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Research article

Artificial Intelligence–Driven Educational Technologies for Personalized Learning: Enhancing Student Engagement and Learning Outcomes in Higher Education

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Artificial Intelligence–Driven Educational Technologies for Personalized Learning: Enhancing Student Engagement and Learning Outcomes in Higher Education

Abstract

The integration of artificial intelligence (AI) into educational technologies has transformed higher education institutions (HEIs) by improving student learning, fostering engagement, and promoting better educational outcomes through personalized approaches. Tools such as adaptive learning systems and real-time intelligent analytics enable tailored feedback and individualized learning pathways, making pedagogy more dynamic and learner cantered. However, the effective use of AI tools remains limited by challenges such as inadequate infrastructure, insufficient faculty training, and low institutional preparedness. To address these gaps, the present study investigated the extent to which higher education institutions are prepared to integrate AI-driven educational technologies for personalized learning and the challenges emerging from pedagogical, infrastructural, and institutional perspectives. A mixed-methods approach was employed, combining quantitative and qualitative techniques to capture measurable outcomes and deeper insights. Purposive sampling included 210 BBA and BCA students with prior exposure to educational technologies and 20 educators and administrators. Data were collected using a self-developed AI-Driven Personalized Learning (AIPL) Scale

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comprising four sections—Student Engagement, Personalized Learning Perception, Learning Outcomes, and AI/Technology Use—along with semi-structured interviews to gather qualitative perspectives. Quantitative data were analysed using statistical methods, while qualitative data were organized, coded, and thematically interpreted. The findings revealed that AI-integrated learning enhanced student motivation, comprehension, and performance through personalized engagement, though disparities persisted in infrastructure and institutional support. The study emphasizes the need for policy interventions promoting digital infrastructure, faculty capacity building, and ethical AI use to ensure equitable access and maximize AI's transformative potential in higher education.

Keywords: artificial intelligence, personalized learning, higher education, student engagement, learning outcomes

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Introduction

AI (artificial intelligence) being included into higher education represents a large change in how instructional design, delivery, and evaluation happens. Rather than applying the same pedagogical approach to everyone, as traditional methods do, AI based learning technologies will allow you to tailor an individual's learning experience to their own unique needs, cognitive ability, and personal preference regardless of their demographic (Kochmar et al., 2020; Strielkowski, 2024). This creates intentional and measurable progress towards creating learner-cantered instructional design as HEIs implement adaptive learning systems, ITS (intelligent tutoring systems), and predictive analytics tools. AI has been widely shown to improve student engagement, motivation, and success rates (Design and Assessment of AI-Based Learning Tools, 2025).

AI augmented worldwide seen huge excitement from both academics and organizations for its potential to provide differentiated learning materials for students, immediate and contextualized feedback, and support the development of personal learning paths for individual learners. Evidence-based research demonstrates that adaptive learning programs deliver students measurable improvements in their understanding of content, their ability to retain knowledge, and their ability to recall information by adjusting the complexity of the content and pace of instruction according to real-time student performance metrics (Kochmar et al., 2020). For example, intelligent

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tutoring systems provide students with the same experience as having an individual tutor providing them with targeted pedagogical support, scaffolded hints, problem-solving support, and feedback on formative assessments (Strielkowski, 2024). In addition, AI significantly reduces the administrative workload for professors by automating many routine tasks, such as grading assignments, monitoring student engagement, and identifying students who may be academically at risk, allowing instructors to focus more on higher-level instructional activities (Design and Assessment of AI-Based Learning Tools, 2025).

The National Education Policy (NEP) 2020 is a major influence in the higher education space in India regarding the adoption of AI technologies in education. It supports the digitisation of all forms of education infrastructure and the integration of adaptive systems of learning into education design, thereby improving and promoting quality, access, inclusion and equity at every level of education institutionally and regionally. Evidence from studies that have been carried out in Indian HEIs support the view that how prepared a student is for AI means that there is no single determinable factor; rather, it is determined by interrelated factors such as current level(s) of digital literacy, expected outcome in terms of performance, and degree of institutional support in place for the use of AIs (Evaluating AI-Personalized Learning Interventions, 2025). Additionally, adaptive learning platforms that are being developed and implemented with

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a focus on the development of AI-based platforms, such as Minds Park, are conducted and delivered in multiple regional languages across India, and have proven to yield significant increases in student academic performance and achievement, primarily for those students from economically disadvantaged groups and those with different languages, cultures or living in rural and/or remote areas of India (Revolutionizing Education, 2024).

Within India's unique cultural context, the potential of AI in facilitating learning for all students is truly impressive. AI-based assistive and adaptive technologies are addressing the unique learning needs of students with disabilities through tailored instructional routes that are often unavailable in traditional classroom settings. In addition, AI systems provide students living in remote, rural areas with personalized academic support and mentoring that would otherwise be impossible due to unevenly distributed and insufficient resources and teacher shortages in the regions they live in (see Intelligent Tutoring Systems and Adaptive Learning, 2023). In addition, increasing exposure to AI use through distance learning methods has positively impacted the level of engagement and the academic success rates of a large number of adult students, working adults, and graduate students, demonstrating that AI-based instructional systems can work effectively in a wide range of educational settings (see Evaluating AI-Personalized Learning Interventions, 2025).

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The implementation of AIs into higher education represents a major opportunity; however, there are also substantial institutional, ethical, and structural issues that need to be adequately researched and studied before there will be a wide-scale integration of AIs into higher education (Revolutionizing Education, 2024). Examples of serious issues that need to be addressed are algorithmic biases in the training data used for AIs; concerns regarding student data privacy and institutional data governance; and long-standing inequities regarding access to digital infrastructure, including students who are from low-resource environments, students who attend school in a rural area, and students who are members of marginalized populations. All of these areas demonstrate the need for developing a transparent, accountable, and ethically focused framework for deploying AIs within educational institutions.

In addition, it is important to understand that AIs cannot replace human instruction but rather must complement it. Educators provide invaluable, relational mentorship; help students learn how to think critically and engage in higher-order thinking skill development that AIs cannot presently replicate (Intelligent Tutoring Systems and Adaptive Learning, 2023). Therefore, the successful and responsible integration of AIs requires that the rate of technological change and the rate of change in humanistic-based pedagogy are aligned so that AI-enhanced tools will enhance rather than diminish the relational aspects and overall quality of the educational experience.

