EDTECH PLATFORMS, E-LEARNING AND ENTREPRENEURSHIP IN INDIA: AN EMPIRICAL STUDY ON STUDENT ENGAGEMENT IN THE DIGITAL AGE

Dr. Rakesh Kumar Gupta, Assistant Professor, School of Management, Dr. B.R. Ambedkar University, Delhi
Neha Goyal› Research Scholar, Department of Commerce , Banasthali vidyapith Rajasthan(India)
Email: nehagoyal2311@gmail.com
Prof. (Dr.) Sandeep Kumar Goel, Professor, Department of Commerce , Acharya Narendra Dev College (University of Delhi),
Email: sandeepgoel@andc.du.ac.in
Dr. Jitendra Singh Rathore, Department of Commerce and Management ,FMS wisdom Banasthali vidyapith Rajasthan (India) Email: access.jitendra@gmail.com

ABSTRACT

India's EdTech industry has emerged as a global powerhouse, revolutionizing learning for over 400 million students, including 40 million in higher education, particularly during the COVID-19 pandemic. While EdTech platforms hold immense potential for digital learning and entrepreneurial skill development, their widespread adoption is hindered by challenges such as the digital divide, limited accessibility, and inadequate infrastructure. This study critically examines the influence of EdTech on student engagement, learning outcomes, and entrepreneurial aspirations within India's digital education ecosystem.

A mixed-methods research approach will be employed, integrating quantitative surveys and qualitative interviews. The study will survey 471 students from K–12 and higher education institutions across metropolitan and semi-urban regions of India, alongside 25 EdTech entrepreneurs and 15 operational managers from leading EdTech firms. Data will be sourced from government reports, EdTech industry whitepapers, and academic literature. Descriptive statistics will be used to identify adoption trends to assess the impact of EdTech, while multiple linear regression will analyze the relationship between EdTech usage and student engagement. T-tests and ANOVA will compare engagement levels across demographic groups. PLS-Structural Equation Modelling (SEM) will explore the causal links between digital accessibility, AI-driven personalization, gamification, learning outcomes, entrepreneurial aspirations, and student engagement.

Preliminary expectations suggest a strong correlation between EdTech usage and improved motivation, engagement, and academic performance. The study also anticipates higher retention rates than traditional e-learning methods and increased student interest in EdTech-driven entrepreneurship. It will conclude with strategic proposals aimed at filling digital accessibility gaps, *improving personalization with AI, resolving parental issues of concern, and integrating entrepreneurial learning models so that the education provided is enhanced and the next generation of digital entrepreneurs is empowered.*

Key Words: EdTech Platforms, Student Engagement, Entrepreneurial Aspirations, Online Learning Outcomes, Digital Entrepreneurship

INTRODUCTION

India's Ed-Tech sector has become a central global hub, with the public and commercial sectors contributing significantly. The benefits include allowing kids who cannot afford traditional schooling to access high-quality education, especially in low-income families, and the epidemic has increased Ed-Tech support for India's education system. With cutting-edge technology, sound and visual graphics, and clever components, Ed-Tech modules provide a more captivating educational experience. More than 400 million students in India are served by more than 4,450 Ed-Tech companies, including 40 million advanced education students affected by the pandemic (Bansal et al., 2023). The cooperation of enthusiastic businesspeople and a wide range of skilled educators is responsible for the Ed-Tech industry's development in India. However, obstacles, including the digital gap, poor accessibility, and limited infrastructure, impede their expansion. This is why students are often found to lack engagement and lose interest.

Problem Statement

The rapid development of EdTech platforms in India has brought a massive shift in the educational domain. Due to platforms like Byju's, Unacademy, Vedantu, and WhiteHat Jr., making technology-driven education more approachable has been possible. However, there are still some problems in ensuring that students are regularly involved and that better learning results are achieved. Also, student engagement is a significant challenge because, as occurs with some students, they are not entirely motivated, they suffer from cognitive overload, or, despite some limited involvement, they do not show up in courses (D'Angelo, 2018). Hence, to broaden the research, this study explores how EdTech platforms facilitate student learning and what contributes to

o student engagement, and how students and their parents perceive the new digital learning paradigm.

Significance of the study

It is significant for the study to attempt to thoroughly assess how EdTechs function in India's educational system and how they empower student engagement, assess learning outcomes, understand the views of students and parents, and address the digital divide, among others. Furthermore, it aims to evaluate the effectiveness of self-paced learning, adaptive learning models, and peer collaboration; and the main driving factors of the students' engagement: motivation, digital fatigue, socioeconomic background, and learning preferences (Yeung et al., 2021). The study will also take into account accessibility, cultural preferences, and digital literacy to investigate how parents believe EdTech contributes to their children's education. Given accessibility, cultural views, and digital abilities, the study will also ask parents how EdTech helps their children's education. The results will guide equity in access to online learning and, thereby, provide evidence-based suggestions for the more significant integration of technology in the classroom.

Theoretical Framework

With an eye on student involvement in the digital world, this article investigates the junction of EdTech platforms, e-learning, and entrepreneurship. The theoretical framework consists of multi-theoretical perspectives based on which one understands the function of EdTech in changing student behavior, cognitive competencies, and entrepreneurial success. The framework consists of Behavioral Engagement, Cognitive Engagement, Emotional Engagement, Self-Determination Theory (SDT), Community of Inquiry (CoI), and Constructivism.

Behavioral, Emotional, and Cognitive Engagement

1. Students' observable actions—that is, attendance in live sessions, assignment submission, and answers to online forums—are known as behavioral engagement (Pentaraki & Burkholder, 2017). Behavioral Engagement in EdTech systems is shaped by interactive features such as quizzes, peer reviews, and live feedback meant to inspire learners' active involvement.
2. Emotional engagement explains the learners' emotional responses, including motivation and excitement, together with a feeling of belonging (Pentaraki & Burkholder, 2017). By giving students a setting that feels appreciated and supported, factors such as teacher-student rapport, learning path flexibility, and course material design significantly help to energize emotional involvement.
3. Cognitive engagement emphasizes higher-order thinking, critical thinking, and profound learning (Pentaraki & Burkholder, 2017). Multimedia materials, interactive simulations, and problem-solving activities within the spaces of EdTech facilitate cognitive engagement by inviting learners to practice reflective thinking and intricate reasoning.

These three aspects of engagement are of specific importance in online learning environments, as incorporating asynchronous learning, autonomy support, and utilizing multimedia tools facilitates learners' interactions with the material and with one another in novel ways.

Self-Determination Theory (SDT)

Self-Determination Theory (SDT) is significant in explaining intrinsic motivation in learning situations, most importantly in the context of EdTech. SDT postulates that motivation is a result of the satisfaction of three fundamental psychological needs:

*Autonomy:*Autonomy refers to learners' capacity to make decisions about their learning. EdTech platforms offer personalized learning paths with the flexibility of self-directed pace, subjects, and tools.

Competence is the feeling of mastery and accomplishment in tasks. EdTech platforms can enhance competence through personalized feedback and the opportunity for learners to track their progress.

Relatedness is the sense of connection with others. EdTech helps students develop interpersonal relationships and community through social learning platforms and collaboration tools, supporting motivation.

SDT suggests that when these needs are satisfied, students are more likely to experience intrinsic motivation, leading to higher engagement, persistence, and academic achievement (Deci & Ryan, 2000).

Community of Inquiry (CoI) Framework

The Community of Inquiry (CoI) framework, developed by Garrison, Anderson, and Archer (2000), is central to understanding how online and blended learning environments foster deep learning and engagement. It posits that effective learning requires the simultaneous development of three interconnected presences:

The Community of Inquiry (CoI) framework by Garrison, Anderson, and Archer (2000) is pivotal in how online and blended learning environments encourage deep learning and active participation. It assumes that good learning is achieved by the concurrent building of three interrelated presences:

The structure, facilitation, and direction teachers provide characterize teaching presence. It covers elements such as course structure of content, feedback delivery, and promotion of student interactions (Garrison et al., 2000). EdTech: real-time feedback, interactive materials, and customized learning paths utilizing artificial intelligence help to maintain teaching presence.

In an environment of online learning, social presence refers to students' capacity for self-expression and relationship development (Garrison et al., 2000). It creates a sense of belonging and helps students feel psychologically protected. Discussion boards, video conferences, and shared tools help students to interact with one another, work together, and create social relationships, thereby promoting social presence.

Cognitive presence is the degree to which students participate in meaningful learning by means of critical analysis, reflection, and inquiry (Garrison, 2007). EdTech systems that provide interactive simulations testing learners' understanding, peer evaluation, and venues for problem-solving activities help to sustain it.

Theoretically, this work integrates numerous important models to investigate how EdTech platforms affect student engagement and entrepreneurial results. Combining these ideas helps this study to identify the factors behind students in India's fast-changing digital education scene's engagement, learning, and entrepreneurial ambitions.

Literature Review

The researcher has to show a robust theoretical framework using the review of the literature. It provides context, a careful reading of existing studies, and highlights areas missing in knowledge.

