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The Influence of AI-Facilitated Personalised Education on Improving Student Academic Performance

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ABSTRACT: AI has revolutionised the landscape of personalised learning, empowering learning systems to analyse learner data, tailor learning paths, provide feedback, suggest learning materials, and pinpoint learning challenges. This paper aims at answering the main question: What is the association between AI-facilitated personalisation and students' academic achievement, and what are the implementation conditions that influence this association? This paper introduces a systematic, evidence-based review that integrates findings from peer-reviewed systematic reviews, scoping reviews, meta-analyses, and selected empirical research in the fields of artificial intelligence in education, adaptive learning, intelligent tutoring, personalised recommendations, and digitally-delivered feedback. The findings suggest that personalised adaptive learning is linked with higher academic achievement in a significant number of the studies examined. A 2024 scoping review of 69 studies found that 41 studies (59%) showed improvements in student academic achievement and 25 studies (36%) showed improvements in students' engagement. A 125 study synthesis from the systematic review in the education sectors in 2025 found that adaptive learning, machine learning, natural language processing, recommendation systems, intelligent tutoring, and generative AI are key technical methods to personalisation. There were 29 empirical studies chosen for a 2025 meta-analysis of AI and academic outcomes, and 99 effect sizes from 32 RCTs used in a separate meta-analysis for the effects of AI for personalised STEM education. This suggests that, alongside automation, academic benefits for AI depend on adaptive feedback in instruction, diagnostic assessment, appropriate sequencing in instruction, control by the learner, involvement of the teacher, and pedagogical alignment. The paper presents a conceptual model that connects the concepts of AI-assisted Learner Profiling, Adaptive Content, Feedback, Engagement, Self-regulation, and Academic Achievement. The analysis also highlights data privacy, unequal access, algorithmic limitations, educator readiness, and over-reliance on automated outputs as conditions that need to be protected within institutional contexts. The results encourage a human-centred approach in which AI is used as an adaptive teaching layer, not to replace teachers.

The topics include, but are not limited to, the following: artificial intelligence, personalised education, adaptive learning, academic performance, intelligent tutoring systems, learning analytics, student engagement, educational technology.

1. INTRODUCTION

1.1 Background and Context

Personalised education is an education approach where instructional content, learning pathways, pacing, feedback, assessment and support are tailored to individual learner differences. Many traditional classroom set-ups deliver the same learning content and the same timing of learning in the same sequence to students who have varying levels of prior knowledge, learning speed, motivation, language abilities, and support needs (Brummer et al., 2024). The development of digital learning environments has made differentiated instruction more feasible by capturing information about the learner's interactions and applying these data to determine next steps in instruction. AI also brings in the ability to use machine learning, natural language processing, recommender systems, knowledge tracing, predictive analytics, computer vision, and generative models.

AI-driven personalisation, then, is not just about creating content automatically, it is a more encompassing concept. A personalised system can estimate a learner's current state of knowledge, detect misconceptions, suggest the next activity, modify difficulty, give feedback, and notify an educator if there is a difficulty pattern. It is possible to offer step-level guidance with intelligent tutoring systems and change the order and complexity of the learning material with adaptive platforms. Generative AI can also generate explanations, examples, practice questions, summaries, and help in the form of dialogue. The teaching value of these skills relies on the ability to create adaptation that meets the curricular aims, criteria for evaluation, and principles for learning.

There has been a significant increase in research in the field of AI and personalised learning in recent years, as evidenced by various evidence syntheses. Zawacki-Richter et al. (2019) highlighted key areas of higher education in which AI can be used: adaptive systems and personalisation; intelligent tutoring; assessment/evaluation; and profiling and prediction (Farhood et al., 2025).

. They reviewed 146 articles from among a potential pool of 2,656 articles. Recent reviews have shifted from general mapping to evidence on learning outcomes, and have begun to focus more on academic achievement, engagement, implementation, ethics, and equity.

Scoping review by the personalised adaptive learning study's authors published in 2024 included 69 eligible studies, with 41 reporting academic gains, and 25 reporting engagement gains. The 2025 systematic review on AI in personalised learning coordinated by Dr. Seiji Ishihara, Dr. E. Boynton, and Dr. K. Deitrevis and their colleagues compiled 125 studies from January 2015 to June 2025. This review was conducted on K–12 education, higher education, and institutionally-supported online learning, and technical approaches and their impacts on teaching, learning, and assessment. The results provide a strong foundation for the study of the mechanisms by which AI-integrated personalisation can impact academic performance.

Meanwhile, AI personalisation also brings in restrictions unique to conventional digital learning. UNESCO's recommendations for the use of generative AI in teaching and learning highlight the importance of keeping the human element in focus, ensuring privacy, using AI in an age-appropriate way, ethical validation, and preparing institutions for the use of AI. Having a technically competent system does not guarantee a valid system (Hariyanto et al., 2025). A recommender system can boost incomplete information about the learner, a generative model can generate false explanations, and an automatic evaluator can misunderstand the language and/or context. Therefore, the academic performance should be assessed as a result of an educational system, but not as a result of the use of AI.

