# Determinants of AI Adoption Intention among Open and Distance Learning Practitioners in Malaysian Public Education: A Preliminary Study

**Siti Haslina Md Harizan**

**School of Distance Education, Universiti Sains Malaysia, 11800 USM, Penang, Malaysia**

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## ABSTRACT

The rapid expansion of open and distance learning across Malaysian public higher education institutions, accelerated by the COVID-19 pandemic and mandated through the national Digital Education Policy, has created an urgent need to understand what motivates ODL practitioners to adopt artificial intelligence tools. The study investigates the determinants of artificial intelligence adoption intention among Open and Distance Learning practitioners in Malaysian public education institutions by extending the Technology Acceptance Model with institutional expectation, proactive AI behaviour, and prior AI experience. A quantitative cross-sectional survey was conducted involving 60 AI users employed across the Ministry of Education, Ministry of Higher Education, public universities, and affiliated educational agencies. Data were analysed using descriptive statistics, reliability analysis, Pearson correlation, and multiple regression analysis. Findings reveal that perceived usefulness and proactive AI behaviour are the two strongest significant predictors of AI adoption intention, collectively supporting an extended TAM framework that explains 77.4% of the variance in behavioural intention. In contrast, perceived ease of use, institutional expectation, and prior AI experience were not statistically significant in the controlled regression model, although institutional expectation demonstrated a practically meaningful descriptive trend. The study further identifies a substantial AI adoption depth gap whereby chatbot and conversational AI usage is nearly universal, while adoption of pedagogically transformative applications such as predictive analytics, recommendation systems, and adaptive learning tools remains minimal. These findings suggest that Malaysian ODL practitioners are digitally engaged with AI but have not fully transitioned toward applications capable of improving learner retention, personalised learning, and scalable learner support. The study contributes theoretically by positioning proactive AI behaviour as an independent dispositional pathway influencing AI adoption intention beyond traditional TAM constructs. Practical implications are provided for policymakers, higher education institutions, and quality assurance agencies, particularly regarding the strategic enhancement of AI-driven ODL quality initiatives in Malaysia.

**Keywords:** Artificial intelligence; Malaysian higher education; Open and distance learning; ODL; Technology Acceptance Model.

## INTRODUCTION

Open and distance learning (ODL) has become one of the defining modes of higher education delivery in Malaysia. From its institutional origins with the founding of *Off-Campus Studies*, Universiti Sains Malaysia in 1971, to the rapid pandemic-driven expansion of blended and fully online delivery across all 20 public universities, ODL now serves hundreds of thousands of Malaysian learners who balance study with work, family, and geographic constraints (Halili, Razak & Zainuddin, 2014; Open University Malaysia, 2023; Zawacki-Richter et al., 2019). The structural imperatives driving this expansion have only intensified: Malaysia's online education market is projected to reach USD 2.1 billion by 2028, growing at 16.4% annually, while the national Digital Education Policy (DEP), launched in November 2023, mandates the adoption of AI-based adaptive learning platforms, AI-assisted tutoring systems, and intelligent learning analytics across all public educational institutions (Ministry of Education Malaysia, 2023; Jamaluddin et al., 2025).

Artificial intelligence holds particular promise for addressing the persistent structural challenges of ODL. High dropout and non-completion rates, estimated at 20–50% globally for distance programmes compared to 10–20% for face-to-face delivery (Frankola, 2001) represent the sector's most critical quality challenge. AI-powered learner analytics can identify at-risk students before dropout occurs; intelligent tutoring systems can provide personalised support at scale; automated feedback tools can close the response-time gaps that face-to-face interaction naturally fills (Roll & Wylie, 2016; Luckin et al., 2016; Dawson et al., 2019). In Malaysia specifically, the COVID-19 pandemic's Movement Control Orders resulted in 21,316 student dropouts between March 2020 and July 2021 (Izzaty et al., 2023), a crisis that AI-enhanced early warning systems are precisely designed to prevent.

