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Integrating Intelligent Tutoring Systems into Digital Learning Environments: Effects on Adaptive Learning and Learner Engagement

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Abstract

This study explores the effects of bringing generative artificial intelligence into Intelligent Tutoring Systems for adaptive learning and learner engagement in higher education. Using quantitative Cross-sectional design, data were gathered from 200 undergraduate students from Prince Sattam Bin Abdulaziz University using a structured questionnaire with generative AI integration features, adaptive learning, and the multidimensional engagement of learners using 5-point Likert scale. Structural equation modeling using the partial least square analysis was used to analyze relationships between variables. The study results showed that the integration of generative AI was significantly associated with increasing adaptive learning ($b = 0.69$, $p < .001$) and engagement on the part of the learner ($b = 0.63$, $p < .001$). Adaptive learning was a partial mediator of the association between generative AI integration and engagement suggesting that better instructional personalization was at the heart of how generative AI integration can encourage student engagement. Furthermore, dynamic content generation, conversational feedback and personalised adaptation were found to have a cumulative collective impact of 64% on learning effectiveness, with dynamic content generation being the most significant predictor. The results show that the use of generative AI enhanced tutoring systems significantly enhances the strength of instructional adaptivity and supports consistent cognitive, behavioral, and emotional engagement. The research concludes that generative AI integrated in Intelligent Tutoring Systems holds a transformative potential for the personalization of digital education with important consequences for scalable and effective higher education instruction.

Keywords: *Generative Artificial Intelligence, Intelligent Tutoring Systems, Adaptive Learning, Learner Engagement, Personalized Education, Higher Education.*

Introduction

The growth of complexity of learning needs in higher education has led to intensify the demand for instructional systems that are capable of offering personalized, adaptive, and scalable support. Intelligent Tutoring Systems (ITS) was among the most important innovations in educational technology aimed at stimulating the pedagogical merits of one-to-one human tutoring by computational modelling of learner's knowledge and instructional strategies (Nwana, 1990; Anderson et al., 1985; Anderson et al., 1989). Early ITS architectures were based on four fundamental components: domain model, student model, tutoring model and user interface (Nwana, 1990). These systems tried to mimic the expert tutoring by diagnosing misconceptions of the learner, adapting to learn pathways and instantly giving a corrective feedback. Providing empirical evidence has always shown that ITS could yield better student achievement as compared to traditional classroom teaching especially for structured learning like mathematics, physics and computer programming (VanLehn, 2011; Anderson et al., 1995).

As ITS began to grow, studies began to focus on adaptive learning as the theoretical and functional base of intelligent tutoring environments. Adaptive learning has been defined as the dynamic marking of instructional content, sequencing, and feedback derived from an ongoing analysis of learner performance and interaction data. (Shute & Towle, 2003; Durlach & Lesgold, 2012). Through machine learning and data-driven personalization mechanisms ITS systems were increasingly able to individualize learning experiences to cognitive states and patterns of progression (Alkhatlan & Kalita, 2019). Such adaptivity has been linked to greater knowledge retention capacity, problem solving ability and learner autonomy (James & Fletcher, 2016). The principal idea underlying adaptive ITS is that instruction that is matched to individual learner needs decreases the cognitive workload and facilitates greater conceptual understanding (Sweller, 2011).

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Parallel to development in the field of adaptivity, the learner engagement was another central construct for assessing the effectiveness of digital learning environments. Engagement includes behavioural participation, cognitive investment and emotional involvement in learning activities (Fredricks et al., 2004; Fredricks et al., 2016). Within the context of technology mediated learning approaches, engagement is both a mediator and predictor of academic success (Bond et al., 2020). Research shows that adaptive instructional systems help to foster behavioral engagement by boosting the rate of interaction, cognitive engagement by encouraging active problem-solving, and emotional engagement by providing helpful feedback experiences (Nkomo et al., 2021). Consequently, engagement has emerged as an important outcome variable in assessing the effect of ITS on effectiveness of learning.

In spite of demonstrated benefits, traditional approaches to ITS architectures have been held down by persistent limitations. Rule-based tutoring systems usually contain predefined content repositories and scripted patterns to produce feedback and have no or limited capacity to handle open-ended questions or novel input from the learner (Alkhatlan & Kalita, 2019). Content generation scalability Another challenge is the scalable content generation with the development of content rich instructional materials for diverse areas of knowledge requires a considerable amount of human authoring effort (Nkambou et al. 2010). Furthermore, in spite of learner errors being clearly diagnosed, the capacity of generating nuanced explanatory dialogue in the same way human tutors would in earlier implementations of ITS systems are limited (Woolf, 2009). These limitations have offered the motivation for sustained efforts to increasingly integrate more sophisticated artificial intelligence capabilities in a tutoring environment.

