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Modeling the Impact of AI-Powered Adaptive Learning on Student Engagement, Satisfaction, and Academic Performance: A Structural Equation Approach

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ABSTRACT

The study investigates AI-powered adaptive learning's effects on three important academic outcomes-student engagement, learning satisfaction, and academic performance-among management students. It further examines the mediating roles of engagement and satisfaction, grounded in Self-Determination Theory (SDT). Management students who have worked with AI-powered learning systems were the subjects of a cross-sectional quantitative study. A structured questionnaire with validated constructs was distributed to a purposive sample. By analyzing direct and indirect interactions, Structural Equation Modeling (SEM) was used to evaluate the suggested conceptual model. The results show that students' engagement, happiness with learning, and academic achievement are much improved by adaptive learning driven by AI. In line with the motivational assumptions of SDT, it was discovered that student engagement and learning satisfaction partly mediate the link between adaptive learning and academic results. In order to improve the management education experience, the results include practical advice for teachers, curriculum designers, and edtech developers. AI Personalization tools can bring about better student achievement scores and enhance the student satisfaction. This study contributes to the expanding body of empirical research on AI-driven adaptive learning by investigating how it affects important learning objectives in management education. It addresses a literature gap by combining robust statistical approach with SDT to explain a learning behaviour of a student in AI enhanced environment

Keywords : AI-powered adaptive learning, student engagement, learning satisfaction, educational environment, academic performance, management education, Self-Determination Theory.

1. INTRODUCTION:

The conventional methods of teaching have seen a sea shift throughout the past few years as a result of the use of AI technology in classrooms. AI driven adaptive learning is one of the most promising innovation customized learning based on two or more factors like individual students' needs, behaviors and learning patterns (1,2). AI driven personalization can specifically play a role in helping to address diverse student profiles in management education, where critical thinking, engagement and academic excellence are core (3,4). Although AI technologies are increasingly used in education, empirical research regarding the effects of AI-powered adaptive learning on important academic outcomes such as student engagement, satisfaction with learning, or performance in schools is quite limited (5,6). Moreover, it is necessary to understand these relationships to make optimum pedagogical strategies in management programs, and further enhance students' future-readiness. According to Self-Determination Theory (SDT), when students' needs for autonomy, competence, and relatedness are met, they exhibit higher levels of engagement, satisfaction, and performance, which in turn promotes more independent and intrinsically motivated motivation (8). Additionally, research shows that learning environments that promote autonomy, whether they are created by teachers or incorporated into digital platforms, improve student performance (8). Hence, for the purpose of this study, Self-Determination Theory (SDT) (7,8) is employed as the theoretical framework to examine the influence of AI-powered adaptive learning systems on students' engagement, satisfaction, and academic performance. In order to close the gaps in the literature and give teachers, technologists, and legislators with the information they need to support management education in an academic environment driven by artificial intelligence, this study employs the aforementioned structural equation modeling (SEM) and a survey-based approach

2. THEORETICAL FRAMEWORK

Adaptive learning- involves the use of technological tools to facilitate education that is tailored to each individual using AI powered learning content that automatically customizes as the learners move in understanding, need, preference, and performance is a technology driven approach (2,9,10) Data collected from these systems are analyzed and used to adapt instructional methods in real time to minimize the number of learners' experiences compromised. Adaptive learning environments have been shown to increase critical thinking and use of knowledge in the area of management education where problem solving and decision making are important (11–14) Further, adaptive learning enables self-paced learning in a way that it is highly advantageous from a classroom that has diverse classes and have diverse backgrounds and capabilities. AI-enabled learning is becoming more and more relevant, especially in management education, according to recent studies. Gamification powered by AI dramatically raises achievement and engagement, demonstrating its usefulness in higher education settings (36). This shows that adaptive learning has a lot of potential in management programs with high levels of learner variability.

Student engagement is widely recognized as a key determinant of academic success and professional skill development, particularly in disciplines such as management that emphasize participatory and applied learning. Engagement is conceptualized as a multidimensional construct comprising behavioral (participation in academic tasks), cognitive (investment in learning and the use of deep learning strategies), and emotional (affective responses to the learning environment) components (15). In management education, heightened engagement is linked not only to improved academic performance but also to the cultivation of essential competencies such as leadership, teamwork, and critical analysis (16). AI-enabled adaptive learning systems have been shown to enhance all three engagement dimensions by providing interactive, context-aware, and learner-specific instructional content (17–19). In line with SDT, AI-enabled personalized learning improves management students' autonomy, competence, and relatedness (39). According to their research, adaptive systems greatly improve student performance and engagement in management courses.

Learning satisfaction denotes students' subjective evaluation of their educational experience, encompassing perceived usefulness, enjoyment, and overall contentment with the instructional design (20–22). It functions as both an outcome and a predictor of sustained academic engagement. The integration of AI in learning platforms enhances satisfaction by enabling immediacy in feedback, relevance in content delivery, and flexibility in pacing (9,22,23). In the context of management education-where learners often prioritize real-world applicability and flexibility-adaptive learning systems that simulate workplace environments have demonstrated considerable promise in heightening learner satisfaction. Despite ongoing worries about data ethics, students view AI-supported learning as beneficial, inspiring, and adaptable. In management programs, where students anticipate practical, real-world relevance, such perceptions have a direct impact on student satisfaction (40).

