

Article

Artificial Intelligence and Digital Competencies: An Importance–Performance Analysis of Future Mathematics Teachers' Perceptions

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Abstract

This study examines how future mathematics teachers perceive the importance of AI-related and digital competencies and their self-reported performance in these areas. The study was conducted in a Mathematics Education course in Spain with 198 Primary Education students. Using an Importance–Performance Map Analysis (IPMA) framework, the questionnaire assessed six dimensions: AI awareness, AI usage, AI evaluation, AI ethics, AI trust, and digital skills, with items adapted from previous studies. The results showed that students assigned higher importance to all competencies than the level of performance they reported. AI evaluation, AI trust, and digital skills received the highest importance scores, whereas AI awareness obtained the lowest scores. The IPMA identified AI usage as the main priority for improvement, as students considered it relevant but reported comparatively lower performance. Differences by academic year and self-reported AI knowledge level suggest that students' stage of training and perceived AI knowledge influenced their perceptions. These findings reveal a gap between the importance future teachers assign to AI-related competencies and their perceived level of development. The study highlights the need for more specific and pedagogically grounded AI training in Mathematics Education and offers practical implications for teacher education curricula in response to the demands of 21st-century classrooms.

Keywords: AI knowledge; AI literacy; digital skills; IPMA; professional development



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1. Introduction

The ongoing technological advancement has led to significant transformations over the past decade (Gorecky et al., 2014). Digital transformation currently constitutes one of the main challenges facing education systems (Hassan et al., 2025). In the European context, this has led to the definition of strategic objectives aimed at developing citizens' digital competences. The European Union has set the target that, by 2030, 80% of the population should possess at least basic digital competence (European Parliament, 2025). However, the available data indicate that, at present, only 56% of individuals reach this minimum level, while projections for 2030 stand at only 59.8%.

In Education, digital transformation cannot be reduced to the incorporation of technological devices, platforms, or digital resources. Rather, it involves rethinking teaching and learning processes, the role of teachers, the nature of educational tasks, and the competencies required to participate critically and responsibly in digital environments (Pingali et al., 2026). This issue is particularly relevant in Higher Education (HE), where institutions are expected to prepare future professionals for increasingly complex, digitalized, and changing social and professional contexts. In teacher education, this challenge is even more significant, since future teachers must not only develop their own digital competence but also learn how to integrate digital technologies pedagogically in their classrooms (Chadha, 2024).

Within this broader context, Mathematics Education (ME) represents a particularly relevant field for analyzing digital transformation (Erdoğan, 2025). Mathematical activity involves specific ways of representing, exploring, conjecturing, justifying, communicating, and validating knowledge. Therefore, the integration of technology in ME cannot be understood as a merely instrumental process (Serin, 2023). Digital tools may support visualization, experimentation, modelling, and interaction with mathematical objects, but their educational value depends on the didactical conditions under which they are used (Marrades & Gutiérrez, 2000). Consequently, future teachers need to develop competencies that allow them to select, evaluate, and orchestrate digital resources according to mathematical, pedagogical, and epistemological criteria.

The emergence of Artificial Intelligence (AI), and particularly Generative Artificial Intelligence (GenAI), further expands this scenario. AI-based technologies are increasingly present in educational contexts and are associated with opportunities for personalized learning, automated feedback, content generation, and academic support (Iqbal et al., 2025; Ramadhani & Ramadhani, 2025). However, they also raise important ethical, epistemological, and pedagogical challenges (Tang, 2025). In ME, these challenges are especially significant because mathematical learning requires not only obtaining correct answers but also interpreting procedures, validating reasoning, identifying errors, constructing arguments, and connecting representations (Jita et al., 2025). As a result, the integration of AI into mathematics teacher education requires more than general digital competence. It requires the development of AI-related pedagogical competence, understood as the capacity to understand, use, evaluate, and critically integrate AI systems in ways that are mathematically meaningful, ethically responsible, and didactically justified (Meylani, 2025).

Despite the growing interest in AI in education, its integration into ME still reveals substantial gaps in the literature. First, there is a lack of clear guidelines and evidence-based strategies to train teachers in the pedagogical use of AI, which limits its effective implementation in the classroom (Bekdemir, 2024). Second, empirical research is scarce regarding how and to what extent AI technologies contribute to improved mathematical learning outcomes (Panqueban & Huincahue, 2024). Third, many AI-based tools are developed without aligning with foundational pedagogical principles of mathematics instruction, which reduces their relevance and impact in real classroom settings (Awang et al., 2025).

In response to these challenges, this study examines the perceptions of future Primary Education teachers regarding AI literacy and digital skills within their training as prospective mathematics teachers. The aim is to provide empirical evidence to support the design of Mathematics Education programmes that respond to the demands of 21st-century teaching and to clarify how AI-related and digital competencies can be integrated into mathematics teacher education.

2. Theoretical Framework

2.1. Digital and AI Competence in Mathematics Teacher Education

Competency-based education emerged in HE in the late 20th century as a response to social, economic, and technological transformations that challenged traditional content-based models. This approach gained strength in the 1990s, driven by the demand for adaptable professionals in complex environments (Chappel et al., 2020). Internationally, initiatives such as the Tuning Project (Dalle Rose & Haug, 2014) and the DeSeCo Project (Rychen & Salganik, 2003) played a central role in defining and organizing educational competencies. These efforts provided a common reference for institutions aiming to align their curricula with workforce needs and societal expectations, contributing to the global discourse on HE reform.

In the European context, the [Bologna Declaration \(1999\)](#) marked a key milestone by launching the European Higher Education Area. This process reinforced the role of competencies in teaching and learning, while also emphasizing quality assurance, student mobility, and employability (Huisman et al., 2012). Within this framework, generic competencies have been considered essential across academic fields, as they contribute to lifelong learning and professional development (Sá & Serpa, 2018). Nevertheless, scholars have also warned that an excessive emphasis on standardized competencies may prioritize market-oriented outcomes and reduce the cultural and contextual richness of academic programmes (Palfreyman, 2008; Wihlborg & Teelken, 2014).

The digital transformation of society has added new demands to this competency-based approach. Although general competencies remain important, the increasing digitalization of educational and professional settings requires the development of more specialized forms of competence. Digital competence includes the knowledge, skills, attitudes, and strategies needed to interact with digital technologies in a critical, safe, ethical, and effective manner (Gallardo-Echenique et al., 2015). In this sense, digital competence is broader than digital skills. While digital skills refer mainly to operational or procedural abilities, such as using software, managing digital resources, or communicating through digital platforms, digital competence also includes critical judgement, ethical awareness, problem-solving, collaboration, and the capacity to evaluate the implications of digital technologies in specific contexts.