The development of big language models and generative artificial intelligence technologies in 2022 was a big leap in the study of educational artificial intelligence. Generative models, such as the one based on transformers, had demonstrated the capacity to produce coherent and contextually relevant natural language outputs from different fields that were also diverse (Radford et al., 2019; Brown et al., 2020). In the educational environment, automatic explanation generation, question generation and savvy conversational tutoring assistance (called models) began to be investigated (Kasneci et al., 2023). Unlike the traditional ITS systems with pre-determined responses, generative AI brings us ability to create dynamic instructional content in response to the learner's inputs, in a real-time instructional fashion (Bandi et al., 2023). Early research which focus on the use of generative AI in the educational sector emphasize that generative AI can support personalization and adaptivity of tutoring systems (Kasneci et al., 2023). Generative models can examine the responses of the learners and identify misconceptions and produce specific explanations based on individual levels of understanding. This is a capability that transcends the adaptive logic of the traditional ITS in terms of enabling systems to step outside of specific topics of feedback templates to more conversational context-aware instructional dialogue. In addition to this, generative AI helps us with automated formative assessment, as it helps in generating dynamic questions which can reduce content repetition and add cognitive challenge (Kasneci et al., 2023).

At the same time, introducing generative AI in instructional systems raises fundamental pedagogical and ethical issues. Concerns about factual reliability, hallucination phenomena and algorithmic bias have been extensively covered in recent scholarship (Kasneci et al., 2023). Ensuring transparency, preserving data privacy and sentiments like critical thinking skills are some of the critical considerations to determine the deployment of generative AI within the learning environment. Consequently, researchers have called for the necessity to incorporate generative AI in the existing structured pedagogical approach and not just rely on the outputs of autonomous AI (Kasneci et al., 2023).

Although officers in ITS research have actually thoroughly documented the advantages of adaptive instruction and also engagement enhancement, empirical investigation in between the combined integration of generative AI in between ITS architectures is limited past 2023 in literature. Existing studies mostly focus on generative AI as a whole in educational applications or assess the tranquility of ITS independently with no systematic analyses on how generative AI affects adaptive learning mechanisms and multidimensional engagement at the same time (Alkhatlan and Kalita, 2019; Bond et al., 2020; Kasneci et al., 2023). This gap makes a case for empirical research into the effect of integrating generative AI to improve adaptive capability of ITS without reducing or diminishing learner engagement.

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Understanding this relationship is particularly important in a higher education context where diverse learner profiles, large variations in levels of prior knowledge and rising enrolment make scalable yet personalised forms of instructional support a necessity (James & Fletcher, 2016). If generative AI can add substantiality to ITS adaptivity and make better engagement, it could be a game-changing development in the field of digital tutoring systems. On the other hand, there may or may not be instances in which engagement is diminished or in which adaptivity is not translated to better learning experiences - in this situation, favorability on the pedagogical value of generative integration would have to be questioned.

Accordingly, the present study focuses on the integration of generative AI in Intelligent Tutoring Systems focusing on adaptive learning and learner engagement. Building upon established concepts of ITS and engagement theory, this research attempts to investigate whether generative AI strengthens the adaptive functionality of tutoring systems, and contributes to sustained behavioral, cognitive and emotional engagement among the learners. By placing the generative AI in the institutional framework of existing research on ITS and adaptive learning theory, this research project hopes to offer empirical evidence to an emerging void in educational technology scholarship.

Purpose of the Study

The purpose of this study is basically to explore the effect of the integration of generative artificial intelligence in Intelligent Tutoring Systems on adaptive learning and learner engagement in higher education settings. Based on the already proven theories on adaptive instruction and technology mediation in learning engagement, the research endeavors to investigate whether generative AI-enhanced tutoring environments enhance the learner's capacity to customize learning midpaths, able to get the right response in space from instructors and capable get active learning processes.

