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The impact of generative artificial intelligence use on pre-service teachers' learner autonomy: A systematic literature review

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ABSTRACT

The rapid adoption of generative artificial intelligence (GenAI) in higher education raises questions about its influence on pre-service teachers' learner autonomy. This study aimed to systematically identify, appraise, and synthesise the reported effects and associations between GenAI use and the self-directed and self-regulated learning of pre-service teachers. A systematic literature review was conducted following PRISMA 2020 using the Scopus database (2023–2026). Eligible studies were peer-reviewed, English-language empirical publications involving pre-service teachers or teacher education students that examined GenAI use in relation to learner autonomy, self-directed learning, or self-regulated learning. Of 86 records screened, 22 studies met the inclusion criteria and were analysed through thematic synthesis, vote-counting, and an appraisal of evidence strength. Five themes emerged: enhancement of self-directed learning, self-regulated learning support through adaptive feedback, learning motivation and autonomy, critical thinking and creativity, and the risk of over-reliance. Vote-counting showed that 16 studies (72.7%) reported predominantly favourable findings, four (18.2%) reported mixed findings, and two (9.1%) reported predominantly risk-oriented findings; these proportions describe the direction of reported findings rather than an effect size, and only two studies used controlled experimental designs. The reported effects and associations between GenAI use and learner autonomy appear conditional: the educational value of GenAI is more strongly associated with the quality of pedagogical integration than with technology availability alone. Teacher education curricula therefore need structured AI literacy training that positions GenAI as a fading scaffold rather than a substitute for learners' own regulation.

INTRODUCTION

The emergence of generative artificial intelligence (GenAI), particularly large language models (LLMs) such as ChatGPT and Gemini, has fundamentally transformed the landscape of higher education. Its pace of adoption has been remarkably rapid. The survey by the Digital Education Council (2024) of 3,839 students in 16 countries found that 86% of students had used AI in their studies, while a national survey in the United Kingdom recorded a surge in the proportion of students using generative AI, from 66% in 2024 to 92% in 2025, with 88% of them using it for assessed work (Freeman, 2025). A similar surge has occurred in academic attention: approximately eight months after the release of ChatGPT, there were already 212 Scopus-indexed research articles discussing ChatGPT in education (Polat et al., 2024), and a bibliometric analysis of the literature on artificial intelligence in teacher education shows a sharp increase in publications since 2023 (Hursen et al., 2024). Students and faculty members in teacher education have also become part of this wave of adoption (Pattier, 2026; Picciano, 2024, 2026; Tsiani et al., 2025).

In the context of teacher education, the integration of GenAI is a critical issue because pre-service teachers play a dual role: they use GenAI to learn, and they will later facilitate their own students' use of similar technologies (Kohnke et al., 2026; Yadav et al., 2026). The use of GenAI by pre-service teachers has been reported to range from lesson planning, academic writing, and mathematical reasoning to the development of foreign language teaching materials (Cabrera-Solano et al., 2026; Choi, 2026; De Asis, 2026; Dilling & Herrmann, 2024; Karakaya et al., 2025; Katsampoxaki-Hodgetts, 2026). The reported benefits generally include fast, personalised feedback; time efficiency; and support for reflective thinking (Colaco & Antao, 2025; Jansen et al., 2024; Kinder et al., 2025). Nevertheless, mapping studies indicate that the use of AI to develop pre-service teachers' pedagogical competence has not yet been comprehensively mapped (Mwananyama & Ngao, 2026).

One of the aspects most frequently discussed in these studies is learner autonomy. To provide a clear conceptual foundation for the synthesis, this study distinguishes three interrelated constructs. First, learner autonomy is understood as the learner's capacity and agency to take responsibility for decisions about their own learning (Holec, 1981). Second, self-directed learning (SDL) refers to a process in which learners take the initiative to diagnose their learning needs, formulate goals, select resources and strategies, and then evaluate their learning outcomes (Knowles, 1975), and also encompasses the dimensions of self-management, self-monitoring, and motivation (Garrison, 1997). Third, self-regulated learning (SRL) refers to the regulation of cognitive, metacognitive, motivational, and behavioural processes during learning, which unfolds in a cycle of forethought (planning), performance (execution and monitoring), and self-reflection phases (Panadero, 2017; Zimmerman, 2002). Accordingly, learner autonomy is positioned as an overarching capacity, SDL as its manifestation at the macro level (that is, what is learned and why), and SRL as its manifestation at the micro level (that is, how a learning task is regulated) (Saks & Leijen, 2014). This distinction is vital because GenAI can influence each level differently: adaptive feedback can foster reflection and self-regulation (Adler & Shani, 2026; Nguyen & Barbieri, 2025; Yessimbekova et al., 2026), experiences of autonomy can strengthen autonomous motivation (Choi, 2026; Li et al., 2025), and GenAI-assisted activities can enhance engagement, collaboration, and critical thinking (Busuttil, 2025; Lehtinen et al., 2026; Salhab & Aboushi, 2026), provided that they are framed by institutional guidelines that safeguard academic autonomy (Cacho, 2024).

However, not all findings are positive. A number of studies warn of the risk of over-reliance, which may undermine learner autonomy when GenAI is used without an appropriate pedagogical framework (Pachava et al., 2026; Sun et al., 2025). Studies outside the teacher education context have even shown that unrestricted access to GenAI can improve performance when the tool is available but reduce it once withdrawn (Bastani et al., 2025), and that it can also trigger

metacognitive laziness (Fan et al., 2025). Among pre-service teachers, these concerns take the form of questions about the authenticity of work, the reliability of information, and the need for AI literacy (Belda-Medina & Kokošková, 2026; Carcary & Buckland, 2025; Ko et al., 2025), while a review of ChatGPT use in language teacher education emphasises that its benefits depend heavily on the context of use (Ebrahimi et al., 2025). In other words, the relationship between GenAI use and learner autonomy appears not to be simply linear and positive but contingent on how the technology is integrated into learning.

Previous reviews remain general. An et al. (2026) synthesised 39 studies on university students' use of GenAI across disciplines and found that the use of GenAI to support self-regulation had the lowest challenge-to-success ratio, but they did not separate the pre-service teacher population. Sardi et al. (2025) reviewed 38 studies on the GenAI influence on SRL and critical thinking, but included the general student population and focused on 2022–2024. Meanwhile, reviews in teacher education (Ebrahimi et al., 2025; Karakaya et al., 2025; Mwananyama & Ngao, 2026) focused on the range of GenAI applications, its integration into language teacher education, or pedagogical competence, rather than on learner autonomy as an outcome. Consequently, it remains unknown (1) how the empirical evidence on GenAI relates specifically to the SDL, SRL, and learner autonomy of pre-service teachers; (2) what proportion of studies report favourable findings compared with those reporting risks; and (3) how strong the research designs underlying these findings are. This gap is significant because pre-service teachers may pass on to their future students the patterns of GenAI use that they themselves have experienced, so teacher education curriculum policy requires an evidence base that separates benefits from risks.