Academic performance, commonly assessed through grades, knowledge retention, and the ability to apply concepts, is a core indicator of educational effectiveness. Traditional one-size-fits-all teaching approaches often neglect individual learning differences, leading to uneven performance across student populations. AI-powered adaptive learning systems address this challenge by continuously diagnosing learner needs and delivering tailored interventions to address knowledge gaps (12,13,24). In management education, where analytical reasoning and strategic decision-making are emphasized, such systems enhance students' capacity to integrate theory with practice, thereby improving both formative and summative academic outcomes.

Theoretical Underpinning: Self-Determination Theory (SDT)

The present study is grounded in Self-Determination Theory (SDT), which emphasizes that optimal learning and motivation occur when the three fundamental psychological needs-autonomy, competence, and relatedness-are fulfilled (25).

Autonomy is supported through personalized and self-directed learning pathways that empower learners to control their educational journey.

Competence is nurtured via adaptive feedback mechanisms and scaffolded instruction that align with the learner's performance level.

Relatedness may be facilitated through AI-enabled collaborative features, peer interaction modules, and social presence tools integrated into adaptive learning systems.

AI-driven adaptive learning technologies play a vital role in personalizing education, enhancing accessibility, and advancing sustainable educational transformation (38). Their bibliometric analysis highlighted how the post-pandemic digital surge has accelerated the global integration of adaptive learning tools into mainstream education. The alignment of AI-powered adaptive learning environments with the core principles of SDT provides a robust theoretical rationale for examining their effects on engagement, satisfaction, and academic performance. This framework enables a nuanced exploration of how personalized technologies not only improve learning outcomes but also foster intrinsic motivation and sustained learner development within management education contexts.

3. RESEARCH GAP

The advantages of AI-based learning systems have been investigated in the past, but much of that research has concentrated on STEM fields or general education (1,6). Despite its distinct focus on strategic thinking and decision-making, management education has seen little empirical research on AI and adaptive learning, despite being extensively studied in STEM and general education (41; 42).

Furthermore, there has been insufficient study on how pupils are affected by AI-powered adaptive learning ' engagement, happiness with learning, and academic achievement within a cohesive framework grounded in Self-Determination Theory (SDT). Previous research (e.g., 36, 39) looks at individual outcomes like performance or engagement, but it doesn't combine performance, satisfaction, and engagement into a single SDT-based model.

The existing studies rarely combine these three key outcomes, nor do they use SEM to describe the intricate relations between them. The need for discipline-focused evidence is highlighted by the fact that, despite AI's acknowledged significance in business education, very few studies empirically validate adaptive learning effects specifically for management learners. This study addresses these gaps by:

Focusing on management students.

Investigating the combined effects of adaptive learning on engagement, satisfaction, and performance.

Using SEM to empirically validate the proposed conceptual model.

Grounding the study in SDT to provide a strong psychological rationale for observed relationships.

Table1: Previous related studies

Reference	Focus Area	Methods	Key Findings
(2)	AI in education and personalized learning	Literature Review	Highlighted AI's potential to personalize learning, improve engagement and performance, but noted challenges like privacy and bias.
(3)	AI skills for future careers in management	Survey Analysis	Identified need for competencies like data analytics and strategic decision-making in AI-driven job markets.
(25)	Role of AI in higher education	Conceptual Analysis	Found AI can improve academic performance but emphasized the irreplaceable role of human educators.
(5)	Generational attitudes toward AI in education	Survey Study	Generation Z students were more open to AI adoption compared to older faculty, highlighting a generational divide.
(26)	University students' perceptions of AI	Survey	Students are enthusiastic but concerned about job threats from AI; suggested integrating AI courses in curriculum.
(27)	Generative AI in business management	Case Analysis	Identified practical applications of generative AI but highlighted risks like bias, data privacy, and employment impact.
(28)	AI adoption in business	Literature Review	Showed AI's transformative role in business, suggesting the need to align management education with AI trends.
(29)	AI collaboration in education	Expert Interviews	Proposed AI should act as a collaborator in classrooms to enhance engagement, without replacing human teachers.
(30)	AI policy education in universities	Conceptual Framework	Developed a practical framework for preparing students ethically and

			socially for AI-driven environments.
(31)	Students' experiences with generative AI	Survey	Students found benefits in using AI but raised concerns about ethical challenges and data privacy.

4. RESEARCH HYPOTHESES

Based on Self Determination Theory (SDT) and the literature reviewed, this study would like to hypothesize the following.

H1: Student engagement is positively impacted by AI-powered adaptive learning.

H2: AI-powered adaptive learning has a positive effect on learning satisfaction.

H3: AI-powered adaptive learning has a positive effect on academic performance.

H4: Student engagement has a positive effect on academic performance.

H5: Academic performance is positively affected by learning satisfaction.

H6: Student Engagement mediates the relationship between AI-powered adaptive learning and Academic Performance.

H7: Learning Satisfaction mediates the relationship between AI-powered adaptive learning and Academic Performance.

