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The Impact of Ai-Driven Personalised Learning on Enhancing Student Academic Performance

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ABSTRACT: Artificial intelligence (AI)-driven personalised learning has altered the design of educational environments by enabling adaptive content selection, automated feedback, learner profiling, progress monitoring, and personalised learning pathways. This study develops and tests a conceptual framework linking AI-driven personalised learning with student academic performance through perceived content relevance, perceived feedback utility, self-regulated learning autonomy, and AI-driven learning engagement. The framework is grounded in the Technology Acceptance Model, self-regulated learning theory, and research on adaptive learning. A quantitative cross-sectional design is specified for higher-education students using a structured five-point Likert questionnaire. The proposed empirical procedure includes reliability analysis, convergent and discriminant validity assessment, descriptive statistics, correlation analysis, and multivariate regression or partial least squares structural equation modelling. For manuscript development, an illustrative dataset of 300 cases is used to demonstrate the analytical structure. The illustrative results produce a model R^2 of 0.639 for student academic performance, with positive standardized coefficients for perceived content relevance ($\beta=0.176$), perceived feedback utility ($\beta=0.199$), self-regulated learning autonomy ($\beta=0.245$), and AI-driven learning engagement ($\beta=0.218$), all with $p<0.001$ in the simulated regression. The descriptive pattern places AI-driven learning engagement at a mean of 3.75, followed by perceived content relevance at 3.72, self-regulated learning autonomy at 3.68, and perceived feedback utility at 3.61 on a five-point scale. The findings section is explicitly illustrative rather than empirical. The paper establishes a research-ready structure for examining whether and through which learning mechanisms AI personalisation is associated with academic performance. The framework also recognises that AI use does not automatically constitute effective learning: the educational value of AI depends on the quality of personalisation, feedback, student agency, assessment design, and the extent to which AI supports rather than substitutes for cognitive activity.

1. INTRODUCTION

1.1 Background and Research Context

Artificial intelligence has become a major component of contemporary educational technology. AI-supported educational systems can analyse learner interaction data, identify patterns in performance, recommend learning resources, generate explanations, provide automated feedback, and adjust task difficulty. These functions extend earlier intelligent tutoring and adaptive learning approaches by combining learner modelling with machine learning, natural-language processing, recommender systems, and generative AI. A systematic review of 2,223 AI-in-education publications by Wang et al. identified a broad research landscape spanning instructional, assessment, and administrative applications, indicating that AI in education

is no longer restricted to a single technological application. Recent reviews also show growing attention to adaptive and generative AI solutions for personalised learning pathways.

Personalised learning refers to the adjustment of educational content, sequence, pace, feedback, examples, or learning support according to learner characteristics and performance. AI makes this adjustment increasingly scalable because large numbers of learner interactions can be processed automatically. In higher education, personalised adaptive learning has been associated in the literature with academic performance and engagement, although implementation constraints involving technological resources, time, infrastructure, and instructional integration remain relevant. A 2024 scoping review reported that academic performance increased in 59% of the reviewed adaptive-learning studies and engagement increased in 36%, illustrating both the potential of personalisation and the heterogeneity of reported outcomes. □ cite □ turn1search7 □

The present research focuses on the mechanisms represented in the supplied conceptual model. AI-driven personalised learning is positioned as the technological antecedent of perceived content relevance, while perceived content relevance, perceived feedback utility, self-regulated learning autonomy, and AI-driven learning engagement are positioned as proximal learning constructs associated with student academic performance. This structure moves beyond a simple technology-use model by treating academic performance as an outcome of the learner's interaction with personalised content, feedback, autonomy, and engagement.

1.2 Problem Statement

Despite rapid adoption of AI-enabled learning tools, the relationship between AI personalisation and academic performance remains methodologically complex. AI systems can provide immediate assistance, but the presence of assistance does not establish that students have learned more. Academic performance may depend on whether recommended content matches learning needs, whether feedback is actionable, whether students retain control over learning decisions, and whether AI interaction produces sustained cognitive and behavioural engagement. Recent experimental evidence on generative AI illustrates this distinction. A 2025 systematic review and meta-analysis of experimental ChatGPT studies reported a positive aggregate effect on academic performance but also substantial heterogeneity across studies and methodological limitations involving assessment design, intervention duration, and study power. □ cite □ turn1search1 □

A second issue concerns self-regulated learning. Personalisation can support goal setting, task selection, monitoring, and self-evaluation, but excessive delegation to AI can reduce the learner's direct involvement in cognitive work. Recent work on generative-AI-supported self-regulated learning therefore distinguishes productive assistance from assistance that substitutes for learner activity. This distinction is central to the proposed framework because self-regulated learning autonomy is not equivalent to unrestricted AI access.