1.2 Problem Statement

With the explosive growth of AI-powered learning, there has been a significant and diverse body of research. Educational levels, subject areas, uses of AI, length of time, outcome measures, comparison condition, and teachers' involvement vary across studies. This diversity can make it difficult to determine if the academic results are a direct effect of personalisation, due to greater frequency of feedback, more practice, better engagement, or due to other shifts in the instructional design. There is also variability in the way that research is measured—either by standardised exams and/or by course exams, assignment scores, retention, learning gains, etc.

For this is the reason why a focused synthesis is necessary to link the technical aspects of AI personalisation with the measurable educational outcomes. The present paper responds to this need by synthesising evidence provided by systematic reviews, scoping reviews, meta-analyses and empirical studies (UNESCO, 2023). The analysis views AI personalisation as a

multi-dimensional intervention that encompasses the learner modelling, adaptive sequencing, personalised feedback, resource recommendation, and conversational support.

1.3 Research Objectives

The first goal is to compile evidence on the correlation between AI supported personalised learning and student performance. The second aim is to understand how and in what ways AI personalisation might impact learning outcomes, such as adaptive sequence, diagnostic feedback, practice opportunities, and engagement. The third goal is to explore the conditions and threats of implementing personalisation with AI. The fourth is to build an evidence-based conceptual model of how AI capabilities are related to intermediate learning processes and academic outcomes.

1.4 Research Questions

RQ1: Does evidence exist to support the claim that AI enabled personalised education is effective in enhancing student academic achievement?

RQ2: What are the most frequently linked AI tools that enable personalisation that are effective in enhancing learning outcomes?

RQ3: What is the relationship between learner engagement, feedback, adaptation, and teacher involvement in the context of AI personalisation and academic performance?

RQ4: What are the limitations in terms of technology, pedagogical, ethical, and organizational factors that restrict the impact of AI enabled personalised education?

2. LITERATURE REVIEW

2.1 Conceptual Foundations of Personalised Education

The concept of personalised education is based on the idea that learning outcomes can be enhanced if learning is adapted or responds to the difference in learners. The idea encompasses multiple aspects: pace, level of content, sequence, modality, feedback, and assessment. These dimensions could be customized in the traditional classroom by using formative assessment and differentiated instruction. AI systems have been able to automate parts of these processes, as learner interaction data is fed into them continuously (Boolzen et al., 2026). The resulting model is dynamic: Learner performs an activity, model watches the activity, learns about either knowledge or difficulty, and chooses a next learning action.

Typical examples of adaptive learning systems include the use of diagnostic questions, prior achievement, level of accuracy, time spent on task, interactions, and results from assessment. The 2024 scoping review of personalised adaptive learning found pre-knowledge quizzes to be one of the most prevalent indicators for activation of adaptive content delivery. This type of facilities offers a working link between evaluation of the learner and personalised teaching.

Personalisation also relates to feedback. The effects of digitally delivered instructional feedback have been studied as a stand-alone intervention that impacts learning. A meta-analysis in 2024 of 116 interventions found a summary effect size of 0.41 for digitally delivered instructional feedback and that some variations in the size of the effect could be explained by differences in the focus of the feedback, discipline, assessment method, and control of the learner. This evidence suggests that the adaptability of AI personalisation is only a partial technical feature; it also appears to be related to the timing and availability of feedback.

2.2 AI in Higher Education and Adaptive Systems

An influential map of AI applications in higher education was given by Zawacki-Richter et al. (2019). They reviewed and found four main areas – profiling and prediction, assessment and evaluation, adaptive systems and personalisation, and intelligent tutoring systems. The 146 articles included were divided into three groups: 92 articles related to academic support services, 48 articles related to administrative and institutional services, and six articles related to both groups (Zawacki-Richter et al., 2019). It was also observed that 73.3% of the studies employed quantitative techniques; this suggests that measurable outcomes and system performance were a major focus of the studies.

Personalised learning was cited as around 38.7% of all the advantages identified in a later meta-systematic review of AI in higher education. It also noted the overall lack of theoretical backing, collaboration between teachers and technical researchers, and the lack of emphasis on ethics and research rigor.

The addition of rule-based adaptive systems has been expanded to machine learning and generative AI to provide a wider spectrum of personalisation functions. Classification can be used to categorize learners or foresee performance, natural language processing can be used to analyze written responses and provide explanations, resource selection can be used to recommend learning resources, knowledge tracing can be used to determine mastery, and generative models can be used to generate context-specific feedback and dialogue.

2.3 Evidence on Academic Performance

The most tangible measure of the educational impact of personalisation with AI is academic achievement. A 2024 scoping literature review of a sample of 69 personalised adaptive learning studies found that 59% (or 41 of the studies) showed positive academic outcomes. In 36% of the studies (25%), there was a report of higher student engagement, as reported in the same review. These numbers are not a “pooled” effect size, but they are large enough to suggest that there is a significant percentage of literature claiming improvements in performance.

The 2025 meta-analysis on AI and students' academic achievement used six databases to identify 29 empirical studies (Examining et al., 2025). It took into account moderators such as educational level, type of AI, intervention duration, type of learning, educational subject area, AI role, and sample size. The moderator framework is crucial as it shields from an overall AI effect, making it possible to understand the differences between intelligent tutoring, adaptive learning, generative AI assistance, automated assessment, and other applications.

