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Artificial Intelligence Adoption in Open, Distance, and Digital Education: Examining the Mediating Effect of Learning Engagement

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Abstract
This study examines the adoption of artificial intelligence (AI) in enhancing student learning within open, distance, and digital education (ODDE) higher education institutions. While AI offers significant potential to personalise learning, improve engagement, and overcome geographical barriers, empirical evidence on its adoption in ODDE contexts remains limited. To address this gap, the study investigates the relationships between perceived usefulness (PU), perceived ease of use (PEU), and learners' autonomy (LA) in influencing AI adoption, with learning engagement (LE) examined as a mediating variable. A quantitative research design was employed using a structured questionnaire comprising 23 validated items. Data were collected from 297 ODDE students through purposive sampling and analysed using Structural Equation Modelling (SEM) via SmartPLS. The findings reveal that perceived usefulness and learners' autonomy have significant positive effects on AI adoption. Learning engagement plays a critical mediating role, indicating that positive perceptions and autonomy must translate into active involvement to support adoption. In contrast, perceived ease of use does not directly influence AI adoption, although it positively contributes to learning engagement. The study extends the Technology Acceptance Model (TAM) by incorporating learner-centred constructs and highlights the importance of engagement in AI adoption. Practically, the findings suggest that institutions should focus on fostering learner autonomy, meaningful engagement, and clear value communication when integrating AI into ODDE environments.

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

Introduction

Artificial Intelligence (AI) adoption is becoming increasingly vital in Open, Distance, and Digital Education (ODDE) as higher education embraces online platforms and digital tools. AI applications such as adaptive learning systems, chatbots, and intelligent tutoring systems enhance engagement, knowledge retention, and accessibility, while addressing challenges of distance and limited support (Yang et al., 2024; Wang & Huang, 2025; Rosak-Szyrocka et al., 2023). For ODDE learners, AI enables personalised, flexible learning that improves outcomes and satisfaction. Despite its promise, research on AI in ODDE remains limited. Most studies focus on traditional or corporate learning, leaving gaps in understanding adoption factors, barriers, and effectiveness across diverse cultural and infrastructural contexts (George & Wooden, 2023; Negoiță & Popescu, 2023). Challenges such as digital literacy, ethics, and the digital divide further restrict adoption, yet strategies to overcome these remain underexplored (Abulibdeh et al., 2025). This study has broad implications. For policymakers, it informs digital infrastructure, policy design, and literacy training (Deckker & Sumanasekara, 2025). For institutions, it supports curriculum enhancement, faculty training, and AI integration (Achruh et al., 2024). For students, especially from marginalised groups, AI offers equitable opportunities and improved motivation (Grájeda et al., 2024). Advancing AI adoption also supports lifelong learning, workforce readiness, and development of digital competencies essential in a technology-driven economy (Walter, 2024; Qian et al., 2025). Accordingly, this research examines the direct and indirect relationships between perceived usefulness, perceived ease of use, learner autonomy, and AI adoption, with learning engagement as a mediator, among students in ODDE higher education institutions.

Despite increasing scholarly attention to artificial intelligence (AI) in higher education, contemporary social science debates continue to highlight concerns related to digital inequality, learner agency, and meaningful engagement in technology-mediated learning, particularly within open, distance, and digital education (ODDE) contexts (George & Wooden, 2023; Abulibdeh et al., 2025). Recent empirical studies have predominantly examined AI adoption in conventional or campus-based learning environments, often emphasising technological readiness and instructional efficiency, while offering limited insight into learner-centred mechanisms such as autonomy and engagement that are critical for sustained adoption in flexible learning systems (Falebita & Kok, 2024; Sibarani, 2025). Furthermore, existing findings remain mixed regarding the roles of perceived ease of use and perceived usefulness when behavioural processes such as learning engagement are considered (Or, 2025; Rahman et al., 2025). In response to these gaps, this study is guided by the following objectives:

- to examine the relationship between perceived usefulness and artificial intelligence adoption among ODDE students
- to examine the relationship between perceived ease of use and artificial intelligence adoption among ODDE students
- to examine the influence of learners' autonomy on artificial intelligence adoption
- to investigate the mediating role of learning engagement in the relationships between perceived usefulness, perceived ease of use, learners' autonomy, and artificial intelligence adoption.

The scope of this study is limited to students enrolled in ODDE higher education institutions and focuses on the use of AI-supported learning technologies, thereby contributing empirical evidence that extends technology acceptance research by incorporating learner engagement into ongoing debates on autonomy, equity, and sustainable digital transformation in education.

