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Research article

Scale development and validation of knowledge-attitudes-practices (KAP) on artificial intelligence (AI) productivity tools in education

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Abstract: Despite the growing presence of artificial intelligence (AI) productivity tools in education, there remains a lack of standardized instruments to assess teachers' readiness and engagement with such technologies. Addressing this gap, the present study developed and validated a comprehensive scale to measure teachers' knowledge, attitudes, and practices (KAP) related to AI productivity tools. Guided by the KAP framework, the study employed a sequential exploratory design. Initial items were generated through literature review and expert input, followed by content validation by AI and education specialists. The scale was pilot-tested and refined using data from a stratified convenience sample of 300 pre-service teachers in a state university in Central Visayas, Philippines. Exploratory and confirmatory factor analyses supported an 11-factor structure across the KAP domains. The finalized 58-item scale demonstrated strong psychometric properties, including high internal consistency and construct validity. By providing a valid and reliable tool, the study contributes to AI readiness assessment and intervention designs that promote responsible AI integration and use.

Keywords: artificial intelligence, attitudes, education, knowledge, practices, productivity tools

1. Introduction

Artificial intelligence (AI) has rapidly started to significantly influence many areas, including education [1]. It has transformed how knowledge is shared [2], how learning is assessed [3], and how teaching is structured [4]. With applications such as intelligent tutoring systems, adaptive learning platforms, automated grading, and learning analytics, AI can personalize education [5], simplify teaching tasks [6], and improve student involvement [7]. These improvements not only promise efficiency but also aim to address long-standing educational problems through various teaching methods and data-driven decision-making. As AI continues to develop, it is crucial that educators, especially future teachers, understand and use its potential responsibly and effectively.

In pre-service teacher education, AI tools, especially AI productivity tools, are becoming more relevant. These include generative AI platforms such as ChatGPT [8], Grammarly [9], QuillBot [10], Canva [11], and other tools that aid in content creation, lesson planning, assessment design, and communication [12]. By automating routine tasks and providing intelligent support, these tools create opportunities to enhance teaching productivity [13], creativity [14], and flexibility [15]. For pre-service teachers, who are still developing their instructional skills and professional identity, becoming familiar with these tools could significantly affect their teaching readiness and future classroom practices. However, it remains unclear how well prepared they are to use these tools meaningfully.

Existing literature indicates that pre-service teachers exhibit varying levels of awareness, readiness, and acceptance of AI technologies. Some studies suggest that future teachers exhibit optimism [16–18] and curiosity [19,20]. However, others raise concerns about ethical use, data privacy, and job loss [21–23] as well as insufficient training or exposure [24,25]. These mixed reactions suggest that while interest in using AI in education is increasing, many pre-service teachers remain unsure or unprepared to utilize AI productivity tools in their teaching practices effectively. Their readiness depends not only on access or exposure but also on a complex mix of their knowledge about AI, their feelings about its use, and how they apply it in educational settings.

To understand this readiness, researchers in educational technology have used several models, including the Technology Acceptance Model (TAM) [26–28], the Extended TAM (ETAM) [29–31], the Unified Theory of Acceptance and Use of Technology (UTAUT) [32-34], and the Theory of Planned Behavior (TPB) [35–37]. These models highlight cognitive and attitudinal factors that affect technology adoption [38–41]. However, many of these frameworks mainly focus on perceived usefulness, ease of use, or behavioral intention, which may not fully reflect the reality of actual practice. Additionally, tools created from these models often evaluate general digital or technological readiness rather than focusing on AI productivity tools. As a result, these tools may overlook the specific behavioral, ethical, and teaching aspects related to using AI in education.

The Knowledge–Attitudes–Practices (KAP) model provides a behavior-focused and comprehensive approach to evaluate readiness and views on technology use [42–44]. This framework comes from the health and social sciences, having developed especially during the pandemic [45]. It has been commonly used to study how people gain knowledge, develop attitudes, and change behaviors when faced with new practices or innovations [42–44]. In education, KAP enables a detailed insight into how pre-service teachers think about AI, their feelings toward it, and how these aspects influence their actual teaching methods. Unlike the TAM or TPB, which usually focus only on intentions, KAP examines the whole journey from awareness to use. This makes it especially useful for assessing readiness in new areas, such as AI in education.

Despite its potential, limited studies [46,47] have been conducted to design and validate a tool to assess pre-service teachers' knowledge, attitudes, and practices regarding AI productivity tools using the KAP framework. This gap limits our understanding of how future educators engage with AI during their training and how they might use it in their future classrooms. With the rapid rise of generative AI tools and the growing expectations for teachers to incorporate these technologies, there is an urgent need for a reliable tool that can assess the cognitive, emotional, and behavioral aspects of AI readiness. Filling this gap is crucial for enhancing teacher preparation programs, informing policy development, and developing targeted interventions that encourage responsible and effective AI use in education.

This study aimed to create and validate a KAP-based tool that measures pre-service teachers' knowledge, attitudes, and practices regarding the use of AI productivity tools in education. By assessing these three interconnected areas, the tool sought to provide a complete view of AI readiness among future educators. The development process involved thorough steps, including item creation, expert review, and psychometric testing to ensure the scale is reliable, valid, and valuable for teacher education programs.

This KAP tool is different from other instruments in several essential ways. First, it focuses specifically on AI productivity tools, which may not be included in broader technology readiness assessments. Second, it employs a framework that captures actual practices, rather than just intentions or perceptions. This provides a clearer picture of how pre-service teachers utilize AI in their coursework and training. Third, the tool includes new generative AI platforms, making it relevant to today's educational environment. Its wide-ranging scope, theoretical basis, and practical focus set it apart from other models and add value to AI education research.

Overall, this study is crucial for efforts to integrate AI into education in a responsible manner. It offers a tested tool to evaluate pre-service teachers' readiness and engagement with AI productivity tools. This helps teacher education institutions identify training needs, develop responsive curricula, and promote ethical and practical use of AI. The study also contributes to the discussion on educational technology by introducing a novel approach to measuring AI adoption using the KAP framework. In this way, the study supports both theory and practice. It helps ensure that future teachers are prepared to handle the complexities and opportunities of AI-enhanced education.

1.1. Literature review

1.1.1. Artificial intelligence in education

Artificial intelligence (AI) has transformed numerous sectors, with education undergoing a quick change due to innovative technology [1–4]. Over the years, AI's role in education has changed from experimental models to more widely used systems in formal learning settings [48]. The use of AI in education encompasses personalized instruction, adaptive feedback systems, predictive analytics, and administrative support [5–7]. These technologies are changing how content is delivered and assessed [2–4], which affects the roles of teachers [49,50] and learners [7,51,52] in ways that challenge traditional teaching structures. Researchers emphasize that AI in education (AIED) aims to enhance learning through systems that can mimic cognitive tasks, such as reasoning, problem-solving, and decision-making [49,53,54].

Recent studies have highlighted how AI can transform student engagement and improve learning outcomes. Baidoo-Anu and Owusu-Ansah [55] pointed out both the benefits and challenges of AI in education. They noted that tools like ChatGPT and Grammarly help with personalized instruction and streamline administrative tasks. Huang et al. [56] found that AI-driven personalized video recommendations in a flipped classroom significantly improved student engagement and performance, especially among moderately motivated learners. Yuan and Liu [57] demonstrated that using Duolingo in EFL classrooms increased student engagement, motivation, and enjoyment. Similarly, Bachiri et al. [58] reported that AI-based gamified assessments raised motivation and learning outcomes in MOOCs. However, Eteng-Uket and Ezeoguine [59] found no significant improvement in results using chatbots alone, indicating a need for balanced AI integration. These findings highlight the diverse impacts of AI in education and underscore the importance of implementing it carefully.

Teachers' experiences with AI are becoming a key area of research due to their significant role in adopting AI. Some studies indicate that teachers are open to using AI tools, particularly those that help reduce repetitive tasks, as revealed by Hashem et al. [60] and Kim and Kim [61], or those that support data-driven decision-making, as found by Schelling and Rubenstein [62] and Obery et al. [63]. However, other findings suggest reluctance due to limited knowledge of AI, fear of job loss, or concerns about data privacy and professional independence [21–25]. Dieterle et al. [64] emphasized the need for ethical and practical guidelines to promote the responsible and ethical use of AI in educational settings, such as classrooms. Teachers often feel overwhelmed by the rapid growth of AI tools, especially when professional development fails to keep up with advancements [65]. These challenges underscore the growing need to comprehend not only AI's capabilities but also the real-life experiences and perspectives of educators who have to integrate these tools.

