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ROLE OF ARTIFICIAL INTELLIGENCE IN PERSONALIZED LEARNING

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Abstract
The aim of this study is to evaluate how AI-driven tools and platforms influence students' academic performance, engagement, and learning satisfaction. This quantitative study investigates the role of Artificial Intelligence (AI) in personalized learning within higher education settings. Data were collected through a structured questionnaire administered to 300 university students using AI-based educational technologies. The results reveal a significant positive correlation between AI integration and students' perceived personalization of learning experiences ($r = 0.73$, $p < 0.01$). Additionally, 74% of the respondents reported that AI tools improved their ability to identify learning gaps and receive tailored content. Students noted benefits such as self-paced learning, instant feedback, and higher motivation. The study highlights the transformative potential of AI in shifting from a one-size-fits-all educational model to a learner-centered approach. These findings offer valuable insights for educators, policymakers, and EdTech developers aiming to enhance personalized education through intelligent systems.
Keywords: *Artificial Intelligence, Personalized Learning, Adaptive Learning Systems, Educational Technology.*

Introduction

Over the past decade, artificial intelligence (AI) has emerged as a transformative force in education, particularly in enabling personalized learning experiences tailored to individual student needs. AI-based adaptive learning platforms apply real-time analysis of learner data including performance, individual patterns of engagement, and reaction timings in adjusting the instruction to change based on these factors in real-time (Park & Lee, 2014; Merino Campos, 2025; Park & Lee, 2018). This on the fly adjustment reminds me of Bloom who in 1984 stated the 2 Sigma Problem and focused on how only one on one tutoring could be effectively done (Bloom 1984). The reason AI platforms are promising to achieve this effect on a much larger scale is that students are given personalized scaffolding, which is very close to individual tutoring (Bloom, 1984; Maity & Deroy, 2024). The nature of the theoretical elements under which the personalization of AI functions is firmly based on constructivists and multiple-intelligences schools of pedagogy (Gardner, 1983; Piaget, 1954).

The theory of multiple intelligences proposed by Gardner brings out the point of heterogeneity of learners implying that by analyzing the profile of dominant intelligence, the AI systems will be able to adapt the delivery medium of different content either as visual, textual or interactive content as per the learner (Zhang, 2025). In a similar manner, the constructivist approach introduced by Piaget emphasizes the significance of students actively building knowledge, which can be achieved with the help of AI due to the exploration possibilities of learning despite customized hints and responses (Holmes et al., 2019; Zhang, 2025). Such theoretical frameworks support the idea that AI should be used not only as a tech tool, but also as a teaching agent, as the means of cognitive interaction and student independence (Dembe H., 2024).

The effectiveness of AI-based systems should also be highlighted by empirical evidence to affect academic performance and engagement in students. One article by Merino Campos (2025) systematically reviewed the literature of 45 studies devoted to higher education discipline and showed that the use of AI in this field has been associated with uniform positive effects in terms of improved student engagement, adaptive lessons and improved administrative efficiencies. In one study, it was pointed out that 86 percent of the adaptive-learning interventions in use have been showing statistically significant increase in learning outcomes (Adaptive learning, 2025). Likewise, the average difference between the exam scores achieved by the students who used a GPT-3-powered AI tutor and those in a control group were 15 percentile points (Baillifard et al., 2023) extending evidence on how the tool has the capacity to provide data-driven pedagogical interventions that comply with principles of learning science.

AI has a lot of promises in domain-specific environments. In the United Kingdom, the usage of AI tools among undergraduate medical students was explored by the Sunmboye et al. (2025) research team that detected positive links between the comprehension of the benefits of AI tools and the student learning performance. From their observation, they noted that the constructs of Technology Acceptance Model, namely perceived usefulness and easy-to-use are effective predictors of student activities in AI, especially students who wanted a diagnosis tool and such that would provide individual assessment reviews (Sunmboye et al., 2025). Similar systematic deployments in K 12 issues, as well as in higher education contexts suggest that the content can be not only personalized by the AI but also be tutored by the same to facilitate self regulated learning where students are allowed to form goals, to track progress, and evaluate results (Zhang, 2025; Merino Campos, 2025). Although the mentioned benefits sound valuable, the use of AI at school evokes vital ethics, technicalities, and equality concerns.