1.3 Research Gap

Three gaps guide the present framework. First, much of the literature examines AI adoption, perceived usefulness, or general engagement without integrating the specific learning mechanisms shown in the conceptual model. Second, academic performance is frequently treated as a broad outcome without sufficient attention to the role of content relevance, feedback utility, self-regulation, and engagement. Third, the evidence base remains heterogeneous in educational level, subject, intervention design, and duration. A systematic review of AI in science education similarly identifies substantial diversity in applications and research designs, supporting the need for more clearly specified explanatory models. □ cite □ turn0search1 □

1.4 Research Objectives

The study has four objectives. The first is to examine the association between perceived content relevance and student academic performance. The second is to examine the association between perceived feedback utility and academic performance. The third is to examine the role of self-regulated learning autonomy in academic performance. The fourth is to examine whether AI-driven learning engagement is associated with academic performance. A further conceptual objective is to position AI-driven personalised learning as an antecedent that shapes learners' perception of content relevance.

1.5 Research Questions

RQ1: How is perceived content relevance associated with student academic performance in AI-supported personalised learning environments? RQ2: How is perceived feedback utility associated with student academic performance? RQ3: How is

self-regulated learning autonomy associated with student academic performance? RQ4: How is AI-driven learning engagement associated with student academic performance? RQ5: How does AI-driven personalised learning contribute conceptually to perceived content relevance?

1.6 Hypotheses

H1: Perceived content relevance has a significant positive relationship with student academic performance. H2: Perceived feedback utility has a significant positive relationship with student academic performance. H3: Self-regulated learning autonomy has a significant positive relationship with student academic performance. H4: AI-driven learning engagement has a significant positive relationship with student academic performance. The conceptual antecedent relationship proposes that AI-driven personalised learning increases the likelihood that learners perceive educational content as relevant to their needs, prior knowledge, progress, and learning goals.

2. LITERATURE REVIEW

2.1 AI-Driven Personalised Learning

AI-driven personalised learning combines learner data, computational models, educational resources, and adaptive decision rules to generate or recommend learning experiences. Personalisation can occur through content recommendation, pacing, sequencing, question difficulty, examples, feedback, and learning-resource selection. Unlike static digital learning systems, adaptive environments attempt to respond to evidence about learner performance. The resulting learning pathway can therefore differ across students even when the course objectives remain common.

Recent systematic reviews indicate that research on AI-mediated personalised learning has expanded rapidly. A 2024 review of 78 studies published between 2019 and 2024 found that higher education represented a major application context, adaptive learning technologies remained prominent, and generative language models were becoming increasingly visible. [cite]turn0search9[A broader systematic review of AI in education also identifies multiple application categories and substantial diversity in theoretical and methodological approaches. [cite]turn0search5[These findings establish personalisation as a multidimensional construct rather than a single technological feature.

2.2 Perceived Content Relevance

Perceived content relevance refers to the extent to which learners judge AI-selected or AI-generated educational materials as aligned with their learning needs, current knowledge, academic goals, and task requirements. Relevance can reduce unnecessary information search and increase the probability that learning activities are connected to an immediate academic problem. In adaptive systems, relevance may result from learner profiling, performance analytics, recommendation algorithms, or conversational interaction.

Relevance has a direct theoretical connection with perceived usefulness. Davis's Technology Acceptance Model established perceived usefulness and perceived ease of use as central determinants of technology acceptance. [cite]turn1search0[In an educational setting, the usefulness of AI can be expressed through the perceived relevance of the content delivered by the system. When content is closely matched to a student's task and learning level, the learner may allocate cognitive resources more efficiently. The present framework therefore treats perceived content relevance as a proximal mechanism between AI personalisation and academic performance.

2.3 Perceived Feedback Utility

Feedback utility concerns the degree to which students regard AI-generated feedback as timely, specific, understandable, actionable, and relevant to the learning task. Feedback is educationally meaningful when it identifies the difference between current performance and the required standard and provides information that can guide subsequent action. AI systems can increase the frequency and immediacy of such feedback, particularly in large classes where individual instructor feedback is resource intensive.