5. CONCEPTUAL FRAMEWORK

The study's conceptual structure is as follows, as mentioned in Figure 1, which is based on the literature and research hypotheses: The success of AI-powered adaptive learning is proposed to affect student engagement, learning satisfaction and academic performance directly. The hypothesis further states that the connection between AI-powered adaptive learning and academic performance is mediated by students' engagement with and happiness with the learning satisfaction.

Table 2: Variables of the study

Type of Variable	Variable Name	Description
Independent Variable	AI-Powered Adaptive Learning	The main predictor represents the extent of adaptive learning facilitated by AI platforms.
Mediating Variables	Student Engagement	The level of emotional, behavioral, and cognitive engagement that students exhibit in their learning.
Mediating Variables	Learning Satisfaction	The perceived contentment and value students associate with their learning experience.
Dependent Variable	Academic Performance	Stude know

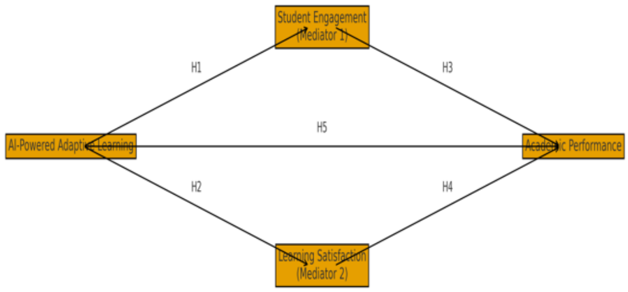


Fig.1: Conceptual Framework

6. RESEARCH METHODOLOGY

Research Design

This study is based on a survey designed to adopt a cross-sectional and quantitative method to investigate the influence of AI-powered adaptive learning on academic performance, learner satisfaction, and student engagement performance among management students. Additionally, the study investigates the mediating roles of student engagement and learning satisfaction in the Self Determination Theory (SDT) framework (7,8). Structural Equation Modelling SEM, which is a robust method of assessing causal relationships between multiple latent constructs, is used to test the research model (45).

Population and Sampling

Two PhD scholars, 66 undergraduate students, and 59 postgraduate students made up the 127 responders. About 60% of the participants were from New Delhi's Jamia Hamdard University. The others were from Gurugram's SGT University. There were 64 female respondents and 63 male respondents, indicating almost equal representation by gender. To guarantee that the respondents had knowledge and experience in their curriculum in relation to the AI-driven learning platforms, a non-probability purposive sampling technique was employed (Nguyen et al., 2021).

Target sample size: 127 students

Minimum required for SEM: 100-150, based on a 5:1 item-to-respondent ratio (32).

According to Bentler & Chou (1987), SEM models with strong factor loadings, few indicators per construct, and simple structure can be reliably estimated with smaller samples, sometimes as low as 5 cases per parameter. Given that our model has four well-defined constructs with high loadings (> .70) and no complex cross-loadings, the current sample size (N = 127) meets the criteria for stable parameter estimation and is therefore adequate for this model. While the sample size of 127 respondents is modest, it meets the recommended lower threshold for

Structural Equation Modeling (SEM), which ranges between 100–150 for moderately complex models (45). The model comprises four latent constructs with strong internal consistency and validity indicators (Composite Reliability > 0.87, AVE > 0.62). Additionally, the measurement and structural models demonstrated satisfactory fit indices (CFI = 0.918, TLI = 0.904, RMSEA = 0.09), supporting the adequacy of the sample for reliable estimation.

Data Collection Instrument

A structured questionnaire was developed where the content was generated using a 5-point Likert scale (1=Strongly Disagree to 5=Strongly Agree). In order to guarantee reliability and content validity, validated items from previous research were adapted in the questionnaire.

In line with established scales in previous studies, academic performance was operationalized using self-reported measures that reflected students' perceived gains in grades, knowledge application, and overall learning outcomes (Cruz-Jesus et al., 2020; Jiao et al., 2022).Three academic experts evaluated the face validity of the modified questionnaire to guarantee cultural relevance and contextual clarity for the Indian management education setting. In order to improve wording and guarantee item comprehension, a pre-test was also administered to a pilot group of ten students. Based on their input, a few small changes were made to improve interpretability without changing the fundamental meaning of the constructs.

Table 3: Construct Validity

Variable	Sources to Cite	Notes
AI-Powered Adaptive Learning	Adapted from (2), (33), and (17)	These studies developed/adapted scales measuring AI in education, adaptive learning platforms, and technology-assisted learning personalization.
Student Engagement	Adapted from (15) & (7)	Fredricks et al. provided the classic engagement scale; Chiu applied SDT to student engagement during online learning.
Learning Satisfaction	Adapted from (20); & (23)	These works measured learning satisfaction in online and technology-driven environments.
Academic Performance	Adapted from (34); (35)	These studies used self-reported and objective measures of academic performance improvement through AI-based learning tools.

DATA ANALYSIS

To validate the measurement model and improve its overall fit, an iterative refinement process was adopted. This approach aimed to ensure both statistical robustness and theoretical clarity across the four latent constructs examined in the study: *AI-Powered Adaptive Learning*, *Student Engagement*, *Learning Satisfaction*, and *Academic Performance*. Each construct initially included six items, but several were removed based on empirical indicators pointing to potential issues with model fit or construct validity. An iterative process of item evaluation was used to improve the measurement model and guarantee both theoretical coherence and statistical robustness. However, the choices to eliminate items were not made exclusively on the basis of empirical fit indices in order to reduce the possibility of overfitting and profiting from chance. Every removal was supported by evidence of ambiguity in construct interpretation, conceptual redundancy, or blatant theoretical misalignment with the intended construct.