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With the advent of proximate generative AI, heterogeneous configurations through adaptive learning architecture, and real-time intelligent feedback mechanisms; higher education institutions now have a remarkable opportunity to recreate effective instructional design from an equitable, whole person, and responsive to the diverse needs of contemporary learners. As India has a convoluted higher education system with many structural inequalities (access to resources, languages, etc.), the potential of using AI-assisted learning to create personalized learning experiences in an equitable manner is tremendously transformational. Therefore, the purpose of this research is to critically explore how AI-related technologies can promote personalisation, create engagement, and enhance academic achievement in Indian HEIs and add to the expanding research base at the nexus of educational technology, inclusive pedagogy, and institutional equity.

The use of Artificial Intelligence (AI) in higher education is changing the way instructional principles are designed. AI allows for a level of personalization to be offered that is simply not possible with traditional pedagogical practices (Means et al., 2014). This theoretical framework provides a synthesis of four foundational learning theories, which will be mediated by an AI Personalization Engine, and explain how to use technology to provide personalized learning experiences that will increase both student engagement and achieve higher student learning outcomes. The framework is composed of five interrelated levels that are all based on established scholarship.

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i). Foundational Theories

The theoretical framework consists of four pillars/levels of complementary theories.

a. Constructionism, as developed by Vygotsky (1978), and Piaget (1970), suggests that learners build constructs of meaning from their learning experiences. One of the most powerful concepts of both theorists is that of a learner developing within the zone of proximal development (ZPD), or the amount of potential learning possible from a current level to the next. AI supports a learner's development through the application of the ZPD by positioning tasks along the zone of proximal development in relation to the individual learner, and by providing scaffolded support, and gradually removing that support as the learner's development increases (Belland et al, 2017; Vygotsky, Piaget).

b. Self-Determination Theory (Deci and Ryan's 1985) states that intrinsic motivation is determined by satisfying three psychological needs: autonomy, competence, and relatedness. AI-based systems create autonomy through flexible pathways, competence through adaptively calibrated tasks, and relatedness by providing collaborative features in order to establish the conditions necessary for deep processing and persistence (Ryan and Deci, 2000).

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c. Cognitive Load Theory (Sweller 1988) provides an understanding of the limitations of working memory and the distinctions between intrinsic load (complexity of the task), extraneous load (unproductively designed), and germane load (useful effort to build schemas). AI solutions help users minimize extraneous load through well-designed adaptive interfaces and facilitate management of intrinsic load by providing sequenced content, thereby allowing maximum cognitive resources available for real learning (Paas et al. 2003).

d. Connectivism (Siemens 2005) puts learning in the context of digital networks of knowledge. The knowledge is contained in multiple locations and disseminates among nodes that are interconnected to each other, so being able to traverse these networks and compile knowledge is defined as learning. AI platforms exemplify being able to do this through the use of knowledge graphs to depict the relationships between concepts and provide users with customized routes through dynamic domains or areas/structures (Siemens & Baker 2012).

ii). AI-mediated personalization engine

The operational essence of the framework is represented by this AI-mediated personalization engine, which is composed of six interrelated mechanisms: adaptive algorithms, learning analytics, natural language AI, knowledge tracing, learner profiling, and feedback loops. Adaptive algorithms modify content difficulty

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and sequencing in real time. Knowledge tracing originally developed by Corbett and Anderson (1995) and later expanded upon by Piech et al. (2015) using recurrent neural networks to develop deep knowledge tracing, estimates each student's mastery probability within a domain using a knowledge graph, with an update at every interaction. The learner profiling mechanism integrates cognitive, motivational and behavioural data into a dynamic student model, which drives all personalization decisions (Brusilovsky & Millán 2007). The use of natural language AI enables the automated essay scoring and writing feedback as well as conversational tutoring; thus, providing scalable and responsive feedback (Graesser et al. 2004). The feedback mechanisms ensure that the output data continuously recalibrates the system so that the learning platform is genuinely adaptive rather than just being interactive (Roll & Wylie, 2016).

iii). Instructional Design Dimensions

Personalized learning is achieved by three distinct methods.

a. Content personalization provides the learner with individualised content delivery based upon their learning preferences and needs (i.e., time/pace, depth, type & order of work). AI systems apply the mastery learning model of Blooms (1968), where students progress through a set of criteria based upon their mastery and ability to demonstrate understanding — rather than a fixed timetable for

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assessment. The scaffolding of learning will help this to occur in a continuous manner through a variety of learning activities that can be used together (Wood et al., 1976).

b. Formative feedback is one of the most successful instructional methods used today in relation to student learning. Black and Wiliam (1998) reported an effect size of between 0.40 and 0.70 on student learning outcomes, and Hattie and Timperley (2007) identified formative feedback as having the greatest impact on student achievement (effect size of approximately 0.73). There are three types of formative feedback that AI based educational systems provide, including corrective feedback — to identify and explain a student's error; elaborative feedback — providing the student with hints and/or Socratic questioning to encourage them to think; and feed-forward feedback (i.e., helping students know what they should focus on in order to achieve success). Perhaps the biggest difference between traditional and AI based educations systems is that the AI provides real-time formative feedback to the learner(s) — which is believed to be when feedback has the greatest potential impact on achievement (Shute, 2008). Finally, AI tutors produced nearly as much learning gain as one-on-one human tutors (effect size of approximately 0.76) (VanLehn, 2011).