In 2025, a separate meta-analysis of AI-based personalized STEM learning combined 32 randomized controlled trials (RCTs) to yield 99 effect sizes. The study found that the overall effect of the use of AI technologies in personalised K–12 STEM education was medium, and that significant moderation was found for school level, type of AI application used, personalised learning model, and subject. The results suggest that there is a need to consider the context of implementation, and that the effects of AI cannot be assumed to be consistent in educational contexts.

There is also evidence from related intelligent tutoring research that can provide a relevant mechanism. The mean effect size for 19 studies on intelligent tutoring systems (ITS) for reading comprehension in grades K-12 was $g = 0.60$ [$K=0.5$, $L=0.5$, $M=0.6$, $S=0.6$, $T=0.7$, and $U=0.6$] in a synthesis reported in the educational technology literature. While this evidence is specific to one learning domain, this does not necessarily imply that this places it on the same level as a general AI-personalisation effect, but it does lend some support for the idea that adaptive feedback and tutoring can help to achieve measurable learning gains.

2.4 Student Engagement and Self-Regulated Learning

Intermediate processes (engagement, persistence, practice, self-regulation) mediate academic performance. These processes can be aided by AI personalisation, which can decrease irrelevant complexity, give instant feedback, give more examples, and show progress. The scoping review in 2024 indicated that engagement is a pathway relevant to the design of the intervention, but not a universal outcome; 36% of the studies included showed an increase in engagement.

There is not necessarily a linear relationship between engagement and performance. Time-on-task can actually be increased, but the conceptual understanding may be missed, if tasks are not well designed. A system can alternatively involve reducing the time spent on learning content that has already been mastered, and using more efficient sequences to improve achievement. So, there is a need to differentiate between the amount and the quality of engagement, and to use both behavioural and learning measures for evaluation.

Self-regulated learning is also relevant because Personalised systems can take some of the control of pacing and practice from the teacher to the learner (Artificial et al., 2025). With respect to the impact of learner control though, variable impacts can be seen based on the background of the learners and the learner's metacognition skills. Personalisation should, therefore, not equate with offering more choice, but with guidance and structured feedback.

2.5 Generative AI and Personalised Feedback

Unlike previous adaptive platforms, Generative AI has ushered in conversational personalisation on a new level. A learner may ask for a different explanation, want some examples, get a practice problem, and/or get feedback on a draft. The 2025 systematic review of AI in personalised learning highlighted large language models such as ChatGPT, machine learning, natural language processing, intelligent tutoring systems, and recommendation systems as key elements of today's personalised learning.

There is also a new "validity issue" with generative AI. A response may be grammatically correct and yet incorrect or inappropriate pedagogically. The UNESCO guidance thus focuses on human-centred design, privacy of the data, ethical validation, and institutional readiness. As a result, academic performance improvements should be measured in relation to the learning outcomes that are assessed by external bodies, and not solely on the quality or flow of the AI interaction.

2.6 Equity, Privacy, and Implementation Conditions

Learner data is essential to personalisation. These data may be assessment scores, interaction history, written responses, learning preferences, and behavioural indicators. The collection and treatment of such information generate privacy and government needs. UNESCO highlights the following as key considerations in the context of AI in education: data privacy, equitable access, human agency, and appropriate regulations.

Implementation is impacted by access to devices, reliable connectivity, technical support, and high-quality digital content (Generative et al., 2025). It is possible to offer different learning experiences for students who have different infrastructure needs in a personalised system, but not different learning needs. Another condition is educator readiness. Teachers need enough knowledge about AI outputs to be able to understand the recommendations, validate explanations created by AI, and determine whether or not an intervention needs to be tweaked or dropped.

Private issues and faculty support continue to be challenges, according to a review of adaptive learning platforms with AI features in 2025. A recent review on generative AI and educational equity also highlighted personalised learning, support for teachers, access to learning and learning analytics as key opportunity areas, and cautioned that inequalities in access and protection measures can exacerbate educational inequities.

3. THEORETICAL FRAMEWORK

3.1 AI-Personalisation-Achievement Model

This paper proposes a conceptual framework in which the use of AI to facilitate personalisation is conceived as an instructional mechanism, not as a goal to achieve. The framework consists of five interrelated elements: Learner Data and Profiling, Adaptive Instructional Decisions, Personalised Interaction, Learner Processes and Academic Outcomes. The input is from the learner data. An AI model converts those data into an estimate or a recommendation. The system then adapts content, difficulty, sequence, feedback, or support (A et al., 2025). These adaptations affect engagement, practice, cognitive processing, and self-regulation. The last measurable product is academic performance.

The pathway is assumed to be moderated by teacher involvement in the model. Adaptation can be aligned with the educational goals when teachers validate the recommendations from AI and weave them into curriculum and assessment. On the other hand, automated, unchecked recommendations may cause instruction to go wrong. This framework thus considers teacher supervision as a quality-control tool and an important context factor.

3.2 Hypothesised Relationships

H1: AI-enabled personalised instruction is positively associated with student academic performance.

H2: Adaptive feedback partially explains the relationship between AI personalisation and academic performance.

H3: Student engagement functions as an intermediate mechanism between AI personalisation and academic performance.