Recent research directly supports the relevance of personalised AI feedback. Xu et al. studied 1,079 Chinese college students and reported positive relationships between AI-driven personalised feedback, goal achievement, academic self-efficacy, and learning engagement. The study used questionnaire data and structural equation modelling, providing evidence that feedback

can operate through motivational and engagement-related mechanisms. □ cite □ turn0search0 □ Research on analytics feedback also connects students' engagement with feedback to self-regulated learning competence and course performance. □ cite □ turn0search16 □

2.4 Self-Regulated Learning Autonomy

Self-regulated learning describes the processes through which learners plan, monitor, control, and evaluate their learning. Autonomy within this process concerns the learner's ability to make purposeful decisions about goals, strategies, pacing, resource use, and evaluation rather than depending entirely on external direction. AI personalisation can support autonomy by providing options and scaffolds, but the effect depends on how the learner uses those resources.

Research on personalised self-regulated online learning provides direct support for this relationship. A quasi-experimental study of personalised self-regulated learning reported higher post-test and learning-gain scores for the personalised condition than for the conventional self-regulated condition. The study also identified perceived usefulness of learning suggestions, goal setting, task strategies, time management, and self-evaluation as relevant factors. □ cite □ turn0search15 □ A 2024 pilot study involving 74 secondary students found that an AI-based self-regulated-learning chatbot enhanced science knowledge, behavioural engagement, and motivation, with interaction frequency predicting variation in self-regulated learning. □ cite □ turn0search8 □

2.5 AI-Driven Learning Engagement

Learning engagement represents the behavioural, cognitive, and affective involvement of students in learning activities. AI-driven engagement can arise through interactive questioning, adaptive tasks, immediate feedback, conversational explanation, progress indicators, and personalised recommendations. Engagement is theoretically relevant because academic performance depends not only on access to learning resources but also on sustained participation in activities that require attention and cognitive processing.

Personalised chatbot frameworks have been proposed specifically to integrate AI interaction with active and self-regulated learning. CHAT-ACTS, for example, combines personalised chatbot interaction with evaluation, feedback, planning, goal setting, and study tactics. □ cite □ turn0search11 □ The literature therefore supports a view in which AI is most educationally meaningful when it is embedded within a learning process rather than treated as an independent source of answers.

2.6 Academic Performance

Student academic performance is operationalised in the proposed study as a composite outcome involving perceived improvement in assessment scores, course grades, task completion quality, and demonstrated understanding. Where institutional records are available, objective grades or standardised assessment scores should replace or complement self-reported measures. This distinction is necessary because perceptions of learning and demonstrated learning are not identical constructs.

The evidence base contains positive findings but also substantial variation. The 2025 meta-analysis by Deng et al. reported a significant aggregate effect of ChatGPT interventions on academic performance, with considerable heterogeneity across studies. □ cite □ turn1search1 □ A 2024 systematic review of AI adoption in open and distance learning similarly concluded that the academic-performance relationship requires attention to context and research design. □ cite □ turn0search22 □ Consequently, the proposed study treats academic performance as an outcome requiring direct measurement rather than assuming that AI use itself guarantees improvement.

2.7 Theoretical Foundation

The framework integrates three theoretical perspectives. The Technology Acceptance Model explains how perceived usefulness and ease of use shape technology acceptance and provides a basis for interpreting perceived relevance and utility. Self-regulated learning theory explains how learners transform external resources into goal-directed learning through planning, monitoring, strategy use, and self-evaluation. Adaptive-learning theory explains how learner data can be used to modify content and learning pathways. The integration of these perspectives places the learner between the technological system and the academic outcome.

3. CONCEPTUAL FRAMEWORK

The supplied conceptual model is reproduced as Figure 1. AI-driven personalised learning is placed at the top of the framework and is connected to perceived content relevance. Four learning constructs then connect to student academic performance: perceived content relevance (H1), perceived feedback utility (H2), self-regulated learning autonomy (H3), and AI-driven learning engagement (H4). The structure represents a mechanism-oriented explanation in which personalisation is meaningful when it changes the quality of learning experiences.