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c. Artificial intelligence (AI) agents are used by Intelligent Tutoring to help engage students in a Socratic dialogue, which involves questioning their reasoning, challenging their assumptions, and leading them to discover things on their own (Anderson et al., 1985). By comparing the average effect sizes reported for Intelligent Tutoring Systems (ITS) against those reported for traditional instruction (Ma et al., 2014), ITS approaches Bloom's (1984) "2-sigma" standard, or the level of one-on-one tutoring with an average effect size range of 0.40 - 0.76.

iv). Identifies two related constructs

a. Student Engagement will be measured using Fredricks et al.'s (2004) 4-component model, which uses four indicators: behaviour (persistence, participation), cognitive (deep processing, self-regulation), affective (belongingness, interest), and agentic (to the extent that students initiate and respond to opportunities for learning). Personalisation provided by Artificial Intelligence supports all components of engagement: Behavioural engagement can be aided through the creation of optimal challenges; Cognitive engagement will be aided through elaborative feedback; Emotional engagement will be aided through the provision of experiences that produce a sense of mastery; and Agentic engagement will be aided by providing

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students with opportunities to initiate and follow through with exploratory behaviour.

b. Learning Outcomes are set in Bloom's revised taxonomy, by Anderson and Krathwohl, according to the 6 levels of knowledge: recall (remembering), comprehension (understanding), application (applying), analysis (analyzing), evaluation (evaluating), and creation (creating); Other assessed outcomes include: retention (by ways of spaced repetition), transfer (by means of varied and interleaved practice), and academic self-efficacy (by Bandura) — The belief that one can succeed in an academic setting. Zimmerman found (2000) that experiences of success, created through properly formatted adaptive systems, boosted students' feelings of self-efficacy, which led to greater levels of engagement and persistence when they encountered challenges.

Ultimately, this framework is designed to provide equitable and effective higher education at scale, as well as personalized AI-enabled support that eliminates barriers to learning and student success in disadvantaged populations. Measurable improvements in retention rates, graduation rates, and student capacity for lifelong learning (Holmes et al., 2019) will result from such education. A continuous data flow will return results to the AI engine as part of an ongoing feedback loop, thereby creating a means by which to improve success at an increasing rate (Siemens, 2013).

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Overcoming student engagement challenges related to learning needs, learning paces, and diverse levels of complexity has been addressed at the post-secondary education levels, with traditional pedagogy which focuses on standardization and one-size-fits-all methods creating barriers to achieving optimal and personalized learning outcomes. The potential of learning technologies that utilize artificial intelligence (AI) to improve personalized learning in higher education through adaptive personalized learning, individualized feedback, and analytics for instructional adjustment is well documented. Conversely, there is a lack of empirical research that addresses the gap between the effective use of AI educational technologies, the pedagogy, the fostering of student engagement, and the related learning outcomes in post-secondary education, which is highly context bound, fragmented, and in some cases, interstitial. Additionally, the problem of inadequate faculty digital and AI literacy, plus the concerns of data ethics, algorithmic opacity, and the state of the Digital Divide in institutional infrastructure are problems that warrant a more rigorous inquiry. The purpose of the chosen title, *"Artificial Intelligence–Driven Educational Technologies for Personalized Learning: Enhancing Student Engagement and Learning Outcomes in Higher Education"* is to innovate research regarding AI educational technologies and emphasize pedagogical strategies to improve student engagement and learning outcomes in higher education. Objectives of the Study:

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i). To assess the level of student engagement in AI-driven personalized learning environments.

ii). To examine students' perceptions of personalized learning facilitated by AI technologies.

iii). To evaluate the impact of AI-driven tools on students' learning outcomes.

iv). To analyse students' AI/technology use, including ease, frequency, and comfort in interacting with learning tools.

v). To explore the pedagogical, infrastructural, and institutional challenges faced by educators and administrators in implementing AI-driven personalized learning.

Literature Review

Student engagement is defined as the extent to which students involve themselves in their academic activities through active participation, continuing interest, and intrinsic motivation (Fredricks et al., 2004) and is therefore a fundamental part of measuring the effectiveness of AI-based educational interventions. Student engagement has been repeated throughout the research literature as a key mediator between instructional design and learning outcomes. AI has created new ways to support the systematic development and ongoing advancement of student engagement.

In the context of Indian higher education, empirical data indicates that adaptive learning platforms designed in regional languages have resulted in increased student

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attention and motivation, particularly for students in linguistically diverse and underrepresented institutional settings (Adaptive Learning Platforms in Indian Languages, 2024). Similarly, research conducted in Uttarakhand found that implementing adaptive e-learning platforms resulted in statistically significant increases in student participation; therefore, AI-enabled localised design uniquely enhanced student behavioural engagement (Adoption of Adaptive Learning-Based E-Learning Platforms in Uttarakhand, 2024). Finally, rural universities have reported that AI-based mentorship programs have increased student participation; therefore, AI provides a means to extend engagement support to geographically underrepresented students (Mind Craft, 2025).

Intelligent Tutoring Systems with automatic feedback components have also been found to improve student attention and interaction with content in many types of educational environments outside of India (Kochmar et al., 2020). Further amplification of student to teacher interaction in AI enhanced assessment contexts occurs when teachers serve as facilitators; clearly highlighting the importance of human-robot partnerships in enhancing engagement (Revolutionizing Education: AI and Teacher Roles in India, 2024). In addition, AI Personalised Learning tools have also increased student engagement for students with learning difficulties; providing a larger base of inclusivity for all students who participate with AI Engagement interventions (AI Driven Personalised Learning for Students with Disabilities, 2024). When taken collectively,

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these studies indicate that real-time feedback, adaptive delivery of content and creation of inclusive AI systems are reinforced mechanisms of enhancing student engagement across a variety of learning profiles and institutional settings (Design and Assessment of AI Based Learning Tools, 2025).

Personalised learning refers to the ways that instruction can be customised to the characteristics, needs, and preferences of individual students. Personalisation involves using adaptive algorithms, learner profiles, and real-time content adjustments so that learners can control their own instruction. In an analysis of research conducted at Indian Higher Education Institutions, findings indicate positive associations between AI-enabled personalisation and the relevance and satisfaction that learners feel with their online learning experience (AI-Enabled Transformation of Online Learning through Personalisation, 2024). This positive relationship is also enhanced when AI tools provide language support in learners' first languages, as providing multilingual capabilities increases learners' ability to receive supportive instruction, while decreasing the cognitive barriers often caused by using a second language in instructional settings (Strengthening e-Education in India Using Machine Learning, 2021). Additionally, teacher-facilitated AI-enhanced instruction in Indian universities increases learners' perceptions of receiving personalisation. Thus, although personalised instruction results from algorithmic adaptation, perceptions of personalised instruction are influenced by pedagogical context

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and the involvement of an instructor (Students' Perceptions and Readiness for AI-Enhanced Learning, 2025).