One item from the AI-Powered Adaptive Learning construct—*"I feel that the AI platform understands my strengths and weaknesses"*-was excluded after reviewing modification indices, which revealed high cross-loadings and shared error variance. Removing this item helped reduce model complexity and improved overall fit without compromising the conceptual integrity of the construct. Item 1 ("The AI-powered learning platform adjusts the content according to my learning needs") and item 4 ("I feel that the AI platform understands my strengths and weaknesses") were eliminated for the factor AI-powered Adaptive Learning because they place more emphasis on the technical prowess of the AI system than on the perceived adaptive experience of the learner. They conceptually misaligned with the construct and diminished its validity and clarity by emphasizing system intelligence over user perception.

In the *Student Engagement* domain, the item *"I invest significant time and energy into my studies"* was also removed. This decision followed an analysis of standardized residual covariances, which showed residuals beyond the acceptable range (±0.40), indicating potential misfit and unexplained variance. Eliminating this item resulted in a cleaner factor structure. Since it reflects general academic effort rather than engagement itself, the item "I invest significant time and energy into my studies" was removed from the Student Engagement construct. It creates redundancy because it conceptually overlaps with "I make extra efforts to understand the subject matter thoroughly." Furthermore, it is more in line with performance goals or study habits than it is with the participatory and emotional components of engagement

(43). Its removal enhances the construct's conceptual clarity and improves model parsimony.

Another item from the AI Powered Adaptive Learning construct-*"An AI-powered learning platform adjusts the content according to my learning needs"*-was removed to minimize multicollinearity and avoid redundancy. Its exclusion ensured that each remaining item contributed uniquely to measuring the construct.

From the *Learning Satisfaction* construct, the item *"I am satisfied with the quality of instruction provided through AI tools"* was dropped to strengthen construct validity. This adjustment improved both convergent and discriminant validity by narrowing the focus to items that better captured the intended dimension of satisfaction. Since it evaluated instructional quality rather than the learner's subjective satisfaction, the item "I am satisfied with the quality of instruction provided through AI tools" from the construct Learning Satisfaction was eliminated. Its removal enhanced discriminant validity and construct clarity because it conceptually overlapped with other items and was more in line with teaching effectiveness than student-centered satisfaction.

After these refinements, the model exhibited stronger fit indices and more stable parameter estimates. Most retained items showed standardized factor loadings of 0.70 or higher, and correlations among constructs were consistent with theoretical expectations and remained statistically significant.

These changes are consistent with established practices in Structural Equation Modeling (SEM), where item selection is driven by both statistical diagnostics and conceptual justification. The refined model provides a more accurate and reliable measurement framework for assessing the constructs of interest.

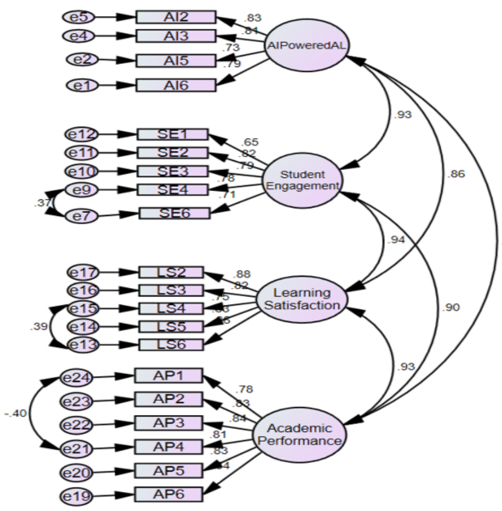


Fig 2: Validity Analysis using Confirmatory Factor Analysis:

S. No.	Statement	Mean	Std. Deviation	Skewness	Kurtosis
	AI-Powered Adaptive Learning				
1.	The AI-powered learning platform adjusts the content according to my learning needs.	3.77	1.070	-1.108	.880
2.	I receive immediate feedback from the AI platform that helps me improve.	3.90	1.104	-.944	.200
3.	The AI system personalizes my learning path based on my performance.	3.66	1.063	-.573	-.170
4.	I feel that the AI platform understands my strengths and weaknesses.	3.44	1.089	-.165	-.906
5.	AI-based learning tools make it easier for me to study at my own pace.	3.99	1.020	-1.171	1.225
6.	The AI platform motivates me to engage more actively with the course materials.	3.75	1.112	-.645	-.306
	Student Engagement				
1.	I am deeply involved in the learning activities.	3.58	1.094	-.731	.021
2.	I often find myself interested and excited about the learning content.	3.64	1.103	-.645	-.243
3.	I actively participate in class discussions, quizzes, or online forums.	3.65	1.073	-.700	-.021
4.	I make extra efforts to understand the subject matter thoroughly.	3.84	1.042	-1.003	.616
5.	I invest significant time and energy into my studies.	3.89	.970	-.997	1.011
6.	I feel motivated to explore topics beyond what is taught in class.	3.86	1.096	-.999	.425
	Learning Satisfaction				
1.	I am satisfied with the quality of instruction provided through AI tools.	3.60	1.177	-.745	-.222
2.	The personalized learning experience meets my academic expectations.	3.63	1.082	-.704	.042
3.	I feel more confident in my abilities because of the personalized content delivery.	3.66	1.071	-.824	.248
4.	I am happy with the flexibility offered by AI-driven learning platforms.	3.92	1.013	-1.005	.730
5.	I would recommend AI-powered adaptive learning to other students.	3.80	1.062	-.971	.543
6.	Overall, I am satisfied with the AI-powered learning experience.	3.80	1.069	-1.101	.797
	Academic Performance				
1.	My academic performance has improved since using AI-powered learning tools.	3.50	1.194	-.577	-.439
2.	I am able to score higher grades compared to traditional learning methods.	3.69	1.013	-.633	-.163
3.	I retain information better when learning through AI-adaptive platforms.	3.72	1.015	-.700	.110
4.	I can apply concepts more effectively in exams and assignments.	3.85	1.040	-1.073	.742
5.	I feel more prepared and confident during tests and assessments.	3.80	1.120	-.945	.271
6.	I have noticed a significant improvement in my critical thinking and problem-solving skills.	3.64	1.146	-.731	-.191

