Integrating TAM and Organisational Support Theory to Explain Employees' Acceptance of Artificial Intelligence in Malaysian Open and Distance Learning Higher Education Institutions

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ABSTRACT

Artificial intelligence (AI) is changing teaching, administration and learner support in higher education, yet employee resistance remains a major obstacle to its use. Drawing on the Technology Acceptance Model (TAM) and Organisational Support Theory (OST), this study examines how perceived usefulness and organisational support influence employees' acceptance of AI in Malaysian private open and distance learning (ODL) higher education institutions, with attitude and intention as mediators. Survey data were collected from 331 academic and administrative employees and analysed using partial least squares structural equation modelling (PLS-SEM). Fifteen of the 16 hypotheses were supported. Perceived usefulness influenced attitude and intention but had no direct effect on acceptance, while organisational support influenced attitude, intention and acceptance. Attitude and intention mediated the effects of both antecedents, and intention was the strongest predictor of acceptance. The findings show that TAM and OST complement each other: employees' own judgement of AI and the support they receive from their institution both shape acceptance, largely by changing how employees feel about AI and whether they decide to use it. ODL institutions should therefore demonstrate the practical benefits of AI, provide sustained training and technical support, and help employees turn positive attitudes into firm plans to use AI. Future research should use longitudinal designs, include objective usage data and test moderators such as digital literacy and AI anxiety.

Keywords: Open and distance learning, Perceived usefulness, Organisational support, Technology Acceptance Model, Artificial intelligence acceptance

INTRODUCTION

Artificial intelligence (AI) is becoming part of everyday work in higher education institutions. Generative tools can now draft emails, summarise documents, prepare assessment items and respond to student queries at any time, and institutions have to decide how these tools should be used and how to prepare their employees for them (Dwivedi et al., 2023; Kasneci et al., 2023). Malaysia has made its direction clear. The National Artificial Intelligence Roadmap 2021-2025 placed AI talent and the wider acculturation of AI at the centre of national strategy (Ministry of Science, Technology and Innovation [MOSTI], 2021). This was followed by the National Guidelines on AI Governance and Ethics (MOSTI, 2024) and the launch of the National AI Office in December 2024 (National AI Office, 2024).

Open and distance learning (ODL) higher education institutions have particular reason to pay attention to these developments. Almost every communication with their learners, from enrolment and tutoring to assessment and learner support, already takes place through digital systems, which makes them natural settings for AI-supported services (Bozkurt et al., 2023). However, acquiring an AI tool does not mean that employees will use it. If employees do not see its value, do not feel supported by their institution, or do not intend to change the way they work, the tool is likely to remain underused. For this reason, employee resistance rather than technology itself is often the main barrier to AI adoption in these institutions.

Research has not kept pace with this apprehension. Much of the existing work on AI in higher education focuses on students or academics or on describing possible applications, rather than on explaining why employees accept or resist AI (Zawacki-Richter et al., 2019). Studies involving academics and employees generally confirm the importance of perceived usefulness (Wang et al., 2021; Zhang et al., 2023), and recent Malaysian studies point to attitude as an important mediator of AI acceptance among higher education employees (Osman et al., 2024; Osman & Yatam, 2024). Studies of lecturers elsewhere in Malaysia and Asia point in the same direction. Sadiq et al. (2026) found that attitude was the strongest predictor of Malaysian lecturers' intention to use AI tools for assessment, while a large study of lecturers in China showed that intention is a strong driver of actual use of generative AI (Luo & Day, 2026). However, these studies concentrate on lecturers in conventional universities and on individual beliefs about AI. Three gaps therefore remain. ODL higher education institutions have received little attention, organisational support is rarely examined together with perceived usefulness in the same model, and the mediating roles of attitude and intention have seldom been tested within a single framework.

This study addresses these gaps by drawing on the Technology Acceptance Model (TAM) and Organisational Support Theory (OST) to examine the influence of perceived usefulness and organisational support on employees' acceptance of AI in private ODL higher education institutions in Malaysia, with attitude and intention as mediating variables. TAM explains how employees judge the usefulness of AI, while OST explains how the support they receive from their institution shapes their response to it. By bringing the two theories together, the study offers a fuller explanation of AI acceptance than either theory provides alone. It also gives ODL higher education institutions management practical evidence on whether to focus on demonstrating the usefulness of AI, strengthening organisational support, or both. The rest of the paper reviews the relevant literature and develops the hypotheses, describes the methodology, presents the data analysis, and closes with the discussion and conclusion.

LITERATURE REVIEW

Underpinning Theories

The Technology Acceptance Model (TAM) and Organisational Support Theory (OST) serve as the foundation of this research, which offers a thorough framework for analysing employees' acceptance of AI in ODL higher education institutions. According to TAM, perceived usefulness is a key factor that affects users' attitudes toward a technology, which then influences their actual acceptance and behavioural intention (Davis et al., 1989). According to the model in this study, perceived usefulness has a direct impact on employees' attitudes toward AI, and attitude acts as a mediating mechanism that connects perceived usefulness to intention and, in the end, to AI acceptance. This supports the fundamental idea of TAM that attitude and intention serve as mediators between technology-related beliefs and acceptance behaviour.

In addition to TAM's tech-focused approach, OST describes the organisational path. According to OST, employees create general impressions regarding the degree to which the company values their contributions and is concerned about their welfare (Eisenberger et al., 1986). Organisational support, which includes training, technical assistance, and management encouragement, is predicted to have a beneficial impact on employee's attitudes and readiness to adopt AI in ODL institutions. Employees are more likely to adopt a positive attitude toward and intention to accept AI when they believe their organisation supports its use.