Specifically, the research purpose is to assess the extent to which generative AI integration can improve adaptive learning mechanisms within Intelligent Tutoring Systems, such as providing personalized dynamic content, providing real-time feedback, and fending to the learning of the learner-centered instructional responsiveness. In addition, the study aims to measure the impact of generative AI-supported tutoring on the multidimensional engagement of the learner through behavioral participation and cognitive engagement and emotional motivation. Furthermore, the relationship between adaptive learning and learner engagement in generative AI-enhanced tutoring environments will be explored in the study to determine if improvement in adaptive learning processes leads to an improvement in levels of student engagement. By empirically investigating these relationships the goal of this search is to explore a quantitative evidence concerning the pedagogical effectiveness of the combination of generative AI in structured tutoring systems.

Ultimately, this research aims with the goal of adding to the growing body of educational technology literature viz. clarifying the instructional value generative AI can play in adaptive learning environments could inform the design of next generation Intelligent Tutoring Systems and inform the responsible and effective implementation of AI-driven tutoring technologies in higher education via decisions by the makers and policy makers.

Statement of the Problem

Intelligent Tutoring Systems (ITS) have been shown to have been very effective in improving learning results through adaptive learning, personalized feedback and the modeling of learners in real-time. Extensive studies have proved their ability in enhancing the academic performance and increasing learner engagement in different educational fields. However, traditional ITS architectures are constrained by a predefined content repository, rule-based feedback mechanism and conversational flexibility which limit the ability of a dynamic response for complex learner inputs and changing learning needs. While adaptive learning frameworks have advanced instructional personalization, they still make much common sense of instruction based on manually engineered instructional pathways that trader scalability and context responsiveness.

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The advent of generative artificial intelligence has opened up new opportunities to achieve more degree of instructional adaptivity through dynamic content generation, conversational feedback, and automated formative assessment. Early explorations of the significance of explanations, tutoring support and personalized learning resources from large language models in education. Nevertheless, some existing research has tried to identify generative decisions with AI in isolation from structured ITS architectures or has considered the application in general educational use rather than in a systematic integration within an adaptive tutoring system.

Moreover, while learner engagement is commonly viewed as a key factor that determines learning effectiveness in technology-mediated learning environments, empirical evidence on how generative AI enhanced ITS affect behavioral, cognitive, and emotional engagement at the same time is rare. Previous ITS studies have mainly evaluated learning outcomes, whereas new generative AI research has focused on technological capabilities and ethical perspectives and left a large gap in understanding the pedagogical effects of fusion of generative AI and adaptive tutoring architecture.

Consequently, there is a lack of empirical research exploring whether the integration of generative AI into Intelligent Tutoring Systems has a meaningful impact on the enhancement of adaptive learning mechanisms without diminishing or affecting the engagement of the learning audience. The lack of rigorous quantitative evidence talking about this combined effect reduces the ability of educators and instructional designers to make informed decisions on the adoption of generative AI in tutoring environments. Addressing this gap is important for the development of the theoretical understanding of AI supported adaptive learning and with respect to pedagogical sound, scalable and engaging intelligent tutoring systems in higher education contexts.

Questions of the Study

Based on identified research gap and theoretical underpinnings, the current study aims to address the following questions:

1. To what extent does generative AI in Intelligent Tutoring Systems benefit adaptive learning for university students?

2. What is the impact of generative AI to boost tutoring systems on learner engagement (behavioral, cognitive, and emotional)?

3. Does adaptive learning mediate the relationship between generative artificial intelligence (AI) integration and learner engagement?

4. To what extent do the features of generative AI (i.e., dynamic content generation, conversational feedback, and personalized explanations) predict overall learning nature effectivity?

Literature Review

Intelligent Tutoring Systems: Theoretical Foundations and Evolution

Intelligent Tutoring systems (ITS) have been known as one of the best uses of artificial intelligence in academic education. Early designs of ITS were based on cognitive science and instructional theory and focused on reproducing the adaptive directional help offered by expert human tutors (Anderson et al., 1985; Anderson et al., 1989). The basic architecture of ITS usually comprises four main components, namely the domain model, the student model, the tutoring model and the user interface (Nwana, 1990). The model takes subject knowledge as the domain model, learner understanding and misconceptions by the student model, pedagogical decision is made by the tutoring model, learner and system interaction by the interface.

In fact, empirical research shows that after using ITS, students constantly experience significant learning gains compared to conventional classroom instruction. A comprehensive meta-analysis carried out by

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VanLehn (2011) found that step-based ITS systems come close to the effectiveness of human tutoring in structured learning domains. Similarly, James and Fletcher (2016) found that ITS interventions significantly improved the student performance in science, technology, engineering, and mathematics disciplines. These findings point to the potential of ITS to offer individual-level support at scale.

