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Comparing Gen AI adoption in pre- and in-service mathematics teachers

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Abstract: This study examines Generative Artificial Intelligence (Gen AI) integration in a Swedish mathematics education context by investigating readiness, usage patterns, and approaches among pre-service (N=17) and in-service (N=22) mathematics teachers. Using a mixed-methods approach within a teacher training program in spring 2025, the research addresses three questions: (1) current Gen AI readiness levels, behavioral intentions, and attitudes; (2) differences between groups in integration approaches; and (3) practical applications, challenges, and coping strategies. Data collection included quantitative readiness measures and qualitative responses about experiences. Results revealed that both career stage and usage frequency influence Gen AI adoption: career stage shapes the qualitative nature of integration (purposes, approaches, sophistication), while usage frequency emerges as a stronger predictor of learning changes and readiness levels. Pre-service teachers demonstrated higher usage for learning, while in-service teachers showed selective, professionally-informed usage despite similar readiness levels. High-frequency users reported significantly greater learning changes and higher readiness scores, highlighting hands-on experience's role in developing AI competencies. The study identifies two tentative patterns: pre-service teachers' developmental integration as learning scaffolds versus in-service teachers' selective, professionally-informed integration with more sophisticated strategies. These exploratory findings offer preliminary evidence of how mathematics educators at different career stages conceptualize Gen AI integration, and point to directions for future research, targeted professional development and teacher training programs.

Keywords: generative AI, teacher education, mathematics education, Gen AI adoption, Gen AI readiness

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1 Introduction

Mathematics education stands at a critical point as Generative Artificial Intelligence (Gen AI) introduces both unprecedented capabilities and complex challenges for computational thinking, problem representation and pedagogical practices (Bui et al., 2025a). The emergence of sophisticated large language models (LLMs) capable of interpreting mathematical concepts, generating step-by-step solutions, and creating contextual applications marks a potential shift in how mathematics can be taught, learned, and assessed (Gurl et al., 2025; Li et al., 2023). In this article, artificial intelligence (AI) refers broadly to computational systems designed to perform tasks associated with human intelligence, while Gen AI denotes AI systems based on deep learning that generate statistically plausible content in response to user prompts (Stryker & Scapicchio, 2024); and LLMs constitute a prominent class of Gen AI models trained on large-scale text corpora to produce contextually coherent language-based outputs (Bommasani et al., 2021; Tankelevitch et al., 2024).

Gen AI technologies have experienced significant organic uptake since its public launch in late 2022 (Liu & Wang, 2026). This broad accessibility has resulted in students' greater exposure and habitual use that often exceed teachers' familiarity and before formal educational frameworks or institutional support have been established (American Association of Colleges and Universities, 2025; Bergdahl & Sjöberg, 2025; Freeman, 2025). This acceleration in adoption, coupled with persistent gaps in educators' Gen AI readiness and teacher preparation program alignment (Bui et al., 2025b; Granström & Oppi, 2025), underscores the need to understand how educators at different career stages engage with Gen AI in their professional development (Chatfield, 2025).

Gen AI systems fundamentally differ from predecessor "intelligent assistants" that operated within predetermined functional boundaries (Schellaert et al., 2023). Unlike tools with fixed task capabilities, Gen AI platforms demonstrate variable performance outcomes influenced by numerous factors including prompt engineering precision and model specifications. Consequently, Gen AI tools are considered highly user-dependent (Schellaert et al., 2023), with their effectiveness hinges significantly on individual users' AI-interaction competencies and their capacity for critical interpretation of outputs.

This user-dependency introduces a novel dynamic in educational settings. An emerging exposure gap has surfaced whereby students' potentially more advanced engagement patterns with Gen AI create challenges for educators who must simultaneously cultivate their own AI familiarity and competence while guiding students' responsible use. Within mathematics education specifically, Gen AI tools have been reported to assist educators in tasks ranging from content differentiation to formative assessment generation (Alhazzani, 2024; Biton & Segal, 2025; Gurl et al., 2025; Li et al., 2023). However, effectively leveraging these affordances requires teachers to draw upon their foundational pedagogical and content expertise, integrated with technological knowledge -a relationship commonly conceptualized through the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006).

However, the emergence of Gen AI extends and complicates this framework, necessitating a reconceptualization of TPACK that accounts for AI-specific characteristics and competencies (Mishra et al., 2023).

Crucially, the competencies required for effective Gen AI engagement, including prompt engineering, critical evaluation of AI-generated content, and ethical reasoning - are not just instrumental. Without them, the use of Gen AI raises concerns related to students' mathematical reasoning, risks of over-reliance on AI-generated solutions, and broader questions about the development of mathematical knowledge in AI-integrated learning environments(Dahal et al., 2023; Getenet, 2024; Yoon et al., 2024). Effective and responsible engagement with AI technologies requires what scholars term AI literacy - a set of competencies enabling individuals to understand how AI systems function, use them effectively, critically evaluate their outputs, and consider ethical implications (Ng et al., 2021). Within the Swedish context, the Swedish National Agency for Education highlights the need for developing AI literacy, emphasizing critical evaluation of AI-generated content within subject-specific contexts (Skolverket, 2024). However, the limited empirical evidence available suggests weak institutional support and a gap between policy aspirations and classroom practice (Bergdahl & Sjöberg, 2025; Pettersson et al., 2024; Söderström et al., 2024).

Current research rarely compares Gen AI adoption across career stages, often focusing on either in-service or pre-service teachers without distinction (Moorhouse, 2024; Ogunleye et al., 2024; Zhang et al., 2023). This reflects a broader international gap, despite the need to understand teacher preparedness amid the rapid rise of Gen AI in education. Addressing this gap, the present case study examines Gen AI readiness, perceptions, behavioral intentions, and usage patterns among Swedish pre-service (N=17) and in-service (N=22) mathematics teachers. Situated within a Geometry course in a teacher education program in south-central Sweden from April-June in 2025, the study provides timely insights into how educators are navigating and conceptualizing Gen AI in their learning and teaching practice. Specifically, we ask the following research questions:

1. What differences emerge between two groups of participants in their initial approaches to Gen AI in mathematics education?
2. What are the current levels of Gen AI readiness, behavioural intentions, perceptions and attitudes of the participants toward the integration of Gen AI in mathematics education?
3. In what ways are participants utilizing Gen AI tools in their learning and teaching practices in mathematics education, what challenges do they face and how do they cope with them?

2 Research background

2.1 Teachers' engagement with Gen AI in mathematics education

A growing body of research suggests that teachers' engagement with Gen AI is shaped by the professional knowledge and experience they bring to the interactions (Bergdahl & Sjöberg, 2025; Moorhouse, 2024). The distinction between *learning mathematics with technology* and *learning to teach mathematics* with technology takes on particular significance with the emergence of Gen AI (Niess, 2011). Unlike more stable educational technologies, Gen AI tools are considered highly user-dependent (Schellaert et al., 2023), with their effectiveness shaped by the domain knowledge and Gen AI competencies that users bring to the interaction. This user-dependency means that career stage - and the professional knowledge it reflects - may influence how teachers engage with Gen AI in mathematics education.

Regarding pre-service teachers, learning to teach mathematics with technology involves simultaneously developing pedagogy while exploring such tools-which are often not systematically integrated into their own learning experiences (Biton & Segal, 2025; Gurl et al., 2025). The rapid adoption rate of Gen AI in mathematics education suggests expanded competencies beyond traditional frameworks, including *AI pedagogical competency*-the ability to use Gen AI in ways that support rather than undermine learning objectives (Bui et al., 2025a; Mishra et al., 2023; Petko et al., 2025).