Underpinning Theories

This study integrates the Technology Acceptance Model (TAM) and Constructivist Learning Theory to explain AI adoption in education. TAM (Davis, 1989) highlights perceived usefulness (PU) and perceived ease of use (PEOU) as key determinants of technology acceptance, where positive perceptions shape behavioural intentions and actual usage. In learning contexts, students adopt AI tools when they believe these tools enhance outcomes and are easy to use. Constructivist Learning Theory (Piaget, 1954; Vygotsky, 1978) emphasises active, learner-centred engagement, where knowledge is built through exploration, reflection, and collaboration. AI-enabled personalised learning reflects these principles by supporting learner autonomy, peer interaction, and motivation. By combining the two theories, the model proposes that PU and PEOU influence willingness to adopt AI, which enhances autonomy and engagement. Engagement then mediates the link between technology acceptance and learning outcomes, consistent with constructivist principles. This framework clarifies how perceptions of AI foster autonomy, active participation, and improved educational results.

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

Learners' autonomy refers to their ability to direct and control their learning, set goals, and select suitable methods (Iyer, 2025). AI tools strengthen autonomy by offering personalised pathways, adaptive feedback, and tailored content, enabling greater responsibility in learning (Hidayat-ur-Rehman, 2024). Increased autonomy enhances motivation and engagement, characterised by active participation and sustained attention (Al-Mamary & Abubakar, 2025). AI further boosts engagement by making learning interactive, relevant, and personalised (Yuan & Liu, 2025), while studies confirm its role in improving learner experience (Sibarani, 2025). Key factors such as AI competence and chatbot use also support this process (Iyer, 2025). As engagement rises, learners adopt AI tools more effectively, creating a positive cycle that improves outcomes and lifelong learning skills. Accordingly, the following hypotheses were proposed:

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

Perceived ease of use refers to how effortless learners find interacting with AI tools. When students and educators perceive AI as user-friendly, they are more likely to adopt it without frustration, reducing barriers and encouraging active use (Aldraiweesh & Alturki, 2025; Hang, 2024). User-friendly AI enhances motivation and participation, as learners feel more comfortable exploring features, which deepens involvement and understanding (Naidoo, 2023). An intuitive experience fosters sustained engagement, better knowledge retention, and integration into daily learning activities (Rahman et al., 2025). This cycle strengthens adoption, as accessibility encourages learners to experiment, adapt, and incorporate AI tools more effectively (Ateş & Gündüzalp, 2025). Ultimately, ease of use positively influences both engagement and long-term AI adoption in education. Accordingly, the following hypotheses were proposed:

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

Perceived usefulness reflects learners' belief that AI tools improve understanding, efficiency, and overall outcomes, directly shaping their willingness to adopt and consistently use AI (Mayr, 2025). When students see AI as valuable, they are more motivated to integrate it into daily academic routines, which strengthens learning engagement through active participation, motivation, and sustained effort (Sibarani, 2025). Technological readiness, self-efficacy, and positive attitudes towards AI also reinforce perceptions of usefulness and further boost engagement (Falebita & Kok, 2024). This synergy leads to deeper content interaction, better comprehension, and a positive outlook towards continued AI use, ultimately enhancing performance and motivation (Or, 2025). Thus, perceived usefulness not only drives AI adoption but also acts as a catalyst for sustained engagement and long-term integration in education. 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.

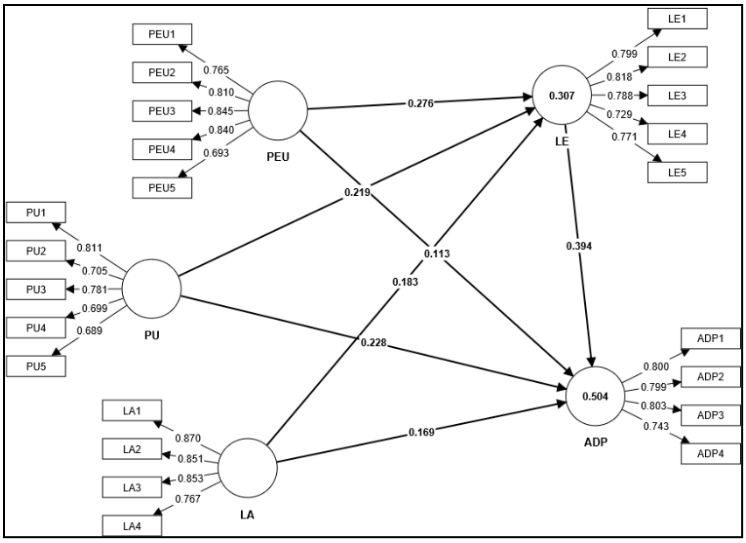

Figure 1: Research Model
Note: PEU=Perceived Ease of Use PU=Perceived Usefulness LA=Learners' Autonomy LE=Learning Engagement ADP=Adoption