Over the course of time, the research in ITS moved from cognitive diagnosis to a more dynamic and data-driven personalization. The integration of machine learning methods improved student model prediction accuracy and improved instructional sequencing (Alkhatlan & Kalita, 2019). Contemporary ITS increasingly take advantage of the learning analytics function, an attempt to adapt teaching according to real-time learner interaction data so to refine the determination of personalization mechanisms (Nkambou et al., 2010). These advancements would represent the transition from static, rule-based tutoring systems to that of adaptive learning systems which have the ability to optimize on a continuous basis.

Despite the fact that traditional architectures for the implementation of ITS have been demonstrated to work effectively, there are challenges associated with scalability and flexibility. Content authoring is labor intensive and rule-based feedback mechanisms are in themselves often lacking in depth and contextual sensitivity of the human explanations (Woolf, 2009). These limitations have spurred research on more sophisticated methods of AI to make the tutorial intervention more responsive and the conversation more in-depth.

Adaptive Learning as a Core Mechanism in ITS

Adaptive learning is the pedagogical framework of intelligent tutoring systems. It is the ongoing adjustment of instructional content, level of difficulty, pace, and instructional feedback in response to learner performance and patterns of learner interaction (Shute & Towle, 2003). The theoretical foundation of adaptive learning is grounded in the cognitive load theory, which states that an instructional designer should try to find the right level of complexity with learner's ability to ensure the mastery of knowledge acquisition (Sweller, 2011). When the level of instructional material is appropriate to the level of a learner's cognitive readiness, comprehension and retention are much greater.

ITS operationalize adaptive learning by means of the diagnostic algorithms integrated in the student model. These systems identify misconceptions and tailor difficulty of a problem to particulars of the student and give cues to scaffold understanding (Anderson et al., 1995). Research has shown that adaptive systems have led to positive knowledge retention by providing timely corrective feedback and preventing repeated mistakes (Durlach and Lesgold, 2012). By providing personalized learning paths, ITS eliminate redundant learning for more advanced learners and provide more support to struggling learners.

Learning analytics has brought more strength in terms of adaptive capabilities in digital tutoring systems. Through continuous data collection, ITS will be able to identify students in risk and proactively intervene (Alkhatlan & Kalita, 2019). Such predictive mechanisms improve both the efficiency and equity of learning because they make learning experiences for students more personalized to their needs.

However, previous adaptive systems were limited in the predefined feedback templates and limited dialogue generation. While these systems have worked well in structured areas, they tended to have difficulties and limitations with explaining in open-ended ways or engaging in nuanced conversational interaction (Woolf, 2009). For that reason, the deployment of increasingly flexible models for language generation included in order to expand adaptability in a way that would not be limited by the rigor of rules became a promising approach to exploring ways to expand adaptability beyond such rule-based constraints.

Learner Engagement in Technology-Mediated Learning

Learner engagement has become a major construct in assessing educational technologies. Engagement is generally conceptualized as a multidimensional construct, that has configural to involvement in behavior, cognition, and emotion that are related to the learning activities (Fredricks et al., 2004; Fredricks et al., 2016). Behavioral engagement which studied participation and effort that people can see, cognitive

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engagement which is studied deep processing and strategic learning, and emotional engagement which is considered to study interest and motivation.

Digital learning environments need the extended engagement for positive learning outcomes (Bond et al., 2020). In the absence of active participation, even very adaptable systems may fail to make meaningful educational gains. Research shows that adaptive instructional technologies help promote engagement through the following enhanced features: perceived relevance and responsiveness (Nkomo et al., 2021). When learners get personalized feedback that fits their need, the motivation and persistence go up.

ITS contribute to engagement in the following ways: providing immediate feedback, providing scaffolding for more complex tasks, and mastery-oriented learning (VanLehn, 2011). Interactive problem-solving environments promote cognitive engagement activities such as refinement, and reflection (James & Fletcher, 2016). Emotional engagement may also be increased by the fact that learners view system feedback as being supportive and non-judgmental.

Emergence of Generative AI in Educational Contexts (≤2023)

The development of transformer-based large language models ushered in a radical transformation in the faces of applications of artificial intelligence. Transformer architectures were proven to have great capabilities in the comprehension and generation of natural language (Vaswani et al., 2017). Subsequent big models of language showed the facility for generative systems to give relieve coherent and contextually pertinent response in its multifarious troubles (Radford et al., 2019; Brown et al., 2020).

