AI-enabled personalized learning: empowering management students for improving engagement and academic performance

Adil Ellikkal and S. Rajamohan
Alagappa Institute of Management, Alagappa University, Karaikudi, India

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Abstract

Purpose – In today's highly competitive world, the purpose of this research is to emphasize the increasing significance of management education and advocate for the adoption of innovative teaching approaches, specifically focusing on artificial intelligence (AI)-driven personalized learning (PL). This study aims to explore the integration of self-determination theory (SDT) principles into management education, with a primary focus on enhancing student motivation, engagement and academic performance (AP).

Design/methodology/approach – This interdisciplinary research adopts a multifaceted approach, combining perspectives from AI, education and psychology. The design and methodology involve a thorough exploration of the theoretical foundations of both AI-driven education and SDT. The research demonstrates how these two elements can synergize to create a holistic educational experience. To substantiate the theoretical claims, empirical data-driven analyses are employed, showcasing the effectiveness of AI-enabled personalized learning (AIPL). The study integrates principles from SDT, such as autonomy, competence and relatedness, to create an environment where students are intrinsically motivated, receiving tailored instruction for optimal outcomes.

Findings – The study, rooted in SDT, demonstrates AIPL's transformative impact on management education. It positively influences students' autonomy, competence and relatedness, fostering engagement. Autonomy is a key driver, strongly linked to improved AP. The path analysis model validates these relationships, highlighting AI's pivotal role in reshaping educational experiences and intrinsically motivating students.

Practical implications – This study holds substantial significance for educators, policymakers and researchers. The findings indicate that the AIPL model is effective in increasing student interest and improving AP. Furthermore, this study offers practical guidance for implementing AI in management education to empower students, enhance engagement and align with SDT principles.

Originality/value – Contribute original insights through an interdisciplinary lens. Synthesize AI and SDT principles, providing a roadmap for a more effective educational experience. Empirical data-driven analyses enhance credibility, offering valuable contributions for educators and policymakers in the technology-influenced education landscape.

Keywords Academic performance, Self-determination theory, Management education, Educational technology, Students engagement, AI-enabled personalized learning

Paper type Research paper

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1. Introduction

The dynamic landscape of contemporary education is witnessing a transformative era driven by the convergence of advanced technologies and innovative teaching methods. The acceleration of technological progress has propelled artificial intelligence (AI) into various domains, and education stands as a prime sector for its transformative impact. It is in the area of teaching and learning that AI educational technologies are expected to have the most transformative impact (Rodway and Schepman, 2023). AI educational technologies are poised to revolutionize management education by empowering students with a powerful toolkit. This toolkit includes data-driven insights on market trends, personalized learning (PL) experiences through adaptive learning platforms, and innovative problem-solving methodologies powered by machine learning algorithms. These tools equip students to tackle complex business challenges effectively. Chatbots have been used for many different purposes in various felds, including marketing, customer service, tourism and education (Bhargava *et al.*, 2020; Casillo *et al.*, 2020; Rao *et al.*, 2020; Schmidlen *et al.*, 2019). In the field of economics and finance, ChatGPT can be used to advance research in a number of ways (M Alshater, 2022). AI can be used to create dynamic simulations and scenarios for economic and financial models. The potential of AI extends beyond classrooms, with AI poised to play a significant role in supporting students throughout their higher education journey.

Understanding the drivers behind academic performance (AP) is an everlasting global challenge that concerns students, their families and teachers, but also public decision-makers, and everyone concerned about development and wellbeing at a global level (Noell *et al.*, 2019; Valli Jayanthi *et al.*, 2014). This study highlights the convergence of AI and education as a critical turning point. This convergence has the potential to revolutionize the traditional "one-size-fits-all" pedagogical model. AI's ability to analyze vast amount of data and adapt instructional content in real-time paves the way for PL. This approach offers a promising solution by catering to the diverse learning styles, paces and preferences of management students. Furthermore, this study goes beyond just personalization. It aims to integrate the core tenets of self-determination theory (SDT)-autonomy, competence and relatedness-into the PL framework. By doing this, the study aims to create an environment that fosters intrinsic motivation. In this environment, students will not just receive tailored instruction; they will also find themselves naturally driven to learn, explore and excel. The potential of SDT to explain AI attitudes has been discussed, but there is a lack of research on the matter (Cascio and Montealegre, 2016).