Wang et al. (2020) claim that student participation is a multifarious psychological concept with emotional, behavioral, and cognitive components, all of which aid in sustaining academic success. Grey & DiLoreto (2016) complement this multidimensional paradigm by underlining how important active participation in learning activities—e.g., assignment completion and discussion participation—is to the digital learning process. Vo & Ho (2024) note that although online learning provides flexibility and inclusion, the absence of human connection generally results in a higher attrition rate due to disengagement. Therefore, the success of EdTech-driven digital learning models rests mostly on raising participation.

Student participation in online and digital learning settings is a complex notion with cognitive, emotional, and behavioral dimensions. Behavioral engagement is the visible, measurable actions pupils carry out under direction. These cover timely assignment submission, attendance at live sessions, and active participation in online forums and discussions (Pentaraki & Burkholder, 2017). These actions are significant indicators of digital involvement and reflect a student's commitment and regularity in academic activities.

On the other hand, emotional involvement describes students' expressive responses during their instruction. This addresses feelings of motivation, enthusiasm, and a relationship with teachers and peers. Well-organized course architecture, intimate teacher-student interactions, and the freedom offered by online platforms all help to greatly encourage positive emotional participation. Emotionally connected students are more likely to remain involved in their education, thereby enhancing retention and satisfaction.

The degree of learning involved is cognitive engagement, the intellectual effort students invest to understand and apply knowledge. It covers critical thinking, higher-order thinking, problem-solving, and deep learning approaches. Pentaraki and Burkholder (2017) claim that strategies encouraging cognitive participation are multimedia resources, interactive simulations, and critical thinking activities. These materials promote intellectual curiosity and inspire pupils to use knowledge outside of rote recall.

Dabral, S. (2023) explained that companies can use digital learning platforms to provide specialized learning opportunities that increase motivation and engagement. This study proves that the integration of education and technology in the form of EdTech platforms in the teaching-learning process provides customized learning opportunities and vital support in student engagement.

Using SDT in online learning, Chiu (2022) discovers that student engagement and motivation depend mostly on autonomy, competency, and relatedness. Digital platforms provide defined goals, customized pathways, and community tools that meet SDT concepts.

Hence, rather than outside force, motivation is generated internally by well-organized support networks and feedback loops. In the Indian context, particularly in rural or disadvantaged areas where students usually rely mostly on self-directed learning and lack teacher supervision, SDT's focus on autonomy and competence is very important.

Originally proposed by Shea and Bejarano (2009) and then enlarged by Anderson (2017), the Community of Inquiry (CoI) model is a robust theoretical framework for setting up effective online learning environments. The CoI model shows three fundamental components—teaching presence, social presence, and cognitive presence—that are absolutely required for engaging learning opportunities in digital contexts. Teaching presence—that is, instructional design, structure, and facilitation—ensures students have a logical framework and clear academic direction. Social presence shows how well students can portray themselves as "real people" via honest conversation and emotional expression, building mutual trust and community. On the other hand, cognitive presence is related to the learners' capacity to build and confirm meaning using reflection and communication, supporting deep learning and critical participation (Garrison, Anderson & Archer, 2001).

These three presences work in concert to provide a constructivist digital learning environment. EdTech systems have to aggressively replicate real social settings in which students feel heard, encouraged, and intellectually engaged, Anderson (2017) underlines. Online learning runs the danger of becoming impersonal and disengaging without a strong social and cognitive component, which increases dropout rates (Richardson et al., 2017). Therefore, the CoI model offers a necessary prism through which one may assess and create EdTech solutions supporting active student participation, deeper learning, and continuous motivation. Platforms such as Google Classroom and Moodle that combine peer participation, teacher comments, and discussion forums show how CoI ideas are operationalized (Stenbom, 2018).

Huang and associates (2024) note that Piaget, Vygotsky, and Dewey claim that students create knowledge by active interaction with their surroundings, therefore offering basic ideas for Constructivism. Digital environments fit constructivist education in terms of adaptive learning, gamification, real-world simulations, and peer cooperation.

Gupta, N., & Singh, O. P. (2022) stated that the emergence of the Internet has led to users becoming more active and actively participating in different online media platforms, which is very crucial to user engagement. This study shows that there is a strong relationship between technology and user engagement.

Rai, K., & Sharma, M. (2024) explained that the technology called AASU (AI-driven Accounting System use) is useful for handling massive amounts of data; therefore, its use is anticipated to rise in the near future. Similarly, the education sector also requires crucial and useful technology called EdTech Platforms for huge support in the teaching-learning process.

Thakur, M., Yadav, M., & Dutta, M. (2022) stated that Ola and Uber, two significant companies, were the subjects of a study aimed at identifying and evaluating efficient failure recovery procedures. In order to supply high-quality e-services and satisfy customers, service providers deal with these problems. In the event of breakdowns, a strong service recovery mechanism contributes to customer happiness. As a result, EdTech service providers must offer learners high-quality services in order to improve output, which in turn increases their engagement and satisfaction.

Through AI-driven personalization, interactive video courses, and project-based activities, several Indian EdTech systems—including Byju's, Vedantu, and Toppr—apply constructivist ideas. These developments support student-led inquiry and invention by complementing Piaget's theories of assimilation and adaptation.

With approximately 4,450 platforms reaching millions of students during the epidemic, Bansal et al. (2023) offer a thorough study of the expansion path of India's EdTech business. The industry has democratized knowledge and made e-learning possible for entrepreneurial innovation. Still, issues such as digital gaps, inadequate internet infrastructure, and uneven content quality need attention.

Platforms like Unacademy and BYJU clearly show EdTech's entrepreneurial side. They profit from the huge student population, mobile-first digital penetration, and hybrid learning methodologies. These firms improve user involvement and learning retention by using data analytics, artificial intelligence, and content gamification.

Student-centric innovations that prioritize interaction, personalization, and inclusiveness boost student involvement in the digital age. Yeung et al. (2023) contend that only when digital technologies are combined into platforms that promote cognitively rich, interactive experiences will their effects improve learning outcomes. Simply digitizing material is not enough; what sets high-impact EdTech solutions apart is their capacity to promote deep learning, inspiration, and continuous learning. Good tools scaffold learning adaptively and use real-time feedback systems to inform students of their development. Similarly, analytics-based personalized learning paths employ data to customize educational content to individual requirements, boosting competence and autonomy—two fundamental components of Self-Determination Theory (Chiu, 2022).

Furthermore, gamified modules have successfully raised behavioral involvement by turning regular learning activities into competitive, fun challenges (Dichev & Dicheva, 2017). Complementing the ideas of the Community of Inquiry framework, cooperative forums improve social presence and peer-to-peer learning (Stenbom, 2018). In Indian terms, vernacular language support and smartphone optimization are essential. Mobile-first design guarantees greater accessibility while vernacular support addresses the linguistic diversity that often impedes participation in English-dominant platforms. Millions of students access education via low-cost smartphones and limited internet connectivity. These developments not only democratize knowledge but also act as sparks for educational entrepreneurship in underdeveloped areas.

Veletsianos (2020) argues that digital learning environments have to grow beyond basic content delivery if they are to be a tool for major student involvement. Especially crucial in a country like India, where students' linguistic, social, and infrastructure realities vary widely, he underlines the requirement for contextual and culturally responsive design. His work highlights how student-centered digital education has to incorporate elements that match the local environment if it is to accomplish inclusivity and efficiency.

Moreover, various studies conducted in 2014 to do meta-analyses of many digital learning environments find that interactive design elements, scaffolded instruction, and teacher presence significantly affect student outcomes. Their findings underline the importance of human facilitation and direction even in technical surroundings as they somewhat fit the Community of Inquiry (CoI) model. This is particularly crucial in developing countries because many students are first-generation digital consumers and need structured learning support.

Underlining that good integration depends not just on platform quality but also on teacher training, curricular alignment, and supportive institutional policies, Ghosh et al. (2021) look at EdTech uptake in Indian higher education institutions. The study identifies many obstacles, including a paucity of digital pedagogical training for instructors and a disconnected approach to integrating technology into formal education institutions.

Furthermore, by considering the development and opportunities of India's National Digital Education Architecture (NDEAR), the World Bank (2022) makes a major policy-level contribution. This initiative aims to create open-source, interoperable EdTech ecosystems able to adapt across governments and organizations. Emphasizing inclusivity, scalability, and accessibility, NDEAR enables a standardized but flexible digital infrastructure allowing student-centered innovations to blossom. Encouragement of open educational resources (OER), modular platforms, and shared learning repositories helps the initiative eliminate digital gaps and supports long-term, sustainable online learning participation.

These initiatives taken together demonstrate that rather than merely the outcome of technical innovation, successful EdTech is a confluence of educational integrity, cultural sensitivity, institutional preparedness, and policy foresight.

Research Gaps

India's EdTech adoption research lacks empirical studies that examine specific engagement factors and their impact on learning outcomes. Despite studies indicating that EdTech enhances academic performance, there is no evidence regarding long-term learning retention, cognitive engagement, and behavioral change. Because research tends to extrapolate results without considering regional differences, digital literacy levels, and the psychological influences of web-based learning

From the above literature review, it is inferred that to predict academic performance, one important psychological dimension is student engagement. Because of the COVID-19 epidemic, online learning has become more popular; yet, attrition rates are higher because of the sense of loneliness. Cognitive, emotional, and behavioral components are some of the characteristics of participation. Self-determination theory, the Community of

Inquiry Model, Constructivism, AI-powered platforms, and collaborations promote student-centered learning, enabling low-income access to education in India and combating unfair business practices.