H4: Pedagogical alignment and teacher involvement strengthen the association between AI personalisation and academic performance.

H5: Implementation constraints, including inadequate infrastructure, privacy limitations, inaccurate AI outputs, and insufficient educator readiness, reduce the consistency of observed academic benefits.

4. METHODOLOGY

4.1 Research Design

This study is designed in a structured evidences synthesis design. It does not show a constructed dataset for primary students. The numerical results presented in the tables and the figures are based on published systematic reviews, scoping reviews, meta-analyses and documented empirical research obtained from the literature search. This design allows for the numerical comparison of data, while maintaining separation between data that is published and data that is collected.

4.2 Literature Identification

The search was limited to combinations of the following terms: Artificial Intelligence, AI, Personalised Learning, personalized learning, Adaptive Learning, intelligent tutoring systems, Academic Performance, academic achievement, Student Engagement, learning analytics, Generative AI, and Educational Technology(Examining et al., 2024). Sources of peer-reviewed articles, articles from reputable academic publishers and international organizations indexed in major scholarly databases were used. Special focus was placed on the most recent reviews that have been published from 2024-2026 as the technology landscape has rapidly changed.

4.3 Inclusion and Exclusion Criteria

Studies were deemed relevant if they included AI or AI related adaptive technologies in their study and included evidence of learning, achievement, engagement, personalisation, feedback or implementation in the study in an educational context. When adequate methodologic information was available, systematic reviews, scoping reviews, meta analyses and empirical intervention studies were included. The evidence synthesis excluded items where AI was mentioned in passing without being applied to an educational context. Only where necessary, opinion pieces were used to provide contextual interpretation.

4.4 Data Extraction and Synthesis

The variables extracted were the publication year, level of education, application of AI, personalisation mechanism, sample size / number of studies, outcome type, direction of effect reported and implementation conditions. If a source provided a precise number or percentage, then this was used. Percentages were calculated where both the numerator and denominator were given. They did not mix incompatible effect sizes, but rather used narrative comparison and descriptive statistics.

4.5 Validity and Research Integrity

Numbers are shown using the original unit of analysis. The number of studies involved in a study type is not interpreted as a number of students involved in the study type, and the percentage of studies reporting an outcome is not interpreted as the percentage of students that improved their score in that outcome(Saleem et al., 2025). This distinction is important because the 59% result from the 2024 scoping review is a percentage of the studies included, rather than a “pooled” treatment effect. Likewise, the medium effect cited in the 2025 STEM meta-analysis is a meta-analytic conclusion based on effect sizes, and should not be interpreted as a percentage increase in examination scores.

4.6 Evidence Base

Source	Design / Scope	Evidence size	Main numerical finding
Zawacki-Richter et al. (2019)	Systematic review of AI in higher education	146 included articles	73.3% quantitative; 92 academic-support studies
Personalized adaptive learning review (2024)	Scoping review in higher education	69 studies	41 (59%) reported improved academic performance; 25 (36%) reported increased engagement
AI and academic achievement meta-analysis (2025)	Meta-analysis across education	29 empirical studies	Moderators included level, AI role, duration, sample size, strategy, subject, and AI type

AI-personalised learning review (2025)	Systematic review, K–12 and higher education	125 studies	Covered AI approaches, impacts, implementation challenges, and future directions
AI-personalised STEM meta-analysis (2025)	Meta-analysis of personalised K–12 STEM	32 RCTs; 99 effect sizes	Reported a medium overall effect; several moderators were significant
Generative AI STEM meta-analysis (2026)	Systematic review and meta-analysis	85 eligible; 49 studies / 59 effects meta-analysed	Positive overall effect with substantial heterogeneity ($I^2=96.32\%$)

RESULTS AND ANALYSIS

5.1 Evidence of Academic Performance Improvement

The most obvious numerical evidence is found in the 2024 scoping review of personalised adaptive learning in higher education. Of those 69 studies that were eligible, 41 reported that academic performance improved(Joshi, 2026). This is equivalent to 59.4% rounded off to 59% in the source. The results from 25 studies or 36.2% indicated that student engagement was positively increased. The remaining three studies were not in either of the reported-outcome categories. The distribution shows that the most common positive outcome reported in this evidence base was academic performance.

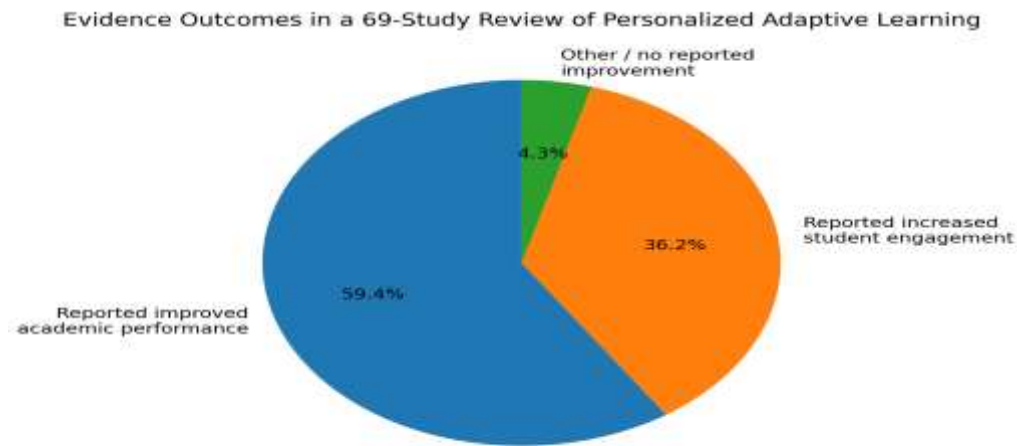


Figure 1. Distribution of reported outcomes in the 69-study personalised adaptive learning review. Source: 2024 scoping review.