Students have shown mixed responses to AI in their learning environments. AI has enhanced engagement and supported independence through personalized learning paths [7,51,52,55–58]. However, some students worry about relying too heavily on automated feedback [66] and missing out on the benefits of human interaction [67,68]. AI platforms that offer multilingual support [69,70] and diverse materials [71,72] have successfully met the varied needs of the learners. Still, the long-term effects on critical thinking [73,74] and creativity [75,76] remain a matter of debate. In this situation, educators must strike a balance between the benefits of automation and teaching values that highlight human judgment and emotional intelligence. As AI becomes more advanced, discussions about its ethical, cognitive, and cultural impacts in education are intensifying.

Overall, the literature presents a complex view of AI’s increasing role in education. Evidence supports its ability to improve teaching methods and increase access to knowledge [55–58,60–63]; however, issues related to ethics, training, infrastructure, and readiness persist [66–68,73–76]. Understanding AI’s role requires not only technical evaluation but also an examination of how different stakeholders perceive, interact with, and adapt to AI tools. This expanding field of research sets the stage for further investigation into how teachers prepare for and respond to the new challenges of education, including AI.

1.1.2. AI frameworks in education

To explore how teachers interact with AI, researchers have employed various theoretical models that examine the adoption and behavior of technology. One of the most referenced models is the TAM, which suggests that the perceived usefulness and ease of use of technology affect whether people accept it [38]. Studies using TAM in education have found that teachers are more willing to use AI based on their beliefs about its effectiveness and how comfortable they are with its interface [26–28]. However, TAM has drawbacks [77,78], as it does not fully capture complex realities, especially in teaching and challenging educational settings. While it predicts intentions, it overlooks key ethical issues, cultural factors, and institutional barriers that influence the adoption of AI.

The UTAUT expands on TAM by incorporating additional factors, such as social influence, enabling conditions, and behavioral intention [40]. Research on UTAUT in AI education emphasizes the importance of peer support, leadership, and training in helping teachers integrate AI [32–34]. Still, like TAM, UTAUT mainly focuses on intentions and ignores emotional and behavioral aspects [79,80], such as reactions to AI, long-term adjustments, and changes in teaching methods. Therefore, while both models provide valuable insights, their relevance to AI in education, particularly in terms of teachers' readiness and ongoing use, is limited.

Other behavioral models, such as the TPB, have also been used to examine educators' views on AI technologies, including attitudes, social norms, and perceived control to predict technology usage, offering a more psychological perspective [41]. However, its accuracy heavily relies on specific conditions and assumes that people always make rational choices [41,81], which may not apply to unplanned behavior [82], including in fast-changing or resource-limited educational settings. Furthermore, these models typically encompass broad technology categories and do not specifically address AI-related aspects, such as automation, unclear algorithms, and data ethics.

In this regard, the KAP model has emerged as a valuable alternative for understanding technology adoption, particularly in the context of educational innovation [42–44]. The KAP model considers not only what users know and feel about a specific technology but also how they apply it in practice. It aligns with the growing need for behavioral frameworks that represent real-world classroom use and the ongoing processes of trial, error, reflection, and adjustment that characterize teachers' interactions with AI. Although KAP has been widely applied in areas such as public health and environmental studies, its use in the context of AI in education is still in development, marking a significant opportunity for future research and expansion.

1.1.3. Developed and validated scales on AI in education

In response to the growing role of AI in education, several recent studies have developed and tested tools to measure different aspects of AI engagement. One notable example is the Artificial Intelligence Literacy Scale for Teachers (AILST) [83], which evaluates teachers’ knowledge, views, and ethical awareness about AI. This tool offers a multidimensional framework grounded in practical teaching skills. Similarly, the Generative Artificial Intelligence Attitude Scale [84] measures students' attitudes toward generative AI platforms, such as ChatGPT, capturing factors including enthusiasm, skepticism, and perceived educational value. These studies are significant for quantifying attitudes toward AI, but they often have a limited focus or cater to specific groups.

Other tools examine motivation and ethical perspectives. The AI Motivation Scale (AIMS) [85], based on self-determination theory, gauges students' motivation to learn with AI across five areas, including both intrinsic and extrinsic factors. Meanwhile, the AI and Ethics Perception Scale (AEPS) [86] examines views across five ethical domains: transparency, accountability, privacy, fairness, and human oversight. This highlights the importance of ethical understanding in AI engagement. These instruments demonstrate a growing interest in specific measurement tools; however, they often focus on either cognitive or attitudinal aspects and rarely capture actual behaviors.

Scales aimed at educational professionals include tools like the Artificial Intelligence Attitude Scale for Nurses [87] and a Turkish version of the AI Literacy Scale for university students [88]. While these tools are not explicitly designed for teacher education, they offer valuable insights into methods suitable for validating AI-related constructs. The literature reflects a growing variety of target groups, including students, professionals, and pre-service teachers; however, relatively few tools offer frameworks that combine knowledge, attitudes, and actions on a single scale.

There is also new work on perception-based tools, such as that conducted by Amani and Bisriyah [89], which gathered qualitative data on how students view AI's role in writing and academic success. While these are not validation studies for scales, they help shape future instrument design by identifying important themes in student interactions with AI. Additionally, studies such as Yazid and Aziz [90] on the readiness of primary and secondary school teachers to use AI-generated content offer valuable insights into the professional development needs of educators in this area.

Despite these advances, a clear gap remains: current tools often focus either on single constructs (such as literacy, motivation, or ethics) or specific groups (such as students or nurses), without offering a unified framework for understanding teachers' overall engagement with AI. Few tools use the KAP model to capture what teachers know, how they feel, and how they use AI tools in real-world situations. Addressing this gap is crucial for enhancing measurement accuracy and developing interventions that cater to the diverse and evolving needs of AI integration in education.

1.2. Research questions

This study developed and validated a KAP-based scale to measure the pre-service teachers' knowledge, attitudes, and practices regarding AI. The following questions guided the instrumentation study:

1. What items are created for the KAP-based scale?
2. What are Aiken's V values for the scale's content validity?
3. What are the infit, outfit, and person reliability measures based on the scale's item analysis?
4. What is the underlying factor structure of the scale as revealed by the exploratory factor analysis (EFA)?
5. Does the factor structure of the scale demonstrate a good fit as observed using confirmatory factor analysis (CFA)?
6. How does the scale establish construct validity through CFA?
7. To what extent is the scale internally consistent and reliable across its subscales?

2. Methods

This study employed a sequential exploratory research design, following the three-phase procedure recommended by Boateng et al. [91] for scale development in social and behavioral research: (1) item development, (2) scale development, and (3) scale evaluation. This design guided the formulation, testing, and refinement of the KAP-based scale on AI productivity tools in education. Each phase integrated procedures to ensure strong content validity, construct validity, discriminant validity, and internal consistency, supported by both expert judgment and rigorous statistical techniques.

In the item development phase, an initial pool of 60 items (20 for each of knowledge, attitudes, and practices) was generated based on a comprehensive literature review of artificial intelligence in education, KAP studies, and related theoretical constructs. Instead of adopting existing instruments, the researchers identified key concepts and trends in AI applications and translated them into item statements. *Knowledge* items were constructed as dichotomous (True/False), while *attitudes* and *practices* items used a 5-point Likert scale. The initial items were evaluated by seven experts in education, ICT, and AI integration. Content validity index (CVI) was determined using Aiken's V, with values of 0.80 or higher indicating good content relevance and clarity [92].

During the scale development phase, the instrument was pre-tested with 15 pre-service teachers for clarity and comprehensibility, resulting in minor rewording. The revised version was then administered to 300 pre-service teachers from the 4200 student population of the teacher education college from a state university in Central Visayas, Philippines, selected using stratified convenience sampling to represent a mix of gender and academic levels. This sample size is adequate per the recommendation of Clark and Watson [134]. The demographic profile of the respondents is shown in Table 1.

Table 1. Demographic profile of the survey respondents.

Profile	Category	Frequency	Percentage
Age	Below 21 years old	134	44.67
	21–23 years old	157	52.33
Sex	Male	9	3.00
	Female	239	79.67
Year level	First year	37	12.33
	Second year	87	29.00
	Third year	93	31.00
	Fourth year	83	27.67
Socioeconomic status	Below Php 10,957	180	60.00
	Php 10,957 – Php 21,914	78	26.00
	Above Php 21,914	42	14.00

According to Table 1, most of the respondents were aged 21–23 years (52.33%) and female (79.67%). Respondents were fairly distributed across year levels, with third-year students comprising the largest group (31.00%). In terms of socioeconomic status, the majority (60.00%) reported a monthly household income below Php 10,957. Data obtained from these respondents were analyzed using the Rasch model, employing dichotomous analysis for *knowledge* items and polytomous analysis for *attitudes* and *practices* items. This approach enabled the evaluation of item difficulty measures, including infit and outfit statistics with acceptable values of 0.40–1.60 [93] and person reliability (≥0.80) [94]. Rasch analysis also ensured that each item measured along the intended latent trait continuum without redundancy or excessive misfit.