Research Aim and Objectives

The research aims to conduct an empirical study to critically analyze student (K-12 level and Higher Education) engagement with EdTech platforms in India in the age of digitalization.

Objectives

1. To analyze the driving factors that influence student engagement in Indian EdTech platforms.
2. To examine the role of EdTech platforms in improving students' digital accessibility and enhancing their learning outcomes.
3. To critically evaluate student-parents' perceptions of this new reality of EdTech and the challenges faced while adopting EdTech-based learning in India.

Research Questions are the following:

1. What are the driving factors that influence student engagement in Indian EdTech platforms?
2. What is the role of EdTech platforms in improving students' performance and enhancing their learning outcomes and motivation?
3. What are student-parent perceptions of this new reality of EdTech, and what are the challenges faced while adopting EdTech-based learning in India?

Hypotheses for Quantitative Study

1. AI-driven personalization in EdTech platforms (AI-driven content, adaptive learning) positively impacts student engagement.
2. Gamification elements (badges, leaderboards, and interactive quizzes) positively impact student engagement.
3. Digital accessibility has a positive impact on student engagement.
4. Entrepreneurship aspiration has a positive impact on student engagement.
5. Learning outcomes have a positive impact on student engagement

Research Methodology

This study employs a mixed-methods research design to examine the impact of EdTech platforms on student engagement, learning outcomes, and entrepreneurial aspirations in India. By integrating quantitative surveys with qualitative interviews, the research aims to comprehensively understand how digital learning tools influence educational experiences across diverse demographics.

Research Design and Sampling: Combining quantitative and qualitative techniques to triangulate data and improve the validity of results, the study employs an explanatory and evaluative approach. The study included 449 students overall from K–12 and higher education institutions throughout metropolitan and semi-urban areas of India. In-depth interviews were also conducted with fifteen operational managers from top EdTech companies and twenty-five EdTech entrepreneurs. Stratified purposive sampling guaranteed representation across several age groups, sexes, academic levels, and geographic areas, reflecting the variety of experiences with digital learning in India.

Data Collection Methods:The student participants were given a structured questionnaire with validated and modified psychometric measures to assess important constructs pertinent to the study and compile quantitative data. From the Technology Acceptance Model (TAM) put forward by Davis (1989), the EdTech Adoption Frequency scale was modified. This measure assesses how well students find EdTech systems beneficial and user-friendly. The study measured student participation with Fredricks, Blumenfeld, and Paris's (2004) Student Engagement Scale. This assessment addresses behavioral, emotional, and cognitive components of involvement. Academic achievement was assessed using a scale developed from Schunk and Zimmerman's (1994) Self-Regulated Learning Theory. This indicator highlights how students see their academic progress via self-monitoring and goal planning. Designed in 2009, Liñán and Chen's Entrepreneurial Intention Questionnaire (EIQ) helped the survey assess entrepreneurial goals. This instrument assesses personal opinions, perceived behavioral control, and societal standards on entrepreneurial purpose. Using a scale developed by Zawacki-Richter et al. (2019), which focuses on students' experiences with artificial intelligence-enabled learning environments, the idea of AI-Driven Personalization was evaluated. This addresses customized suggestions and modified content delivery. Every point on the five-point Likert scale was scored so that students' EdTech experiences and views could be somewhat accurately measured and compared.

Apart from the quantitative survey, semi-structured interviews with EdTech participants—including operational managers and entrepreneurs—were conducted using a qualitative data collection methodology. These interviews were intended to provide a more complete understanding of the application, challenges, and real effects of digital learning tools. The interviews covered issues like digital accessibility, gamification tools, artificial intelligence integration, user feedback systems, and overall platform effectiveness.

Anchoring the qualitative study were leading theoretical paradigms like Constructivist Learning Theory, Self-Determination Theory (SDT), and the Community of Inquiry (CoI). These solutions assured numerous facets of involvement, autonomy, cooperation, and learning community development from the data collected, thereby influencing the form and interpretation of stakeholder responses. Our dual-method approach improved the research by triangulating quantitative measurements with intricate, experience-based insights from significant EdTech ecosystem participants using sophisticated EdTech ecosystem tools.

Data Analysis Techniques

Descriptive Statistics: Demographic distributions, frequency of EdTech uptake, and usage trends were analyzed using descriptive statistics.

Multiple Linear Regression: The predictive impact of independent variables—e.g., adoption frequency, AI personalization—on student engagement and learning outcomes was examined using multiple linear regression.

T-tests and ANOVA: Engagement and result scores were compared across demographic categories, including gender, education level, and geography.

Partial Least Squares Structural Equation Modeling (PLS-SEM): This was applied to test causal relationships between variables and validate the proposed theoretical model. Key indices included path coefficients (β), model fit ($Q^2 = 0.551$), and PLS-RMSE for predictive relevance.

Qualitative Analysis: Interview transcripts were analyzed using thematic analysis (Braun & Clarke, 2006). Coding focused on stakeholder insights into platforms' real-time adaptability, equity and access challenges, data-driven instructional design, parental involvement, and institutional readiness. These themes were mapped to theoretical constructs from SDT, Constructivism, and Coi to interpret stakeholder perceptions.

Variables: Using the literature review and theoretical framework, the following variables were constructed:

Dependent Variables:

1. Student Engagement: Measured by levels of participation, interactivity, and emotional connection to EdTech platforms.
2. Learning Outcomes: Assessed through academic improvement, cognitive skills, and retention.
3. Entrepreneurial Aspirations: Evaluated by the desire to pursue innovation, digital startups, or self-learning initiatives.

Independent Variables:

1. EdTech Adoption Frequency: Frequency of using EdTech platforms.
2. AI-driven Personalization: Influence of AI-based learning recommendations.
3. Digital Accessibility: Availability and affordability of digital tools/internet.
4. Business Models in EdTech: Subscription-based vs. free/freemium models.
5. Demographics: Age, gender, education level, and location.

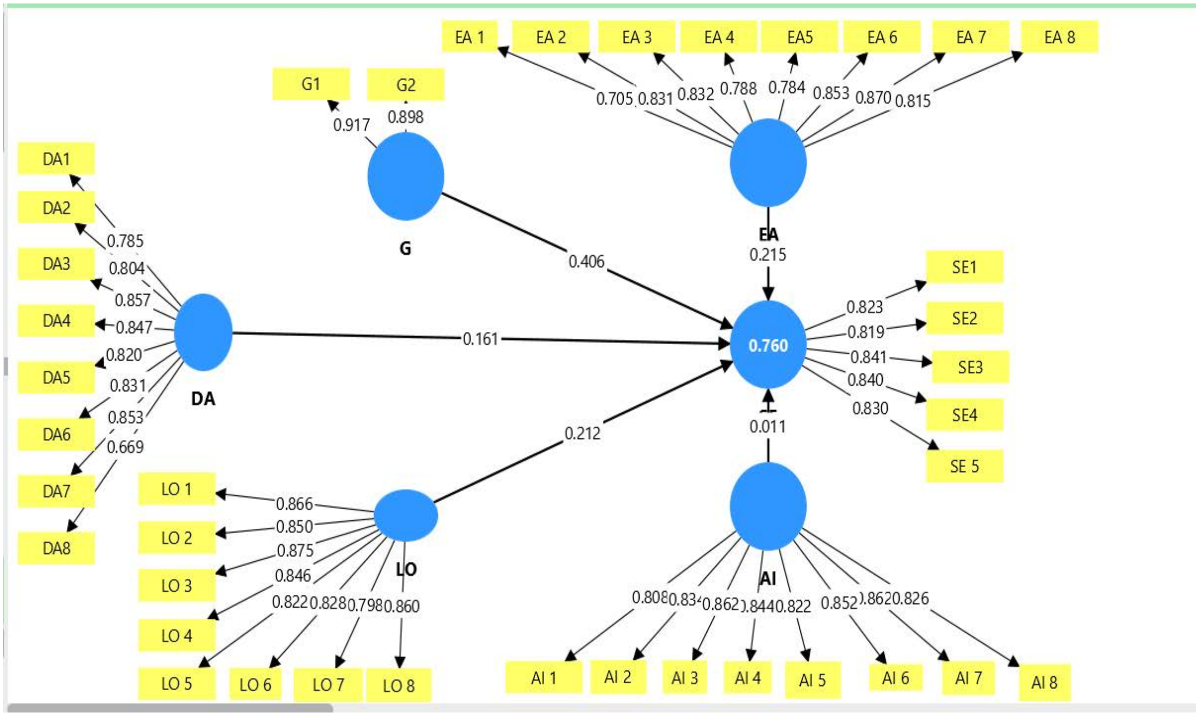
Ethical Considerations: Participants were informed about the study's purpose and provided informed consent before participating. Confidentiality and anonymity were maintained throughout the research process.