The study aims to explore how AI-enabled personalized learning (AIPL) functions within management education, considering a blend of technology, psychology and education. In this context, AI represents the technological component, forming the basis for PL systems. SDT embodies the psychological aspect, focusing on students' intrinsic motivations and drivers for effective learning. The study also examines students' engagement and AP through an educational perspective. Investigating how customized educational approaches can improve student outcomes and create more effective learning environments. This interdisciplinary approach aims to uncover the interconnectedness among these dimensions and enhance our understanding of AI-driven PL in management education.

2. Review of literature

The integration of AI in education is gaining significant attention. AI holds the potential to revolutionize management education by facilitating PL, creating adaptive pathways, and provides educators with crucial data for improvement. This review of literature examines the current state of research on AIPL for management students, highlighting emerging trends, challenges and opportunities. Scholars like Tominc and Rožman (2023) have explored the impact of AI on management education, specifically focusing on how undergraduate (UG) and postgraduate (PG) students perceive the skills needed for future careers. They recognize the growing influence of AI in industries and the imperative to align education with these changes. Their findings underscore the emergence of competencies such as data analytics and strategic decision-making as crucial in an AI-driven business world. This research serves as a foundation for understanding how education must adapt to meet students' expectations in an AI-dominated job market. Likewise, Chan and Tsi (2023) examine the influence of AI in higher education, addressing its potential to assist or replace teachers. Their exploration of AI applications in PL and teaching support highlights its benefits in improving AP and freeing up teachers' time. However, they emphasize the irreplaceable role of human educators in nurturing critical thinking and emotional intelligence. This perspective aligns with the broader discourse on AI's role in education, emphasizing the need to strike a balance between technology and human interaction. Furthermore, Chan and Lee (2023) delve into the generational gap in attitudes toward AI adoption in education. They investigate how Generation Z students, who have grown up with technology, tend to embrace AI as a valuable resource for PL. In contrast, some older teachers may exhibit scepticism due to concerns about AI's limitations and its impact on traditional teaching methods. This research underscores the importance of bridging this gap to effectively integrate AI tools like ChatGPT into education.

Chen *et al.* (2020) explored AI's role in education, emphasizing its potential to personalize learning, provide adaptive pathways and offer insights for educators. They discuss diverse AI tools and techniques in education, from tutoring systems to personalized platforms. Importantly, they address challenges such as privacy and bias while emphasizing the ethical use of AI. Their study underscores AI's positive impact on student engagement and performance, further highlighting its potential in the context of AIPL. Keleş and Aydın (2021) shift the focus to university students' perceptions of AI, particularly its implications for education and careers. Their research reveals students' enthusiasm about AI's potential but also their concerns about job opportunities and misconceptions. The recommendation to integrate AI-related content into university curricula aligns with the broader goal of preparing students for an AI-dominated future.

Shifting the focus to the business sector, Loureiro *et al.* (2021) provide a comprehensive analysis of AI adoption, highlighting its transformative impact on various business functions and real-world applications. Their work identifies emerging trends and challenges, including AI techniques like analytics, big data and ethics. This comprehensive perspective offers valuable understanding of how to prepare students for AI-driven careers by aligning with the integration of AIPL in management education. Bi (2023) conducts an analysis of generative AI's application in business management. The article defines generative AI and explores its practical applications, highlighting its potential in automating creative tasks and addressing real-world examples. However, it also critically assesses challenges like data privacy, biases and workforce impact. This examination of generative AI provides ideas into preparing management students for AI-enabled careers.

Kim *et al.* (2022) shift the focus to educators' perspectives on integrating AI in education and promoting student-AI collaboration. This method shows an important aspects related to the potential of AI for personalized learning and student engagement This highlights AI's role as a supportive tool, complementing rather than replacing educators. This perspective aligns with the broader goal of empowering management students in AI-driven education through ethical AI use and student motivation. Chan (2023) offers a practical framework for integrating AI policy education into university programmes, recognizing the importance of preparing management students for AI's ethical, social and economic implications. This framework covers technical and societal dimensions while fostering critical thinking and ethical reasoning. Its relevance lies in the preparation of future business leaders to make informed decisions and contribute positively to the AI landscape. Chan and Hu (2023) provide a student-centered perspective on integrating generative AI in higher education. Their focus on students' perceptions and experiences with AI, highlighting its benefits and challenges, aligns with the goal of empowering management students through AI adoption, considering their perspectives.