The distribution should be interpreted as support for the evidence, NOT as the magnitude of the effects. This does not imply an increase in average grades by 59% for 41 out of 69 studies reporting improvement. It implies findings were positive for the study level direction in 41 studies. This difference is crucial in research reporting since a study-count percentage and an effect size are a response to different questions.

The application profile consists of 20 statements.The application profile has 20 statements.

The 2019 systematic review offers a wider view of the situation regarding the use of AI in higher education(Wu, 2026). One hundred and forty-six articles were included, of which 92 were academic support, 48 were administrative/institutional services, and six were both. About 63.0% of the review corpus thus consisted of academic support. Assessment, feedback, adaptive systems, personalisation and intelligent tutoring were included in the academic-support category.

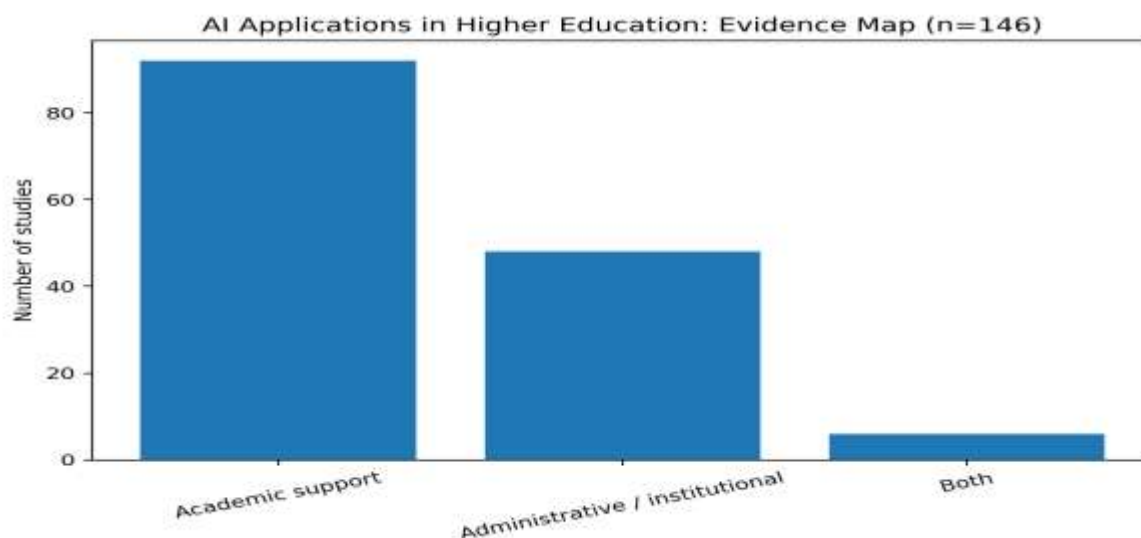


Figure 2. Distribution of AI applications in the 146-article higher-education review. Source

The pronounced academic support is pertinent to personalised education because personalisation has the biggest impact on the teaching and learning interface. Systems can be designed to profile and predict those who need more support and adapt accordingly to provide tailored instruction. This is a feedback loop between measurements and interventions.

5.3 Methodological Profile of AI-in-Education Research

According to the 2019 review, 73.3% of the studies employed quantitative approach, 20.5% were theoretical or descriptive, 5.5% were mixed methods, and 0.7% were qualitative (Abdullah, 2025). This distribution shows that measurable learning outcomes have been a key focus in the work on AI in education, but that the learner experience and teachers' decisions making have been less studied in the reviewed corpus, at least from a qualitative perspective.