Despite this policy mandate and documented need, the adoption of AI tools by ODL practitioners in Malaysian public education remains empirically understudied at the individual level. Institutional deployment of AI infrastructure does not automatically translate into practitioner adoption. Educators must perceive AI tools as useful and aligned with their professional roles before they will integrate them consistently into their ODL design, delivery, and support workflows (Davis, 1989; Venkatesh et al., 2003). A 2020 Malaysian government review found that nearly half of educators stopped using digital tools once introduced. This is not due to technical failure, but because of a mismatch between technological capability and pedagogical confidence (HIVE Educators, 2025). Understanding what determines whether ODL practitioners intend to adopt AI is therefore a prerequisite for effective implementation strategy.

The Technology Acceptance Model (TAM), originally formulated by Davis (1989), provides the most widely validated theoretical framework for predicting technology adoption intention, positing that perceived usefulness and perceived ease of use are the primary cognitive antecedents of behavioural intention. However, standard TAM may be insufficient for the Malaysian ODL context, which involves additional structural forces. The national DEP creates institutional expectations that may independently shape individual intent, the ODL environment's self-directed character may amplify the role of proactive AI behaviour as a dispositional predictor, while educator profile of Malaysian public education staff may render ease-of-use a less discriminating predictor than in novice populations.

This study addresses these gaps by extending TAM with institutional expectations, proactive AI behaviour, and prior AI experience to examine AI adoption intention among ODL-engaged practitioners drawn from Malaysian public educational organisations. The objective of the study is to examine the effects of perceived usefulness, perceived ease of use, institutional expectation, proactive AI behaviour, and prior AI experience on the behavioural intention to adopt AI tools among ODL practitioners. It intended to make three original contributions. First, by providing the first TAM-based AI adoption analysis scoped to Malaysian public ODL practitioners using primary field data. Second, it introduces and empirically tests proactive AI behaviour as a novel predictor beyond standard TAM, and third, it documents a critical AI adoption depth gap i.e. chatbot saturation to coexisting with near-zero adoption of pedagogically transformative AI tools, together with direct implications for the DEP's implementation strategy.

## LITERATURE REVIEW

### Technology Acceptance in ODL Contexts

TAM was introduced by Davis (1989) to explain individual acceptance of information systems through two core cognitive beliefs i.e. perceived usefulness which refers to the degree to which a system is believed to enhance job performance and perceived ease of use, i.e. the degree to which using it is free of effort. Davis et al. (1989) demonstrated strong predictive validity across multiple technology contexts, and subsequent meta-analyses confirmed TAM's robustness across educational technology settings (King & He, 2006; Scherer et al., 2019).

In ODL specifically, TAM-based research has predominantly examined learner acceptance of learning management systems (LMS) and e-learning platforms. Pituch and Lee (2006) confirmed perceived usefulness and perceived ease of use as significant predictors of student intention to use web-based distance learning systems. Šumak et al.'s (2011) meta-analysis of 42 e-learning TAM studies confirmed PU's consistent dominance over perceived ease of use across diverse national and institutional contexts. However, the vast majority of this research has focused on student adoption rather than practitioner adoption including the faculty, instructional designers, academic administrators, and learner support staff who construct, deliver, and sustain ODL programmes. This distinction matters when practitioners face professional accountability pressures, institutional mandates, pedagogical integrity concerns, and role-specific utility calculations that differ fundamentally from learners' cost-benefit assessments (Teo, 2011).

The emergence of AI-specific tools has introduced new dimensions of complexity for ODL practitioners. Unlike conventional LMS platforms, which is designed with established pedagogical workflows, AI tools such as generative AI assistants, adaptive learning engines, automated assessment tools, and learner analytics dashboards possess characteristics that create distinctive acceptance challenges. This includes probabilistic outputs that may be unreliable for educational purposes, opacity in reasoning that conflicts with academic standards of transparency, and rapid evolution that outpaces institutional policy development (Gursoy et al., 2019; Zawacki-Richter et al., 2019). For ODL contexts, where practitioners already navigate complex multi-platform digital environments and must maintain learner engagement without face-to-face interaction, the incremental demand of AI tool adoption requires careful understanding.

