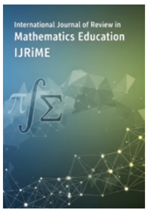

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Adaptive Learning and Generative AI in Mathematics Teacher Education: A Systematic Review

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Abstract

This study presents a systematic review of the current literature on the integration of adaptive learning and generative AI (GenAI) in developing technological pedagogical content knowledge (TPACK) and statistical literacy of prospective mathematics teachers. By analyzing 76 selected articles published between January 2023 and May 2025, this study uses the PRISMA framework and thematic synthesis with the help of NVivo 12 Plus software. The results of the study indicate that adaptive learning environments supported by GenAI can strengthen learning personalization, provide responsive feedback, and visualize content, which significantly contributes to the development of TPACK, especially in the TPK and TCK domains. In addition, GenAI supports the strengthening of statistical literacy through data-driven instructional tools that foster the ability to interpret, represent, and understand the context of data. This study successfully formulated a conceptual framework for adaptive learning integrated with GenAI that reflects the pedagogical needs and specific content in mathematics education. These findings have important implications for teacher education programs, especially in facilitating professional competencies that are adaptive to technological advances and the demands of ethical and reflective data-driven learning.

Keywords: Adaptive Learning; Generative-AI (GenAI); TPACK Framework; Statistical Literacy

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1. Introduction

The rapid development of digital technology has triggered a major transformation in the educational landscape, particularly in how teachers deliver content and students construct knowledge. One innovation currently receiving significant attention is Generative Artificial Intelligence (GenAI), an artificial intelligence technology capable of automatically generating content, analyzing student learning patterns, and providing personalized and adaptive learning interactions. GenAI's potential in education has been proven to enrich the learning process by providing dynamic content, instant feedback, and learning paths tailored to individual needs (Guettala et al. 2024; Guo et al. 2024). In the context of mathematics education, this technology holds significant potential to increase learning motivation, increase student engagement, and reduce cognitive load through a flexible and targeted approach (Guo et al. 2024; Heffernan et al. 2016).

On the other hand, the complexity of modern education requires prospective teachers to not only understand the content of the material being taught but also master effective teaching strategies and be able to utilise technology appropriately. In this regard, the Technological Pedagogical Content Knowledge (TPACK) framework, as developed by Mishra & Koehler (2006) serves as an important conceptual framework that explains the integration of content knowledge, pedagogy, and technology in teaching practice. TPACK is a primary reference in digital-era teacher education, particularly in supporting technology-based instructional decision-making. Furthermore, in the context of the emergence of new technologies such as GenAI, Mishra et al. (2024) proposed expanding TPACK with Contextual Knowledge (CK) elements, namely knowledge of the social, ethical, and cultural contexts that play a role in educational technology practices. This is crucial given that the integration of GenAI carries more complex consequences, including algorithmic bias and risks to autonomous decision-making in learning (Celik, 2023).

In line with the importance of strengthening TPACK, statistical literacy is also a key competency that prospective mathematics teachers must develop. Statistical literacy encompasses not only an understanding of statistical concepts and procedures but also the ability to critically interpret, evaluate, and communicate data-based information in various contexts (Gal, 2002). In a data-driven society, statistical literacy is a key skill to support evidence-based decision-making, both in the classroom and in social life. However, statistics instruction is often delivered conventionally, is not responsive to the diversity of student learning styles, and lacks the integration of technology that can increase effectiveness and participation.

An adaptive learning model that integrates GenAI could be the answer to these challenges. Sun & Zhou (2024) stated that the use of GenAI in higher education contexts has shown a positive impact on improving learning outcomes. Research by Martin et al. (2025) even confirmed that a load reduction instruction-based approach combined with GenAI can help simplify material complexity, accelerate understanding, and improve overall learning effectiveness. In the context of mathematics, this approach aligns with findings by Hoyles (2018), who emphasized that digital technology has the potential to revolutionize mathematics learning practices by providing visual representations, automated assessments, and data-driven pedagogical support. Sun & Zhou (2024) stated that the use of GenAI in higher education contexts has shown a positive impact on improving learning outcomes. Research by Martin et al. (2025) even confirmed that a load reduction instruction-based approach combined with GenAI can help simplify material complexity, accelerate understanding, and improve overall learning effectiveness. In the context of mathematics, this approach aligns with findings by Hoyles (2018), who emphasized that digital technology has the potential to revolutionize mathematics learning practices by providing visual representations, automated assessments, and data-driven pedagogical support.

However, despite its great potential, the use of GenAI in learning is not without challenges. A study by Lee et al. (2025) showed that the use of GenAI can reduce students' cognitive effort, which, if uncontrolled, can negatively impact the development of critical thinking skills.

Therefore, it is important to design adaptive learning that not only leverages GenAI's capabilities but also encourages active participation, reflection, and the development of autonomous learning. Furthermore, UNESCO (2023) emphasizes that the integration of GenAI must adhere to the principles of inclusivity, fairness, and ethics to ensure this technology truly supports the goals of equitable and sustainable education.

While there is considerable research on adaptive learning and GenAI separately, there has been no systematic review examining how the two can be integrated to support the development of TPACK competencies and statistical literacy, particularly for prospective mathematics teachers. This conceptual gap provides an important basis for developing a theoretical and practical synthesis through a systematic literature review. Furthermore, a small number of articles in this review demonstrated results that deviate from the main trend, indicating variation in findings or potential contradictions in the impact of GenAI and adaptive learning on teacher competency development.

This research was conducted as a Systematic Literature Review (SLR) using the PRISMA protocol, encompassing 76 selected articles from the ScienceDirect, ProQuest, and Google Scholar databases. The analysis was conducted using NVivo 12 Plus software to support a valid and systematic thematic synthesis. Furthermore, this study explored anomalies or inconsistencies in findings emerging from various studies as part of the critical synthesis.

This study aims to formulate a conceptual framework for GenAI-integrated adaptive learning to improve the TPACK competencies and statistical literacy of prospective mathematics teachers. The four main questions focused on in this study are:

a. What is the general description of the publication characteristics of the articles included in this systematic review?
b. How is the conceptual structure of GenAI-integrated adaptive learning studied in literature?
c. How does the integration of adaptive learning and GenAI affect the TPACK competencies of prospective mathematics teachers?
d. How does the integration of adaptive learning and GenAI affect the statistical literacy of prospective mathematics teachers?

What are the forms of anomalies or inconsistent findings in the literature review regarding the integration of adaptive learning and GenAI in the development of TPACK and statistical literacy?

2. Method

This study was structured as a Systematic Literature Review (SLR) to explore and synthesize relevant findings related to the integration of adaptive learning and Generative Artificial Intelligence (GenAI) in developing the competencies of prospective mathematics teachers. Specifically, the review focused on the contribution of these two approaches to strengthening Technological Pedagogical Content Knowledge (TPACK) and statistical literacy. The review was conducted in a structured manner, adhering to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which encompass four main stages: identification, screening, eligibility, and inclusion.

To support the thematic synthesis of qualitative data, NVivo 12 Plus software was used as a tool for grouping and content analysis. Five focus questions were formulated to guide the study, including a description of the selected articles, the conceptual structure of GenAI-based adaptive learning, its impact on TPACK competencies and statistical literacy, and the identification of findings that indicated inconsistencies or anomalies in the analyzed literature.

