase 1: Development of CI-GAI

The first phase aimed to develop a measurement instrument to assess teachers' critical intelligence in analyzing, evaluating, and making critical decisions when using Gen AI in instructional practices and professional decision-making. The scale was developed through the synthesis of theoretical and empirical literature related to Critical thinking, Intelligence, and Critical intelligence, as well as studies on the use of generative AI in education.

Identification of Components and Operational Definitions

A comprehensive literature review was conducted to identify the construct structure of Critical Intelligence in the use of Gen AI. The synthesis resulted in six key components: Analytical reasoning, Metacognition, Cognitive adaptability, Ethical decision-making, Epistemic awareness, and Cultural intelligence. Operational definitions were then established to guide the development of indicators and measurement items.

Development of Indicators and Items

Indicators were derived from the operational definitions to represent observable critical intelligence behaviors in teachers' use of Gen AI. Measurement items were developed using a five-point Likert scale to assess teachers' abilities to evaluate AI-generated information, reflect on their thinking processes, adapt to new information, consider ethical implications, recognize knowledge limitations, and consider socio-cultural contexts.

Content Validity Assessment

The draft scale was evaluated by five experts in educational measurement, cognitive psychology, and related fields. Content validity was assessed using the Content Validity Index (CVI) at both the item level (I-CVI) and scale level (S-CVI). Expert feedback was used to revise and refine the items.

Pilot Testing and Item Analysis

The revised scale was pilot tested with 30 teachers who had characteristics similar to the target population. Item quality was analyzed using corrected item–total correlation coefficients and

Cronbach's alpha reliability coefficients. The results were used to further refine the scale before conducting the main data collection.

Phase 2: Data Collection Procedure

This phase involved collecting data to examine the psychometric properties of the CI-GAI. The sample consisted of 538 teachers from private schools in Thailand with at least one year of teaching experience, which exceeded the minimum recommend sample size for confirmatory factor analysis (Hair et al., 2010; Kline, 2016). Participants were selected using multistage sampling from different regions to ensure sample diversity and adequacy for Confirmatory Factor Analysis (CFA).

Data were collected through an online questionnaire administered via Google Forms. The questionnaire consisted of two sections: (1) demographic information (e.g., gender, age, education level, teaching experience, and grade level taught), and (2) the Critical Intelligence Inventory, which was developed based on six components: Analytical reasoning, Metacognition, Cognitive adaptability, Ethical decision-making, Epistemic awareness, and Cultural intelligence.

Before completing the questionnaire, participants received information about the research objectives, procedures, confidentiality measures, and their right to withdraw at any time. Informed consent was obtained electronically prior to participation. The questionnaire was accessible through digital devices such as computers, smartphones, or tablets.

After the data collection period, data screening was conducted to check for completeness and response quality. Incomplete responses and questionnaires with abnormal response patterns (e.g., straight-lining or extreme response patterns) were excluded before proceeding to the statistical analysis stage.

Phase 3: Data Analysis and Scale Validation

This phase evaluated the psychometric quality of the CI-GAI by examining its construct validity and reliability. Data collected from teachers in private schools in Thailand were analyzed using Confirmatory Factor Analysis (CFA) with the LISREL program.

First, CFA was conducted to examine the consistency between the measurement model and the empirical data. The model consisted of six latent components: Analytical reasoning, Metacognition, Cognitive adaptability, Ethical decision-making, Epistemic awareness, and Cultural intelligence. Model fit was assessed using several goodness-of-fit indices, including Chi-square, RMSEA, NFI, NNFI, CFI, RMR, and SRMR.

Second, the quality of the measurement scale was evaluated by examining factor loadings, Construct reliability (CR), and Average variance extracted (AVE) to confirm convergent validity and the internal reliability of each construct.

Finally, the statistical results were summarized to confirm the structural validity, construct validity, and reliability of the scale, verifying that the instrument is appropriate for assessing the CI-GAI.