From a global perspective, AI-enabled systems that can change what students are learning to account for how they performed at any moment are showing consistent improvements in terms of perceived personalization by students around the world, regardless of the country or type of institution they attend (Evaluating AI-Personalized Learning for Students, 2025). A comparative research study comparing Indian and Polish students found that adaptive AI — implemented through the use of ChatGPT — increased the students' perceptions of having individualized support. This finding demonstrates the relevance of AI-based personalized approaches in a cross-cultural context (Unlocking the Power of ChatGPT, 2025). In addition, AI-enabled adaptive interventions in online postsecondary education have been shown to help students feel more satisfied and perceive the material they are learning to be more relevant, supporting the premise that personalization directly impacts student engagement over time and can help motivate students to succeed academically (AI-Powered Adaptive Learning for Sustainable Transformation, 2024). Combining these data points, it is clear that personalized learning environments using AI, especially when they incorporate multilingual capabilities, real-time adaptiveness, and pedagogical oversight, represent an innovative improvement over traditional, one-size-fits-all teaching strategies.

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Learning objectives are used to assess how well instructors do their job. They also measure achievement across many cognitive levels, some of which are academic performance, retention of information, the ability to solve problems, and the acquisition of new skills, all of which fit into the higher cognitive domain of Bloom's Taxonomy. Research from both India and internationally has shown that using artificial intelligence (AI) and personalised learning through AI will improve students' learning outcomes.

As part of the Indian Higher Education system, AI-based education has been associated with significant increases in comprehension, skill acquisition, and academic success; specifically, improvements have been noted in lower-order thinking skills and applied problem-solving skills (A Study on the Role of Artificial Intelligence in Indian Higher Education System, 2025). AI-based recommendation systems provide an additional level of performance enhancement by enabling students to identify and access appropriate academic resources for study. This results in students being able to focus on areas in which to invest time and effort most efficiently (Mapping the Landscape in HEIs: AI Adoption and Challenges, 2024). Adaptive learning platforms in local/regional languages have provided additional evidence of the benefits of linguistic access to learning, thus, indicating that linguistic access is a significant moderator variable in the relationship between AI and personalised learning outcomes (Adaptive Learning Platforms in Indian Languages, 2023).

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The use of automatic teacher feedback and AI-related teaching assistants has positively affected students' understanding, performance on assignments, and overall success in all subject areas at all levels of education throughout the world (Automated Feedback and Personalized Learning, 2020). In addition, AI-powered adaptive learning technologies have been recognized as a means of producing higher-order knowledge through complex problem solving in diverse global learning environments (Strielkowskyd, 2024). These findings provide strong empirical support for the premise that AI-driven personalized learning environments can generate significant and quantifiable improvements in cognitive learning outcomes when designed with appropriate considerations for content adaptability, quality of feedback, and linguistic accessibility.

When it comes to utilizing AI-enhanced educational technologies, students' level of digital literacy, access to infrastructure for technology, and the institutional readiness of their host institutions to support sustained AI use will play a large role in the degree to which they engage with those technologies and derive value from them. These variables are major contributors to the degree to which AI-enhanced personalization becomes an actual improvement in both engagement and student learning outcomes; thus, they are critical moderating factors in the conceptual framework for this study.

A body of literature consistently indicates that digital literacy and equitable access to

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technology are principal determinants of the rate of population use of AI technologies (Adoption of E-Learning Platforms in India: Challenges and Opportunities, 2023). Better and easier-to-use digital interfaces and the existence of digital education platforms that provide educational services in the regional language are important facilitators of regular use of technology, which points to the conclusion that inclusion in design impacts both the frequency and depth of student interactions with AI systems (Digital Education in India: Implementation of AI, 2024). Conversely, classroom teachers who cannot effectively support their students in using AI-enabled tools and institutions that are not prepared to implement AI technologies effectively will adversely moderate the engagement of students with AI tools, demonstrating the interconnectedness of technology, pedagogy, and institutions in producing effective adoption outcomes (Enhancing Technology Use in Higher Education, 2022).

Global research has found that the interaction of students with AI educational technologies is shaped by intuitive interface design, accessibility features, and adaptive AI — all of these factors work together to create a lower threshold for participation among diverse populations (Intelligent Tutoring Systems and Adaptive Environments, 2023; Design and Implementation of AI Learning Tools, 2025). Furthermore, real-time feedback and inclusive AI design have been shown to promote the more frequent and effective use of AI in heterogeneous educational environments (Global Perspectives on

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AI-Driven Learning, 2024). Taken as a whole, these findings suggest that technology use is not a single variable that stands alone, but rather one that is dynamic and shaped by the intersection of individuals with digital competence, institutional infrastructure, and the contextual sensitivity of AI system design.

While AI-based personalized learning continues to grow, research pertaining to Indian higher education continues to remain underdeveloped. Most research studies concentrating on disconnected pieces, such as adaptive learning frameworks, online learning, or AI-assisted learning done by teachers. Few studies examine the four components of the AIPL Scale—student engagement, personalized learning perception, learning outcomes, and AI/technologies together. There is a lack of longitudinal studies which makes it difficult to ascertain the impact of prolonged engagement with AI tools on student engagement and achievement. Variables such as organizational AI readiness, digital literacy, and infrastructural components, are acknowledged as important variables but remain unconsidered in the described context. Research on AI tools designed for students with disabilities is also absent, and the understanding of how such tools help diverse learners is underdeveloped. Research in Indian higher education continues to lack the application of adaptive AI and intelligent tutoring systems. Finally, students' perception, satisfaction, and interaction with AI centre are crucial for adoption and prolonged engagement, are basically unstudied.

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Research Methodology

This study adopted a mixed-methods approach, integrating both quantitative surveys and qualitative interviews to gain a comprehensive understanding of AI-driven personalized learning.

i). Research Design

a) Mixed-Methods Design: Combined structured surveys and semi-structured interviews, providing both quantitative breadth and qualitative depth.

b) Descriptive and Exploratory: Descriptive in outlining levels of engagement and adoption, and exploratory in investigating perceptions, challenges, and institutional perspectives.

ii). Data Collection Methods

A. Primary Data Collection

a) Surveys: Were administered to BBA and BCA students to assess engagement, perceptions, learning outcomes, and AI/technology use. AI-Driven Personalized Learning Scale (AIPL Scale) – a self-developed Likert scale comprising four sections:

Section A: Student Engagement

Section B: Personalized Learning Perception

Section C: Learning Outcomes

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Section D: AI/Technology Use

b) Semi-Structured Interviews: Were conducted with educators and administrators to understand implementation challenges, experiences, and institutional support for AI adoption.