**Behavioural Intention of AI in ODL Context**

The transformative potential of AI for ODL addresses precisely the modality's structural vulnerabilities. Intelligent tutoring systems provide personalised, adaptive support that compensates for the absence of real-time instructor responsiveness in asynchronous ODL (VanLehn, 2011). Learner analytics dashboards equip tutors with early warning signals such as dropout risk scores, engagement trajectory data, and assessment performance patterns that replicate the informal monitoring signals available through face-to-face observation (Dawson et al., 2019). Natural language processing tools enable automated feedback on writing and assessment at the scale required by large ODL cohorts, where individual tutor feedback is chronically constrained by student-to-staff ratios (Litman, 2016). AI-powered chatbots provide always-available administrative and academic support that reduces the cognitive burden on both learners and support staff (Winkler & Söllner, 2018). Though, the national macro-level found that 73% of Malaysian AI adopters use only basic applications (AWS/TechWireAsia, 2025), which represents the central empirical paradox that motivates this study whereby practitioners are digitally engaged with AI but have not bridged to the applications that could most directly improve ODL outcomes.

**Perceived Usefulness**

In AI adoption contexts specifically, Xu et al. (2020) found perceived usefulness to be a significant predictor of healthcare professionals' intention to use AI diagnostic tools. In this study, perceived usefulness, which can be understood as the ODL practitioner's belief that AI tools will enhance their professional effectiveness is theoretically expected to be the dominant predictor of behavioural intention in this context. In educational technology adoption research, Scherer et al.'s (2019) meta-analysis confirmed perceived usefulness as the single strongest predictor across 114 studies (weighted mean $r = 0.57$). In AI-specific educational adoption studies, Chen et al. (2020) found that Chinese university lecturers' AI utility perceptions were the strongest predictors of adoption intention, and Zawacki-Richter et al.'s (2019) systematic review of AI in higher education identified utility perceptions as the most commonly reported adoption determinant among practitioners.

For ODL practitioners specifically, perceived usefulness is likely operationalised along a spectrum. At the basic level, AI tools that reduce time spent on routine communications and content formatting. At the intermediate level, tools that improve feedback quality and assessment consistency while at the transformative level, tools that enable personalisation and early intervention at the scale ODL demands. Looking into the current situation, it is believed that Malaysian ODL practitioners broadly perceive AI tools as valuable which may suggest an important finding given that pedagogical scepticism about AI's educational value is a commonly documented as adoption barrier (Selwyn, 2019). Therefore, the following hypothesis is postulated:

**H1:** Perceived usefulness will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners.

### Perceived Ease of Use

Perceived ease of use in ODL contexts captures practitioners' assessments of the cognitive effort required to learn, operate, and integrate AI tools into their established digital workflows. Al-Azawei et al. (2017) found that the direct effect of perceived ease of use on behavioural intention attenuated significantly in blended learning environments where participants had substantial prior digital experience, with perceived usefulness fully mediating the relationship in experienced samples. Venkatesh and Morris (2000) established theoretically that for experienced users, perceived ease of use influences behavioural intention primarily through its effect on perceived usefulness rather than directly. Therefore, it is hypothesized that:

**H2:** Perceived ease of use will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners.

### Institutional Expectation

Institutional expectation refers to the perceived social, regulatory, and cultural pressures exerted by external environments on an organisation or individual to conform to specific norms, values, and operational standards (Oliver, 1991). Grounded fundamentally in Institutional Theory (DiMaggio & Powell, 1983; Scott, 2014), institutional expectations dictate what is considered a legitimate, acceptable, or modern practice within a given field. These expectations are structurally divided into three pillars namely coercive pressures (such as formal regulations, laws, or government mandates), mimetic pressures or the expectation to copy successful competitors or industry leaders during times of high uncertainty, and normative pressures, which comprises professional standards, ethical codes, and cultural expectations propagated through education and professional networks. In the context of AI, institutional expectations create an environment where adopting AI is viewed as an essential benchmark for maintaining corporate legitimacy, regardless of whether the technology yields immediate economic benefits.