Research Findings

Content Validity

CI-GAI was evaluated for content validity by five experts in cognitive psychology, educational measurement, and related fields using the Content validity index (CVI).

The scale consisted of six components: Analytical reasoning, Metacognition, Cognitive adaptability, Ethical decision-making, Epistemic awareness, and Cultural intelligence. Initially, 54 items were developed, with nine items for each component. The Item-level content validity index (I-CVI) results showed that 46 items had an I-CVI of 1.00, while 9 items had an I-CVI of 0.80.

At the scale level, the Scale-level content validity index (S-CVI/Ave) was 0.97, exceeding the recommended criterion of 0.90 (Lynn, 1986; Polit & Beck, 2006, 2007), indicating high content validity. Based on expert feedback, several items were revised for clarity and alignment with the operational definitions, some items were reassigned to more appropriate components, and one redundant item was removed. Consequently, the revised instrument consisted of 53 items for the pilot testing stage.

Pilot Testing (Try-Out)

After revision based on expert feedback, the scale was pilot-tested with 30 teachers similar to the target population to evaluate item quality and reliability. Item quality was examined using item–total correlation, while reliability was assessed using Cronbach’s alpha, following the recommendations of Nunnally and Bernstein (1994) and Ebel and Frisbie (1991).

First pilot test: The overall reliability was Cronbach’s alpha = .788, indicating acceptable internal consistency for a developing instrument. Item analysis using a minimum item–total correlation of .20 showed that 20 items did not meet the criterion. These items were revised to improve clarity and alignment with the operational definitions and to better reflect teachers’ cognitive behaviors in using Gen AI.

Second pilot test: The revised scale was administered again to 30 participants, yielding Cronbach’s alpha = .947, indicating high internal consistency. Item analysis showed that most items met the criterion, although three items had item–total correlations below .20 and were removed.

After removing these items, the scale contained 50 items, with an overall Cronbach’s alpha of .955, indicating very high internal consistency. The instrument was therefore considered suitable for the main data collection phase.

Construct Validation of the Measurement Model

The revised scale was administered to 538 teachers from private schools in Thailand with at least one year of teaching experience. The sample size for confirmatory factor analysis (CFA) followed the recommendation that it should be at least 10 times the number of indicators (Hair et al., 2010; Kline, 2016). Since the instrument contained 50 indicators, the minimum required sample size was 500 participants. Therefore, the collected data were considered sufficient for analysis.

Demographic Characteristics of the Sample

Most participants were female (86.80%), while 13.20% were male. The majority were 20–35 years old (50.00%), followed by 36–45 years (31.60%) and 46–55 years (14.13%). Most respondents held a bachelor's degree (89.41%), followed by a master's degree (10.41%), while 0.19% held a doctoral degree. In terms of teaching experience, most had 1–5 years (29.74%), followed by 6–10 years (25.09%) and 11–15 years (23.42%). Regarding teaching level, the majority taught at the primary level (41.08%), followed by kindergarten (34.01%) and secondary education (24.91%).

Confirmatory Factor Analysis (CFA)

First-order Confirmatory Factor Analysis: A first-order Confirmatory Factor Analysis (CFA) was conducted to examine the consistency between the indicators and the components of CI-GAI. The analysis considered factor loadings, statistical significance, and overall model fit.

The results indicated that some indicators had low factor loadings or did not meet the established criteria. These indicators were therefore removed from the model to improve the model fit. As a result, the number of indicators was reduced from 50 to 41 indicators. The results for each component are summarized as follows:

Component 1 Analytical Reasoning

Initially consisted of 8 indicators. Two indicators were removed due to low factor loadings, resulting in 6 remaining indicators. The factor loadings ranged from 0.48 to 0.82, with Construct Reliability (CR) = 0.80 and Average Variance Extracted (AVE) = 0.41. Although some factor loadings were relatively low, they were retained based on their theoretical relevance and contribution to content coverage.

Component 2 Metacognition

Initially consisted of 7 indicators. Two indicators were removed due to low factor loadings, leaving 5 indicators. The factor loadings ranged from 0.41 to 0.80, with CR = 0.71 and AVE = 0.34.