Various frameworks and conceptual foundations address digital competence in education (Asagar, 2025). Within the European context, two frameworks are particularly relevant for understanding this domain. The European Digital Competence Framework for Citizens (DigComp 3.0) defines digital competence from a civic perspective and organizes it around areas such as information and data literacy, communication and collaboration, digital content creation, safety, and problem solving (Cosgrove & Cachia, 2025). In parallel, the European Framework for the Digital Competence of Educators (DigCompEdu) focuses on teachers' professional digital competence and on the pedagogical use of digital technologies in teaching, learning, assessment, and professional engagement (Redecker, 2017). These frameworks are useful because they show that digital competence is not limited to technical proficiency. Rather, it involves the capacity to use digital technologies critically, creatively, ethically, and pedagogically.

However, digital competence cannot be understood as a generic set of abilities that can be transferred identically to all educational contexts (Niess, 2005). Its development takes on specific meanings when situated within disciplines, since each field has its own particularities. The Technological Pedagogical Content Knowledge model, or TPACK, is especially relevant in this regard, as it emphasizes that effective technology integration requires the articulation of technological knowledge, pedagogical knowledge, and content knowledge (Koehler & Mishra, 2009; Mishra & Koehler, 2006). In ME, the widespread use

of TPACK has reinforced the idea that technology integration must be analyzed in relation to a specific discipline (Abebe & Trainin, 2024; Aldemir Engin et al., 2023; Khoza & Biyela, 2020). From this perspective, the use of technology in mathematics teaching is not merely instrumental, but is embedded in disciplinary and didactical decisions.

Research in ME has shown that the educational value of technology depends on the way it is integrated into mathematical tasks and classroom interactions. For example, Goos et al. (2000) identified different roles in the relationship between users and technology, ranging from dependence on the tool to its autonomous and mathematically meaningful use. Similarly, studies on dynamic geometry environments have shown that these tools can support exploration, conjecture formulation, and the search for counterexamples, but that their impact depends on task design and teacher mediation (Marrades & Gutiérrez, 2000; Sinclair, 2003).

The teacher's role has also been examined from this perspective. In this line, Drijvers et al. (2010) demonstrated how mathematics teachers guide student-tool interactions through diverse instrumental orchestrations. These include explaining on-screen content, linking digital representations with board work, facilitating whole-class discussions, and selecting student-generated digital artifacts for collective analysis. In a similar direction, Thomas and Edson (2019) argued that the evaluation of digital resources in mathematics should not be based only on their technical characteristics, but on the extent to which they support meaningful mathematical teaching practices. Furthermore, Li et al. (2025) showed that technology integration in Primary Mathematics Education is influenced by internal factors, such as teachers' attitudes, perceived usefulness, and technological pedagogical content knowledge, as well as external factors, such as infrastructure, professional development, students' technological literacy, and family or community support.

Together, these contributions suggest that future teachers need to be prepared not only to use digital technologies but also to select, evaluate, adapt, and orchestrate them in relation to mathematical content, students' learning processes, classroom conditions, and contextual factors. This argument becomes even more relevant with the emergence of AI (Leffia et al., 2024), which requires extending traditional models of technology integration. In this regard, AI-TPACK has emerged as an extension of TPACK that accounts for the specific knowledge required to integrate AI into educational practice. Although recent studies have begun to use AI-TPACK in teacher education (Hava & Babayiğit, 2025; Runge et al., 2025), its application in ME remains limited. This gap is relevant because AI integration in mathematics teaching requires teachers to evaluate the mathematical validity, pedagogical appropriateness, ethical implications, and responsible classroom use of AI-generated outputs.

In this study, AI literacy is understood as the broader set of knowledge, skills, and dispositions that enables individuals to understand, use, evaluate, and critically engage with AI systems. However, when situated in mathematics teacher education, this construct is better understood as AI-related pedagogical competence. This term emphasizes future teachers' capacity to analyze AI-generated responses, identify possible errors or biases, evaluate the mathematical and pedagogical appropriateness of outputs, and decide how these tools can be integrated responsibly into classroom practice. Therefore, AI-related pedagogical competence should be understood as an extension and specialization of digital competence, with particular emphasis on critical evaluation, ethical responsibility, pedagogical decision-making, and disciplinary adequacy.

Nevertheless, defining and developing AI-related pedagogical competence remains challenging. Existing frameworks must reflect the specific demands and responsibilities of teaching and learning with AI (Carolus et al., 2023; Chiu et al., 2024). At the same time, teacher preparation should move beyond purely formal training. It should also include

collaborative and practice-based approaches, such as communities of practice and shared professional cultures (Seufert & Scheffler, 2016).

2.2. AI Literacy and Generative Artificial Intelligence in Mathematics Education

The growing presence of AI in educational contexts has generated increasing interest in the competencies required to understand, use, evaluate, and critically engage with AI systems (Bond et al., 2024). While digital competence refers broadly to the critical, safe, ethical, and effective use of digital technologies, AI literacy focuses specifically on AI systems, their functioning, uses, limitations, risks, and implications. In teacher education, AI literacy must also be connected to pedagogical decision-making and disciplinary knowledge. For this reason, this study uses the expression AI-related pedagogical competence to refer to future teachers' capacity to integrate AI into mathematics teaching in ways that are pedagogically meaningful, ethically responsible, and mathematically appropriate.

Several frameworks have been proposed to conceptualize AI literacy. Long and Magerko (2020) define AI literacy as a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with them, and use them meaningfully in everyday and professional contexts. This definition is particularly relevant for education because it moves beyond the technical use of AI tools and emphasises critical assessment, interaction, and meaningful application. It also provides a useful basis for considering how future teachers may engage with AI systems not only as users, but also as professionals who must make pedagogical decisions about their use.

Other models have operationalized AI literacy through more specific dimensions. Building on broader competence approaches such as the KSAVE model (Wilson et al., 2015), B. Wang et al. (2023) developed the AI Literacy Scale (AILS), which includes four key constructs: awareness, usage, evaluation, and ethics. (i) awareness "refers to the ability to identify and comprehend AI technology during the use of AI-related applications" (p. 3); (ii) usage, "refers to the ability to apply and exploit AI technology to accomplish tasks proficiently" (p. 4); (iii) evaluation "refers to the ability to analyse, select, and critically evaluate AI applications and their outcomes" (p. 4); and (iv) ethics "refers to the ability to be aware of the responsibilities and risks associated with the use of AI technology" (p. 4). These dimensions are especially relevant for future teachers because they include not only knowing how to use AI, but also being able to evaluate its outputs and implications.