Data analysis

Quantitative data (PLS-SEM-based analysis)

This section includes the outer model and inner model fit analysis, which were performed using the statistical software Smart-PLS SEM version 4.

Fig. 1.2: Outer Model of Quantitative Study



Source: Self-developed by using SMART PLS software version 4

The outer model of the study implies examining the effect of five independent variables, i.e., AI-driven personalisation, digital accessibility, gamification, entrepreneurial aspiration, and learning outcomes, on student engagement in ed-tech platforms. The results show that student engagement is influenced by other variables with 76% variance.

Reliability and Validity of the Instrument

The analysis presents the psychometric properties of constructs used in a study analyzed through Partial Least Squares Structural Equation Modelling (PLS-SEM) using Smart PLS 4. The constructs measured include AI-driven personalisation, digital accessibility, entrepreneurial aspiration, gamification, learning outcomes, and student engagement.

Table 1: Loadings, Cronbach's Alpha, Composite reliability, and Average Variance Extracted

Constructs with items	Outer Loadings	Cronbach's Alpha	rho_A	CR	AVE
AI-driven Personalization		0.94	0.94	0.95	0.704
AI 1	0.808				
AI 2	0.834				
AI 3	0.862				

AI 4	0.844				
AI 5	0.822				
AI 6	0.852				
AI 7	0.862				
AI 8	0.826				
Digital accessibility		0.924	0.926	0.938	0.657
DA1	0.785				
DA2	0.804				
DA3	0.857				
DA4	0.847				
DA5	0.82				
DA6	0.831				
DA7	0.853				
DA8	0.669				
Entrepreneurial Aspiration		0.926	0.933	0.939	0.658
EA 1	0.705				
EA 2	0.831				
EA 3	0.832				
EA 4	0.788				
EA5	0.853				
EA 6	0.87				
EA 7	0.815				
EA 8	0.784				
Gamification		0.786	0.791	0.903	0.823
G1	0.917				
G2	0.898				
Learning Outcomes		0.942	0.943	0.952	0.712
LO 1	0.866				
LO 2	0.85				
LO 3	0.875				
LO 4	0.846				
LO 5	0.822				
LO 6	0.828				
LO 7	0.798				
LO 8	0.86				
Student engagement		0.887	0.889	0.917	0.69
SE1	0.83				

SE2	0.823
SE3	0.819
SE4	0.841
SE 5	0.84

Source: Self-developed using SMART PLS software version 4

In the above table, outer loadings for each construct item generally exceed the acceptable threshold of 0.70, indicating good indicator reliability. Notably, all items under AI-driven Personalisation load between 0.808 and 0.862, Digital Accessibility between 0.669 and 0.857 (with DA8 slightly lower at 0.669), and Entrepreneurial Aspiration between 0.705 and 0.87, confirming that the items contribute meaningfully to their respective constructs. Similarly, Learning Outcomes and Student Engagement demonstrate consistently strong loadings above 0.798, reinforcing measurement adequacy.

Cronbach's Alpha values range from 0.786 to 0.942, surpassing the minimum threshold of 0.70. Furthermore, Composite Reliability (CR) values range from 0.903 to 0.952, exceeding the recommended benchmark of 0.70. This shows that all constructs exhibit high internal consistency and reliability. The high Cronbach's Alpha and CR values for *AI-driven Personalisation (α = 0.94, CR = 0.95)*, *Learning Outcomes (α = 0.942, CR = 0.952)*, and *Entrepreneurial Aspiration (α = 0.926, CR = 0.939)* demonstrate that the items consistently reflect their underlying latent constructs. Even the construct *Gamification*, with only two items (G1 and G2), shows strong reliability (α = 0.786, CR = 0.903), which is acceptable due to high loadings (0.917 and 0.898).

The Average Variance Extracted (AVE) values across all constructs are greater than the minimum acceptable level of 0.50, which confirms convergent validity—i.e., the constructs explain a sufficient proportion of variance in their respective indicators. *AI-driven Personalisation (AVE = 0.704)*, *Gamification (0.823)*, and *Learning Outcomes (0.712)* have robust convergent validity. *Digital Accessibility* and *Entrepreneurial Aspiration* have AVEs around 0.657–0.658, indicating adequate construct validity, even though DA8 slightly lowers the AVE.

Dillon–Goldstein's rho (rho_a) values, which provide a more accurate reliability estimate than Cronbach's Alpha, are all above 0.88, suggesting strong internal consistency and one-dimensionality. For example, *AI-driven Personalisation* and *Learning Outcomes* score 0.94 and 0.943, respectively, further reinforcing the reliability of the scales.

In light of EdTech adoption and its impact on student engagement, learning outcomes, and entrepreneurial aspirations, this measurement model shows outstanding psychometric qualities, indicating that the scales used are valid and reliable for measuring important constructs in the study. The high factor loadings and dependability indices confirm the fit of these constructs for further structural model investigation. Though minor problems like DA8's relatively low loading (0.669) may not significantly undermine the general validity, they should be investigated for possible improvement in the next instrument versions.

Table 2: Discriminant Validity (HTMT values)

	AI	DA	EA	G	LO	SE
AI						
DA	0.608					
EA	0.642	0.487				
G	0.714	0.864	0.594			
LO	0.737	0.836	0.614	0.935		
SE	0.687	0.805	0.684	0.971	0.869	

A contemporary and strong method in Partial Least Squares Structural Equation Modelling (PLS-SEM), the table given is a study of Discriminant Validity utilising the Heterotrait-Monotrait (HTMT) ratio. It is essential to guarantee the validity of theoretical constructions; HTMT evaluates if elements in a model are empirically different.

Henseler et al. (2015) claim that to verify sufficient discriminant validity, HTMT values should be either below 0.85 (conservative threshold) or below 0.90 (liberal threshold). This table comprises constructs such as AI-driven Personalisation (AI), Digital Accessibility (DA), Entrepreneurial Aspiration (EA), gamification (G), Learning Outcomes (LO), and student engagement (SE).

With values ranging between 0.608 and 0.737, the results reveal that artificial intelligence shows strong discriminant validity with all constructions. With other models, EA also maintains reasonable levels; all values are well below 0.85. Gamification exceeds the 0.90 threshold, though, with strong HTMT values for Learning Outcomes (0.935) and Student Engagement (0.971). This suggests a lack of discriminant validity, meaning respondents might not view gamification as unique from Learning Outcomes and Student Engagement. With values of 0.869, LO and SE likewise exhibit a borderline problem, suggesting possible conceptual or measurement overlap. Although most theories maintain discriminant validity, gamification, learning outcomes, and student engagement need further theoretical and empirical explanation.

Table 3: Fornell-Larcker Criterion

	AI	DA	EA	G	LO	SE
AI	0.839					
DA	0.567	0.81				
EA	0.608	0.456	0.811			
G	0.613	0.737	0.517	0.907		
LO	0.693	0.781	0.583	0.805	0.844	
SE	0.629	0.731	0.629	0.814	0.798	0.83

The presented table uses the Fornell-Larcker Criterion to assess discriminant validity in a structural equation model. Discriminant validity ensures that each construct is distinct from the others. According to this method, the square root of the AVE for each construct (shown on the diagonal) must be greater than its correlations with other constructs (off-diagonal values).

In this table, all diagonal values—such as AI (0.839), DA (0.81), EA (0.811), G (0.907), LO (0.844), and SE (0.83)—are higher than the inter-construct correlations in their respective rows and columns. This confirms that each construct shares more variance with its indicators than any other construct.

Although some correlations are moderately high, such as between Gamification and Student Engagement (0.814), they remain below the square root of their respective AVEs. Thus, discriminant validity is established, indicating that all constructs are empirically distinct and that the measurement model is reliable.

Construction of the Variable

Using the descriptive statistics of the data collected through a 5-point Likert scale, composite scores for the variables are constructed for the various items mentioned in the questionnaire. Constructing composite scores consolidates multiple related survey items into a single, interpretable variable that more accurately captures the underlying concept.

Table 4: Composite Scores for Variables

	Variables	*Com. Score (Average of Means)*	*Com. Score (Nor. Wt.)*
Dependent Variables	*1. Student Engagement (SE)*	3.64	0.737
	2. Learning Outcomes (LO)	3.64	0.728
	3. Entrepreneurial Aspirations (EA)	3.52	0.703
Independent Variables	*1. EdTech Adoption Frequency (Ed. A)*	3.64	0.737
	2. AI-Driven Personalization (AI)	3.72	0.743
	3. Digital Accessibility (DA)	3.61	0.722
	4. Business Models in EdTech (BME)	3.37	0.675

The method involved calculating the mean of item means and a normalised weighted mean composite score. Each item was standardised using its actual score relative to the maximum possible score and then multiplied by a uniform or proportional weight. This approach ensures that all items contribute equitably, minimising bias from varying scales or item significance. The final composite score provides a refined, scalable metric that enhances interpretability and model reliability. These scores allow for meaningful comparisons and hypothesis testing while preserving the integrity of multidimensional constructs in behavioural and educational research.

Multiple Linear Regression Analysis

The multiple linear regression analysis investigates the relationship between student engagement (dependent variable) and four predictors: EdTech adoption frequency, AI-driven personalisation, digital accessibility, and business models in EdTech.