Building on this conceptual framework, the contribution of this review is formulated in three respects. First, at the construct level, the synthesis focuses on learner autonomy, SDL, and SRL as reported outcomes (Holec, 1981; Zimmerman, 2002), rather than merely on perceptions or intentions to use GenAI. Second, at the population level, the review is limited to pre-service teachers, taking into account their dual role as learners and as models for their future students (Lunenberg et al., 2007). Third, at the interpretive level, supportive and risk-related findings are synthesised in a balanced manner through the lens of scaffolding and the principle of fading (van de Pol et al., 2010; Wood et al., 1976), so that it is possible to distinguish when GenAI acts as a scaffold that strengthens self-regulation and when it acts as a substitute that weakens it. Given that the evidence base is still relatively small (22 studies) and drawn from a single database, this contribution is best understood as a systematic initial mapping accompanied by a conceptual framework that requires further testing.

Based on these issues, this study aims to identify, appraise, and synthesise the reported effects and associations between GenAI use and the learner autonomy of pre-service teachers through a systematic literature review (SLR). Specifically, it addresses the following questions: (1) how GenAI supports the SDL and SRL of pre-service teachers; (2) how GenAI use is related to learning motivation and autonomy; (3) how GenAI contributes to critical thinking and creativity; (4) what risks of over-reliance accompany GenAI use; and (5) what the direction and strength of the evidence are in the existing studies. The results of the synthesis are expected to serve as a basis for developing teacher education curricula that optimise the benefits of GenAI without compromising pre-service teachers' learner autonomy.

METHOD

This study employed the SLR method in accordance with the PRISMA 2020 guidelines (Page et al., 2021), so the searching, screening, and selection of articles were conducted transparently and can be replicated. The data source was the Scopus database, chosen for its broad coverage of reputable journals in education and learning technology, standardised metadata, and filtering features, which facilitate replication of the search. The use of a single database is a limitation

recognised from the outset because it may overlook studies indexed only in Web of Science, ERIC, or Google Scholar; this limitation is discussed at the end of the Discussion section. The search was conducted in August 2026 with a publication-year range of 2023–2026. The year 2023 was chosen as the starting point because ChatGPT was released to the public only in late November 2022, so empirical studies on LLM-based GenAI could only have been published from 2023 onwards. The search strategy combined keywords related to generative artificial intelligence, ChatGPT, and large language models; self-directed learning, self-regulated learning, and learner autonomy; and pre-service teachers and teacher education students.

The inclusion criteria were established before screening, namely: (a) empirical studies (qualitative, quantitative, mixed-methods, experimental, or design-based research) that had undergone peer review, in the form of journal articles or conference papers; (b) participants who were pre-service teachers or students in teacher education programmes, including postgraduate teacher education programmes; (c) the use of LLM-based GenAI as the focus or as part of the intervention; (d) reporting of findings related to learner autonomy, SDL, SRL, or their accompanying aspects, such as autonomous motivation, critical thinking in the use of GenAI, and over-reliance; and (e) publication in English. The exclusion criteria included opinion articles, editorials, and non-systematic reviews without empirical data; studies that did not involve teacher education populations; and studies on non-generative AI.

The article selection process followed the PRISMA flow (Figure 1). The initial search yielded 86 unique records. Title and abstract screening excluded 46 records because they did not address teacher education, were unrelated to GenAI in learning, or did not contain aspects of learner autonomy.

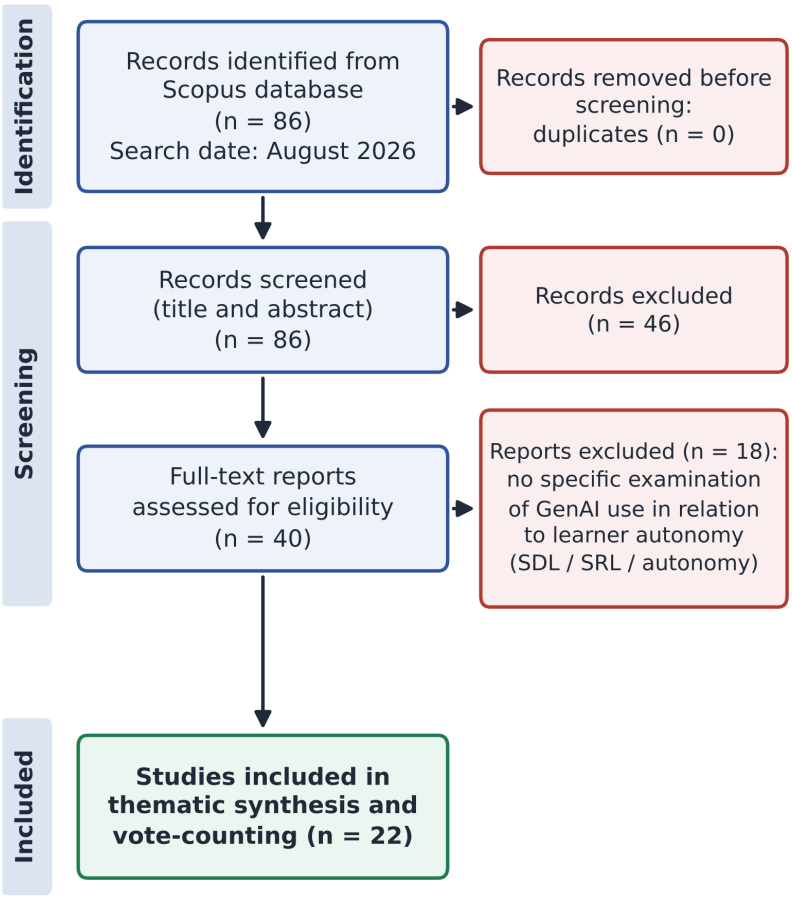


Figure 1. PRISMA 2020 flow diagram of the article selection process

A total of 40 articles then underwent full-text assessment, and 18 articles were excluded because they did not specifically address the relationship between GenAI use and pre-service teachers' learner autonomy, leaving 22 articles to be included in the synthesis. To reduce selection bias, title–abstract screening and full-text assessment were carried out independently by two authors, guided by predetermined eligibility criteria; disagreements between them were resolved through discussion until consensus was reached.

Data from each article were extracted using an extraction sheet that recorded the authors and year of publication, the journal, the research objectives, the research design, participant characteristics, the type of GenAI used, and the main findings related to learner autonomy (Table 1). They were analysed using thematic synthesis (Thomas & Harden, 2008) with a deductive–inductive approach. Deductively, five initial theme categories were established before coding on the basis of the conceptual framework and the research questions, namely SDL, SRL, learning motivation and autonomy, critical thinking and creativity, and the risk of over-reliance. Inductively, more detailed codes within each theme, such as adaptive feedback, self-monitoring, critical evaluation of AI outputs, and cognitive offloading, emerged from repeated reading of the results section of each article and were then used to sharpen the boundaries and operational definitions of each theme. One article could be assigned to more than one theme when it addressed several aspects of learner autonomy at once. The coding process was conducted manually by the researchers.

Because 13 of the 22 studies (59.1%) used qualitative or mixed-methods designs and the measurement instruments were not uniform, an effect-size meta-analysis could not be validly conducted. As a descriptive complement, the vote-counting technique was used, based on the direction of findings, with the unit of analysis being the main findings in the results section of each article related to learner autonomy, SDL, or SRL. The classification criteria were as follows: (a) predominantly favourable (positive), when all relevant main findings showed support for learner autonomy, for example, improved self-regulation, autonomous motivation, or quality of independent work, whereas risks were not reported as findings and were at most mentioned as notes or recommendations; (b) mixed, when an article reported benefits and risks to learner autonomy as equally substantive findings; and (c) predominantly risk-oriented (negative), when the main findings were dominated by risks, barriers, or perceived threats to learner autonomy without any substantive benefits being reported. Classification was based on the results section rather than on speculation in the discussion section. It should be emphasised that vote-counting describes only the proportion of studies by the direction of their findings and does not take sample size or effect magnitude into account; it therefore does not constitute an effect estimate (Borenstein et al., 2009).