One of the main challenges of using AI to predict student AP is the lack of data. Many schools and universities do not collect the kind of data that would be needed to train an accurate AI model. Another challenge is that student AP is influenced by a wide range of factors, many of which are difficult to measure or quantify. These factors can include student motivation, study habits, socioeconomic status and home environment. As with other global challenges (Choi *et al.*, 2018), AI has the potential to be a valuable tool for predicting student AP. AI model hold significant promise for education, with applications in identifying students at risk and developing PL plans. While prior research detailed in Table 1 explores the use of AI in AP, a critical gap exists. There is a lack of cohesive analysis on the impact of AIPL specifically in empowering management students. This gap necessitates further investigation into how such PL approaches can improve engagement and AP in this student population.

3. Theoretical background

SDT is a well-established psychological theory developed by Deci and Ryan in the 1980s. SDT provides a theoretical framework for motivation that has strong implications for both classroom practice and educational reform policies (Ryan and Deci, 2017, 2020). It is concerned with understanding human motivation and the factors that drive individuals to engage in activities. SDT posits that intrinsic motivation is fostered by three fundamental psychological needs: Firstly, autonomy, which refers to the need to experience a sense of choice and volition in one's actions. When individuals feel that they have control over their learning process, they are more likely to be engaged and motivated to excel in their educational endeavors. Secondly, competence, which relates to the need to feel capable and effective in one's actions. When students perceive their learning efforts as successful and witness progress, they are more inclined to remain engaged and motivated to continue learning and improving their skills. Previous studies suggest that individuals who feel more competent and autonomous in their use of technology are more likely to have positive attitudes toward it (Kaya *et al.*, 2022; Lu *et al.*, 2019; Sahin and Sahin, 2022). Finally, relatedness, which emphasizes the need to connect and feel a sense of belonging with others. Positive and supportive social interactions within the learning environment enhance motivation and engagement among students. An SDT based teaching approach in AI education led to more positive perceptions of learning and reduced achievement gaps between genders and ability levels (Xia *et al.*, 2022). Another study employs SDT to examine the effect of the three motivational needs on user interaction outcome variables of decision-making chatbots. Specifically, this study looks at the influence of relatedness, competence and autonomy on user satisfaction, engagement, decision efficiency and decision accuracy. SDT can explain student engagement in online learning. It found that all three psychological needs of SDT were important for engagement (Chiu, 2022). Similarly, the AI enabled personalized digital support strategies could effectively address these needs in online environment. The motivational needs of relatedness, competency and autonomy significantly impact user satisfaction and engagement with AI-assisted chatbots (de Vreede *et al.*, 2021). By analyzing data and learning patterns, AI systems can identify areas of

Table 1. Previous studies on academic performance

References	Methods	Findings
Hoxby (2000)	Regression models	There is no significant impact of class size on student achievement
Fan and Chen (2001)	General linear model	A positive link between parental involvement and student achievement
Barnett *et al.* (2002)	Linear programming techniques	A positive association between larger secondary school size and effectiveness, even when considering cost constraints. This suggests larger schools might outperform smaller ones in terms of academic performance
Rivkin *et al.* (2005)	Regression models	The study found teacher quality, not class size, has the biggest impact on student achievement, with good teachers benefitting all students
Archibald (2006)	Hierarchical linear models	The study suggests that expenditures on instruction and instructional support have a positive impact on students' achievement
Lee and Bowen (2006)	Hierarchical linear model	Parent involvement benefits student achievement more for dominant cultural backgrounds
Marks *et al.* (2006)	Item response theory; regressions models	Cultural capital plays a key role in influencing students' educational outcomes
Codjoe (2007)	Interviews	Supportive home environment and parental encouragement were significant factors contributing to the academic performance
Lei and Zhao (2007)	Hierarchical linear models; ANOVA tests	Quantity of technology use alone does not impact achievement, but focused and quality uses were linked to higher academic achievements
Steinmayr and Spinath (2008)	Regression models	Personality traits and achievement motivation did not explain gender differences in German school marks
Caro *et al.* (2009)	Hierarchical linear models; panel data models	Socioeconomic background has a significant impact on students achievement
Mensah and Kiernan (2010)	Tobit regression models; univariate and multivariate analyses	The study found that boys from families with less educated mothers achieved lower educational outcome compared to girls in similar situations
Hartas (2011)	Univariate analyses of variance; chi-square tests	Socioeconomic factors have a stronger influence on children's language and literacy development than on their socio-emotional competence
S. Huang and Fang (2013)	Regression model, artificial neural networks, radial basis function and support vector machines	Past academic performance is the best predictor of students achievement
Wally-Dima and Mbekomize (2013)	Descriptive statistics T-tests	The study link female students' stronger work ethic to their outperformance in accounting compared to males
Bosworth (2014)	Regression models	The study found that smaller classes have a smaller achievement gap
Hodis *et al.* (2015)	Hierarchical linear models	Secondary school students with both high aspirations and a focus on meeting minimum requirements achieve better academically

(*continued*)

Table 1.