Methodology
This study examined the relationships among perceived ease of use, perceived usefulness, learner autonomy, and AI adoption in ODDE higher education, with learning engagement as a mediator. Data were collected using a survey of 23 items drawn from established literature: five each for perceived usefulness and perceived ease of use (Davis, 1989), four for learner autonomy (Vygotsky, 1978), five for learning engagement (Grájeda et al., 2024), and four for AI adoption (Wang & Huang, 2025). All items were measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Due to the absence of a complete population list, purposive sampling was applied. Of 445 distributed surveys, 328 responses were received (73.7% response rate), and 297 valid responses remained after cleaning. Data were analyzed using SmartPLS (Ringle et al., 2022), which enabled structural equation modelling (SEM) to assess both measurement and structural models and test the proposed hypotheses.

Findings and Discussion
Respondents' Profile
The study involved 297 valid participants with a balanced gender distribution: 140 males (47.1%) and 157 females (52.9%). Most respondents were aged 31–40 years (43.8%), followed by 51–60 years (31.7%), 41–50 years (13.8%), under 30 (10.4%), and over 60 (0.3%). By year of study, Year Three had the largest group (23.9%), followed by Year Two (22.2%), Year One (20.5%), Year Four (15.8%), Year Five (10.4%), and more than five years (7.1%). In terms of study level, most were pursuing Diploma or Bachelor's degrees, both listed as 197 participants (66.3%), while 27 were Master's students (9.1%) and 10 were Doctoral students (3.4%).

Notably, the Diploma and Bachelor's percentages appear to total over 100%, suggesting a reporting oversight.

Common Method Bias

Full collinearity analysis (Kock & Lynn, 2012; Kock, 2015) was used to test for common method bias. According to Kock, variance inflation factors (VIFs) below 3.3 indicate bias is not an issue. As shown in Table 1, all constructs, Adoption, Perceived Ease of Use, Perceived Usefulness, Learners' Autonomy, and Learning Engagement recorded VIFs well below the threshold. The highest was 1.946 for Learning Engagement with Perceived Usefulness, still within the acceptable range. This confirms the study is not significantly affected by common method bias, strengthening the validity of the findings.

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). All constructs showed acceptable internal consistency with CA values above 0.7: Adoption (0.795), Learner Autonomy (0.856), Learning Engagement (0.841), Perceived Ease of Use (0.852), and Perceived Usefulness (0.791). CR values also exceeded the 0.7 threshold, confirming reliability: Adoption (0.802), Learner Autonomy (0.858), Learning Engagement (0.845), Perceived Ease of Use (0.876), and Perceived Usefulness (0.794). Convergent validity was established as AVE values were above 0.5 for most constructs—Adoption (0.619), Learner Autonomy (0.699), Learning Engagement (0.611), Perceived Ease of Use (0.628)—with Perceived Usefulness slightly lower at 0.546, but still acceptable. Item loadings mostly exceeded 0.7, confirming strong indicator reliability. Discriminant validity, tested via HTMT (Henseler et al., 2015) in Table 3, showed all values below 0.85–0.90, such as Adoption–Learner Autonomy (0.537), Adoption–Learning Engagement (0.746), and Adoption–Perceived Ease of Use (0.608). These results confirm reliable, valid measurement properties suitable for structural analysis

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 Autonony	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

The structural model was evaluated using PLS with 5,000 bootstrap samples, following Hair et al. (2017). Path coefficients (β), t-statistics, and p-values are presented in Table 4. Learners' Autonomy (LA) significantly influenced Adoption (ADP) (H1: β=0.169, t=3.048, p=0.002) and Learning Engagement (LE) (H2: β=0.183, t=3.395, p=0.001). LA also indirectly affected ADP via LE (H3: β=0.072, t=3.025, p=0.002). Perceived Ease of Use (PEU) had no direct effect on ADP (H4: β=0.113, t=1.584, p=0.113), but significantly influenced LE (H5: β=0.276, t=3.985, p=0.000) and indirectly impacted ADP through LE (H6: β=0.109, t=3.232, p=0.001). Perceived Usefulness (PU) showed a significant direct effect on ADP (H7: β=0.228, t=3.366, p=0.001) and LE (H8: β=0.219, t=3.530, p=0.000). LE itself strongly predicted ADP (H9: β=0.394, t=7.565, p=0.000) and mediated the PU–ADP link (H10: β=0.086, t=3.453, p=0.001). Overall, most hypotheses are supported, emphasising the critical roles of learners' autonomy, perceived usefulness, and Learning Engagement as a key mediator.