TAM explains how individuals judge a technology, but it says little about the setting in which that judgement is made. OST does the opposite. It explains how employees respond to the way their organisation treats them, but it does not explain how they evaluate a particular tool. Used together, the two theories cover both sides of the decision to accept AI: employees' own view of whether AI will help them in their work, and their belief that the institution will help them to use it. Both are expected to work through the same route, by shaping attitude and intention. This extends AI acceptance research in higher education, which has mostly focused on individual beliefs and has tended to treat organisational factors as background conditions.

Perceived Usefulness

Perceived usefulness refers to the degree to which a person believes that using a particular system would improve their job performance (Davis, 1989). For employees in ODL institutions, this could mean responding to learner queries more quickly, marking more consistently, identifying at-risk learners earlier or spending less time on routine administrative work. TAM proposes that perceived usefulness shapes both attitude and intention, and both links have been supported in many settings (Davis et al., 1989; Zhang et al., 2023). Davis et al. (1989) also found that people may form an intention to use a system mainly because they expect it to improve their performance, even when their feelings about the system are not strongly positive. This explains why perceived usefulness is often found to affect intention directly as well as through attitude.

Studies on AI in higher education support these relationships. Wang et al. (2021) found that these beliefs shaped university teachers' intention to use AI-based applications, and Zhang et al. (2023) confirmed the TAM-based determinants of pre-service teachers' intention to use AI in education. In Malaysia, Mohd Rahim et al. (2022) found that performance expectancy, a construct closely related to perceived usefulness, predicted postgraduate students' intention to use AI chatbots, while Osman and Yatam (2024) reported that perceived usefulness influenced AI acceptance among higher education employees. On this basis, perceived usefulness is expected to be related to employees' intention (H1), acceptance (H2) and attitude (H3).

The effect of perceived usefulness on acceptance may not be entirely direct. In TAM, beliefs about a system influence behaviour mainly through attitude and intention, and Davis et al. (1989) found that intention, rather than beliefs, was the main determinant of usage. Employees may recognise that AI is useful, yet accept it only after they have come to view it favourably and have decided to use it. Accordingly, intention is expected to mediate the relationship between perceived usefulness and acceptance (H4), attitude is expected to mediate the relationship between perceived usefulness and acceptance (H5), and attitude is expected to mediate the relationship between perceived usefulness and intention (H6).

Organisational Support

Organisational support in this study refers to the extent to which employees believe their institution provides the training, technical assistance, resources and management encouragement they need to use AI. The concept draws on OST, which holds that employees form general beliefs about how far their organisation values their contributions and cares about their well-being, and that these beliefs shape how they respond to the organisation and its initiatives (Eisenberger et al., 1986). It also overlaps with facilitating conditions in the Unified Theory of Acceptance and Use of Technology (UTAUT), which reflects the belief that organisational and technical infrastructure exists to support the use of a system (Venkatesh et al., 2003). In this study, organisational support is measured as a single construct whose items cover the practical help an institution gives employees to use AI. This includes technical assistance, such as helpdesk services and troubleshooting; training, such as workshops and hands-on guidance; resources, such as access to licensed AI tools; institutional policies, including guidelines on ethical use and data privacy; and encouragement from management.

Support is especially relevant for AI because the technology changes quickly and raises concerns about data privacy, academic integrity and job security. When institutions offer clear guidelines, training and visible encouragement from leaders, employees are more likely to see AI as something they can manage rather than something imposed on them. Choi (2021) found that employees were more willing to accept AI when their role alongside it was clear and they felt able to use it, both of which institutions can influence through guidance and training. Hoi et al. (2024) also found that perceived organisational support strengthened university students' intention to use AI language models. UTAUT further proposes that facilitating conditions can influence use directly, because available resources make action possible regardless of what people plan (Venkatesh et al., 2003). Organisational support is therefore expected to be related to intention (H7), acceptance (H8) and attitude (H9).

In line with OST, support from the institution is also likely to work indirectly. Employees who feel supported tend to respond more favourably to what their organisation asks of them (Eisenberger et al., 1986), which suggests that support may improve how employees feel about AI and strengthen their intention to use it, and

that these responses then lead to acceptance. Intention is therefore expected to mediate the relationship between organisational support and acceptance (H10), attitude is expected to mediate the relationship between organisational support and acceptance (H11), and attitude is expected to mediate the relationship between organisational support and intention (H12).

Attitude

Attitude refers to an individual's overall positive or negative evaluation of using a technology (Fishbein & Ajzen, 1975). In TAM, attitude sits between beliefs about a system and the intention to use it (Davis et al., 1989). AI tends to provoke stronger feelings than most workplace systems, ranging from enthusiasm about saving time to concern about surveillance, fairness or being replaced, so attitude is likely to play a larger part in employees' decisions about it. Osman et al. (2024) showed that attitude played a central role in explaining AI acceptance among Malaysian higher education employees. Employees who view AI favourably are more likely to form an intention to use it and to accept it as part of their work. Thus, attitude is expected to be related to intention (H13) and acceptance (H14).