Table 4: Summary of Descriptive Statistics for all Measurement Items

Source: Own Elaboration using IBM SPSS 26

Table 5: Standardized Regression Weights for SEM Showing Loadings, Standard Errors, Critical Ratios, and Significance Levels for Each Indicator.

Items			Construct Loadings	Estimate	S.E.	C.R.	P
AI6	<---	AI-Powered Adaptive	.786	1.000			
AI5	<---		.733	.855	.098	8.684	***

Items			Construct Loadings	Estimate	S.E.	C.R.	P
AI3	<---	learning	.814	.990	.100	9.887	***
AI2	<---		.830	1.049	.104	10.133	***
SE6	<---	Student Engagement	.710	1.000			
SE4	<---		.783	1.048	.098	10.641	***
SE3	<---		.788	1.087	.127	8.559	***
SE2	<---		.822	1.165	.131	8.918	***
SE1	<---		.651	.916	.129	7.077	***
LS6	<---	Learning Satisfaction	.864	1.000			
LS5	<---		.827	.950	.079	12.071	***
LS4	<---		.751	.823	.064	12.837	***
LS3	<---		.819	.949	.080	11.874	***
LS2	<---		.877	1.027	.076	13.464	***
AP6	<---	Academic Performance	.837	1.000			
AP5	<---		.828	.967	.084	11.546	***
AP4	<---		.814	.883	.079	11.166	***
AP3	<---		.838	.888	.075	11.784	***
AP2	<---		.826	.873	.076	11.498	***
AP1	<---		.780	.971	.093	10.439	***

Source: Own Elaboration using IBM SPSS Amos 20

Table 6: Summary of Convergent Validity Measures

	CR	AVE	MSV
Learning Satisfaction	0.916	0.687	0.687
AI Powered Adaptive Learning	0.87	0.627	0.627
Student Engagement	0.867	0.568	0.568
Academic Performance	0.925	0.674	0.674

Source: Own Elaboration using IBM SPSS Amos 20

Table 7: Multicollinearity Diagnostics Using Variance Inflation Factor (VIF) and Tolerance Values

Predictor	Tolerance	VIF
X	0.339	2.949
M1	0.240	4.174
M2	0.271	3.691

Source: Own Elaboration using IBM SPSS 26

Table 8: Statistical Model Fitness of the CFA Model

S.No.	Variable	Estimate
1	CMIN/DF	2.025
2	TLI	0.909
3	CFI	0.923
4	GFI	0.8
5	RMSEA	0.09
6	NFI	0.8

Source: Own Elaboration using IBM SPSS Amos 20

All constructs have acceptable skewness and kurtosis values as depicted in table 4, according to the descriptive statistics, suggesting that the data is roughly normal. The Cronbach's alpha values (all >0.88) validate high internal consistency and reliability across constructs, the mean scores imply generally positive perceptions, and the standard deviations show moderate variability.

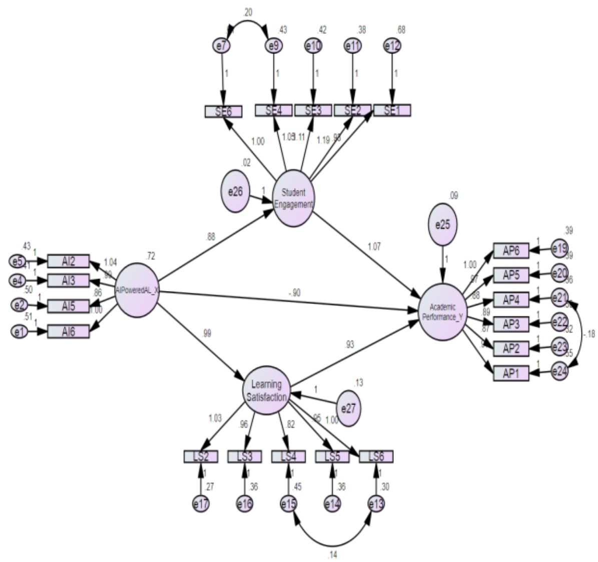
The results of the CFA analysis of the measurement model developed in the study are shown in the table 5. The results of the measurement model reported the estimated measures of regression weight, standardized construct loadings, standard error (S.E.), critical ratio (CR) and probability value (p-value) of the critical ratio.