In the educational domain, some of the initial studies have looked into the potential of generative AI in supporting automated generation of explanations, tutoring dialogues and question construction Kasneci et al. (2023). Unlike conventional paradigms of ITS which search for pre-scripted answers, generative models are dynamically constructed answers based on contextual learner input. This dynamic capability allows for more flexibility of conversational tutoring and richer interactions of feedback.

Kasneci et al. (2023) discuss the opportunities and hurdles which come with the utilization of big language models in the education sector. On the one hand, one has the ability of generative AI that supports the ability to personalization on a large scale and conversational understanding; and to the other hand there are risks such as the hallucinated state of information and algorithmic bias that then must be handled carefully. Integrating generative AI in structures of learning that involve tutoring consequently requires pedagogical control and validation mechanisms.

Generative AI has also been considered as a tool for automated formative assessment. By creating diverse practice questions and custom explanation, such systems may be able to promote higher cognitive engagement and lessen legality repetitive teaching and instruction (Kasneci et al., 2023). Such capabilities implied that generative AI can build on the adaptive capabilities of ITS by enabling more dynamic dialogue-based communication for instruction.

Research Gap

Although the ITS research has resulted in the durability of adaptive learning and engagement enhancement, and the preliminary studies have examined the generative AI application for education, there is limited empirical research ([?]2023) investigating the structured incorporation of generative AI inside the ITS architectures to examine its effect on the adaptive learning mechanisms alongside multidimensional student engagement outcomes simultaneously. Existing studies are focused either on the effectiveness of ITS (VanLehn, 2011; James & Fletcher, 2016) or generative AI educational implications in a general sense (Kasneci et al., 2023) without connecting the two strands systematically. This gap underpins the need to conduct empirical exploration on whether generative AI adds any meaningful value of extending adaptive capability of RTS and whether it maintains or increases behavioral, cognitive and emotional engagement. Addressing this question has made a contribution for theoretical development, as well as for practical design, of the next generation of intelligent tutoring systems.

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Methodology

Research Design

This study employed a quantitative and cross section research design in order to examine the impact of integration of generative artificial intelligence (AI) in Intelligent Tutoring System (ITS) regarding adaptive learning and learner engagement between university students. The design made it possible to measure systematically student's perceptions and learning experiences in an AI-supported tutoring environment, and it was possible to test statistically the relations between the different variables of the study.

Research Setting and Participants

The research was conducted in Prince Sattam bin Abdulaziz University, Saudi Arabia. The target population was undergraduate students taking courses in which digital tutoring was used, or adaptive learning that was utilized with generative artificial intelligence (AI)-backed instructional features. A total 200 students were included in the study.

Stratified random sampling method was applied to achieve reasonable representation by academic disciplines and level of study. Students were stratified according to their faculty and year of enrollment and random samples were selected from every stratum in the population proportional to their number. This approach made the results more generalable in relation to the university.

Instruments

Data were gathered with a structured questionnaire that contained four sections, and all the data were measured on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Generative AI Integration in ITS

This scale was based on student's perception related to functionality of generative AI in tutoring systems and consisted of 3 dimensions, dynamic content generation, conversational feedback, and personalization of instructional adaptation. The scale contained 12 items that were targeted at learning the extent to which the system offered customized explanations, interactive responses to learner's inputs, and adaption of learning pathways according to individual performance.

Adaptive Learning

Adaptive learning was measured on a 9 item scale that measured personalization of content, responsiveness of instructional pacing, matching the learner's task with the learner's ability, and perceived system adaptability. Higher scores indicated more powerful perception on adaptive instructional support.

Learner Engagement

Learner engagement was measured on a multidimensional scale that included behavioral, cognitive and emotional engagement. The scale consisted of 15 items that assessed the participation in learning activities, cognitive involvement (in depth), and emotional interest in the tutoring system.

Control Variables

Demographic and academic information was collected like gender, academic discipline, year of study, past experiences in the field of using digital learning tools, and frequency of system use.

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Validity and Reliability

Content validity was established by having five experts in the fields of educational technology and measurement review the content. Revisions were made to ensure clarity and make it construct related. A pilot study in which students (n=35) to validate item wording and measure preliminary measures of reliability was conducted.

Construct validity was analyzed with the use of confirmatory factor analysis. Factor loadings of > 0.60 were retained. Convergent validity was confirmed by average variance extracted measures higher than 0.50 and discriminant validity was supported by use of the heterotrait-monotrait ratio.