The extent to which AI tool use is institutionally expected, ranging from completely voluntary, through encouraged, to mandated represents a structural dimension of technology adoption that TAM has not systematically addressed. This construct draws from subjective norm in the Theory of Planned Behaviour (Ajzen, 1991), perceived mandatoriness in enterprise information system adoption (Brown et al., 2002), and facilitating conditions in the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; Venkatesh et al., 2012). Oliver's (2001) institutional theory perspective on educational technology adoption specifically emphasises that institutional cultures of innovation which is communicated through policy, leadership behaviour, and resource provision which formed primary determinants of technology integration success in educational settings.

However, in contexts where institutions communicated mixed or restrictive signals about AI, even when individual proactive inclinations were present, the adoption intention was reduced (Zohouri et al.; 2024). Nevertheless, the Malaysian ODL sector is extensively policy mediated. The DEP (2023) mandates AI integration in teaching and learning; the National AI Roadmap 2021–2025 (MOSTI, 2021) establishes cross-sectoral AI adoption targets including in education while MQA, through its COPPA-ODL sets minimum standards for learner support, technology use, and instructional quality in accredited ODL programmes (MQA, 2020). Within this policy landscape, the degree to which an individual practitioner's institution signals that AI adoption is expected through senior leadership endorsement, integration of AI tools in official programmes, provision of AI training, or explicit linkage of AI use to professional review constitutes an institutional expectation that may independently shape adoption intention. Therefore, the following hypothesis is formulated:

**H3:** Institutional expectation will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners.

### Proactive AI Behaviour

Rooted in the broader psychological construct of "proactive work behaviour" (Crant, 2000), this concept implies that the actor does not merely react to technological changes or wait for training programmes. Instead, they actively scan the environment for AI capabilities, manipulate AI inputs to test boundaries, and independently seek configurations that could optimise future tasks. In AI literature, it represents a high degree of personal agency and exploratory behaviour intended to reduce uncertainty regarding algorithmic outputs.

Proactive behaviour in the workplace, which is characterised by self-initiated and future-oriented action aimed at changing or improving the work environment has been extensively theorised in organisational psychology (Crant, 2000; Parker et al., 2010). In the context of technology adoption, proactive technology behaviour reflects employees' tendency to actively explore, experiment with, and advocate for AI tools beyond the minimum requirements of their roles. This construct subsumes elements of technology innovativeness (Agarwal & Prasad, 1998), personal initiative (Frese & Fay, 2001), and technology exploration (Jasperson et al., 2005). In this context, proactive AI behaviour renders self-initiated, future-oriented tendency to explore, experiment with, advocate for, and independently develop competencies in AI tools.

Proactive AI behaviour has a particular theoretical relevance in ODL contexts. Distance education, by its nature, demands self-directed competencies from practitioners who design and deliver it i.e. the ability to navigate ambiguous technological environments, independently discover pedagogical applications, and adapt instructional strategies without immediate collegial scaffolding. Practitioners who proactively engage with AI may be structurally better positioned for the sustained, iterative adoption that effective ODL AI integration requires.

Several investigations have established a significant inverse relationship, where highly proactive AI behaviour actually reduces the intention to adopt. Liu et al.'s (2026) study on organisational AI adoption and job crafting behaviours provides further evidence that proactive responses to AI integration can take the form of avoidance rather than approach. When AI adoption generated AI anxiety or a documented consequence of proactive exposure to rapidly evolving AI systems, employees were motivated to engage in avoidance job crafting, which operationally represents a reduced intention to continue engaging with AI tools despite initial proactive exposure. This negative phenomenon stems from the "proactivity paradox"; proactive users are the first to encounter the intricate limitations of AI, including algorithmic biases, integration complexities, and data governance risks. Quan et al. (2025) explicitly identifies 'the double-edged sword effect' of proactive AI engagement, documenting conditions under which proactivity predicts lower rather than higher intended AI integration on employee service performance.