Component 3 Cognitive Adaptability

Initially consisted of 9 indicators. Three indicators were removed, resulting in 6 indicators. The factor loadings ranged from 0.53 to 0.69, with CR = 0.82 and AVE = 0.43.

Component 4 Ethical Decision-Making

Initially consisted of 8 indicators. One indicator was removed due to not meeting the criteria, leaving 7 indicators. The factor loadings ranged from 0.18 to 0.80, with CR = 0.77 and AVE = 0.35.

Component 5 Epistemic Awareness

This component consisted of 8 indicators, all of which met the CFA criteria. The factor loadings ranged from 0.17 to 0.83, with CR = 0.83 and AVE = 0.41.

Component 6 Cultural Intelligence

This component consisted of 9 indicators, all of which met the CFA criteria. The factor loadings ranged from 0.14 to 0.80, with CR = 0.81 and AVE = 0.38.

Some AVE values were below the recommended threshold of .50, indicating moderate convergent validity; however, composite reliability (CR) values exceeded acceptable levels, supporting the internal consistency of the constructs.

After the model refinement process, CI-GAI consisted of six components and 41 indicators. The resulting measurement model of the construct is presented in the following figure.

Figure 1
The Factor Model of CI-GAI

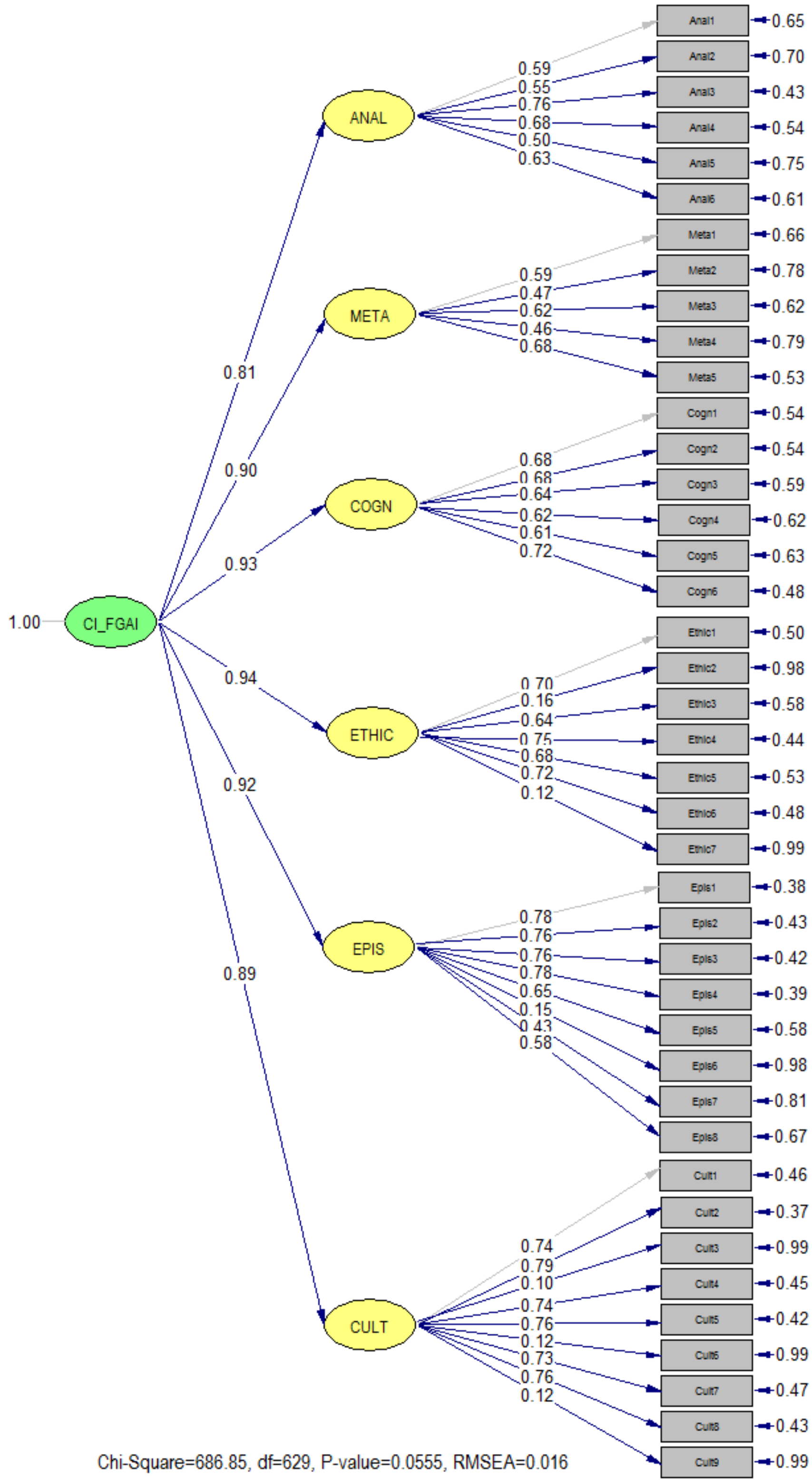

Figure 1 illustrates the second-order factor structure of critical intelligence, showing the relationships between the six components and the overall latent construct.

Second-Order Confirmatory Factor Analysis (Second-Order CFA)

A second-order Confirmatory Factor Analysis (CFA) was conducted to examine the structural model of CI-GAI which comprises six primary components: analytical reasoning, metacognition, cognitive adaptability, ethical decision-making, epistemic awareness, and cultural intelligence.