The quality of evidence in each study was appraised by drawing on the logic of the Mixed Methods Appraisal Tool (MMAT) (Hong et al., 2018), which is suitable for reviews that include qualitative, quantitative, and mixed-methods designs, particularly its principle of alignment between the design and data and the claims being made. Because this review is concerned with the extent to which studies can support inferences about the impact of GenAI on learner autonomy, the appraisal focused on two criteria: (1) whether the design included a comparison condition, such as a control group; and (2) whether outcomes were measured directly through performance, artefacts, or records of learning behaviour, or only through self-reported perceptions and intentions. Studies were categorised as having strong evidence if they met both criteria, moderate evidence if outcomes were measured directly without a comparison condition, and limited evidence if they relied only on perceptions or intentions. This appraisal was not used to exclude studies but to weight the interpretation: findings supported by studies with strong or moderate evidence were given greater weight in the discussion, and the vote-counting results were re-reported by evidence-strength category (Table 2).

RESULTS

A total of 22 articles met the inclusion criteria and were analysed in this SLR (Table 1). Although the search range began in 2023, no articles published in 2023 passed the selection; all of the included articles were published in 2024 (4 articles; 18.2%), 2025 (9 articles; 40.9%), and 2026 (9 articles; 40.9%) (Figure 3). The absence of articles from 2023 is probably due to the time lag required for empirical studies involving pre-service teachers to complete data collection, peer review, and publication after the release of ChatGPT, whereas publications in that year were still mostly conceptual and opinion pieces that did not meet the inclusion criteria. The fact that the number of articles for 2026, which covers only January–August, has already matched that for 2025 indicates that attention to this topic continues to grow. In terms of design, 7 articles (31.8%) used qualitative designs, 6 articles (27.3%) used mixed methods, 2 articles (9.1%) used experiments, 1 article (4.5%) used a quantitative survey, and 6 articles (27.3%) used other designs such as process mining, design-based research, and analytical reviews (Figure 4). Participants ranged from small-scale qualitative studies (6–17 pre-service teachers) to large-scale studies (269–486 participants), with a geographical spread covering Germany, Greece, China, Finland, the Philippines, Hong Kong, and the United States. ChatGPT was the most frequently studied GenAI tool (14 articles; 63.6%), followed by generic or unspecified GenAI (6 articles; 27.3%) and combinations of several platforms such as Gemini, Copilot, and Claude (2 articles; 9.1%).

The thematic synthesis produced five main themes (Figure 2), namely learning motivation and autonomy (8 articles; 36.4%), the risk of over-reliance (6 articles; 27.3%), SRL support through adaptive feedback (5 articles; 22.7%), critical thinking and creativity (4 articles; 18.2%), and enhancement of SDL (3 articles; 13.6%). Because one article could address more than one aspect of learner autonomy, the total number of theme assignments (26) exceeds the number of articles. The predominance of qualitative and mixed-methods designs reflects the exploratory nature of the topic at the current stage of research development.

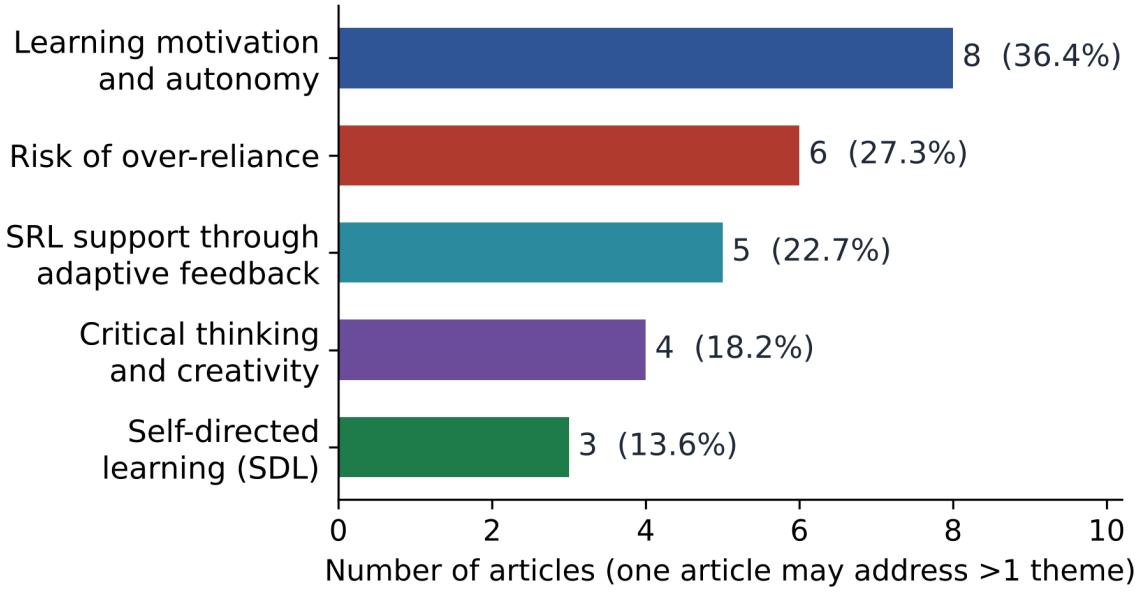
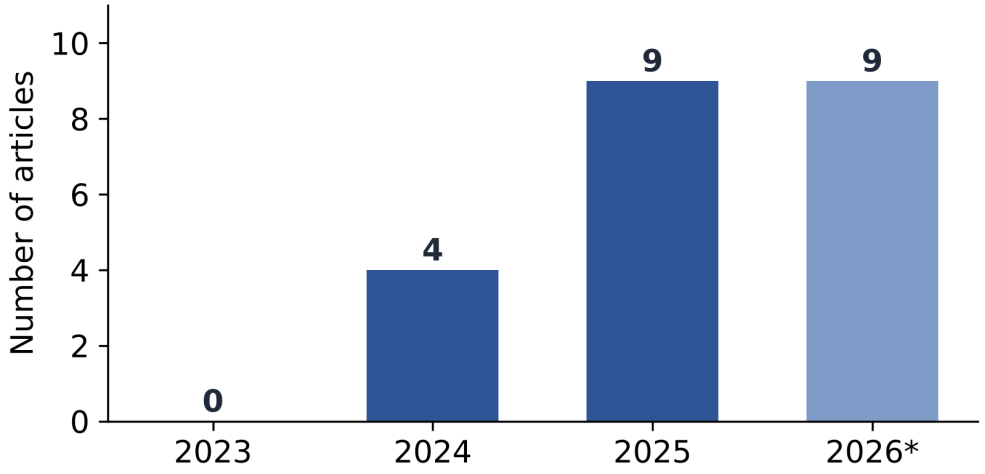


Figure 2. Distribution of themes across the 22 core articles



**2026 covers January–August only (search conducted in August 2026)*

Figure 3. Number of core articles by publication year (2023–2026)