In the scale evaluation phase, EFA was conducted to determine the underlying factor structure. Assumption testing was performed using Bartlett's test of sphericity ($p < 0.001$) and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (KMO ≥ 0.60) [95]. Principal axis factoring with varimax rotation was applied. Items with factor loadings above 0.40 were retained [96], while those below 0.40 were removed from the scale, including items K1 and K10. CFA was then conducted on the same dataset to test the hypothesized factor structure. Model fit was evaluated using indices including the Comparative Fit Index (CFI ≥ 0.95), Tucker - Lewis Index (TLI ≥ 0.95), and root mean square error of approximation (RMSEA ≤ 0.06) [97]. Construct validity was assessed through strong standardized factor loadings (≥0.50), discriminant validity was determined by examining the inter-factor covariances and heterotrait-monotrait ratio (HTMT), ensuring that no values exceeded 0.85, and the multicollinearity assumption was ascertained through the variance inflation factor (VIF) [98,99]. To assess internal consistency, Cronbach's alpha values were computed for each KAP domain. Alpha values of ≥0.70 were considered acceptable, ≥0.80 good, and ≥0.90 excellent [100].

All analyses were conducted using the Jamovi software, version 2.3.25.0, at a 95% confidence level, except for HTMT and VIF, which were performed using PLS-SEM, version 4.1.0.9. All p-values lower than 0.05 were considered significant.

3. Results

3.1. KAP scale items

Twenty items were generated for each KAP domain, totaling 60 items for the whole scale. These items are presented in Table 2.

Table 2. Items in the KAP scale (N = 60 items).

Code	Items	Reference
K1	AI in education is only humanoid robots that teach.	[48]
K2	AI can personalize learning for students.	[48,52,54,56]
K3	AI in education aims to replace human teachers.	[49,50]
K4	AI systems in education are unbiased.	[64,86]
K5	AI understands student emotions better than human teachers.	[49]
K6	AI can predict student success based solely on past performance.	[48]
K7	AI is limited to grading multiple-choice questions.	[48]
K8	AI can adjust teaching strategies based on student feedback.	[48,52,84]
K9	Using AI hinders students' critical thinking.	[66,73,74]
K10	AI technology is too expensive for schools.	[71]
K11	AI systems in education are always fair to all students.	[64,86]
K12	AI technology always protects student privacy.	[64,86]
K13	AI can worsen existing inequalities among students.	[64,86]
K14	Student data collected by AI is always secure.	[64,76,86]
K15	AI encourages a diverse and inclusive learning environment.	[69-71]
K16	AI integration means replacing traditional teaching methods.	[49,50]
K17	AI can adapt to different learning styles.	[54,59]
K18	AI focuses only on academics, neglecting skills like creativity.	[75]

K19	Teachers will become obsolete with AI.	[49,50]
K20	AI has the potential to improve education.	[48,55,84]
A1	AI can enhance the quality of education.	[48,55,84]
A2	AI integration is a positive step for modernizing education.	[48,84]
A3	AI can adapt to diverse learning styles.	[59]
A4	AI use is necessary to keep up with technology.	[48,84]
A5	AI complements, rather than replaces, teachers.	[49,50,60]
A6	I am concerned about AI bias in education.	[64,84]
A7	AI respects students' privacy.	[64,76,86]
A8	AI can address education inequalities.	[64,71]
A9	There should be strict regulations for AI use.	[64,86]
A10	AI should be transparent in its decisions.	[64,86]
A11	AI can provide personalized learning.	[56,72,84]
A12	I am confident that AI can assess various assignments.	[48]
A13	AI use promotes critical thinking and problem-solving.	[52]
A14	AI can positively influence student academic achievements.	[56,59]
A15	AI can adapt its teaching strategies based on feedback.	[56]
A16	AI may hinder creativity and collaboration skills.	[75]
A17	Teachers may feel threatened by AI.	[50,65]
A18	I am concerned AI might lead to job losses in education.	[50]
A19	The cost of AI in education outweighs the benefits.	[71]
A20	Resistance to AI is mainly due to a lack of understanding.	[68]
P1	I actively use AI-powered educational tools.	[51,53-55,89]
P2	I use AI applications to understand academic subjects.	[51,53-55,89]
P3	I have participated in AI integration workshops.	[51,53-55,89]
P4	I use AI resources when facing academic challenges.	[51,53-55,89]
P5	I share beneficial AI tools with peers.	[51,53-55,89]
P6	I use AI resources in my academic projects.	[51,53-55,89]
P7	I use AI tools for presentations and reports.	[51,53-55,89]
P8	I collaborate with AI platforms to improve learning.	[51,53-55,89]
P9	I seek feedback from AI systems on assignments.	[51,53-55,89]
P10	I use AI tools for tasks like note-taking.	[51,53-55,89]
P11	I am comfortable interacting with AI chatbots for school.	[51,53-55,89]
P12	I collaborate with AI platforms for group projects.	[51,53-55,89]
P13	I use AI-driven communication tools with peers and educators.	[51,53-55,89]
P14	I contribute to online forums that use AI for learning.	[51,53-55,89]
P15	I am open to AI-generated student material recommendations.	[51,53-55,89]
P16	I reflect on how AI tools affect my academics.	[51,53-55,89]
P17	I seek teacher feedback on using AI in my learning.	[51,53-55,89]
P18	I adjust my AI use based on teacher feedback.	[51,53-55,89]
P19	I regularly assess AI's impact on my study habits.	[51,53-55,89]
P20	I actively seek new AI tools to enhance my education.	[51,53-55,89]

As shown in Table 2, the developed KAP scale consists of 60 items across three domains: *knowledge* (K), *attitudes* (A), and *practices* (P), with 20 items per domain. The *knowledge* items address both accurate concepts and common misconceptions about AI in education. For example, some items reflect misunderstandings such as AI being limited to humanoid robots (K1) or eventually replacing human teachers (K3, K19). In contrast, other items highlight AI's more advanced capacities, such as personalizing learning (K2), adapting instruction (K8), and protecting student privacy (K12). The *attitudes* items capture respondents' beliefs, concerns, and levels of acceptance regarding AI use, ranging from supportive views on AI's potential to modernize education (A1, A2, A4) to reservations about bias, privacy, and job security (A6, A17, A18). The *practices* items, on the other hand, focus on respondents' actual use and engagement with AI tools in their academic tasks, including using AI for academic support (P1, P6, P10), collaboration (P12, P13), reflection (P16, P19), and seeking feedback (P17, P18). Each item was aligned with relevant literature to ensure theoretical grounding.

3.2. Content validity index

The results of the content analysis were subjected to Aiken's V test to determine the CVI of the KAP scale dimensions and items. The results are presented in Table 3.

Table 3. Aiken's V coefficients for the content validity of the KAP scale.

Item	Aiken's V	Description	Item	Aiken's V	Description	Item	Aiken's V	Description
K1	0.86	Valid	A1	1.00	Valid	P1	1.00	Valid
K2	1.00	Valid	A2	1.00	Valid	P2	1.00	Valid
K3	1.00	Valid	A3	1.00	Valid	P3	1.00	Valid
K4	1.00	Valid	A4	0.95	Valid	P4	1.00	Valid
K5	1.00	Valid	A5	0.95	Valid	P5	1.00	Valid
K6	0.95	Valid	A6	0.90	Valid	P6	1.00	Valid
K7	0.95	Valid	A7	0.95	Valid	P7	1.00	Valid
K8	0.90	Valid	A8	0.95	Valid	P8	1.00	Valid
K9	0.90	Valid	A9	0.95	Valid	P9	1.00	Valid
K10	0.86	Valid	A10	0.95	Valid	P10	1.00	Valid
K11	0.95	Valid	A11	1.00	Valid	P11	1.00	Valid
K12	0.95	Valid	A12	0.95	Valid	P12	0.95	Valid
K13	0.95	Valid	A13	1.00	Valid	P13	1.00	Valid
K14	1.00	Valid	A14	1.00	Valid	P14	1.00	Valid
K15	1.00	Valid	A15	0.90	Valid	P15	0.95	Valid
K16	0.95	Valid	A16	0.90	Valid	P16	1.00	Valid
K17	0.95	Valid	A17	0.95	Valid	P17	1.00	Valid
K18	0.95	Valid	A18	0.95	Valid	P18	0.95	Valid
K19	0.95	Valid	A19	1.00	Valid	P19	0.95	Valid
K20	1.00	Valid	A20	1.00	Valid	P20	1.00	Valid
Overall	0.95	Valid	Overall	0.96	Valid	Overall	0.99	Valid

Legend: Not valid (0.00–0.79), valid (0.80 and above)

Table 3 shows that all 60 items received Aiken's V coefficients ranging from 0.86 to 1.00, surpassing the commonly accepted threshold of 0.80 for content validity. *Knowledge* items such as K2, K3, K4, K5, K14, K15, and K20 achieved perfect agreement, while K1 and K10 had the lowest ratings (0.86) but were still considered valid. *Attitude* items also showed consistently high validity, with A1–A3, A11, A13, A14, A19, and A20 rated at 1.00. The *practices* domain recorded the highest average, with the majority of items scoring a perfect 1.00, except for P12, P15, P18, and P19, which slightly trailed with V values between 0.95 and 0.99. Overall, the mean Aiken's V coefficients for each domain were 0.95 for K, 0.96 for A, and 0.99 for O, affirming strong content validity across the scale.