Intention

Intention refers to an employee's readiness and willingness to use AI in their work. The Theory of Reasoned Action and the Theory of Planned Behaviour both treat intention as the most immediate predictor of behaviour (Ajzen, 1991; Fishbein & Ajzen, 1975), and TAM follows the same reasoning (Davis et al., 1989). Intention explains a substantial share of the variance in behaviour, although a gap between what people intend and what they actually do remains (Conner & Norman, 2022). Because AI tools are still new in many ODL institutions and are not yet part of daily routines, employees often need to make a deliberate decision to use them, and that decision should lead to greater acceptance (H15). Since attitude is expected to shape intention, and intention is expected to shape acceptance, intention is also expected to mediate the relationship between attitude and acceptance (H16).

Acceptance

Acceptance is the outcome variable in this study. It refers to the extent to which employees willingly take AI into their work, are prepared to rely on it and support its wider use within their institution. Earlier TAM studies often measured acceptance as actual system use (Davis, 1989). For AI, usage alone can be misleading, because many AI features are built into platforms that employees must use as part of their jobs, and a person may use such a platform every day without accepting the AI functions within it. Research on employee acceptance of AI shows that willingness to accept the technology depends on how employees see their role alongside it, their motivation and their ability to use it (Choi, 2021). In Malaysian higher education, Osman and Yatam (2024) and Osman et al. (2024) found that employees' acceptance of AI was shaped by their beliefs about the technology and their attitude toward it. Taken together, these studies suggest that acceptance depends on what employees believe about AI, how they feel about it and the support they receive from their institution, which forms the basis of the framework tested in this study.

Research Hypotheses

Based on the above conceptual development, the following research hypotheses were proposed for this study:

H1: There is a relationship between perceived usefulness and intention towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

H2: There is a relationship between perceived usefulness and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H3: There is a relationship between perceived usefulness and attitude towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

H4: There is a mediating effect of intention on the relationship between perceived usefulness and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H5: There is a mediating effect of attitude on the relationship between perceived usefulness and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H6: There is a mediating effect of attitude on the relationship between perceived usefulness and intention towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

H7: There is a relationship between organisational support and intention towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

H8: There is a relationship between organisational support and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H9: There is a relationship between organisational support and attitude towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

H10: There is a mediating effect of intention on the relationship between organisational support and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H11: There is a mediating effect of attitude on the relationship between organisational support and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H12: There is a mediating effect of attitude on the relationship between organisational support and intention towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

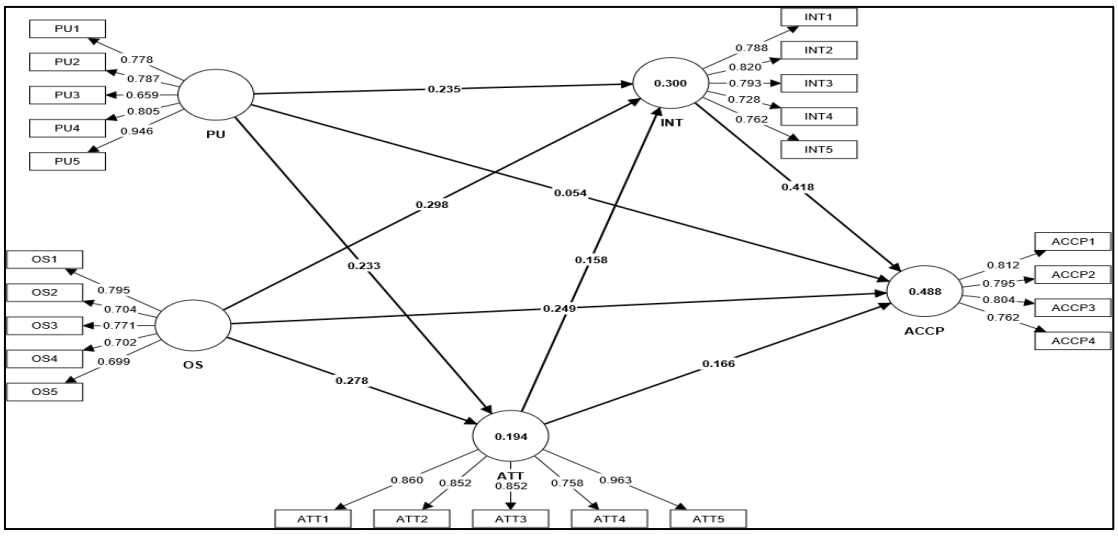
H13: There is a relationship between attitude and intention towards employees' acceptance of artificial intelligence in open & distance higher education institutions.

H14: There is a relationship between attitude and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H15: There is a relationship between intention and employees' acceptance of artificial intelligence in open & distance higher education institutions.

H16: There is a mediating effect of intention on the relationship between attitude and employees' acceptance of artificial intelligence in open & distance higher education institutions.

