INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS & SOCIAL SCIENCES

Vol 16, Issue 1, (2026) E-ISSN: 2222-6990

Bridge the Gap: Artificial Intelligence Adoption among Students in Open, Distance, and Digital Education: The Mediating Role of Learning Engagement

Zahir Osman*
Open University Malaysia
*Corresponding Author Email: zahir_osman@oum.edu.my

Bibi Nabi Ahmad Khan
Open University Malaysia
Email: bibi_ahmadkhan@oum.edu.my

Noral Hidayah Alwi
Open University Malaysia
Email: noral@oum.edu.my

DOI Link: http://dx.doi.org/10.6007/IJARBSS/v16-i1/27418

Published Date: 28 January 2026

Abstract

This study investigates the adoption of artificial intelligence (AI) among students in learning enhancement within open, distance, and digital education (ODDE) higher institutions, a context where AI holds huge potential to personalise learning experiences, bridge geographical barriers, and enhance engagement. Given the fragmented research landscape and the unique challenges faced by ODDE students, this study aims to examine the complex relationships between perceived usefulness, perceived ease of use, learners' autonomy, and AI adoption, with learning engagement acting as a mediator. Employing a comprehensive survey instrument comprising 23 observable variables adapted from established scales, data were collected from 297 valid responses obtained through purposive sampling. Structural equation modelling (SEM) was utilised via SmartPLS software to analyse the data and test the proposed hypotheses. The results generally support the proposed model, revealing that learners' autonomy and perceived usefulness positively influence AI adoption, with learning engagement playing a crucial mediating role. However, perceived ease of use did not directly impact AI adoption. These findings highlight the importance of strategic implementation of AI, with an emphasis on creating user-friendly interfaces and fostering learner autonomy. Future research could explore longitudinal dynamics, contextual barriers, and specific design features to enhance AI adoption further. This study offers valuable theoretical implications by integrating the Technology Acceptance Model (TAM) with constructivist learning principles, while also providing actionable managerial insights for higher education institutions aiming to optimise AI integration for improved learning outcomes and organisational competitiveness. By focusing on perceptual and behavioural factors, institutions can foster sustainable and impactful AI adoption in the digital education landscape.

Keywords: Perceived Ease of Use, Perceived Usefulness, Learners' Autonomy, Learning Engagement, Adoption

Introduction

Artificial Intelligence (AI) adoption in learning enhancement is increasingly vital among students in Open, Distance, and Digital Education (ODDE) higher institutions worldwide. As the landscape of higher education evolves, especially with the proliferation of online platforms and digital tools, AI presents opportunities to personalise learning experiences, facilitate real-time feedback, and support autonomous learning (Yang, Chen, He, Sun, & Salas-Pilco, 2024). Globally, integrating AI-driven solutions such as adaptive learning systems, chatbots, and intelligent tutoring systems enhances learner engagement, improves knowledge retention, and bridges gaps created by geographical and socio-economic barriers (Wang & Huang, 2025). For ODDE students, who often face challenges such as limited access to immediate support or personalised instruction, AI offers tailored interventions that cater to individual learning paces, styles, and needs, thereby fostering improved academic outcomes and learner satisfaction (Rosak-Szyrocka et al., 2023). Despite its promising potential, research on AI adoption in learning enhancement within ODDE higher institutions remains fragmented. Most studies focus on traditional classroom contexts or corporate training environments, leaving a significant knowledge gap regarding how AI influences the unique dynamics of open and distance learning (George & Wooden, 2023). There is limited empirical data on the barriers to AI implementation, factors influencing acceptance and usage among ODDE students and educators, and the effectiveness of AI tools across diverse cultural, technological, and infrastructural contexts (Negoiță & Popescu, 2023). Furthermore, issues such as digital literacy gaps, ethical concerns, and the digital divide hinder widespread adoption, yet there is insufficient research to develop comprehensive strategies that address these challenges (Abulibdeh et al., 2025). The importance of this study extends beyond academic inquiry. For policymakers, understanding AI's role in transforming open and distance education can inform the development of supportive policies, investment in digital infrastructure, and training programs aimed at enhancing digital literacy (Deckker & Sumanasekara, 2025). ODDE higher institutions can leverage the findings to improve curriculum design, faculty training, and student support systems through AI integration (Achruh et al., 2024). For students, especially those from marginalised communities, AI can offer equitable learning opportunities, personalised support, and increased motivation to persist in their studies (Grájeda et al., 2024). This research highlights the crucial need for strategic implementation of AI in ODDE higher education to ensure inclusive, effective, and innovative learning environments that meet the demands of the digital age (Qian et al., 2025). Furthermore, advancing AI adoption in ODDE higher institutions addresses the growing demands of lifelong learning and workforce readiness in a rapidly changing global economy (Walter, 2024). As industries evolve with technological innovations, students equipped with AI-enhanced skills will have a competitive advantage in the labour market (Achruh et al., 2024). This emphasises the significance of understanding how AI can be optimally integrated into open and distance learning frameworks to develop critical digital competencies. Additionally, the study can contribute to designing sustainable and scalable AI-powered educational models that are adaptable to different contexts and resource availabilities (Qian et al., 2025). Ultimately, advancing research in this domain not only enhances academic effectiveness but also promotes digital presence, empowering learners from diverse backgrounds to participate fully in the global knowledge economy (Rosak-Szyrocka et al., 2023). This study aims to assess the direct and indirect relationship between perceived usefulness, perceived ease of use, learners' autonomy, and artificial intelligence adoption with learning engagement as a mediator among students in open, distance, and digital education higher institutions.