3.3. Item analysis

The KAP scale underwent item reduction analysis through the Rasch model to ensure the items were parsimonious. These numbers show how well each item fits within the underlying construct that the scale measures. Table 4 displays the measure, infit, and outfit statistics for each item in the domains.

Table 4. Item analysis of the KAP items.

Item	Measure	Infit	Outfit	Item	Measure	Infit	Outfit	Item	Measure	Infit	Outfit
K1	-0.88	0.98	0.96	A1	-2.54	0.90	0.87	P1	-2.20	0.63	0.68
K2	-1.46	1.02	1.03	A2	-2.56	0.80	0.79	P2	-2.60	0.70	0.70
K3	-3.09	0.96	0.72	A3	-1.73	0.88	0.88	P3	-0.79	1.11	1.14
K4	-0.06	0.94	0.93	A4	-2.53	0.89	0.89	P4	-2.66	0.79	0.80
K5	-3.30	0.96	0.68	A5	-2.89	1.28	1.29	P5	-2.02	0.92	0.91
K6	-1.46	1.03	1.08	A6	-2.51	1.03	1.11	P6	-1.80	0.98	0.97
K7	-0.34	0.95	0.93	A7	-1.21	0.96	0.98	P7	-2.27	1.09	1.04
K8	0.10	1.09	1.11	A8	-1.62	0.72	0.76	P8	-2.32	0.72	0.71
K9	1.17	1.01	1.02	A9	-3.51	1.06	1.01	P9	-2.06	1.15	1.12
K10	0.52	1.01	1.03	A10	-3.15	0.86	0.82	P10	-1.43	1.34	1.32
K11	-0.11	0.93	0.92	A11	-1.97	0.90	0.89	P11	-2.01	1.00	0.96
K12	-1.00	1.03	1.04	A12	-1.42	0.86	0.87	P12	-1.54	1.01	1.01
K13	-0.43	1.08	1.08	A13	-1.08	1.03	1.04	P13	-1.73	1.42	1.36
K14	-1.50	0.99	0.97	A14	-2.15	0.64	0.64	P14	-0.91	1.14	1.12
K15	0.70	1.11	1.13	A15	-1.57	0.90	0.90	P15	-2.39	0.92	0.90
K16	-1.26	0.94	0.89	A16	-1.94	1.46	1.50	P16	-2.61	0.77	0.78
K17	-0.71	1.08	1.10	A17	-1.78	1.39	1.40	P17	-1.70	1.43	1.40
K18	0.00	0.93	0.92	A18	-1.86	1.50	1.60	P18	-2.94	1.25	1.17
K19	-1.22	0.94	0.87	A19	-1.77	0.98	1.01	P19	-2.56	1.06	1.03
K20	-1.67	1.03	1.04	A20	-2.21	0.87	0.87	P20	-2.32	0.66	0.64
person reliability		0.80		person reliability		0.86		person reliability		0.94	
p-value		0.001		p-value		0.001		p-value		0.001	

Legend: Infit/outfit: unacceptable (below 0.40 and above 1.60), acceptable (0.40–1.60); Person reliability: unacceptable (below 0.80), acceptable (above 0.80)

Table 4 displays the item fit statistics, specifically the infit and outfit mean square values, for all items in the three domains of the KAP scale. All items fall within the acceptable Rasch model fit range of 0.40–1.60, indicating that each item contributes meaningfully to its respective construct without producing noise or distortion in measurement. Furthermore, person reliability indices show good reliability for the *knowledge* and *attitudes* domains and excellent reliability for the *practices* domain, reflecting how consistently the items measure the intended traits across respondents. The model fit is further supported by statistically significant p-values in all three domains, indicating good model-data fit and confirming the internal validity of the items retained after item analysis.

3.4. Exploratory factor analysis

With the items fit for the KAP domains, the researchers subjected them to EFA to determine the latent factors within the KAP scale. Before such factor analysis, assumption checks were done, and the results are presented in Table 5.

Table 5. Results of the assumption checks before EFA.

Domain	Bartlett's test of sphericity	KMO measures
Knowledge	$c^2 = 1.041$; $p = 0.001$	Overall = 0.72; Individual items = 0.60–0.81
Attitudes	$c^2 = 2.624$; $p = 0.001$	Overall = 0.86; Individual items = 0.67–0.91
Practices	$c^2 = 4.059$; $p = 0.001$	Overall = 0.95; Individual items = 0.90–0.97

Legend: Bartlett's test: acceptable ($p < 0.001$); KMO measures: acceptable (0.60 and above)

Based on Table 5, the Bartlett's test of sphericity was significant for all domains, confirming sufficient inter-item correlations and not identity matrices. The KMO values were above 0.60, indicating acceptable to excellent sampling adequacy. Individual KMO values ranged from 0.60 to 0.97, further supporting the data's suitability for EFA. Hence, EFA was conducted on the data set, and the results are presented in Table 6.

Table 6. Results of the EFA of the KAP scale items.

Domain	Factor	No. of items	Items	SS loadings	% variance	Cum. %
Knowledge (18 items)	Personalized learning potential	7	K17, K8, K2, K15, K6, K13, K20	1.75	8.74	8.74
	Ethical and privacy concerns	3	K11, K12, K14	1.36	6.79	15.53
	Role of AI in education	3	K3, K5, K16	1.35	6.75	22.28
	Limitations and challenges	5	K18, K7, K9, K19, K4	1.32	6.62	28.90
Attitudes (20 items)	Benefits and confidence in AI integration	7	A15, A12, A11, A13, A3, A7, A8	3.12	15.61	15.60
	Perceptions of AI advantages	5	A4, A2, A1, A20, A14	2.84	14.18	29.80
	Teacher concerns and job impact	4	A17, A18, A16, A19	1.91	9.54	39.30
	Ethical considerations and human–AI collaboration	4	A9, A10, A5, A6	1.93	9.64	49.00
Practices (20 items)	Active integration and utilization	12	P2, P1, P4, P8, P11, P9, P7, P6, P5, P16, P20, P15	5.95	29.70	29.70
	Engagement in AI education and collaboration	5	P14, P3, P10, P13, P12	3.31	16.60	46.30
	Adaptation and feedback in AI usage	3	P18, P17, P19	2.08	10.40	56.70

Table 6 revealed four underlying factors within the *knowledge* domain after the removal of two items (K1 and K10) due to their factor loadings falling below the acceptable threshold of 0.40. The remaining 18 items clustered into: (1) Personalized learning potential (PLP), which reflects knowledge of AI's ability to tailor instruction, predict performance, and promote inclusive learning; (2) Ethical and privacy concerns (EPC), focusing on respondents' awareness of data security, fairness, and ethical implications of AI use in education; (3) Role of AI in Education (RAE), encompassing beliefs about AI's capacity to replicate or transform teacher roles and traditional pedagogies; and (4) Limitations and challenges (LC), representing recognition of the risks associated with AI, such as hindering creativity or neglecting non-academic skills. These four dimensions cumulatively explained 28.90% of the variance in the *knowledge* domain.

For the *attitudes* domain, four dimensions also emerged from the 20-item scale. The first factor, benefits and confidence in AI integration (BCA), reflects optimistic perceptions and strong confidence in AI's capability to improve educational outcomes. The second factor, perceptions of AI advantages (PAA), clusters items that agree with AI's potential to modernize and transform education. The third factor, teacher concerns and job impact (TCJ), centers on perceived threats posed by AI to employment and traditional teaching roles. The fourth factor, ethical considerations and human-AI collaboration (ECH), emphasizes attitudes toward the importance of maintaining transparency, privacy, and cooperation between educators and AI systems. Together, these factors reflect both enthusiasm and caution among respondents in adapting to AI-enhanced education, explaining 49.00% of the variance in the *attitudes* domain.

In the *practices* domain, three robust factors surfaced from the 20-item pool. The first and most dominant factor, active integration and utilization (AIU), comprises behaviors involving proactive use of AI tools for instruction, tasks, and learning enhancement. Second, engagement in AI education and collaboration (EAE) relates to respondents' participation in AI-related programs, communities, and collaborative practices. Third, adaptation and feedback in AI usage (AFA) focus on reflective practices, including evaluating AI's impact, soliciting feedback, and adapting AI use based on insights. These three factors account for a cumulative 56.70% of the variance in the *practices* domain, highlighting a well-structured framework of how AI is currently being utilized in educational practice.