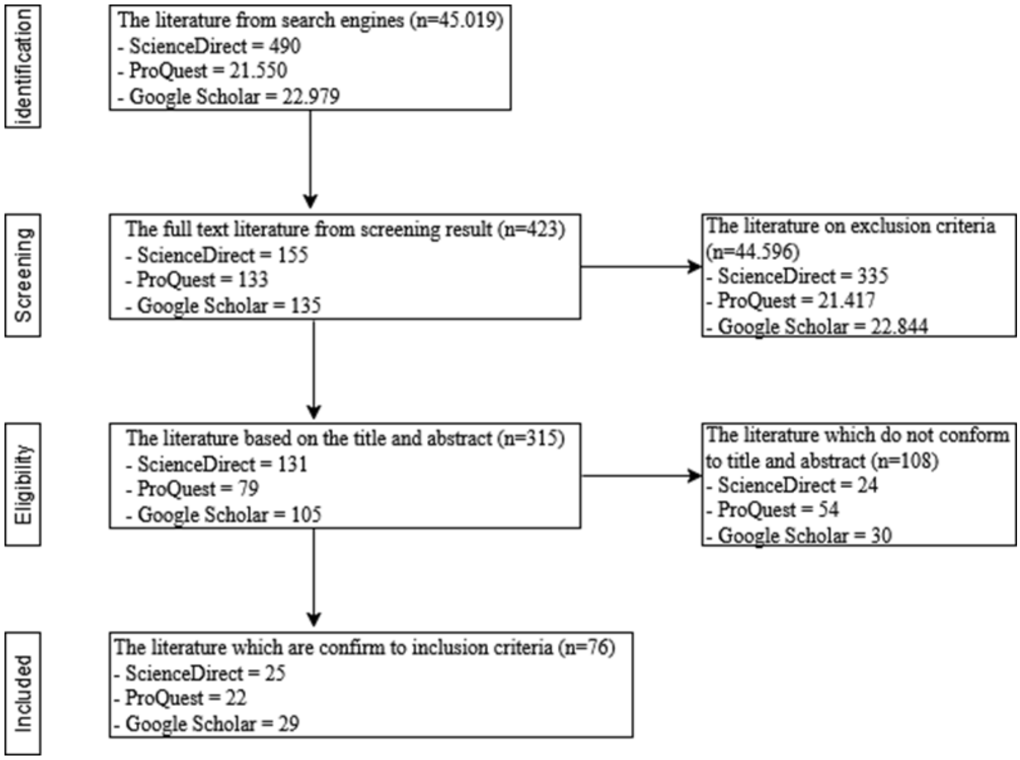

Figure 1. PRISMA Flow diagram for the systematic review search process

The data sources for this study were English-language scientific articles published between January 2023 and May 2025, covering topics including adaptive learning, Generative Artificial Intelligence (GenAI), Technological Pedagogical Content Knowledge (TPACK), and statistical literacy. The units of analysis in this study included teachers, pre-service teachers, or university students, as well as elementary and secondary school students. This selection of units was intended to gain a comprehensive understanding of the use of GenAI in learning contexts from various educational perspectives.

The literature search strategy was conducted through three primary databases: ScienceDirect, ProQuest, and Google Scholar. Additionally, a supplementary search was conducted using the Google search engine to identify relevant articles not yet indexed in these academic databases. Keywords used in the search process included combinations of terms such as "adaptive learning," "Generative AI," "GenAI," "Technological Pedagogical Content Knowledge," "TPACK," and "statistical literacy." The use of this variety of terms aimed at broadening the scope of the articles reviewed without compromising the study's relevance. The systematic procedure for selecting articles refers to the principles of literature review suggested by (Fink, 2014), which emphasises the importance of transparency and accuracy in documenting the review process. The selection process is shown visually in Figure 1.

After passing the selection and eligibility assessment stages, 76 articles were deemed to meet the criteria for analysis using a content analysis approach. Researchers developed a thematic analysis framework to guide the data coding and interpretation process. This framework comprises four main categories: adaptive learning (AL), Generative Artificial Intelligence (GenAI), Technological Pedagogical Content Knowledge (TPACK), and statistical literacy

(SL). Each category was analysed based on several subcategories covering concept definitions, key aspects, relationships between variables, and additional variables or discrepant findings.

Table 1. The analytical framework to guide the content analysis

Categories	Sub-categories
Independent Variabel	
Adaptif Learning (AL)	1. Definition
	2. Key Aspects
	3. Relationship between AI and GenAI
	4. Other Variables or Different Findings
Generative Artificial Intelligence (GenAI)	1. Definition
	2. Key Aspects
	3. Relationship between GenAI and TPACK
	4. Other Variables or Different Findings
Dependent Variable	
Technological Pedagogical Content Knowledge (TPACK)	1. Definition
	2. Key Aspects
	3. Relationship between TPACK and GenAI
	4. Other Variables or Different Findings
Statistical Literacy (SL)	1. Definition
	2. Key Aspects
	3. Relationship between SL and GenAI
	4. Relationship between SL and TPACK
	5. Other Variables or Different Findings

The analysis procedure began with initial coding to identify the underlying themes of each article, followed by axial coding to identify patterns of relationships between categories. This approach aims to integrate and compare findings from previous studies systematically. The structure of the analysis framework used in this study is presented in detail in Table 1 and serves as a guideline for the data exploration process using NVivo 12 Plus software.

In addition to synthesizing dominant patterns, this review also identifies divergent findings and inconsistencies reported across studies. This step is important to ensure a balanced synthesis and to avoid overly deterministic interpretations of GenAI integration in adaptive learning contexts.

To ensure methodological rigor, the quality of the included studies was evaluated using the **Mixed Methods Appraisal Tool (MMAT, 2018 version)**. The MMAT was selected due to its suitability for systematic reviews that include qualitative, quantitative, and mixed-method studies.

Each study was assessed based on five core criteria relevant to its research design. Scores were calculated as percentages and categorized into three levels: high quality (≥80%), moderate quality (60–79%), and low quality (<60%).

Studies classified as low quality were not excluded but were interpreted with caution during thematic synthesis. The quality appraisal results informed the weighting of evidence when interpreting patterns and drawing conclusions.