Additional contributions have expanded the scope of AI literacy in education. Ng et al. (2021), drawing on Bloom's taxonomy, identified domains related to knowing and understanding AI, applying AI, evaluating and creating with AI, and addressing ethical issues. Also, Alamäki et al. (2024) developed an AI literacy framework that supports learning and teaching about the relationship between AI and sustainable development. Their framework consists of six key learning objectives and draws on the revised Bloom's taxonomy (Kratwohl, 2002) as well as the International Technology Education Association's (2007) technological literacy model. More recently, Zhou et al. (2025) extended the discussion by incorporating dimensions such as AI-TPACK, AI readiness, professional AI competence, and emotional or self-reflective components. These frameworks show that AI literacy is multidimensional and that its educational relevance depends on the capacity to connect technical, ethical, cognitive, affective, and professional dimensions.

However, in the context of ME, AI literacy must be interpreted in relation to the specific demands of mathematical teaching and learning. Future teachers do not only need to know what AI is or how to use AI tools. They must also be able to judge whether an AI-generated explanation is mathematically valid, whether it supports or hinders students' reasoning, and whether it promotes meaningful mathematical activity. For example, a GenAI system may generate a plausible solution that includes subtle mathematical errors. In such a

case, the teacher's role is essential in interpreting, validating, adapting, or rejecting the AI-generated output.

Research on GenAI and ME is still emerging, but recent studies provide important insights. [Sureda et al. \(2023\)](#) analyzed how mathematics teachers interacted with GenAI when solving mathematical problems, comparing their own solutions with those generated by ChatGPT-5. Their findings showed different modes of relationship with GenAI: rejection of its didactical value, instrumental use, and critical use of AI-generated errors as opportunities for mathematical analysis and learning. These results suggest that the value of GenAI in ME depends not only on the tool itself, but on the teacher's capacity to interpret and use its outputs critically.

In initial teacher education, [Parra et al. \(2024\)](#) compared teaching sequences designed by prospective mathematics teachers and by chatbots using the Theory of Didactical Situations (TSD) framework. Their findings indicate that chatbot-generated proposals may resemble human-produced designs in general categories, for example, in terms of educational level, mathematical topic, timing, or resources. However, important differences appear when more specific didactical categories are considered, such as the phases of the TSD (action, formulation, validation, and institutionalization). In chatbot-generated proposals, these phases may appear blurred or incorrectly interpreted. This finding is especially relevant because it shows that AI-generated educational materials may seem adequate superficially while lacking deeper didactical coherence.

Similarly, [Pochulu and Font \(2025\)](#) evaluated the design of mathematical tasks generated by prospective teachers while using GenAI and based on a set of reference indicators. They prompted ChatGPT to provide arguments both supporting and opposing how the task met these indicators. Furthermore, after adjusting or reformulating the mathematical tasks, participants had to solve them to verify their pedagogical appropriateness. Finally, they were asked to apply the criteria of didactic suitability to guide the assessment of the developed mathematical tasks.

These studies reinforce the need to approach AI in ME critically. The integration of GenAI does not automatically improve teaching and learning. Its educational value depends on the criteria used to design tasks, analyse outputs, guide student interaction, and connect AI-mediated activity with mathematical learning objectives. Therefore, future teachers require AI-related pedagogical competence that includes awareness, use, evaluation, ethics, and disciplinary judgement. In this study, these dimensions are considered central for understanding how prospective Primary Education teachers perceive their preparation to integrate AI into mathematics teaching.

2.3. Importance–Performance Analysis Map

The IPMA is an analytical method that has been infrequently applied in studies related to technology and digital competencies in education ([Chaw & Tang, 2022](#)). Originally developed by [Martilla and James \(1977\)](#), IPMA was designed to assess consumer perceptions by comparing their experienced reality against their expected outcomes. To conduct this analysis, the authors introduced two core dimensions: importance and performance. These measures were used to identify which aspects had the greatest influence on user satisfaction and which required strategic improvement. Although widely used in consumer research, its potential for educational contexts has only recently begun to be explored.

Building on this method, [Chaw and Tang \(2022\)](#) investigated the role of digital competencies in students' academic performance within the DigComp 2.2 framework. Their study evaluated 21 digital competencies and identified that the most influential competencies in academic success were problem-solving, information and data literacy, and communication and collaboration. The application of IPMA allowed the authors not only

to prioritise competencies but also to highlight performance gaps that may undermine learning outcomes.

Further extending the application of IPMA, [Ahmed \(2023\)](#) revealed that personal innovation and computer self-efficacy were rated as highly important but demonstrated low performance levels in business students. By emphasising competencies that are both valued by learners and underdeveloped, IPMA offers practical guidance for enhancing digital literacy through tailored support.

[Sobodić et al. \(2022\)](#) identified teacher feedback, clarity of assessment criteria, and the development of applied digital skills as dimensions considered highly important yet underperforming in students' perceptions of an educational technology tool. Similarly, [Balaban and Sobodić \(2022\)](#) found that the quality of information provided through the system had the greatest impact on its perceived effectiveness, reinforcing the importance of reliable content in digital learning environments when using this type of tool.

3. Materials and Methods

3.1. Research Questions

Based on the above-described related work and our aims outlined in Section 1, the following research questions guided this investigation:

- RQ1. What are the relationships between the importance and self-reported performance dimensions of AI-related digital competencies?
- RQ2. What are future mathematics teachers' perceptions of the importance and self-reported performance of AI-related digital competencies, and are there significant differences between both dimensions?
- RQ3. Which AI-related digital competencies should be prioritized according to the Importance–Performance Map Analysis?
- RQ4. In what way do perceived importance and self-reported performance differ according to students' academic year?
- RQ5. In what way do perceived importance and self-reported performance differ according to students' self-reported AI knowledge level?

3.2. Participants

Our sample consisted of 198 Primary Education students at one Spanish university during the 2024/2025 academic year. Among these students, 71.2% were women, 28.3% were men, and one student chose not to disclose their gender. The average age was 21 years. In terms of academic standing, 49% of the participants were in their second year, 15.2% in their third year, and 29.3% in their fourth year. Additionally, 6.6% were fifth-year students enrolled in a dual degree program in Early Childhood and Primary Education. All participants were currently taking or had previously taken the course Didactics of Mathematics.

3.3. Instrument

We used questionnaire items that were adapted from previous validated instruments and studies on AI literacy, AI-related attitudes, and digital competencies. The final instrument included 24 items, each assessed from two perspectives: perceived importance and self-reported performance. Therefore, participants responded to the same 24 items twice: first to indicate how important they considered each competence and then to report their perceived level of performance in relation to that competence.

The items were grouped into six dimensions according to their theoretical origin: AI awareness, AI usage, and AI evaluation were taken from [B. Wang et al. \(2023\)](#); AI ethics from [Carolus et al. \(2023\)](#); AI trust from [Choung et al. \(2023\)](#); and digital skills from [Vitezić](#)

and Perić (2024). These sources were selected because they address key dimensions of AI-related competence and digital readiness relevant to future teachers. The adapted items are provided in Appendix A.