Figure 1 shows the scree plots to visualize the EFA results. These plots support the EFA results, confirming the retention of four factors for *knowledge*, four for *attitudes*, and three for *practices*. These clear breaks align with the eigenvalues and the explained variance, validating the multidimensional structure of the KAP construct.

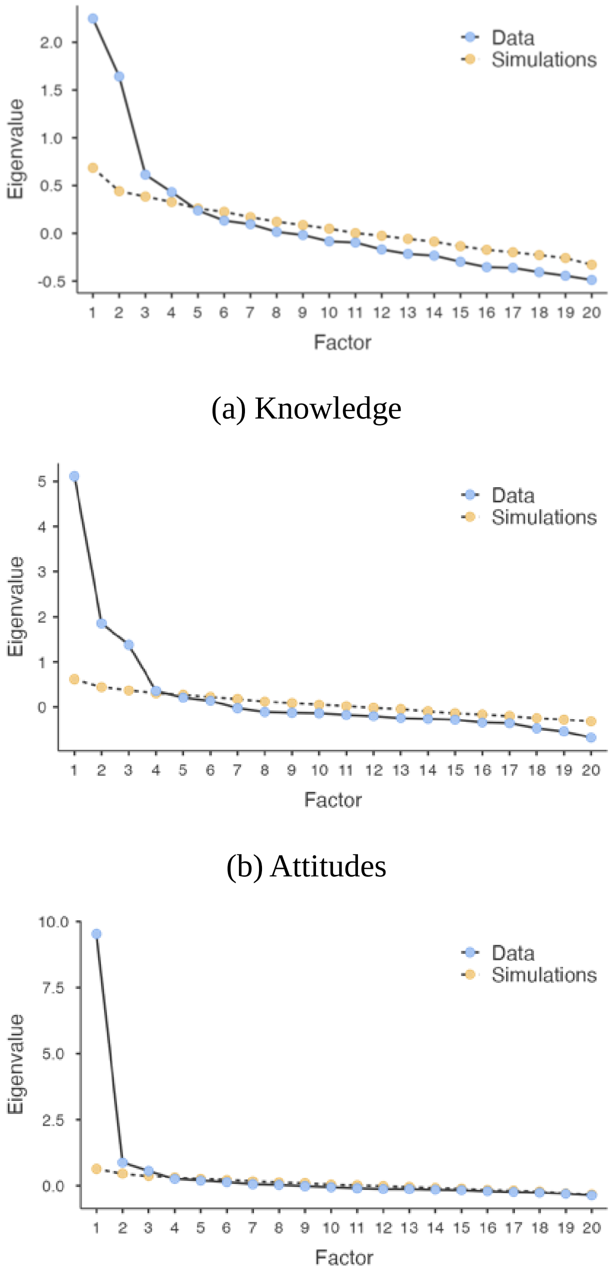
3.5. Confirmatory factor analysis

After extracting the underlying factors from the KAP scale, the KAP domain factors were subjected to CFA. First, the fit indices were obtained, and the results are highlighted in Table 7.

Table 7. Fit indices of the KAP scale domains.

Domain	CFI	TLI	RMSEA
Knowledge	1.00	0.96	0.05
Attitudes	0.97	0.94	0.06
Practices	1.00	0.98	0.06

Legend: CFI: acceptable (0.95 and above); TLI: acceptable (0.95 and above); RMSEA: acceptable (0.06 and below)



(a) Knowledge

(b) Attitudes

(c) Practices

Figure 1. Scree plots for knowledge, attitudes, and practices.

As shown in Table 7, the CFA results indicate that the KAP scale demonstrates a good model fit across all three domains. The CFI values range from 0.97 to 1.00, meeting the recommended threshold of 0.95 and above. Similarly, the TLI values range from 0.94 to 0.98, with two domains exceeding the acceptable cutoff and one very close to it. The RMSEA values are all within the acceptable limit of 0.06 or below. These results confirm that the proposed factor structures for each domain adequately fit the observed data, validating the dimensionality derived from the EFA.

The factor loadings for each item are reflected in Table 8.

Table 8. Factor loadings of the KAP items according to CFA.

Factor	Item	Loading	p	Factor	Item	Loading	p	Factor	Item	Loading	p
PLP	K17	0.66	<0.001	BCA	A15	0.75	<0.001	AIU	P2	0.79	<0.001
	K8	0.63	<0.001		A12	0.70	<0.001		P1	0.76	<0.001
	K2	0.54	<0.001		A11	0.71	<0.001		P4	0.76	<0.001
	K15	-0.57	<0.001		A13	0.64	<0.001		P8	0.80	<0.001
	K6	-0.52	<0.001		A3	0.71	<0.001		P11	0.70	<0.001
	K13	0.50	<0.001		A7	0.58	<0.001		P9	0.65	<0.001
	K20	0.51	<0.001		A8	0.52	<0.001		P7	0.74	<0.001
EPC	K11	0.57	<0.001	PAA	A4	0.71	<0.001		P6	0.68	<0.001
	K12	0.62	<0.001		A2	0.82	<0.001		P5	0.70	<0.001
	K14	0.66	<0.001		A1	0.78	<0.001		P16	0.74	<0.001
RAE	K3	0.59	<0.001		A20	0.52	<0.001		P20	0.81	<0.001
	K5	0.65	<0.001		A14	0.66	<0.001		P15	0.71	<0.001
	K16	0.54	<0.001	TCJ	A17	0.81	<0.001	EAE	P14	0.75	<0.001
LC	K18	0.66	<0.001		A18	0.78	<0.001		P3	0.67	<0.001
	K7	0.51	<0.001		A16	0.53	<0.001		P10	0.73	<0.001
	K9	0.52	<0.001		A19	0.51	<0.001		P13	0.76	<0.001
	K19	0.51	<0.001		A9	0.50	<0.001		P12	0.74	<0.001
	K4	0.50	<0.001	ECH	A10	0.68	<0.001	AFA	P18	0.73	<0.001
					A5	0.67	<0.001		P17	0.68	<0.001
					A6	0.50	<0.001		P19	0.74	<0.001

Legend: Acceptable (0.50 and above)

As reflected in Table 8, all items across the KAP domains of the developed scale demonstrated acceptable factor loadings, with values ranging from 0.50 to 0.82 and all p-values less than 0.001, indicating statistical significance. For the *knowledge* domain, the highest loading was observed for LC with K18, while others, such as PLP, EPC, and RAE, also showed strong item loadings, particularly K14 and K5. In the *attitudes* domain, items loaded well under their respective factors, with A2 under PAA and A17 under TCJ reflecting particularly strong alignment. Similarly, in the *practices* domain, items under AIU, such as P20 and P8, along with other items under EAE and AFA, consistently exceeded the 0.50 threshold, confirming strong factor-item relationships.

The factor covariances were also looked into to ascertain collinearity and discriminant validity. These covariances are shown in Table 9. The factor covariances were analyzed to evaluate the relationships between latent constructs within each KAP domain. All covariance estimates fell below the accepted threshold of 0.85, indicating the absence of multicollinearity and supporting discriminant validity. In the *knowledge* domain, covariance estimates suggest meaningful but distinct conceptual dimensions. Similarly, in the *attitudes* domain, factor covariances indicate moderate associations while preserving factor independence. The *practices* domain showed the highest inter-factor covariances, yet still within the acceptable range. These results confirm that the KAP scale measures theoretically related but empirically distinct constructs, satisfying the conditions for discriminant validity.

Table 9. Factor covariances as measures of discriminant validity and multicollinearity in CFA.

Domain	Factor pair	Estimate
Knowledge	PLP-EPC	-0.50
	PLP-RAE	-0.23
	PLP-LC	0.24
	EPC-RAE	0.38
	EPC-LC	0.12
	RAE-LC	0.33
Attitudes	BCA-PAA	0.63
	BCA-TCJ	0.08
	BCA-ECH	0.44
	PAA-TCJ	-0.12
	PAA-ECH	0.71
	TCJ-ECH	0.23
Practices	AIU-EAE	0.81
	AIU-AFA	0.81
	EAE-AFA	0.67

Legend: Acceptable (less than 0.85)

Aside from the factor covariances, the study also included the heterotrait-monotrait ratio (HTMT) to further ascertain the discriminant validity of the tool. The results are shown in Tables 10–12.

Table 10. HTMT of the *knowledge* domain of the KAP tool.

Construct	EPC	LC	PLP	RAE
Ethical and privacy concerns				
Limitations and challenges	0.38			
Personalized learning potential	0.54	0.58		
Role of AI in education	0.20	0.64	0.39	

Legend: Acceptable (less than 0.85)

Based on Table 10, the HTMT of the *knowledge* domain confirms discriminant validity among the constructs, indicating that while related, the constructs remain distinct. The lowest correlation between EPC and RAE shows clear differentiation, while the higher value between LC and PLP suggests a stronger conceptual link between understanding AI's potential and recognizing its constraints.