3. Results and Discussion

This section presents the main results of the literature synthesis process for the 76 selected articles. The analysis was conducted systematically, starting with a review of the general characteristics of the publications and continuing with thematic exploration guided by a previously developed analytical framework. Findings are classified based on five study focuses:

Table 2. Descriptive Characteristics of Articles Analyzed in the Systematic Review

No	Year	Author	Country	Methodology	Unit of Analysis	Key Findings
1	2023	Aksin and Alpay	Turkey	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
2	2023	Ali et al.	Pakistan	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
3	2023	Celik, Ismail	Turkey	Quantitative	Teachers	Adaptive AI systems enhance personalization and self-regulated learning.
4	2023	Chan et al.	Hong Kong	Quantitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
5	2023	Chan et al.	Hong Kong	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
6	2023	Gromik et al.	Australia	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
7	2023	Kryvenko et al.	Ukraine	qualitative	University student	Adaptive AI systems enhance personalization and self-regulated learning.
8	2023	Michel et al.	Taiwan	qualitative	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
9	2024	Mishra et al.	USA	Quantitative	Teachers	TPACK significantly predicts technology integration and student learning outcomes.
10	2023	Sh et al.	Turkey	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
11	2023	Sharples, Mike	UK	Quantitative	University student	Adaptive AI systems enhance personalization and self-regulated learning.
12	2023	Utari et al.	Indonesia	qualitative	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
13	2023	Yeralan et al.	Azerbaijan	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
14	2024	Aldossary et al.	Saudi Arabia	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
15	2024	Azis et al.	Indonesia	Quantitative	University student	Adaptive AI systems enhance personalization and self-regulated learning.
16	2024	Backfisch et al.	Germany	Quantitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
17	2024	Badjeber et al.	Indonesia	Mixed method	Teachers	TPACK significantly predicts technology integration and student learning outcomes.

No	Year	Author	Country	Methodology	Unit of Analysis	Key Findings
18	2024	Bozkurt, Aras	Turkey	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
19	2024	Callingham et al.	Australiad	Quantitative	Pri/middle students	Adaptive AI systems enhance personalization and self-regulated learning.
20	2024	Cha et al.	Hong Kong	Quantitative	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
21	2024	Chiu, Thomas K F	Hong Kong	qualitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
22	2024	Chiu, Thomas K.F.	Hong Kong	qualitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
23	2024	Collie et al.	Australia	Quantitative	Teachers	Adaptive AI systems enhance personalization and self-regulated learning.
24	2024	Cordero et al.	Ecuador	Mixed method	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
25	2024	Fischer et al.	UK	qualitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
26	2024	Fromm et al.	German	qualitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
27	2024	Giannakos et al.	Norway	qualitative	University student	Adaptive AI systems enhance personalization and self-regulated learning.
28	2024	Han et al.	China	Mixed method	Pri/middle students	GenAI improves engagement and academic performance with moderate effect sizes.
29	2024	Hayati and Zaim	Indonesia	Quantitative	Pri/middle students	TPACK significantly predicts technology integration and student learning outcomes.
30	2024	Hidayat et al.	Malaysia	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
31	2024	Idris et al.	Indonesia	Mixed method	University student	Adaptive AI systems enhance personalization and self-regulated learning.
32	2024	Kohen et al.	Israel	qualitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
33	2024	Kurnia et al.	Indonesia	Mixed method	Pri/middle students	TPACK significantly predicts technology integration and student learning outcomes.
34	2024	Kurtz et al.	Israel	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
35	2024	Lee and Song	Korea	Mixed method	Pri/middle students	Adaptive AI systems enhance personalization and self-regulated learning.
36	2024	Mejeh and Rehm	Swiss	Mixed method	Students & teachers	GenAI improves engagement and academic performance with moderate effect sizes.

No	Year	Author	Country	Methodology	Unit of Analysis	Key Findings
37	2024	Mishra et al.	USA	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
38	2024	Moorhouse and Kohnke	Hong Kong	qualitative	Teachers	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
39	2024	Morales et al.	Philippines	Quantitative	Teachers	Adaptive AI systems enhance personalization and self-regulated learning.
40	2024	Moundridou et al.	Greece	Quantitative	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
41	2024	O'Dea, Xianghan	UK	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
42	2024	Polly, Drew	USA	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
43	2024	Qu et al.	Singapore	Mixed method	University student	Adaptive AI systems enhance personalization and self-regulated learning.
44	2024	Sahoo, Binapani	Odisha	Quantitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
45	2024	Sonsupap et al.	Thailand	Quantitative	Teachers	TPACK significantly predicts technology integration and student learning outcomes.
46	2024	Tafazoli, Dara	Iran	qualitative	Teachers	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
47	2024	Jibril and Shittu	Nigeria	qualitative	Teachers	Adaptive AI systems enhance personalization and self-regulated learning.
48	2024	Tho, Luu Huu	Vietnam	Quantitative	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
49	2024	Uras et al.	German	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
50	2024	Utari et al.	Indonesia	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
51	2024	Wahba et al.	Saudi Arabia	Quantitative	University student	Adaptive AI systems enhance personalization and self-regulated learning.
52	2024	Wang et al.	USA	qualitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
53	2024	Wood and Moss	USA	Mixed method	Pri/middle students	TPACK significantly predicts technology integration and student learning outcomes.
54	2024	Yusuf et al.	Nigeria	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
55	2024	Zhu, Yiting	China	R&D	University student	Adaptive AI systems enhance personalization and self-regulated learning.

No	Year	Author	Country	Methodology	Unit of Analysis	Key Findings
56	2025	Adarkwah, Michael Agyemang	German	Quantitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
57	2025	An et al.	USA	qualitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
58	2025	Cheah et al.	USA	Mixed method	Teachers	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
59	2025	de Putter et al.	Netherlands	qualitative	Teachers	Adaptive AI systems enhance personalization and self-regulated learning.
60	2025	Katona and Gyonyoru	Hungary	Mixed method	University student	GenAI improves engagement and academic performance with moderate effect sizes.
61	2025	Koga, Shunya	Japan	Quantitative	Pri/middle students	TPACK significantly predicts technology integration and student learning outcomes.
62	2025	Lee et al.	UK	Quantitative	Teachers	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
63	2025	Lyu et al.	USA	Quantitative	Teachers	Adaptive AI systems enhance personalization and self-regulated learning.
64	2025	Mei et al.	UK	Quantitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
65	2025	Naseer et al.	Pakistan	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
66	2025	Ng et al.	Hong Kong	Quantitative	Teachers	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
67	2025	Raveh et al.	Israel	Quantitative	University student	Adaptive AI systems enhance personalization and self-regulated learning.
68	2025	Rodríguez and Aguerrea	Chile	qualitative	Teachers	GenAI improves engagement and academic performance with moderate effect sizes.
69	2025	Schoen et al.	USA	Quantitative	Students & teachers	TPACK significantly predicts technology integration and student learning outcomes.
70	2025	Smith et al.	USA	Mixed method	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.
71	2025	Sousa and Cardoso	Portugal	Quantitative	Pri/middle students	Adaptive AI systems enhance personalization and self-regulated learning.
72	2025	Strielkowski et al.	USA	Quantitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.
73	2025	Tbaishat et al.	Saudi Arabia	Quantitative	University student	TPACK significantly predicts technology integration and student learning outcomes.
74	2025	Xiao et al.	China	Quantitative	University student	Statistical literacy remains moderate, particularly weak in higher-order reasoning.

No	Year	Author	Country	Methodology	Unit of Analysis	Key Findings
75	2025	Yao and González	Ireland	R&D	University student	Adaptive AI systems enhance personalization and self-regulated learning.
76	2025	Yaseen et al.	Jordan	qualitative	University student	GenAI improves engagement and academic performance with moderate effect sizes.

(1) publication characteristics, (2) aspects of GenAI-integrated adaptive learning, (3) its contribution to TPACK competencies, (4) implications for statistical literacy, and (5) anomalous or inconsistent findings in literature.

The purpose of this section is to highlight key patterns in the development of adaptive learning and GenAI and to provide a theoretical foundation for building a conceptual framework relevant to the educational needs of prospective mathematics teachers in the era of digital transformation.