References	Methods	Findings
Lee and Mallik (2015)	Ordinary least squares	Higher entrance scores, age and grades in specific core subjects positively impact academic achievement in online undergraduates programs
Migu_eis *et al.* (2018)	Random forests, decision trees, support vector machines and naïve bayes	A two part data mining model precisely predicted average grades and graduation time, enabling early intervention to improve student success
Ya_gci and Çevik (2019)	Artificial neural networks	Artificial neural networks effectively predicted science course performance for vocational high schools students in Turkey and Malaysia
Cruz-Jesus *et al.* (2020)	Regression models, artificial neural networks, decision trees, extremely randomized trees, random Forest, Support vector machines, K-Nearest Neighbors	AI techniques predicted high school achievement in Portugal
Jiao *et al.* (2022)	Genetic programming	In an online engineering course, the study identified participation, knowledge gain and past performance as key predictors of student achievement using AI
García-Martínez *et al.* (2023)	Systematic review and meta analysis	AI and computational sciences positevly impact student performance and motivation, especially in STEM fields

Source: Table created by authors

strengths and weaknesses in each student and deliver customized learning content, pace and feedback.

The integration of AIPL with the principles of SDT holds tremendous potential for improving management students' engagement and AP: Firstly, AIPL systems can provide autonomy support to management students, empowering them to have greater control over their learning journey. By offering choices in topics of interest, setting learning goals and allowing students to navigate through educational materials at their own pace, the technology fosters a sense of autonomy. As emphasized by SDT, when students feel in control of their learning process, they are more likely to be intrinsically motivated, leading to increased effort and engagement in their studies. Secondly, AI systems can analyze individual students' performance data and provide real-time feedback and adaptive learning paths. Through this personalized feedback and successful learning experiences, management students' sense of competence and mastery improves. The positive feedback loop between perceived competence and intrinsic motivation can lead to better AP as students become more driven to succeed in their educational pursuits. Moreover, despite being technology-driven, AIPL can also facilitate social interaction and relatedness among management students. The AIPL platform integrates features such as discussion forums and social learning elements. This integration fosters collaborative learning opportunities and establishes peer support networks within the learning environment. As a result, students can strengthen their sense of community and belonging. This would enhance their overall learning outcome.

The amalgamation of AIPL with the principles of SDT presents a promising approach to empower management students and enhance their engagement. This integration aims to ultimately improve their AP. By addressing the fundamental psychological needs of autonomy, competence and relatedness, PL approaches driven by AI have the potential to create a more meaningful and effective educational experience for students in the management domain. Drawing from the theoretical background, we propose the following hypotheses regarding the relationships between the variables, which are further illustrated in Figure 1:

H1. AI-enabled personalized learning positively influences autonomy.

H2. AI-enabled personalized learning positively influences competence.

H3. AI-enabled personalized learning positively influences relatedness.

H4. Autonomy positively influences engagement.

H5. Competence positively influences engagement.

H6. Relatedness positively influences engagement.

H7. Engagement positively influences AP.

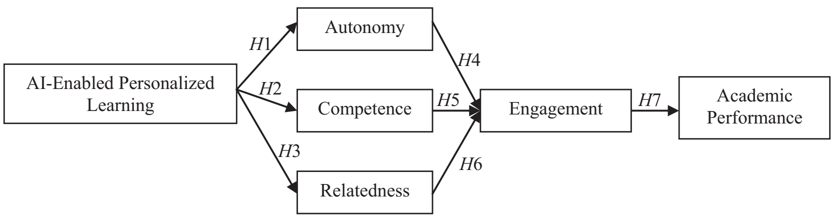

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Figure 1. AI-enhanced self-determination model (AI-SDM)