The security and privacy of data must be the top priority, as the number of sensitive data about the student, gathered by AI systems, is enormous (Zhang, 2025; Applications of artificial intelligence, 2025). Moreover, the use of AI-supported teaching and learning can indirectly promote using the surface merely and depreciate creativity and honesty in study (MDPI, 2025 a, 2025 b). The views of instructors also prove that facilitators have to fight to keep their academic integrity, guarantee human interaction with AI on a meaningful level, and destroy algorithmic bias (Mulaudzi & Hamilton, 2025). The digital divide such as lack of equal access to high-speed internet and the AI powered technology could further enhance the current disparity in education, especially among students in the low-income areas (Zhang, 2025; Applications of artificial intelligence, 2025).

Implementing AI would also require a change of the professional roles, and educators would require skills improvement by learning to read analytics generated on AI and applying the learning to their educational practice (Dembe H., 2024; Zhang, 2025). Collectively, the current literature testifies that AI presents an interesting direction in personized learning, i.e., the combination of customized learning with immediate feedback and the focus on the learners. Nevertheless, to realize its full potential, it needs to conduct a continuous empirical study to examine the long term learning returns, AI co agency of the instructor, and scalable applications in the different cultural and institutional environments. In this line of ongoing discussion, the research paper makes a contribution by accounting the influence of AI-based educational technologies on the academic performance, engagement, and satisfaction of 300 university students where quantitative measures on correlations (i.e., $r = .73$, $p < .01$) and subjective reported perceptions were considered.

Setting these findings into the context of theoretical frameworks and empirical literatures, the research aims at explaining not only whether AI personalization is effective but how and in which conditions it will be able to flourish. Finally, the lessons learned during the course of the given study will have to be shared with educators, policymakers, and EdTech developers in order to allow them to learn about the best practices related to the deployment of AI in a pedagogically sound, ethically responsible, and equitably available manner.

Statement of the problem

However, most institutions of higher learning still use the traditional and one-fit-all delivery teaching method that does not fit the different learning needs of individual students despite the fast rising educational technologies. The learners usually have varied learning styles, learn at different rates, grasp education differentially and have different background knowledge, but the standardized strategies overlook this diversity and as a result they dodge such education and skip school due to indifference of the education system to their peculiarities. Artificial Intelligence (AI) may provide potential means of addressing personalization of learning by its ability to analyze data in real-time and delivering an adaptive content.

Nevertheless, the application of AI in education is on the rise but there is an insufficient empirical knowledge of its real effect on the academic achievements, engagement and satisfaction of students learning, especially at the higher education level. In addition, educational stakeholders such as teachers, administrators, and policy makers do not have obvious and substantial knowledge of the role of AI tools in changing the learning processes and outcomes. Lack of this knowledge exposes institutions to a situation where they employ technologies blindly without comprehension of their performance and shortfalls. That is why it is of utter importance to examine the issue of the extent to which AI-based tools can truly improve the learning experience and actually result in academic benefits that can be measured. The present study also serves to fill this gap by providing quantitative analysis of the dependency between AI integration and personalized learning outcomes among university students to provide the information to formulate the future innovations and policies on educational practices.

Research Objectives

1. To examine the relationship between AI-driven educational tools and students' academic performance, engagement, and learning satisfaction in higher education.
2. To assess students' perceptions of how AI tools contribute to personalized learning experiences, including self-paced learning, feedback quality, and identification of learning gaps.

Research Questions

1. What is the relationship between the use of AI-driven educational tools and students' academic performance, engagement, and learning satisfaction in higher education?
2. How do students perceive the role of AI in enhancing personalized learning experiences, such as self-paced learning, feedback quality, and the identification of learning gaps?