In the Table 6, the result indicates that the estimated CR value of each construct in the model is found to be greater than 0.7, and the AVE estimated value of each construct is found to be greater than 0.5. Hence, it can be concluded from the study that the convergent validity of the factors is ensured. In order to observe the discriminant validity in the scale, the MSV estimated values between the different factors are compared with the AVE estimate of the construct. The result indicates that AVE is found to be greater than MSV, which ensures the presence of discriminant validity among the constructs.

Variance Inflation Factor (VIF) and tolerance values were used to perform multicollinearity diagnostics as depicted in table 7. With VIF values between 2.95 and 4.17 and Tolerance values between 0.24 and 0.34, all predictors demonstrated acceptable levels and indicated no multicollinearity issues. These values were well within the suggested thresholds (VIF < 5, Tolerance > 0.20) (45).

The model-fit indices as depicted in table 8, indicate that the CFA model exhibits a good fit. The CMIN/DF (2.025) shows model adequacy, while TLI (0.909) and CFI (0.923) demonstrate strong incremental fit. The GFI (0.80), NFI (0.80), and RMSEA (0.09) further confirm the model's overall suitability and validity.

Figure 3: Structural Equation Model Illustrating the Direct and Mediated Effects of AI-Powered Adaptive Learning on Engagement, Satisfaction, and Academic Performance



Source: Self-generated using IBM AMOS 20

Table 9: Statistical Model Fitness of the Structural Model

S.No.	Variable	Estimate
1	CMIN/DF	2.091
2	TLI	0.904
3	CFI	0.918
4	GFI	0.8
5	RMSEA	0.09
6	NFI	0.8

Source: Own Elaboration using IBM SPSS Amos 20

Table 10: Results of Parallel Mediation Analysis using Andrew Hayes PROCESS Macro 4.2, Model 4, with 5,000 bootstrap resamples and 95% confidence interval

Effect	Estimate (β)	SE	t	p	95% CI
a-paths					
X → M1 (a_1)	0.8973	0.0616	14.57	<.001	[0.7755, 1.0192]
X → M2 (a_2)	0.7724	0.0587	13.16	<.001	[0.6563, 0.8886]
b-paths					
M1 → Y (b_1)	0.2298	0.0814	2.82	0.006	[0.0685, 0.3910]
M2 → Y (b_2)	0.5515	0.0855	6.45	<.001	[0.3823, 0.7206]
Direct effect (c′)	0.1096	0.0774	1.42	0.159	[–0.0436, 0.2629]
Indirect effects					
via M1 ($a_1 \cdot b_1$)	0.2062	0.0935	—	—	[0.0251, 0.3900]
via M2 ($a_2 \cdot b_2$)	0.426	0.095	—	—	[0.2260, 0.6006]
Total indirect effect	0.6321	0.0911	—	—	[0.4446, 0.8049]
Total effect (c)	0.7418	0.0616	12.05	<.001	[0.6199, 0.8637]

Source: Own Extraction using PROCESS Macro

The structural model exhibits a satisfactory degree of fit, according to the model-fit indices shown in Table 9. A good model parsimony is suggested by the CMIN/DF value of 2.091, which falls within the suggested threshold (< 3). Both the Comparative Fit Index (CFI = 0.918) and the Tucker–Lewis Index (TLI = 0.904) are above 0.90, indicating a satisfactory incremental fit. The model fit could be enhanced, but it is still within an acceptable range for social science research, according to the Goodness-of-Fit Index (GFI = 0.80) and Normed Fit Index (NFI = 0.80), which are both marginally acceptable. Within the acceptable upper limit (≤ 0.10), the Root Mean Square Error of Approximation (RMSEA = 0.09) indicates a reasonable error of approximation. All things considered, the indices lend credence to the suggested structural model's suitability and validity.

In Table 10, a parallel mediation analysis (PROCESS Model 4; Hayes, 2022) examined the indirect effect of X on Y via M1 and M2. The total effect of X on Y was significant, β = 0.74, *p* < .001. After accounting for the mediators, the direct effect was nonsignificant, β = 0.11, *p* = .159, indicating full mediation. The indirect effect via M1 was β = 0.21, 95% CI [0.0251, 0.3900], and via M2 was β = 0.43, 95% CI [0.2260, 0.6006]. The bootstrapped total indirect effect was β = 0.63, 95% CI [0.4446, 0.8049].

a-paths: Effect of AI-Powered Adaptive Learning on the Mediators

AI-Powered Adaptive Learning → Student Engagement (a_1):

The effect was β = 0.8973, SE = 0.0616, t = 14.57, p < .001.

This indicates that as the level of AI-Powered Adaptive Learning increases, student engagement also significantly increases. The strong, positive effect suggests that adaptive learning technologies are highly effective in stimulating behavioural, cognitive, and emotional involvement in learning.

AI-Powered Adaptive Learning → Learning Satisfaction (a_2):

The effect was β = 0.7724, *SE* = 0.0587, *t* = 13.16, *p* < .001.