According to the AILS proposed by B. Wang et al. (2023), we employed a seven-point Likert scale to collect the data. It was also used because Finstad (2010) suggested that seven-point scales are more suitable for electronically distributed usability surveys. An IPMA was conducted to assess both the perceived importance and the reported level of development for each variable. The reliability showed high internal consistency with a Cronbach's alpha of 0.94.

3.4. Procedure

First, a preliminary literature review was conducted to identify studies focused on AI and digital competencies, as well as research using IPMA. Based on the results of this literature review, an online questionnaire was developed using the Microsoft Forms platform, and it was distributed using two methods: (i) through personalised messages shared via social media and email, and (ii) using QR codes posted in classrooms and common areas of the faculty. Data collection took place from 1 March to 1 April 2025. A reminder was sent after fifteen days to encourage participation. Participation was voluntary, anonymous, and data confidentiality was ensured following the Declaration of Helsinki on Human Research. Upon accessing the survey, participants were provided with a summary of the purpose of the study as well as relevant ethical considerations. Before starting to respond, they had to actively consent to their participation in the study.

3.5. Data Analysis

Data analysis was performed using the statistical software JAMOVI v2.4.8 (R Core Team, 2022; The Jamovi Project, 2023). Descriptive statistics were first calculated to summarize the characteristics of the sample and to answer the research questions related to students' perceptions of AI-related digital competencies. Means and standard deviations were calculated for quantitative variables, while frequencies and percentages were estimated for qualitative variables. Before conducting inferential analyses, the normality of the data was assessed using the Kolmogorov–Smirnov test. Since the results indicated that the data were not normally distributed, non-parametric statistical tests were used. Spearman's rho was applied to examine correlations between the importance and self-reported performance dimensions of AI-related digital competencies. The Wilcoxon signed-rank test was used to compare paired scores of perceived importance and self-reported performance for each competence.

To examine group differences, the Mann–Whitney U test was used to compare students according to academic year, specifically between second-year students and upper-year students. Participants were grouped by academic year because the Mathematics Education course is taken in the second year. Thus, second-year students were compared with upper-year students, who had already completed the course. The Kruskal–Wallis test was used to compare students according to their self-reported AI knowledge level, which included three groups: low, medium, and high AI knowledge. Students' AI knowledge level was measured through a self-reported Likert-scale item (1. I know nothing; 7. I am an expert). Responses at the lower end of the scale were classified as low AI knowledge, responses at the upper end as high AI knowledge, and intermediate responses as medium AI knowledge.

Contingency tables were constructed to compare groups across qualitative variables. Finally, Importance–Performance Map Analysis (IPMA) was conducted to identify priority areas for improvement in teacher education. Competencies with high perceived importance

and comparatively lower self-reported performance were interpreted as areas requiring greater pedagogical attention. The significance level was set at $p < 0.05$. Effect sizes were reported and interpreted following the guidelines proposed by Domínguez-Lara (2018).

4. Results

To answer RQ1, correlations among the importance and self-reported performance dimensions were examined (Table 1). The results showed that all variables were positively and significantly correlated. For importance, correlations ranged from moderate to high. The weakest association was found between digital skills and AI awareness ($r = 0.385$), whereas the strongest association was observed between AI evaluation and AI ethics ($r = 0.758$). In comparison, correlations among the self-reported performance dimensions were generally weaker.

Regarding RQ2, related samples tests were conducted to compare the importance assigned by future teachers to each competence with their self-reported performance in that same competence (Table 2). Overall, students assigned higher importance to their competencies than to the level of performance they reported in them. The competences perceived as most important were AI evaluation and digital skills (both $M = 5.12$), followed by AI trust ($M = 5.11$). In contrast, AI awareness received the lowest importance score ($M = 4.25$).

Regarding self-reported performance, the highest scores were observed for AI trust ($M = 4.52$) and AI ethics ($M = 4.41$), whereas AI awareness obtained the lowest score ($M = 4.18$). Statistically significant differences between importance and self-reported performance were found for all variables ($p < 0.001$). These differences were especially noticeable for AI awareness, AI evaluation, and AI trust, which showed large effect sizes. This indicates that the gap between perceived importance and self-reported performance in these competences was not only statistically significant but also educationally relevant.

Table 1. Correlations of variables according to importance and self-reported performance.

Importance	1	2	3	4	5	6
1. AI awareness	-					
2. AI usage	0.593 **	-				
3. AI evaluation	0.537 **	0.694 **	-			
4. AI ethics	0.391 **	0.614 **	0.758 **	-		
5. AI trust	0.464 **	0.540 **	0.584 **	0.632 **	-	
6. Digital skills	0.385 **	0.553 **	0.571 **	0.661 **	0.753 **	-
Performance	1	2	3	4	5	6
1. AI awareness	-					
2. AI usage	0.324 **	-				
3. AI evaluation	0.471 **	0.455 **	-			
4. AI ethics	0.416 **	0.395 **	0.587 **	-		
5. AI trust	0.288 **	0.333 **	0.412 **	0.282 **	-	
6. Digital skills	0.294 **	0.330 **	0.381 **	0.362 **	0.442 **	-

Note: ** $p < 0.001$. The number in the horizontal first row represents the variable with the same name in the first column.

In line with RQ3, the IPMA was used to identify priority areas for improvement. Figure 1 presents the coordinates of the variables according to their perceived importance and self-reported performance. The IPMA map was interpreted using four quadrants. Competencies located in the high-importance/high-performance quadrant represent strengths that should be maintained. Competencies located in the high-importance/low-performance quadrant represent priority areas for improvement. Competencies located in the low-importance/low-performance quadrant were considered lower priorities, whereas

competencies located in the low-importance/high-performance quadrant indicate areas where self-reported performance exceeds perceived importance.

The results indicate that AI trust, AI ethics, and AI evaluation were located among the competences considered important and relatively well developed, suggesting that they should be maintained. AI awareness showed the lowest scores and therefore appeared as a lower-priority area in this analysis. Digital skills showed relatively high self-reported performance compared with their perceived importance, which may suggest that students feel comparatively more confident in this area. Finally, AI usage emerged as the main priority for improvement, as students perceived it as relevant but reported comparatively lower performance. Therefore, AI usage should receive greater attention in teacher education programmes.

Table 2. Descriptive results of importance–performance of the variables.