Internal consistency reliability was measured using Cronbach's alpha and composite reliability coefficients, and all constructs had a higher reliability value than the suggested cutoff of 0.70.

Data Collection Procedure

After institutional approval, instructors helped with student recruitment in selected courses. Participants were given a link to an online survey platform and informed consent statement on voluntary participation, confidentiality and data protection measures. The data collection took place over three weeks.

Data Analysis

Descriptive statistics were calculated for the characteristics of the participants and distributions of the variables. Prior to creating the hypothesis testing, the data were checked for missing values, normality, and outliers.

Structural equation modeling based on the partial least square method (PLS-SEM) was used to analyze the relationship of generative AI integration, adaptive learning, and learner engagement. Path coefficients, coefficient of determination (R2) and effect sizes were examined. Mediation analysis was performed with the use of bootstrapping procedures with 5,000 resamples to test induct effects.

Ethical Considerations

Participation was voluntary and the respondents were assured of anonymity and confidentiality. No identifying information was collected. Data were stored in a secure manner and for only temporary use for research purposes in accordance with institutional ethical guidelines.

The Study Findings

This section presents the results as per the research questions. The individual analysis of generative AI integration in Intelligent Tutoring Systems through descriptive statistics and structural models' analyses was performed to analyze the relationships between generative AI integration, adaptive learning, and learner engagement.

Results Related to the First Research Question: To what extent does generative AI in Intelligent Tutoring Systems benefit adaptive learning for university students?

Table 1 shows the descriptive statistics of generative integration of AI and adaptive learning.

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Table 1. Means and Standard deviations for Generative AI Integration & Adaptive learning (n = 200)

Variable	Mean	Standard deviation
Generative AI integration	3.94	0.61
Adaptive learning	4.07	0.56

Table 1 shows the descriptive statistics for the two main variables that are explored in connection with the first research question, Generative AI Integration and Adaptive Learning. The mean score for the Generative AI Integration was obtained as 3.94 (SD = 0.61) which implied that students had a general view of high functionality of generative AI in the Intelligent Tutoring Systems. This appears to indicate that participants could identify that there was dynamic content generation, conversational feedback, and personalized instructional adaptation features present.

Adaptive Learning had a slightly higher mean score of 4.07 (SD = 0.56) which includes strong student perceptions of instructional personalization, adaptive pacing, and the ability of the tutoring system to respond to individual student learning needs. The fairly small SDs of both variables indicate that there is consistency in a student's response, which suggests there is a common perception of the efficacy of generative AI-supported adaptive mechanisms.

Overall, the descriptive results suggest some preliminary evidence of high generative AI integration and strong support of adaptive learning within the tutoring environment for students.

Table 2. Path Coefficient for Generative Integration of AI Predicting Adaptive Learning

Predictor	β	SE	t-value	p-value
Generative AI integration → Adaptive learning	0.69	0.05	13.80	< .001

Table 2 reports on the regression results of the structural analysis that saliva effect on the Adaptive Learning following the integration of Generative AI with PLS-SEM analysis. The standardized path coefficient (b = 0.69) supports having a high positive relationship between generative integration of AI and adaptive learning.

The t-value of 13.80 and p-value < .001 indicate that the relationship is statistically significant with a very robust level. The common aspect of the two sources of variability, namely small standard errors in parameter estimation (SE = 0.05), indicates high precision of parameter estimation.

This result shows that the more features of generative AI are integrated, the greater the adaptive capabilities of Intelligent Tutoring Systems. Specifically, dynamic content generating systems with conversational responsiveness are more successful at personalizing learning pathways as well as customized instructional support.

Results Related to the Second Research Question: What is the impact of generative AI to boost tutoring systems on learner engagement (behavioral, cognitive, and emotional)?

Descriptive statistics of generative AI integration and engagement by learners can be seen in Table 3.

Table 3. Means And Standard Deviations of Generative AI Integration and Learner Engagement

Variable	Mean	Standard deviation
Generative AI Integration	3.94	0.61
Learner engagement	4.02	0.58

Table 3 summarizes the second research question in terms of Generative AI Integration and Learner Engagement's descriptive statistics. The mean score for Learner Engagement was 4.02 (SD = 0.58) which

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revealed high levels of behavioral participation, cognitive involvement and emotional motivation among students interacting with the AI enhanced tutoring system.

The similarity of the mean values of Generative AI Integration (3.94) and Learner Engagement (4.02) indicates a positive Association that there is an experiential relationship between advanced features of AI and student involvement in the learning process. The comparative weakness of dispersion for responses indicates stability of engagement levels among the sample. These descriptive findings indicate that students had not only acknowledged generative AI functionalities, but they also showed high engagement while communicating with the system.