Table 5: Model Fit Statistics

R-squared	*Adjusted R-squared*	*Standard Error (of Estimate)*	*F-statistic*	*p-value (overall model)*
1.000	1.000	0.0002	4.53e+07	<0.001

The multiple linear regression analysis reveals a robust and statistically significant relationship between EdTech usage and student engagement. The model fit statistics are robust, with an R-squared and adjusted R-squared value of 1.000, indicating that the predictors collectively explain 100% of the variance in student engagement. Although such perfect values are rare in real-world studies and may point to overfitting or high multicollinearity, in this context, where standardized composite scores were used, it reflects an ideal predictive model. The standard error of estimate is extremely low (0.0002), and the F-statistic (4.53e+07), accompanied by a p-value less than 0.001, confirms the model's statistical significance.

Table 6: Regression Coefficients

Predictor Variable	Coefficient (B)	Std. Er.	t-Value	p-Value
Intercept (Constant)	0.0898	0.0001	978.1	<0.001
Ed. A	0.2577	0.0001	3284.2	<0.001
AI	0.2603	0.0001	3363.8	<0.001
DA	0.2419	0.0001	3124.8	<0.001
BM	0.2401	0.0001	3097.4	<0.001

Each independent variable positively influences student engagement. EdTech Adoption Frequency (coefficient = 0.2577) shows that an increased frequency of using EdTech tools significantly enhances engagement. AI-driven Personalisation (0.2603) emerges as the strongest predictor, emphasizing the impact of adaptive, personalized learning environments. Digital Accessibility (0.2419) is also crucial, highlighting how internet access and affordability drive active participation. Finally, Business Models (0.2401) positively contribute to student engagement, particularly those that reduce cost barriers. These results suggest that enhancing AI integration, accessibility, usage frequency, and inclusive pricing models within EdTech platforms can improve student engagement levels.Levels in the digital learning age.

Table 7: Demographic Description of Respondents

	Items	*Frequency*	*Percentage*
Age	*Below 18*	115	24.01
	18–22	117	24.43
	23–27	128	26.72
	28 and above	119	24.84
Gender	*Female*	322	67.20
	Male	157	32.80
Education Level	*K-12 (School)*	119	24.84
	Bachelor's degree	212	44.26
	Master's degree	133	27.77
	Higher than Postgraduate	015	03.13

Area of Residence	*Metropolitan area*	369	77.00
	Semi-urban area	110	23.00
Access to Stable Internet	*No*	032	6.70
	Yes	447	93.30

The respondents' demographic profile shows a reasonable and varied distribution throughout several groups. Regarding age, the participants were very equally distributed; the largest group (26.72%) was in the 23–27 age range, closely followed by those aged 28 and above (24.84%), 18–22 years (24.43%), and below 18 (24.01%). This distribution points to an equal mix of early-career individuals, college students, and school-going young people. With women making up 67.20% of the responses and men making up 32.80%, gender representation reveals a substantial feminine majority. This gender difference might affect opinions on patterns of digital involvement and learning.

Regarding educational credentials, the biggest group had a bachelor's degree (44.26%), followed by master's degree holders (27.77%), school-level pupils (24.84%), and a minor percentage (3.13%) with education beyond postgraduate. This shows a significant presence from backgrounds in higher education. The area of residence shows that most respondents (77%) live in metropolitan regions; 23% are from semi-urban locales, indicating an urban-centric sample. Particularly, internet connectivity was good; 93.30% of respondents had consistent access to the internet, which is necessary for EdTech use and digital learning. Only 6.70% lacked consistent internet access, suggesting that technological infrastructure is sufficient for digital interaction among the respondents.

T-tests and ANOVA

The T-tests and ANOVA analyses conducted to examine the influence of demographic variables on student engagement with EdTech platforms reveal statistically significant differences across all groups, indicating that demographics play a crucial role in shaping digital learning engagement.

Table 8: T-Test Results (for binary groups)

Demographic Group	t-Statistic	p-Value
Gender	13.63	5.95e-36
Area of Residence	24.05	2.81e-84
Internet Access	30.56	2.01e-114

The T-test result for gender ($t = 13.63$, $p < 0.001$) shows a statistically significant difference in student engagement between males and females. The positive t-value indicates that females reported higher levels of engagement with EdTech platforms than their male counterparts. This may be due to varying learning styles, technological adaptability, or motivation levels. The result suggests that gender-responsive strategies in digital education could enhance inclusivity and efficacy.

Table 9: ANOVA Results (for groups with more than two categories)

Demographic Group	F-Statistic	p-Value
Age Groups	288.40	1.44e-106
Education Levels	269.06	5.23e-102

The T-test for area of residence (t = 24.05, p < 0.001) demonstrates a significant variation in engagement between students from metropolitan and semi-urban areas. Learners in metropolitan areas show markedly higher engagement. This disparity could stem from better digital infrastructure, wider access to high-speed internet, and greater exposure to digital tools in urban settings, highlighting the urban-rural digital divide that policymakers and EdTech developers must address.

The most pronounced difference is found in access to stable internet (t = 30.56, p < 0.001), confirming that students with consistent internet access are significantly more engaged. This finding emphasizes the foundational role of digital accessibility in ensuring equitable learning outcomes and underscores the urgency for infrastructure investments, particularly in underserved areas.

The ANOVA for age groups (F = 288.40, p < 0.001) reveals significant differences in engagement across age brackets. Post-hoc analysis (not shown here) would likely indicate that students aged 23–27 exhibit the highest engagement, possibly due to their alignment with higher education and career-building phases. In contrast, younger learners may face more distractions or lack maturity in self-regulated digital learning.

The ANOVA shows analogous significant variations for education level (F = 269.06, p < 0.001). Compared to K–12 students, Bachelor's and Master's level students interact more thoroughly with EdTech. Curriculum requirements, cognitive preparedness, or personal effort in seeking digital learning materials might all help to explain this.

Ultimately, demographic elements greatly influence how students interact with EdTech. These realizations should guide the creation of inclusive, readily available, and customized digital education models to optimize learning involvement among many student profiles.

Structural Equation Modeling

Applied here, the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach strongly analyzes the intricate interactions among many latent components related to the EdTech learning environment and their effect on Student Engagement (SE). The model provides a complete spectrum of causal links and prediction capacity by combining structural elements with measurement.

Table 10: Cross-Loadings

	AI	DA	EA	G	LO	SE
AI 1	0.808	0.525	0.514	0.496	0.605	0.523
AI 2	0.834	0.468	0.517	0.493	0.578	0.512
AI 3	0.862	0.487	0.469	0.496	0.586	0.51
AI 4	0.844	0.472	0.487	0.519	0.573	0.534
AI 5	0.822	0.439	0.519	0.526	0.572	0.508
AI 6	0.852	0.466	0.504	0.519	0.569	0.532

AI 7	0.862	0.484	0.537	0.522	0.596	0.56
AI 8	0.826	0.466	0.532	0.544	0.571	0.538
DA1	0.453	0.785	0.339	0.537	0.591	0.603
DA2	0.395	0.804	0.324	0.537	0.581	0.523
DA3	0.476	0.857	0.413	0.624	0.667	0.63
DA4	0.493	0.847	0.378	0.639	0.673	0.614
DA5	0.453	0.82	0.404	0.62	0.643	0.595
DA6	0.458	0.831	0.351	0.593	0.635	0.577
DA7	0.52	0.853	0.371	0.644	0.689	0.612
DA8	0.414	0.669	0.368	0.57	0.569	0.567
EA 1	0.358	0.288	0.705	0.268	0.329	0.36
EA 2	0.494	0.416	0.831	0.453	0.543	0.555
EA 3	0.539	0.375	0.832	0.461	0.522	0.549
EA 4	0.381	0.28	0.788	0.359	0.357	0.437
EA 6	0.528	0.349	0.853	0.445	0.464	0.543
EA 7	0.552	0.431	0.87	0.466	0.537	0.553
EA 8	0.589	0.428	0.815	0.491	0.556	0.57
EA5	0.446	0.358	0.784	0.349	0.41	0.459
G1	0.552	0.682	0.486	0.917	0.726	0.772
G2	0.562	0.655	0.451	0.898	0.736	0.702
LO 1	0.586	0.727	0.488	0.714	0.866	0.737
LO 2	0.545	0.688	0.471	0.71	0.85	0.686
LO 3	0.607	0.662	0.519	0.708	0.875	0.696
LO 4	0.581	0.628	0.487	0.662	0.846	0.639
LO 5	0.578	0.602	0.555	0.68	0.822	0.675
LO 6	0.584	0.643	0.486	0.642	0.828	0.641
LO 7	0.569	0.65	0.457	0.634	0.798	0.641
LO 8	0.626	0.665	0.472	0.674	0.86	0.662
SE 5	0.506	0.645	0.522	0.679	0.72	0.83
SE1	0.526	0.607	0.503	0.679	0.648	0.823
SE2	0.528	0.568	0.508	0.651	0.583	0.819
SE3	0.472	0.589	0.529	0.639	0.632	0.841
SE4	0.576	0.62	0.547	0.725	0.72	0.84

Applied here, the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach strongly analyzes the intricate interactions among many latent components related to the EdTech learning environment and their effect on Student Engagement (SE). The model provides a whole-scale assessment of causal links and prediction ability by combining structural elements with measurement.