4. Methodology

Students utilized AIPL tools within management education to improve engagement, comprehension and performance. These tools included intelligence tutoring systems, adaptive platforms, gamification elements and chatbots. The usage of AI tools could vary among students. Some students may have used these tools as part of their regular coursework. Others might have voluntarily utilized them outside of class to supplement their learning or address specific educational needs. Research on AP has traditionally been survey-driven (surveying a student cohort and following them for a specified period to determine their success) (Caison, 2007). The questionnaire served as the data collection instrument for assessing the impact of AI in management education. The study gathered and evaluated data from a total of 206 students specializing in management across three prominent public institutions in India, namely Pondicherry University, Alagappa University and Calicut University. The main objective was to assess their perceptions of AIPL and its impact on various factors, including their level of engagement, levels of autonomy, competence, relatedness and AP. The study exclusively relied on primary data collection methods and collected data underwent rigorous statistical analysis. Initially, descriptive statistics were employed to summarize the demographic characteristics of the respondents and provide an overview of their perceptions. Path analysis, a form of structural equation modeling, was then used to assess the model fit of the AI-enabled self-determination model (AI-SDM). This analysis helped identify the relationships and causal pathways between AIPL, engagement, autonomy, competence, relatedness and AP.

4.1 Data collection

To gather data, a questionnaire was developed specifically for this study. The questionnaire included questions related to students' perceptions of AIPL, their engagement in the learning process, their perceived autonomy, competence and relatedness within the educational context and their AP. The survey was administered to a stratified sample of 206 management students from the three selected public universities in India. These universities were chosen based on their reputation and ranking (NIRF) within their respective states in South India. The selection of participants was conducted through a stratified random sampling technique, considering factors such as program level (UG, PG, PhD) and academic year (1st, 2nd, 3rd, etc.) to achieve a diverse and representative sample. This approach was relevant because it allowed for the inclusion of students at different stages of their academic journey. This could potentially influence their perception of AIPL and its impact on various factors, including engagement, autonomy, competence, relatedness and AP.

5. Results and discussion

This demographic profile is given in Table 2 represent a heterogeneous mix of students within the field of business. In relation to the distribution of gender, the predominant proportion of participants identified as male, comprising 59.2% of the whole sample, while female participants constituted 40.8%. In terms of age distribution, the largest percentage was seen within the 19–22 age categories, accounting for 54.3% of the sample. This was followed by those below the age of 18, constituting 20.4% of the total population. In contrast, individuals within the age range of 31–33 years and those over 33 years constituted the least significant percentages, accounting for 3.9% and 3.4%, respectively. In relation to academic programmes, the largest proportion of individuals in the sample consisted of PG students, accounting for 49%. UGs constituted 32.5% of the sample, while PhD scholars comprised 18.5%. Finally, with relation to the academic year, the predominant cohort consisted of students in their second year, comprising 52.9% of the total, while first-year students

Variables	Frequency	%
Gender		
Male	122	59.2
Female	84	40.8
Age group		
Below 18 years	42	20.4
19–22	112	54.3
23–26	19	9.2
27–30	18	8.8
31–34	8	3.9
Above 34 years	7	3.4
Programme		
UG	67	32.5
PG	101	49
PhD	38	18.5
Year of study		
1st yr	62	30.1
2nd yr	109	52.9
3rd yr	25	12.1
4th yr	8	3.9
5th yr and above	2	1.0

Source: Table created by authors

Table 2. Demographic characteristics

constituted 30.1%. The category consisting of students in the 5th year and higher was found to comprise the smallest proportion, accounting for only 1% of the total population.

A survey examining student adoption of PL techniques, as demonstrated in Table 3, highlights a strong preferences for immersive learning experiences. VR and AR simulations received the highest number of responses ($n = 60$), indicating that many students value their ability to create engaging and interactive learning environment (Delello *et al.*, 2023). Additionally, chatbots for personalized assistance followed closely ($n = 56$), suggesting a significant recognition among students of their potential to provide tailored support (Okonkwo and Ade-Ibijola, 2021). Furthermore, NLP for language learning ranked third ($n = 54$), highlighting student use of these technologies to improve language acquisition. Adaptive learning platforms secured the fourth rank ($n = 45$), indicating students' recognition of their capacity to address to individual needs. Machine learning-based recommendation systems ranked fifth ($n = 42$), followed by intelligent tutoring systems in