B. Sampling Strategy

a) Technique: Purposive sampling targeted students and faculty with prior exposure to educational technologies.

b) Sample Size:

- Students: 210 BBA/BCA responses
- Educators/Administrators: 20 responses

iii). Data Analysis Techniques

a) Quantitative Data (Survey Results)

- Descriptive statistics (mean, SD) were used to summarize findings.
- Inferential statistics (correlation) were applied to examine relationships and trends.

b) Qualitative Data (Interviews)

- Thematic Analysis: Transcripts were organized and coded to identify patterns and insights.
- Direct Quotes: Were included to support evidence-based interpretations.

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iv). Ethical Considerations

- Informed Consent: Participants were informed about the study's objectives and participated voluntarily.
- Confidentiality and Anonymity: Personal identifiers were removed to ensure privacy.
- Right to Withdraw: Participants could exit the study at any time without penalty.

v). Limitations of the Study

- Generalizability: Limited sample size of educators/administrators may have reduced applicability to other institutions.
- Response Bias: Participants may have provided socially desirable responses regarding AI use.
- Digital Literacy Variability: Differences in familiarity with AI tools may have affected response accuracy.
- These procedures provided our better understanding of factors affecting AI adoption and implementation in higher education.

Result Analysis

Interpretation and Analysis Based on Interview Responses. While discussing the perceptions of AI generally, its use and benefits within teaching and learning, and the personalization of learning, the majority of respondents appeared to have a reasonably

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good grasp of AI use within higher education, and its potential applications. They pointed out that AI affords personalized learning and adaptive assessments, instantaneous feedback, real-time assessments, and overall engagement, with a significant rise in administrative efficiency. AI performance analytics to create adaptive paths and next steps in learning with feedback has been shared numerous times and assist teachers to close learning gaps and re-teach. Though, some of the respondents did not answer some questions, which may constitute AI tools not being used or exposure being limited at their own institutions.

When discussing the tools and platforms used to AI create learning adaptive, the impact of AI on teaching strategies and the initiatives being taken to foster learning through AI, respondents frequently described the use of Learning Management Systems (LMS), chatbots, adaptive testing, and analytics. AI has been enabled responsive lesson adjustments, real-time feedback, and personalized lesson creation. AI has been incorporated by some institutions during trainings with the use of the lesson, development of pilot projects, and the provision of training sessions to educators; however, these efforts often lacked breadth or consistency across the institution. A handful of specialists showed incomplete responses to some questions in this section, indicating varying degrees of AI integration engagement.

Participants reported challenges in the technical (software glitches, and connection

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issues), pedagogical (curriculum alignment), and ethical (bias and privacy) domains. Responses from students, albeit more positive, showed some resistance, especially from the less digitally literate. This might explain why some experts did not respond to all the questions in this section. Not all participants seemed to have direct institutional experience or exposure to AI-assisted pedagogies. While some participants said institutions did provide basic training, AI accessibility, and minimal motivational resources, many of the professionals suggested comprehensive professional training, ready AI integration resources, and balanced adoption policies. Most participants seemed to hold guardedly hopeful views, seeing potential in AI for personalized learning, automation of administrative work, and enhanced predictive analytics, provided there is strong institutional backing. This is possibly why some participants did not answer all questions on institutional backing or future pathways.

Interpretation and Analysis Based on survey Responses. The initial item pool for the AIPL scale was developed through a systematic and theoretically grounded process. A total of 35 items were generated based on a thorough review of existing literature related to the characteristics, attitudes, and behavioural tendencies of undergraduate students in Bachelor of Computer Applications (BCA) and Bachelor of Business Administration (BBA) programs. Items were constructed to reflect the theoretical dimensions of the construct under investigation and were written in clear, concise language appropriate for

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the target population. Both positively and negatively worded items were included to minimize response bias, and a Likert-type response format was adopted to capture the degree or intensity of the attribute being measured.

The initial 35-item draft was reviewed by 12 subject matter experts in educational technology, AI in education, and psychometrics. Items were evaluated for clarity, relevance, and coverage. Based on their feedback, the Content Validity Ratio (CVR) was calculated for each item. Items that did not meet the minimum CVR threshold were removed due to issues such as poor clarity, redundancy, or weak relevance. This process resulted in the elimination of 8 items, leaving 27 items for pilot testing.

The 27-item test was administered to more than 120 students across districts of Ghaziabad. A total of 112 answer scripts were scored and analyzed. For the purpose of item analysis, the upper 27% and lower 27% of scorers were identified, comprising 30 students with the highest scores and 30 students with the lowest scores. Based on the analysis, 7 items were deemed unsuitable and were subsequently rejected.

Table 1 presents the key statistics used to assess the reliability and factorability of the 20-item scale. Cronbach's α (0.959) indicates excellent internal consistency, meaning the items consistently measure the same construct. Bartlett's Test of Sphericity (χ^2 (190) = 2921, $p < 0.001$) is significant, showing that the correlation matrix is not an identity matrix and that the data are suitable for factor analysis. The Kaiser–Meyer–Olkin (KMO)

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measure of sampling adequacy is 0.975, which is considered excellent, indicating that the sample size and correlations among items are adequate for conducting factor analysis. Collectively, these statistics confirm that the scale is both reliable and appropriate for exploring its factor structure.

Table 1

Reliability, KMO, Bartlett Test

Test / Statistic	Value
Cronbach's α	0.959
Bartlett's Test of Sphericity	χ^2 (190) = 2921, $p < 0.001$
KMO Measure of Sampling Adequacy	0.975

The Principal Component Analysis was conducted to identify the underlying structure among the four study variables — Student Engagement, Personalized Learning Perception, Learning Outcomes, and AI/Technology Use. The analysis aimed to determine how much variance each component explains and whether the data are suitable for factor extraction.