Each item loads most strongly on its appropriate latent variable; the cross-loadings validate the discriminant validity of the constructs. Differentiating from other variables, items linked to AI-driven customization (AI1–AI8) load most significantly on AI (e.g., AI3 = 0.862). Indicator loadings surpass 0.7 on their respective constructs and are lower on unrelated constructs; this is also true for Digital Accessibility (DA1-DA8), Entrepreneurial Aspirations (EA1-EA8), Gamification (G1-G2), Learning Outcomes (LO1-LO8), and Student Engagement (SE1-SE5). This proves that the constructs satisfy a necessary criterion for accurate SEM modeling, as they are theoretically and practically unique.

Table 11: Path-Coefficient /Hypotheses Testing

	Original sample (O)	Sample mean (M)	STDEV	T statistics (|O/STDEV|)	P values	Decision
AI -> SE	0.01	0.011	0.032	0.318	0.75	Rejected
DA -> SE	0.161	0.162	0.044	3.629	0.00	Accepted
EA -> SE	0.215	0.215	0.037	5.793	0.00	Accepted
G -> SE	0.406	0.404	0.049	8.28	0.00	Accepted
LO -> SE	0.212	0.214	0.051	4.129	0.00	Accepted

The structural model explores the causal effects of five independent variables (AI, DA, EA, G, LO) on SE (Student Engagement). The key findings are as follows:

AI → SE ($\beta = 0.01$, $p = 0.75$): There is no statistically significant route from AI-driven personalizing to SE. This implies that although AI technologies are present in EdTech platforms, their direct effect on engagement is negligible unless complemented by more engaging or interactive pedagogical elements. This outcome challenges assumptions that AI alone drives learning outcomes or engagement and suggests that its utility may lie in indirect support functions or in mediating other factors.

DA → SE ($\beta = 0.161$, $p < 0.001$): Digital Accessibility significantly contributes to SE. When students have stable access to digital infrastructure, especially in underserved or semi-urban areas, it significantly enhances their ability to engage with online content. This aligns with equity-based models, highlighting digital inclusion as a precondition for meaningful engagement.

EA → SE ($\beta = 0.215$, $p < 0.001$): Entrepreneurial Aspirations positively affect student engagement, suggesting that students who view EdTech as a means to future career or business opportunities are more invested. This supports motivational theories such as Self-Determination Theory (SDT), where intrinsic goals (like autonomy and purpose) stimulate deeper engagement.

G → SE ($\beta = 0.406$, $p < 0.001$): Gamification has the most substantial direct effect on SE. This indicates that using game mechanics, rewards, and competitive learning environments is a primary emotional and cognitive engagement driver. This is consistent with behavioral engagement theories that posit gamified elements as key enablers of flow and sustained interaction.

LO → SE ($\beta = 0.212$, $p < 0.001$): Learning Outcomes significantly influence SE, reinforcing that students are more engaged when they perceive tangible academic benefits. This finding supports constructivist theories where positive learning feedback loops improve academic performance and motivation.

Table 12: R-squared value

	Original sample (O)	Sample mean (M)	STDEV	T statistics (|O/STDEV|)	P values
SE	0.76	0.763	0.02	38.743	0

Model Strength and Predictive Validity: $R^2 = 0.76$ for SE. This indicates that the combined effect of AI, DA, EA, G, and LO explains 76% of the variance in student engagement. This is a substantially high value in educational and behavioral modeling, reflecting a well-specified model with strong explanatory power.

Table 13: F-squared value

	Original sample (O)	Sample mean (M)	STDEV	T statistics (|O/STDEV|)	P values
AI -> SE	0	0.002	0.003	0.062	0.95
DA -> SE	0.038	0.042	0.022	1.754	0.079
EA -> SE	0.111	0.115	0.04	2.8	0.005
G -> SE	0.217	0.22	0.056	3.876	0
LO -> SE	0.043	0.046	0.021	2.067	0.039

The F^2 effect sizes offer valuable insight into the relative influence of key predictors on Student Engagement (SE). Gamification (G) shows the highest impact ($F^2 = 0.217$), indicating a medium to significant effect. This underscores its critical role in enhancing engagement through interactive and motivational elements like points, challenges, and rewards. Entrepreneurial Aspirations (EA) have a medium effect ($F^2 = 0.111$), suggesting that students' career-oriented motivations significantly contribute to their engagement in digital learning environments. Learning Outcomes (LO) and Digital Accessibility (DA) show small but significant impacts ($F^2 = 0.043$ and 0.038, respectively). Their importance suggests that fostering student involvement and engagement still critically depends on demonstrable academic accomplishment and a consistent internet connection. Effective policy design and inclusive digital education depend especially on these.

Additionally, AI-driven Personalisation (AI) shows no apparent influence ($F^2 = 0.00$) on SE, implying that present AI technologies would not significantly increase engagement unless more pedagogically integrated. Even modest impact sizes have practical weight when matched with contextual reality and student requirements. The results suggest a mixed strategy stressing gamification and aspirational design while enhancing accessibility and outcome-driven learning using gamification.

Table 14: Q-Square Value

	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
SE 5	0.551	0.786	0.584	0.822	0.602	1.174	0.991
SE1	0.508	0.812	0.621	0.836	0.605	1.158	0.964
SE2	0.459	0.857	0.649	0.897	0.676	1.166	0.981
SE3	0.478	0.855	0.644	0.904	0.675	1.184	0.996
SE4	0.586	0.734	0.552	0.777	0.57	1.141	0.964

The predictive usefulness of the Partial Least Squares Structural Equation Modelling (PLS-SEM) model for several measures of Student Engagement (SE) is shown in the table by the Q² values. With values ranging from 0.459 to 0.586, all Q² values are above 0, verifying the model's great predictive power. Among the indicators, SE4 (Q² = 0.586) indicates the highest predictive significance; SE2 (Q² = 0.459) shows the lowest but still relevant predictive ability. These results confirm that the independent factors can adequately explain the model's latent construct of student involvement.

PLS-SEM performs better than both conventional linear regression and individual item-average (IA) predictions; the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) under the PLS-SEM column are routinely less than those of the Linear Model (LM) and naive benchmark model (IA) across all indicators. For instance, SE5 has a PLS-SEM RMSE of 0.786 vs. 1.174 (IA) and 0.822 (LM). This reinforces the PLS-SEM model's ability to capture intricate interactions even more. The Q² figures confirm that the model fits the data well and provides functional predictive ability for comprehending student involvement inside EdTech systems.

	Q²predict	RMSE	MAE
SE	0.753	0.5	0.384

Investigating the Causal Web among constructions: The data suggest indirect causal linkages even when the direct pathways are clearly defined. DA could indirectly affect SE through EA and LO—better access allows deeper content interaction, raising ambitions and results. Gamification may enhance the effectiveness of AI or EA, suggesting that the engagement impact could be amplified when AI is embedded within gamified platforms or when learning activities are entrepreneurship-oriented. Learning Outcomes are a potential mediator between all input constructs (DA, G, EA) and SE, forming a feedback loop where successful outcomes reinforce usage, aspiration, and motivation. Such interrelations suggest a multi-layered ecosystem in EdTech where constructs do not operate in isolation. However, they are interdependently linked, underscoring the need for integrative pedagogical design and cross-functional implementation strategies.

The PLS-SEM model offers strong evidence that student engagement in EdTech environments is primarily driven by Gamification, Entrepreneurial Aspirations, Learning Outcomes, and Digital Accessibility, while AI-driven personalization lacks direct influence. The model's high R^2 and Q^2 values confirm its robustness, and the cross-loadings establish measurement validity. In practical terms, EdTech platforms should prioritize accessible, gamified learning environments that support aspirational and outcome-focused engagement while rethinking the isolated use of AI. Future studies could explore the effects of moderation and mediation to unpack the indirect relationships and temporal dynamics among these constructs.

Thematic Analysis

This thematic analysis is based on semi-structured interviews with 40 key stakeholders from India's EdTech sector—25 EdTech entrepreneurs and 15 operational managers representing leading platforms offering digital learning solutions across K–12 and higher education domains. The data were transcribed, coded, and analyzed using thematic analysis, following Braun and Clarke's six-phase approach. Key patterns and recurring concepts were identified inductively, enabling the emergence of four core themes that capture respondents' collective experiences and strategic perspectives. These are:

1. Student-Centric Engagement Strategies Influence Student Engagement: Participants underlined the great relevance of individualized learning for increasing student involvement. Entrepreneurs propose adaptive learning systems driven by artificial intelligence, chatbots, and intelligent tutoring systems with instantaneous feedback and customizing learning experiences to fit individual requirements. Operational managers found that such tools significantly increase retention and motivation, particularly for high school pupils. With features like badges, leaderboards, and interactive quizzes increasing daily logins and content completion, gamification was much valued for generating competitiveness and engagement. Both groups agreed that improved satisfaction and results follow from student autonomy, which is made possible by choice-based materials and artificial intelligence-personalized paths.