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 Shmueli et al. (2016, 2019), the PLS-SEM predictions in Table 6 outperform Linear Model benchmarks, as all PLS-RMSE values are lower than LM-RMSE values across eight indicators, with differences ranging from –0.001 to –0.021. This confirms the superior predictive accuracy of the PLS approach for Adoption (ADP) and Learning Engagement (LE). The CVPAT results (Table 7), in line with Hair et al. (2022) and Liengaard et al. (2021), further validate the model's predictive power. Significant negative average loss differences (ADP = –0.121; LE = –0.088; Overall = –0.103) and strong t-values (ADP = 5.310; LE = 4.106; Overall = 5.343, p = 0.000) indicate that the model consistently outperforms benchmarks. These findings confirm the robustness and reliability of the model in predicting both ADP and LE.

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 IPMA results (Table 8) and following Ringle and Sarstedt (2016) and Hair et al. (2018), **Learning Engagement (LE)** shows the highest importance (0.394) but the lowest performance (60.725), marking it as a priority area for improvement. Learners' Autonomy (LA: importance = 0.241, performance = 67.366), Perceived Usefulness (PU: 0.314, 65.992), and Perceived Ease of Use (PEU: 0.222, 66.463) demonstrate moderate importance with higher performance, indicating relative effectiveness but room for enhancement. To strengthen AI adoption, improving LE should be central—through engaging training, practical AI applications, resource support, and incentives to foster sustained participation. Addressing LE's low performance is essential to maximize its strong impact on 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
This study provides actionable insights for ODDE institutions aiming to enhance AI adoption. Findings highlight learner autonomy (LA) as a central driver, with significant effects on AI adoption (β=0.169) and learning engagement (LE) (β=0.183). Institutions should cultivate a learner-centric environment by offering flexible pathways, self-directed goal setting, and personalised resources. The mediating role of LE in the LA–adoption link (β=0.072) reinforces the need to foster active participation and deep involvement. Perceived usefulness (PU) also

plays a key role, directly influencing adoption (β=0.228) and engagement (β=0.219). Institutions must communicate AI's tangible benefits—improved understanding, efficiency, and outcomes—through practical applications and real-world examples. Learning engagement (LE) itself strongly impacts adoption (β=0.394), highlighting the importance of supportive, stimulating learning environments. Strategies include engaging training programs, clear demonstrations of AI advantages, and fostering community participation. Although perceived ease of use (PEU) significantly affects LE (β=0.276), it does not directly influence adoption. Barriers such as institutional readiness, digital infrastructure, resistance to change, or technological anxiety may limit its effect. Addressing these challenges—by ensuring accessibility, relevance, and digital literacy—can strengthen the role of PEU and PU in driving adoption. Overall, the findings emphasise LA, PU, and LE as critical levers for advancing AI adoption in ODDE contexts.

Theoretical Implications

This study extends the Technology Acceptance Model (TAM) by integrating constructivist learning principles to explain AI adoption in open, distance, and digital education. The findings reaffirm TAM's constructs of perceived usefulness (PU) and perceived ease of use (PEU) while showing that their effects are significantly mediated by learning engagement (LE), supporting the view that acceptance depends not only on perceptions but also on active participation (Davis, 1989). Engagement thus emerges as a central psychological mechanism translating perceptions into behavioural outcomes, enriching TAM's explanatory power. The results also align with constructivist theory, which highlights learner autonomy (LA) and engagement as essential for meaningful learning (Piaget, 1954; Vygotsky, 1978). Autonomous learners are more likely to view technology as useful and easy to use, thereby enhancing adoption. A key theoretical contribution is recognising LA as both a motivator and facilitator of engagement, suggesting that future models should explicitly incorporate learner-centred variables alongside TAM constructs, advancing a more holistic, socio-constructivist perspective that accounts for psychological and contextual factors in higher education digital transformation.