Literature Review

Underpinning Theories

The proposed research model integrates the Technology Acceptance Model (TAM) and Constructivist Learning Theory to provide a comprehensive explanation of AI adoption in learning environments. TAM, developed by Davis (1989), emphasises that perceived usefulness and perceived ease of use are key determinants influencing individuals' intentions and behaviours toward adopting new technologies. In educational contexts, students and instructors are more inclined to use AI tools if they believe these tools will enhance learning outcomes and are easy to interact with. These perceptions directly shape behavioural intentions, which lead to actual usage, thereby facilitating technology acceptance. Constructivist Learning Theory, articulated by Piaget (1954) and Vygotsky (1978), highlights the importance of active, learner-centred engagement where learners construct knowledge through interaction, exploration, and reflection. AI-driven personalised learning environments exemplify constructivist principles by enabling learners to control their learning paths, collaborate with peers, and actively construct knowledge. Such environments foster autonomy and motivation, key components of meaningful learning. By integrating these theories, the model suggests that perceived usefulness and ease of use influence learners' willingness to adopt AI tools, which subsequently enhances learner autonomy and active engagement. In turn, learner engagement mediates the relationship between technology acceptance and learning outcomes, aligning with constructivist emphasis on active participation. Positive perceptions of AI foster autonomous learning behaviours, leading to better engagement and improved educational results. This combined theoretical framework provides a clear understanding of how technology acceptance factors influence engagement and learning enhancement, emphasising the relationship between perceived technological benefits and active knowledge construction.

Relationship between Learners' Autonomy, Learning Engagement & Artificial Intelligence Adoption

The relationship between learners' autonomy, learning engagement, and artificial intelligence (AI) adoption is interconnected and mutually reinforcing in the context of learning enhancement. Learners' autonomy refers to their ability to independently control and direct their learning processes, set personal goals, and choose resources or methods that suit their preferences (Iyer, 2025). When AI tools are integrated into educational settings, they can significantly support learner autonomy by providing personalised learning pathways, adaptive feedback, and tailored content, empowering students to take greater responsibility for their learning journey (Hidayat-ur-Rehman, 2024). Learning engagement, characterised by active participation, motivation, and sustained attention, is often heightened when learners feel empowered and in control of their learning experiences. AI can foster deeper engagement by making learning more interactive, relevant, and responsive to individual needs. As learners become more autonomous through AI-supported environments, their motivation and commitment typically increase, resulting in higher levels of engagement (Al-Mamary & Abubakar, 2025). Conversely, increased engagement encourages learners to utilise AI tools more effectively, creating a positive feedback loop that enhances learning outcomes (Yuan & Liu, 2025). Studies also suggest that AI enhances overall learner experience, further boosting engagement levels (Sibarani, 2025), while key drivers such as AI competence and chatbot use play important roles in this process (Iyer, 2025). AI adoption facilitates greater learner autonomy, which in turn promotes higher engagement. This synergy enhances the overall learning experience, making it more personalised, motivating, and effective, ultimately leading to better academic achievements and lifelong learning skills. Therefore, the following hypotheses were proposed for this study:

H1: There is a relationship between learners' autonomy and artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H2: There is a relationship between learners' autonomy and learning engagement towards artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H3: There is a mediating effect of learning engagement on the relationship between learners' autonomy and artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

Relationship between Perceived Ease of Use, Learning Engagement & Artificial Intelligence Adoption

The relationship between perceived ease of use, learning engagement, and artificial intelligence (AI) adoption plays a crucial role in enhancing learning experiences. Perceived ease of use refers to how effortless learners find interacting with AI tools and systems. When students or educators perceive AI applications as easy to operate, they are more likely to incorporate these tools into their learning routines without frustration or confusion (Aldraiweesh & Alturki, 2025). This positive perception reduces barriers to adoption, making it more likely that users will actively engage with the technology (Hang, 2024). Learning engagement, which involves motivation, active participation, and sustained attention, is significantly influenced by how user-friendly the AI tools are perceived to be. When AI systems are easy to use, learners tend to feel more comfortable exploring their features, leading to increased involvement in the learning process (Naidoo, 2023). Higher engagement levels foster deeper understanding, better retention, and more meaningful interactions with content. Furthermore, an intuitive AI experience encourages continuous use and integration into daily learning activities, reinforcing a cycle where ease of use directly boosts adoption rates (Rahman et al., 2025). When learners view AI tools as accessible and straightforward, they are more inclined to experiment, adapt, and successfully incorporate these innovations into their educational journey. This positive relationship ultimately enhances learning outcomes and promotes ongoing adoption of AI in educational environments (Ateş & Gündüzalp, 2025). Thus, the following hypotheses were proposed for this study:

H4: There is a relationship between perceived ease of use and artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H5: There is a relationship between perceived ease of use and learning engagement towards artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H6: There is a mediating effect of learning engagement on the relationship between perceived ease of use and artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

Relationship between Perceived Usefulness, Learning Engagement & Artificial Intelligence Adoption

The relationship between perceived usefulness, learning engagement, and artificial intelligence (AI) adoption is central to understanding how AI can effectively enhance learning experiences. When learners perceive AI tools as useful, they believe these technologies will improve their understanding, efficiency, and overall learning outcomes. This perception of usefulness directly influences their willingness to adopt and consistently use AI-driven platforms and applications (Mayr, 2025). As learners recognise the benefits of AI, they are more motivated to incorporate these tools into their daily academic routines. Learning engagement, characterised by active participation, motivation, and sustained attention, tends to increase when learners see AI as a valuable resource that helps them achieve their educational goals. When AI tools are perceived as useful, learners are more inclined to interact deeply with the content, make use of interactive features, and invest effort in learning activities (Sibarani, 2025). This heightened engagement not only enhances comprehension and retention but also fosters a positive attitude towards continued use of AI in education. Furthermore, AI adoption and perceived usefulness are influenced by learners' technological readiness, self-efficacy, and attitudes toward AI, which further shape engagement levels (Falebita & Kok, 2024). Perceived usefulness acts as a catalyst that encourages the adoption and sustained usage of AI tools, which in turn stimulates higher levels of engagement. This synergy creates a more dynamic and effective learning environment, leading to improved academic performance, greater motivation, and long-term integration of AI in educational practices (Or, 2025). Thus, the following hypotheses were proposed for this study:

H7: There is a relationship between perceived usefulness and artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H8: There is a relationship between perceived usefulness and learning engagement towards artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H9: There is a relationship between learning engagement and artificial intelligence adoption among students in Open, Distance, and Digital Education (ODDE) higher education institutions.

H10: There is a mediating effect of learning engagement on the relationship between perceived usefulness and artificial intelligence adoption among students in the Open, Distance, and Digital Education (ODDE) higher education institutions.