The results indicated that the structural model demonstrated a good fit with the empirical data, with several goodness-of-fit indices meeting acceptable criteria, as shown in Table 2. Specifically, the Chi-square (χ^2) value was 686.85 with 629 degrees of freedom (df) and p = 0.06, which is greater than .05, indicating that the model does not significantly differ from the empirical data. In addition, the χ^2/df ratio was 1.09, which is below the recommended threshold (≤ 2), suggesting a satisfactory model fit.

Further examination of additional fit indices showed that the Root Mean Square Error of Approximation (RMSEA) was 0.02, which is below the criterion of 0.05, indicating a low level of approximation error. The comparative fit indices, including NFI = 0.98, NNFI = 0.99, and CFI = 0.98, were all higher than the recommended threshold of 0.90, demonstrating that the model fits the empirical data well. Moreover, the Root Mean Square Residual (RMR) = 0.04 and Standardized Root Mean Square Residual (SRMR) = 0.04 were both below the acceptable criterion of 0.08, further supporting the adequacy of the model.

Regarding the absolute fit indices, the results showed that GFI = 0.94 and AGFI = 0.91, both exceeding the recommended threshold of 0.90. These results indicate that the developed structural model is appropriate and effectively explains the relationships among the variables in the model.

Table 1
Model Fit Indices of the Structural Model for CI-GAI

Goodness-of-Fit Index	Index Value	Model Fit Interpretation
1. χ^2	686.85	-
2. *df*	629.00	-
3. *p*	0.06	Good Fit
4. χ^2/df	1.09	Good Fit
5. RMSEA	0.02	Good Fit
6. NFI	0.98	Good Fit
7. NNFI	0.99	Good Fit
8. CFI	0.98	Good Fit
9. RMR	0.04	Good Fit
10. SRMR	0.04	Good Fit
11. GFI	0.94	Good Fit
12. AGFI	0.91	Good Fit

The results indicate that CI-GAI consist of six main components: 1) Analytical reasoning, 2) Metacognition, 3) Cognitive adaptability, 4) Ethical decision-making, 5) Epistemic awareness, and 6) Cultural intelligence.

All six components demonstrated high factor loadings (0.81, 0.90, 0.93, 0.94, 0.92, and 0.89, respectively), indicating that each component had a significant positive relationship with the overall construct of CI-GAI. The developed scale consisted of 41 indicators across six components.