3.1 General Characteristics of Analysed Publications

To gain a comprehensive understanding of the research landscape related to adaptive learning and Generative AI (GenAI), the first step is to examine the general characteristics of the articles analysed. This section outlines the distribution patterns of publications based on year of publication, country of origin, methodological approach used, and the unit of analysis focused on. This information provides important initial context for understanding the direction of development, trends in focus, and geographic distribution of research in this study. The results of mapping the article analysis framework identify the classification of findings into homogeneous groups, presented in Table 2.

Table 2 summarises the main characteristics of the 76 articles analysed in this systematic review. Information presented includes the year of publication, author(s), country of origin, methodological approach, and unit of analysis. The articles reviewed were distributed between January 2023 and May 2025, with the highest concentration of publications in 2024. The countries of origin of the articles show a global distribution, with a predominance of Asia, North America, and Europe, reflecting the growing global interest in the use of adaptive learning and Generative AI (GenAI) in higher education and teacher training. Quantitative approaches were the most commonly used method, followed by qualitative and mixed methods approaches. Meanwhile, the unit of analysis was dominated by pre-service teachers or university students, followed by active teachers and students at the primary and secondary levels. This distribution indicates that the primary focus of current research is on the use of technology in teacher-based learning and pre-service teachers.

3.2 Conceptual Structure of GenAI-Integrated Adaptive Learning in the Literature

The literature analysed in this study demonstrates a diversity of approaches to integrating adaptive learning with Generative Artificial Intelligence (GenAI) technology. In general, this integration is rooted in the principles of personalised learning supported by the use of real-time data, dynamic content adjustment, and algorithm-based automated feedback. Many studies emphasize that the combination of AI's adaptive characteristics and generative capabilities can create learning environments that are more responsive to individual needs, while supporting the achievement of more measurable and meaningful learning objectives. While there are variations in the terminology and approaches used, a similar conceptual pattern emerges in nearly all publications: a data-driven learning system that combines learning process monitoring, knowledge gap detection, and automatic adjustment of instructional strategies.

3.2.1. Adaptive learning

Adaptive learning is understood as an approach that actively adjusts content, delivery sequence, learning pace, and type of feedback based on the needs and cognitive and affective characteristics of learners (Kryvenko & Chalyy, 2023; Mejeh & Rehm, 2024). These systems generally use data analytics and machine learning algorithms to create personalised learning trajectories, to support optimal learning outcomes and encourage self-regulation (Fromm & Ifenthaler, 2024). Adaptive learning has the power to efficiently and contextually accommodate the varying learning needs of individuals (Katona & Gyonyoru, 2025). Some literature also links adaptive learning with differentiated learning approaches, student-centred learning, and instruction that responds to individual learning styles.

3.2.2. GenerativeAI

Generative Artificial Intelligence (GenAI) is a subfield of artificial intelligence designed to generate new content, such as text, images, code, or other media, based on big data analysis and specific linguistic or visual patterns (Aldossary et al., 2024; Giannakos et al., 2024; Kurtz et al., 2024; Moorhouse & Kohnke, 2024; Wood & Moss, 2024). Unlike traditional predictive AI, which only processes data to recognise patterns and make classifications, GenAI has creative capabilities by generating new, unprecedented information through prompting or text triggering techniques (Kurtz et al., 2024; Michel-Villarreal et al., 2023). Tools such as ChatGPT, DALL·E, and Midjourney are concrete examples of this technological development, which has seen widespread global adoption since late 2022 (Collie et al., 2024; Kurtz et al., 2024; Mishra et al., 2024; Moorhouse & Kohnke, 2024; Warr et al., 2023). With increasing accessibility, GenAI has transformed into various fields (Cordero et al., 2024). GenAI is widespread and impacts various dimensions of educational practice (Chiu, 2024b), presenting both opportunities and challenges for traditional educational models (Chiu, 2024a).

Conceptually, GenAI has become an influential entity in various sectors, including education, due to its ability to simplify the learning process by providing adaptive content, strengthening conceptual understanding, and automatically creating individual learning paths (Kohen-Vacs et al., 2024; Sousa & Cardoso, 2025). A study Hayati & Zaim, (2024) revealed that technology and education influence each other; in the educational context, technology encompasses not only devices and applications but also how teachers integrate them into learning models and content, and respond to user requests by producing original output (Chan & Hu, 2023). On the other hand, Generative AI (GenAI) is considered capable of supporting a learning process that is responsive to the diversity of learning styles, needs, and individual preferences of students (Tafazoli, 2024). This approach emphasises the importance of recognising the unique characteristics of each generation of learners, so that learning strategies can be designed appropriately to optimise the potential of each student (Adarkwah, 2025). Studies also show that GenAI integration can strengthen learning motivation, accelerate feedback, and facilitate collaboration and problem-based learning (Tbaishat et al., 2025; Xiao et al., 2025). Similarly, findings by Sh & Supriyono (2023), revealed that AI significantly enhances learning through content personalisation, real-time analytics, and automated support, resulting in improved student achievement and engagement, as well as educator efficiency. Meanwhile, in teaching, AI can provide better educational resources (Han et al., 2024).

However, the use of GenAI in education also presents many challenges, such as ethical issues, the risk of plagiarism, and limited user understanding in interpreting or evaluating the generated content (de Putter-Smits et al., 2025; Michel-Villarreal et al., 2023). The use of GenAI, such as ChatGPT, in education has opened up opportunities for learning development, but also poses challenges to traditional educational approaches (Chiu, 2024a). The integration of GenAI in education has attracted significant interest and sparked discussion about its pedagogical value (S. Lee & Song, 2024). Generative AI can impact the quality of creative thinking and risks reducing the diversity of representations and ideas (Mei et al., 2025). Furthermore, the advancement of GenAI raises concerns about the potential for automation in teaching and research (Yusuf et al., 2024). Therefore, several researchers emphasise the need for policy guidance and increased technological literacy for educators and students to responsibly optimise the potential of GenAI (Moorhouse & Kohnke, 2024; Ng et al., 2025). The rapid advancement of AI demands its integration into digital transformation policies (O'Dea, 2024). Considering these dynamics, the operational definition of GenAI in this study encompasses all generative, adaptive, and transformative characteristics that directly impact learning design, educational interactions, and competency achievement in the 21st century.

Overall, operational definitions of GenAI in contemporary literature represent its emergence as a technology that is not only technically generative but also transformative in a pedagogical context. GenAI is understood as an artificial intelligence-based system capable of creating new content through large-scale data analysis and has demonstrated significant potential in enhancing personalisation, efficiency, and engagement in the learning process. While numerous studies highlight the benefits of GenAI in supporting adaptive learning and improving the quality of educational interactions, literature also cautions against the importance of ethical policies and increased digital literacy to address the risks of inappropriate use.