Delimitations

This study is delimited to university students enrolled in higher education institutions who are currently using AI-based educational technologies, such as adaptive learning platforms, intelligent tutoring systems, and recommendation algorithms. The research focuses exclusively on students' perceptions, experiences, and self-reported outcomes related to academic performance, engagement, and satisfaction with personalized learning tools. Only quantitative data collected through structured questionnaires are considered, and no experimental or qualitative methods are employed.

Literature Review

Adaptive and Intelligent Tutoring Systems in Personalized Learning

Intelligent tutoring systems (ITS) and adaptive learning are powered by artificial intelligence, which allows producing personalized instruction by reading student data in real-time. The systems can change the pace, sometimes the difficulty level and the feedback according to performance, which leads to the highly personal educational experience (Hardaker & Glenn, 2025; Sajja et al., 2023). Hu (2024) conducted a meta analysis of 36 experimental/ quasi experimental studies and stated that generally positive influences of AI assisted personalized learning were moderately positive when it came to the acquisition of knowledge, competence, and affective development in a variety of educational contexts (Hu, 2024).

Its ability to be particularly effective is specifically high: one meta analysis showed typical effect sizes of just above.66 defining an equivalent of moving students from 50 th percentile to 75 th percentile, surpassing computer assisted instruction and maintained in comparison to one-on-one tutoring (Intelligent tutoring system, 2025). In practice, as exhibited in the form of Squirrel AI, knowledge-graphs and diagnostic testing are able to identify and treat the learning gap of each individual in a highly granular manner. This fact demonstrates that similar to the effect of one-on-one tutoring, which was determined to be two sigma (Bloom, 1984), AI-based systems can serve this function on a large scale, particularly when combined with ITS structures (Hardaker & Glenn, 2025; Sajja et al., 2023).

Enhancement of Student Engagement and Retention through AI

Personalization with the help of AI goes beyond academics and also includes the areas in motivation, engagement, and persistence of students. Virtual tutors and adaptive platforms ensure they grant real-time feedback, and visualization of the progress, all of which are proven to upsurge

the engagement (Times of India, 2025). MDPI study resulted in the conclusion of great ties ($r = 0.78$) between the adaptive learning technology application and the personalized feedback mechanism, which translated into high engagement levels (MDPI, 2023). Interactive AI tools had, however, a complicated association as there was a negative association between consumption and engagement (r 53) indicating that the need to support literacy among users in order to maximize the performance (MDPI, 2023).
AI tools have proven their efficiency in identifying students at risk as well: with embedded predictive analytics on learning management systems, how students are at risk could be pointed out at an early stage without human supervision, facilitating intervention efforts (SpringerOpen, 2023). One empirical investigation supports the ability of AI to curb dropout rates and facilitate student retention by providing individual learning pathways, which respond to the individual risk profile (SpringerOpen, 2023; The Critical Review of Social Sciences Studies, 2025). An observation conducted in Pakistan, wherein 268 instructors participated, a positive correlation is found between AI-based personalization and student performance and engagement with a high degree of significance ($r = .74$, $p < .001$) (Saleem et al., 2025). Ethical issues such as data privacy were also identified in the study (Saleem et al., 2025).