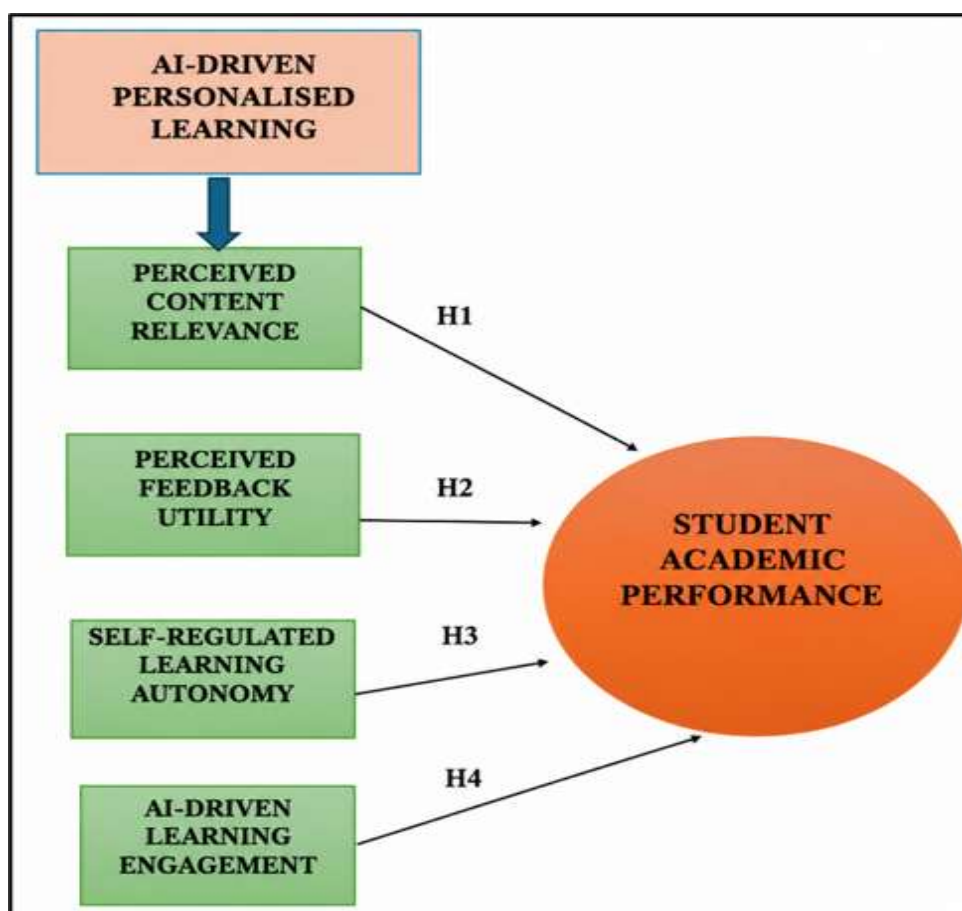


Figure 1. Conceptual framework of AI-driven personalised learning and student academic performance.

4. METHODOLOGY

4.1 Research Design

A quantitative, explanatory, cross-sectional research design is proposed. The unit of analysis is the individual student participating in an AI-supported personalised learning environment. The design is appropriate for testing hypothesised associations among latent constructs. For a publishable empirical study, data should be collected from students who have used an AI-supported learning system for a defined period and whose academic outcomes can be measured consistently.

4.2 Population and Sampling

The target population comprises undergraduate and postgraduate students who use AI-supported learning technologies for academic study. A minimum sample of approximately 250–300 responses is suitable for the proposed multivariate model, subject to power analysis and the final estimation technique. Stratified or purposive sampling can be used where the study requires representation across academic disciplines, study levels, or institutional types. The manuscript's illustrative analysis uses N=300 solely to demonstrate the numerical reporting format.

4.3 Instrument Development

A structured questionnaire can be developed using established constructs and adapted items. Perceived content relevance can be measured through statements concerning alignment with learning needs, topic relevance, appropriate difficulty, and usefulness for current tasks. Perceived feedback utility can be measured through timeliness, specificity, clarity, actionability, and relevance. Self-regulated learning autonomy can be measured through goal setting, planning, monitoring, strategy selection, time management, and self-evaluation. AI-driven learning engagement can be measured through frequency of meaningful interaction, sustained attention, participation, cognitive effort, and continued use for learning tasks. Academic performance should ideally use objective course or assessment records; a validated self-report scale can be used when institutional records are unavailable.

4.4 Measurement Scale

All perceptual items are specified on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Higher scores indicate stronger perceptions of relevance, utility, autonomy, engagement, and academic performance. Before full data collection, the questionnaire should undergo expert review and a pilot test to establish clarity, content validity, response time, and preliminary reliability.

4.5 Data Analysis Procedure

Data analysis should begin with missing-data inspection, outlier assessment, descriptive statistics, and normality diagnostics. Internal consistency should be examined using Cronbach's alpha and composite reliability, with values around 0.70 or above generally treated as acceptable for established constructs. Convergent validity can be assessed using standardized loadings and average variance extracted, while discriminant validity can be evaluated using the heterotrait-monotrait ratio and construct correlations. Multicollinearity can be examined through variance inflation factors. Hypotheses can be tested using multiple regression or PLS-SEM. The latter is suitable when the objective is prediction and the framework contains multiple latent constructs. Bootstrapping can provide confidence intervals for path coefficients.