Table 11. HTMT of the *attitudes* domain of the KAP tool.

Construct	BAC	ECH	PAA	TCJ
Benefits and confidence in AI integration				
Ethical considerations and human–AI collaboration	0.36			
Perceptions of AI advantages	0.57	0.58		
Teacher concerns and job impact	0.44	0.50	0.22	

Legend: Acceptable (less than 0.85)

As gleaned in Table 11, the HTMT results confirm acceptable discriminant acceptability, with coefficients below the recommended 0.85 threshold. This demonstrates that the constructs are empirically distinct from one another. Each construct contributes a specific dimension of teachers' attitudes toward AI, and the values indicate that these domains do not overlap excessively.

Table 12. HTMT of the *practices* domain of the KAP tool.

Construct	AIU	AFA	EAE
Active integration and utilization			
Adaptation and feedback in AI usage	0.83		
Engagement in AI education and collaboration	0.84	0.74	

Legend: Acceptable (less than 0.85)

According to Table 12, the HTMT results indicate satisfactory discriminant validity, with coefficients within acceptable thresholds. These results affirm that the constructs are distinguishable from each other. Although interrelated, they represent different dimensions of teachers' practical engagement with AI tools, ensuring that the scale captures nuanced variations in practice rather than overlapping constructs.

To establish the collinearity of the items, the variance inflation factors (VIF) were computed. These values are highlighted in Table 13.

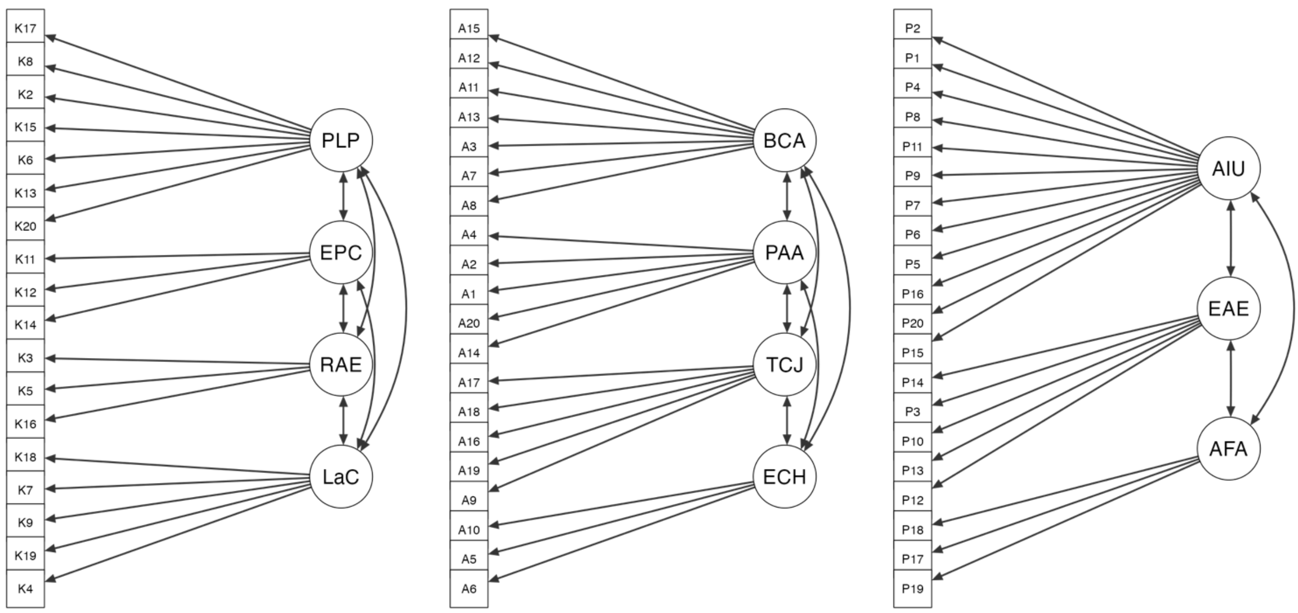
Table 13. VIF values of the items in the KAP tool.

Knowledge items	VIF	Attitude items	VIF	Practice items	VIF
K2	1.19	A1	1.52	P1	2.65
K3	1.20	A2	1.66	P2	3.00
K4	1.14	A3	1.43	P3	2.02
K5	1.24	A4	1.21	P4	2.64
K6	1.17	A5	1.11	P5	1.91
K7	1.35	A6	1.32	P6	2.15
K8	1.38	A7	1.38	P7	2.93
K9	1.07	A8	1.19	P8	3.00
K11	1.32	A9	1.69	P9	1.86
K12	1.54	A10	1.79	P10	1.56
K13	1.09	A11	1.61	P11	2.03
K14	1.38	A12	1.75	P12	1.38
K15	1.40	A13	1.31	P13	1.60
K16	1.09	A14	1.53	P14	2.26
K17	1.36	A15	2.06	P15	1.66
K18	1.43	A16	1.19	P16	1.78
K19	1.11	A17	1.95	P17	1.46
K20	1.03	A18	1.77	P18	1.54
		A19	1.13	P19	1.31
		A20	1.20	P20	2.59

Legend: Acceptable (less than 5.00)

As presented in Table 13, the VIF values for the domains of the KAP tool fall well below the commonly accepted thresholds for multicollinearity. For the *knowledge* items, the values ranged from 1.03 to 1.54, indicating a low degree of collinearity among items. *Attitude* items exhibited slightly higher values, ranging from 1.11 to 2.06, while *practice* items showed values between 1.31 and 3.00. All values are within the acceptable threshold of 5.0, suggesting that none of the items demonstrated problematic multicollinearity. This indicates that each item contributes uniquely to its respective construct, reinforcing the structural soundness of the measurement model and supporting the reliability of the KAP tool in capturing distinct dimensions of knowledge, attitude, and practice related to AI in education.

Furthermore, the path diagrams of the factor items are shown in Figure 2.



(a) Knowledge (b) Attitudes (c) Practices

Figure 2. CFA path diagrams for knowledge, attitudes, and practices.

Based on these diagrams, the factor structures for each KAP domain effectively captured the hypothesized latent constructs related to teachers' application of AI productivity tools in the classroom. The model demonstrated excellent fit, as evidenced by the acceptable CFI, TLI, and RMSEA values. These fit indices affirm that the data sufficiently support the hypothesized structure of the KAP scale, indicating that the relationships between observed items and their underlying factors are both statistically and conceptually sound.

3.6. Reliability analysis

After the dimensionality test, the researchers subjected the KAP scale to reliability analysis. The reliability analysis results are shown in Table 14 as Cronbach's alpha values.

Table 14. Cronbach's alpha values of the KAP scale.

Factor	No. of items	Cronbach's alpha	Interpretation	Dimension	Cronbach's alpha
PLP	7	0.806	Good	Knowledge	0.714
EaPC	3	0.758	Acceptable		(Acceptable)
RoAiE	3	0.700	Acceptable		
LaC	5	0.748	Acceptable		
BaCiAi	7	0.843	Good	Attitudes	0.831
PoAA	5	0.819	Good		(Good)
TcaJI	4	0.735	Acceptable		
EcaHC	4	0.726	Acceptable		
AiaU	12	0.932	Excellent	Practices	0.946
EiAEaC	5	0.849	Good		(Excellent)
AaFiAU	3	0.755	Acceptable		

Legend: Acceptable (0.70–0.79), good (0.80–0.89), excellent (90 and above)

The individual factors within the KAP scale demonstrate acceptable to excellent internal consistency as reflected in their respective Cronbach's alpha values. The *knowledge* factors recorded alpha values ranging from 0.700 to 0.806, indicating acceptable to good reliability. Additionally, the *attitude* factors ranged from 0.726 to 0.843, also reflecting acceptable to good reliability. Furthermore, the *practices* domain showed strong internal consistency, yielding values of 0.849 and 0.755, indicating good to acceptable reliability.

At the domain level, the internal consistency estimates remain consistent with the individual factor results. The *knowledge* domain recorded a composite Cronbach's alpha of 0.714, indicating acceptable reliability. The *attitudes* domain yielded a value of 0.831, which is considered good, while the *practices* domain demonstrated excellent internal consistency with a domain-level alpha of 0.946. These values affirm that each domain reliably captures the constructs they were intended to measure, supporting the multidimensional structure of the KAP framework and ensuring that responses across items within each domain are coherent and dependable.

4. Discussion

The development of the KAP scale to assess pre-service teachers' engagement with AI productivity tools in education was grounded in a rigorous and systematic psychometric process, resulting in a valid and reliable instrument. The scale's content reflects the multifaceted nature of AI use in education, capturing both technical knowledge and ethical concerns, emotional responses ranging from optimism to apprehension, and a broad spectrum of behavioral practices. It was deliberately designed to move beyond surface-level familiarity with AI tools and instead assess deeper conceptual understanding and reflective use. This is consistent with assertions that AI is most beneficial in education when seen as a co-agent that supports teachers and not as a substitute [101,102]. The inclusion of concerns about creativity and equity also mirrors findings in the published literature that highlight both the promise and the challenges of AI integration in learning contexts [103,104].