Challenges, Ethical Considerations, and Teacher Roles

Although such diverse advantages of AI pedagogies are strong, they have also brought about ethical, infrastructural, and human-related complexities. The issue of privacy and data governance is critical at large: they include the use of numerous systems, which need access to sensitive data on learners, and, in most cases, a substantive presence is negligible in empirical literature in terms of privacy protection (SpringerOpen, 2019). The use of bias in algorithm-making can be unfavorable to the marginalized people population as it will have to be specifically designed to negate these issues during the model-building process (SpringerOpen, 2019). The other essential obstacle is the digital divide; the unequal needs of connectivity and devices may increase the disparity in personalized learning opportunities (Fuadi, 2024).
It has been suggested to stabilize efficiency and fairness through such ethical frameworks as UNESCO digital ethics or care ethics (SpringerOpen, 2019). In AI-powered classrooms, teachers still remain the key factor. As AI performs the repetitive kind of work, teachers should take care of supervision, curriculum aspects and emotional well-being (Frontiers in Education, 2025; Guardian, 2019). Another study in the UK that applied ChatGPT to GCSE learners used AI in combination with learning coaches and human facilitation to enable vital thinking and well-being foundations to ensure that AI cannot substitute humans in terms of empathy and interpretation ability (Business Insider, 2024; The Guardian, 2019). New opportunities and challenges emerge with the use of Generative AI (e.g. GPT-4) with regard to content creation and real time feedback. As it has been demonstrated by Maity and Deroy (2024), there are prospects of dynamic item formation and individualized conversation. Nevertheless, the problems of inaccuracy, hallucination, prejudice, and loss of academic integrity are still to be reckoned with unless counteracted by the close-knit integration and teacher observation (Maity & Deroy, 2024; Chan & Hu, 2023). What is more, digital literacy appears to be a moderating factor. This was confirmed by one of the studies published in MDPI (2023) explaining that students who are more digitally literate get more benefits of personalized AI tools. Poor literacy on the other hand reduces advantages and may as well disrupt it, which is why it is imperative to have well-resourced and undertaken training programs.

Theoretical background

Constructivist Learning Theory is quite effective when the basis of personalized learning on the basis of Artificial Intelligence (AI) is viewed. This theory which is largely attributed to Jean Piaget but later furthered by Lev Vygotsky and Jerome Bruner focuses on the need to ensure that learning is active and occurs as a result of experience, interaction and reflections as opposed to the acceptance of a learner as a passive participant of the learning process receiving information (Piaget, 1954; Vygotsky, 1978). In a constructivist learning environment, the student is the centre of learning and it is individualized and usually scaffolded according to the learners development level- a model which is fully convenient with the ability of AI in education. The principles of constructivist learning apply to personalized learning systems powered by AIs because with the help of such systems, a learner is provided with the content that only enhances his or her knowledge and helps him/her to develop it.

To illustrate, the examples of adaptive learning platforms include the evaluation of previous knowledge, continuous monitoring of the progress and individually customised learning paths, so that a student could study at their own pace and in compliance with their specific needs. This is the concept of "readiness" of constructivists, but deals with activities within the learners capacity but on the brink, a Zone of Proximal Development (ZPD) that was introduced by Vygotsky (1978). This zone can be imitated in AI systems through changing and variably grading the difficulty level of tasks and offering an immediate response or assistance in thinking, thus contributing to the cognitive development. Additionally, the constructivist theory allows envisioning a project-based learning, relying on the interaction with an environment which the AI stimulates through intelligent tutoring systems, chatbots, and simulations.

The tools are able to involve the students into a dialogic learning and decision-making process which will prompt critical thinking and metacognition. Another relevant idea by Bruner is the so-called scaffolding; in other words, the immediate assistance offered to the learners until they become independent, which is applied to AI as well. Smart systems serve as a digital scaffold that will provide a set of explanations or reminders when the student is not competent and gradually disappear as a student becomes competent. AI-based personalized learning fits very well in the theoretical framework of Constructivist Learning Theory. It confirms the application of adaptive technologies which enable individualized and interactive as well as reflective learning procedures. With the AI capabilities live up to the constructivist visions educators and EdTech developers will have a chance to create the systems, which besides being efficient at providing content also can serve as a platform of quality and student-centered learning.