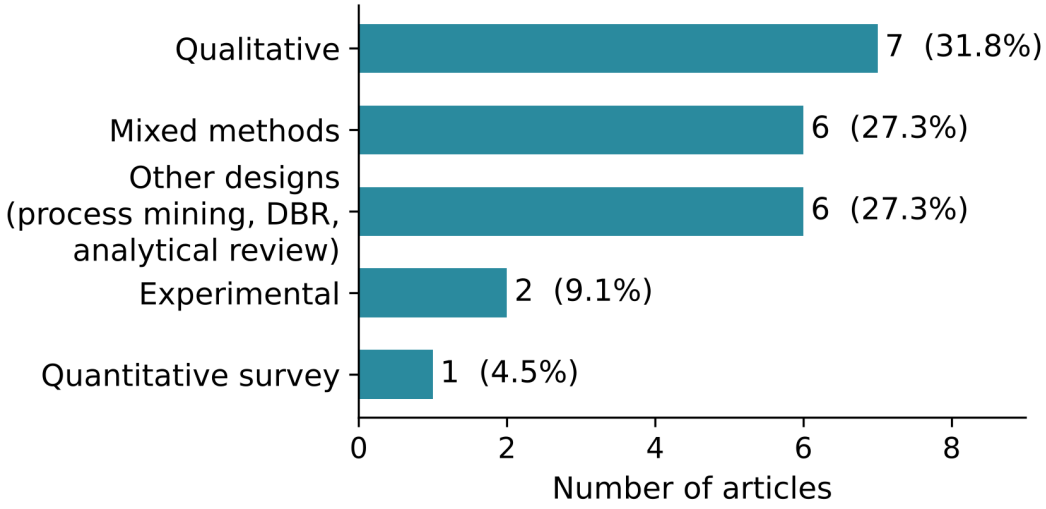


Figure 4. Distribution of research designs across the 22 core articles

Enhancement of self-directed learning

Three articles reported findings relevant to the strengthening of self-directed learning. Picciano (2024) found that graduate students in education used ChatGPT as an exploratory aid in essay writing, enabling them to explore ideas independently before composing the final text. Dilling & Herrmann (2024) reported that pre-service elementary school mathematics teachers interacted with ChatGPT to construct geometric proofs in an exploratory manner, although their understanding of how the language model works remained limited. Cabrera-Solano et al. (2026) found that integrating ChatGPT, Gemini, and Copilot into a flipped classroom model improved the language accuracy and the quality of independent writing of 242 pre-service teachers of English as a foreign language (EFL), with AI feedback complementing instructor feedback more rapidly.

Support for self-regulated learning through adaptive feedback

Five articles reported the role of GenAI in supporting SRL. In this review, the SRL support theme was operationally defined as findings showing that GenAI helped pre-service teachers carry out one of the phases of the SRL cycle (Zimmerman, 2002), namely planning goals and strategies, monitoring progress while working on tasks, or evaluating and reflecting on learning

outcomes, primarily through adaptive feedback. In the planning and monitoring phases, Nguyen & Barbieri (2025) found that GenAI provided tactical and emotional guidance for 151 pre-service teachers before and during field placements, whereas Adler & Shani (2026) developed a hybrid Human-GenAI course that equipped pre-service teachers as SRL agents, although engagement in metacognitive discourse remained limited. In the evaluation and reflection phases, Kinder et al. (2025) showed that LLM-based adaptive feedback improved the quality of diagnostic reasoning among 269 pre-service teachers compared with a group that received static feedback, whereas Jansen et al. (2024) found that LLM feedback was rated as useful for revision in 59% of argumentative texts, lower than expert feedback (88%). De Asis (2026) added that the effectiveness of GenAI as a scaffold for academic writing among 46 pre-service teachers in the Philippines was strongly influenced by their digital literacy and ethical awareness. Accordingly, the most consistent SRL support was observed in the evaluation and reflection phases through feedback, whereas the evidence for the planning phase remains limited.

Enhancement of learning motivation and autonomy

Eight articles, the largest number of any theme, reported findings related to learning motivation and autonomy. Drawing on self-determination theory, Choi (2026) found that critical evaluation and adaptation of ChatGPT content when designing science lessons gave rise to experiences of autonomy, competence, and relatedness among six elementary pre-service teachers. Li et al. (2025) reported that human–machine collaboration with ChatGPT in inclusive STEM teacher training also supported autonomous motivation. Sun et al. (2025) found, through a survey of 486 students in China, that AI self-efficacy was a strong predictor of the intention to continue using GenAI. Bui et al. (2025) reported the readiness and positive attitudes of 77 Finnish pre-service teachers towards GenAI, while Markos et al. (2024), Mustroph & Steinbock (2024), Tsiani et al. (2025), and Picciano (2026) likewise confirmed similar positive attitudes regarding time efficiency and learning support, although the level of readiness varied across geographical contexts.

Development of critical thinking and creativity

Four articles reported contributions of GenAI to higher-order thinking skills. Busuttil (2025) found that an Assessment as Learning approach using ChatGPT encouraged 63 pre-service teachers to engage in critical reflection while developing and evaluating teaching materials. Kartal (2024) found, through a narrative inquiry involving 12 pre-service English teachers, that the use of ChatGPT during teaching practice fostered the development of reflective and creative perspectives. Lehtinen et al. (2026) found that conceptual and pedagogical prompting patterns among 75 pre-service teachers in a collaborative lesson-plan development task were closely related to the group's level of critical thinking. Belda-Medina & Kokošková (2026) found that the critical evaluation of ChatGPT-generated texts by 58 pre-service EFL teachers in a collaborative writing task also sharpened their linguistic analysis skills.

Risk of over-reliance on generative AI

Six articles identified the risk of over-reliance on GenAI. Kohnke et al. (2026) found that 17 pre-service teachers in Hong Kong were aware of the risks of over-reliance, data privacy concerns, and access disparities as major challenges. Tsiani et al. (2025) reported concerns about the information reliability and academic integrity. Carcary & Buckland (2025) concluded that perceived risk significantly and negatively affects attitudes towards GenAI adoption. Adler & Shani (2026) noted that interaction with GenAI chatbots can hinder positive learning experiences when the characteristics of the dialogue do not support metacognitive discourse. Markos et al. (2024) and Belda-Medina & Kokošková (2026) also reported similar concerns about the authenticity of work and the reliability of AI outputs in students' writing tasks.

Descriptive quantitative analysis (vote-counting) and strength of evidence

As a complement to the thematic synthesis, each article was classified by the direction of its findings, based on the criteria described in the Method section (Figure 5).