4.6 Ethical Considerations

Participation should be voluntary, informed consent should be obtained, and personally identifiable information should be minimised. Academic records should be used only with appropriate institutional permissions. AI-generated responses should not be treated as evidence of student learning without verification because generated content may contain factual errors, incomplete reasoning, or inappropriate recommendations. Data storage, access control, retention, and deletion procedures should conform to the applicable institutional and legal requirements.

5. RESULTS AND ANALYSIS

5.1 Data-Status and Descriptive Results

The numerical results in this section are illustrative. They demonstrate how the results section can be written after collection of an actual dataset. The illustrative sample contains 300 cases. The mean scores are above the scale midpoint for all four explanatory constructs, indicating a hypothetical pattern of generally positive perceptions of AI-supported learning.

Construct	Mean	SD	Interpretation
Perceived Content Relevance	3.72	0.63	High
Perceived Feedback Utility	3.61	0.68	Moderately high
Self-Regulated Learning Autonomy	3.68	0.65	High
AI-Driven Learning Engagement	3.75	0.61	High

Table 1. Illustrative descriptive statistics for the principal constructs.

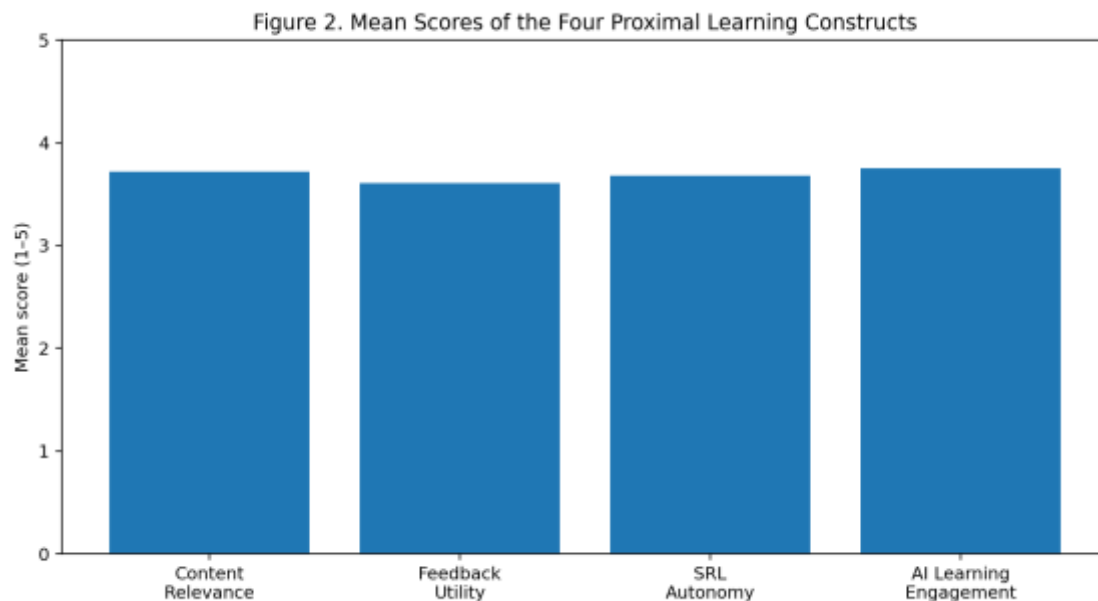


Figure 2. Illustrative mean scores of the four proximal learning constructs.

The illustrative mean pattern places AI-driven learning engagement at 3.75, followed by perceived content relevance at 3.72, self-regulated learning autonomy at 3.68, and perceived feedback utility at 3.61. The values indicate that the four constructs are distributed within a relatively narrow range. Such a pattern is consistent with a framework in which AI personalisation, feedback, autonomy, and engagement operate as interconnected components of the learning experience rather than isolated technological attributes.