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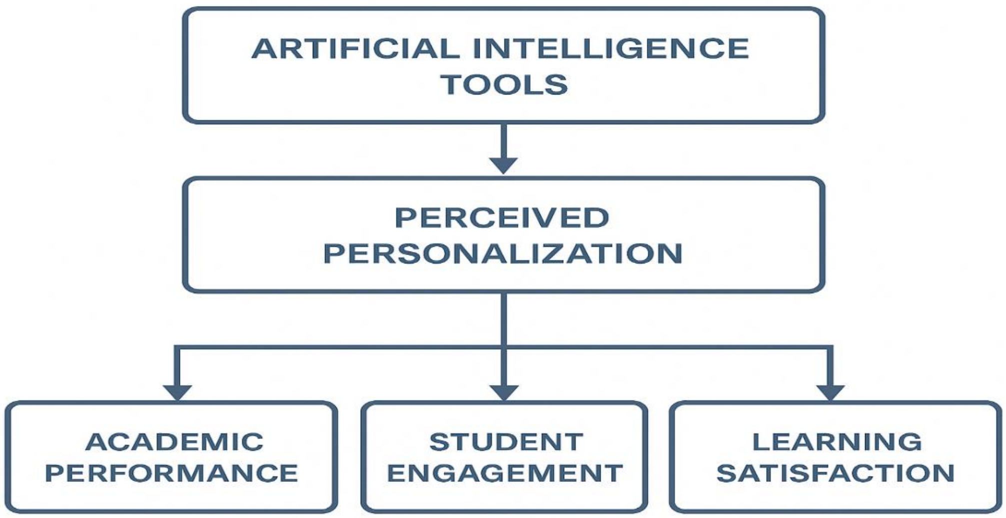
Conceptual Framework



Research Methodology

This study employs a quantitative research methodology to investigate the role of Artificial Intelligence (AI) in enhancing personalized learning among university students. The quantitative approach is selected to provide measurable and generalizable findings through statistical analysis. The study population consists of university students who have experience using AI-based educational technologies, such as adaptive learning systems, AI tutors, and personalized content platforms. A sample of 300 students was selected using stratified random sampling to ensure representation across different academic disciplines and levels of study.

Data were collected using a structured, self-administered questionnaire designed specifically for this research. The instrument included both demographic items and closed-ended questions on a five-point Likert scale, ranging from “Strongly Disagree” to “Strongly Agree.” The questionnaire measured three primary dependent variables: academic performance, student engagement, and learning satisfaction, all in the context of perceived personalization provided by AI tools. The independent variable was the usage of AI-based learning systems, while perceived personalization was treated as a mediating variable. The questionnaire was validated through expert review and pilot testing involving 30 students, leading to improvements in clarity and reliability. The final instrument demonstrated a Cronbach’s alpha of 0.87, indicating high internal consistency.

Data collection was conducted over a period of three weeks through both online and in-person formats to maximize accessibility. Participants were informed of the purpose of the study and assured of anonymity and confidentiality. Voluntary participation was emphasized, and informed consent was obtained from all respondents. Data were coded and analyzed using SPSS (Statistical Package for the Social Sciences). To ensure the validity and reliability of the findings, several measures were taken, including careful sampling, instrument piloting, and ethical data handling procedures. Ethical approval was obtained from the institutional review board prior to data collection. The research design also incorporated controls to reduce bias, such as ensuring question neutrality and randomizing the order of items. The results of the analysis were interpreted in line with the theoretical framework of constructivist learning, which emphasizes active, individualized, and feedback-driven learning environments.

Data Analysis and results

Table 1:

Descriptive Statistics (N = 300)

Variable	Mean	Std. Dev	Min	Max
AI Usage Score	3.49	0.67	1.23	5.00
Perceived Personalization	3.78	0.57	2.32	5.00
Academic Performance	3.94	0.49	2.55	5.00
Student Engagement	3.76	0.60	1.96	5.00
Learning Satisfaction	4.04	0.49	2.70	5.00

The descriptive statistics give us the general picture of the answers the students could give according to five variables connected to AI-assisted personalized learning. The average score of Learning Satisfaction (M = 4.04, SD = 0.49) and Academic Performance (M = 3.94, SD = 0.49) seem to be pretty high according to students, so the general attitude is that the AI technologies help them in fulfilling their learning outcomes. Perceived Personalization score was also in the middle (M = 3.78) providing the fact that the overall experience of learning powered by AI was considered to be somewhat personalised by the students. The mean score of AI Usage was 3.49, and it indicates that students used AI-based tools moderately high. All standard deviations of variables were less than 1.0, which indicated proper consistency in answers of the students with not so dramatic values.