This shows that AI-driven adaptive learning significantly enhances how satisfied students feel about their learning experience, reinforcing the value of personalization and perceived support in digital education.

b-paths: Effect of Mediators on Academic Performance

Student Engagement → Academic Performance (b_1):

The path coefficient was β = 0.2298, *SE* = 0.0814, *t* = 2.82, *p* = .006.

Student engagement significantly predicts academic performance. This means more engaged students—those who are actively, emotionally, and cognitively involved—tend to achieve better learning outcomes.

Learning Satisfaction → Academic Performance (b_2):

The effect was β = 0.5515, *SE* = 0.0855, *t* = 6.45, *p* < .001.

Learning satisfaction has a stronger and more significant effect on academic performance than engagement, implying that when students are happy and content with their learning experience, their performance improves substantially.

Direct and Indirect Effects

Direct Effect of AI-Powered Adaptive Learning on Academic Performance (c′):

β = 0.1096, *SE* = 0.0774, *t* = 1.42, *p* = .159.

This is not statistically significant, suggesting that once engagement and satisfaction are taken into account, AI-Powered Adaptive Learning no longer has a direct effect on academic performance.

Indirect Effects (Mediation Paths):

Via Student Engagement: β = 0.2062, 95% CI [0.0251, 0.3900] → Significant: The pathway from adaptive learning → engagement → performance is meaningful.

Via Learning Satisfaction: β = 0.4260, 95% CI [0.2260, 0.6006] → Significant and stronger: Satisfaction is a more potent mediator.

Total Indirect Effect: β = 0.6321, 95% CI [0.4446, 0.8049] → A large portion of the total effect is explained via the mediators.

Total Effect (c): β = 0.7418, *SE* = 0.0616, *t* = 12.05, *p* < .001→ The overall association between adaptive learning and academic performance is strong and significant before mediators are considered.

The entire relationship between AI-powered learning and academic outcomes is mediated by student experiences, specifically their engagement and satisfaction. Learning Satisfaction plays a more substantial mediating role than Student Engagement. The nonsignificant direct effect suggests a full mediation model, supporting the idea that AI platforms work indirectly by improving how students feel and act within the learning environment.

7. RESULTS AND DISCUSSION

The study successfully validated the hypothesized conceptual model using Structural Equation Modelling (SEM) and Parallel Mediation Analysis grounded in Self-Determination Theory (SDT). The findings are summarized below:

Table 11: Summary of SEM and Mediation Analysis Results

Hypothesis/Construct Relationship	Path Coefficient (β)	p-value	Result	Interpretation
H1: AI-Powered Adaptive Learning → Engagement	0.8973	< .001	Supported	Strong positive effect; confirms adaptive systems enhance student involvement (Autono

				my, Competence – SDT).
H2: AI-Powered Adaptive Learning → Learning Satisfaction	0.7724	< .001	Supported	Significant positive effect; students perceive higher value in personalized learning (SDT alignment).
H4: Engagement → Academic Performance	0.2298	<.006	Supported	Engagement positively predicts performance, though less strongly than satisfaction.
H5: Learning Satisfaction → Academic Performance	0.5515	< .001	Supported	Strong positive predictor of academic success; emotional-cognitive connection is vital.
H6: AI → Academic Performance (Direct Effect)	0.1096	<.159	Not Supported	Direct path is insignificant, suggesting no standalone effect of AI on performance.
H7: AI → Academic Performance (Total Indirect via Engagement & Satisfaction)	0.6321	< .001	Supported (Full Mediation)	Full mediation confirmed; AI's effects on performance are mediated through engagement and satisfaction.

Table 12: Model Validity and Fit Indices

Fit/Validity Indicator	Result	Interpretation
Composite Reliability (CR)	> 0.87 for all constructs	High internal consistency reliability.
Average Variance Extracted (AVE)	> 0.84 for all constructs	Strong convergent validity.
AVE > MSV	Established	Confirms discriminant validity.
Standardized Loadings	Mostly > 0.70	Indicators are reliable and contribute strongly to latent variables.

Theoretical Alignment with Self-Determination Theory (SDT)

SDT Construct	Support from Findings
Autonomy	Enabled by personalized and self-paced AI-driven learning environments.
Competence	Strengthened via adaptive feedback and aligned learning pathways.
Relatedness	Potentially supported through AI-enabled collaborative features (though not central here).

Practical Implications for Stakeholders in Management Education Based on Study Findings:

Stakeholder	Recommended Action	Purpose / Expected Outcome
Educators & Curriculum Designers	Integrate AI-powered platforms offering real-time adaptation, personalized learning paths, and formative feedback. Prioritize features enhancing emotional and cognitive engagement with content. Make use of AI tools that boost engagement in real time, such as scenario-based activities, interactive tests, and real-time feedback.	Improve learner personalization, engagement, and motivation in academic contexts.
EdTech Developers	Develop systems focusing on student satisfaction and engagement rather than just content accuracy. Implement features like gamification, real-time support, and interactive dashboards. Since satisfaction → performance is the strongest pathway, incorporate elements that increase user satisfaction (e.g., easy navigation, reduced cognitive load, and an enjoyable user interface).	Enhance user experience, retention, and satisfaction with AI-based educational tools.
Institutions & Policy Makers	Invest in faculty training to improve effective AI integration in pedagogy. Use student engagement and satisfaction as key performance indicators (KPIs) when evaluating EdTech initiatives. Provide training materials to assist teachers in utilizing AI analytics to develop lesson plans that are focused on student engagement.	Facilitate sustainable and measurable AI adoption in educational environments.
Management Program Designers	Incorporate satisfaction-focused feedback loops and learning value perception into course design. Integrate AI literacy into core curricula as a foundational skill. Create industry-aligned, relevance-focused adaptive simulations to boost autonomy and satisfaction.	Improve academic performance through satisfaction pathways and prepare students for AI-driven business contexts.