In-service teachers face a different but equally complex challenge. Their established pedagogy and content knowledge must be adapted to technologies capable of generating mathematical explanations, solutions, and instructional content (Alhazzani, 2024; Busuttil & Calleja, 2025). For in-service teachers, this involves not only technical proficiency but also pedagogical judgment about when AI-generated content supports learning objectives, curriculum standards, and students' needs (Gurl et al., 2025; Kim et al., 2025). Moreover, the rapid evolution of Gen AI demands continual updating of both technological and pedagogical knowledge, creating adaptation challenges that differ from more stable educational technologies (Liu & Wang, 2026). Understanding these differences in content knowledge, professional experience, and technological familiarity between pre-service and in-service teachers is essential for examining their respective readiness and intentions regarding Gen AI integration (Koehler & Mishra, 2009; Niess, 2005).

TPACK as a contextualising lens

The differences outlined above can be further contextualized through the Technological Pedagogical Content Knowledge (TPACK) framework. Developed by Mishra & Koehler (Mishra & Koehler, 2006), TPACK conceptualizes effective technology integration as the dynamic intersection of three core knowledge domains: Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). Their intersections produce composite forms of knowledge, including Technological Content Knowledge (TCK), Technological Pedagogical Knowledge (TPK), and TPACK-the integrated expertise required for effective domain-specific technology use. Mishra et al. (2023) argued that four of these domains-TK, TCK, TPK, and TPACK-require reconsideration given that Gen AI simultaneously reshapes content representation, pedagogical possibilities, and the nature of technological competence itself.

Mishra et al. (2023) identified five core characteristics of Gen AI technology: *protean* (flexible and general-purpose), *opaque* (difficult to interpret internally), *unstable* (variable and fallible), *generative* (producing novel outputs dynamically from user input), and *social* (encouraging anthropomorphization through interactive responses). These properties mean that effective Gen AI use demands not only operational proficiency but conceptual understanding of why outputs are variable, fallible, and non-deterministic (Mishra et al., 2023). Unlike earlier tools, Gen AI does not simply support existing practices but introduces new dynamics into teaching and learning (Law, 2024; Mishra et al., 2023; Tankelevitch et al., 2024), requiring teachers to reinterpret how this technology interacts with pedagogy and content.

Within mathematics education, TCK encompasses the capacity to formulate effective prompts that elicit mathematically accurate outputs, critical evaluation of AI-generated mathematical content, and recognition of Gen AI's affordances and limitations for specific mathematical tasks and concepts (e.g., documented limitations in geometric visualization; see Botana & Recio, 2024). TPK addresses how Gen AI can support pedagogical processes central to mathematical activity, such as differentiation in task complexity, scaffolding of problem-solving processes, or formative assessment of students' reasoning (Schoenfeld, 2016). Pre-service and in-service teachers are likely to engage differently with these knowledge demands, reflecting how their content, pedagogical, and technological knowledge are integrated through distinct professional experiences and stages of development(Mishra et al., 2023; Niess, 2011).

2.2 Gen AI Readiness

Recent developments in understanding teachers Gen AI preparedness and readiness are noted in different fields (Bergdahl & Sjöberg, 2025; Bui et al., 2025b; Moorhouse, 2024; Ozdemir & Mede, 2024). Ozdemir & Mede (2024) conducted a mixed method study to explore in-service English teachers' Gen AI readiness (N=27) using Teacher AI Readiness (Ayanwale et al., 2022), semi-structured interviews (n=7) and reflection papers (n=5). Results suggested that English teachers indicated moderate AI anxiety, mixed confidence in their ability to teach AI or access to resource, but high perceived usefulness and positive attitudes towards AI. Despite generally positive attitudes, teachers identified significant implementation barriers including technical challenges, ethical concerns, and pedagogical worries (Ozdemir & Mede, 2024). Moorhouse (2024) interviewed 27 beginning and first-year English teachers in Hong Kong, finding a clear gap: first-year teachers showed greater Gen AI readiness due to practical experience, while beginning teachers lacked both knowledge and preparedness.

Similarly, Bui and colleagues explored Finnish pre-service teachers' readiness, perceptions and behavioral intentions towards Gen AI readiness through a mixed-method study in April-June 2024 (Bui et al., 2025b). Drawing from the Technology Acceptance Model (TAM) frameworks (Davis, 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000), Teacher AI Readiness (Ayanwale et al., 2022) and Technology Readiness Index (Parasuraman & Colby, 2015), they piloted the Gen AI Readiness scale (N=56) that address the specific characteristics of Gen AI tools. Combining qualitative data (N=56), findings reported that generally participants have low perceptions of Gen AI accuracy. However, frequent users still found Gen AI tools useful and intended to continue using them -indicating perceived benefits outweigh accuracy concerns.

In Swedish context, Bergdahl & Sjöberg (2025) examined AI self-efficacy (N=312) of Swedish K-12 teachers through TAM and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks. Their results suggested that subject relevance and prior experience significantly predicted AI integration readiness, while ethical and pedagogical confidence were crucial factors in AI adoption decisions, with strong correlations between subject-specific teaching confidence and ethical implementation ability. These indicate that effective Gen AI integration depends not only on technical proficiency but on teachers' perceptions of relevance to their discipline, ethical alignment, and pedagogical suitability. These findings, however, are drawn mainly from general contexts, and how Gen AI readiness manifests within mathematics education - with its distinct epistemic demands and disciplinary practices - remains underexplored.

2.3 Gen AI in mathematics education

The integration of LLMs and other Gen AI tools in mathematics instruction represents an emerging shift in how mathematics are taught, learned, and assessed (Biton & Segal, 2025; Busuttil & Calleja, 2025; Pepin et al., 2025). These tools can produce highly accurate math explanations, support learners with tailored feedback (Li et al., 2023), and introduce new ways of thinking about and solving problems (Getenet, 2024) - often in ways that might go beyond what traditional educational tools can offer (Contel & Cusi, 2025). However, current research remains small-scale and exploratory, which requires further examinations to investigate Gen AI tools' actual impact in diverse and authentic educational settings(Bui et al., 2025a). Furthermore, these opportunities come with complex challenges that educators and researchers are only beginning to understand.

Mathematical accuracy and precision are critical concerns, as Gen AI tools can produce plausible-looking solutions that contain subtle errors in reasoning or calculation. ChatGPT's struggles with mathematical problems are highlighted in recent research (Sayeg-Sánchez & Rodriguez-Paz, 2024; Taani & Alabidi, 2024; Yoon et al., 2024; Yunianto et al., 2024). In a study involving 109 teachers, over 60% of participants reported encountering inaccuracies when using ChatGPT (Taani & Alabidi, 2024). In the context of Geometry, Botana & Recio, (2024) noted that ChatGPT and similar LLM(s) are not equipped to understand or perform mathematical procedures related to positions or paths of points in geometric loci, as these require a precise understanding of positional relationships and logical rules that go beyond the model's algorithm.

The integration of Gen AI tools into learning environments also introduce pedagogical challenges and implementation issues. One concern is the nature of classroom interaction, with both teachers and students needing to adjust to a less human-centered learning environment. This shift raised worries about weakening teacher-student relationships and the emotional nuances they involve (Ergene & Ergene, 2025; Wardat et al., 2023). Another problem involves Gen AI tools' limited capacity to interpret the broader learning context, including cultural influences and the specific needs of individual learners, which raise ethical concerns (Getenet, 2024). Gen AI tools are typically trained on large datasets that may reflect dominant cultural norms or biases (Law, 2024; Mai et al., 2024; Pettersson et al., 2024), making them less responsive - or even insensitive - to diverse educational backgrounds. There is a risk of reinforcing stereotypes, marginalizing underrepresented groups, or promoting content that lacks cultural relevance.