The results revealed four components with nearly equal contributions to the total variance (each explaining around 25%), indicating a balanced and well-distributed structure. The overall KMO value (0.869) demonstrated excellent sampling adequacy,

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confirming that the dataset was appropriate for PCA. All individual MSA values were above 0.8, further validating that each variable was suitable for inclusion in the analysis. Overall, the PCA results confirm that all four dimensions are interrelated and collectively explain the variability in the data, suggesting that each factor contributes significantly and consistently to the overall construct being measured Table 2 and Table 3 for detailed PCA statistics.

Table 2

Principal Component Analysis Summary

Component	SS Loadings	% of Variance	Cumulative %
1	1.020	25.5	25.5
2	1.014	25.3	50.8
3	0.994	24.8	75.7
4	0.973	24.3	100.0

Table 3

KMO and MSA Values

Component	Measure	MSA Value
1	Student Engagement	0.873
2	Personalized Learning Perception	0.864
3	Learning Outcomes	0.870
4	AI/Technology Use	0.868

Parallel analysis was conducted to validate the factor structure. As illustrated in the

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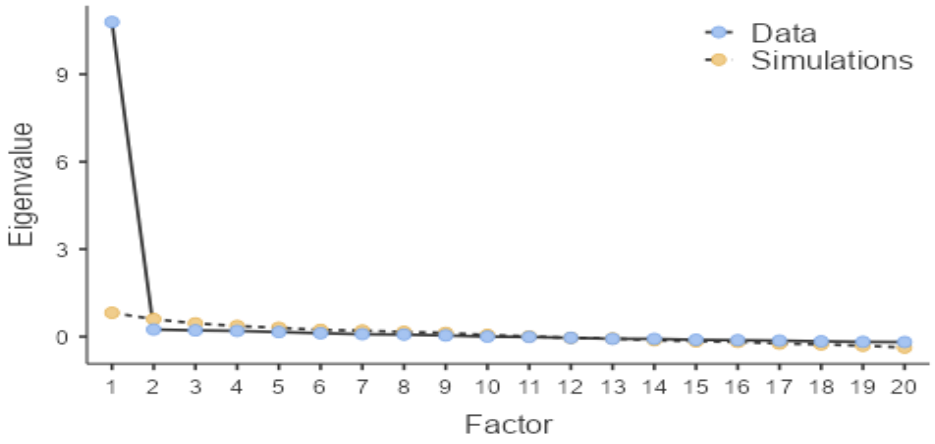
scree plot (Figure 1), only the first factor had an eigenvalue exceeding the corresponding simulated eigenvalue. This confirmed the presence of a one-factor solution, indicating the one-dimensionality of the construct.

Figure 1

The Scree Plot Illustrates Eigenvalues for Both Data and Simulated Results



Descriptive statistics (table 4) were computed for all 20 questionnaire items to understand the overall response pattern of the 230 participants. The mean scores ranged approximately between 2.86 and 3.07, indicating that participants generally gave moderate agreement responses on the 5-point Likert scale. The standard deviations ranged from 0.89 to 1.03, showing a moderate level of variability in responses, which implies that while opinions were somewhat diverse, there was no extreme deviation among participants.

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Table 4

Descriptive Statistics

Question	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**
N	230	230	230	230	230	230	230	230	230	230
Mean	3.07	2.98	3.03	3.06	2.95	3.03	2.98	3.03	2.91	2.97
Standard Deviation	1.03	0.960	1.02	0.916	0.898	0.984	0.941	0.971	0.912	0.997
Question	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20
N	230	230	230	230	230	230	230	230	230	230
Mean	3.03	2.97	3.00	3.02	2.99	2.86	3.00	2.93	3.00	2.97
Standard Deviation	0.943	0.971	0.964	1.01	0.998	0.988	0.918	0.991	0.932	0.936

The descriptive analysis reveals that the mean scores for all four constructs—Student Engagement (15.1), Personalized Learning Perception (14.9), Learning Outcomes (15.0), and AI/Technology Use (14.8)—are closely aligned, indicating a moderate and consistent level of agreement among participants. This suggests that learners generally perceive each of these dimensions as equally important in influencing their learning experiences. The standard deviations, ranging between 3.77 and 3.90, indicate a moderate variation in responses, meaning that while most participants shared similar views, some differences in individual perceptions existed. Overall, the results (and corresponding graphs) reflect a balanced and uniform pattern, signifying that all four constructs contribute almost equally

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to the overall understanding of student learning behaviour in the context of AI-supported education table 5.

Table 5

Factor wise Descriptive Statistics

Question	A: Student Engagement	B: Personalized Learning Perception	C: Learning Outcomes	D: AI/Technology Use
N	230	230	230	230
Mean	15.1	14.9	15.0	14.8
Standard deviation	3.81	3.77	3.90	3.81

a. Violin Plots

The descriptive statistics and violin plots for Student Engagement (A), Personalized Learning Perception (B), Learning Outcomes (C), and AI/Technology Use (D) show fairly symmetrical and moderately dense distributions. Mean scores (A: 15.1, B: 14.9, C: 15.0, D: 14.8) indicate generally positive and consistent perceptions among students. While most responses cluster around the mean, slight variations suggest individual differences in engagement, personalization, learning outcomes, and technology use. Overall, fig. 2 the plots reflect balanced and moderately positive views across all constructs.