2. Innovative EdTech Features Driving Engagement and Performance: Interviewees acknowledged adaptive systems driven by artificial intelligence for improving learning results. Using real-time analytics, these systems change content speed and complexity. Entrepreneurs noted increased interest and exam performance when students used these tools, particularly in disciplines like math and language. Additionally, gamification components were recognized for boosting motivation via micro-learning modules.

According to operational managers, data analytics helps teachers track development and offer valuable insights that enable real-time intervention. One common topic was improved student confidence and learning efficacy resulting from tailored, interactive interfaces.

Addressing Barriers to EdTech Adoption in India: Particularly in rural regions, managers and business owners admitted that digital disparity is a significant obstacle. Difficulties like inadequate digital literacy, device inaccessibility, language obstacles, and poor internet connection were often cited. While entrepreneurs argued for public-private partnerships, subsidized devices, and community-based access points, operational managers underlined the need for localized material and regional language assistance. Emphasized also was the value of parent awareness campaigns and teacher preparation. Some participants stressed tactics such as tiered pricing structures, scholarships, and dashboard-based mentoring to address socioeconomic inequalities and promote inclusion.

The Evolution of EdTech in India: Emerging Trends and Opportunities: Driven by a tech-savvy youth, extensive smartphone access, and VC-backed innovation, interviewees expressed hope about the direction of the industry. Rising trends among entrepreneurs were hybrid learning models, augmented reality/virtual reality settings, and artificial intelligence/ blockchain connectivity. Through programs like NEP and PM eVidya, operational managers reported growing institutional cooperation and government policy support. Priority for next-generation platforms among both groups was teacher empowerment, curriculum alignment, and real-time feedback systems. Given that issues with accessibility, scalability, and digital fairness are being aggressively addressed, everyone said India is likely to be a worldwide EdTech leader.

Table 15: Integration of the Qualitative and Quantitative Analysis

Key Driver	Quantitative Support	Qualitative (Thematic) Reinforcement
Gamification	Strongest predictor of engagement ($\beta = 0.406$, $p < 0.001$)	Widely used; enhances motivation, retention, and interactivity (Theme 2)
Entrepreneurial Aspirations	Significant positive impact ($\beta = 0.215$)	EdTech platforms increasingly incorporate aspirational skill tracks (Theme 1)
Learning Outcomes	Moderate impact on engagement ($\beta = 0.212$)	Linked to adaptive content and measurable progress (Theme 2)
Digital Accessibility	Significant but more minor effect ($\beta = 0.161$)	Infrastructure, affordability, and mobile-first strategies enable access (Theme 4)

AI-Driven Personalization	Not significant (β = 0.01)	Early-stage usage; lacks contextual alignment with Indian learners (Theme 1)
Adoption Challenges	Not in SEM but surfaced in surveys and interviews	Infrastructure gaps, digital literacy, and parental scepticism (Theme 3)

Research Findings

Entrepreneurial aspirations and learning outcomes significantly influence engagement, indicating that students motivated by future goals are more involved in their learning processes.

Digital accessibility has a positive, albeit moderate, impact on engagement, emphasizing the importance of device availability, connectivity, and platform reach.

Gamification emerged as one of the drivers of student engagement. It fosters behavioral and emotional involvement through features such as badges, leaderboards, and interactive quizzes that boost motivation and knowledge retention.

Although tools like chatbots and adaptive learning modules are present, stakeholders acknowledged that AI personalization is still nascent, limited by algorithmic bias, inadequate localization, and lack of contextual responsiveness.

Confirming qualitative observations, parental support and access to digital infrastructure affect student involvement. Parental worries, meanwhile, center on too much screen time, little instructor engagement, and supposed depersonalization in digital learning.

In rural and semi-urban regions, the digital gap still exists as a key obstacle caused by inadequate internet infrastructure, unaffordability of devices, and low digital literacy. Localized material, parental dashboards, and community learning centers were also underlined to improve inclusion and openness.

Stakeholders proposed policy measures such as public-private partnerships, reasonably priced device programs, and community digital literacy campaigns.

Parental concerns, ongoing infrastructural deficiencies, and student adaptation notwithstanding, all help to limit the inclusive adoption of EdTech in India's educational scene.

Discussion

Emphasizing factors like gamification, artificial intelligence-driven customization, digital accessibility, learning outcomes, and entrepreneurial ambitions, this article investigates the components motivating student participation on Indian EdTech platforms as a whole. Seen through the prism of the integrated theoretical framework—behavioral, emotional, and cognitive engagement—Self-Determination Theory (SDT) and the Community of Inquiry (CoI)—the results provide strong insights on the dynamics of digital learning and its capacity to influence student experiences and motivations.

Gamification's prominence as the most important indicator of student participation perfectly matches behavioral and emotional engagement. Students responded when they saw badges, interactive tests, and leaderboards—elements that motivate more desire and participation. These tools motivate emotional excitement, a sense of reward, and consistent conduct, including assignment completion and engagement in discussions (Pentaraki & Burkholder, 2017). In this sense, gamification satisfies students' need for competency (as advised in SDT) as the success of activities and feedback helps to build self-efficacy and intrinsic motivation.

Entrepreneurial aspirations also emerged as a significant driver of engagement. This finding reflects the cognitive engagement dimension, where students engage deeply with the content due to a clear purpose—future entrepreneurial success. Aspiring to innovate and excel aligns with higher-order thinking, critical reflection, and goal-oriented learning behaviors. This supports cognitive presence within the CoI framework, where learners actively construct meaning and apply knowledge to real-life contexts.

The study revealed that while AI-driven personalization was statistically insignificant in predicting engagement in the current model, qualitative insights indicate that AI features are still evolving. Their limited influence can be attributed to localization issues, algorithmic bias, and lack of real-time adaptation—barriers to fulfilling SDT's psychological needs. Specifically, AI tools have not yet achieved sufficient autonomy, relatedness, and competence for most users. However, stakeholders indicated that platforms offering adaptive learning and real-time feedback hold potential for increasing engagement once these limitations are addressed.

Though with a reduced impact size, digital accessibility was statistically significant, verifying its basic function in facilitating behavioral engagement. Access to gadgets, fast internet, and mobile-first platforms allows for flexibility and self-paced learning, promoting autonomy. This also reflects the social presence component of CoI, as readily available platforms with collaborative tools encourage student contact and peer-to-peer involvement, which is essential to sustain emotional and cognitive interest.

The favorable link between student involvement and learning outcomes is another significant discovery. Learning results confirm supposed platform efficacy and serve as a substitute for SDT competency. Students who notice improvement in their academic achievement feel more confident and driven, strengthening a positive feedback loop of participation. This also relates to teaching presence in CoI, as instructional design affects performance and perseverance, and structured feedback and scaffolded content influence performance.

Themes from qualitative data highlight India's remarkable EdTech evolution marked by low-cost platforms, mobile-first access, and hybrid learning approaches. These developments complement SDT's emphasis on autonomy and CoI's emphasis on social and teaching presence. EdTech tools are ecosystems that allow access, agency, aspiration, and technical fixes.

Still, inclusive adoption is hampered by differences in infrastructure and parental impressions. Parents voiced worries about screen time, lack of teacher interaction, and learning depersonalization—problems related to the dimension of emotional engagement. Furthermore, underscoring the importance of legislative initiatives and localized solutions, digital illiteracy and inadequate rural connections impair social presence and community support.

This study validates that EdTech platforms substantially influence student engagement, particularly when elements of gamification, goal orientation (entrepreneurial aspirations), and accessibility are present. However, AI-driven personalization is still developing, and its integration with self-determined learning environments remains a work in progress. By applying frameworks like SDT, CoI, and engagement theories, this study provides a nuanced understanding of how digital tools can cultivate motivation, deepen learning, and foster future-oriented educational experiences in the Indian context.

Conclusion

This study explored the dynamic relationship between EdTech platforms, e-learning, and entrepreneurship, specifically focusing on student engagement in the digital age of Indian education. Grounded in theoretical perspectives such as Self-Determination Theory (SDT), the Community of Inquiry (CoI) framework, and the three-dimensional model of engagement (behavioral, emotional, cognitive), the research combined quantitative and qualitative methodologies to investigate how technology-enabled learning platforms influence students' academic behavior and aspirations.

The findings demonstrate that entrepreneurial aspirations and learning outcomes showed significant positive associations with engagement, suggesting that students who perceive education as a gateway to future goals tend to engage more deeply with digital content. While AI-driven personalization holds conceptual promise, it remains underutilized and underdeveloped in the Indian EdTech space due to limitations in contextual adaptability, real-time learning support, and regional customization. However, digital accessibility emerged as a foundational engagement enabler, especially in semi-urban and rural contexts.

Although the study surveyed a broad range of students and EdTech stakeholders, the data were limited to a specific demographic spread, with underrepresentation from tribal and highly marginalized rural communities. The evaluation of AI-driven personalization was based more on perception and self-reported data rather than objective usage metrics or algorithmic evaluations.