Managerial Implications

The findings suggest that higher education institutions seeking to enhance AI adoption in open, distance, and digital learning should simultaneously improve perceived usefulness by demonstrating tangible benefits such as personalised learning, automated assessments, and efficiency gains; strengthen perceived ease of use through user-friendly design, clear instructions, and continuous support; foster learner autonomy by offering flexible, self-directed pathways and encouraging self-regulation; invest in digital literacy training to empower learners; and create a supportive culture that values experimentation, feedback, and continuous improvement, recognising that learning engagement mediates perceptions and adoption, and that a holistic approach combining usefulness, ease of use, and autonomy will most effectively boost AI acceptance, sustained use, and institutional competitiveness.

Suggestions for Future Studies

Future research could advance this work by conducting longitudinal studies to trace how perceptions of usefulness, ease of use, and autonomy evolve over time; applying qualitative methods such as interviews or case studies to reveal contextual barriers and facilitators; examining the influence of organisational culture, educator attitudes, and digital literacy on adoption; investigating how specific AI design features shape ease of use and engagement;

exploring cross-cultural variations to broaden generalisability; and assessing the long-term effects of AI-driven learning on academic outcomes and learner satisfaction, thereby refining adoption models and guiding sustainable AI integration in higher education.

Conclusion

This study highlights the critical importance of perceived usefulness, perceived ease of use, and learner autonomy as key drivers of AI adoption in open, distance, and digital higher education. These factors strongly influence learner engagement, which plays a mediating role in translating positive perceptions into actual technology acceptance. Institutions can enhance adoption by providing user-friendly AI tools, encouraging learner independence, and fostering engaging and supportive learning environments. A holistic approach that integrates both perceptual and behavioural factors not only improves technology acceptance and learning outcomes but also strengthens institutional competitiveness in the digital era. Overall, the findings provide valuable guidance for designing effective interventions that support sustainable and impactful AI integration in higher education.

References

Abulibdeh, A., Baya Chatti, C., Alkhereibi, A., & El Menshawy, S. (2025). A Scoping Review of the Strategic Integration of Artificial Intelligence in Higher Education: Transforming University Excellence Themes and Strategic Planning in the Digital Era. *European Journal of Education*, *60*(1), e12908.

Achruh, A., Rapi, M., Rusdi, M., & Idris, R. (2024). Challenges and Opportunities of Artificial Intelligence Adoption in Islamic Education in Indonesian Higher Education Institutions. *International Journal of Learning, Teaching and Educational Research*, *23*(11), 423-443.

Aldraiweesh, A. A., & Alturki, U. (2025). The Influence of Social Support Theory on AI Acceptance: Examining Educational Support and Perceived Usefulness using SEM analysis. *IEEE Access*.

Al-Mamary, Y. H., & Abubakar, A. A. (2025). Empowering ChatGPT adoption in higher education: A comprehensive analysis of university students' intention to adopt artificial intelligence using self-determination and technology-to-performance chain theories. *The Internet and Higher Education*, *66*, 101015.

Ateş, H., & Gündüzalp, C. (2025). Proposing a conceptual model for the adoption of artificial intelligence by teachers in STEM education. *Interactive Learning Environments*, 1-27.

Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, 98(2), 310-357. https://doi.org/10.1037/0033-2909.98.2.310

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.

Deckker, D., & Sumanasekara, S. (2025). The role of artificial intelligence in education: Transforming learning and teaching. *EPRA International Journal of Research and Development (IJRD), 10 (3), 5. https://doi. org/10.36713/epra20429*.

Falebita, O. S., & Kok, P. J. (2024). Artificial intelligence tools usage: A structural equation modelling of undergraduates' technological readiness, self-efficacy and attitudes. *Journal for STEM Education Research*, 1-26.

George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, *13*(9), 196.

Grájeda, A., Burgos, J., Córdova, P., & Sanjinés, A. (2024). Assessing student-perceived impact of using artificial intelligence tools: Construction of a synthetic index of application in higher education. *Cogent Education*, *11*(1), 2287917.

Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2019). *Multivariate data analysis (8th ed.)*. Cengage Learning.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Thousand Oaks, CA: SAGE.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (3 ed.).* Thousand Oaks, CA: Sage.