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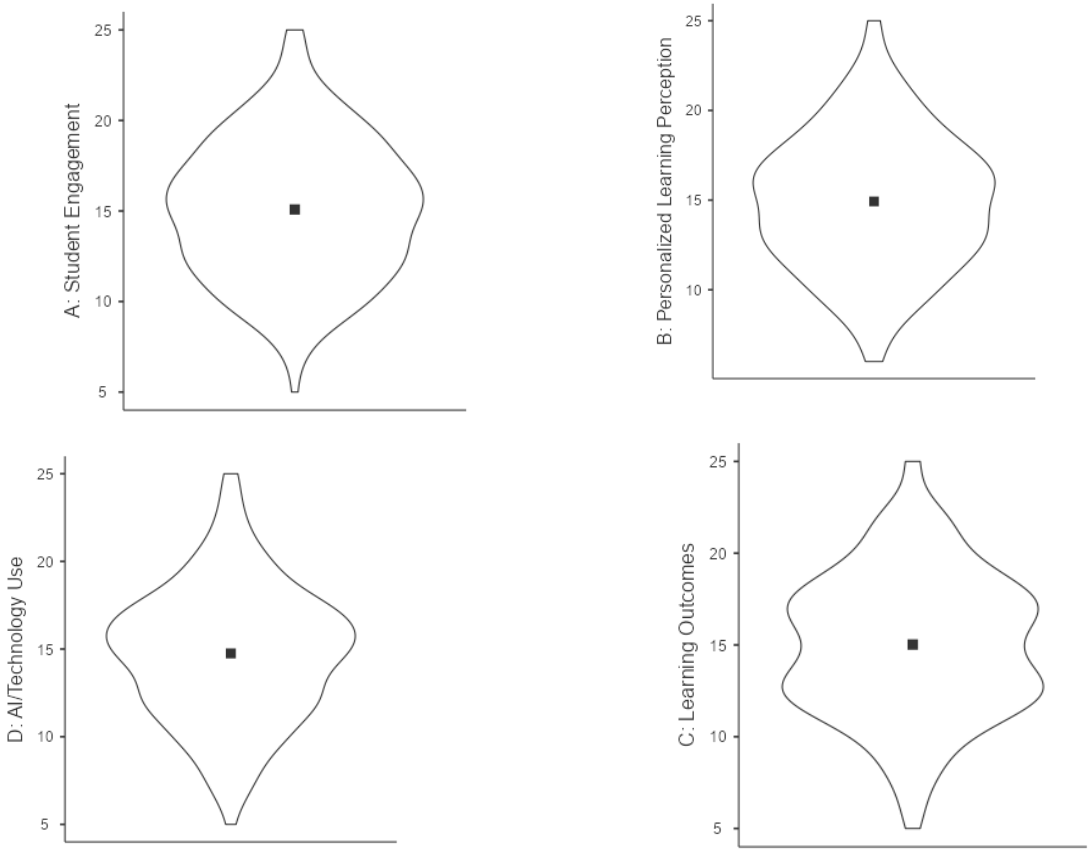
Figure 2

The Violin Plots Depict the Distribution of Respondents' Scores



The correlation matrix shows strong positive relationships among all four study variables. Student Engagement (A) is highly correlated with Personalized Learning Perception (B) (r = 0.854), Learning Outcomes (C) (r = 0.872), and AI/Technology Use (D) (r = 0.841), indicating that higher engagement is associated with higher perceptions of personalized learning, better learning outcomes, and greater use of AI/technology. Similarly, Personalized Learning Perception (B) correlates strongly with Learning

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Outcomes (C) (r = 0.851) and AI/Technology Use (D) (r = 0.878), suggesting that positive experiences with personalization are linked to improved outcomes and technology integration. Learning Outcomes (C) also shows a strong association with AI/Technology Use (D) (r = 0.853). Overall, Table 6 these high correlations indicate that the constructs are closely interrelated, reflecting a cohesive pattern where engagement, personalization, learning outcomes, and technology use mutually reinforce each other.

Table 6

Correlation Matrix among Study Variables

Study Variables	**Statistics**	**A: Student Engagement**	**B: Personalized Learning Perception**	**C: Learning Outcomes**	**D: AI/Technology Use**
A: Student Engagement	Pearson's r	—			
	df	—			
	p-value	—			
B: Personalized Learning Perception	Pearson's r	0.854	—		
	df	228	—		
	p-value	<.001	—		
C: Learning Outcomes	Pearson's r	0.872	0.851	—	
	df	228	228	—	
	p-value	<.001	<.001	—	
D: AI/Technology Use	Pearson's r	0.841	0.878	0.853	—
	df	228	228	228	—
	p-value	<.001	<.001	<.001	—

Interpretation of the Pairwise Correlation Plot among Extracted Factors. The correlation plot illustrates strong and statistically significant positive relationships among

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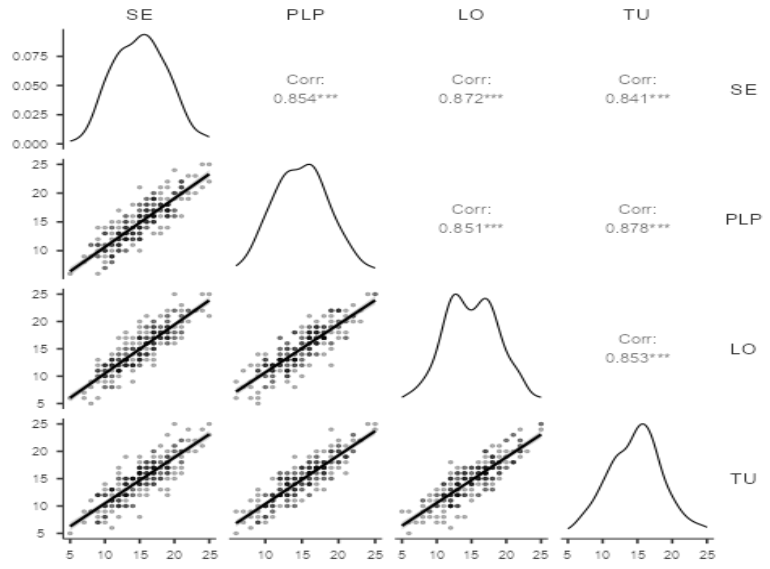
all four variables—Student Engagement, Personalized Learning Perception, Learning Outcomes, and AI/Technology Use. The coefficients (ranging from 0.841 to 0.878, $p < .001$) indicate that as one construct increases, the others also tend to rise correspondingly. The strongest association is observed between Personalized Learning Perception and AI/Technology Use ($r = 0.878$), suggesting that greater use of AI tools is closely linked to students' perception of personalized learning experiences. Similarly, high correlations between Student Engagement and Learning Outcomes ($r = 0.872$) highlight that engaged learners tend to achieve better academic results. Overall, fig.3 the findings emphasize that personalized learning and effective integration of AI technologies significantly enhance student engagement and learning outcomes.