The first component, Analytical reasoning, consisted of six indicators reflecting teachers' ability to analyze information generated by AI systems, distinguish between facts and opinions, verify sources of information, use evidence to support conclusions, and consider the consequences of decisions. These indicators represent teachers' capacity to evaluate information logically and make reasoned judgments when using Gen AI.

The second component, Metacognition, consisted of five indicators related to teachers' ability to monitor and regulate their own thinking processes. This component reflects teachers' capacity to examine whether personal beliefs influence their interpretation of AI-generated information, reflect on the strengths and weaknesses of their reasoning, and adjust their cognitive strategies when necessary.

The third component, Cognitive adaptability, included six indicators that represent teachers' ability to adapt their thinking in response to new or conflicting information. This component reflects openness to multiple perspectives, the ability to revise previous assumptions, and the application of prior experiences to new situations when interacting with AI-generated information.

The fourth component, Ethical decision-making, consisted of seven indicators reflecting teachers' ability to consider ethical implications when using Gen AI. These indicators emphasize the importance of fairness, social responsibility, and the consideration of potential impacts on others and society when making decisions based on AI-generated information.

The fifth component, Epistemic awareness, included eight indicators representing teachers' understanding of the nature and limitations of knowledge, particularly in the context of AI-generated information. This component reflects teachers' ability to critically evaluate the credibility of information, recognize the limitations and potential biases of AI systems, and question underlying assumptions before accepting information as valid.

The sixth component, Cultural intelligence, consisted of nine indicators reflecting teachers' sensitivity to social and cultural diversity when using AI in educational contexts. This component emphasizes the ability to consider learners' cultural backgrounds, adapt communication across cultural contexts, respect diverse perspectives, and collaborate effectively with individuals from different cultural backgrounds.

Discussion

The findings of this study confirm that the CI-GAI represents a multidimensional construct comprising six key components: Analytical reasoning, Metacognition, Cognitive adaptability, Ethical decision-making, Epistemic awareness, and Cultural intelligence. The measurement model demonstrated a good fit with the empirical data, and most indicators showed statistically significant factor loadings. These results suggest that the critical use of Gen AI requires not only logical reasoning and data analysis but also the ability to regulate one's own thinking, adapt to new information, evaluate ethical implications, understand the nature of knowledge, and consider socio-cultural contexts. These findings are consistent with Sternberg's (2012) theory of intelligence, which emphasizes adaptive and analytical thinking in complex and dynamic environments, as well as with Brochard (2025), who highlighted the role of executive functions in regulating cognitive processes involved in critical evaluation.

First, the findings indicate that Analytical reasoning is a fundamental component of the construct. The use of Gen AI in education requires the ability to verify the accuracy of information, use evidence to support conclusions, and systematically evaluate the consequences of decisions. This result suggests that teachers who use AI critically must be able to distinguish between factual information and opinions and verify the credibility of information sources before applying them in instructional practices or professional decision-making. This finding is consistent with Facione (1990) and Ennis (2011), who emphasized that critical thinking involves the evaluation of evidence, assessment of information credibility, and reasoned judgment.

Second, Metacognition emerged as another essential component of the model. CI-GAI involves not only evaluating the outputs produced by the system but also examining one's own thinking processes. Teachers must be able to question their own decisions, assess whether personal beliefs or biases influence their interpretation of information, and reflect on the appropriateness of the cognitive strategies used in a given situation. These findings align with Flavell (1979), who defined metacognition as the ability to monitor and regulate one's own cognitive processes, and with Sternberg (1986), who emphasized the importance of metacognitive control in intelligent behavior.

Third, Cognitive adaptability plays an important role in explaining the structure of CI_GAI. The context of Gen AI represents a dynamic environment in which information changes rapidly, multiple alternatives are available, and reinterpretation is often required. Teachers must therefore be able to remain open to new perspectives, revise existing cognitive frameworks, and apply past experiences to solve problems in novel situations. This finding is consistent with Sternberg (2012) and Wechsler (2025), who conceptualized intelligence as the ability to adapt to changing environments and apply flexible cognitive strategies.