Figure 1: Research Model



Notes: PU=Perceived Usefulness OS=Organisational Support ATT=Attitude INT=Intention ACCP=Acceptance

METHODOLOGY

This study aimed to examine the direct and indirect impacts of perceived usefulness and organisational support on AI acceptance, with intention and attitude acting as mediators, among employees at higher education institutions that provide ODL. In order to achieve this, a survey was conducted in which primary data were gathered, and the measurement instruments were carefully chosen after a thorough evaluation of the current literature to verify their reliability and validity. Due to the absence of a thorough population list, questionnaires were given out to chosen participants through email, social media, and in person utilising non-probability snowball sampling. The adequacy of the sample size was checked against three criteria. The guideline of ten observations per measurement item (Hair et al., 2010; Schreiber et al., 2006) required at least 240 responses for the 24 items. A power analysis in G*Power for a model with four predictors of acceptance, a medium effect size ($f^2 = 0.15$), a significance level of 0.05 and statistical power of 0.95 indicated a minimum of 129 responses (Cohen, 1988). The inverse square root method for PLS-SEM, based on the smallest significant path coefficient in the model ($\beta = 0.158$), indicated a minimum of 248 responses (Kock & Hadaya, 2018). The analysis included 24 observed variables, among which were exogenous variables like organisational support (5 items) and perceived usefulness (5 items) that were adapted from Chatterjee et al. (2021). Acceptance, adapted from Venkatesh et al. (2003) (4 items), was the dependent variable, while the identified mediators were intention, based on Venkatesh et al. (2003) (5 items), and attitude (5 items) adapted from Davis et al. (1989). Participants responded to each item on a five-point Likert scale, ranging from strongly disagree to strongly agree. All items were reworded to refer specifically to the use of AI in ODL work. 363 usable replies were received from 467 disseminated surveys, giving a 77.7% response rate, which was enough for structural equation modeling (SEM). After screening, 32 responses that did not meet the quality criteria were removed, leaving 331 valid responses for analysis, which exceeds all three minimum sample size requirements. Using SmartPLS 4 software, which is well-known for its proficiency in SEM methodologies, data analysis and hypothesis testing were carried out. This was done in accordance with the study's objectives and the guidelines established by Ringle et al. (2022) because of its excellent evaluation features and capacity to manage sophisticated multivariate data. Comprehensive testing of the proposed hypotheses was made possible by this application, which also aided in a thorough assessment of both measurement and structural models.

Data were collected from employees of three private ODL higher education institutions in Malaysia. Initial respondents were contacted through institutional email and professional networks and were asked to pass the survey on to eligible colleagues. To be included, respondents had to (1) be employed by one of the participating institutions as academic staff (such as lecturers, tutors and module developers) or administrative staff (such as IT support, student services and registry staff), on a full-time, part-time, contract or freelance basis; (2) have worked at the institution for at least six months, so that they had experienced its technology infrastructure and support arrangements; and (3) use the institution's digital platforms or learning management system in their work. Participation was voluntary and anonymous. Because snowball sampling does not produce a statistically representative sample, the findings should be generalised with care, as noted in the limitations of the study.

RESULTS AND DISCUSSION

The data were analysed in SmartPLS 4 following the two-stage approach recommended for PLS-SEM (Hair et al., 2019). The measurement model was first assessed for indicator reliability (outer loadings), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted) and discriminant validity (HTMT ratio), as reported in Tables 3 and 4. The structural model was then assessed for collinearity and common method bias using the full collinearity test (Table 2), the significance of the path coefficients and indirect effects using bootstrapping (Table 5), effect sizes and explanatory power (Table 6), and out-of-sample predictive power using PLSpredict (Table 7). An importance-performance map analysis was also carried out to identify priority areas for management (Table 8).

Respondents' Profiles

A descriptive analysis of the demographic profile of the 331 respondents was conducted. The findings are summarised in Table 1. Of the 331 respondents, 54.1% were female, and most were aged between 41 and 59 years (66.1%). Three quarters were academic staff (75.5%), nearly half had served their institution for more than 15 years (48.6%), and most held a master's (48.3%) or doctoral degree (29.0%). Part-time employees formed the largest group (47.4%), followed by full-time employees (42.9%).

Table 1: Respondents' Profile (n = 331)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	152	45.9
	Female	179	54.1
Age	≤ 35 years	30	9.1
	36 – 40 years	24	7.3
	41 – 49 years	103	31.1
	50 – 59 years	116	35
	≥ 60 years	58	17.5
Role	Academic	250	75.5
	Non-Academic	81	24.5
Years of Service	< 1 year	29	8.8
	1 – 3 years	44	13.3
	4 – 6 years	15	4.5
	7 – 10 years	40	12.1
	11 – 15 years	42	12.7
	> 15 years	161	48.6
Education Level	Diploma	13	3.9
	Bachelor's Degree	61	18.4
	Postgraduate Diploma	1	0.3
	Master's Degree	160	48.3
	Doctoral Degree (PhD)	96	29
Employment Status	Full-time	142	42.9
	Part-time	157	47.4
	Contract	19	5.7
	Freelance	13	3.9

Common Method Bias

In Table 2, the VIF values are all below the 3.3 threshold, indicating that the model is free of common method bias, as suggested by the full collinearity test from Kock and Lynn (2012) and Kock (2015). To be exact, none of the VIF values for each construct in the table, which range from 1.276 to 1.914, are greater than 3.3. Kock (2015) states that if all the VIF values in the complete collinearity test are at or below 3.3, the model can be deemed free of common method bias. The highest VIF for ACCP (acceptance) predicted by PU (perceived usefulness) is 1.914, which is still well below the threshold, indicating that multicollinearity between constructs is not serious and that shared variance caused by the measurement method is restricted. As a result, the validity of the study's conclusions is not significantly endangered by common method bias.

Table 2: Full Collinearity (VIF)

	ACCP	PU	OS	ATT	INT
ACCP		1.914	1.790	1.847	1.550
PU	1.448		1.340	1.419	1.409
OS	1.513	1.498		1.596	1.600
ATT	1.276	1.295	1.304		1.322
INT	1.413	1.697	1.725	1.744	

Notes: PU=Perceived Usefulness OS=Organisational Support ATT=Attitude INT=Intention ACCP=Acceptance. Full collinearity VIF; all values below the 3.3 threshold (Kock, 2015).