3.2.3. Key Aspects of GenAI's Use in Education

A literature analysis shows that GenAI's use in education encompasses several key interrelated aspects, including content generativity, learning personalisation, feedback automation, metacognitive support, and data-driven interactivity. *First*, generativity enables GenAI to generate various forms of content, such as narrative text, practice problems, visual illustrations, and programming scripts, tailored to the learning context, thereby enhancing personalisation and learning engagement. This capability broadens the exploration space in mathematics learning, particularly when used to visualise abstract concepts or provide contextual examples quickly and with a variety of contexts. Furthermore, GenAI is also used by educational staff to develop exam questions, policies, and administrative guidelines, demonstrating its cross-functional application within educational institutions (Yeralan & Lee, 2023).

Second, personalisation of learning is a prominent feature of GenAI. Through integration with adaptive learning systems, GenAI can respond to each student's specific needs based on their interaction history, level of understanding, and learning style (Katona & Gyonyoru, 2025). This facilitates a more inclusive and differentiated instructional approach, particularly in mathematics instruction, which often requires an individualised approach. This customisation is further enhanced by GenAI's ability to access specialised knowledge bases to generate learning assistants tailored to the student's context (Yao & González-Vélez, 2025).

Third, automated feedback is supported by the GenAI feature, which provides instant evaluation or correction of student answers or work, including providing scaffolding for further guidance (Tbaishat et al., 2025). This not only accelerates the learning cycle but also reduces the administrative burden on teachers. Organised feedback through adaptive technology and AI has been shown to increase student engagement, especially when tailored to students' digital literacy levels (Yaseen et al., 2025).

Fourth, support for self-regulation and metacognition is evident in GenAI's ability to guide students in reflecting on their thinking processes, restructuring problem-solving steps, and encouraging exploratory inquiry (Michel-Villarreal et al., 2023; Smith et al., 2025). Studies also show that interactive experiences with GenAI can increase students' awareness of their cognitive strengths and weaknesses in solving mathematical problems. *Fifth*, the data-driven interactivity aspect enables the GenAI system to act as a dialogue partner, not only delivering one-way information but also adapting the format and difficulty of the material based on real-time analytical results of students' learning activities (Lyu et al., 2025; Sousa & Cardoso, 2025). Furthermore, the effective implementation of GenAI in learning contexts also requires institutional readiness, teacher training, and the development of policies that support ethical and inclusive use (Ng et al., 2025).

Taken together, these aspects represent GenAI's potential as an educational technology capable of integrating large-scale data processing with an adaptive and contextual pedagogical approach. Understanding these aspects is a crucial foundation for designing digital learning models that meet the demands of the 21st century, particularly in the education of prospective mathematics teachers.

3.2.4. GenAI-integrated adaptive learning

GenAI-integrated adaptive learning is demonstrated by its ability to expand the scope of personalisation and accelerate data-driven learning responses. Significant advances in AI are driving the development of intelligent adaptive learning (Zhu, 2024). GenAI not only plays a role in content management but also acts as an intelligent agent capable of analysing learning behaviour and generating personalised instructional materials and strategies in real time. A study by Katona & Gyonyoru (2025) demonstrated that AI-based adaptive learning systems can provide contextual scaffolding, enhance self-directed learning, and tailor content based on student needs. Similar findings are supported by Naseer et al. (2025), who underscore the advantages of AI-based adaptive learning and personalisation in supporting students' cognitive achievement and learning performance.

More broadly, Strielkowski et al. (2025) emphasise that AI-driven adaptive learning technology not only promotes educational efficiency and accessibility but also contributes to sustainable development goals. Through continuous analysis of student interactions, this technology enables personalised support, targeted feedback, and optimised learning paths. The use of GenAI can complement conventional teaching methods (Chan & Lee, 2023). This approach enables education to be more inclusive and responsive to the diversity of students' abilities and learning styles. This transformation has been identified as part of a profound educational evolution, contributing to social innovation and the growth of a knowledge-based economy.

In practice, the GenAI-based flipped classroom model has been shown to increase student active participation, conceptual understanding, and motivation (Katona & Gyonyoru, 2025). However, the study also emphasised the importance of maintaining a balance between student autonomy and AI system intervention to prevent technology from overly dominating the learning process. This challenge aligns with broader ethical issues in the application of AI in education, as discussed by Strielkowski et al. (2025), including issues of data privacy, algorithmic transparency, and potential bias in AI-based recommendation systems. Given that the GenAI system relies on large amounts of personal data, the risk of ethical violations and inequitable access must be addressed through strict regulation and fair and inclusive technology design.

Other implementation challenges include the need for teacher training, the readiness of digital education infrastructure, and funding for ongoing technology development and maintenance (Mishra et al., 2024). Therefore, strengthening national policies, integrating AI-based curricula, and building institutional capacity are crucial for the effective, ethical, and sustainable implementation of GenAI-based adaptive learning. In line with this, GenAI guidelines and policies will continue to evolve with technological advances, making communication of policy changes crucial (An et al., 2025). GenAI systems need to be refined to support student-centred learning experiences (Cha et al., 2024). Meanwhile, university leaders are required to design appropriate and effective AI strategies to address contemporary and future higher education issues (Fischer et al., 2024).

Overall, the conceptual structure of GenAI's integrated adaptive learning reflects a paradigm shift in the design and management of learning experiences. This synthesis provides a critical foundation for developing more flexible, data-driven, and inclusive learning models in the digital age. In the context of pre-service mathematics teacher education, this approach can be an innovative strategy for enhancing technology-integrated pedagogical competencies while equipping them with adaptive skills to face the complex challenges of 21st-century learning.

3.3 The Impact of Adaptive Learning and GenAI Integration on TPACK Competencies

In the 21st-century educational landscape, technology integration into learning is no longer an optional element, but rather an essential part of teachers' professional competencies. One widely used conceptual framework for understanding this integration is Technological, Pedagogical, and Content Knowledge (TPACK), as formulated by Mishra dan Koehler (2006). TPACK describes the complex interaction between content knowledge (CK), pedagogy (PK), and technology (TK), which together form the foundation for teaching practices responsive to digital developments. In this study, TPACK is operationalised as an integrated knowledge framework required by prospective teachers, particularly in the context of mathematics education, to design, implement, and evaluate technology-based learning reflectively. Understanding the structure of TPACK is becoming increasingly important in efforts to improve prospective mathematics teachers' readiness to face pedagogical challenges in the era of intelligent technology.

3.3. 1. Technological Pedagogical Content Knowledge (TPACK)

In mathematics education studies, Technological Pedagogical and Content Knowledge (TPACK) has been widely accepted as a conceptual framework to explain the complex knowledge required for teachers to integrate technology into their learning practices effectively. As formulated by Mishra & Koehler (2006), TPACK is not simply a combination of three knowledge domains—content, pedagogy, and technology—but rather a dynamic interaction that forms the foundation of teacher professionalism in the digital age. Recent research emphasises that this framework is not only relevant in the context of teacher training but also crucial as a benchmark for assessing prospective teachers' readiness to design meaningful technology-based learning experiences.

Most sources indicate that TPACK can be positioned as a foundation for understanding how teachers adapt traditional learning methods to digital environments, including in disciplines like mathematics that demand conceptual precision and complex visual representations (Aksin, 2023; Morales et al., 2024; Sonsupap et al., 2024). In this context, technological knowledge does not stand alone but is simultaneously integrated into pedagogical and content understanding. This framework is also recognised for its ability to facilitate improved learning interactions, achieve better learning outcomes, and design learning that is responsive to student needs (Ali et al., 2023; Polly, 2024).