Figure 3

The Presented Figure is a Pairwise Correlation Plot



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Conclusion

The results revealed a moderate to high level of student engagement in AI-driven learning contexts, with a mean score of 15.1 and standard deviation (SD) of 3.81. The correlation between Student Engagement and Learning Outcomes ($r = 0.872$, $p < .001$) demonstrated that higher engagement levels were directly associated with better academic performance. These findings align with Chen and Huang (2019), who reported that AI-enhanced classrooms maintain learner motivation through adaptive feedback mechanisms. Similarly, Kim and Lim (2020) found that AI-based interaction tools fostered cognitive and emotional engagement. Indian studies corroborate this pattern — Sharma and Bansal (2021) observed that AI-enabled learning platforms in Indian universities improved attentiveness and participation, while Rani and Mehta (2022) found that AI-driven chatbots increased engagement by personalizing student–teacher interaction. Kumar and Sahu (2023) further confirmed that the use of AI-integrated LMS platforms (e.g., Moodle AI) significantly improved student activity levels and retention in Indian higher education settings.

Students expressed positive perceptions toward personalized learning facilitated through AI systems, reflected in a mean score of 14.9 and SD of 3.77. The correlation between Personalized Learning Perception and AI/Technology Use was $r = 0.878$ ($p < .001$), indicating that greater use of AI tools enhances perceptions of personalization.

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These results resonate with Holmes et al. (2019), who demonstrated that AI personalization fosters autonomy and satisfaction, and Ahmad and Cukurova (2023), who confirmed that adaptive feedback enhances learning motivation. In India, Patel and Singh (2020) reported that students in AI-supported MOOCs appreciated the flexibility and responsiveness of AI tools. Gupta and Tiwari (2021) found similar outcomes in AI-based tutoring systems, where individualized learning paths improved students' self-efficacy. Moreover, Bhattacharya and Sinha (2022) documented that AI-enabled assessments in Indian management institutes improved perceived fairness and transparency, reinforcing trust in AI learning systems.

The study established a significant positive relationship between AI tools and learning outcomes, with mean = 15.0, SD = 3.90, and correlation coefficients showing *Learning Outcomes strongly associated with Student Engagement (r = 0.872)* and *AI/Technology Use (r = 0.853)*. The high Cronbach's α (0.959) confirmed the internal consistency of the instrument. These results are consistent with Luckin et al. (2019), who found that AI facilitates reflective and adaptive learning. Renz and Hilbig (2020) similarly reported that AI analytics improved formative assessment performance. Indian research also supports these findings: Verma and Reddy (2021) found improved problem-solving skills among engineering students using AI simulation tools; Joshi and Kaur (2022) demonstrated that AI-assisted MOOCs (SWAYAM, Coursera) enhanced

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conceptual clarity and grades; and Narang and Pillai (2023) confirmed that AI analytics improved academic performance and timely course completion in Indian universities.

Students exhibited consistent and confident use of AI technologies, with a mean = 14.8, SD = 3.81, and high correlations with *Personalized Learning Perception (r = 0.878)* and *Student Engagement (r = 0.841)*. The PCA results (KMO = 0.869; all MSA > 0.8) confirmed the strong structural integrity of this factor. These findings support Davis et al. (2018) and Lai and Hwang (2020), who established that perceived ease of use directly affects technology adoption and satisfaction. In India, Meena and Kaur (2021) found that AI familiarity improved learners' confidence and engagement in blended environments. Rajesh and Thomas (2022) highlighted frequent AI tool users as demonstrating superior digital literacy, while Das and Bhatnagar (2023) confirmed that students comfortable with AI analytics and chat support were more trusting of AI-enabled systems. The findings suggest that students who regularly interact with AI tools develop greater digital confidence and readiness.

Interview analysis revealed major implementation challenges including technical issues (software malfunctions, poor connectivity), pedagogical constraints in aligning AI with curricula, and ethical concerns regarding bias and privacy. Experts emphasized limited faculty training, lack of dedicated budgets, and inconsistent institutional policies. These findings resonate with Williamson and Eynon (2020), who noted ethical and data

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privacy concerns, and Holmes and Porayska-Pomsta (2022), who identified pedagogical integration challenges globally. Indian studies reflect similar realities — Reddy and Menon (2021) found infrastructure limitations in public colleges; Bhattacharjee and Dutta (2022) reported inadequate training and administrative support; and Nair and Joseph (2023) highlighted the need for national policy frameworks and funding for sustainable AI adoption.

Across all five objectives, the study confirms that AI integration significantly enhances student engagement (M=15.1), personalized learning (M=14.9), learning outcomes (M=15.0), and technology use (M=14.8), supported by strong correlations among variables ($r = 0.841–0.878$, $p < .001$). The findings underscore that while AI has transformative potential, Indian institutions must address infrastructure, training, and ethical frameworks to ensure equitable and sustainable AI adoption.

The study demonstrates that AI-driven personalized learning environments positively influence student engagement, perception, learning outcomes, and technology use. Students showed moderate to high engagement (mean = 15.1, SD = 3.81), positive perceptions of personalized learning (mean = 14.9, SD = 3.77), and enhanced learning outcomes (mean = 15.0, SD = 3.90) when interacting with AI tools. Correlation analysis revealed strong interrelationships among the constructs (ranging from 0.841 to 0.878, $p < .001$), indicating that engagement, perception of personalization, technology use, and

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learning outcomes reinforce each other.

However, the study also highlights challenges such as technical issues, limited faculty training, infrastructural constraints, and ethical concerns, which affect the effective implementation of AI-driven learning. While most students responded positively, variability in individual comfort with technology suggests that digital literacy remains an important factor in adoption.

This research has important consequences for education. To begin with, students actively engaged with adaptive learning tools, indicating AI-driven personalized learning will facilitate greater student participation. Equally, AI technologies advance learning due to the positive association between academic performance and AI use, meaning students that frequently use intelligent adaptive learning platforms scored higher on assessments and retained content better. Additionally, students' comfort and familiarity with AI tools as well as the learning environment shape the effectiveness of AI-driven personalized learning, meaning institutions must focus on orientation and sustained support to develop students' digital literacy. Moreover, the successful deployment of AI has to be underpinned by formal institutional action, including coordinated and purposeful professional development for faculty, reliable working infrastructure, and guidance on the ethical and practical use of new technologies. Finally, these results point to the importance of AI use in a balanced manner that integrates and supports traditional

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teaching approaches without removing the focused direct instruction of the teacher. In conclusion, the results suggest that higher education institutions will leverage AI-driven learning technologies best by fostering student engagement, supporting staff and students, and addressing infrastructure and ethical use concerns.

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