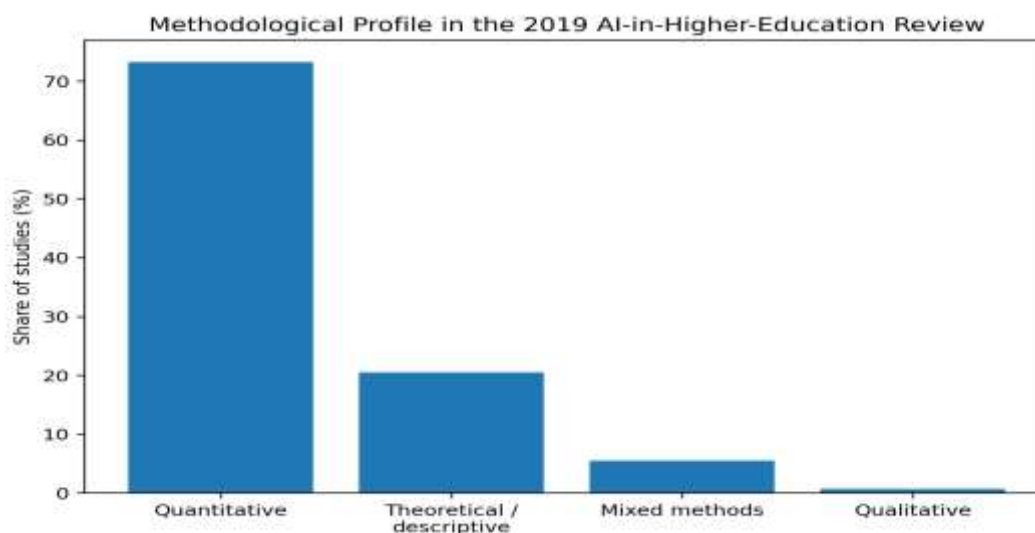


Figure 3. Methodological distribution in the 2019 systematic review of AI in higher education. Source: Zawacki-Richter et al. (2019).

A quantitative approach can facilitate an analysis of academic achievement, but can fail to address implementation mechanisms. For instance, a significant learning gain could not be used to determine if the improvement was due to adaptive sequencing, more practice, better feedback, increased motivation, or better teacher intervention (Ibrahim et al., 2025). Mixed

method designs can then be complemented with outcome measurement by studying student/teacher interactions with personalised systems.

5.4 Expansion of the Evidence Base

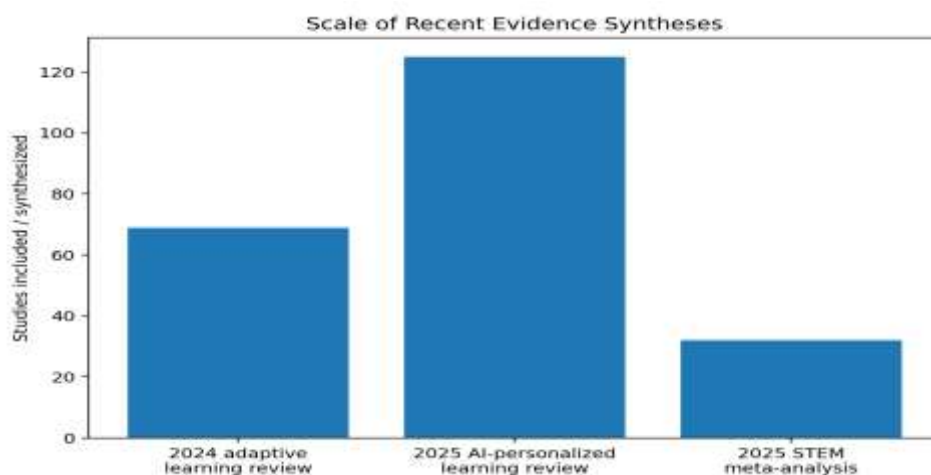


Figure 4. Study counts across recent evidence syntheses. The counts are not directly additive because the reviews have different inclusion criteria and may overlap.

The volume of evidence has grown significantly. In 2024, 69 studies were included in the scoping review; in 2025, 125 studies were included in the systematic review of AI-based personalised learning and 32 RCTs with a total of 99 effect sizes were included in the personalised STEM meta-analysis. The volume of evidence is growing, with a more methodological variety of methods in evidence such as systematic reviews, randomised trials, quasi-experiments, learning analytics studies and studies of generative AI(Wan et al., 2025)

5.5 Numerical Evidence Matrix

Indicator	Numerical result	Interpretation
Personalised adaptive learning studies reporting improved academic performance	41/69 = 59.4%	Positive direction reported in a majority of included studies
Personalised adaptive learning studies reporting increased engagement	25/69 = 36.2%	Engagement improvement reported in over one-third of studies
Academic-support AI studies in higher education	92/146 = 63.0%	Academic applications dominated the 2019 evidence map
Administrative/institutional AI studies	48/146 = 32.9%	A substantial secondary application area
Both academic and administrative	6/146 = 4.1%	Cross-functional applications were comparatively limited
Quantitative methods	73.3%	Outcome measurement was the dominant research approach
Theoretical/descriptive studies	20.5%	Conceptual and descriptive work formed about one-fifth
Mixed methods	5.5%	Integrated qualitative-quantitative designs were limited
Qualitative studies	0.7%	Qualitative-only designs were rare in the 2019 review
AI-personalised STEM meta-analysis	99 effect sizes from 32 RCTs	Provides experimental evidence with moderator analysis
Generative-AI STEM meta-analysis (2026)	49 studies; 59 effects; $I^2=96.32\%$	Positive pooled direction but very high heterogeneity

5.6 Mechanisms Associated with Performance

The following 5 mechanisms appear repeatedly in the literature reviewed. Adaptive sequencing is the first: When the system adapts the sequence or complexity of learning activities based on the learner's performance (Raikoti et al., 2025). The second is personalised feedback provided near the point of performance and this can be used to assess errors and misconceptions. Diagnostic assessment is the third, providing information for learner modelling. The fourth is resource recommendation, in which content is recommended for the students based on their current needs. The fifth is conversational or generative assistance, where learners can ask questions, provide examples and do practice.