Figure 3. Illustrative Distribution of AI-Supported Learning Frequency

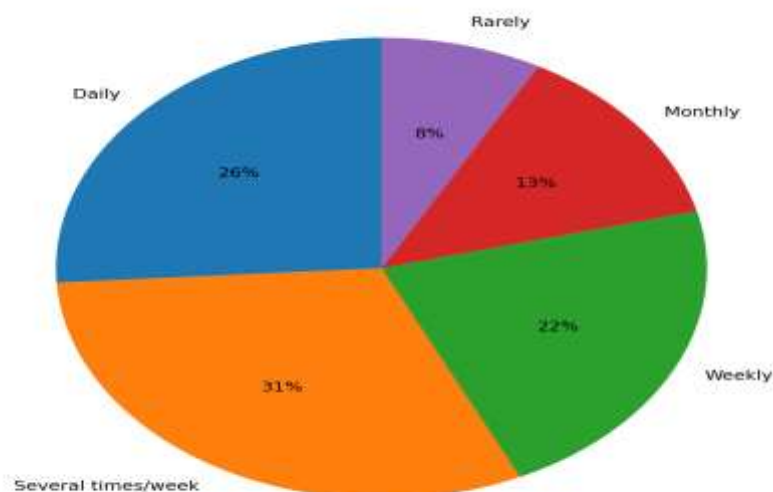


Figure 3. Illustrative distribution of AI-supported learning frequency.

The illustrative frequency distribution assigns 26% of students to daily AI-supported learning, 31% to several-times-per-week use, 22% to weekly use, 13% to monthly use, and 8% to rare use. These proportions are examples rather than observed population estimates. In an empirical study, frequency should be measured using a defined recall period and should distinguish learning use from general-purpose AI use.

5.2 Reliability and Validity Analysis

Construct	Items	Cronbach α	Composite Reliability	AVE
Perceived Content Relevance	5	0.88	0.91	0.67
Perceived Feedback Utility	5	0.9	0.92	0.7
Self-Regulated Learning Autonomy	6	0.91	0.93	0.68
AI-Driven Learning Engagement	5	0.89	0.92	0.7
Student Academic Performance	5	0.87	0.9	0.64

Table 2. Illustrative reliability and convergent-validity statistics.

The illustrative reliability coefficients exceed conventional minimum levels for internal consistency. Composite reliability values are also above 0.90, while average variance extracted values exceed 0.50. In a real dataset, these statistics would support an initial assessment of measurement quality, but they would not by themselves establish construct validity. Item loadings, cross-loadings, discriminant validity, and common-method bias should also be examined.

5.3 Correlation Analysis

Variable	PCR	PFU	SRLA	AILE	SAP
PCR	1.00	0.45	0.40	0.42	0.48
PFU	0.45	1.00	0.48	0.45	0.51
SRLA	0.40	0.48	1.00	0.50	0.56
AILE	0.42	0.45	0.50	1.00	0.54
SAP	0.48	0.51	0.56	0.54	1.00

Table 3. Illustrative correlation matrix. PCR = perceived content relevance; PFU = perceived feedback utility; SRLA = self-regulated learning autonomy; AILE = AI-driven learning engagement; SAP = student academic performance.

The illustrative correlations are positive and moderate. The strongest bivariate relationship is between self-regulated learning autonomy and academic performance ($r=0.56$), followed by AI-driven learning engagement ($r=0.54$), perceived feedback utility ($r=0.51$), and perceived content relevance ($r=0.48$). These relationships support multivariate testing because the constructs are related but not identical. In an empirical dataset, variance inflation factors would be examined before interpreting regression coefficients.

5.4 Hypothesis Testing

Hypothesis	Path	β	t	p	Illustrative decision
H1	PCR $\rightarrow$ SAP	0.176	4.209	<0.001	Supported in illustrative data
H2	PFU $\rightarrow$ SAP	0.199	4.537	<0.001	Supported in illustrative data

H3	SRLA → SAP	0.245	5.292	<0.001	Supported in illustrative data
H4	AILE → SAP	0.218	4.718	<0.001	Supported in illustrative data

Table 4. Illustrative multiple-regression hypothesis testing.

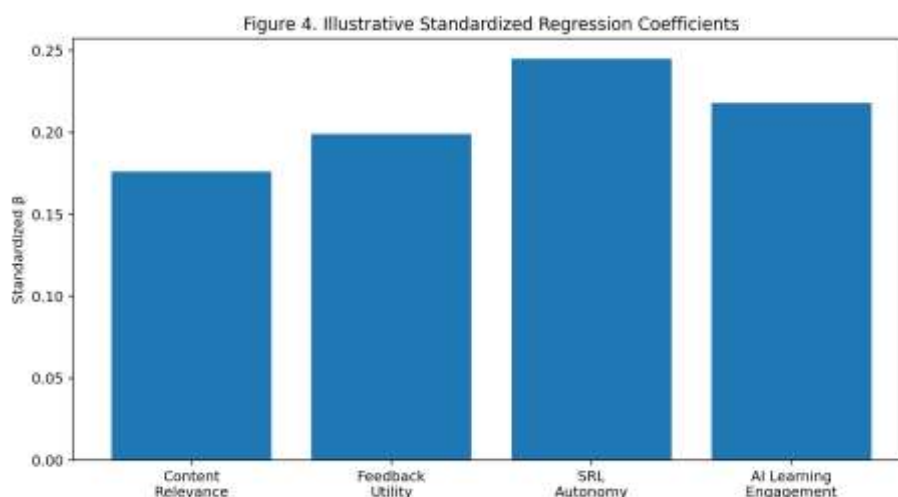


Figure 4. Illustrative standardized regression coefficients for student academic performance.