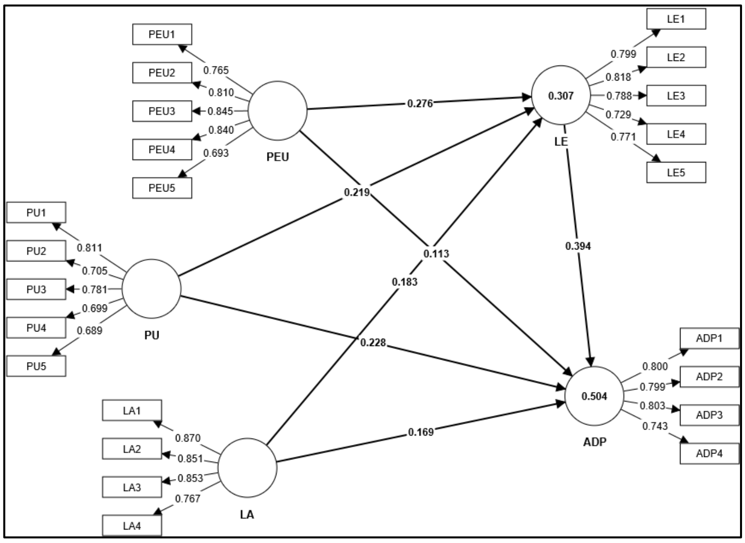

Figure 1: Research Model
Note: PEU=Perceived Ease of Use PU=Perceived Usefulness LA=Learners' Autonomy LE=Learning Engagement ADP=Adoption

Methodology
This research investigated the complex interrelationships among perceived ease of use, perceived usefulness, learners' autonomy, and artificial intelligence (AI) adoption in the context of learning enhancement within open, distance, and digital education (ODDE) higher education institutions. Additionally, the study examined the mediating role of learning engagement. A comprehensive data collection strategy was employed to ensure the reliability and validity of the measurements, with tool selection guided by existing scholarly literature. The survey instrument comprised 23 observable variables: five items measuring each perceived usefulness and perceived ease of use, adapted from, adapted from Davis (1989); four items assessing learners' autonomy, based on Vygotsky (1978); five items representing learning engagement, sourced from Grájeda et al. (2024); and four items evaluating AI adoption, adapted from Wang and Huang (2025). Respondents rated each construct using a 5-point Likert scale, ranging from strongly disagree to strongly agree. Due to the lack of a comprehensive population list, purposive sampling was adopted. Out of 445 surveys distributed, 328 responses were received, resulting in a response rate of 73.7%, which supported the application of structural equation modelling (SEM) for the analysis. After data cleaning, 297 valid responses remained for detailed examination. The study utilised SmartPLS software, known for its SEM functionalities, to analyse the data and test the hypotheses, leveraging its strong assessment features and capacity to handle multivariate data, in line with the objectives and recommendations established by Ringle et al. (2022). SmartPLS

facilitated an in-depth evaluation of both measurement and structural models, enabling a comprehensive understanding of the relationships examined.

Data Analysis

Respondents' Profile

The table provides demographic details of the study participants, showing a balanced gender distribution with 140 males (47.1%) and 157 females (52.9%). In terms of age, the majority are between 31-40 years, comprising 130 participants (43.8%), followed by 51-60 years with 94 participants (31.7%), 41-50 years at 41 participants (13.8%), under 30 years with 31 participants (10.4%), and over 60 years with just 1 participant (0.3%). Regarding the year of study, participants are fairly distributed across Years One to Five, with Year Three having the highest number at 71 participants (23.9%), followed by Year Two with 66 participants (22.2%), Year One with 61 participants (20.5%), Year Four with 47 participants (15.8%), and Year Five with 31 participants (10.4%), while those studying for more than five years account for 21 participants (7.1%). As for the level of study, most are pursuing a Diploma or Bachelor's degree, both categories inexplicably showing 197 participants each (66.3%), with Masters and Doctorate levels accounting for 27 (9.1%) and 10 (3.4%) participants respectively; however, it's worth noting that there may be an oversight in the percentages totalling over 100% for Diploma and Bachelor's levels.

Common Method Bias

The full collinearity analysis presented in the table addresses concerns about common method bias, as recommended by Kock & Lynn (2012) and Kock (2015). Common method bias occurs when measurement errors are attributed to the data collection method. One way to assess it is through full collinearity variance inflation factors (VIFs). According to Kock, a VIF of 3.3 or lower indicates that common method bias is not a significant problem. In Table 1, all VIF values for the constructs, including Adoption, Perceived Ease of Use, Perceived Usefulness, Learners' Autonomy, and Learning Engagement, are well below the threshold of 3.3. The highest VIF is 1.946, related to Learning Engagement's relationship with Perceived Usefulness, but it remains comfortably within the accepted range. This suggests that the study data does not suffer significantly from common method bias, ensuring that the observed relationships between variables are not artificially inflated due to the measurement technique used. This strengthens the validity of the study's findings regarding the relationships among these constructs.