AI-tools	No. of students	Rank
Intelligent tutoring systems (ITS)	39	6
Adaptive learning platforms (ALP)	45	4
Virtual reality (VR) and augmented reality (AR)	60	1
Natural language processing (NLP)	54	3
Chatbots for personalized assistance (CPA)	56	2
Machine learning(ML) based recommendation systems	42	5
Gamification elements in learning platforms (GELP)	21	7

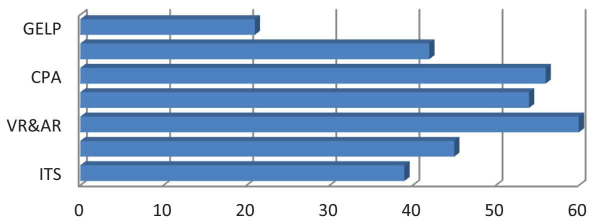
Source: Table created by authors

Table 3. Adoption of AI-tools among students

sixth rank ($n = 39$). Interestingly, Gamification elements within learning platforms garnered the least interest among students ($n = 21$). This finding contrast with the positive outcomes reported by Gafni *et al.* (2018) who found that a gamified e-learning platform fostered a more active learning process and increased participant motivation. In summary, the data presented in Table 3 and the corresponding visualization in Figure 2 provide compelling evidence that AI tools are exerting an increasingly influential role in shaping the educational landscape.

Table 4 provides individuals at various educational levels on the impact of AIPL tools or techniques on their AP. Responses are categorized into five distinct options, representing varying degrees of impact from a significant decline to a significant improvement. It is evident that a majority of respondent's at all educational levels did not report a decline in their AP as a result of utilizing AIPL tools. In fact, a substantial proportion of individuals expressed experiencing either a moderate or significant improvement in their AP due to these AIPL tools or techniques. For UG students, 37.3% noted a moderate improvement, while 25.4% reported a significant improvement. Similarly, at the Postgraduate level, 42.6% of respondents expressed a moderate improvement, with 25.7% indicating a significant improvement. In the case of PhD scholars, a noteworthy 57.9% reported a significant improvement in their AP, and no significant declines were reported by PhD scholars. This highlights that AIPL tools have had a notably positive impact on the AP of the respondents, particularly in terms of moderate to significant improvements. The chi-square analysis (see Table 5) conducted on the relationship between the dependent variable "Have you noticed any improvement in your AP since using AIPL tools or techniques?" and the independent variable "Educational level" yielded highly significant results. Both the Pearson Chi-Square

AI-Tools



Source: Figure created by authors

Figure 2.
Adoption of AI-tools among students

Table 4.
Impact of AIPL tools or techniques on their AP

Educational levels	No, a significant decline	No, a moderate decline	No significant improvement	Yes, a moderate improvement	Yes, a significant improvement	Total
	Have you noticed any improvement in your academic performance since using AIPL tools or techniques?					
UG	5	6	14	25	17	67
PG	3	7	22	43	26	101
PhD	0	0	5	11	22	38
Total	8	13	41	79	65	206

Source: Table created by authors

and Likelihood Ratio statistics, with p-values of 0.001 and 0.000 respectively, demonstrated a strong association between these variables, indicating that students' educational levels significantly influence their perception of improvement in AP through the use of AIPL tools or techniques. The Linear-by-Linear Association statistic further reinforced this finding, indicating a significant linear trend. This highlights the impact of educational level on students' perceptions of the effectiveness of AIPL tools or techniques in enhancing their AP.

5.1 Path analysis

This analysis aims to understand how AI-powered personalized learning (AIPL) influences the engagement and AP of management students. It considers autonomy, competence and relatedness as key mediating factors based on the SDT. Statistical software (SPSS and AMOS Graphics) was used to analyze data and assess the direct and indirect effects of these variables. Specifically, the study evaluates how AIPL shapes engagement and AP through autonomy, competence and relatedness. This research contributes to understanding AIPL's role in enhancing student outcomes in management education, utilizing SDT to explore underlying mechanisms.

The model fit summary (see Table 6) for the path analysis, as illustrated in Figure 3, indicates that the AI-enabled self-determination path model provides an acceptable fit. The Chi-Square/DF ratio is close to 1, which is typically a sign of good fit. Moreover, various fit indices, including NFI, IFI, TLI and CFI, all approach or exceed 0.95, indicating a strong fit. Additionally, the RMSEA value is well below 0.05, a widely accepted threshold for good fit, and the confidence intervals around this estimate are well-constrained. Collectively, these results suggest that the path analysis model effectively captures the relationships among the variables in the study and fits the data well. However, it is essential to consider other relevant fit indices, theoretical considerations and potentially compare alternative models for a comprehensive assessment of model fit.