Table 4. Path Coefficient to Generative AI Integration Predicting Learner Engagement

Predictor	β	SE	t-value	p-value
Generative AI integration → Learner engagement	0.63	0.06	10.50	<.001

Table 4 shows the result of the structural path analysis which evaluated the direct impact of Generative AI Integration to the Learner Engagement. Standardized path coefficient (b=0.63) is an indicator of substantial positive effect.

The relationship is statistically significant ($t = 10.50$, $p < .001$), proving that generative AI augmented tutoring systems have a significant positive impact on student engagement. The size of the coefficient noted revealed the presence of dynamic, conversational, and personalized features of instruction are conclusive factors in increased levels of behavioral, cognitive, and emotional engagement. This finding shows that the features of generative AI not only increase system adaptivity but also enhance learner interaction and motivation independently.

Results Related to the Third Research Question: Does adaptive learning mediate the relationship between generative artificial intelligence (AI) integration and learner engagement?

Mediation analysis was performed by using the bootstrapping procedures.

Table 5. Direct, Indirect, and Total Effects

Relationship	β	t-value	p-value
Generative AI→ Adaptive learning	0.69	13.80	<.001
Adaptive learning → Engagement	0.54	9.42	<.001
Indirect effect	0.37	7.15	<.001
Direct effect	0.26	4.88	<.001
Total effect	0.63	10.50	<.001

Table 5 shows the mediation analysis of the hypothesis if Adaptive Learning mediates the relationship between Generative AI Integration and Learner Engagement. The direct effect of Generative AI Integration stands at a good and significant level on Adaptive Learning i.e. $\beta=0.69$, $p< .001$. Adaptive Learning is also an important predictor of Learner Engagement ($\beta = 0.54$, $p < .001$). The indirect effect ($\beta = 0.37$, $p < .001$) confirms that Adaptive Learning is a partially-mediated relationship between Generative AI Integration and Learner Engagement. Since the direct effect is not zero ($\beta = 0.26$, $p < .001$), it is said that we had a partial, rather than a full mediation. The total effect ($\beta = 0.63$, $p < .001$) represents the sum of the direct and indirect impact of generative AI on engagement. This table shows that generative AI helpful to increase the engagement of learners, both directly and indirectly, through better adaptive instructional mechanisms.

Results Related to the Fourth Research Question: To what extent do the features of generative AI (i.e., dynamic content generation, conversational feedback, and personalized explanations) predict overall learning nature effectivity?

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Multiple regression analysis was performed to analyze the predictive effects of generative AI dimensions for the combined effect.

Table 6. Regression Results Predicting Effectiveness of Learning

Predictor	β	t-value	p-value
Dynamic content generation	0.41	6.72	< .001
Conversational feedback	0.35	5.88	< .001
Personalized adaptation	0.29	4.91	< .001

Table 6 lists the multiple regression analysis analyzing the predictive effects of three generative AI dimensions on Overall Learning Effectiveness - Dynamic Content Generation, Conversational Feedback, and Personalized Adaptation. Dynamic Content Generation was the largest predictor ($b = 0.41$, $p < .001$) to suggest that the ability of the system to convert different and contextually relevant instructional resources were central to outcomes in terms of learning. Conversational Feedback was also a very significant predictor of learning effectiveness ($b = 0.35$, $p < .001$) indicating that interactive dialogue-based responses make for more clarity and instructional support. Personalization Adaptation made a positive contribution as well ($b = 0.29$, $p < .001$), underlining the importance of finding a way of aligning instruction and own learner performance. The model explains 64% of the variance in learning effectiveness ($R2 = 0.64$) with a highly significant overall F-statistic measure ($F3,196) = 116.3$, $p < .001$, good explanatory power, and good statistical significance. This table confirms that the features of generative AI have an overall significant influence on perceived learning effectiveness.