From a policy perspective, education authorities have started to address mathematics-specific consideration for Gen AI use. Early 2024, the National Council of Teachers of Mathematics, United States (NCTM) released an official statement of AI and mathematics teaching (National Council of Teachers of Mathematics, 2024) that acknowledges Gen AI potential to personalize learning experiences while emphasizing that "*AI tools do not replace the need to teach math or problem-solvin*g". The statement notes that AI tools can be useful, but teachers must foster critical skepticism about AI-generated results, particularly regarding potential biases in training data. NCTM explicitly states that effective AI integration demands for experienced math educators. However, while studies have examined teachers' general experiences with Gen AI, research specifically investigating the impacts of Gen AI tools on pre-service teachers and in-service math teachers' learning habits, pedagogical approaches, perceptions of mathematics teaching, and readiness for Gen AI implementation still remains scarce.

3 Methodology

3.1 Research design and data collection

Employing a mixed-methods design, we collected quantitative data through a survey measuring Gen AI readiness and usage patterns, followed by qualitative data collection through open-ended questions that explored participants' experiences, challenges, and coping strategies when using Gen AI tools in mathematics learning and teaching contexts (see Instruments). An online survey was developed and administrated through a secure web-based survey platform (Survey & Report) and strictly followed the Ethical Guidelines of the Karlstad University, Sweden. The study was conducted within the scope of a Geometry course for mathematics education teacher training program at a state university in southwest-central Sweden from April-June in 2025. The questionnaire and research information were provided to participants via Canvas, a learning management system, where participants had access to the course's materials, project information, and data management. Participants' consents were obtained, and only those who gave permission for their data to be used in research were included in the analysis. Students are compiled of both pre-service teachers who are pursuing mathematics teacher education degree, and in-service teachers who have been working as mathematics teachers, and now pursuing additional credentials.

Participants

The study included a total of 39 participants comprising 17 pre-service teachers (52.9% female, 41.2% male, 5.9% others; predominantly aged 21-24 years) and 22 in-service teachers (54.5% female, 45.5% male; predominantly aged 33+). This sample represents two distinct career stages with notable differences in age distribution, with pre-service teachers being significantly younger (M=21-24 years) than their in-service counterparts (90.9% aged 33+).

Instruments

Data were collected through an online survey that included both quantitative and qualitative components (see Appendix A). The first part collected non-identifiable data and questions about general Gen AI usage. The second part combined quantitative and qualitative measures examining Gen AI usage in mathematics learning contexts, including: usage frequency (rarely, sometimes, often, always), time allocation, and learning activities. Close-ended items were paired with open-response elements. For example, when responding to "*Has using AI tools changed the way you approach learning mathematics*?" participants selected one option (*No, not at all; No, only slightly; Yes, somewhat; Yes, significantly*) and provided written explanation for their choice. The third part has three open-ended questions about participants' experiences with Gen AI tools in mathematics learning. Lastly, the survey included 26 items to measure seven dimensions of Gen AI readiness, which were used in Bui et al., (2025b): Perceived Usefulness (USE), Behavioral Intention (BEHA), Relevance of Gen AI (RELE), Perceived Accuracy (ACC), Gen AI Anxiety (ANX), Confidence in Using Gen AI (CONFI), and Gen AI Readiness (REDI). To ensure linguistic equivalence and cultural appropriateness within the Swedish context, we adopted the back-translation method (Brislin, 1970), involving four native Swedish speakers who are also fluent in English.

3.1 Data analysis

Quantitative data

Quantitative data were analyzed using SPSS 28 software. Given the exploratory nature of this study and our modest sample sizes (pre-service N=17; in-service N=22), statistical analyses were selected to address our specific research questions while acknowledging interpretive limitations. Results should be interpreted as preliminary indicators rather than definitive conclusions. Different statistical methods were conducted, including: descriptive statistics, Levene's test, Student's t-test, Welch test, Mann Whitney U test, and reliability analysis. Cronbach's alpha was calculated for the constructs of the Gen AI Readiness (see Table 1).

Table 1. Cronbach's α of seven constructs in the Gen AI Readiness Scale

Constructs	Items	Cronbach's α
ANX	3	0.81
USE	4	0.84
BEHA	3	0.82
REDI	4	0.82
RELE	4	0.7
ACC	2	0.56
CONFI	4	0.81

Cronbach's α values for most constructs indicate acceptable to good reliability ($\alpha \geq 0.70$), except for Perceived Accuracy (ACC). ACC scale showed low reliability when all original items were included (4 items). Following standard scale refinement procedures, items were removed if their removals increased Cronbach's alpha (Field, 2024). This process resulted in a 2-item scale with improved reliability, though still moderate, reliability. While current value is below optimal thresholds (<0.7), it represents the maximum achievable reliability for this construct given the current item pool and sample size. All subsequent analyses used only the retained items from the refined scale. We retain this construct in our analyses but interpret findings related to Perceived Accuracy with appropriate caution.

Qualitative data

Qualitative data were organized and imported into MAXQDA24 for manual coding and data anonymization. Two types of qualitative data were collected and therefore analyzed differently (see Instruments). First, brief open-response explanations paired with closed-ended items in the survey were coded and analyzed through frequency counting.

Recurring responses were identified and grouped by category. These findings are reported alongside corresponding quantitative results.

Second, extended responses to our three open-ended questions (see Appendix A) were analyzed using hybrid thematic analysis (Braun & Clarke, 2006). All responses were read multiple times to achieve familiarity with the data. Initial themes were initially identified based on our research questions and theoretical frameworks (Gen AI Readiness and TPACK), while remaining open to inductively emerging themes. Coding was conducted iteratively, with codes refined through regular discussions among the author team. The first author served as the primary coder with the last author acting as the co-coder. All main themes, subthemes, and illustrative code examples were reviewed by the full author team prior to finalization. Selected quotations were jointly examined to ensure they accurately represented participants' perspectives. This process produced seven subthemes within three thematic areas: (1) Experiences with Gen AI (*Gen AI as instructional support tool; Technical literacy and limitations*); (2) Challenges and coping strategies (*Accuracy and error management; Prompting issues; Content misalignment issues*); and (3) Mathematics learning approaches (*AI-enhanced learning impacts; Limited changes and future implementations*). The qualitative component was essential for understanding not only whether participants use Gen AI, but how they experience, navigate, and make sense of these tools in their mathematics learning practices. Frequency counts within each theme enabled comparison between groups.

4 Results

4.1 Approaches to Gen AI integration in mathematics education

This section examines how participants approached Gen AI integration through: usage frequency, weekly time allocation (see Table 2), and mathematical activities using Gen AI tools (see Figure 3). The analysis combines quantitative data with qualitative explanations from paired open-response components.