Mechanisms are interconnected. Diagnostic assessment that doesn't lead to adaptation yields information, but doesn't necessarily lead to changes in instruction. When adaptation is not accompanied by feedback, it can change the difficulty of the task, but it will not aid the learner in understanding errors. Feedback that is out of order can confuse students. A coherent instructional cycle that connects assessment, adaptation, feedback, and practice, is needed for an effective personalised system.

5.7 Moderating Conditions

School level, AI application type, personalised learning model type and subject were found to be important moderators in the 2025 meta-analysis of AI in personalised STEM education. The study also found that the effects were greater in the junior and senior high school context and that differences emerged in terms of the type of application and the learning model. The results confirm that AI personalisation is not a unified intervention. Another example of heterogeneity in the 2026 meta-analysis on the use of generative AI in STEM education (Atianashie et al., 2025). It reported an overall positive effect, but it had an I^2 value of 96.32%, meaning that there was a wide range of causes of the effects in the studies included. The prediction interval was also found to be negative to strongly positive, suggesting that the mean value cannot be considered as a promise of benefit for all educational contexts. This evidence may be used to evaluate at the level of specific interventions, specific subjects, learner groups, and specific instructional designs.

6. DISCUSSION

6.1 Interpretation of the Evidence

The evidence shows that using AI to personalise learning is associated with better academic outcomes, but not a determinative link. The most consistent pattern is when AI is coupled with adaptive instructional processes, with learner assessment giving information to a model of current understanding, the model informing the choice of content or feedback, and the model then being used to inform the instructional pathway based on subsequent performance. This cycle goes beyond personalisation as a simple description – it becomes concrete.

The 59% reported in the 2024 review is suggestive of a prevalence of positive findings, and the 2025 STEM meta-analysis supplements this with quantitative evidence from RCTs and effect-size analysis. Overall, these sources provide evidence for the potential of academic benefits in a variety of contexts, and evidence for varying effect sizes, depending on the education level, subject, technology, and implementation.

6.2 Role of Feedback

One of the most straightforward ways AI personalisation can impact academic results is by offering feedback. AI systems can deliver immediate information following a response, generate further information and provide specific practice. The 2024 meta-analysis of digitally delivered feedback showed a summary effect of 0.41 for 116 interventions, and also showed that there were differences in performance that were related to the feedback focus and learner control.

The implication for personalised education is that feedback should be designed in terms of the learning task and not in terms of the availability of AI. Correctness feedback might just tell if an answer is correct or incorrect, while explanatory feedback can help clarify why an answer is incorrect, and which strategy might be tried next (Liang et al., 2025). Personalised feedback, if it is based on the learner's evidence, is more pedagogically useful to the learner.

6.3 Role of Engagement

Engagement is not the same as achievement, it is a potential pathway. Personalised systems can enhance engagement by minimising repetitive things, offering appropriate challenge, and enabling students to get instant feedback. But, engagement

data (e.g. logins, time-on-platform, number of interactions) does not equate learning. The assessment of academic achievement should thus be tied to the knowledge, skills, or competency that is assessed independently.

6.4 Teacher-AI Collaboration

The literature shows there is a need to include teachers in the process of personalisation using AI. AI-generated content may not fully address all students' needs, and teachers interpret their needs, define learning goals, evaluate AI generated content for appropriateness, and manage social and emotional aspects of learning that might not be reflected in system data (Wang et al., 2026). Teachers can give pedagogical judgement and accountability, AI can offer judgement and support on a high frequency basis.

Generative AI is a key area where this division becomes significant. Dropping off an explanation is a characteristic of fluency that can lead to the impression that the content is correct, even if it isn't. As such, human editing, source checking, curriculum fit, and assessment reliability are still critical. UNESCO's human-centred guidance puts user control, safety, equity and data protection at the heart of the use of AI in education.

6.5 Data and Algorithmic Governance

Data-driven modelling of learners is a key aspect of AI personalisation. Data governance should define which information needs to be gathered, for what purpose, for how long, by whom and how automated decisions can be challenged and amended. Algorithmic models should also be tested on relevant sub groups of learners to see if there are systematic error rates and/or error suggestions.

Compliance is not the only reason to protect privacy. It can impact on participation and trust. Constantly checking of all interactions if there is no clear purpose or safeguards may lead to changed behaviour by learners that undermines the credibility of the data for the purposes of personalisation. Transparent data practices thus benefit both in terms of ethical quality and measurement quality.

6.6 Equity and Access

Personalisation may help to mitigate learning gaps by offering extra explanations, practice and support on a large scale. Meanwhile, disparities in device access, internet or connectivity, access to high-end tools, technical support, or quiet learning spaces can create inequitable exposure to AI-powered learning. To achieve equity, however, more than simply distributing an AI platform is needed. Institutions need to take into account the accessibility, language support, disability inclusion, infrastructure, teacher capacity and quality of content for various learner groups.

6.7 Implications for Educational Institutions

For institutions that are seeking to implement AI personalisation, there is a need for an evaluation framework that incorporates academic outcomes, learner experience, teacher workload, system accuracy, privacy, accessibility, and cost. Pre-implementation baselines are essential because it is important to be able to measure improvements in performance where there is a baseline of performance and a situation for comparison. When practical, quasi-experimental or randomised designs can yield greater causal inferences than before-and-after comparisons.