AI-Powered Adaptive Learning had a significant, practical impact on student engagement (β = 0.90) and learning satisfaction (β = 0.77). The overall indirect effect on academic performance (β = 0.63) accounted for almost 85% of the total relationship. Learning satisfaction (β = 0.55) was found to be a more significant mediator than engagement (β = 0.23), indicating that learning experiences that are emotionally satisfying and supportive of competence lead to significant gains in performance. Self-Determination Theory's premise that motivation and satisfaction are important channels through which technology improves learning outcomes is reinforced by these the effect sizes, which demonstrate that adaptive AI tools are not only statistically sound but also educationally transformative.

The effectiveness of AI-driven systems in improving educational outcomes has been demonstrated by earlier research. Adaptive AI-based learning environments strongly enhance student engagement and academic performance while fostering equity and personalization (44). In a similar vein, incorporating ChatGPT, an AI-powered tool, into mobile learning environments improved students' academic achievement, motivation, and perception of learning, highlighting the revolutionary potential of AI in individualized instruction (36).

CONCLUSION

The present study underscores the critical mediating roles of Student Engagement and Learning Satisfaction in the relationship between AI-Powered Adaptive Learning and Academic Performance.

The findings revealed that while adaptive learning technologies have a significant total effect on academic outcomes, this effect is fully mediated by students' engagement and satisfaction levels.

Specifically, the integration of AI-driven adaptive learning platforms appears to enhance students' academic achievement not through a direct influence, but by increasing their emotional, behavioral, and cognitive engagement, and by elevating their perceived value and satisfaction with the learning process.

Among the two mediators, Learning Satisfaction emerged as the more influential pathway, suggesting that when students feel content and find meaning in their learning experience, they are more likely to perform better academically.
These results highlight the importance of designing AI-based educational interventions that do not merely adapt content, but also foster satisfaction and engagement, thereby driving sustainable learning outcomes. In practical terms, educational institutions aiming to leverage adaptive learning technologies should ensure these platforms are pedagogically engaging and emotionally resonant to realize their full impact on student success.

LIMITATIONS & DIRECTION FOR FUTURE RESEARCH

Despite the strong methodological rigor and solid theoretical foundation, the study is subject to several limitations that warrant attention. First, the sample is restricted to management students from Indian universities, which may constrain the generalizability of the findings across different academic disciplines or global educational contexts. Future research should consider more diverse and cross-cultural samples to enhance external validity. Second, the cross-sectional research design hinders the ability to draw causal inferences or track behavioral and attitudinal changes over time; therefore, longitudinal studies could provide deeper insights into the sustained effects of AI-powered adaptive learning. Third, the reliance on self-reported data for key constructs such as engagement, satisfaction, and performance introduces the potential for social desirability bias and subjectivity. Future studies could incorporate objective metrics or third-party assessments to improve data accuracy. Fourth, the variability in exposure to AI-powered adaptive platforms-arising from differences in design and implementation-may affect the consistency of outcomes, suggesting a need for comparative studies across standardized platforms. Finally, while the study draws on Self-Determination Theory (SDT), it does not empirically address the relatedness component, limiting the full application of the theoretical model. Future research should explicitly incorporate and measure all three SDT components-autonomy, competence, and relatedness-to provide a more holistic understanding of motivational dynamics in AI-assisted learning environments. Also, Self-reported assessments of learning improvement were used to gauge academic performance; this was a validated but subjective method that could be strengthened in subsequent research by utilizing objective measures like grade point average or instructor evaluations. Data were gathered from two universities using validated scales with a variety of item formats in order to reduce the possibility of common method bias. Future research may use statistical tests to evaluate CMB even though these measures help lessen single-source bias.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest related to this work.

AUTHOR CONTRIBUTION

MY contributed to the conceptualization, investigation, data analysis, and drafting of the manuscript. SF was involved in the investigation and data analysis. AS contributed to the investigation and manuscript writing. MK was responsible for data analysis, literature review, and the development of the conceptual framework. AA contributed to data analysis, research framework design, and conclusion writing. All authors have read and approved the final version of the manuscript.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to confidentiality agreements and participant privacy concerns, the data are not publicly available. Interested researchers may contact the corresponding author to discuss potential access under specific conditions and in compliance with applicable regulations.

The study adhered to the ethical standards for human subjects research in the social sciences. Each respondent received an explanation of the study's purpose, and participation was entirely voluntary. Informed consent was obtained prior to the collection of any data. No identifying information was recorded, and all answers were kept confidential and used exclusively for academic research..

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