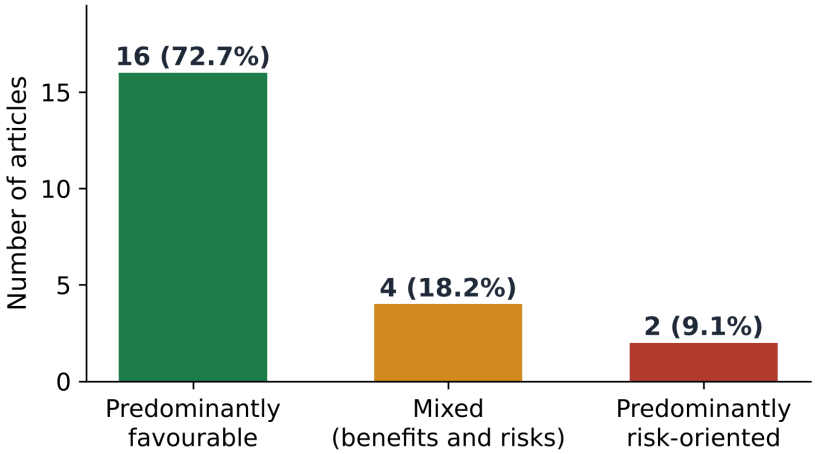


Figure 5. Vote-counting results by direction of findings (n = 22); proportions describe the direction of findings, not the magnitude of effects

Of the 22 articles, 16 (72.7%) reported predominantly favourable findings for learner autonomy; 4 articles (18.2%) reported mixed findings, namely Tsiani et al. (2025), Markos et al. (2024), Adler & Shani (2026), and Belda-Medina & Kokošková (2026); and 2 articles (9.1%) reported predominantly risk-oriented findings, namely Kohnke et al. (2026) and Carcary & Buckland (2025). The 72.7% should be read as the proportion of studies with favourable findings, not the magnitude of GenAI's effect on learner autonomy. Overall, 6 of the 22 studies (27.3%) reported concerns about over-reliance, a proportion that cannot be neglected when formulating policies on GenAI integration in teacher education.

The appraisal of evidence strength (Table 2) showed that only 2 studies (9.1%) were classified as having strong evidence, namely two experimental studies with comparison conditions (Jansen et al., 2024; Kinder et al., 2025), whereas 10 studies (45.5%) had moderate evidence and 10 studies (45.5%) had limited evidence because they relied only on perceptions or intentions. When the vote-counting was re-reported by these categories, the proportion of predominantly favourable findings was 2 of 2 studies with strong evidence, 8 of 10 studies with moderate evidence (80%), and 6 of 10 studies with limited evidence (60%). Conversely, both predominantly risk-oriented studies and two of the four mixed studies came from the limited-evidence category. This pattern suggests that the risk of over-reliance has so far been captured mostly through perceptions and has not been widely measured directly, whereas directly measured benefits are generally short-term and tied to specific tasks. Both sides of the findings therefore need to be interpreted with caution.

VOSviewer bibliometric analysis

As a complementary analysis, a bibliometric co-occurrence analysis of author keywords was conducted on the 22 core articles using VOSviewer and visualised in three maps, namely a density map, an overlay map by publication year, and a cluster network map (Figure 6). The density map (Figure 6a) shows that the terms “teacher education”, “chatgpt”, “artificial intelligence”, and “generative ai” represent the four highest density points, confirming that these four concepts are at the core of the discussion in most of the articles reviewed. The overlay map (Figure 6b), which colours keywords by average publication year, shows that terms such as “personnel training”, “teacher training”, “collaborative learning”, and “digital literacy” (in yellow) are relatively more recent topics than the terms “students”, “qualitative research”, and “artificial intelligence” (in purple-blue), which have been research foci for longer, indicating a shift in research attention towards aspects of training and practical collaboration.

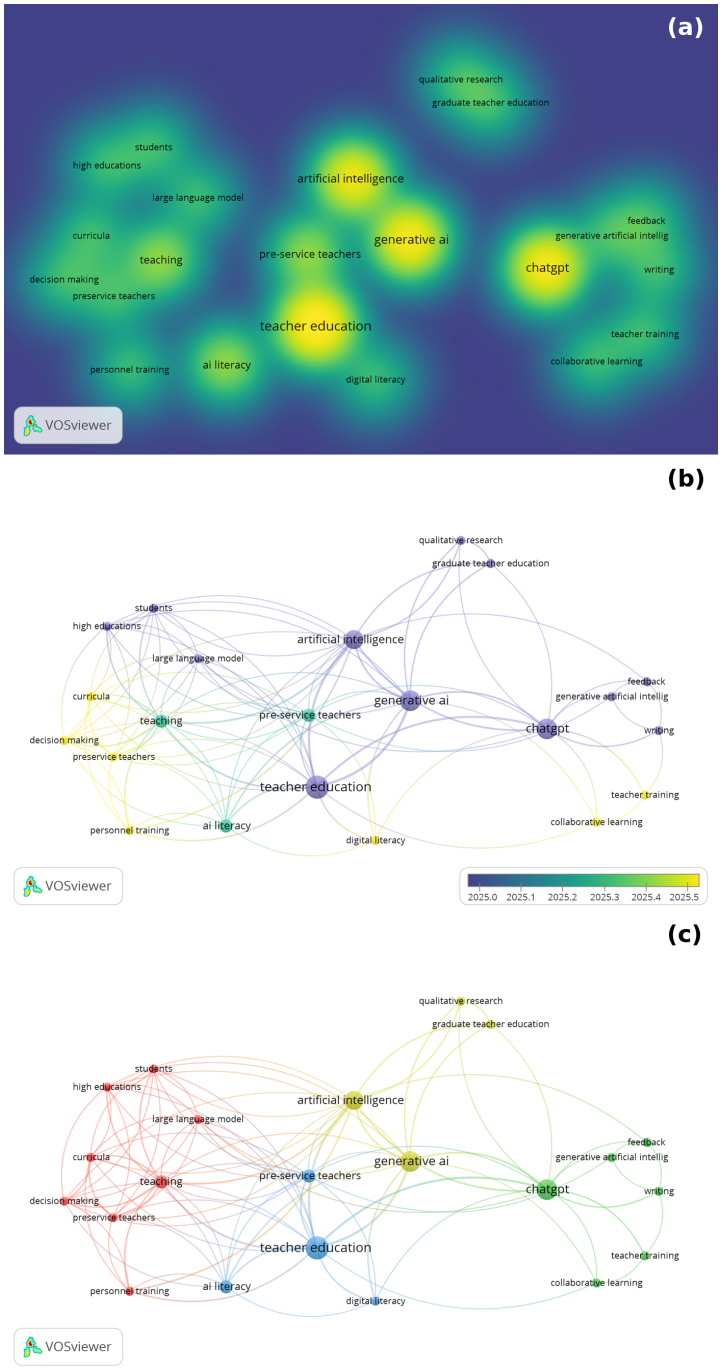


Figure 6. VOSviewer bibliometric maps: (a) density visualisation, (b) overlay visualisation by year, (c) network visualisation of keyword clusters

Table 1. Summary of data extraction for the 22 core articles

No	Authors (Year)	Method/Design	Participants	GenAI Type	Main Theme
1	Nguyen N.N.; Barbieri W. (2025)	Mixed-methods (survey, interviews, practicum scores, correlation & thematic analysis)	151 pre-service teachers	GenAI (general chatbot)	SRL support (adaptive feedback)
2	Tsiani M.; Lefkos I.; Fachantidis N. (2025)	Mixed-methods (survey & hands-on intervention)	Undergraduate & master's pre-service teachers	Generative AI (general)	Learning motivation & autonomy; Risk of over-reliance