However, several studies have noted that TPACK mastery among prospective teachers remains moderate and uneven across disciplines and educational levels (Raveh et al., 2025; Sahoo, 2024). Structural barriers such as limited access to technology, lack of targeted training, and alienation from new pedagogical approaches remain key challenges (Badjeber et al., 2024; Gromik et al., 2023). In the context of the increasingly widespread development of GenAI, the TPACK framework also faces demands for evolution, by integrating new dimensions such as algorithmic skills and data literacy as part of digital pedagogical competencies (Celik, 2023; Qu et al., 2024). Therefore, in this study, TPACK is operationalised as a conceptual framework that not only underpins the integration of technology in mathematics learning but is also expanded reflectively and adaptively to accommodate the development of intelligent technologies based on GenAI in improving the quality of professional practice of prospective teachers.

3.3. 2. Conceptual Dimensions in the TPACK Framework

The Technological, Pedagogical, and Content Knowledge (TPACK) framework, as formulated by Mishra & Koehler (2006) emphasises the importance of an integrative understanding of the three main components of teacher professional knowledge: content knowledge (CK), pedagogical knowledge (PK), and technological knowledge (TK). This structure represents the systemic and interconnected complexity of teacher knowledge, which does not stand alone but rather forms intersectional domains that reflect teaching competency in the digital age.

Content knowledge (CK) refers to an individual's in-depth understanding of the concepts, principles, and structure of the material focused on in a particular academic discipline (Aksin, 2023). In the context of prospective mathematics teachers, content knowledge (CK) reflects a deep understanding of the structures, principles, and key concepts in mathematics, which directly contributes to increased confidence in designing and delivering meaningful learning (Turmuzi, 2025). Meanwhile, pedagogical knowledge (PK), in an in-depth study by Mishra & Koehler (2006) refers to a comprehensive understanding of the processes, strategies, and approaches to teaching and learning, including a holistic understanding of the goals, values, and direction of education. Furthermore, technological knowledge (TK) encompasses an

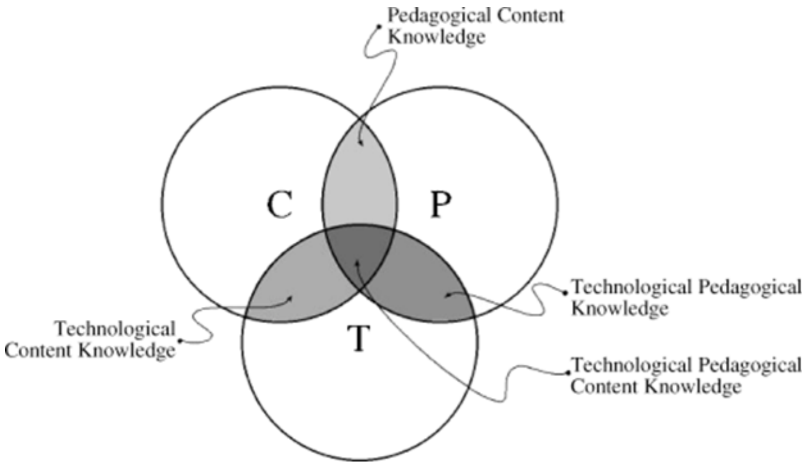

Figure 2. Technological Pedagogical Content Knowledge

understanding of various forms of technology, both conventional ones such as books, blackboards, and stationery, and more advanced digital technologies such as the internet and audio-visual media. This aspect also involves practical skills in using technology effectively to support the learning process. In the context of cutting-edge technological developments, technological knowledge (TK) is not limited to a basic understanding of computer use but also encompasses broader insights into various devices and applications related to developments in the field of information and communication technology (ICT) (Aksin, 2023).

Among these three domains, four intersectional areas are crucial aspects of the TPACK structure. *First*, Pedagogical Content Knowledge (PCK) integrates content and pedagogical understanding in delivering material effectively and adaptively to student characteristics. *Second*, Technological Content Knowledge (TCK) refers to an understanding of the relationship between technology and the substance of teaching materials (Mishra & Koehler, 2006), including the ability to utilise technology strategically to teach certain concepts (Jibril & Adedokun-Shittu, 2024; Warr et al., 2023). *Third,* Technological Pedagogical Knowledge (TPK) reflects an understanding of how technology can be utilised pedagogically to support certain learning strategies, including the implementation of adaptive learning systems and AI-based feedback mechanisms (Warr et al., 2023; Yeralan & Lee, 2023). Figure 2 illustrates the conceptual framework of TPACK, where knowledge of content, pedagogy, and technology are three main components that interact to form the basis for developing good teaching practices (Mishra & Koehler, 2006).

The pinnacle of integrating content knowledge, pedagogy, and technology lies in the TPACK framework, which represents a form of teacher professional knowledge that combines these three domains holistically, contextually, and flexibly (Mishra & Koehler, 2006). In practice, prospective mathematics teachers who master TPACK not only teach material conceptually and communicatively but also integrate technology adaptively to adapt their learning approaches to the diverse and dynamic needs of their students. In the context of mathematics learning, TPACK plays a crucial role in fostering student resilience, particularly when teachers successfully integrate pedagogical strategies, understanding of mathematical content, and effective use of technology to create a learning environment that supports student resilience and growth in facing mathematical challenges (Hamidy & Wibowo, 2023).

Recent literature indicates that developments in AI-based technology and personalised learning approaches have expanded the scope of the TPACK structure. The integration of adaptive learning systems and Generative AI (GenAI) significantly contributes to the dimensions of Technological Pedagogical Knowledge (TPK) and Technological Content Knowledge (TCK), by providing learning experiences that are data-driven and adaptive to students' needs. Furthermore, reflective and ethical aspects in the use of technology are also beginning to be integrated into strengthening the TPACK structure, particularly in terms of protecting student privacy and implementing the principle of ethical responsibility in the use of AI in educational environments (Mishra et al., 2024; Sousa & Cardoso, 2025). Thus, TPACK is not only relevant as a conceptual framework for understanding the professional competence of prospective teachers in the digital era but also develops as a dynamic model that adapts to changes in technology, pedagogical practices, and ethical expectations of the teaching profession in the future.

3.3. 3. The Impact of Adaptive Learning and GenAI Integration on TPACK Competencies

The integration of adaptive learning and Generative AI (GenAI) technology shows significant potential in strengthening the TPACK structure of prospective teachers, particularly in the Technological Knowledge (TK) dimension and at cross-domain intersections such as Technological Pedagogical Knowledge (TPK) and Technological Content Knowledge (TCK). GenAI acts as a catalyst in developing prospective teachers' technological skills through hands-on exploration and experimentation with various interactive AI-based tools, which in turn increases their confidence in utilising technology to support the learning process (Adarkwah, 2025; Ng et al., 2025).

Technological-Pedagogical Knowledge (TPK) reflects an understanding of how technology, including GenAI, can be leveraged to support pedagogical strategies effectively. This includes using technology to address learning barriers experienced by students and opening opportunities for the development of innovative approaches to creatively expressing and evaluating learning outcomes (Warr et al., 2023). In the context of mathematics learning, mastery of TPK enables prospective teachers to design adaptive and responsive learning experiences through the use of GenAI. For example, AI technology can be used to generate questions based on student ability levels, provide automatic formative feedback, and visualise abstract concepts such as functions or limits. This integration strengthens the connection between pedagogical strategies, content understanding, and student learning needs.