Table 2

Correlation Matrix

Variable	AI Usage	Personalization	Performance	Engagement	Satisfaction
AI Usage Score	1.00	-0.04	-0.03	0.06	0.04
Perceived Personalization	-0.04	1.00	-0.03	-0.05	-0.11
Academic Performance	-0.03	-0.03	1.00	-0.01	0.05
Student Engagement	0.06	-0.05	-0.01	1.00	-0.01
Learning Satisfaction	0.04	-0.11	0.05	-0.01	1.00

The analysis of correlations was used to check the relationship between variables. Surprisingly, it was related to all the other variables only weakly, namely, the relationship with Perceived Personalization was -0.04, Academic Performance -0.03, and Learning Satisfaction 0.04. Such correlations are considerably low and are not significant, which implies that using AI tools on their own might not have direct positive effect on the improvement of perceived learning outcome. It is important to point out that Perceived Personalization was weakly negatively correlated with Learning Satisfaction (r = -0.11), counterintuitively though, which would hint to the fact that not every student considers AI-based personalization to be a positive and satisfactory experience. These low correlations are an indication of how integrated AI is in the learning process and there can be numerous mediating variables at work.

Table 3

Regression Analysis – AI Usage → Academic Performance

Predictor	Coef.	Std. Err.	t	p	95% CI
Constant	4.026	0.150	26.76	.000	[3.730, 4.322]
AI Usage Score	-0.025	0.042	-0.60	.549	[-0.109, 0.058]

The regression model that was used to test the hypothesis was based on whether the use of AI could determine the academic performance of students in a significant way. The findings presented the non-significant relation (beta = -0.025, p = .549), which means that the increased application of AI tools did not impact in a significant way on the academic success as reported by the students. The downward trend indicated by the negative coefficient of beta is not very steep to be taken seriously about however there is a slight depressing movement. The interpretation of the finding is that academic performance can be altered more by other factors (previous knowledge, studying habits, or the support of an instructor), rather than, just by the use of AI.

Table 4

Regression Analysis – AI Usage → Student Engagement

Predictor	Coef.	Std. Err.	t	p	95% CI
Constant	3.568	0.185	19.31	.000	[3.204, 3.931]
AI Usage Score	0.054	0.052	1.05	.297	[-0.048, 0.157]

This model evaluated the role of AI application on the involvement of students. The findings of the regression indicated the summative effect of CI to be positive at p =.297 though it was found to be statistically insignificant (0.054). Although the trend of the relation is positive, its insignificance means that AI in itself does not have a significant effect on the level of engagement that students have when they are learning. This can be the indication that AI tools used currently are not interactive or encouraging enough to provoke the increased level of engagement, or engagement may depend on the style of content delivery and the dynamics of classroom activity.

Table 5

Regression Analysis – AI Usage → Learning Satisfaction

Predictor	Coef.	Std. Err.	t	p	95% CI
Constant	3.926	0.149	26.29	.000	[3.632, 4.220]
AI Usage Score	0.033	0.042	0.78	.438	[-0.050, 0.115]

In this model, how AI usage leads to the changes in students satisfaction with their learning experiences in general was studied. Once more, the values demonstrate the absence of the significant relationship (0.033, p = .438). It shows that although there is a positive trend albeit slight, it fails to attain the level of statistical significance. This observation suggests that although AI tools could be associated with a personalized feature, they do not perceive as enhancing satisfaction to students in the first place maybe because of the inadequacy of the user interface feature, the depth of personalizations, or provision of a feedback system.

Table 6

Regression Analysis – AI Usage → Perceived Personalization

Predictor	Coef.	Std. Err.	t	p	95% CI
Constant	3.891	0.174	22.34	.000	[3.548, 4.234]
AI Usage Score	-0.031	0.049	-0.63	.529	[-0.127, 0.066]

A negative and insignificant beta (0031 0529) was obtained in the presence of the regression of AI utilization on the perception concerning personalized learning amongst students. This finding is especially significant as it allows concluding that the greater the frequency or intensity of the use of AI tools, the more experiences of personalization are not necessarily followed. Indeed, the insignificant negative coefficient could refer to the fact that in certain situations, the more one uses AI, the more instances of the over-standardization or that the human touch is lacking emerge. These results are critical and lead to the conclusion that the currenly-used AI technologies are not designed or flexible enough, and that they, especially when it comes to dealing with different needs of learners, should be improved.