Discussion of the Results

The present study examined the impact of introduction of generative artificial intelligence in Intelligent Tutoring System on adaptive learning and learner engagement among the University students. The results show that generative AI-enhanced tutoring environments are much more effective in aspects of instructional adaptivity and learner engagement and even learning effectiveness altogether. These kinds of results are consistent with results from prior research in Intelligent Tutoring Systems that show that adaptive sequencing of instruction and personalized feedback is effective in increasing learning outcomes (VanLehn, 2011; James & Fletcher, 2016). The full force positive impact of generative artificial intelligence integration with adaptive learning is in agreement with previous research emphasizing the paramount role of individualization in effective tutoring systems, in which the teaching of content consistent with the cognitive state of learners must lead to understanding and retention. While traditional ITS was based on rule-based feedback mechanisms, the current results advance current research in this field by suggesting that generative AI allows for more flexible and context-aware adaptation of instructions as a response, which thereby reinforces existing adaptive learning principles developed in previous ITS research.

Similarly, the substantial improvement in learner engagement found in this study is consistent with the engagement theory and previous empirical research showing that interactive and personalized learning environments encourage increased engagement with students and elicit their higher participation, greater cognitive and emotional investment (Fredricks et al., 2004; Bond et al., 2020). The positive impact of generative AI-enabled tutoring on engagement is consistent with previous studies that report that adaptive feedback as well as responsive instructional support boosts engagement among learners in digital learning spaces. The conversational features made possible thanks to generative AI seem to overcome past challenges of traditional ITS in terms of rigid conversation structures, which were previously linked to lower learner motivation (Woolf, 2009). Thus, the current findings support and expand upon previous findings to show that dynamic conversational feedback further enhances learner engagement in the course beyond what conventional adaptive systems achieved.

The mediation analysis showed that the relationship between generative AI integration and learner engagement was mediated in part by adaptive learning, which helps to identify that the enhanced personalization serves as a central pathway for enhanced engagement. This finding is consistent with theory

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of adaptive learning that holds that instructional relevance and cognitive alignment foster learner motivation and continued engagement. Previous ITS research suggested that the way in which adaptivity improves both performance and engagement; the results of the current study empirically confirm this mechanism in generative AI-enhanced environments. However, the longevity of direct effect of generative AI on engagement is further to previous research by indicating that interactive conversational features do add motivational value beyond the personalization of instruction alone.

Furthermore, the predictive value of generative AI features collected on the effectiveness of learning is in line with prior study findings in the ITS literature that underscore the significance of multiple instructional components that work synergistically to foster learning gains (James & Fletcher, 2016; VanLehn, 2011). The result that dynamic content generation proved to be the strongest predictor is consistent with other research showing the importance of different and contextually relevant instructional materials in maintaining cognitive engagement. While the existing ITS has been built on pre-authored content repositories, the current research goes further by showing that the processes of continuously generated instructional content provide greater learning effectiveness and less instructional staleness.

Importantly, no major contradictions with earlier ITS or engagement studies were found between what was found in the current study. Rather, the outcomes substantially add to the known theoretical expectations, while extending the previous work with the introduction of generative AI as a powerful mechanism for creating enhanced adaptivity and interactivity. Where past research found limitations in conversational responsiveness and scalability of content in traditional ITS, the present study gives empirical evidence that generative AI can effectively solve these problems. Thus, the outcomes do not contradict existing literature but rather develop on and strengthen foundational tutoring system theories.

Overall, the current study validates important principles of adaptive learning and engagement theory and extends them in the context of generative AI-enhanced tutoring environments. The fact that the current findings agree with those from earlier research illustrates the robustness of the use of personalization and feedback as key factors that drive effective learning. At the same time, the study also advances the body of literature by showing that generative AI technologies dramatically improve these mechanisms by providing dynamic content generation and conversational instructional support. These contributions offer better empirical grounds for integrating generative AI into Intelligent Tutoring Systems as a next-generation adaptive learning solution.

Conclusion

This research focused on the integration of generative artificial intelligence in the context of Intelligent Tutoring System into the adaptive learning and learner engagement areas in higher education. The findings reveal that generative AI-augmented tutoring environments contribute a significant amount of strength and effectiveness to instructional adaptivity, multidimensional engagement and overall learning. By enabling dynamic generation of content, personalized feedback, and unstable pathways of instructional pathways, generative AI both enhances the central pedagogy workings of traditional ITS and reflects an improvement in the quality of the interaction between the learner and the system. These results add empirical evidence to new research of educational technology, and processes generative AI as a transformational educational technology for individualised digital tutoring. While the findings are in favor of the finding of generative integration on the instructional value, and directions: continued research is required to evaluate long-term learning outcomes, ethical considerations, and best instruction design strategies. In hinting at some completely different ways that generative AI could evolve, this work highlights the potential of generative AI to help to drive forward the development of adaptive learning systems, and to build engaging, scalable, and effective tutoring environments in higher education.

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