The illustrative regression model produces $R^2=0.639$ and adjusted $R^2=0.633$, indicating that the four predictors collectively account for approximately 63.9% of the variance in the simulated academic-performance outcome. The coefficients are positive for all four predictors. Self-regulated learning autonomy has the largest standardized coefficient ($\beta=0.245$), followed by AI-driven learning engagement ($\beta=0.218$), perceived feedback utility ($\beta=0.199$), and perceived content relevance ($\beta=0.176$). These coefficients are not rankings of educational importance; they describe the relative regression coefficients within the illustrative model only. Actual empirical coefficients must be estimated from observed data.

5.5 Model Interpretation

The model suggests four complementary pathways through which personalised AI environments may be connected with academic performance. Perceived content relevance represents the alignment of learning materials with individual academic needs. Perceived feedback utility represents the usefulness of information supplied after a learning attempt. Self-regulated learning autonomy represents the learner's capacity to manage the learning process. AI-driven learning engagement represents sustained interaction with AI-supported learning tasks. The combined model therefore treats academic performance as an outcome of technological personalisation operating through learner-level processes.

The proposed interpretation is consistent with recent evidence. A 2026 study of a generative-AI personalised recommender system reported that students who perceived the system as useful showed greater gains in self-regulated learning proficiency and that frequent users displayed stronger learning performance. [cite] turn0search2[At the same time, research on AI use demonstrates that the way students delegate tasks matters. A 2026 field experiment in chess training reported lower performance gains when students could request AI help freely compared with a system-regulated assistance condition, with productive struggle and engagement identified as mechanisms. [cite] turn0search3[Such findings reinforce the need to distinguish personalised support from unrestricted answer provision.

6. DISCUSSION

6.1 Perceived Content Relevance and Academic Performance

The H1 pathway connects personalisation to performance through the learner's judgement that content matches academic needs. When an AI system identifies weak areas and recommends targeted resources, learning time can be concentrated on

topics requiring additional practice. Content relevance can also reduce the mismatch between task difficulty and learner readiness. The mechanism is therefore compatible with adaptive-learning theory, where learner data inform subsequent instructional decisions.

However, relevance should not be equated with accuracy or pedagogical quality. An AI system can generate highly relevant but incorrect content. Relevance also depends on the quality of learner modelling. If the system misclassifies a student's proficiency, personalisation may reinforce an incorrect learning pathway. Therefore, empirical research should measure both perceived relevance and objective content quality.

6.2 Perceived Feedback Utility and Academic Performance

The H2 relationship is explained by the function of feedback as information for subsequent learning action. AI systems can deliver feedback immediately after a response and can generate multiple explanations when a student requests clarification. The potential value lies in reducing feedback delay and increasing specificity. Personalised feedback research also indicates relationships with goal achievement, self-efficacy, and engagement. □ cite □ turn0search0 □

Feedback utility is nevertheless dependent on student interpretation. A technically detailed explanation may be less useful than a concise explanation aligned with the student's current error. In addition, students may accept AI feedback without verification. Effective implementation therefore requires feedback literacy, opportunities for verification, and instructional designs that ask students to explain or apply feedback rather than merely receive it.

6.3 Self-Regulated Learning Autonomy and Academic Performance

The H3 pathway places learner agency at the centre of AI-supported learning. Personalised systems can recommend goals and resources, but students still need to decide how to use those recommendations. Goal setting, planning, monitoring, strategy selection, and self-evaluation form the regulatory processes through which AI support can be converted into learning activity. The personalised self-regulated learning literature supports this mechanism, including evidence from quasi-experimental online learning research. □ cite □ turn0search15 □

The autonomy construct also provides a mechanism for explaining negative outcomes from inappropriate AI use. If a student transfers planning, reasoning, drafting, and evaluation entirely to an AI system, the visible completion of a task may increase while underlying learning decreases. Recent work on human-AI learning similarly distinguishes productive inference and self-explanation from simply recording AI outputs. □ cite □ turn0search14 □ Thus, autonomy should be operationalised as active regulation of AI-supported learning, not as unrestricted access to AI assistance.