Table 1
Full Collinearity

	ADP	PEU	PU	LA	LE
ADP		1.936	1.852	1.871	1.609
PEU	1.887		1.463	1.881	1.855
PU	1.853	1.502		1.942	1.946
LA	1.264	1.304	1.312		1.309
LE	1.420	1.679	1.717	1.942	

Measurement Model

Table 2 provides an analysis of construct reliability and validity based on Cronbach's Alpha (CA), Composite Reliability (CR), Average Variance Extracted (AVE), and item loadings, as recommended by Hair et al. (2019). Construct reliability is assessed through Cronbach's Alpha, where values above 0.7 indicate acceptable internal consistency. All constructs, including Adoption (CA = 0.795), Learner Autonomy (CA = 0.856), Learning Engagement (CA = 0.841), Perceived Ease of Use (CA = 0.852), and Perceived Usefulness (CA = 0.791), meet this criterion, reflecting reliable scales. Composite Reliability further supports reliability, with all constructs showing values above the threshold of 0.7, indicating adequate reliability: Adoption (CR = 0.802), Learner Autonomy (CR = 0.858), Learning Engagement (CR = 0.845), Perceived Ease of Use (CR = 0.876), and Perceived Usefulness (CR = 0.794). For construct validity, examined through AVE, values above 0.5 suggest sufficient convergent validity. All constructs, except Perceived Usefulness (AVE = 0.546), demonstrate strong validity: Adoption (AVE = 0.619), Learner Autonomy (AVE = 0.699), Learning Engagement (AVE = 0.611), and Perceived Ease of Use (AVE = 0.628). Item loadings also indicate strong individual item reliability, with most loading values exceeding the 0.7 threshold, reinforcing the robustness of the constructs. Overall, the constructs exhibit reliable and valid measurement properties, suitable for further structural analysis. Further, the Heterotrait-Monotrait (HTMT) analysis was performed, as recommended by Henseler et al. (2015), to assess discriminant validity, with values below 0.85 indicating adequate validity. In Table 3, all HTMT ratios are below this threshold of 0.9: Adoption-Learner Autonomy (0.537), Adoption-Learning Engagement (0.746), Adoption-Perceived Ease of Use (0.608), and so on, confirming satisfactory discriminant validity (Henseler et al., 2015).

Table 2
Construct Reliability and Validity & Items Loadings

Constructs	Items	Loadings	CA	CR	AVE
Adoption	ADP1	0.800	0.795	0.802	0.619
	ADP2	0.799			
	ADP3	0.803			
	ADP4	0.743			
Learner Autonomy	LA1	0.870	0.856	0.858	0.699
	LA2	0.851			
	LA3	0.853			
	LA4	0.767			
Learning Engagement	LE1	0.799	0.841	0.845	0.611
	LE2	0.818			
	LE3	0.788			
	LE4	0.729			
	LE5	0.771			
Perceived Ease of Use	PEU1	0.765	0.852	0.876	0.628
	PEU2	0.810			
	PEU3	0.845			
	PEU4	0.840			
	PEU5	0.693			
Perceived Usefulness	PU1	0.811	0.791	0.794	0.546
	PU2	0.705			