No	Authors (Year)	Method/Design	Participants	GenAI Type	Main Theme
3	Cabrera-Solano P.; Castillo-Cuesta L.; Ochoa-Cueva C. (2026)	Mixed-methods, design-based research	242 pre-service EFL teachers	ChatGPT, Gemini, Copilot	Enhancement of self-directed learning
4	Kohnke L.; Zou D.; Lai C.; Gu M.M. (2026)	Qualitative (interpretive interviews)	17 pre-service teachers (Hong Kong)	GenAI (general)	Risk of over-reliance
5	Dilling F.; Herrmann M. (2024)	Exploratory qualitative (instrumental genesis)	Pre-service elementary mathematics teachers	ChatGPT (LLM)	Enhancement of self-directed learning
6	Kinder A.; Briese F.J.; Jacobs M.; Dern N.; Glodny N.; Jacobs S.; Leßmann S. (2025)	Experiment (control vs. adaptive group)	269 pre-service teachers (Germany)	ChatGPT (LLM)	SRL support (adaptive feedback)
7	Busuttil L. (2025)	Assessment as Learning, thematic analysis	63 pre-service teachers	ChatGPT	Critical thinking & creativity
8	Li T.; Zhan Z.; Ji Y.; Li T. (2025)	Two exploratory studies (Self-Determination Theory)	Pre-service STEM teachers	ChatGPT	Learning motivation & autonomy
9	Kartal G. (2024)	Narrative inquiry (weekly narratives & interviews)	12 pre-service English teachers	ChatGPT	Critical thinking & creativity
10	De Asis R.D. (2026)	Mixed-methods (survey, interviews, focus group discussion)	46 pre-service teachers (Philippines)	GenAI (general)	SRL support (adaptive feedback)
11	Lehtinen A.; Channa F.; Näykki P.; Ahlström E.; Hiljanen M. (2026)	Process mining, video analysis	75 pre-service teachers	ChatGPT	Critical thinking & creativity
12	Sun J.; Wu Q.; Ma Z.; Zheng W.; Hu Y. (2025)	Quantitative survey, PLS-SEM	486 students (China)	GenAI (general)	Learning motivation & autonomy
13	Markos A.; Prentzas J.; Sidiropoulou M. (2024)	Structured questionnaire, SWOT analysis	257 pre-service teachers (Greece)	ChatGPT	Learning motivation & autonomy; Risk of over-reliance
14	Mustroph C.; Steinbock J. (2024)	Survey/qualitative	Pre-service EFL teachers (Germany)	ChatGPT	Learning motivation & autonomy
15	Choi Y.-S. (2026)	Four-week qualitative study (project, reflective journals)	6 pre-service elementary teachers	ChatGPT	Learning motivation & autonomy
16	Adler I.; Shani Y. (2026)	Design-based research	Pre-service teachers (Human-GenAI course)	GenAI chatbot (TeachPal)	SRL support (adaptive feedback); Risk of over-reliance
17	Jansen T.; Höft L.; Bahr L.; Fleckenstein J.; Möller J.; Köller O.; Meyer J. (2024)	Comparative experiment (blind evaluation)	89 pre-service teachers	ChatGPT 3.5-Turbo	SRL support (adaptive feedback)
18	Picciano A.G. (2024)	Qualitative study	15 graduate students in education	ChatGPT	Enhancement of self-directed learning
19	Picciano A.G. (2026)	Longitudinal study (2 years)	K-12 teachers (graduate programme)	ChatGPT, Gemini, Claude	Learning motivation & autonomy

No	Authors (Year)	Method/Design	Participants	GenAI Type	Main Theme
20	Bui P.; Korhonen T.; Kontkanen S.; Karme S.; Piispa-Hakala S.; Veermans M. (2025)	Mixed-methods (quantitative & qualitative survey)	77 pre-service teachers (Finland)	GenAI (general)	Learning motivation & autonomy
21	Carcary M.; Buckland P. (2025)	Review & empirical analysis of risk perceptions	Higher education students	GenAI (general)	Risk of over-reliance
22	Belda-Medina J.; Kokošková V. (2026)	Mixed-methods (convenience sampling, text analysis)	58 pre-service EFL teachers	ChatGPT	Critical thinking & creativity; Risk of over-reliance

Table 2. Strength of evidence and direction of findings across the 22 core articles (study numbers refer to Table 1)

Strength of evidence	Criteria	Predominantly favourable	Mixed	Predominantly risk-oriented	Total
Strong	A comparison condition is present and outcomes are measured directly	6, 17	–	–	2
Moderate	Outcomes are measured directly (performance, artefacts, records of behaviour) without a comparison condition	1, 3, 5, 7, 8, 10, 11, 15	16, 22	–	10
Limited	Only self-reported perceptions or intentions	9, 12, 14, 18, 19, 20	2, 13	4, 21	10
Total		**16 (72.7%)**	**4(18.2%)**	**2 (9.1%)**	**22**

The cluster network map (Figure 6c) groups the keywords into four main clusters that align with the themes from the synthesis in the preceding section. The first cluster ("teaching", "curricula", "decision making", "preservice teachers", "personnel training") captures curriculum and institutional decision-making. The second cluster ("teacher education", "pre-service teachers", "ai literacy", "digital literacy") reflects AI literacy readiness and pre-service teachers' learner autonomy. The third cluster ("artificial intelligence", "generative ai", "qualitative research", "graduate teacher education") represents the general conceptual discourse on GenAI. The fourth cluster ("chatgpt", "feedback", "writing", "collaborative learning", "teacher training") represents the practical application of ChatGPT in providing feedback and in writing. The correspondence between these bibliometric clusters and the five themes from the thematic synthesis provides complementary confirmation of the thematic structure; however, given the small number of articles, this analysis is descriptive and not intended as a test of validity.

DISCUSSION

The findings on the SDL and SRL themes support the view that GenAI can function as an external scaffold that expands students' metacognitive capacity (Cabrera-Solano et al., 2026; Picciano, 2024). This aligns with Zimmerman (2002) SRL cycle model, which positions feedback as the link between the performance and self-reflection phases: immediate, specific feedback helps learners monitor the gap between goals and attainment and then adjust their strategies. However, the quality gap between LLM feedback and expert feedback (Jansen et al., 2024) suggests that GenAI cannot yet replace human mentors, consistent with Nguyen & Barbieri (2025), who find that GenAI is most effective when it strengthens, rather than replaces, human mentorship. Accordingly, the benefits of GenAI for SRL are complementary, and pedagogical integration designs need to position GenAI as a supplement to human support.

On the theme of learning motivation and autonomy, the consistency of the findings of Choi (2026) and Li et al. (2025) reinforces the self-determination theory proposition that autonomous motivation grows when the basic needs for autonomy, competence, and relatedness are satisfied (Ryan & Deci, 2000). In the context of GenAI, these needs appear to be satisfied when students

are positioned as active evaluators of AI outputs rather than passive recipients. The finding of Sun et al. (2025) on self-efficacy as a predictor of the intention to use GenAI extends the Technology Acceptance Model (Davis, 1989), which originally emphasised perceived usefulness and ease of use, by showing that the acceptance of GenAI is also determined by students' beliefs in their ability to manage the technology independently. It should be noted that most studies in this theme measured attitudes, readiness, or intentions (Table 2), so their relationship to actual independent learning behaviour remains to be tested. Variation in readiness levels across contexts (Bui et al., 2025; Tsiani et al., 2025) also indicates that cultural factors and institutional infrastructure moderate the relationship between GenAI and autonomous motivation, so generalisation across contexts should be undertaken with caution.