	Importance		Performance		Wilcoxon W	p-Value	r _{bis}
	M	SD	M	SD			
1. AI awareness **	4.75	1.1	4.18	1.0	10,700	0.001	0.51
2. AI usage **	4.91	1.2	4.36	1.0	10,779	0.001	0.43
3. AI evaluation **	5.12	1.2	4.33	1.1	10,927	0.001	0.56
4. AI ethics **	5.08	1.2	4.41	1.1	11,197	0.001	0.47
5. AI trust **	5.11	1.1	4.52	1.0	13,151	0.001	0.60
6. Digital skills **	5.12	1.1	4.29	1.1	11,570	0.001	0.49

Note: ** $p < 0.01$; r_{bis}: rank biserial correlation; low effect: 0.10; medium effect: 0.30; large effect: 0.50.

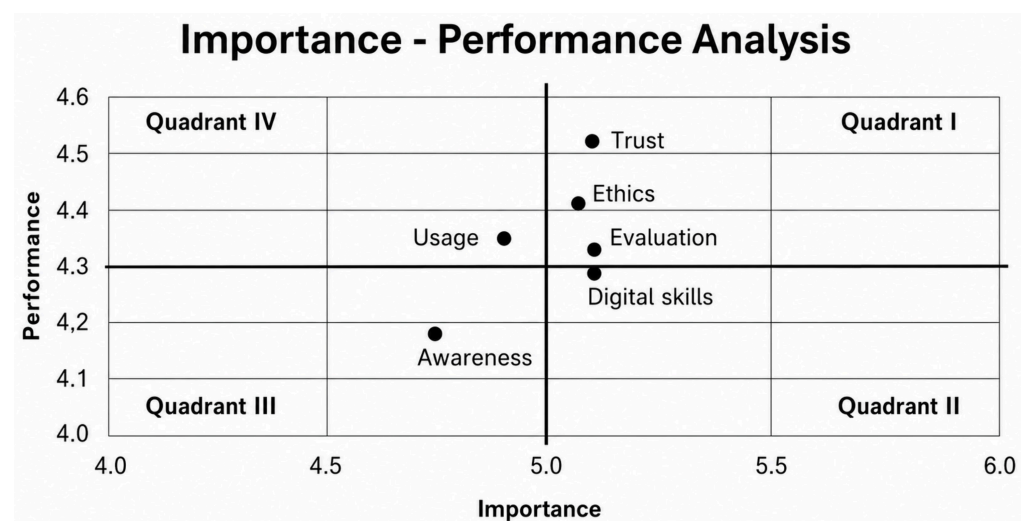


Figure 1. Importance–performance map analysis of AI and digital competences. Own source.

In relation to RQ4, which examined whether perceived importance and self-reported performance differ according to academic year, second-year students were compared with upper-year students (Table 3). In general, second-year students assigned greater importance to AI-related competences and digital skills than upper-year students. However, upper-year students reported higher self-reported performance in these competences. Among second-year students, digital skills received the highest importance score ($M = 5.40$), followed by AI trust ($M = 5.37$). In contrast, upper-year students assigned the highest importance to AI evaluation, followed by AI trust. In both groups, AI awareness was perceived as the least important competence.

Regarding self-reported performance, both groups reported the highest scores in AI trust and AI ethics, whereas AI awareness was perceived as the least developed competence. Upper-year students reported higher performance in AI usage than second-year students, suggesting a possible progression in students' perceived ability to use AI tools after com-

pleting the ME course. Statistically significant differences between academic-year groups were observed in all AI-related competences except AI awareness, both in importance and self-reported performance ($p < 0.05$). For importance, AI trust showed a moderate effect size, indicating a meaningful difference between groups. For self-reported performance, the effect size for AI usage was close to moderate ($r_{bis} = 0.26$), suggesting that academic year may be associated with students' perceived ability to use AI.

Table 3. Comparative analysis of the variables according to grade.

Importance	2nd-Year (n = 97)		Upper Year (n = 101)		MW-U	p-Value	r_{bis}
	M	SD	M	SD			
AI awareness	4.84	1.0	4.67	1.3	4519	0.344	0.08
AI Usage *	5.09	1.0	4.74	1.2	4075	0.040	0.17
AI evaluation	5.29	1.1	4.97	1.2	4122	0.053	0.16
AI ethics **	5.32	1.2	4.85	1.2	3748	0.004	0.23
AI trust ***	5.37	1.0	4.86	1.1	3445	0.001	0.30
Digital skills ***	5.40	1.0	4.85	1.1	3548	0.001	0.25
Performance	M	SD	M	SD			
AI Awareness	4.01	0.8	4.34	1.1	4177	0.072	0.12
AI usage **	4.10	0.8	4.60	1.2	3640	0.002	0.26
AI evaluation	4.18	1.2	4.47	1.1	4214	0.088	0.14
AI ethics *	4.21	1.0	4.60	1.2	4025	0.029	0.18
AI trust *	4.29	1.0	4.75	1.0	3983	0.023	0.19
Digital skills **	4.09	1.1	4.47	1.1	3781	0.005	0.23

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; U-MW: Mann-Whitney U; r_{bis} : rank biserial correlation; low effect: 0.10; medium effect: 0.30; large effect: 0.50.

Finally, in relation to RQ5, differences in perceived importance and self-reported performance were analysed according to students' self-reported AI knowledge level (Table 4). In general, the results showed a progressive pattern: students with higher self-reported AI knowledge tended to report higher performance in AI-related competencies and digital skills. Regarding importance, students with high AI knowledge assigned the highest scores to digital skills and AI usage. Students with medium AI knowledge prioritised AI evaluation, whereas students with low AI knowledge assigned the highest importance to AI ethics. The least important competencies also differed across groups. Students with high AI knowledge assigned the lowest importance to AI ethics, while students with medium AI knowledge assigned the lowest importance to AI awareness, and students with low AI knowledge assigned the lowest importance to AI usage.

Regarding self-reported performance, students with high AI knowledge reported the highest scores in AI evaluation and AI ethics. Students with medium AI knowledge reported the highest scores in AI trust and AI ethics, whereas students with low AI knowledge reported the highest scores in AI trust and AI usage. AI awareness was the lowest-rated competence among students with high and medium AI knowledge, while AI evaluation was the lowest-rated competence among students with low AI knowledge.

Statistically significant differences in importance were observed for AI awareness and AI usage ($p < 0.05$). However, the effect sizes were small, indicating that although the differences between AI knowledge groups were statistically significant, their practical magnitude was limited. In other words, students with different levels of AI knowledge assigned relatively similar importance to these competencies. In contrast, self-reported performance showed statistically significant differences across all competences ($p < 0.05$), with more noticeable differences between students with high and low AI knowledge. This suggests that AI knowledge level had a stronger practical effect on how competent students

perceived themselves to be than on how important they considered AI-related competences. Therefore, students' perceived AI knowledge appears to be more closely associated with self-reported performance than with perceived importance.