Measurement Model

The findings for construct reliability and validity are shown in Table 3, along with the item loadings, Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE). Convergent validity is established when loadings are greater than 0.70, CA and CR are at least 0.70, and AVE is 0.50 or higher, according to Hair et al. (2019). Item loadings range from 0.659 to 0.963, and most exceed 0.70; the few that are below this threshold (PU3 = 0.659 and OS5 = 0.699) are still over the 0.40 acceptable lower bound advised by Hair et al. (2019), and their constructs continue to show sufficient reliability and validity, indicating that these items are important and should not be removed. In terms of reliability, CA values range from 0.787 (Organisational Support) to 0.910 (Attitude), and CR values range from 0.854 to 0.934. All of these values are significantly higher than the 0.70 threshold, demonstrating that the items within each construct are highly interrelated and consistently measure the same construct. All of the AVE values, which range from 0.541 (Organisational Support) to 0.739 (Attitude), are higher than the 0.50 threshold for convergent validity. This shows that each construct accounts for more than half of the variation in its indicators and that the items properly converge on their individual constructs. The greatest AVE is found for Attitude (0.739), demonstrating remarkably strong convergence. Despite having the lowest AVE (0.541), Organisational Support nonetheless exceeds the benchmark. Together, the loadings, CA, CR, and AVE findings confirm construct reliability and convergent validity for all five constructs, fulfilling Hair et al.'s (2019) requirements and supporting the measurement model's appropriateness for further structural analysis. Table 4 shows HTMT ratios ranging from 0.413 to 0.746, all below the conservative threshold of 0.85 recommended by Henseler et al. (2015), and well below the more lenient criterion of 0.90. This confirms discriminant validity among all constructs, indicating that each construct is empirically distinct from the others.

Table 3: Construct Reliability and Validity & Item Loadings

Constructs	Items	Loadings	CA	CR	AVE
Acceptance	ACCP1	0.812	0.804	0.872	0.629
	ACCP2	0.795			
	ACCP3	0.804			
	ACCP4	0.762			
Attitude	ATT1	0.860	0.910	0.934	0.739
	ATT2	0.852			
	ATT3	0.852			
	ATT4	0.758			
	ATT5	0.963			
Intention	INT1	0.788	0.838	0.885	0.607
	INT2	0.820			
	INT3	0.793			
	INT4	0.728			
	INT5	0.762			
Organisational Support	OS1	0.795	0.787	0.854	0.541

	OS2	0.704			
	OS3	0.771			
	OS4	0.702			
	OS5	0.699			
Perceived Usefulness	PU1	0.778	0.855	0.898	0.640
	PU2	0.787			
	PU3	0.659			
	PU4	0.805			
	PU5	0.946			

Notes: CA=Cronbach's alpha CR=Composite Reliability AVE=average variance extracted

Table 4: Heterotrait-Monotrait (HTMT) Ratios

	ACCP	ATT	INT	OS
ATT	0.505			
INT	0.746	0.413		
OS	0.663	0.455	0.572	
PU	0.499	0.414	0.510	0.588

Notes: All values below the 0.85 threshold (Henseler et al., 2015).

Structural Model

The hypothesis testing results reveal that 15 of the 16 proposed hypotheses are supported, with only H2 failing to reach statistical significance. *H1* (PU → INT) is supported (β = 0.235, t = 4.135, p < .001), indicating that perceived usefulness significantly enhances employees' intention to accept AI. *H2* (PU → ACCP) is not supported (β = 0.054, t = 1.018, p = 0.309), as the relationship is non-significant with a confidence interval spanning zero (-0.048 to 0.159), suggesting perceived usefulness does not directly influence AI acceptance. *H3* (PU → ATT) is supported (β = 0.233, t = 3.537, p < .001), confirming that perceived usefulness significantly shapes attitudes toward AI. The mediating hypotheses are all supported: *H4* (PU → INT → ACCP; β = 0.098, t = 3.459, p = 0.001), *H5* (PU → ATT → ACCP; β = 0.039, t = 2.496, p = 0.013), and *H6* (PU → ATT → INT; β = 0.037, t = 2.176, p = 0.030), demonstrating that intention and attitude mediate the relationship between perceived usefulness and acceptance. For organisational support, *H7* (OS → INT; β = 0.298, t = 5.747, p < .001), *H8* (OS → ACCP; β = 0.249, t = 4.464, p < .001), and *H9* (OS → ATT; β = 0.278, t = 4.489, p < .001) are all supported, showing that organisational support significantly influences intention, acceptance, and attitude. The mediating paths *H10* (OS → INT → ACCP; β = 0.125, t = 4.905, p < .001), *H11* (OS → ATT → ACCP; β = 0.046, t = 2.254, p = 0.024), and *H12* (OS → ATT → INT; β = 0.044, t = 2.311, p = 0.021) are also supported. Furthermore, *H13* (ATT → INT; β = 0.158, t = 2.939, p = 0.003) and *H14* (ATT → ACCP; β = 0.166, t = 3.144, p = 0.002) are supported, confirming attitude's significant role in shaping intention and acceptance. *H15* (INT → ACCP) is strongly supported (β = 0.418, t = 8.242, p < .001), representing the strongest relationship in the model, while *H16* (ATT → INT → ACCP; β = 0.066, t = 2.757, p = 0.006) is also supported. Overall, the results confirm that intention and attitude serve as significant mediators, with intention emerging as the strongest predictor of AI acceptance.