The findings on critical thinking and creativity show a consistent pattern: the higher-order cognitive benefits of GenAI (Busuttil, 2025; Kartal, 2024; Lehtinen et al., 2026) emerge primarily when students engage in active evaluation and revision of AI outputs rather than merely accepting the answers generated. Belda-Medina & Kokošková (2026) reinforced this pattern by showing that collaborative tasks requiring linguistic analysis of ChatGPT texts, in fact, become a space for practising critical thinking. This finding is consistent with the idea of productive failure in the constructivist perspective, which holds that meaningful learning occurs when learners actively grapple with a problem before receiving the solution, rather than merely consuming ready-made information (Kapur, 2008).

On the other hand, the findings on the risk of over-reliance (Adler & Shani, 2026; Carcary & Buckland, 2025; Kohnke et al., 2026) provide evidence that runs counter to the optimistic narrative of the four preceding themes. This contradiction does not mean the findings cancel each other out; rather, it underscores that the relationship between GenAI and learner autonomy is conditional and double-edged, in line with Tsiani et al. (2025), who found that the benefits and risks of GenAI can emerge simultaneously within the same student population. Adler & Shani (2026) specifically showed that it is the quality of discourse in human–AI interaction, rather than the availability of the technology itself, that determines whether GenAI supports or undermines students' metacognitive processes.

The risk of over-reliance warrants further analysis because it appeared repeatedly in 6 of the 22 studies. At least three mechanisms explain why this risk arises. The first is the cognitive offloading mechanism: humans tend to shift cognitive load to external tools when those tools are available and reliable (Risko & Gilbert, 2016). Unlike earlier aids, GenAI can take over the SRL phases themselves, namely planning, monitoring, and even reflecting, so that what is offloaded is not merely the burden of remembering but the process of self-regulation. The experiment by Fan et al. (2025) showed that learners assisted by ChatGPT obtained higher task scores without a commensurate improvement in knowledge acquisition and transfer, and exhibited symptoms of metacognitive laziness, whereas Darvishi et al. (2024) found that students tended to depend on AI assistance instead of learning from it. The second is the scaffolding-without-fading mechanism: effective scaffolds are contingent and are gradually reduced until responsibility shifts to the learner (van de Pol et al., 2010; Wood et al., 1976), whereas GenAI is always available and does not automatically reduce its assistance. Bastani et al. (2025) showed that students with unlimited access to GPT-4 performed worse after access was removed, whereas a tutor version designed with pedagogical safeguards largely avoided this effect. The third is the ecological mechanism: cognitive, social (norms of use among peers), and institutional (the absence of clear policies) factors intertwine to form patterns of over-reliance (Pachava et al., 2026). Among pre-service teachers, these three mechanisms may be amplified by heavy workloads, assessment oriented towards final products, and inadequate digital literacy (De Asis, 2026; Kohnke et al., 2026). Accordingly, the root of over-reliance lies not in GenAI technology alone but in the interaction among technology design, task design, and the learning ecosystem.

Conversely, when GenAI is integrated with an explicit pedagogical framework, for example, through feedback at scale in project-based learning (Yessimbekova et al., 2026) or structured microlearning (Salhab & Aboushi, 2026), its benefits for students' engagement and learning autonomy tend to be more consistent. This reinforces the conclusion that pedagogical design is the most decisive factor, rather than merely a moderating variable, in the relationship between GenAI and learner autonomy.

These findings also address the question of whether GenAI can serve as a pedagogical agent or a scaffolder for learners. In the literature, a pedagogical agent is a character or system designed to facilitate learning through socio-cognitive interaction, for example, as a mentor or learning companion (Kim & Baylor, 2006). The evidence in this review indicates that GenAI can perform some of these functions: the TeachPal chatbot in a hybrid cognitive apprenticeship model acted as a mentor that modelled and coached SRL-supporting practices (Adler & Shani, 2026), adaptive feedback functioned as a responsive tutor (Kinder et al., 2025), and GenAI served as a companion to mentors during field placements (Nguyen & Barbieri, 2025). However, GenAI qualifies as a true scaffolder only when three characteristics of scaffolding are met, namely contingency (support adjusted to needs), fading (support decreasing as competence increases), and transfer of responsibility to the learner (van de Pol et al., 2010; Wood et al., 1976). The first characteristic is relatively easy for GenAI to achieve, whereas the second and third must be deliberately designed by educators because they are not inherent in the technology.

Therefore, educators are key to ensuring that GenAI supports high-quality learning. Based on the synthesis of findings, at least five strategies can be applied by teacher educators. First, design tasks that require students to evaluate, critique, and revise AI outputs rather than merely produce them (Belda-Medina & Kokošková, 2026; Busuttil, 2025). Second, use configurations or prompts that direct GenAI to provide hints and guiding questions instead of direct answers, as in the safeguarded tutor version in the study by Bastani et al. (2025). Third, combine AI feedback with feedback from instructors or cooperating teachers so students learn to compare and weigh the quality of feedback (Jansen et al., 2024; Nguyen & Barbieri, 2025). Fourth, implement fading in a planned manner, for example through AI-free working phases and a gradual reduction of support throughout the semester. Fifth, require process documentation, such as prompt logs and reflections on decisions to accept or reject AI suggestions, so that students' reasoning remains visible and assessable (Katsampoxaki-Hodgetts, 2026). Through these strategies, teacher educators simultaneously model the wise use of GenAI, which pre-service teachers can later emulate in their own classrooms (Lunenberg et al., 2007).

These findings also add a vital nuance to the optimism that often emerges in studies of technology acceptance in teacher education. Katsampoxaki-Hodgetts (2026) emphasised that GenAI-assisted lesson planning is effective only when students have a clear framework for critically evaluating AI outputs, supporting Belda-Medina & Kokošková (2026) and Busuttil (2025). Without such a framework, the risks identified by Carcary & Buckland (2025) and Kohnke et al. (2026) could materialise, especially among students with limited digital literacy (De Asis, 2026). The vote-counting results (Figure 5) are consistent with this pattern: the predominance of favourable findings (72.7% of studies) indicates a positive tendency but does not indicate effect magnitude, while concerns about over-reliance appearing in 27.3% of studies signal that this risk is a recurring empirical pattern, even though it has mostly been captured through perceptions (Table 2). Accordingly, the relationship between GenAI and learner autonomy is not deterministic but depends on the quality of instructional design and on the AI literacy readiness of students and institutions.

Overall, the Scaffold–Substitute conceptual model (Figure 7) summarises patterns across the five themes and is proposed as this review's theoretical contribution. The model assumes GenAI is pedagogically neutral: the same function, such as adaptive feedback, content generation, or dialogic support, can follow two different pathways.