The scale's content validity was firmly established through expert judgment using Aiken's V, where all items achieved high relevance scores, supporting their clarity and alignment with the KAP framework. Aiken's V is a rigorous method for quantifying expert agreement, particularly suitable when raters are few but well-versed in the construct [105]. Similar to past findings [94], the strong values across all domains demonstrate that the items captured the theoretical intent of the scale, an essential first step in scale construction [91] that was reaffirmed by best practices in instrument development for educational assessment [91,94]. These results ensured that subsequent statistical analyses were performed only on conceptually sound and contextually relevant items.

Item performance under the Rasch model further confirmed the robustness of the KAP scale. All items showed productive fit within the acceptable infit and outfit range [93,95] and were also highlighted in Rasch measurement guidelines [93,94]. This indicates that each item contributed meaningfully to the measurement of its respective latent trait without introducing noise. The consistency of item fit across domains supports the scale's structural validity and shows that pre-service teachers interpreted the items as intended. This strong item performance across all three domains reinforces the construct validity of the scale and its utility for accurate trait estimation. Similar methodological rigor has been observed in other educational instrument development efforts [106,107], which also employed Rasch modeling and confirmatory factor analysis to ensure psychometric robustness.

Person reliability estimates also offered additional support for the scale's psychometric soundness. These values suggest the instrument's strong capacity to distinguish between individuals across varying levels of the measured traits [95,100]. The lower reliability observed in the *knowledge* domain, while still acceptable, may reflect disparities in AI exposure and background knowledge among respondents, a phenomenon similarly identified by existing literature [101,103]. On the other hand, the higher reliability of the *attitudes* and *practices* domains is consistent with previous studies, noting that attitudes and self-reported behaviors tend to demonstrate stronger internal consistency due to their more stable and personal nature [108].

EFA revealed clear, interpretable factor structures within each domain of the KAP scale, supported by high KMO values and significant Bartlett's tests, which confirm the dataset's suitability for factor analysis [96,109]. The resulting factor structures reflected theoretical expectations: the *knowledge* domain captured factual and conceptual understanding, *attitudes* measured both positive beliefs and ethical apprehensions, and *practices* reflected both tool usage and reflective engagement. These multidimensional structures align with published findings that underscore the importance of both cognitive and affective dimensions in understanding how educators respond to AI [110,111].

CFA further validated the scale's structure, with model fit indices, such as CFI, TLI, and RMSEA, indicating a strong alignment between the theoretical model and observed data. The clear separation between factors in each domain was reinforced by covariance and HTMT values all falling below the 0.85 threshold and VIF values below 5.00, confirming discriminant validity and the absence of multicollinearity [99,112]. This suggests that while the constructs are related, they capture distinct aspects of teachers' engagement with AI tools. A strong model fit in CFA provides confidence that latent variables are being accurately measured [113], making the KAP scale a psychometrically robust instrument for educational research.

Internal consistency was also supported by Cronbach's alpha values ranging from acceptable to excellent across all factors and domains. These values exceed commonly accepted thresholds for research instruments [97,98,114], affirming that the items within each dimension work well together to measure their respective constructs. The scale's reliability is essential for its use in educational diagnostics and policy planning, where valid and consistent measurements are crucial for shaping interventions and decisions.

Taken together, the findings across various analyses establish the KAP scale as a psychometrically sound instrument for assessing pre-service teachers' readiness to integrate AI productivity tools in education. It captures the complexity of AI engagement in classrooms, not merely as a set of tools to be used but as a technological paradigm that affects teaching identity [49,50,65,90], pedagogy [51–54,56,59,89], and ethics [64,86]. Positive attitudes and informed practices around AI are key predictors of successful integration [115]. The KAP scale can thus serve both as a diagnostic tool and as a basis for targeted teacher education programs aimed at fostering responsible and effective AI use in classrooms.

4.1. Theoretical and practical implications

The findings of this study contribute meaningfully to the theoretical understanding of how pre-service teachers engage with artificial intelligence in education by offering a validated instrument that operationalizes the constructs of KAP in the context of AI productivity tools. Prior studies have explored AI adoption from either a technological or pedagogical lens. Still, the present scale bridges these domains by systematically capturing the cognitive, affective, and behavioral dimensions of AI integration. This multidimensional framework reinforces and extends TAM [38], wherein perceived usefulness and ease of use are considered central predictors of technology adoption. However, the inclusion of ethical awareness, professional responsibility, and reflective practice in this scale suggests that TAM alone is insufficient for capturing the depth of educators' interaction with emerging AI technologies. This scale aligns more closely with recent extensions of TAM, such as UTAUT [116] and the AI literacy frameworks [117], by accounting for contextual, ethical, and pedagogical considerations. In this regard, the KAP model has emerged as a valuable alternative for understanding technology adoption, particularly in the context of educational innovation [42–44]. The KAP model considers not only what users know and feel about a technology but also how they apply it in practice. It aligns with the growing need for behavioral frameworks that represent real-world classroom use and the ongoing processes of trial, error, reflection, and adjustment that characterize teachers' interactions with AI. Although KAP has been widely applied in areas such as public health and environmental studies [45], its use in the context of AI in education is still in development, marking a significant opportunity for future research and expansion.

By empirically demonstrating that knowledge, attitudes, and practices surrounding AI are distinguishable yet interrelated constructs, the scale also contributes to theoretical discourses on digital competence and AI readiness. Researchers have argued for the importance of teacher agency in AI adoption [103,104], emphasizing that teachers must not only understand AI's functions but also its limitations, risks, and societal implications. The strong factor loadings related to ethical concerns, equity, creativity, and the impact of AI on learner diversity substantiate these concerns and position this scale as an innovative tool to assess readiness for AI adoption beyond instrumental knowledge. This echoes findings by Liubarska [14], who highlighted the creative potential of AI in teacher education, and by Nguyen et al. [7], who emphasized AI's role in enhancing student engagement and critical thinking. Furthermore, recent work on the multiple representations framework and science educational videos [118] also supports the theoretical stance that technological engagement must be coupled with cognitive depth and pedagogical alignment.

The validated factor structures also lend empirical support to constructivist and sociocultural theories of technology adoption. Tools, including digital ones, mediate learning and transform social interactions [119]. The *practices* domain of the scale, which includes collaborative, reflective, and adaptive uses of AI tools, captures this sociocultural dimension of tool-mediated learning. Moreover, the *attitudes* domain, particularly the factors addressing emotional orientations and professional values, echoes the concept of self-efficacy and the role of beliefs in shaping behavior [120]. These theoretical underpinnings underscore the importance of evaluating not only what teachers know but also how they feel about and apply that knowledge in complex educational environments. This insight is supported by the dual perceptions of pre-service teachers [24], balancing enthusiasm and concern, as critical to understanding responsible AI integration. Similarly, the findings reinforce that teacher perceptions of generative AI shape how they integrate such technologies into science education [18].

Practically, the three-domain, multi-factor structure of the KAP scale offers educators, curriculum developers, and policymakers a powerful diagnostic tool to identify strengths and gaps in pre-service teacher preparation for AI integration. For teacher education institutions, the scale can inform curriculum enhancement by targeting specific competencies, such as ethical decision-making or adaptive tool usage, that are identified as underdeveloped. Its fine-grained factor structure allows for targeted interventions, such as workshops focusing on improving knowledge about generative AI applications or reflective seminars addressing apprehensions about creativity and data privacy. Several studies have emphasized the importance of these differentiated responses that include stressing the value of personalized AI-assisted learning [5] and demonstrating the effectiveness of generative AI in facilitating inquiry-based lesson design [12]. Additionally, the development of instructional materials such as flexible STEM education modules [121] provides a parallel model of how validated tools can guide curriculum improvements in complex, technology-integrated fields.

For school systems and policymakers, the scale enables large-scale benchmarking of AI readiness, which is essential in an era where AI policies are being crafted rapidly without sufficient ground-level data. Institutional support and teacher beliefs play crucial roles in the successful implementation of AI [19], while performance gaps and instructional limitations are experienced during the shift to distance learning [122], underscoring the need for preparedness frameworks like KAP. Moreover, technology integration in higher education is undergoing a paradigm shift that requires tools for evaluating teacher readiness across technical and affective dimensions [123]. This is especially crucial in the post-pandemic educational landscape, where digital equity and tool competence have become central concerns.