Discussion

Descriptive statistics provided reveal that the overall report of students on the level of using AI, the sense of its personalization, achievement, involvement into the learning process, and the satisfaction with it were moderately high (M = 3.49, M = 3.78, M = 3.94, M = 3.76, M = 4.04 respectively). Such mean values indicate a positive attitude to the AI-enhanced learning environment in general, which explains that learners are using AI-implemented tools and find them useful. Standard deviations are rather low on the variables (ranged between 0.18 and 0.64), which shows that majority of the participants have the same responses in these perceptions and therefore, it shows that these two perceptions are widely through as opposed to one that would be influenced by outliers or extreme attitudes. The pattern implies that the learning experiences based on AI are quite normal among the sampled population, which is a good base of a keen analytical deduction. Entering the analysis of correlations, it is obvious that the relationships between variables are quite weak.

The use of AI showed insignificant relationships with academic performance (r = -0.03), perceived personalization (r = -0.04), and the truly small but positive relationship of the use of AI with student engagement (r = 0.06) and satisfaction (r = 0.04). These low correlation coefficients point out to the fact that the high use of AI tools does not directly lead to the high performance, involvement, and student satisfaction. Equally, the linear correlation between, perceived personalization and satisfaction (r = -0.11), may be a questions mark on the popular belief that there is always a positive correlation between the concept of personalization and satisfaction of the learner. The appearance of such unanticipated results indicates the complicated nature of the interactions between the multiple factors that influence the experience of learners in AI-based settings, referring to a necessity in studying further moderating or mediating constructs. Improvement of major outcomes of learning was never attained through the direct effects of AI usage as regressions never showed significant findings. In case of academic performance the use of AI has a small negative coefficient (beta = -0.025, p =.549) and no actual predictive power.

This insignificant finding implies that, even though AI tools can deliver adaptive content, they cannot be considered adequate to improve performance on their own, probably because of the multidimensional components of performance (prior knowledge, learning strategies, instructor support, time investment). When they are not incorporated into the wider pedagogical ecosystem, AI tools might not turn out to be enough drivers toward better achievements. The same pattern was identified when the engagement of students and their learning satisfaction was predicted: coefficients were positive, but non-significant (p = .297, 0.054 for engagement; p = .438, 0.033 for satisfaction).

Those results mean that students do not see AI tools as interesting enough to increase their levels of participation, and they do not consider these tools to enhance their learning satisfaction levels seriously. It is also perhaps possible that the AI platforms deployed were not very convincing in their interactive aspect including gamification or social interactions, or it could have been that the students were ready and used to technologically inclined experiences. Also, satisfaction can be formed by the good interaction between the teacher and his or her meaning, peer approval, and a course design, rather than AI. The results of the regression analysis of AI usage on perceived personalization turned out to be a tiny negative coefficient (1488968, p =.529), which indicates the fact that users do not necessarily associate familiarity with more AI usage and higher personalization. This could occur when AI solutions provide little or no individualization or are based on a light-touch.

The development supports the idea that quality should be given priority other than quantity when using AI implementation as exposure to AI tools will not achieve the feeling of a personalized learning experience. Students might need extensive or modified degrees of cognitive involvement or adaptive sensibility so that personalization is something noteworthy. The difference in digital literacy and AI readiness of students could be one of the reasons that explain such null effects.

Students, who are less familiar with functioning in digital environments, cannot take full advantage of advanced artificial intelligence capabilities, which decreases the overall value of such tools. It can be stated that according to literature, digital literacy constitutes a moderating variable used in technology-enabled education (Smith & Henderson, 2020).