Mediation was tested by bootstrapping the specific indirect effects, which does not assume that the indirect effect is normally distributed (Preacher & Hayes, 2008). An indirect effect was considered significant when its 95% confidence interval did not include zero, and the type of mediation was identified by comparing each indirect effect with the corresponding direct effect (Zhao et al., 2010). Full mediation occurs when the indirect effect is significant but the direct effect is not, while partial mediation occurs when both are significant and point in the same direction. On this basis, the relationship between perceived usefulness and acceptance was fully mediated. The indirect effects through intention (β = 0.098, 95% CI [0.046, 0.158]) and attitude (β = 0.039, 95% CI [0.015, 0.078]) were significant, whereas the direct effect was not (β = 0.054, 95% CI [-0.048, 0.159]). The remaining mediating relationships were partial. Organisational support influenced acceptance directly (β = 0.249) as well as indirectly through intention (β = 0.125, 95% CI [0.079, 0.178]) and attitude (β =

0.046, 95% CI [0.014, 0.094]). Attitude partially mediated the effects of perceived usefulness (β = 0.037, 95% CI [0.011, 0.080]) and organisational support (β = 0.044, 95% CI [0.014, 0.091]) on intention, and intention partially mediated the effect of attitude on acceptance (β = 0.066, 95% CI [0.022, 0.117]). In other words, perceived usefulness affects acceptance only by first shaping attitude and intention, whereas organisational support works both directly and through these mediators.

Table 5: Hypothesis Testing Results

Hypothesis	Beta	T statistics	P values	95% CI LL	95% CI UL	Decision
H1: PU → INT	0.235	4.135	0.000	0.123	0.347	*Supported*
H2: PU → ACCP	0.054	1.018	0.309	-0.048	0.159	*Not Supported*
H3: PU → ATT	0.233	3.537	0.000	0.097	0.358	*Supported*
H4: PU → INT → ACCP	0.098	3.459	0.001	0.046	0.158	*Supported*
H5: PU → ATT → ACCP	0.039	2.496	0.013	0.015	0.078	*Supported*
H6: PU → ATT → INT	0.037	2.176	0.030	0.011	0.080	*Supported*
H7: OS → INT	0.298	5.747	0.000	0.192	0.394	*Supported*
H8: OS → ACCP	0.249	4.464	0.000	0.137	0.357	*Supported*
H9: OS → ATT	0.278	4.489	0.000	0.152	0.393	*Supported*
H10: OS → INT → ACCP	0.125	4.905	0.000	0.079	0.178	*Supported*
H11: OS → ATT → ACCP	0.046	2.254	0.024	0.014	0.094	*Supported*
H12: OS → ATT → INT	0.044	2.311	0.021	0.014	0.091	*Supported*
H13: ATT → INT	0.158	2.939	0.003	0.050	0.262	*Supported*
H14: ATT → ACCP	0.166	3.144	0.002	0.060	0.268	*Supported*
H15: INT → ACCP	0.418	8.242	0.000	0.316	0.514	*Supported*
H16: ATT → INT → ACCP	0.066	2.757	0.006	0.022	0.117	*Supported*

Notes: Significant at $p<0.05$, $t>1.96$

Effect Sizes (f^2) and Coefficient of Determination (R^2)

Table 6 reports effect sizes (f^2) and the coefficient of determination (R^2). Following Cohen's (1988) benchmarks (0.02 = small, 0.15 = medium, 0.35 = large), INT → ACCP shows a medium effect ($f^2 = 0.239$), while OS → INT (0.091), OS → ACCP (0.079), OS → ATT (0.074), PU → INT (0.057), PU → ATT (0.052), ATT → ACCP (0.042), and ATT → INT (0.029) represent small effects; PU → ACCP (0.004) is negligible, consistent with its non-significant path. The R^2 values indicate that the model explains 48.8% of the variance in ACCP, 30.0% in INT, and 19.4% in ATT, indicating moderate explanatory power for ACCP and weak-to-moderate explanatory power for INT and ATT (Hair et al., 2019).

Table 6: Effect Sizes (f^2) and Coefficient of Determination (R^2)

	ACCP	ATT	INT
ATT	0.042		0.029
INT	0.239		
OS	0.079	0.074	0.091
PU	0.004	0.052	0.057
	R-square		
ACCP	0.488		
ATT	0.194		

INT	0.300		

Notes: Columns show the endogenous (target) constructs.

PLSpredict

Following Shmueli et al. (2016, 2019), PLSpredict was used to assess the model's out-of-sample predictive power. All Q^2predict values are positive (ranging from 0.087 to 0.268), confirming that the model outperforms the naive benchmark (Table 7). Comparison of PLS-RMSE and LM-RMSE values shows that 13 of the 14 indicators have PLS-RMSE smaller than LM-RMSE, with differences ranging from -0.003 to -0.026; only INT1 shows a marginally higher PLS-RMSE (0.627 vs. 0.626, difference = 0.001). As the majority of PLS-RMSE values are lower than their LM counterparts, this indicates that the model has medium out-of-sample predictive power, following the guidelines of Shmueli et al. (2016, 2019).