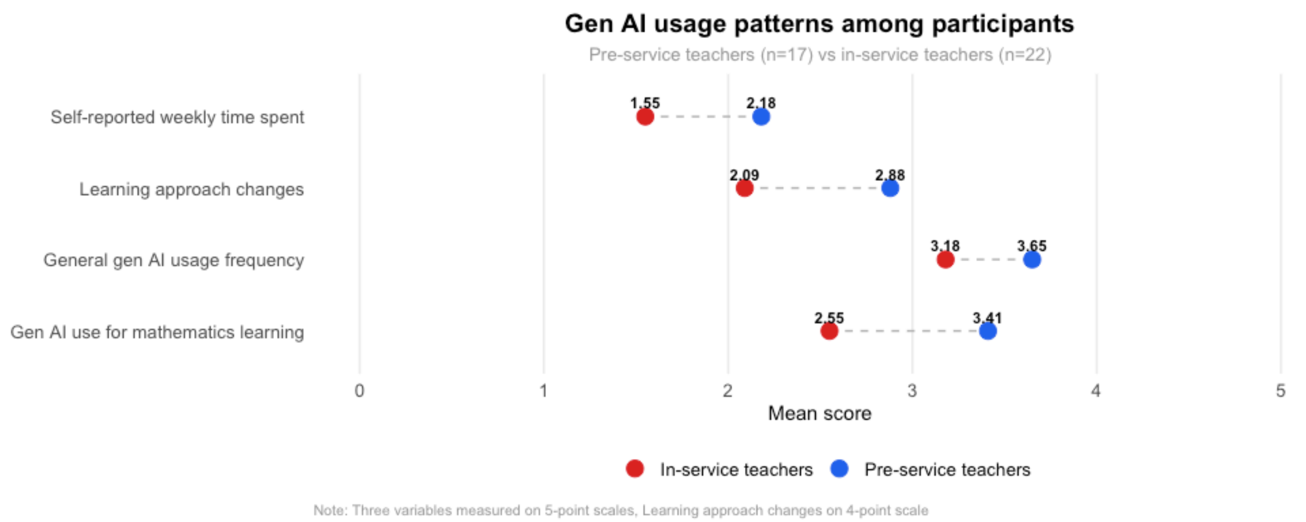
Table 2. Gen AI usage patterns and learning approach among participants

Variables	**Pre-service teachers (n=17) M(SD)**	**95% CI**	**In-service teachers (n=22) M(SD)**	**95% CI**
General Gen AI usage frequency	3.65 (0.70)	[3.29, 4.01]	3.18 (1.22)	[2.64, 3.72]
Gen AI use for mathematics learning	3.41 (0.94)	[2.93, 3.90]	2.55 (1.10)	[2.06, 3.03]
Self-reported weekly time spent	2.18 (0.95)	[1.69, 2.67]	1.55 (0.91)	[1.14, 1.95]
Learning approach changes	2.88 (0.70)	[2.52, 3.24]	2.09 (1.07)	[1.62, 2.56]

Note. CI = confidence interval. General Gen AI usage frequency and Gen AI use for mathematics learning were measured on 5-point scales (1 = never, 5 = daily). Weekly time spent was measured on a 5-point scale (1 = less than 30 minutes, 5= more than 5 hours). Learning approach changes was measured on a 4-point scale (1 = No, not at all, 4 = Yes, very much).

Pre-service teachers reported fairly high frequency of general Gen AI usage more than for mathematics learning (M=3.65 vs M=3.41). Their average time spent weekly using these tools for math learning was more than 1 hour /week (M=2.18; SD=0.95), and Gen AI tools has an impact in their mathematics learning approach (M=2.88; SD=0.70). In-service teachers also used Gen AI more generally than specifically for mathematics learning (M=3.18 vs M=2.55), averaged time spent weekly for math learning was more than 30 minutes but less than 1 hour (M=1.55; SD=0.91); they reported minimal impact of Gen AI tools in their mathematics learning (M=2.09; SD=1.07) (see Figure 2).

Figure 1. Gen AI usage patterns among pre-service and in-service math teachers



To examine differences in Gen AI integration between two groups, we used Mann-Whitney U tests due to non-normal distributions and small, unequal group sizes (see Table 3).

Table 3. Mann-Whitney U test results: Pre vs in-service mathematics teachers' Gen AI usage

Variables	**U**	**p**	**r**	**95% CI for r**
General Gen AI usage frequency	236.50	.149	0.27	[-0.10, 0.57]
Gen AI use for mathematics learning	273.00	.012*	0.46	[0.13, 0.70]
Self-reported weekly time spent	258.50	.029*	0.38	[0.03, 0.65]
Learning approach changes	272.00	.013*	0.46	[0.12, 0.70]

Note. N = 39 (Pre-service = 17, In-service = 22). U = Mann-Whitney U test; r = rank-biserial correlation (effect size); CI = confidence interval. *p < .05.

Pre-service teachers demonstrated significantly higher Gen AI engagement in three variables: mathematics-specific Gen AI use (U=273.00, $p<.05$, r=0.46), time spent weekly (U=258.50, $p<.05$, r=0.38), and learning approach changes (U=272.00, $p < .05$, r=0.46). Medium effect sizes suggest that the differences between groups were practically meaningful at the time of measurement.

To gain deeper insight into these differences, we analyzed open-ended responses related to these data. Table 4 summarizes response frequencies.

Table 4. Frequency of open-responses categories paired with survey items

Thematic areas	Response categories	Pre-service teachers	In-service teachers
Gen AI use in mathe-matics learning	Response rate	100%	72%
	Problem solving support	9	-
	Help when “getting stuck”	6	-
	Help to understand concepts / strategies	4	-
	Creating mathematical problems	-	4
	Professional use (e.g. in teaching)	-	3
	Limited use / No perceived needs	-	5
Mathematics learning habit changes	Response rate	100%	64%
	Reported changes		
	Immediate access to support	9	-
	Efficiency gains	5	-
	Supplemental help / new ways of thinking	4	-
	Complementary resources	-	4
	Minimal or no changes		
	Minimal use / impact	-	9
	Preference for traditional methods	3	3
	Unfamiliarity with AI	-	3
	Concerns about accuracy	1	2

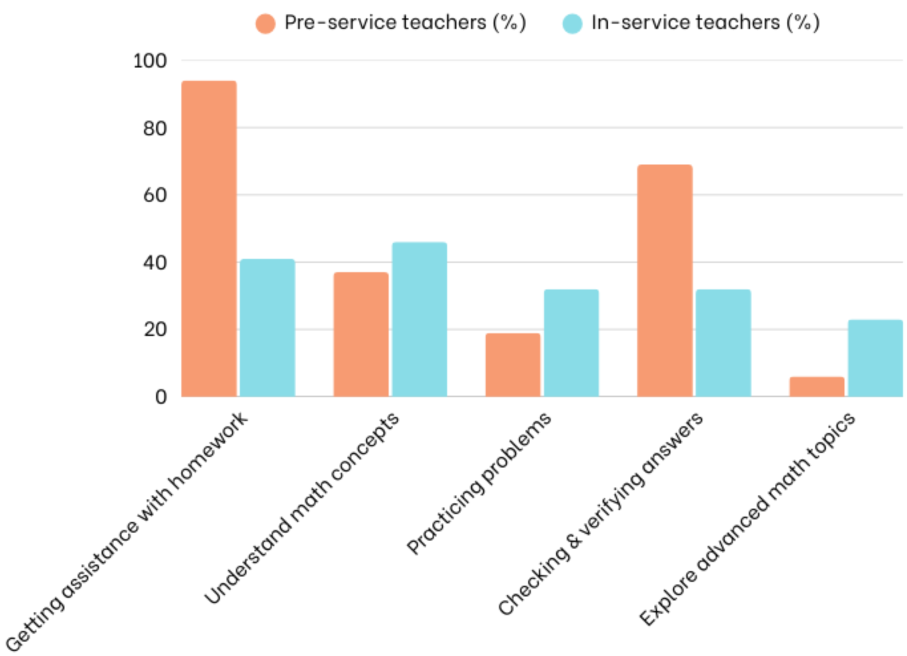
Note: “ - “indicates no or negligible mentions in that group. Some participants mentioned more than one category in their responses.