	PU3	0.781		
	PU4	0.699		
	PU5	0.689		

Notes: CA=Cronbach Alpha CR=Composite Reliability AVE=Average Variance Extracted

Table 3
Heterotrait-Monotrait (HTMT) Ratios

	ADP	LA	LE	PEU
LA	0.537			
LE	0.746	0.441		
PEU	0.608	0.445	0.561	
PU	0.68	0.456	0.564	0.785

Structural Model
This study assessed the structural model following the guidelines outlined by Hair et al. (2017), focusing on analysing the pathway coefficients (β) and the coefficients of determination (R^2). Using a Partial Least Squares (PLS) approach, the analysis employed 5,000 bootstrap samples to determine the significance of the path coefficients. The results of the hypothesis tests are summarized in Table 4, which displays the beta estimates, t-statistics, and p-values, offering valuable insights into the strength and significance of the relationships between the variables.*H1*, which posits that learners' autonomy (LA) influences adoption (ADP), is supported by a beta of 0.169, a t-statistic of 3.048, and a p-value of 0.002, leading to its acceptance and indicating that greater learners' autonomy enhances adoption. Similarly, *H2*, suggesting that LA impacts Learning Engagement (LE), is confirmed with a beta of 0.183, t=3.395, and p=0.001, supporting the notion that increased Learners' autonomy positively influences learning outcomes. *H3*, which hypothesised that LA affects ADP indirectly through LE, is supported by a beta of 0.072, t=3.025, and p=0.002, indicating that LE mediates this relationship. Conversely, *H4*, proposing that perceived ease of use (PEU) directly influences ADP, is rejected as the p-value of 0.113 indicates non-significance despite a beta of 0.113 and t=1.584. However, *H5*, which states PEU impacts LE, is supported with a beta of 0.276, t=3.985, and p=0.000, confirming a significant positive influence. *H6*, suggesting PEU affects ADP via LE, is also supported, with a beta of 0.109, t=3.232, and p=0.001. Similarly, *H7*, which proposes perceived usefulness (PU) directly influences ADP, is supported with beta=0.228, t=3.366, and p=0.001. *H8*, hypothesising that PU impacts LE, is confirmed with beta=0.219, t=3.530, and p=0.000. The significant effect of LE on ADP in *H9* further supports the model, with a beta of 0.394, t=7.565, and p=0.000. Lastly, *H10* supports the mediating role of LE, indicating that PU influences ADP indirectly through LE, with a beta of 0.086, t=3.453, and p=0.001. Overall, most hypotheses are supported, emphasising the critical roles of learners' autonomy, perceived usefulness, and Learning Engagement in fostering adaptive processes.

Table 4
Hypothesis Testing Results

Hypotheses	Beta	T statistics	P values	2.50%	97.50%	Decision
H1: LA -> ADP	0.169	3.048	0.002	0.053	0.269	*Accepted*
H2: LA -> LE	0.183	3.395	0.001	0.076	0.288	*Accepted*
H3: LA -> LE -> ADP	0.072	3.025	0.002	0.029	0.124	*Accepted*
H4: PEU -> ADP	0.113	1.584	0.113	-0.032	0.245	*Rejected*
H5: PEU -> LE	0.276	3.985	0.000	0.135	0.405	*Accepted*
H6: PEU -> LE -> ADP	0.109	3.232	0.001	0.049	0.181	*Accepted*
H7: PU -> ADP	0.228	3.366	0.001	0.097	0.358	*Accepted*
H8: PU -> LE	0.219	3.530	0.000	0.094	0.337	*Accepted*
H9: LE -> ADP	0.394	7.565	0.000	0.289	0.492	*Accepted*
H10: PU -> LE -> ADP	0.086	3.453	0.001	0.041	0.138	*Accepted*

Note: Significant at $p<0.05$

Effect Sizes (f^2)

According to Cohen's (1992) guidelines, the effect sizes (f^2) in Table 5 indicate small effects across most relationships. Learners' autonomy (LA) has a small effect on Adoption (ADP) ($f^2=0.045$) and LE ($f^2=0.04$). Perceived ease of use (PEU) shows a very small effect on ADP ($f^2=0.013$) and LE ($f^2=0.06$). Perceived usefulness (PU) has small effects on ADP ($f^2=0.056$) and LE ($f^2=0.038$). Overall, these effect sizes suggest that while the variables influence each other, the magnitude of these effects is generally modest, indicating that other factors may also play a significant role in shaping ADP and LE.

Table 5
Effect Sizes (f^2)

	ADP	LE
LA	0.045	0.04
LE	0.217	
PEU	0.013	0.06
PU	0.056	0.038

PLS predicts & Cross-Validated Predictive Ability Test (CVPAT)

Following the recommendations by Shmueli et al. (2016, 2019), the PLS-SEM predictions in Table 6 demonstrate better performance than the Linear Model benchmarks, as reflected in the RMSE values. All PLS-RMSEs are lower than the LM-RMSEs across the eight examined indicators, indicating superior predictive accuracy. Specifically, each PLS-RMSE is smaller than its corresponding LM-RMSE, with differences ranging from -0.001 to -0.021. This consistently shows that the PLS approach offers more reliable predictions for the variables related to adaptive process and Learning Engagement, confirming its added value in predictive modelling within this study's context. The CVPAT results in Table 7, in line with the guidelines by Hair et al. (2022) and Liengaard et al. (2021), show that the model has significant predictive ability, as indicated by the negative average loss differences and high t-values (ADP: 5.310, LE: 4.106, Overall: 5.343) with p-values of 0.000. These results suggest that the model predictions outperform benchmark models, confirming its robustness and validity. The significant negative differences indicate that the model can reliably predict both adaptive process and Learning Engagement, supporting its suitability for forecasting these constructs within the studied context.