Table 7: PLSpredict Results

	Q^2predict	PLS-RMSE	LM-RMSE	PLS-LM
ACCP1	0.268	0.619	0.631	-0.012
ACCP2	0.174	0.628	0.637	-0.009
ACCP3	0.196	0.679	0.689	-0.01
ACCP4	0.127	0.724	0.731	-0.007
ATT1	0.17	0.76	0.775	-0.015
ATT2	0.123	0.76	0.786	-0.026
ATT3	0.087	0.77	0.774	-0.004
ATT4	0.115	0.79	0.802	-0.012
ATT5	0.145	0.678	0.693	-0.015
INT1	0.211	0.627	0.626	0.001
INT2	0.187	0.629	0.638	-0.009
INT3	0.132	0.672	0.675	-0.003
INT4	0.112	0.697	0.713	-0.016
INT5	0.157	0.627	0.64	-0.013

Notes: Negative PLS-LM values indicate higher predictive accuracy for PLS-SEM.

Importance-Performance Map Analysis (IPMA)

Following Hair et al. (2018) and Ringle and Sarstedt (2016), an IPMA was conducted with acceptance (ACCP) as the target construct to identify which constructs offer the greatest scope for improvement (Table 8). Intention (INT) shows high importance (0.418) but the lowest performance (60.510), placing it in the high-importance, low-performance area and making it the first priority for intervention. Organisational Support (OS) has the highest importance (0.438) and moderate performance (65.655), so further gains in support are likely to produce the largest overall improvement in acceptance. Attitude (ATT) shows moderate importance (0.233) and the highest performance (67.834), suggesting that current levels should be maintained, while Perceived Usefulness (PU) has the lowest importance (0.207) and moderate performance (65.217), making it a lower priority. In practice, institutions should first strengthen employees' intention to use AI through clear implementation plans, incentives and visible leadership support, and second, sustain organisational support through training, technical assistance and helpdesk services. Demonstrations and practical workshops that

show the benefits of AI in ODL work remain useful, but mainly as a way of building the attitudes and intentions that lead to acceptance.

Table 8: Importance-Performance Map Analysis (IPMA)

	Importance	Performance
ATT	0.233	67.834
INT	0.418	60.51
OS	0.438	65.655
PU	0.207	65.217

Notes: Target construct: ACCP. Importance = total effects. Performance = rescaled scores (0 to 100).

DISCUSSION

The results give ODL higher education institutions that want to increase employee acceptance of AI straightforward, practical advice. Institutions should emphasise demonstrating the practical advantages of AI through engaging workshops, real-time demonstrations of administrative and instructional AI-powered technologies, and evidence-based presentations of productivity gains in ODL contexts, given that perceived usefulness significantly influences both attitude ($\beta = 0.233$) and intention ($\beta = 0.235$). Nevertheless, perceived usefulness did not directly affect acceptance ($\beta = 0.054$), implying that usefulness alone is insufficient; its impact is completely mediated via intention and attitude ($\beta = 0.098$ and $\beta = 0.039$, respectively). Therefore, institutions ought to concentrate their efforts on developing positive attitudes and strengthening intentions rather than anticipating direct outcomes. Organisational support was found to be a major factor that had a considerable impact on intention ($\beta = 0.298$), acceptance ($\beta = 0.249$), and attitude ($\beta = 0.278$), with all of its mediating routes being significant ($\beta = 0.125$, $\beta = 0.046$, and $\beta = 0.044$). To help employees feel valued and have their well-being supported, organisations must offer sustained and visible support, such as technical aid, customised AI training courses, helpful helpdesks, management encouragement, and recognition of early adopters. Intention ($\beta = 0.158$) and acceptance ($\beta = 0.166$) were both significantly influenced by attitude, while intention was the strongest predictor of acceptance ($\beta = 0.418$), and the mediating path from attitude through intention to acceptance was also significant ($\beta = 0.066$). As a result, institutions should create programmes that foster a good attitude via peer leaders, success stories, and participatory decision-making, while turning positive attitudes into tangible plans using straightforward implementation roadmaps, incentives, and opportunities for practical experimentation.

Intention emerged as the strongest predictor of acceptance ($\beta = 0.418$, $f^2 = 0.239$), which is consistent with the reasoning behind TAM and the Theory of Reasoned Action, in which intention is the most immediate step before behaviour (Davis et al., 1989; Fishbein & Ajzen, 1975). Luo and Day (2026) likewise found that intention strongly predicted lecturers' actual use of generative AI. There are also reasons specific to this setting. For most ODL employees, using AI is still largely voluntary and has not yet become part of daily routines, so taking it up requires a conscious decision to change familiar ways of working, such as how assignments are marked or how learner queries are answered. Once that decision is made, employees are more likely to invest the time needed to learn the tools and to keep using them, which is what acceptance reflects. Intention also brings together the effects of the other constructs in the model, since it is shaped by perceived usefulness, attitude and organisational support ($R^2 = 0.300$) and carries much of their combined influence forward to acceptance. Even so, intention does not guarantee acceptance, as people do not always act on what they plan (Conner & Norman, 2022), which may explain why attitude and organisational support also retained direct effects on acceptance.