Regarding Gen AI use in math learning, clear differences emerged. Pre-service teachers primarily reported using Gen AI for problem-solving support, particularly when “getting stuck” or seeking to understand concepts. In-service teachers more often reported no perceived need, citing comfort with traditional methods (e.g., textbooks, Google).

Those who did use Gen AI described professional applications such as creating mathematical problems or exploring alternative explanations. Regarding learning habit changes, pre-service teachers predominantly reported meaningful impacts, emphasizing immediate access to support and efficiency. One described Gen AI as "*a game changer*." In contrast, most in-service teachers reported minimal impact, attributing this to preferences for traditional methods or unfamiliarity with AI. Concerns about accuracy were mentioned by both groups but did not appear to be the primary barrier to adoption.

Regarding the mathematical activities participants used Gen AI tools, six categories were reported (multiple selections allowed) (see Figure 3).

Figure 2. Mathematical activities using Gen AI tools



While pre-service teachers predominantly used Gen AI for homework assistance and answer verification, in-service teachers showed wider usage patterns. Both groups reported similar usage for understanding mathematical concepts. In-service teachers reported lower usage for homework assistance and answer verification but higher engagement with other mathematical topic exploration, and generating mathematical problems.

4.2 Gen AI readiness, attitudes, and perceptions

This section examines participants' Gen AI readiness, attitudes and perceptions through quantitative measure (see Table 5). In-service teachers reported slightly higher anxiety (M=2.77 vs M=2.48), though both groups indicated relatively low anxiety regarding Gen

AI. For usefulness, pre-service teachers reported marginally higher (M=4.56 vs. M=4.36), and similar patterns were observed in confidence and behavioral intention. Pre-service teachers perceived Gen AI tools to be somewhat more accurate (M=3.66 vs M=3.25), with both groups showed moderate trust with concerns remain. The largest difference was observed in relevance, where in-service teachers rated Gen AI as more relevant (M=4.32 vs M=3.93). In-service teachers showed higher variation across variables, particularly for anxiety and Gen AI readiness. This suggests that while some in-service teachers felt more prepared and confident, others were more hesitant - potentially reflecting diverse experiences and exposure to AI tools in practice.

Table 5. Descriptive statistics of the seven constructs of Gen AI Readiness among participants

Variables	Group	N	Mean	SD	SE	Coefficient of variation
ANX	Pre-service	16	2.48	0.78	0.20	0.31
	In-service	22	2.77	1.38	0.30	0.50
USEFUL	Pre-service	16	4.56	0.89	0.22	0.20
	In-service	21	4.36	1.17	0.26	0.27
CONFI	Pre-service	16	4.11	0.79	0.20	0.19
	In-service	21	4.19	1.15	0.25	0.27
BEHA	Pre-service	16	4.69	0.93	0.23	0.20
	In-service	21	4.64	1.19	0.26	0.26
RELE	Pre-service	15	3.93	0.59	0.15	0.15
	In-service	22	4.32	0.98	0.21	0.23
REDI	Pre-service	15	3.93	0.87	0.23	0.22
	In-service	22	3.74	1.22	0.26	0.33
ACC	Pre-service	16	3.66	0.77	0.19	0.21
	In-service	22	3.25	1.03	0.22	0.32

To examine potential differences in participants' Gen AI readiness and learning approaches, participants were sorted into two groups based on their frequency of using Gen AI for mathematics learning. Those who answered "Rarely" and "Sometimes" are grouped into Low Frequency (n=14); while those who answered "Often" and "Always" are grouped into High frequency (n=24) (see Table 6).

Table 6. Descriptive statistics of Gen AI Readiness constructs and learning approach based on frequency of Gen AI usage in mathematics learning

Variables	Group	N	Mean	SD	SE	Coefficient of variation
Learning approach	Low-frequency	14	1.79	0.98	0.26	0.55
	High-frequency	24	2.83	0.82	0.168	0.29
ANX	Low-frequency	14	2.93	1.22	0.33	0.42
	High-frequency	24	2.49	1.12	0.23	0.45
USEFUL	Low-frequency	13	4.16	1.35	0.38	0.33
	High-frequency	24	4.60	0.84	0.17	0.18
CONFI	Low-frequency	13	4.02	1.16	0.32	0.28
	High-frequency	24	4.23	0.91	0.19	0.22
BEHA	Low-frequency	13	4.26	0.16	0.32	0.27
	High-frequency	24	4.88	0.98	0.20	0.20
RELE	Low-frequency	14	4.02	1.06	0.28	0.26
	High-frequency	23	4.25	0.72	0.15	0.17
REDI	Low-frequency	14	3.32	1.16	0.31	0.35
	High-frequency	23	4.12	0.94	0.31	0.35
ACC	Low-frequency	14	3.36	1.00	0.27	0.30
	High-frequency	24	3.46	0.92	0.19	0.27

Descriptive statistics suggested higher frequency users reported to have more changes in learning approaches to mathematics, greater behavior intentions to continue using Gen AI in the future. Higher frequency users reported higher in usefulness and readiness towards Gen AI. Therefore, we conducted independent t-tests (except for USEFUL due to unequal variances) to see if the differences were significant (see Table 7). An independent Welch's t-test show no significant difference on USEFUL variable.

Table 7. Gen AI Readiness and learning approach t-test between frequency groups

Variables	t	df	p	Cohen's d	SE Cohen's d	95% CI for Cohen's d	
						Lower	Upper
Learning approach	-3.55	36	0.001*	-1.19	0.40	-1.90	-0.47
ANX	1.14	36	0.26	0.38	0.34	-0.29	1.05
CONFI	-0.61	35	0.55	-0.21	0.35	-0.89	0.47
BEHA	-1.72	35	0.09	-0.59	0.36	-1.28	0.10
RELE	-0.80	35	0.43	-0.27	0.34	-0.94	0.4
REDI	-2.30	35	0.02*	-0.78	0.37	-1.46	-0.08
ACC	-0.32	36	0.75	-0.11	0.33	-0.76	0.55

Note. t = independent t test; df = degree of freedom; CI = confidence interval; *p < .05.

A significant difference in approaches to learning mathematics was observed, $t(36)=-3.55$, $p=.001$, $d=-1.19$, 95% CI[-1.90,-0.47], with high-frequency users reporting greater changes in their learning approaches. High-frequency users also reported greater readiness to integrate GenAI tools, as indicated by the Readiness measure, $t(35)=-2.30$, $p<.05$, $d=-0.78$, 95% CI[-1.46,-0.08].

4.3 Thematic insights from open-ended responses

This section presents key themes derived from participants' open-ended responses to three questions about their experiences, challenges, coping strategies, and more detailed changes in learning approaches related to Gen AI use in mathematics education. Findings are presented alongside interpretation to provide a coherent account in which analytical observations and their significance are intertwined.

4.3.1 Experiences with Gen AI in mathematics learning

Analysis of participants' Gen AI experiences (75% response rate) revealed two subthemes that differentiated pre-service and in-service teachers.

Gen AI as instructional support tool

Many participants - particularly pre-service teachers - viewed Gen AI tools as readily available learning partners, providing support by offering feedback, which aligned with our quantitative findings. This perception was more common among pre-service teachers (n=16) than in-service teachers (n=7), aligning with quantitative findings showing higher usage frequency among pre-service teachers. One pre-service teacher described using AI to "*ask for step-by-step methods*," receive explanations for calculation errors, and "*compare with how I would have solved it*." This exploratory, content-focused use reflects early-stage TK and TCK development - participants leveraged Gen AI for understanding mathematical concepts.