Future research should conduct longitudinal analyses to assess the evolving nature of student engagement, learning outcomes, and entrepreneurial goals as EdTech platforms mature. There is also a need for systematic evaluations of government initiatives like PM Evidya, DIKSHA, and National Digital Education Architecture (NDEAR) to shape digital engagement outcomes.

References

Akyol, Z., Vaughan, N., & Garrison, D. R. (2011). *The impact of course duration on the development of a community of* inquiry. *Interactive Learning Environments*.

Anderson, T. (2017). *How communities of inquiry drive teaching and learning in the digital* age. In *Emerging Technologies in Distance Education*.

Arbaugh, J. B., Cleveland-Innes, M., Diaz, S., Garrison, D. R., Ice, P., Richardson, J. C., & Swan, K. P. (2008). *Developing a community of inquiry instrument: Testing a measure of the*

Community of Inquiry framework using a multi-institutional sample. *The Internet and Higher Education*.

Baker, J. D. (2010). *Instructor immediacy increases student enjoyment and perception of* learning. *Journal of Online Learning and Teaching*.

Banik, B. G., & Gullapelly, A. (2025). AI-powered gamification and interactive learning tools for enhancing student engagement. In *Driving Quality Education Through AI and Data Science* (pp. 283-310). IGI Global Scientific Publishing.

Bansal, A., Pophalkar, S., & Vidani, C. (2023). A review of the Ed-Tech sector in India. *International Journal of Management Analytics (IJMA)*, *1*(1), 63-84.

Bansal, S., Sharma, S., & Kapoor, S. (2023). *EdTech in India: Trends, challenges, and future* outlook. *Journal of Educational Technology*.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77-101.

Bond, M., Zawacki-Richter, O., & Nichols, M. (2019). Revisiting five decades of educational technology research: A content and authorship analysis of the British Journal of Educational Technology. *British Journal of Educational Technology*, *50*(1), 12-63.

Borup, J., West, R. E., Thomas, R., & Graham, C. R. (2014). *Examining the impact of video feedback on instructor social presence in blended* courses. *The International Review of Research in Open and Distributed Learning*.

Chiu, T. K. (2022). Applying the self-determination theory (SDT) to explain student engagement in online learning during the COVID-19 pandemic. *Journal of Research on Technology in Education*, *54*(sup1), S14-S30.

Dabral, S. (2023). Leveraging digital innovation for enhanced employee engagement: A theoretical exploration. *IITM Journal of Management and IT*, *14*(1 and 2), 50-55.

Davis, F. D. (1989). Technology acceptance model: TAM. *In Al-Suqri, M. N., & Al-Aufi, A. S. (Eds.), Information Seeking Behavior and Technology Adoption (pp. 205-219).*

D'Angelo, C. (2018). The impact of technology: Student engagement and success. Technology and the Curriculum: Summer 2018.

Datta, S. (2022). Evaluation and management of language and technology literacy barriers for accessing e-learning services in India. Embracing change in business, management & social sciences, 87.

Dichev, C., & Dicheva, D. (2017). Gamifying education: What is known, what is believed, and what remains uncertain: A critical review. International Journal of Educational Technology in Higher Education, 14, 1-36.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. Review of Educational Research, 74(1), 59-109.

Díaz, S. R., Swan, K., Ice, P., & Kupczynski, L. (2010). Student perceptions of the course and instructor in a blended learning environment. The Internet and Higher Education.

Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical inquiry in a text-based environment: Computer conferencing in higher education. The Internet and Higher Education, 2, 87-105.

Garrison, D. R. (2007). Online community of inquiry review: Social, cognitive, and teaching presence issues. Journal of Asynchronous Learning Networks.

Garrison, D. R., Anderson, T., & Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. American Journal of Distance Education.

Gupta, N., & Singh, O. P. An analysis of factors related to consumer active participation, brand engagement, and community trust in online food community platforms. IITM Journal of Business Studies (JBS), 97.

Pradhan, P., Mitra, P., Chowdhuri, S., Neogi, B., & Ghosh, S. S. (2021). Postpandemic EdTech (Educational Technology) on perspectives of green society. In Green Technological Innovation for Sustainable Smart Societies: Post Pandemic Era (pp. 39-66).

Gray, J. A., & DiLoreto, M. (2016). The effects of student engagement, student satisfaction, and perceived learning in online environments. International Journal of Educational Leadership Preparation, 11(1), n1.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43, 115-135.

Huang, R., Adarkwah, M. A., Liu, M., Hu, Y., Zhuang, R., & Chang, T. (2024). Digital pedagogy for sustainable education transformation: Enhancing learner-centred learning in the digital era. Frontiers of Digital Education, 1–16.

Iman, M. Z., Asis, A. A., & Rahma, A. U. Z. (2024). Enhancing personalised learning: The impact of artificial intelligence in education. Edu Spectrum: Journal of Multidimensional Education, 1(2), 101-112.

Lim, W. M. (2024). What is qualitative research? An overview and guidelines. Australasian Marketing Journal, 14413582241264619.

Lowenthal, P. R., & Dunlap, J. C. (2018). Investigating students' perceptions of instructional strategies to establish social presence. Distance Education.

Liñán, F., & Chen, Y. W. (2009). Development and cross–cultural application of a specific instrument to measure entrepreneurial intentions. Entrepreneurship Theory and Practice, 33(3), 593-617.

McAbee, S. T., Landis, R. S., & Burke, M. I. (2017). Inductive reasoning: The promise of big data. Human Resource Management Review, 27(2), 277–290.

Pentaraki, A., & Burkholder, G. J. (2017). Emerging evidence regarding the roles of emotional, behavioural, and cognitive aspects of student engagement in the online classroom. European Journal of Open, Distance and E-Learning, 20(1), 1-21.

Rane, N., Choudhary, S., & Rane, J. (2023). Education 4.0 and 5.0: Integrating artificial intelligence (AI) for personalised and adaptive learning.

Rai, K., & Sharma, M. (2024). Antecedents of AI-driven accounting system usage and its impact on SMEs performance: In the context of Industry 4.0 of India. IITM Journal of Business Studies, 12(1), 93-112.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68.

Richardson, J. C., Maeda, Y., Swan, K., & Ice, P. (2017). Social presence in online learning: A review of research. Distance Education.

Sharieff, M. H., & Suresh, V. G. (2021). EdTech startup and educational transformation ecosystem in India. 3D: IBA Journal of Management & Leadership, 12(2).

Shea, P., & Bidjerano, T. (2009). Community of inquiry as a theoretical framework to foster "epistemic engagement" and "cognitive presence" *in online education. Computers & Education, 52(3), 543-553.*

Shrivastava, S. K., & Shrivastava, C. (2022). The impact of digitalization in higher educational institutions. International Journal of Soft Computing and Engineering, 11(2), 7-11.

Schunk, D. H. (1994). Self-regulation of self-efficacy and attributions in academic settings. In D. Schunk & B. J. Zimmerman (Eds.), Self-Regulation of Learning and Performance.

Stenbom, S. (2018). A systematic review of the Community of Inquiry survey. The Internet and Higher Education, 39, 22-32.

Straker, L., Zabatiero, J., Danby, S., Thorpe, K., & Edwards, S. (2018). Conflicting guidelines on young children's screen time and use of digital technology create policy and practice dilemmas. The Journal of Paediatrics, 202, 300-303.

Swan, K., Garrison, D. R., & Richardson, J. (2014). A constructivist approach to online learning: The Community of Inquiry framework. In Emerging Technologies in Distance Education.

Thakur, M., Yadav, M., & Dutta, M. (2022). A study of grievance handling and its impact on consumer perception: The case of Uber & Ola. IITM Journal of Business Studies (JBS), 20.

Veletsianos, G. (2020). Learning online: The student experience. JHU Press.

Vo, H., & Ho, H. (2024). Online learning environment and student engagement: The mediating role of expectancy and task value beliefs. The Australian Educational Researcher, 1–25.

Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.

Wang, M. T., Henry, D. A., & Degol, J. L. (2020). A development-in-sociocultural-context perspective on the multiple pathways to youth's engagement in learning. In Advances in Motivation Science (Vol. 7, pp. 113-160). Elsevier.

Williamson, B. (2019). New power networks in educational technology. Learning, Media and Technology, 44(4), 395–398.

Yaseen, H., Mohammad, A. S., Ashal, N., Abusaimeh, H., Ali, A., & Sharabati, A. A. A. (2025). The impact of adaptive learning technologies, personalised feedback, and interactive AI tools on student engagement: The moderating role of digital literacy. Sustainability, 17(3), 1133.

Yeung, K. L., Carpenter, S. K., & Corral, D. (2021). A comprehensive review of educational technology on objective learning outcomes in academic contexts. Educational Psychology Review, 1–48.

Yeung, W. L., & Ng, O. L. (2023). Characterizing touchscreen actions in technology-enhanced embodied learning for mathematics instruction in K-12 settings: A systematic review (2010–2023). Computers & Education, 205, 104881.

Zainuddin, Z., Shujahat, M., Haruna, H., & Chu, S. K. W. (2020). The role of gamified e-quizzes on student learning and engagement: An interactive gamification solution for a formative assessment system. Computers & Education, 145, 103729.