Fourth, Ethical decision-making is a prominent component of the model, emphasizing that CI_GAI is not solely a matter of cognitive efficiency but also of responsibility toward learners, others, and society. Teachers must consider the ethical implications of using AI-generated information, particularly in contexts where Gen AI systems may produce inaccurate information, inappropriate content, or biased outcomes. This finding is supported by UNESCO (2023) and Holmes and Porayska-Pomsta (2023), which emphasize that the use of artificial intelligence in education should be guided by ethical principles, transparency, and social responsibility.

Fifth, Epistemic awareness plays a crucial role in explaining teachers' ability to evaluate knowledge and information sources in the AI era. Teachers need to recognize that knowledge generated by AI is not always definitive truth but may reflect limitations of training data, embedded biases, or incomplete perspectives. Questioning underlying assumptions, acknowledging that knowledge may evolve with new evidence, and avoiding acceptance of information simply because it appears plausible are therefore essential elements of CI-GAI. This finding aligns with Goldewijk (2021), who emphasized the importance of epistemic awareness in understanding the nature and limitations of knowledge.

Sixth, Cultural intelligence also contributes significantly to the overall structure of the model. AI-generated content may reflect cultural biases embedded in training datasets. Consequently, teachers must be capable of considering learner diversity, understanding socio-cultural contexts, and using Gen AI in ways that respect cultural differences. This finding is consistent with Newbery and Kaunert (2023) and Jyoti and Kour (2021), who emphasized the importance of cultural awareness and the ability to function effectively across diverse contexts.

Overall, the findings indicate that CI-GAI provides a comprehensive and appropriate conceptual framework for understanding how teachers engage with Gen AI in contemporary educational contexts. The developed measurement model reflects not only analytical thinking abilities but also teachers' capacity for cognitive self-regulation, critical evaluation of information, ethical decision-making, and socially responsible technology use. These competencies represent essential attributes of teachers in the twenty-first century.

Summary

This study aimed to develop and validate a measurement model of CI-GAI. Confirmatory factor analysis (CFA) was employed to examine the consistency between the theoretical model and empirical data collected from teachers in private schools in Thailand. The findings indicated that the measurement model consists of six key components: 1) Analytical reasoning, 2) Metacognition, 3) Cognitive adaptability, 4) Ethical decision-making, 5) Epistemic awareness, and 6) Cultural intelligence. The model demonstrated a good fit with the empirical data, and most indicators showed statistically significant factor loadings. These results suggest that the proposed structure appropriately explains the CI-GAI.

Implications

From an academic perspective, the findings expand the conceptual framework of critical intelligence beyond traditional perspectives toward the context of Gen AI. The study suggests that the critical use of Gen AI involves an integrated cognitive process that combines reasoning, metacognition, epistemic awareness, ethical judgment, and socio-cultural considerations.

From a practical perspective, the developed scale can be used as an instrument to assess the level of teachers' or learners' abilities in critically using Gen AI. It can also serve as a framework for designing teacher education curricula or professional development programs aimed at strengthening skills related to evaluating information credibility, reflective thinking, cognitive adaptability, ethical decision-making, epistemic awareness, and socio-cultural understanding in the use of Gen AI.

Limitations

Although this study successfully developed and validated the measurement model, several limitations should be considered. First, the sample consisted only of teachers from private schools in Thailand; therefore, the findings may have limited generalizability to public or international school contexts. Second, the use of self-report measures may introduce response bias, particularly in ethical dimensions. Third, the study focused on the measurement model and did not examine causal relationships among variables. In addition, some AVE values were moderate, suggesting that certain indicators may not fully represent the constructs.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors used generative AI tools to assist in improving language, grammar, and readability. The content was critically reviewed, revised, and validated by the authors. The authors take full responsibility for the integrity and accuracy of the final manuscript.

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