Technical literacy and limitations

Beyond supportive experiences, both groups demonstrated awareness of Gen AI constraints. Pre-service teachers (n=4) and in-service teachers (n=5) emphasized verification needs, though their focus differed. While both groups recognized technical shortcomings (e.g. hallucinated outputs, syntax sensitivity) - pre-service teachers tended to focus on more surface-level issues, including tool comparisons (e.g., ChatGPT and Copilot) and the need to verify or cross-check outputs.

In contrast, the reflections shared by in-service teachers suggested a more nuanced and professionally grounded evaluation of Gen AI's role. One teacher described recognizing that Gen AI tool "*doesn't manage to give correct answer for many of the complex problems*," which prompted them to come up with an adaptive strategy: breaking queries into "*limited questions in several steps*." They demonstrated not only a capacity to detect inaccuracies but also an ability to adapt AI support meaningfully within pedagogical contexts, such as by reformulating tasks for differentiation, or anticipating risks associated with over-reliance on AI. Crucially, this teacher noted that such adaptation required existing expertise – "*without an already good understanding of the mathematical theory, this couldn't have been done*" - highlighting that effective Gen AI use depends on prior content knowledge. The teacher also identified a learning curve in their own prompt formulation: "*using the right words, word order and mathematical symbols in a certain syntax*." This response illustrates an emerging TPACK: integrating content knowledge (e.g., mathematical theory), technological knowledge (e.g., prompt syntax), and strategic judgment to navigate Gen AI limitations (e.g., breaking problem into more AI-suitable and manageable tasks).

Through the TPACK's lens, these experiences reflect the participants' respective professional contexts and TPACK development stages. Pre-service teachers dominantly reported their experiences with Gen AI tools as instructional support tools suggest their early-stage development in TCK & TK - as participants explored how Gen AI can assist in understanding mathematical concepts but largely without integration into pedagogical practice. Their use was exploratory, often focused on content acquisition. In contrast, in-service teachers recalled more about how Gen AI tools can be used to adapt and create content for both learning and teaching-related purposes, which demonstrate their strong PK & PCK thanks to their experiences. The contrast is particularly evident in how each group addressed Gen AI's technical limitations: in-service teachers demonstrated emerging TPACK, using Gen AI with strategic awareness that integrates content, pedagogy, and technology within specific contexts.

4.3.2. Challenges and coping strategies when using Gen AI tools

Analysis of Gen AI-related challenges and coping strategies (82% response rate) suggested three themes - with equal overall representation from pre-service (n=16) and in-service teachers (n=16).

Accuracy and error management

This was the most frequently reported subtheme and focused on challenges posed by Gen AI's inaccuracy and the user strategies developed to verify and manage errors. Pre-service teachers (n=7) encountered inaccuracies in AI-generated solutions, which prompted them to develop habits of cross-checking and critical evaluation. One participant reflected: "*When I notice these "mistakes", I choose to ask someone else how they would have solved the task instead*." Some turned to external tools, such as answer keys: *"(...) I can present the AI model with the answer key, and often it can reconstruct its answer so it becomes right."* These approaches suggest the emerging understanding of the limitations of Gen AI and a growing ability to strategically mediate between technological output and trusted knowledge sources, reflecting the foundational development of TK in tandem with CK.

In-service teachers (n=8) recognized similar challenges but often described more deliberate verification approaches. Drawing from their experience and for some, technological fluency, they approached AI outputs with a clearer sense of pedagogical responsibility. One teacher noted: "*I think visualization is (…) that ChatGPT unfortunately is poor at creating. In certain mathematical tasks, for example within geometry, one would really have wished for a visual representation (…). However, I have gotten much help when it comes to reformulating tasks, which has been valuable for me to adapt them to for example weaker students (…)*". This example suggests that the teacher was able to identify Gen AI's limitations (TK) in creating accurate mathematical visualizations especially within geometry. However, the same teacher found value in using AI for "*reformulating tasks… to adapt them for weaker students*." This response demonstrates a more advanced TPACK - integrating awareness of technological limitations (TK) with content adaptation (TCK), differentiation strategies (PK) and contextual (XK) decisions. The participant's ability to reformulate tasks while noticing conceptual errors (e.g., mistaking a square for a rectangle) illustrates pedagogically informed use of technology.

Prompting issues

This theme captures communicating challenges with Gen AI tools, along with the strategies participants developed to improve the interaction. Both pre-service (n=4) and in-service teachers (n=3) described communication difficulties with Gen AI, often attributing problems to input quality, as one participant had put it: "*AI did not understand my instructions*." Some suggested that this occurred because "*probably my input was poor*" (excerpt from an in-service teachers). One pre-service teacher reflected: "*But if I myself understand the task and the procedure, these mistakes can be easily identified and corrected by sending the AI additional messages about how it should be done or by questioning why the AI did it a certain way*." This underlines an important insight: effective error correction requires existing content knowledge from users - without understanding the mathematics, the pre-service teacher cannot identify or address AI errors effectively.

An in-service teacher added that the "choice of language" when communicating with Gen AI mattered, with "*English [working] best and somewhat worse with Swedish*." Taken together, these observations point to emerging forms of prompt literacy (TK, TCK), as participants recognized that effective interaction with Gen AI requires careful language choices, iterative clarification, and the ability to critically evaluate and refine prompts and outputs.

Content misalignment issues

This theme captures challenges from mismatches between AI-generated solutions and established methods or curriculum, noted only by pre-service teachers (n = 5). Participants described cases where Gen AI gave valid solutions that did not align with their learning goals. For example: "*AI doesn't always answer correctly on assignments, uses different notations than the book. I usually then write in my own solution or the answer key from the book so that AI understands the logic behind my strategy*." Another participant recalled: "*That you sometimes get "strange" solutions that you don't recognize. For example, in the first single-variable calculus course, we weren't allowed to use L'Hôpital's Rule to solve limits, but the chat (AI) used it*." The mismatch between AI outputs and learners' curricular levels caused confusion, prompting participants to try workarounds (e.g. textbook answers) to prompt AI toward more appropriate responses. These experiences reflect limited TCK development: participants recognized misalignments but lacked strategies or content knowledge to guide AI toward curriculum-appropriate responses. This challenge was absent among in-service teachers, possibly because their established pedagogical and content knowledge enabled them to anticipate and manage such mismatches.

4.3.3. Mathematics learning approaches

Analysis of perceived impact on mathematics learning approaches (85% response rate) indicated two distinct themes across 34 responses with pre-service (n=15) and in-service teachers (n=18).

AI-enhanced learning impacts

This theme included all mentions of perceived AI-facilitated improvements, which reported to influence participants' learning approaches. Pre-service teachers (n=11) more frequently reported positive changes than in-service teachers (n=6). Pre-service teachers emphasized accessibility and independence, describing Gen AI as "*like a teacher you can contact anytime*" that supported "*mobile learning*" and reduced dependency on instructors. In-service teachers who reported positive impacts described different benefits: efficiency ("*faster information access*") and, notably, connections to teaching practice ("*create creative and motivating tasks for students*"). One wrote: "*I dare to understand harder problems and also dare to create my own difficult problems*." From a TPACK perspective, findings suggest that while both groups are developing their TK, a few in-service teachers are demonstrating emerging TPACK knowledge, as they began to use Gen AI not just for their own learning (e.g., exploring more challenges tasks and topics), but also to design tasks and explore mathematical content in different ways.