6.4 AI-Driven Learning Engagement and Academic Performance

The H4 pathway is grounded in the principle that sustained engagement provides the behavioural channel through which personalised resources can affect learning. AI-supported learning environments can increase interaction through conversational tutoring, adaptive quizzes, recommendations, progress information, and immediate feedback. Evidence from AI-supported science learning indicates that structured AI interaction can improve knowledge, behavioural engagement, and motivation. □ cite □ turn0search8 □

Engagement should be measured beyond frequency of AI use. A student can interact frequently with an AI tool while performing shallow information retrieval. Stronger measurement combines behavioural indicators, such as time on task and completed activities, with cognitive indicators, such as explanation, elaboration, problem solving, and self-evaluation. The framework therefore treats engagement as meaningful learning interaction rather than simple technology exposure.

6.5 Relationship to Previous Research

The proposed framework corresponds with the broader literature while maintaining a mechanism-oriented structure. Systematic reviews identify positive associations between AI-supported learning and academic outcomes, but they also highlight heterogeneity and implementation constraints. The 2024 scoping review of personalised adaptive learning found increased academic performance in 59% of included studies and increased engagement in 36%, indicating that effects are not uniform across contexts. □ cite □ turn1search7 □ The 2025 meta-analysis of experimental ChatGPT studies likewise reported a positive aggregate effect on academic performance while identifying high heterogeneity. □ cite □ turn1search1 □

These findings support the need for models that specify how AI exposure becomes learning. The present framework identifies relevance, feedback utility, autonomy, and engagement as four mechanisms. The framework can therefore be extended in future empirical studies through mediation tests, longitudinal measurement, experimental conditions, or objective academic outcomes.

7. IMPLICATIONS

7.1 Theoretical Implications

The framework integrates technology acceptance, adaptive learning, and self-regulated learning into a single explanatory structure. Rather than modelling AI as a direct cause of performance, the framework specifies learner-facing mechanisms. This approach can help separate technology characteristics from learning processes and can support mediation models in future research. The model also treats AI-driven personalisation as a pedagogical process rather than only a software feature.

7.2 Educational Implications

Educational institutions implementing AI personalisation can focus on alignment between learner data and instructional objectives. Content recommendation should be linked to curriculum outcomes, feedback should guide revision, and AI interactions should encourage student explanation and self-evaluation. Assessment design should distinguish assisted practice from independent demonstration of learning. Teacher oversight remains relevant because AI-generated content can contain errors and because learning needs may not be fully represented by interaction data.

7.3 Research Implications

Future empirical studies can strengthen the model by using longitudinal designs, objective grade records, experimental comparison groups, and behavioural learning analytics. Multi-group analysis can test whether relationships differ by discipline, educational level, prior AI experience, or type of AI system. Mediation analysis can examine whether feedback utility and engagement transmit the effects of personalisation to performance. Longitudinal designs can also identify whether short-term performance gains persist after AI assistance is removed.

8. LIMITATIONS

The first limitation is the use of illustrative numerical results in the present manuscript because no respondent-level dataset was provided. The values cannot be interpreted as evidence about a real student population. The second limitation is the cross-sectional design proposed for the empirical study, which limits causal inference. The third limitation is potential common-method bias when predictor and outcome variables are collected through the same questionnaire. The fourth limitation concerns self-report measurement, which may diverge from objective academic performance. The fifth limitation concerns variation among AI systems, because different platforms differ in model capability, feedback design, privacy architecture, and degree of human oversight.

9. CONCLUSION

AI-driven personalised learning provides a technological basis for adapting educational content, feedback, pacing, and learning support to individual students. The proposed framework connects this technological capability with academic performance through perceived content relevance, perceived feedback utility, self-regulated learning autonomy, and AI-driven learning engagement. The literature indicates that AI-supported personalisation can be associated with improved learning outcomes, while also demonstrating substantial variation across educational settings and use patterns.

□ cite □ turn1search7 □ turn1search1 □

The illustrative analysis demonstrates a complete quantitative reporting structure in which the four proposed learning mechanisms jointly explain a substantial proportion of simulated variation in academic performance. Self-regulated learning autonomy, AI-driven learning engagement, perceived feedback utility, and perceived content relevance each show positive illustrative coefficients. These numerical values are methodological examples rather than empirical findings. The central research proposition is that academic performance should be examined through the quality of AI-supported learning processes rather than through AI exposure alone. Future research using observed student data, objective academic outcomes,

longitudinal designs, and validated measurement instruments can determine the magnitude, direction, and durability of these relationships.

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