Hair, J.F., M. Sarstedt, C.M. Ringle, and S.P. Gudergan. (2018). *Advanced issues in partial least squares structural equation modeling.* Thousand Oakes, CA: Sage Publications

Hang, N. T. (2024). The Role of Adoption, Ease of Use and Teachers' Experience of Artificial Intelligence on Teaching Effectiveness: Moderating Role of Student Interest. *Journal of Pedagogical Research*, *8*(4), 16-29.

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling, *Journal of the Academy of Marketing Science*, 43(1): 115-135.

Hidayat-ur-Rehman, I. (2024). Examining AI competence, chatbot use, and perceived autonomy as drivers of students' engagement in informal digital learning. *Journal of Research in Innovative Teaching & Learning*, *17*(2), 196-212.

Iyer, S. S. (2025). Key Drivers of Artificial Intelligence on Learner Engagement and Experience. *Next-Generation AI Methodologies in Education*, 57-92.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration*, 11(4), 1-10.

Kock, N., & Lynn, G.S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, 13(7), 546-580.

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, Yet Forsaken? Introducing a Cross-validated Predictive Ability Test in Partial Least Squares Path Modeling. *Decision Sciences*, 52(2), 362-392.

Mayr, K. (2025). The Influence of AI Integration on Teaching Effectiveness: Examining Teacher Adoption, Ease of Use, Experience, and Student Interest. *CURRENT RESEARCH JOURNAL OF PEDAGOGICS*, *6*(03), 1-4.

Naidoo, D. T. (2023). Integrating TAM and IS success model: Exploring the role of Blockchain and AI in predicting learner engagement and performance in E-learning. *Frontiers in Computer Science*, *5*, 1227749.

NEGOIȚĂ, D. O., & Popescu, M. A. M. (2023, December). The use of artificial intelligence in education. In *International Conference of Management and Industrial Engineering* (Vol. 11, pp. 208-214).

Or, C. (2025). Understanding factors influencing AI adoption in education: Insights from a Meta-Analytic Structural Equation Modelling study. *Journal of Applied Learning and Teaching*, *8*(1).

Piaget, J. (1954). *The construction of reality in the child*. Routledge & Kegan Paul.

Qian, L., Cao, W., & Chen, L. (2025). Influence of artificial intelligence on higher education reform and talent cultivation in the digital intelligence era. *Scientific Reports*, *15*(1), 6047.

Vol. 15, No. 1, 2026, E-ISSN: 2226-6348 © 2026

Rahman, M. K., Ismail, N. A., Hossain, M. A., & Hossen, M. S. (2025). Students' mindset to adopt AI chatbots for effectiveness of online learning in higher education. *Future Business Journal*, *11*(1), 30.

Ringle, C.M., and M. Sarstedt. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. *Industrial Management & Data Systems.* 116: 1865–1886.

Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. (2022). SmartPLS 4. *Oststeinbek*: SmartPLS. Retrieved from https://www.smartpls.com

Rosak-Szyrocka, J., Żywiołek, J., Nayyar, A., & Naved, M. (Eds.). (2023). *The role of sustainability and artificial intelligence in education improvement*. CRC Press.

Shmueli, G., M. Sarstedt, J.F. Hair, J.-H. Cheah, H. Ting, S. Vaithilingam, and C.M. Ringle. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing*. 53: 2322–2347.

Shmueli, G., S. Ray, J.M. Velasquez Estrada, and S.B. Chatla. (2016). The elephant in the room: predictive performance of PLS models. *Journal of Business Research*, 69: 4552–4564.

Sibarani, B. E. (2025). Exploring the Impact of Artificial Intelligence in Enhancing the Effectiveness of Distance Education: The Moderating Role of Student Engagement. *Turkish Online Journal of Distance Education*, *26*(2), 133-148.

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

Walter, Y. (2024). Embracing the future of Artificial Intelligence in the classroom: the relevance of AI literacy, prompt engineering, and critical thinking in modern education. *International Journal of Educational Technology in Higher Education*, *21*(1), 15.

Wang, D., & Huang, X. (2025). Transforming education through artificial intelligence and immersive technologies: enhancing learning experiences. *Interactive Learning Environments*, 1-20.

Yang, Y., Chen, L., He, W., Sun, D., & Salas-Pilco, S. Z. (2024). Artificial Intelligence for enhancing special education for K-12: A decade of trends, themes, and global insights (2013–2023). *International Journal of Artificial Intelligence in Education*, 1-49.

Yuan, L., & Liu, X. (2025). The effect of artificial intelligence tools on EFL learners' engagement, enjoyment, and motivation. *Computers in Human Behavior*, *162*, 108474.