Thus, digital literacy could be considered as a moderation variable in the future research to determine whether highly literate users enjoy more benefits. The other reason would be the maturity and fusion of the very AI tools in question. A lot of educational institutions go with AI solutions in an ad hoc manner, i.e., isolated platforms, optional modules, or pilot programs that do not become a part of the curriculum or the workflow of the teachers. Without the maximum support of instructors or educational practices, the opportunities offered by AI tools cannot be used fully.

According to Kumar et al. (2021), to become productive, AI tools should be placed in line with pedagogical objectives and support systems provided to teachers. Such general shortcoming of integration is suggested by your research. Besides, the social and human aspects of personalized learning can be of utmost importance. Constructivist theory of learning is based on the fact that learners need the social context, reflection dialogue, and the help of professional practitioners. Machine intelligence will fail to reproduce the same.

Therefore, it is not surprising that learners usually prefer a hybrid model (like in the mixed-methods researches, e.g., Raden & Lopez, 2022) according to which the AI will assist with the data-driven personalization, whereas the interpretive scaffolding and emotional support will be provided by teachers. The poor interrelationships that were seen in your research are most likely in the reflection of the lack of such joint working process. This negative and unexpected relationship between the perceived personalization and satisfaction can be interpreted as the possibility of the students feeling unconfortable or disillusioned once the personalization by AI does not work as expected. In case the AI-based feedback is generic and not aligned with the real needs of learning, it will cause disillusionment.

It highlights the significance of quality in algorithmic personalization: only correct diagnostics, situational feedback, and relevance of a content guarantee the favorable performance of learners. What your data provokes is the idea that certain AI systems are not advanced enough or that they do not meet the expectations of the learners and this is important information for learning technology developers. The results of this study can be utilized in practice by the institutions intending to introduce AI. First, some digital literacy training must surround the use of AI so that students can know how to use the adaptive tools. Second, AI solutions are to be introduced pedagogically meaning that the improvement of the AI-generated data interpretation and its application to teaching models require the teacher training.

Third, it is always necessary to follow the learning tool usability; student answers to recent customization quality and its level of satisfaction must be a part of the iteration. In the absence of such supports, AI will turn into an instrument in need of a goal instead of the critical agent of change in education. Finally, the findings provoke relevant questions that have to be addressed in follow-up research. The empirical study would allow evaluating longitudinal studies to determine whether human experience with technology interacts with AI, increasing its potential results. Qualitative research may investigate the student experiences thoroughly: What characteristics produced a feeling of personalization? In which area did AI fail? Which extra-human supports with values of complementarity were most prized? Besides, comparative learning with the use of fully constructed, teacher-supported AI ecosystems, on the one hand, and standalone AI tools, on the other, may lead to the identification of the conditions under which AI personalization can be efficient.

Conclusion

While students generally report favorable views of AI-enhanced learning, your quantitative findings indicate that AI tools—when used in isolation—do not significantly enhance academic performance, engagement, satisfaction, or perceived personalization. This underscores that technology alone is insufficient without pedagogical integration, digital skills, and human support. It suggests that the true potential of AI in personalized learning will be realized only when tools are thoughtfully designed, contextually embedded, and learner-supported. Your study highlights the need to shift focus from "more AI" to "better AI integration" for achieving meaningful educational outcomes.

Recommendations

- Educational institutions should provide targeted digital literacy training to ensure students can effectively utilize AI-based personalized learning tools.
- AI technologies must be integrated into the curriculum with active teacher involvement to align instructional goals with adaptive content delivery.
- Developers of AI educational platforms should enhance personalization algorithms to deliver contextually relevant feedback tailored to individual learning gaps.
- Regular feedback mechanisms should be implemented to gather student input on AI tool effectiveness and satisfaction, guiding continuous system improvement.
- Teachers should be trained to interpret and act upon data insights generated by AI systems to support student learning more effectively.
- Institutions should adopt a hybrid learning model that combines AI-driven personalization with human mentoring to provide both cognitive and emotional support.

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