The non-significant direct effect of perceived usefulness on acceptance ($\beta = 0.054$) does not mean that usefulness is unimportant. Rather, it shows that usefulness works through attitude and intention instead of acting on acceptance by itself, which matches the full mediation found in this study and the original TAM findings, in which beliefs about a system influenced use mainly through intention (Davis et al., 1989). A similar pattern was reported among Malaysian lecturers, for whom attitude fully mediated the effects of several

beliefs about AI tools on intention (Sadiq et al., 2026). Several features of AI in ODL institutions may strengthen this pattern. First, recognising that AI could make work faster or easier is not the same as being willing to rely on it. Employees may still have concerns about the accuracy of AI outputs, academic integrity, data privacy or the security of their own jobs, and these concerns need to give way to a more positive attitude and a firm decision to use AI before acceptance follows. Second, almost half of the respondents had served their institution for more than 15 years (Table 1). Long-serving employees are likely to have well-established work routines, and the case for AI's usefulness may need to become a personal commitment before those routines change. Third, organisational support did have a direct effect on acceptance, which suggests that practical help from the institution can remove barriers in a way that perceived benefits alone cannot. This is consistent with Luo and Day (2026), who found that facilitating conditions influenced lecturers' use of generative AI directly and not only through intention. In short, perceived usefulness is a necessary starting point, but it leads to acceptance only when employees come to view AI favourably and decide to use it. ODL institutions should therefore treat usefulness perceptions as a beginning rather than an end, and build them into wider efforts to shape attitudes and intentions.

Theoretical Implications

By combining the Organisational Support Theory (OST) and the Technology Acceptance Model (TAM) to explain employees' acceptance of AI in ODL higher education institutions, this study offers a number of significant contributions to the current theory. By showing how TAM's internal cognitive assessments (perceived usefulness) and OST's external structural factors (organisational support) operate in tandem, the study advances theoretical understanding beyond single-perspective models.

Furthermore, the findings show that attitude, intention and acceptance are distinct constructs, and that attitude and intention carry the effects of both antecedents towards acceptance. First, the study extends TAM (Davis, 1989) by showing that perceived usefulness affects acceptance only through attitude and intention, with no direct effect of its own, which responds to calls to examine the explanatory limits of TAM for emerging technologies such as AI. Second, by establishing that organisational support not only directly affects acceptance but also functions via attitudinal and intentional routes, the research makes a contribution to OST (Eisenberger et al., 1986). This places perceived organisational support as a contextual enabler that enhances technology-related beliefs. This integration provides a fresh theoretical understanding: AI acceptance in ODL institutions is determined by technological cognition (perceived usefulness) and organisational context (organisational support), with attitude and intention serving as the proximate psychological mechanisms through which both distal antecedents have an impact. By demonstrating that neither technology-centric nor organisation-centric viewpoints on their own adequately explain AI acceptance, and that their integration offers a more concise and comprehensive explanation, this dual-pathway conceptualisation advances theoretical understanding. Future studies may extend this integrated TAM-OST framework by assessing it in different institutional environments, adding further contextual moderators like digital literacy and institutional preparedness, and honing theoretical statements about the boundary conditions under which perceived usefulness and organisational support are most successfully converted into acceptance of artificial intelligence.

Suggestions for Future Study

There are several restrictions in this study that future research should address to improve our understanding of AI acceptance in ODL higher education. Firstly, the cross-sectional design restricts causal inference; longitudinal investigations monitoring employees' acceptance over time would shed light on how perceived usefulness, organisational support, attitude, and intention develop over the course of AI deployment phases. Second, the use of non-probability snowball sampling and the focus on three private ODL institutions in Malaysia mean that the sample may not represent all employees of ODL higher education institutions, particularly those in public institutions; future studies should therefore repeat the integrated TAM-OST framework across a variety of public and private ODL institutions, countries and cultural settings, ideally using probability sampling, to increase generalisability. Third, the study used self-reported metrics that are vulnerable to social desirability bias. Future research might employ objective measures like supervisor evaluations or logs of actual AI use. Fourth, future research should empirically examine moderating variables

such as AI anxiety, digital literacy, workload strain, and academic discipline to determine the contextual boundaries under which organisational support and perceived usefulness best convert into acceptance. Fifth, qualitative or mixed-methods approaches might reveal employee experiences and contextual issues that quantitative surveys overlook. In order to further clarify the theoretical framework and offer more insight into how employees embrace AI in ODL environments, future research should also examine additional moderating or mediating mechanisms such as perceived risk, trust in AI, and facilitating conditions.

CONCLUSION

This research developed and empirically tested an integrated TAM-OST framework that explains how ODL higher education institutions' employees accept AI. The research indicates that perceived usefulness and organisational support serve as complementary antecedents, with intention and attitude working as mediators that relay their impact towards acceptance. In particular, intention was the strongest predictor of acceptance, and the perceived usefulness's direct impact on acceptance was negligible, emphasising the necessity of changing cognitive assessments of AI's usefulness into positive attitudes and conscious intentions before acceptance takes place. In addition to these empirical insights, the research promotes theoretical maturity by integrating organisation- and technology-centric views, demonstrating that AI adoption results from the dynamic interaction between technological attributes and organisational context, which is facilitated by psychological processes, rather than just one of those factors. In fact, the results implore ODL institutions to go beyond just demonstrating AI's benefits and instead develop supportive organisational ecosystems, promote positive attitudes, and turn intentions into long-lasting adoption behaviours. As AI continues to change higher education, this research provides a robust, theoretically based basis for understanding employee acceptance. It also encourages further study to test the framework in various situations, include moderating factors, and use longitudinal designs to capture the changing nature of human-AI interaction in ODL environments.

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