On the other hand, strengthening Technological Content Knowledge (TCK) occurs when prospective teachers utilise GenAI-based tools and other digital technologies to design more visual, contextual, and relevant materials. TCK focuses on how technology is utilised in delivering specific content or subject matter (Warr et al., 2023). In the context of mathematics teaching, TCK reflects prospective teachers' ability to use technology to clarify complex, abstract concepts.

Specifically, recent studies addressing the application of GenAI in mathematics education highlight its role in automated problem generation, facilitating pedagogical reflection, and AI-based dialogic interactions. For example, studies by Biton et al. (2025) and Busuttil & Calleja (2025) show that ChatGPT can help teachers design lessons and address mathematics teaching challenges, which contributes to the development of the TPACK dimension. Thus, GenAI provides not only automated visual resources but also an interactive framework for enriching concept representations, providing practice, and facilitating reflective mathematical discussions. This makes technology a strategic tool in bridging abstract material with meaningful and personalized learning experiences in the development of TCK. In the context of mathematics teaching, TCK is strengthened when prospective teachers utilize GenAI-based tools to generate contextualized mathematical problems, provide step-by-step symbolic explanations, and simulate alternative solution strategies. For instance, large language models such as ChatGPT can generate differentiated problem sets based on difficulty levels, while AI-driven systems can dynamically produce visual explanations aligned with specific mathematical concepts.

The integration of adaptive learning in this context also contributes to the enhancement of Pedagogical Content Knowledge (PCK) by providing reflective and data-driven experiences for prospective teachers. Adaptive learning is now seen as an innovative approach to personalized education, leveraging technology and AI to tailor learning experiences to individual students. This system allows for customisation of content, learning pace, and immediate feedback, thereby encouraging increased student participation and learning outcomes (Strielkowski et al., 2025). This ensures that prospective teachers' understanding of teaching strategies is no longer generic but rather based on the dynamics of students' actual needs.

3.4 The Impact of GenAI-Based Adaptive Learning on Statistical Literacy

Statistical literacy is a key competency in mathematics education, especially for prospective teachers who are required to understand and teach data concepts contextually. The integration of Generative AI (GenAI)-based adaptive learning offers new opportunities to support the development of this literacy through personalised, responsive, and relevant learning experiences. With this approach, statistical understanding can be further developed while being tailored to individual cognitive needs.

3.4.1. ***Statistical Literacy***

Operationally, statistical literacy refers to a set of abilities to read, understand, interpret, critically evaluate, and communicate data-based information in various contexts. These abilities include an understanding of statistical concepts, data representations, and decision-making skills based on available statistical information (Kurnia et al., 2024; Rodríguez-Alveal & Aguerrea, 2025). Statistical literacy also involves critical dispositions such as attitudes, beliefs, and awareness of the importance of statistical thinking in everyday and professional decision-making (Callingham & Watson, 2024). Statistical literacy is an essential competency for prospective teachers in interpreting data accurately and making appropriate decisions (Utari et al., 2023), reflecting 21st-century skills that demand critical evaluation and effective utilisation of information, going beyond mere reading and writing skills (Uras et al., 2024)

3.4.2. Dimensions of Statistical Literacy

Statistical literacy encompasses more than simply understanding data concepts; it involves the ability to interpret, critically evaluate, communicate, and make data-based decisions in relevant contexts. Literature emphasises the importance of integrating statistical knowledge, contextual understanding, and data representation as the foundation for comprehensive statistical literacy. Understanding these dimensions is crucial for designing effective learning strategies, particularly for prospective mathematics teachers, who can teach statistics meaningfully and practically.

Statistical literacy encompasses not only the ability to understand basic statistical concepts but also involves some complex skills that play a crucial role in data-based decision-making. In the context of prospective mathematics teacher education, various dimensions of statistical literacy have been identified, including the ability to interpret and evaluate data representations (Koga, 2025), assess statistical claims in various contexts, and use statistical reasoning to solve real-life problems (Uras et al., 2024).

Studies indicate that many prospective teachers still struggle to understand basic concepts, interpret data, and communicate statistical findings (Azis & Dahlan, 2024). This low literacy is influenced by weak learning motivation, a lack of mastery of basic mathematics, and limited experience in reading statistical reports. Therefore, it is important to develop curricula and learning that facilitate structured statistical thinking processes, such as through a statistical literacy process approach (Koga, 2025) and the use of interactive digital media that support simulation-based learning experiences and real-time feedback (Idris et al., 2024). Furthermore, statistical literacy also includes the ability to critically understand and assess the social, cultural, and environmental contexts, as well as the cultural characteristics of data (Uras et al., 2024). These dimensions demonstrate that statistical literacy is multidimensional, and its mastery requires a holistic pedagogical approach and strong preparation during pre-service teacher education.

3.4.3. The Impact of GenAI-Based Adaptive Learning on Statistical Literacy

The integration of GenAI-based adaptive learning has the potential to strengthen the statistical literacy (SL) of prospective mathematics teachers by providing personalised, interactive, and contextually relevant learning experiences. Several studies have highlighted that the use of technologies such as ChatGPT can improve statistical reasoning and positive attitudes toward statistical learning (Wahba et al., 2024). On the other hand, AI-based learning requires a solid foundation of AI literacy, including the ability to think critically about information generated by intelligent systems (Kurtz et al., 2024), including in the context of statistics. This approach enables students not only to understand statistical concepts but also to evaluate the validity of data, apply ethical principles, and consider social and cultural dimensions in data interpretation.

On the pedagogical side, adaptive technology supports active student engagement through real-time feedback and flexible learning pace (Yaseen et al., 2025), while AI-based digital tools and e-learning have been effectively used to address the challenges of teaching statistics at the teacher education level (Idris et al., 2024; Rodríguez-Alveal & Aguerrea, 2025). In other words, GenAI and adaptive systems are not only tools but also catalysts for the formation of an applicable and reflective understanding of statistics, especially in equipping prospective teachers with transnumeracy skills, critical evaluation, and contextual statistical communication.

3.5 Anomalies and Inconsistencies in the Literature Regarding the Integration of Adaptive Learning and GenAI

While various studies indicate that the integration of artificial intelligence in adaptive learning can enhance the personalization and effectiveness of instruction (Katona & Gyonyoru, 2025; Strielkowski et al., 2025), the literature also reveals some contradictory and problematic findings. One crucial issue is the concern about the decline in critical thinking capacity due to the use of GenAI. A study by Lee et al. (2025) showed that excessive reliance on GenAI tends to reduce engagement in deeper critical thinking processes, as users focus solely on verifying information and integrating responses, rather than developing arguments and understanding the substance. This is particularly important in the context of teacher education, where critical thinking is an essential element of pedagogical decision-making and professional reflection.

Furthermore, several studies highlight the risks of over-reliance on GenAI, particularly in tasks such as academic writing and teaching materials development (H. H. Lee et al., 2025; Mei et al., 2025; Sousa & Cardoso, 2025). While tools like ChatGPT have been shown to improve writing productivity and quality, there are concerns that students, especially those in their early years, may miss out on opportunities to develop independent, logical and creative thinking skills if they rely too heavily on this technology.