Table 4. Comparative analysis of variables according to the level of knowledge in AI.

Importance	Low Knowledge (n = 38)		Medium Knowledge (n = 116)		High Knowledge (n = 44)		χ^2 (df)	p-Value	ϵ^2_H
	M	SD	M	SD	M	SD			
AI awareness *	4.39	1.3	4.71	1.1	5.18	1.1	9.02(2)	0.011	0.05
AI usage **	4.37	1.4	4.96	1.0	5.27	1.0	10.46(2)	0.005	0.05
AI evaluation	4.96	1.1	5.16	1.1	5.16	1.3	0.96(2)	0.618	0.01
AI ethics	5.09	1.3	5.07	1.1	5.10	1.3	0.27(2)	0.873	0.01
AI trust	4.82	1.1	5.14	1.1	5.26	1.1	5.48(2)	0.065	0.03
Digital Skills	4.79	1.2	5.15	1.0	5.33	1.1	4.26(2)	0.119	0.03
Performance									
AI awareness **	3.90	1.1	4.11	0.9	4.58	1.1	9.42(2)	0.009	0.05
AI usage **	4.28	1.3	4.20	0.9	4.83	1.1	10.43(2)	0.005	0.05
AI evaluation ***	3.86	1.2	4.24	1.1	4.96	1.0	20.2 (29)	0.001	0.10
AI ethics ***	4.20	1.0	4.27	1.1	4.95	1.1	13.72(2)	0.001	0.04
AI trust *	4.34	1.3	4.45	0.9	4.88	1.0	8.95(2)	0.011	0.05
Digital Skills *	4.13	1.3	4.15	1.0	4.79	1.1	7.71(2)	0.021	0.04

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; ϵ^2_H : Kruskal-Wallis's eta squared; 0.04: low effect; 0.25: medium effect; 0.64: large effect.

5. Discussion

The aim of this study was to analyse how important it is for aspiring teachers to take an ME course that focuses on developing digital and AI-related literacy. Additionally, it aimed to assess their perceived level of acquisition of AI literacy and digital skills within the context of teaching and learning mathematics. First, the correlation results indicated that future teachers placed greater emphasis on the importance of these competencies than on their self-reported performance levels. This discrepancy may reflect a growing AI awareness of the relevance of AI-related literacy for their future professional practice as mathematics educators. However, it also highlights a perceived lack of preparedness to apply such competencies efficiently in educational settings. Similar patterns have been reported in previous research with pre-service and in-service teachers (Vitezić & Perić, 2024; Y. Wang & Lu, 2023).

Furthermore, these findings reveal a trend in teacher training in which future educators struggle to internalize competencies and confidently apply them in real-life teaching contexts (Götl et al., 2024; Scarci et al., 2024). This suggests a gap between theoretical recognition and practical development of competencies. In this study, half of the students reported not having applied these skills in real-life professional settings. Scheel et al. (2022) found that German students with higher digital skills had a greater acceptance of digital learning. Therefore, students with higher levels of proficiency may be more likely to use AI tools. Another study assessed the digital skills of more than 30,000 teachers in Latin America and determined that 70% had an intermediate level (Inamorato dos Santos et al., 2023).

It is also important to highlight the presence of two training gaps. First, the low relationship between AI awareness and digital skills suggested that technical mastery of digital tools does not guarantee a critical understanding of whether these tools incorporate AI. A student may know how to use certain technologies but fail to reflect on their limitations, biases, ethical implications, or pedagogical relevance, which are essential factors for

responsible and meaningful ME (Govender, 2024). This finding also opened opportunities to deepen critical reflection during teacher training through strategies that contextualize technology use in real classrooms (Tobondo, 2025).

Another notable finding was the stronger correlation between AI evaluation and AI ethics in both importance and self-reported performance. From an ME perspective, the consistency of this association reflects a growing awareness of the ethical implications of using AI in educational settings. This result may be linked to the participants' training context and the integration of technology into their courses. The correlation findings were supported by the descriptive results of the IPMA. In this regard, the high-importance/high-performance quadrant included AI trust, AI ethics, and AI evaluation, suggesting that these competencies should be maintained and strengthened. This reinforces the need to continue emphasizing these areas for the responsible and thoughtful use of AI in educational contexts.

In particular, the high emphasis placed on AI evaluation competence is relevant in the field of ME, where interpreting students' thinking processes and errors requires the use of technology based on pedagogical and mathematical principles. For example, Holmes et al. (2022) warned that without critical AI literacy, both teachers and students risk using AI systems uncritically. Educators must be able to interpret AI-generated outputs in mathematics, as these may have significant implications for feedback, assessment, and educational decision-making.

Specifically, AI usage fell into the high-importance/low-performance quadrant, indicating that it represents a priority area for attention in teacher training. This result suggested that future teachers consider AI usage relevant but do not yet perceive themselves as sufficiently competent to integrate AI tools into ME. Luckin et al. (2022) argue that AI knowledge should be established as a transversal competence in HE, comparable to traditional digital literacy. They also propose a multidisciplinary approach that allows students not only to understand how AI works but also to evaluate its social and ethical implications.

In contrast, AI awareness was located in the low-importance/low-performance quadrant. This result should be interpreted cautiously, since AI awareness represents a foundational component of AI literacy rather than a competence that can be considered irrelevant. It may reflect a partial understanding of the role that AI literacy plays in the teaching profession. Zawacki-Richter et al. (2019) observed that most teachers are not sufficiently aware of the presence of AI in educational tools. Thus, Ayanwale et al. (2024) emphasized that educational technology literacy must begin with the development of critical consciousness. This enables pre-service teachers to enhance their awareness, identify which tools incorporate AI, understand their purposes, and adapt them to their needs.

Finally, the position of digital skills in the low-importance/high-performance quadrant may indicate that students perceive themselves as relatively more competent in general digital skills than in more specific AI-related competencies. This result should not be interpreted as evidence that digital skills are unimportant, but rather as an indication that teacher training may need to integrate technical knowledge with awareness of pedagogical purpose, mathematical content, and context. The importance of digital skills for students underscores their awareness of acquiring minimum levels for more effective teaching, including AI. These aspects align with current demands in mathematics education, where technology integration requires a balanced combination of technical ability and critical judgment in both pedagogy and subject knowledge (Akkoc & Alan, 2020; Putri et al., 2024). Along these lines, Uerz et al. (2018) argued that digital teacher competencies should also include the ability to critically reflect on the pedagogical use of technologies, an idea that aligns with AI ethics.