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	38.154[a]	16	0.001
Likelihood ratio	46.235	16	0.000
Linear-by-linear association	23.819	1	0.000
N of valid cases	206		

Notes: [a]10 cells (40.0%) have expected count less than 5. The minimum expected count is 0.74
Source: Table created by authors

Table 5.
Results of Chi-Square

Key goodness of fit parameters	Value	Criteria
Chi-Square	5.005	
Degrees of freedom	4	
Probability level (p-value)	0.000	
Comparative fit index (CFI)	0.990	> 0.9
Tucker–Lewis index (TLI)	0.961	> 0.9
Normed fit index (NFI)	0.955	> 0.9
Incremental fit index (IFI)	0.991	> 0.9
Root mean square error of approximation (RMSEA)	0.038	< 0.05

Source: Table created by authors

Table 6.
Results of goodness of fit parameters

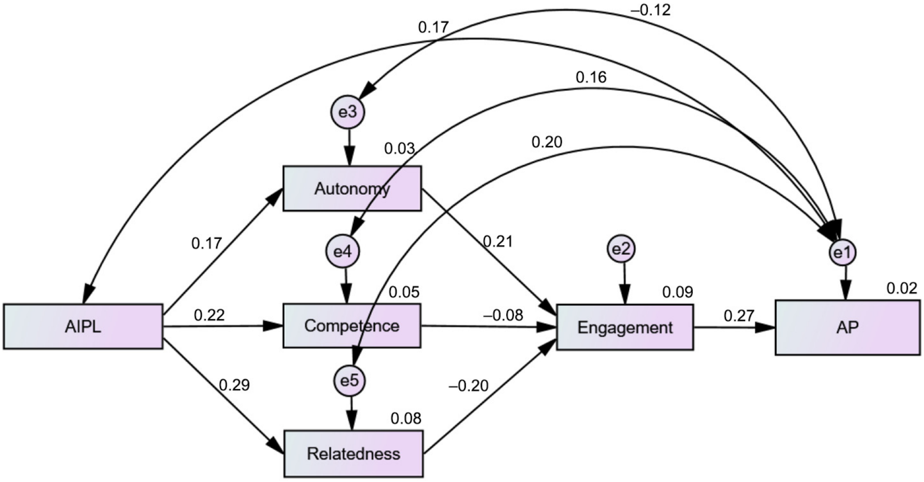


Figure 3.
AI-enabled self-determination path model (AI-SDPM)

Source: Figure created by authors

Table 7 shows the results of a path analysis that looked at the relationship between AIPL, autonomy, competence, relatedness, engagement and AP. It provides some significant findings into the influence of AIPL on various aspects of education. Firstly, AIPL has a significantly positive influence on students' autonomy; it helps them feel more in control of their learning, enabling them to make independent decisions about what and how they learn. Secondly, AIPL also positively affects students' sense of competence. This indicates that AI-driven personalized learning contributes to the development of students' skills and knowledge, boosting their confidence in their ability to learn effectively. Additionally, AIPL has a positive effect on the sense of relatedness among students. It fosters a feeling of connection to peers and teachers, creating a sense of belonging within the learning community. Furthermore, the study found that autonomy plays a crucial role in enhancing student engagement. When students feel more in control of their learning experiences, they are more likely to actively engage in their studies. Interestingly, relatedness has a somewhat unexpected negative impact on engagement. Students who feel strongly connected to their classmates and teachers might actually be less engaged in their learning. Ultimately, the research demonstrates that engagement has a significant positive effect on AP. In other

Table 7.
Results of hypothesis testing

Hypothesis	Independent variable		Dependent variable	Estimate	S.E.	C.R.	P	Outcome
H1	AIPL	→	Autonomy	0.071	0.032	2.229	0.026	Significant
H2	AIPL	→	Competence	0.089	0.030	2.979	0.003	Significant
H3	AIPL	→	Relatedness	0.152	0.038	3.991	0.000	Significant
H4	Autonomy	→	Engagement	0.176	0.061	2.878	0.004	Significant
H5	Competence	→	Engagement	−0.069	0.065	−1.051	0.293	Not significant
H6	Relatedness	→	Engagement	−0.140	0.050	−2.805	0.005	Significant
H7	Engagement	→	AP	0.468	0.118	3.970	0.000	Significant

Source: Table created by authors

words, students who are more engaged in their learning tend to perform better academically. All of the hypothesized relationships were significant, except for the relationship between competence and engagement. It suggests that AIPL has a significant positive effect on autonomy, competence and relatedness, which in turn have a significant positive effect on engagement. Engagement, in turn, has a significant positive effect on AP. The results of this study suggest that AI-powered learning can be a valuable tool for educators to use to improve student learning outcomes.