Limited changes and future implementations

A large proportion of participants - particularly in-service teachers (n=12) - reported minimal impact on learning approaches, with responses such as "*not particularly much*". This aligned with our results reported in the quantitative section. Some expressed future intentions ("*want to learn*," "*maybe after this course*"), while some pre-service teachers (n=4) also acknowledged limited change. These findings suggest that for some readiness and positive attitudes do not automatically translate into changed practice. Contextual factors, sustained engagement, and integration into existing learning or professional routines may be necessary for meaningful change - a pattern consistent with TPACK theory's emphasis on context-dependent knowledge application.

5 Discussions and implications

5.1 Differential Gen AI adoption patterns

Our findings from both quantitative and qualitative data analysis converged to reveal a pattern of developmental integration, where Gen AI tools have become embedded in participants' mathematics learning processes. These adoption patterns appear to be shaped by participants' different career stages and professional contexts. The observed differences from our quantitative data extend beyond simple usage frequency to encompass different approaches to AI integration in mathematics learning. The results indicated that pre-service teachers engage in more developmental integration, where Gen AI tools become embedded in their learning processes as they reported to spend averagely more than 1 hour/ week to learn mathematics with Gen AI tools, with many reported a clear shift in their learning habits. Their primary use for homework assistance and answer verification (e.g. scaffold) indicates Gen AI has evolved from occasional support to a meaningful component of their learning process. Qualitative responses further highlight Gen AI tools' immediate accessibility, efficiency, and ability to support new ways of thinking - particularly when they "get stuck". For some, Gen AI was described as "a game changer, contextualizing the observed quantitative increase in usage frequency and suggesting that heightened engagement reflects not merely habit formation but a perceived transformation in learning approach.

However, the qualitative data also revealed tensions that the quantitative measures alone could not capture. Open-ended responses from pre-service teachers suggest that they face unique content misalignment challenges, where AI-generated solutions, though mathematically correct, often employed methods beyond their curricular levels. This suggests that Gen AI adoption comes with pedagogical costs, as they must develop additional skills to "retrain" AI tools to match their learning context. From a TPACK perspective, as pre-service teachers are still in the process of building their mathematical knowledge, they turn to Gen AI tools to support conceptual understanding and extend their learning. Their use of Gen AI tools also reflects an emerging technological fluency and pedagogical awareness, as they learn to strategically use AI not only to access mathematical content, but also to reflect on their thinking and adjust their learning strategies accordingly.

In contrast, in-service teachers demonstrate more subtle integration, reported less time using and minimal changes to learning approaches. Qualitative responses frequently mentioned continued reliance on traditional methods, skepticism towards Gen AI, or limited perceived need. Majority found no impacts on their mathematics learning approaches. However, our qualitative analysis also indicated that among Gen AI users, they also engaged in professional and pedagogical contemplation (Niess, 2011; Petko et al., 2025). This contemplation was absent among pre-service teachers, indicating that career stage influences not just adoption frequency but the purposes for which AI is employed. In-service teachers used Gen AI for varied tasks, primarily to understand concepts (45.5%), support homework (40.9%), and verify solutions (31.8%). They also explored advanced topics and generated practice problems more often than pre-service teachers.

Most significantly, our qualitative data suggest that both groups demonstrated awareness of Gen AI's technical limitations, but with different levels of sophistication. Pre-service teachers typically employed cross-checking or peer support, in-service teachers exhibited more systematic verification approaches grounded in professional judgment. Some in-service teachers demonstrated emerging TPACK, as they employed Gen AI for task reformulation while maintaining critical oversight of mathematical accuracy and pedagogical appropriateness. This suggests they have developed sophisticated contextual knowledge (XK) about when/how to use AI appropriately (Petko et al., 2025). This contrasts with pre-service teachers more exploratory approach, where AI errors prompted basic verification behaviors but without the sophisticated pedagogical framework evident in experienced educators.

While differences in technology usage between pre-service and in-service teachers reflect well-documented generational trends - where pre-service teachers tend to be more eager toward digital tools (Culp-Roche et al., 2020; Pegler et al., 2010) - the more compelling insight lies not in frequency but in the nature and purpose of their engagement. Previous technologies like calculators (Trouche, 2005), digital textbooks, learning management programs (Lang, 2023; Lee et al., 2023) have largely supported existing pedagogical structures or served as a supplemental or administrative functions, often requiring explicit curricular integration. Our findings suggest that Gen AI tools may introduce more direct engagement with learning processes - particularly in how pre-service teachers describe using them for self-guided problem-solving, feedback, and conceptual re-framing. While these behaviors hint at a shift towards more autonomous and reflective learning, the framing of Gen AI as a cognitive partner remain speculative (Biton & Segal, 2025; Noster et al., 2024). Further research is needed to understand whether these early patterns support deeper learning or simply reframe help-seeking.

Through the TPACK lens (Mishra et al., 2023), participants' engagement with Gen AI reflects their stage of professional knowledge development. For pre-service teachers, whose content, pedagogical, and technological knowledge are still forming, Gen AI provides a flexible space for exploration and autonomy. In-service teachers, guided by established PCK, tend to use Gen AI selectively - not out of resistance but through professional judgment (Leh, 2005), as they aim to integrate new tools in ways that complement their well-established instructional strategies. As they engage with AI's strengths and limits, they develop more nuanced pedagogical reasoning - evaluating not just accuracy but contextual suitability. This evolving TPACK competency blends technological insight with teaching experience, highlighting that Gen AI integration hinges as much on pedagogical fit as on technological readiness (Petko et al., 2025; Priyanda et al., 2025).

5.2 Gen AI readiness, attitudes and perceptions

Both groups of participants reported fairly high perceived usefulness and moderate-to-high behavioral intentions towards Gen AI tools. No significant differences emerged in Gen AI readiness, attitudes and perceptions between pre- and in-service teachers, suggesting that career stage alone may not be a decisive factor. Our result contrasts with previous research with English teachers (Moorhouse, 2024). Instead, usage frequency proved a stronger predictor of readiness and impact. High-frequency users (regardless of career stage) reported greater changes in learning approaches and higher Gen AI readiness, reinforcing the idea that hands-on experience shapes integration strategies more effectively than formal training. This supports findings by Bui et al., who noted that frequent users - despite low trust in Gen AI accuracy - valued the tools as collaborative partners (Bui et al., 2025b). Our results extend this finding to include both pre-service and in-service mathematics teachers, suggesting that experiential learning with Gen AI tools may be more influential than formal training or professional development in shaping readiness. These findings highlight the need for AI-focused professional development that emphasizes practical exposure over abstract instruction, aligning with calls by Ozdemir and Mede (2024) for training that bridges technical and pedagogical dimensions.

5.3 Limitations and conclusions

This study has several limitations. First, our sample size was small (N= 39) and drawn from one university course in Southwest-central Sweden, which limits the generalizability of findings to broader populations or different educational contexts. While this provides an authentic environment where both groups are engaged in similar content and learning environment, offering an ideal opportunity to examine how teachers at different career stages conceptualize and approach Gen AI integration, it does not represent the full spectrum of Swedish mathematics educators' experiences. Second, the design captures participants' Gen AI usage and attitudes at a single point in time during their enrolment in a geometry course. Given the rapid development of Gen AI tools, longitudinal research would be necessary to understand how usage patterns, readiness levels, and pedagogical approaches develop over time. Furthermore, the self-reported nature of data may be subject to recall bias, particularly regarding time allocation and learning approach changes. Future studies could employ more objective measures such as usage logs or learning analytics data to provide more accurate assessments of actual Gen AI engagement patterns.