Developing digital skills in both future and current teachers will require a training approach that goes beyond technical instruction and promotes a contextualized understand-

ing of how AI tools work in ME. This integration should be understood as a cross-cutting element that allows future teachers to understand the potential, limitations, and implications of using AI tools in ME. Thus, [Zawacki-Richter et al. \(2019\)](#) recommend integrating critical thinking as a fundamental step in teacher training.

In terms of self-reported performance, future teachers felt more confident in competencies such as AI trust and AI ethics, but less competent in AI awareness. From a mathematics education perspective, this perception is particularly relevant since the effective integration of AI tools requires, in addition to confidence, an understanding of their potential and limitations ([Panaoura, 2025](#)). In a field such as ME, which involves problem-solving strategies, reasoning processes, modelling, and interpretation of errors, limited AI literacy may restrict the role that AI can play in supporting ME.

Previous studies showed that AI ethics was one of the most highly valued AI competencies, in line with these findings, both among students ([Yaşar & Karagucuk, 2024](#)) and teachers ([Ceylan, 2025](#); [Ng et al., 2024](#); [Shen & Cui, 2024](#)). In contrast, [B. Wang et al. \(2023\)](#) found that the highest valued competence was AI awareness, which was the lowest-rated competence in this study. Other studies have also identified AI evaluation ([Ng et al., 2024](#); [B. Wang et al., 2023](#); [Yaşar & Karagucuk, 2024](#)) or AI usage ([Ceylan, 2025](#); [Shen & Cui, 2024](#)) as among the least developed competences.

The application of IPMA allowed this study to contribute to the literature on digital and AI competences from a teacher-training perspective in ME. Previous studies have focused on the sustainable development of digital competences in vocational training ([Seufert & Scheffler, 2016](#)) or on the DigComp framework in university students ([Chaw & Tang, 2022](#)). [Sobodić et al. \(2022\)](#) and [Balaban and Sobodić \(2022\)](#) explored the integration and assessment of digital competences in school contexts, and [Ahmed \(2023\)](#) emphasized the role of personal and contextual factors in the acquisition of digital competences. In this study, IPMA provides an additional contribution by identifying priority areas for AI-related teacher education in the specific context of mathematics.

On the other hand, the results by academic year showed that second-year students assigned greater importance to AI literacy compared to students in upper years. This comparison was relevant because the Mathematics Education course is taken in the second year; therefore, second-year students were current students of this subject, whereas upper-year students had already completed it. The higher importance assigned by second-year students may be explained by their current exposure to course content and digital tools. Thus, [Tondeur et al. \(2017\)](#) point out that pre-service teachers tend to adopt a functional approach to technology use in the initial stages of their training, gradually developing a more critical and pedagogical integration with greater academic progress. Furthermore, a recent study of first-year German students showed that skills and attitudes toward AI technology had a significant influence on the intention to use AI tools and, secondarily, on their use ([Delcker et al., 2024](#)).

Upper-year students, with more training and experience, assessed their own competencies more clearly and with a more critical perspective. Their higher self-reported performance may suggest a progression in perceived competence after completing the Mathematics Education course and advancing through the degree programme. This change aligns with the process of teacher professionalization, whereby teachers acquire pedagogical and didactic skills as they progress through the courses to become effective professionals ([Chong, 2012](#)). [Inamorato dos Santos et al. \(2023\)](#) found no significant differences, neither between young and experienced teachers, nor between genders.

In ME, these differences are, however, significant, as AI offers the potential to improve fundamental curricular processes such as problem-solving, mathematical reasoning, modelling, and data analysis ([Awang et al., 2025](#); [Rokade & Gore, 2025](#)). Therefore, it is

necessary to strengthen integrated, sustained, and reflective teacher training experiences. Furthermore, the use of AI tools must be aligned with clear instructional objectives and a critical perspective on their impact on ME. Implementing well-designed training programmes improves both technical competencies and pedagogical decision-making skills (Gumiero & Pazuch, 2024).

The theoretical contributions of this study crystallise around the core building blocks of AI literacy in ME. The study revealed mathematics teacher students' perceptions of the importance and self-reported performance of AI literacy and digital skills. Although AI awareness received the lowest scores, it represents the foundational level of AI literacy. Without a sufficient understanding of core AI literacy, the roles of AI and its impacts on nature, the built environment, society, and the economy, competencies regarding ethical use and evaluation of AI remain difficult or limited. This finding aligns with existing AI literacy frameworks (e.g., Ng et al., 2021; Alamäki et al., 2024), which conceptualise AI-related competencies as a hierarchical continuum ranging from awareness and understanding to application, creation, and the critical evaluation of ethical issues. These results highlight that AI literacy in ME is a complex phenomenon requiring fundamental skills to understand the key concepts, roles, and effects of AI in the context of ME; the ability to ethically apply AI in diverse mathematical learning and teaching situations; and the ability to critically evaluate and develop pedagogical practices in which AI is integrated into ME.

Finally, regarding the level of perceived AI knowledge, the study revealed that students with higher perceived AI knowledge also reported higher levels of self-reported performance in AI-related competencies. From a didactic perspective, as future teachers acquire more knowledge about AI, they may also develop a deeper understanding of its educational potential. This is especially important in disciplines such as ME, where AI can support processes such as visualization and modelling (Gadanidis, 2017; Stefanova & Georgiev, 2024).

Limitations and Future Directions

The main limitation of this study concerns the restricted generalizability of the findings, as the sample was selected through convenience sampling and drawn from a single institution within one national context. In addition, participants were pre-service ME teachers; therefore, the findings may not be directly transferable to in-service teachers, secondary mathematics teachers, or students enrolled in other educational programmes. A further limitation is the cross-sectional design, which captures students' perceptions at a single point in time and does not allow causal interpretations. Moreover, the study relied on self-reported measures. Consequently, self-reported performance should not be understood as an objective assessment of AI competence, as students may have overestimated or underestimated their actual level of proficiency.

The use of IPMA also entails certain limitations that need to be considered for future studies. Although this approach is useful for identifying priority areas for improvement, comparisons across dimensions should be interpreted with caution because each competence was measured using different items. Thus, differences between dimensions may partly reflect measurement effects rather than actual differences in perceived importance or performance. In addition, the absence of contextual variables related to students' actual AI use limited the interpretation of the IPMA results. Participation may also have been affected by the data collection period, as many students were completing academic internships in educational centres at the time of the study.

Future research should adopt longitudinal designs to examine how AI-related competences develop throughout teacher education programmes. Experimental or intervention-based studies would also be valuable to assess whether specific training activities improve

pre-service teachers' AI competencies. In addition, future studies should incorporate objective or performance-based measures of AI competence alongside self-reported data. It would also be useful to include participants from different institutions, countries, and educational stages, particularly in-service teachers and secondary mathematics teachers. Finally, mixed-methods studies could provide a deeper understanding of how future teachers perceive, use, and critically evaluate AI in Mathematics Education. Qualitative data may also help refine the classification of AI competence levels and provide a more contextualized interpretation of students' AI-related skills.