Table 6
PLSpredicts

	Q^2predict	PLS-RMSE	LM-RMSE	PLS-LM
ADP1	0.298	0.606	0.614	-0.008
ADP2	0.222	0.611	0.629	-0.018
ADP3	0.242	0.662	0.682	-0.020
ADP4	0.136	0.728	0.741	-0.013
LE1	0.218	0.630	0.631	-0.001
LE2	0.178	0.631	0.648	-0.017
LE3	0.123	0.676	0.682	-0.006
LE4	0.153	0.697	0.718	-0.021
LE5	0.192	0.623	0.636	-0.013

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
ADP	-0.121	5.310	0.000
LE	-0.088	4.106	0.000
Overall	-0.103	5.343	0.000

Importance-Performance Map Analysis (IPMA)
Based on the IPMA results in Table 8, following the recommendations of Ringle and Sarstedt (2016) and Hair et al. (2018), learning engagement (LE) has the highest importance (0.394) but the lowest performance (60.725), indicating a critical area for improvement. Learners' autonomy (LA), perceived usefulness (PU), and perceived ease of use (PEU) have moderate importance but relatively higher performance scores, suggesting they are currently more effective but could benefit from further enhancement. To improve LE's impact on the adoption of artificial intelligence (AI), strategies should focus on strengthening its importance through targeted training, resource allocation, and fostering a culture that values continuous learning. Improving LE's performance can involve designing engaging training programs, providing practical AI use cases, and creating incentives to motivate stakeholders to actively develop their AI competencies. Addressing LE's low performance is crucial for increasing AI adoption, as improving this construct can enhance overall students' artificial intelligence adoption.

Table 8
Importance-Performance Map Analysis (IPMA)

	Importance	Performance
LA	0.241	67.366
LE	0.394	60.725
PEU	0.222	66.463
PU	0.314	65.992

Discussion & Conclusion

The study delivers actionable insights for Open, Distance, and Digital Education (ODDE) higher institutions focused on maximising AI adoption among students. A thorough examination of hypothesis testing results highlights key strategies institutions should prioritise to enhance AI integration and learning outcomes. Central to this strategy is fostering learner autonomy (LA). The significant positive impact of LA on both AI adoption (β = 0.169) and learning engagement (LE) (β = 0.183) suggests that ODDE institutions should actively cultivate a learner-centric environment. This can be achieved by providing flexible learning pathways that empower students to tailor their learning journey. Encouraging self-directed goal setting and offering personalised resources are also critical, as they enable students to take greater control of their educational experience. The study's finding that learning engagement mediates the relationship between learner autonomy and AI adoption (β = 0.072) further underscores the importance of creating a learning environment that fosters active participation and deep involvement. Equally important is emphasising perceived usefulness (PU). The significant direct effect of PU on AI adoption (β = 0.228) and its positive influence on learning engagement (β = 0.219) highlight the need for ODDE institutions to effectively communicate the tangible benefits of AI tools. Demonstrating how AI can improve understanding, enhance efficiency, and facilitate better academic outcomes can significantly influence student attitudes and adoption rates. This requires a strategic approach that showcases AI's value proposition through practical applications and real-world examples. Furthermore, interventions aimed at fostering learning engagement (β = 0.394) are crucial. Since learning engagement positively impacts AI adoption, ODDE institutions should prioritise the creation of a supportive and stimulating learning atmosphere. This can be accomplished through various means, including designing engaging training programs that teach students how to use AI tools effectively. Providing clear demonstrations of AI's advantages can also help to build trust and confidence among students. Creating supportive learning atmospheres that nurture active participation is also vital, as it fosters a sense of community and encourages students to take ownership of their learning. While perceived ease of use (PEU) was found to significantly influence learning engagement (β = 0.276), but not to directly influence AI adoption, the reasons include external factors, such as institutional readiness or digital infrastructure, might limit the direct influence of perceived ease and usefulness and that resistance to change, technological anxiety, or lack of sufficient technological literacy could diminish the effect of perceived usefulness or ease on actual adoption. Therefore, ODDE institutions must address these underlying issues to ensure that AI tools are not only easy to use but also accessible and relevant to all students, thereby maximising their potential impact on learning outcomes.