6. Limitation and future research direction

Despite the valuable insights gained from this study, it is important to acknowledge its limitations and consider future research directions. Firstly, the data was collected from management students in specific Indian universities, which may limit the generalizability of the findings to a broader international context. Future research could include a more diverse and extensive sample to enhance the external validity of the results. Additionally, the study relied on self-reported data, which might introduce response bias and social desirability bias. Incorporating objective measures of AP and engagement, such as standardized test scores or attendance records, could provide a more comprehensive understanding of the relationship between AIPL and student outcomes. Furthermore, this study focused on the positive aspects of AI-enabled personalized learning, and future research could explore potential drawbacks or challenges associated with its implementation. Finally, investigating the long-term effects of AI-driven personalized learning on students' career success and adaptability in the evolving job market could be an intriguing avenue for future research, considering the dynamic nature of technology and its impact on employment.

Future research directions should also explore the optimal design and implementation of AIPL systems, considering factors such as individual differences in learning styles, cultural variations and ethical considerations. Additionally, investigating the role of educators and their attitudes toward AI in the classroom, as well as strategies for effectively integrating AI tools into teaching practices, can contribute to a more holistic understanding of the AI-education landscape. Furthermore, examining the potential role of AI in addressing educational disparities and enhancing access to quality education for underserved populations should be a priority in future research. Finally, given the rapid advancement of AI technology, ongoing research should continue to assess its evolving impact on education and its implications for pedagogy, policy and practice.

7. Conclusion

This comprehensive study has unveiled the transformative potential of AIPL in management education, anchored in the well-established SDT. The findings reveal a significant, positive influence of AIPL on students' fundamental psychological needs of autonomy, competence and relatedness, thereby fostering engagement. Autonomy emerged as a key driver of engagement, which was strongly associated with improved AP. The path analysis model provided a robust fit to the data, reinforcing the validity of these relationships. These findings underscore the pivotal role of AI in reshaping educational experiences and motivating students intrinsically. As we navigate the evolving landscape of education in the digital age, this research offers valuable insights to educators, policymakers and researchers alike. It underscores the significance of tailoring educational content and experiences to individual student needs, thus empowering them to excel and thrive in an AI-driven world.

8. Glossary

Term	Definition
Artificial intelligence (AI)	According to IBM (2024) "Artificial intelligence, or AI, is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities."
Self-determination theory (SDT)	Self-determination theory (SDT), proposed by Edward L. Deci and Richard M. Ryan in 1985, posits that people are motivated to satisfy three basic psychological needs: autonomy, competence and relatedness
Academic performance (AP)	Academic performance is how well a student learns and achieves in their studies
Engagement	Academic engagement is the student's investment of effort and participation in learning activities
AI-enhanced personalized learning (AIPL)	AI-enhanced personalized learning (AIPL) uses artificial intelligence to tailor learning experiences to individual student needs and goals
AI-Tools	AI-Tools are software programs that leverage artificial intelligence to automate tasks or generate creative text, code or images

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About the authors

Adil Ellikkal, a research scholar at Alagappa Institute of Management, Alagappa University, India, pursues PhD under guidance of S. Rajamohan. He has been awarded Doctoral Fellowship by Indian Council of Social Science Research (ICSSR). With an MBA from Pondicherry University, he has published ten articles, presented a few papers in international conferences. Adil Ellikkal is the corresponding author and can be contacted at: adilphd@alagappauniversity.ac.in

S. Rajamohan, senior professor and Director at Alagappa Institute of Management, Alagappa University in India. With a PhD from Gandhigram Rural University, he has 35 years of teaching, 25 years of research and guidance to over 32 PhD scholars. Serving as the Dean at faculty of Management, he has published 300+ papers and authored books in areas like Entrepreneurship, Agri-entrepreneurship and Finance.