Another aspect widely criticised in the literature is the issue of ethics and academic integrity. Several studies indicate that educators tend to limit the use of GenAI to administrative activities or lesson preparation, rather than in direct teaching and learning, due to concerns about the lack of human interaction and the absence of clear ethical guidelines (Cheah et al., 2025). In this context, a dilemma arises when GenAI is used in the evaluation or production of student academic work, potentially leading to covert plagiarism or violations of academic integrity (Lyu et al., 2025). As Mei et al. (2025) noted, while GenAI can support creative expression, it can also degrade the value and learning experience if not managed transparently and reflectively.

Inconsistencies are also evident in the adoption of GenAI by educational institutions. Some institutions reportedly demonstrate a high level of trust in GenAI, while others demonstrate distrust due to unclear regulations, minimal training, and a lack of digital literacy (Lyu et al., 2025). This situation demonstrates that the successful integration of GenAI in adaptive education is highly dependent on the context, institutional readiness, and adequate policy support.

Overall, these findings underscore the importance of a more balanced and critical approach to integrating GenAI into adaptive learning, particularly in the context of pre-service teacher education. Developing an ethical framework, enhancing GenAI literacy, and cultivating reflective and critical thinking habits need to be integral parts of the implementation strategy to ensure this technology truly supports the strengthening of TPACK and statistical literacy without sacrificing core educational values.

4. Discussion

Based on a comprehensive analysis of the impact of GenAI-based adaptive learning integration on strengthening TPACK competencies and statistical literacy of prospective mathematics teachers, this study proposes a new theoretical framework that represents the conceptual

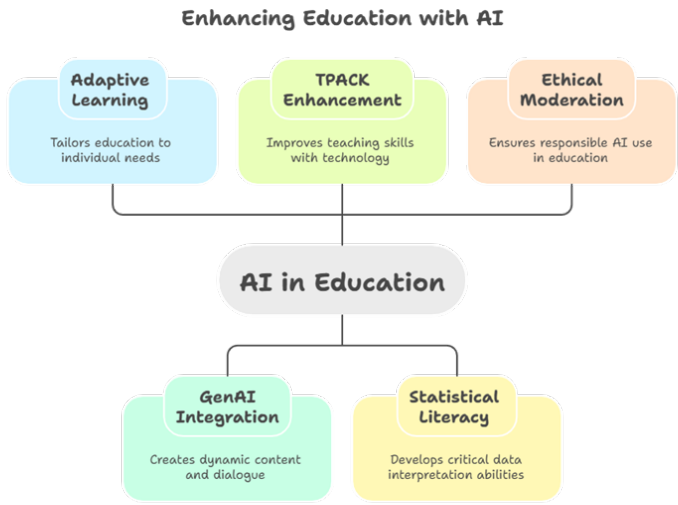

Figure 3. Theoretical Framework of Adaptive Learning Integrated with GenAI to Enhance TPACK and Statistical Literacy in Pre-Service Mathematics Teachers

linkages among these key components. This framework is derived from a synthesis of empirical and thematic findings from the literature, as shown in the following chart.

The results of this study indicate that the integration of adaptive learning and Generative AI (GenAI) technology facilitates the emergence of new learning approaches that are responsive, technology-based, and supported by data analysis. This transformation creates learning conditions that are more personalised, contextual, and aligned with the professional development needs of prospective mathematics teachers, particularly in enhancing their TPACK competencies and statistical literacy.

In the context of TPACK, the application of GenAI in adaptive learning environments opens opportunities for prospective teachers to develop a more comprehensive understanding of the relationship between content, pedagogy, and technology. They are not only trained as users of technology but also as designers of AI-based learning experiences that consider individual learner needs (Katona & Gyonyoru, 2025; Strielkowski et al., 2025). GenAI's role in providing instant feedback and adapting learning strategies also deepens its understanding of the pedagogical and technological domains within the TPACK framework.

Furthermore, prospective teachers' statistical literacy appears to be encouraged through data exploration facilitated by the GenAI-based system. Interaction with intelligent statistical tools, such as NLP-based chatbots (Natural Language Processing) or machine learning-based query answering systems, enables students to develop the ability to interpret, communicate, and critically evaluate data in real-world contexts (Wahba et al., 2024; Yaseen et al., 2025). This supports a shift from simply understanding statistical procedures to applying data to decision-making.

However, findings also indicate significant challenges. Several studies highlight the potential for over-reliance on GenAI technology, which could hinder the development of students' critical and reflective thinking skills (Kurtz et al., 2024; Tlili et al., 2023). Furthermore, concerns have arisen about unethical academic practices resulting from too easy access to instant AI-based solutions, such as plagiarism or data manipulation (Kane et al., 2016; Sousa & Cardoso, 2025). In this regard, it is necessary to consider curricular policies that integrate AI ethical literacy and academic integrity principles as part of strengthening the professional competency of prospective teachers.

The integration of GenAI-based adaptive learning has strategic potential in shaping future teachers who are not only competent in technology and pedagogy but also sensitive to the critical, reflective, and ethical aspects of learning practices. Moving forward, learning design needs to be directed toward balancing the exploitation of technological advantages with the development of cognitive autonomy in order to achieve sustainable educational transformation.

While the dominant trend suggests positive contributions of GenAI-integrated adaptive learning, the variability of findings indicates that its effectiveness is highly context-dependent. Institutional readiness, teaching digital competence, and ethical governance structures mediate the impact of AI adoption. Therefore, GenAI should not be conceptualized as an autonomous driver of educational transformation, but rather as a socio-technical tool whose pedagogical value depends on instructional design and professional competence.

5. Conclusion

This systematic literature review concludes that the integration of adaptive learning and Generative AI (GenAI) technology opens up space for the development of new pedagogical approaches that are responsive, data-driven, and relevant to individual learners' needs. This approach has been proven to support the improvement of prospective mathematics teachers' TPACK competencies, particularly in developing contextual, technology-based pedagogical skills. Furthermore, the application of GenAI also strengthens statistical literacy, particularly in terms of data understanding, representation, and informed decision-making.

However, the synthesis also uncovered several challenges and inconsistencies in literature, including ethical issues, the risk of technology dependency, and limitations in developing independent critical thinking skills. Therefore, efforts to integrate GenAI into teacher education need to be designed holistically, taking pedagogical, technological, and ethical aspects into account in a balanced manner.

Going forward, further research is needed that empirically tests the effectiveness of GenAI-based adaptive learning models, as well as exploration of instructional designs that can strengthen the integration of TPACK and statistical literacy in teacher education contexts. These recommendations are not only relevant for the development of technology education theory but also provide practical contributions to teacher education curriculum design in the era of artificial intelligence.

This review is limited by the relatively short publication window (2023–2025), which reflects the emergent nature of GenAI research. Additionally, the predominance of quantitative studies may influence the thematic distribution of findings. Future studies should include longitudinal empirical investigations to validate the proposed conceptual framework.

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Declarations

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AI Declaration Statement	:	Chatgpt is used to determine the writing outline.

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