6. Conclusions

The main findings of our study show a comparison between those AI-related digital competencies that are considered most important and those in which future ME teachers report higher self-perceived performance. It was conducted in the context of an ME course, which allowed the analysis to focus specifically on how pre-service Primary Education teachers perceive AI-related competencies for mathematics teaching and learning. In general, students assigned higher importance to these competencies than the level of performance they reported. The most valued competencies were AI trust and AI evaluation, while AI awareness was the least prioritized. However, the IPMA results highlight that AI usage is the competency that requires the most attention, as students perceived it as relevant but reported comparatively lower performance in this area. Digital skills showed relatively high self-reported performance, although this result should be interpreted cautiously and not as evidence of excessive allocation of resources.

Considering the year of study, 2nd-year Mathematics Education students placed greater importance on AI-related competencies but reported lower self-perceived performance compared to upper-year students. This comparison is relevant because the Mathematics Education course is taken in the second year; therefore, 2nd-year students were currently enrolled in the course, whereas upper-year students had already completed it. Notably, competencies related to AI awareness and AI evaluation did not show significant differences between the two groups. Finally, in terms of perceived AI knowledge, students with higher AI knowledge levels assigned greater importance and reported higher performance than students with lower levels of AI knowledge. AI evaluation and AI ethics emerged as relevant competencies, with the greatest differences observed between groups.

This study has several theoretical implications for teacher education in higher education and beyond. First, the findings suggest the need to clarify the distinction between general digital competencies and AI-specific competencies in teacher education programmes. While digital skills remain important, AI-specific literacy, such as AI usage, AI evaluation, AI ethics, and AI trust, requires more explicit pedagogical integration, particularly in ME. Regarding digital skills, the results highlight the importance of adopting a more structured assessment approach, guided by solid conceptual frameworks that allow for a better understanding of their dimensions. In this sense, the DigComp framework, widely recognized in academic literature, represents a valid option for guiding future research on digital skills. More recent models also offer promising alternatives, such as the one proposed by Rodafinos et al. (2024), which differentiates six categories of digital skills.

As practical implications, this study offers useful guidance for developing and implementing Mathematics Education training methods, especially for incorporating AI into curricula. The high importance that future teachers assign to AI highlights the need to foster learning experiences that go beyond technical training. This implies that AI should not be addressed only as a general digital tool, but as a pedagogical resource connected to the design, implementation, and evaluation of mathematics teaching and learning activities. Therefore, teacher education programmes should explicitly incorporate AI-related content

into pedagogical subjects, with particular attention paid to how AI can support mathematical problem solving, instructional personalization, critical thinking, ethical decision-making, and equitable access to mathematics learning. Furthermore, the IPMA helps guide curricular approaches by identifying which competencies should be prioritized transversally, according to students' perceived needs and areas of lower self-reported performance.

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Appendix A

Questionnaire items were evaluated on a Likert Scale running from 1 (totally disagree) to 7 (totally agree).

Importance

AI Awareness

Awareness of distinguishing between Mathematics Education teaching tools that use AI and those that do not.

Awareness of how AI can enhance teaching and learning in Mathematics Education.

Awareness of identifying the use of AI in educational applications and platforms for Mathematics Education.

AI Usage

Ability to use AI tools effectively to design educational materials in Mathematics Education.

Ability to learn how to use new AI tools applied to Mathematics Education.

Ability to use AI to personalize instruction and improve students' performance in Mathematics Education.

AI Evaluation

Ability to evaluate the capabilities and limitations of an educational AI tool after using it in Mathematics Education.

Ability to select the most appropriate AI tool to solve specific mathematical problems.

Ability to choose the most suitable AI tool to support Mathematics Education across different learning levels.

AI Ethics

Ability to analyze how the use of AI in Mathematics Education affects the development of students' critical thinking.

Ability to incorporate ethical considerations when using AI-generated data in Mathematics Education activities.

Ability to evaluate the impact of AI tools on equity and accessibility in Mathematics Education learning.

AI Trust

Proper functioning of AI tools in the field of Mathematics Education.

Suitability of AI tool features for carrying out key tasks in Mathematics Education.

Competence of AI tools in Mathematics Education.

Safety of AI tools for use in Mathematics Education.

Reliability of AI tools for use in Mathematics Education.

Digital Skills

Knowledge of the characteristics of digital platforms used in Mathematics teaching and learning.

Knowledge of how to navigate educational platforms and digital tools used in Mathematics teaching and learning.

Ability to successfully use ICT to search for and download virtual Mathematics resources.

Ability to successfully use ICT to evaluate and organize Mathematics-related information for a specific purpose.

Ability to use digital tools to share information and teaching strategies with other Mathematics teachers or peers.

Ability to use digital platforms to create learning communities in Mathematics.

Ability to use ICT to generate ideas and develop new ways of working in Mathematics Education.

Performance

AI Awareness

I can distinguish between tools that use AI and those that do not.

I know how AI can improve the teaching and learning process in Mathematics.

I can identify the use of AI in educational applications and platforms for Mathematics teaching and learning.

AI Usage

I can effectively use AI tools to design educational materials in Mathematics.

I can learn how to use new AI tools applied to Mathematics teaching and learning.

I can use AI to personalize the teaching and learning process and improve performance in Mathematics.

AI Evaluation

I can evaluate the capabilities and limitations of an educational AI tool after using it in Mathematics teaching and learning.

I can select the most appropriate AI tool to solve specific mathematical problems.

I can choose the most suitable AI tool to support Mathematics teaching at different learning levels.

AI Ethics

I can analyze how the use of AI in Mathematics affects the development of critical thinking.

I can incorporate ethical considerations when using AI-generated data in Mathematics-related activities.

I can evaluate the impact of AI tools on equity and accessibility in Mathematics learning.

AI Trust

AI tools function effectively in the field of Mathematics Education.

AI tools possess the necessary features to perform key tasks in Mathematics Education.

AI tools are competent in Mathematics Education.

AI tools are safe to use in Mathematics Education.

AI tools are reliable for use in Mathematics Education.

Digital Skills

I am familiar with the characteristics of digital platforms used in Mathematics teaching and learning.

I can navigate educational platforms and virtual Mathematics teaching tools without difficulty.

I successfully use ICT to search for and download virtual Mathematics resources.

I successfully use ICT to evaluate and organize Mathematics-related information for a specific purpose.

I use digital tools to share information and teaching strategies with other Mathematics teachers or peers.

I use digital platforms to create learning communities in Mathematics Education.

I use ICT to generate ideas and develop new ways of working in Mathematics.

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