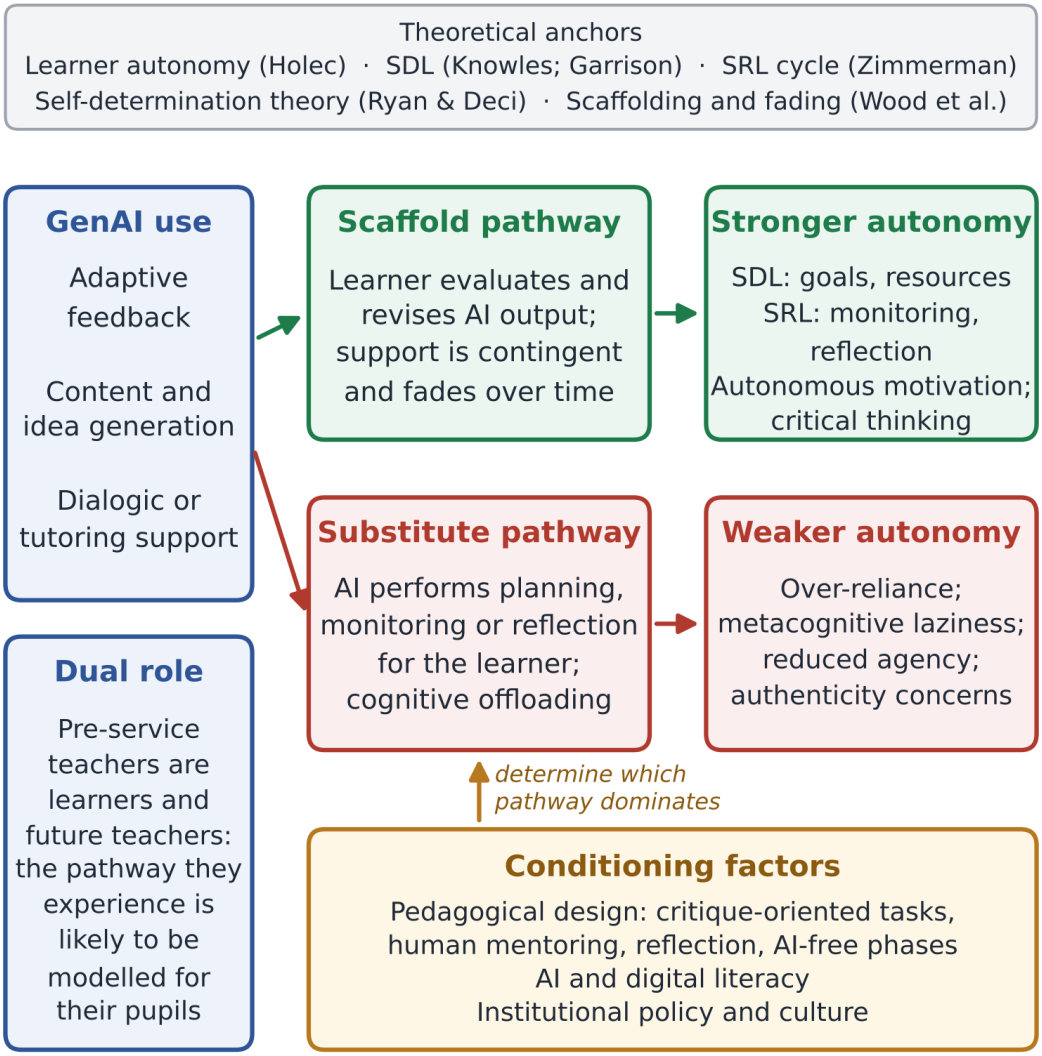


Figure 7. Scaffold–substitute conceptual model: pathways linking genai use to pre-service teachers' learner autonomy

In the scaffold pathway, students evaluate and revise AI outputs while support is contingent and gradually reduced, so that the SRL phases continue to be carried out by the students; this pathway is associated with strengthened SDL, SRL, autonomous motivation, and critical thinking. In the substitute pathway, GenAI takes over planning, monitoring, or reflection, resulting in cognitive offloading. This pathway is associated with over-reliance, metacognitive laziness, and diminished agency. The dominant pathway is determined by conditioning factors, namely pedagogical design, AI literacy and digital literacy, and institutional policy and culture. This model's distinctive contribution to teacher education lies in the dual-role component: the pathway that pre-service teachers experience is likely to be reproduced when they later teach. The model is propositional and needs to be tested empirically, for example, by examining whether task designs that require critical evaluation and planned fading moderate the relationship between the intensity of GenAI use and SRL indicators.

A practical implication of these findings is that teacher education programmes need to design explicit and structured AI literacy training rather than simply introducing GenAI tools without an accompanying pedagogical framework. Such programmes should ideally include explicit self-regulation strategies (goal-setting, self-monitoring, and self-evaluation) in the use of GenAI, so that pre-service teachers are not only skilled in using the technology but also able to model wise use for their future students. Further research based on design-based research that tests the

pathways in the Scaffold–Substitute model against directly measured indicators of learner autonomy would make an important contribution to the development of teacher education curricula in the GenAI era.

This review has several limitations. First, the search covered only one database (Scopus) and was limited to English-language publications, so studies indexed only in Web of Science, ERIC, or Google Scholar, grey literature, and publications in other languages, including those from the Indonesian context, may have been missed. Second, although screening was conducted independently by two authors, inter-rater agreement coefficients were not formally calculated. Third, vote-counting describes only the direction of findings and does not take sample size or effect magnitude into account. Fourth, nearly half of the evidence base was categorised as limited evidence, and only two studies used experimental designs, so causal claims cannot yet be established. Future reviews are advised to expand the search to multiple databases, report inter-rater agreement coefficients (for example, Cohen's kappa) at each stage of selection and coding, and conduct a meta-analysis once a sufficient number of comparable quantitative studies is available.

CONCLUSION

This systematic literature review of 22 articles shows that the reported effects and associations between GenAI use and pre-service teachers' learner autonomy are double-edged and conditional. The thematic synthesis identified that GenAI supports SDL and SRL, particularly in the evaluation and reflection phases through adaptive feedback; is associated with strengthened learning motivation and autonomy; and fosters critical and creative thinking when students act as active evaluators of AI outputs. However, without adequate pedagogical design and AI literacy, the use of GenAI risks producing over-reliance that in turn undermines learner autonomy. In total, 72.7% of the studies reported predominantly favourable findings, but this proportion is not an estimate of effect size, and only two studies used experimental designs. These findings indicate that the educational value of GenAI is more strongly associated with the quality of its pedagogical integration than with the mere availability of the technology. The proposed Scaffold–Substitute model offers a framework for designing such integration, namely by positioning GenAI as a scaffold that is gradually faded rather than as a substitute for students' self-regulation. This study is limited to English-language articles from a single database (Scopus) for the period 2023–2026. Future research is advised to test this model through experimental or longitudinal designs with direct measurement of learner autonomy indicators across cultural contexts, including Indonesia.

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The authors used Claude (Anthropic), a generative AI tool, for clearly bounded tasks: (1) suggesting keyword combinations before the search, which the authors then ran and refined directly in Scopus; (2) drafting narrative summaries of the themes from the authors' own extraction sheet and coding decisions; (3) language editing of the manuscript and translation of the abstract; and (4) during revision, drafting revised passages in response to the reviewers' comments, preparing figures from the authors' data, and organising the response to reviewers. The AI tool was not used to screen records, make inclusion decisions, code studies, assign themes, classify studies in the vote-counting, or appraise evidence strength; these analytic judgements were made by the authors. To safeguard originality and accuracy, every AI-assisted passage was checked against the original articles, all references were verified against their DOIs or publisher records, and the text was revised by the authors, who take full responsibility for the content of this article.

Author Contributions

RAF conceptualisation, methodology, investigation, formal analysis, visualisation, and writing – original draft. R methodology, investigation, validation, and writing – review and editing. M & F validation, supervision, and writing – review and editing. M & S validation and writing – review and editing. All authors read and approved the final manuscript.

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Conflict of Interest

The authors declare that there is no potential conflict of interest.

Data Availability Statement

All data supporting the findings of this study are available from the corresponding author upon reasonable request.

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