Theoretical Implications

This study offers important theoretical implications by extending the traditional framework of the Technology Acceptance Model (TAM) and integrating it with constructivist learning principles to better understand AI adoption in open, distance, and digital higher education contexts. The findings reaffirm TAM's core constructs, perceived usefulness and perceived ease of use, while emphasising that their effects are significantly mediated by learning engagement, thus supporting the view that technological acceptance is not solely driven by perceptions but is also critically dependent on active learner participation. This reinforces prior work suggesting that engagement acts as a central psychological mechanism that translates perceptions into behavioural outcomes, thereby enriching TAM's explanatory power (Davis, 1989). Simultaneously, the study aligns with constructivist learning theory, which asserts that learner autonomy and active engagement are essential for meaningful learning (Piaget, 1954; Vygotsky, 1978). The results highlight that autonomous learners are more likely to perceive technology as valuable and easy to use, which ultimately enhances adoption. A key theoretical insight emerging from this research is the concept of learner autonomy as both a motivator and facilitator of engagement, suggesting that future models should explicitly incorporate learner-centred variables along with traditional technology acceptance constructs. Moreover, the study encourages refinement of existing theories by emphasising the combined roles of perceived usefulness, ease of use, and learner autonomy in shaping engagement, thus advancing a more holistic, socio-constructivist perspective that emphasises the importance of psychological and contextual factors in digital transformation within higher education systems.

Managerial Implications

The findings of this study offer valuable managerial insights for higher education institutions aiming to enhance AI adoption in open, distance, and digital learning environments. First, managers should prioritise improving perceived usefulness by demonstrating the tangible benefits of AI tools, such as personalised learning, automated assessments, and efficiency gains, to foster positive attitudes towards technology. Second, emphasising perceived ease of use through user-friendly interfaces, clear instructions, and ongoing technical support can reduce resistance and increase acceptance among learners and educators. Third, fostering learner autonomy by providing flexible, self-directed learning options and encouraging self-regulation can significantly boost engagement and adoption. Managers should also focus on designing training programs that empower learners with digital literacy skills, enabling them to confidently navigate AI technologies. Additionally, creating a supportive organisational climate that encourages experimentation, feedback, and continuous improvement can address potential barriers and facilitate smoother integration of AI solutions. It is essential to recognise that learner engagement mediates the relationship between perceptions and actual adoption; thus, cultivating an engaging, participative learning environment should be a priority. Overall, adopting a holistic approach that enhances perceived usefulness, ease of use, and learner autonomy will likely lead to higher acceptance and sustained use of AI technologies, ultimately improving educational effectiveness and organisational competitiveness in the rapidly evolving digital landscape.

Suggestions for Future Studies

Future research could explore longitudinal studies to examine how perceptions of usefulness, ease of use, and learner autonomy evolve with continued exposure to AI technologies. Additionally, qualitative approaches such as interviews or case studies could provide deeper insights into contextual barriers and facilitators of AI adoption in diverse educational settings. Investigating the role of organisational culture, educator attitudes, and digital literacy levels may also help refine understanding of factors influencing acceptance. Furthermore, future studies could examine how specific design features of AI tools impact perceived ease of use and engagement, potentially leading to more user-centric innovations. Exploring cross-cultural differences and their effects on perceptions and adoption strategies would also enhance the generalizability of findings. Lastly, assessing the long-term impact of AI-driven learning environments on academic outcomes and learner satisfaction could provide a more comprehensive view of their effectiveness in transformative education. These avenues will help educators and administrators develop more targeted interventions, fostering sustainable AI integration in higher education.

Conclusion

This study highlights the critical importance of perceived usefulness, perceived ease of use, and learner autonomy in driving AI adoption within open, distance, and digital higher education environments. The findings highlight that these perceptions significantly influence learners' engagement, which serves as a key mediator in transforming positive attitudes into actual technology acceptance. Emphasising user-friendly AI tools, fostering learner independence, and creating engaging, supportive learning atmospheres are essential strategies for successful AI integration. By adopting a holistic approach that addresses both perceptual and behavioural factors, institutions can enhance technology acceptance, improve learning outcomes, and stay competitive in a rapidly evolving digital landscape. Overall, this research provides valuable insights for educators and administrators to design more effective interventions, ensuring sustainable and impactful AI adoption in higher education. Continued exploration of these factors will further refine theoretical models and practical strategies, fostering innovative and learner-centred digital learning environments in the future.

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