This study provides important initial insights into how pre-service and in-service mathematics teachers in Swedish context are approaching Gen AI integration in their learning and professional practices. First, our results suggest that career stages influence the qualitative nature of Gen AI integration - purposes, approaches and sophistication, while usage frequency might be a stronger predictor of readiness levels and learning habit changes. Second, our study identified two adoption patterns among participants: pre-service teachers demonstrate more developmental integration to acquire mathematical knowledge through embedded scaffolding use, while in-service teachers exhibit more selective and professionally-grounded integration. Lastly, the study also highlighted three domain-specific challenges and coping strategies utilized by participants in Gen AI integration: accuracy management, prompting issues and content misalignment. While both groups developed coping strategies, in-service teachers demonstrate more sophisticated approaches, whereas pre-service teachers often employ cross-checking with established methods (e.g. peer support, textbooks); they also face unique curricular alignment challenges requiring additional workarounds to train AI toward more appropriate responses. These findings provide concrete evidence of how TPACK development stages influence discipline-specific AI adoption patterns and highlight the need for differentiated professional development approaches that account for both career stage and usage experience.

Research ethics

Author contributions

P.B.: conceptualization, investigation, methodology, data curation, visualization, writing—original draft preparation, writing—review and editing
M.V-B: investigation, project administration, validation, writing—reviewing and editing

Y.L.: methodology, data curation, validation, funding acquisition, writing—review and editing.

All authors have read and agreed to the published version of the manuscript.

Artificial intelligence

The authors use ChatGPT for language checking purpose only.

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Institutional review board statement

This research is reviewed the Ethical Boards of Faculty of Health, Natural Sciences and Engineering, Department of Mathematics and Computer Science, Karlstad University, Sweden. Research registration: HNT 2025/181

Informed consent statement

Informed consent was obtained from all research participants.

Data availability statement

Data is not made publicly available due to privacy and ethical restrictions. Those who interested in the data can contact the first author for more information.

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Conflicts of Interest

The authors declare no conflicts of interest.

Appendix A

Questionnaire on Gen AI interactions

(English translated version)

Note: Instructions such as "Participants choose 1 answer" or "Select all that apply" are added for clarity and ease of understand. In practice, the questionnaire platform guided participants to adhere to the response requirements.

I. Background information

1. **What gender do you identify as?** *(Participants choose 1 answer)*
   - Female
   - Male
   - Others
   - Prefer not to disclose
2. **What is your age?** *(Participants choose 1 answer)*
   - 17-20
   - 21-24
   - 25-28
   - 29-32
   - 33+
   - Prefer not to disclose

3. **Have you ever used Generative AI technologies such as ChatGPT or DALL-E?** *(Participants choose 1 answer)*
   - Never => Why not, please specify.
   - Rarely
   - Sometimes
   - Often
   - Daily

   Participants who chose "Never" option would not continue the questionnaire.
4. **Which of the following Generative AI tools or models have you used?** *(Select all that apply)*
   - OpenAI GPT series (GPT-3, GPT-4) - e.g., ChatGPT
   - Claude
   - Microsoft Copilot
   - Google Bard
   - DALL.E - AI-powered image generation platform
   - Other (please specify) *(Open-ended response)*
5. **How often do you use Gen AI tools for mathematical learning?** *(Participants choose 1 answer and specify the reason for their decision)*
   - Never (specify why)
   - Rarely (specify why)
   - Sometimes (specify why)
   - Often (specify why)
   - Daily (specify why)
6. **How long do you typically spend using Gen AI tools for math learning in a week?**
   - Less than 30 minutes
   - About 30 minutes to less than 1 hour
   - 1–3 hours
   - 3–5 hours
   - More than 5 hours
7. **In the past month, how have you used Gen AI tools in your math learning?** *(Select all that apply)*

   - **Getting assistance with homework** (e.g., receiving hints, partial steps, or full solutions for assigned problems)

- **Understanding math concepts** (e.g., learning general theory, reviewing AI-generated explanations unrelated to specific problems)
- **Practicing problems** (e.g., using AI-generated exercises, drills, or quizzes for extra practice)
- **Checking and verifying answers** (e.g., using AI to confirm correctness or receive feedback on solutions you worked out yourself)
- **Exploring advanced math topics** (e.g., using AI to study concepts beyond what is covered in your current coursework)
- **Other (please specify)**: (Open-ended response)

8. **Has using AI tools changed the way you approach learning mathematics?**
   (Participants choose 1 answer)
   - No, not at all (specify why)
   - No, only slightly (specify why)
   - Yes, somewhat (specify why)
   - Yes, significantly (specify why)
9. **Describe your experiences using Gen AI tools in learning mathematics. What kind of mathematical learning activities you use Gen AI tools for and what were your experiences?**
   - *(Open-ended response)*
10. **What difficulties or challenges have you faced when using Gen AI tools in learning mathematics? How have you addressed these challenges?**
    - *(Open-ended response)*
11. **Has using Gen AI tools changed the way you approach learning mathematics and in what ways?**
    - *(Open-ended response)*

II. Perspectives on Generative AI - Part 1

Indicate for each of the following statements how much you agree or disagree by selecting a number from 1 to 6, where:

1 = Strongly Disagree
2 = Disagree
3 = Somewhat Disagree
4 = Somewhat Agree

5 = Agree
6 = Strongly Agree

1. When I think about Generative AI's capabilities, I worry about how difficult my future will be.
2. I feel anxious about keeping up with the rapid development of Generative AI.
3. I feel uncomfortable or uneasy when thinking about Generative AI.
4. I trust the accuracy and fairness of content generated by Generative AI tools.
5. I am concerned about potential biases in content created by Generative AI tools.
6. I am unsure about the consistency and reliability of Generative AI-generated content for educational purposes.
7. I will ensure the accuracy and reliability of content generated by Generative AI tools before using it.
8. The use of Generative AI enables tasks to be completed more quickly.

Perspectives on Generative AI - Part 2

Indicate for each of the following statements how much you agree or disagree by selecting a number from 1 to 6, where:
1 = Strongly Disagree
2 = Disagree
3 = Somewhat Disagree
4 = Somewhat Agree
5 = Agree
6 = Strongly Agree

9. Using Generative AI increases my productivity.
10. I believe that Generative AI technologies like ChatGPT can offer me unique insights and perspectives I wouldn't have thought of myself.
11. I think Generative AI technologies like ChatGPT can provide personalized and immediate feedback and suggestions for my assignments.
12. I am confident that I can present even the most complex topics about Generative AI in my lessons.
13. I believe I can clarify Generative AI concepts for students if I try hard enough.
14. I am confident that I can support students' learning about Generative AI in my lessons.
15. I am confident that I can teach the basic principles of Generative AI in my lessons.

16. I plan to integrate Generative AI technologies, such as ChatGPT, into my teaching and learning practices in the future.

Perspectives on Generative AI - Part 3

Indicate for each of the following statements how much you agree or disagree by selecting a number from 1 to 6, where:

1 = Strongly Disagree
2 = Disagree
3 = Somewhat Disagree
4 = Somewhat Agree
5 = Agree
6 = Strongly Agree

17. I plan to stay up to date with the latest Generative AI applications in the future.
18. I am motivated to use Generative AI tools to develop learning materials for my students.
19. Studying Generative AI will benefit my future teaching career.
20. I see a strong connection between Generative AI technology and my future teaching practices.
21. I see a clear connection between knowledge of Generative AI and my personal life.
22. I am uncertain about the practical significance of Generative AI in my daily teaching tasks.
23. I feel prepared to handle potential risks associated with Generative AI tools, such as bias, misinformation, or hallucinations.
24. I have up-to-date and relevant knowledge for using Generative AI.
25. I have access to relevant and up-to-date resources to learn about Generative AI in my program.
26. I have the appropriate software for using Generative AI.

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