Furthermore, the scale's structure lends itself to adaptation for in-service teacher development and cross-cultural validation. The modular nature of the factors allows for contextual tailoring while preserving the core theoretical constructs. In this way, the scale can contribute to international comparative studies on AI adoption in education, advancing both empirical and theoretical knowledge across varied settings. Differences in institutional infrastructure [124] and technology beliefs [125] influence how educators receive and utilize technology, including AI. Similar findings suggest that instructional experiences [126] and the learning environment [127] significantly mediate how pre-service teachers engage with digital innovations such as AI. Meanwhile, research reflections by pre-service teachers during online learning [128] further reinforce the need for integrative, theory-informed tools that assess both readiness and experience.

In summary, this study advances theoretical discourse by offering a nuanced and validated framework for understanding how teachers engage with AI tools, incorporating not only technological and pedagogical dimensions but also ethical and affective ones. It bridges gaps in current models of technology adoption and proposes a more holistic view of teacher readiness. Practically, it equips stakeholders with a robust tool for evidence-based decision-making, program development, and policy formulation in the context of AI-integrated education. This aligns with broader efforts in Southeast Asia to evaluate educational innovations in STEM and digital education, as seen in regional studies [129–131], which all affirm the need for thoughtful, grounded approaches to technology use in teaching and learning.

4.2. Potential uses of the KAP scale

The development of the KAP scale for AI productivity tools in education opens multiple opportunities for application across educational levels and contexts. As a diagnostic tool, it allows teacher education institutions and professional development programs to assess educators' knowledge, attitudes, and practices about AI integration. By providing baseline data, it helps identify conceptual, affective, or behavioral gaps, which can then be addressed through targeted training and support. For instance, if results reveal deficiencies in ethical awareness or concerns about algorithmic bias, programs can be restructured to include modules that address AI fairness, transparency, and accountability, reflecting the concerns raised in the literature [64,65,104]. Moreover, studies such as that by Ning et al. [83] highlight the growing need for reliable tools to assess AI literacy, reinforcing the relevance of the KAP scale in contemporary teacher education.

Beyond diagnostics, the KAP scale serves as a valuable instrument for both formative and summative evaluations of training programs. By administering the scale before and after professional development interventions, educators and trainers can measure actual changes in cognitive understanding, value orientations, and instructional behaviors related to AI. This evidence-based approach not only supports responsive and iterative program design but also strengthens accountability mechanisms within teacher education institutions. Such an approach resonates with scholarly recommendations [62,63,117] that emphasize the importance of continuous monitoring in the development of AI-related competencies. Furthermore, Nguyen et al. [51] highlighted how tools like ChatGPT significantly impact student learning behaviors, underscoring the need to equip teachers with the skills to effectively manage AI-enhanced learning environments.

At the policy and system level, the KAP scale offers a robust framework for strategic planning and resource allocation in digital transformation initiatives. Educational leaders can deploy the scale across schools, regions, or systems to generate aggregated data on teacher AI readiness. This information can inform national or institutional strategies and help policymakers identify specific domains, such as adaptability, creativity support, or equity, that require urgent attention. The scale's structure, grounded in 11 interrelated dimensions, allows for nuanced, data-driven planning in line with the principles of equitable and inclusive AI integration advocated by UNESCO [132]. Its utility is further supported by published findings that institutional AI capabilities enhance student outcomes [52] and how AI may shift rather than replace the teacher's role [50].

Individually, the KAP scale enables teachers to engage in reflective self-assessment and personalized professional development. When accompanied by mentoring or coaching, this self-directed approach can support growth-oriented trajectories and facilitate the adoption of innovation. The value of such individualized feedback aligns with relevant theories and frameworks [116,119,120]. Additionally, studies demonstrate how AI-based educational tools impact teacher perceptions [61] and highlight the role of AI in mitigating workload-related burnout [60]. At the same time, cautionary insights on cognitive offloading [73] and diminished student thinking capacities [66] reinforce the need for critically conscious engagement with AI.

In academic research, the KAP scale offers a standardized, theoretically grounded instrument for examining the correlation between teachers' AI-related knowledge, attitudes, and practices and teaching outcomes, student engagement, and institutional support. It can be used for longitudinal studies, cross-cultural comparisons, or evaluations of specific interventions. The scale complements existing AI education instruments [83–85], all of which expand the field's methodological repertoire. These tools support a deeper understanding of AI readiness, student perceptions, and the motivational underpinnings of AI use in education. Additional studies [53–55] also advocate for integrating theory-driven, human-centered approaches into AI systems and their educational evaluation.

Ultimately, the KAP scale supports the ethical, informed, and purposeful integration of AI in education. It empowers teachers not only to adopt AI tools but to adapt and critically reflect on their use in alignment with pedagogical goals and learner diversity. This human-centered stance is echoed by scholars who question whether AI can truly replicate teachers' roles [49] and advocate for inclusive strategies that leverage AI to support multilingual and diverse learners [69,71]. In line with broader concerns about AI's impact on cognition, critical thinking, and student autonomy [74–76], the KAP scale positions teachers at the forefront of innovation while maintaining the ethical and instructional integrity of the learning process. As AI technologies continue to evolve, tools like the KAP scale remain essential in ensuring that educators are not only technologically adept but also pedagogically intentional and ethically grounded.

4.3. Limitations and future directions

While the development and validation of the KAP scale for AI productivity tools in education followed rigorous procedures, there are contextual considerations that may influence how the findings are interpreted or applied in broader settings. For instance, although the sample included a range of educators with varying teaching experiences, subject specializations, and institutional affiliations, it was drawn from a particular national context. The integration of AI in education is shaped by multiple contextual factors, including infrastructure, policy, and culture [103]. This implies that while the results are informative, further research may be warranted to explore how the scale performs in other regions or educational systems with different levels of AI adoption.

In terms of data collection, the study relied on self-reported responses, which are a standard approach in many KAP-type investigations. While this method offers valuable insights into personal perspectives, it may also reflect perceived expectations or social desirability in responses. Such tendencies are common in studies involving emerging educational innovations [116]. Although the instrument was designed to elicit authentic responses, future work may consider complementing self-report measures with additional qualitative or observational methods to enrich the data and offer a more comprehensive picture of actual practices.

From a methodological standpoint, the decision to conduct both EFA and CFA using a single dataset was a practical choice influenced by sample size considerations. While this approach is acceptable in initial scale development, Worthington and Whittaker [133] recommend independent replication to further validate factor structures. Subsequent studies could strengthen the evidence base by testing the instrument across diverse or larger samples to confirm its structural stability and generalizability.

It is also worth considering the evolving nature of AI technologies and their varied applications across disciplines and education levels. Although the current scale was intentionally designed with a generalist perspective, future adaptations might benefit from adding modules or subscales that focus on specific AI tools (e.g., generative AI, learning analytics) or contextual variables (e.g., discipline, educational stage). Educators' engagement with AI can be deeply influenced by the context in which it is deployed [104].

Finally, the dynamic nature of AI integration in education presents exciting opportunities for longitudinal and impact-focused research. The scale offers potential for tracking changes in teacher beliefs and behaviors over time, particularly in response to ongoing exposure to AI or participation in professional development. Aligning the scale with broader digital competence or AI literacy frameworks [117] may also provide a more holistic view of readiness that encompasses both individual and systemic factors. Overall, the KAP scale offers a sound foundation for understanding educators' perspectives on AI productivity tools. Continued exploration across contexts and with complementary methodologies can further strengthen its applicability and contribute to a deeper understanding of the evolving relationship between education and artificial intelligence.

5. Conclusions

This study successfully developed and validated a Knowledge–Attitudes–Practices (KAP) scale that reliably measures educators' engagement with AI productivity tools in education. Through rigorous item construction, expert validation, and robust statistical analyses, including exploratory and confirmatory factor analyses, the scale demonstrated strong psychometric properties and a coherent factor structure across three dimensions. The findings affirm that the scale is both theoretically grounded and practically applicable, offering a valuable instrument for diagnosing teacher readiness, informing targeted professional development, and advancing scholarly understanding of AI integration in educational settings. Ultimately, this scale contributes to the growing efforts to equip educators with the necessary competencies to navigate and harness the transformative potential of AI in 21st-century classrooms.

Author contributions

All authors conceptualized and conducted the study. G. Sumalinog and J. Mananay crafted the introduction and literature review, while C. Goles and C. Fernandez wrote the methods. I. M. Alejandro and J. M. Sanchez curated, analyzed, visualized, and interpreted the data. C. Goles and C. Fernandez contributed to the discussion of the results, while G. Sumalinog and J. Mananay formulated the conclusions and recommendations. All authors contributed to the first draft, and J. M. Sanchez finalized the draft.

Use of Generative-AI tools declaration

The authors declare the use of AI tools in the preparation of this article, exclusively for refining the grammar, structure, and spelling.

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Conflict of interest

The authors declare no conflict of interest in this paper.

Ethics declaration

The study was conducted in accordance with local legislation and institutional requirements. The respondents provided their written informed consent to participate in this study.

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