Escalation rules should be included in institutional implementation. There should be a pathway for human intervention if the AI system detects repeated failure. When multiple or conflicting recommendations are generated by the system, teachers should have the ability to reject the recommendations. These mechanisms shift the focus of AI from being an independent decision maker into an accountable instructional support system.

7. IMPLICATIONS FOR RESEARCH AND PRACTICE

7.1 Implications for Researchers

Future effects should report effect size, confidence interval, length of intervention, learner characteristics, comparison intervention, and fidelity of implementation. The effects of AI should be separated from effects of increased practice and/or feedback. Research should also indicate whether the teachers played an active role in the intervention as teacher involvement can change the way that personalisation has a positive impact on achievement.

Longitudinal studies would be useful to see if gains in performance are maintained beyond the end of the intervention. Further studies are needed to determine if students become more self-directed or dependent on the automatic support (Abiodun et al., 2026). This means that the quality of the conversation is not enough to demonstrate learning, and therefore will require special consideration for externally assessed outcomes in generative AI studies.

7.2 implications for educational practice

The learning outcomes should be set out clearly in educational practice, then the necessary personalisation functions identified. The reason for using AI to create content should not be its ability to do so. When adaptive assessment, feedback and resource recommendation are available to them, they should be used if they are for documenting an instructional need.

Teachers need to be trained in how to interpret recommendations from AI, in how to review materials created by AI, in the protection of student information, and in how to create activities that maintain student reasoning. Students need explicit instruction on appropriate usage of AI, checking work for AI assistance and not using AI to replace their learning.

7.3 Proposed Implementation Framework

The evidence leads to a 5-step implementation framework. The first phase is a learner diagnosis which involves determining what learners know and what they need to learn. The second stage is adaptive planning, which involves the AI system suggesting content, sequence, or practice (Qadeer, 2025). The third stage is personalised interaction, where learners are given differentiated tasks and feedback. The fourth stage is the human review which involves the teacher interpreting the system output and intervening if needed. The fifth one is "outcome evaluation," which involves determining academic achievement in terms of valid assessments of the system and recalibration.

This model keeps the intent of the educational use connected to the AI capability. It also allows institutions to consider if the improvements they observe are caused by the intended mechanisms. The method can be applied to adaptive learning platforms and newer generative AI systems.

8. LIMITATIONS

There are several limitations to the evidence synthesis. First, the reviews that are included vary in search time, population of students studied, definition of AI, and outcome measures. Their numerical results can then not be aggregated to a single pooled result. Second, percentages in studies (such as the 59% found in the 2024 scoping review) reflect the distribution of findings and not the size of the academic improvement (Krishnan et al., 2023). Thirdly, as generative AI rapidly evolves, some evidence may become outdated due to the changes in systems and education.

Fourth, the paper is not based on a new sample of primary students, but rather on published evidence. The results are thus a synthesis and not a new causal estimate. Fifth, there can be publication/reporting bias in the literature. The 2026 meta-analysis of generative AI in STEM revealed significant study-level differences, meaning that average effects should not be taken as representing the true impact across studies.

The limitations do not take away evidence observed, but rather determine how to appropriately interpret it. The most robust one is that personalisation with the help of AI technology can positively affect students' academic outcomes under the given conditions, with the effectiveness of the effects depending on the educational method, the learners' characteristics, the technology used, the topic studied, the teachers' participation, and the quality of implementation.

9. CONCLUSION

AI-powered personalised education has evolved from rule-based adaptive teaching to a comprehensive system with intelligent tutoring systems, learning analytics, recommender systems, machine learning, natural language processing, and generative AI (Haddoumouloud et al., 2025). The evidence examined in this paper suggests that these technologies may be a valuable way to support student academic achievement when used in conjunction with purposeful assessment, adaptive sequencing, targeted feedback, appropriate practice, and teacher-facilitated instructional design.

This conclusion is supported by the numerical evidence. For the 2024 scoping review, there were 69 studies with 41 (59%) showing improved academic performance and 25 (36%) showing increased engagement. A meta-analysis of 2025 was performed on 32 RCTs that included 30 of the studies cited above, and it resulted in a medium effect overall with several

significant moderators. Concurrently, the 2026 generative-AI meta-analysis revealed extremely large heterogeneity, indicating that the average effect of interventions was positive while the range of effects was large.

The results show that personalisation is not an equivalent to automation. AI is empowering academic performance by being integrated with good pedagogy, timely feedback, learner needs, valid assessment, and effective teacher monitoring. Responsible implementation continues to be grounded in data privacy, equity, algorithmic reliability, educator readiness, and agency. Thus, the resulting model of education is a human-AI collaboration model: AI for continuous analysis and adaptation on a scalable level, and educators' responsibility for creating curriculum, making judgement, setting context, verifying, and developing students.

Future research should focus on well-designed comparison research studies, longitudinal evidence, clear presentation of effect size and assessment in a variety of educational settings. Collaborating with AI, autonomy of learners, accessibility, privacy, and the impact of generative AI in the long-term will reinforce the evidence base. When this occurs, AI can be used as a data-driven component of instruction that facilitates differentiated learning without replacing the critical role of teachers and independently measured academic outcomes.

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