Meanwhile, Rogers' (2003) diffusion of innovations framework identifies innovators and early adopters as crucial to educational technology diffusion, with their proactive exploration disproportionately influencing later adopters through modelling and advocacy. Liang et al. (2022) demonstrated that proactive technology behaviour predicted AI adoption intention among knowledge workers over and above TAM constructs. The theoretical importance of testing whether proactive AI behaviour functions as an independent predictor is distinct from utility and usability beliefs and is heightened by the Malaysian educator readiness gap whereby only 15% of Malaysian teachers possess the digital skills to customise technology solutions (MOE, 2024). This suggests that dispositional orientation toward technology exploration may be a more powerful determinant of sustained adoption than either training delivery or institutional mandate. Therefore, it is hypothesized that:

**H4:** Proactive AI behaviour will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners.

### Prior AI Experience

Prior AI experience, which is operationalised as self-rated AI proficiency, is believed to positively predict adoption intention through accumulated competence, reduced uncertainty, and enhanced self-efficacy (Bandura, 1997; Compeau & Higgins, 1995). In AI-specific adoption research, Canziani and MacSween (2021) found that hospitality employees with greater prior AI tool experience demonstrated significantly higher adoption intentions in service context. Jia et al. (2022) observed that in Chinese government settings, experience with digital tools moderated the relationship between trust and intention. On the other hand, the significant relationship between prior AI experience and adoption intention is inconsistently reported (Gursoy et al., 2019) or even having an inverse effect (Rana et al., 2021).

In ODL practice, experience with AI tools matters both for individual confidence and professional credibility with practitioners who have successfully integrated AI into their course design or student support workflows are better positioned to advocate for, model, and extend AI adoption. Contrarian to traditional technology acceptance models, contemporary empirical research demonstrates that prior AI experience does not consistently foster a positive intention to adopt artificial intelligence but rather, it often yields non-significant or even inverse outcomes. Conversely, some studies have identified a distinct negative relationship, wherein individuals with greater prior AI experience exhibit significantly lower intentions to adopt new AI tools. A study by Jiao and Cao (2024) found that knowledge level of designers (operationalised as familiarity with AI-aided design capabilities and limitations) exerted a significant negative moderating effect on the relationship between attitude and behavioural intention. Designers with higher AI knowledge displayed lower intention to use AI because they were better positioned to recognise the technology's limitations and held more sceptical attitudes toward the authenticity and accuracy of AI-generated content, thereby undermining their confidence in using these tools.

Based on the context of the study, the experience profile may reflect an increasingly digitally fluent cohort of Malaysian public education practitioners, consistent with post-pandemic normalisation of AI tool use. Whether prior experience adds independent explanatory power to behavioural intention beyond perceived usefulness and proactive AI behaviour remains an empirical question. Hence, it is postulated that:

**H5:** Prior AI experience will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners.

## METHODOLOGY

### Research Design and Context

A quantitative, cross-sectional survey design was employed, consistent with TAM-based empirical research in educational technology (Venkatesh et al., 2003; Scherer et al., 2019). Data were collected from the Malaysian respondents employed in the education domain which encompasses practitioners at the Ministry of Education (Kementerian Pendidikan Malaysia), Ministry of Higher Education (Kementerian Pengajian Tinggi, Malaysia), public universities and affiliated colleges, as well as matriculation colleges and government-linked educational agencies. The restriction of the sample to the education domain responds to established calls for domain-specific AI adoption research in educational technology (Zawacki-Richter et al., 2019; Selwyn, 2019), recognising that the pedagogical, regulatory, and institutional dimensions of ODL adoption differ sufficiently from other public sector contexts to warrant independent investigation.

### Participants

The preliminary study gathered a total of 60 respondents. Table 1 presents demographic profile of the respondents. The sample was predominantly female (n = 36, 60.0%), consistent with Malaysian public education sector workforce composition. The mean of respondent age was 43.8 years (SD = 9.4), while the mean for public sector experience was 17.6 years (SD = 10.1) which represents a seasoned, mid-career to senior cohort with extensive institutional knowledge. This experience profile is directly relevant to ODL contexts, whereby instructional design and learner support decisions draw heavily on accumulated pedagogical expertise. Educational attainment was high, with 28 respondents (46.7%) held bachelor's degrees, 21 respondents (35.0%) with master's degrees, and 6 respondents (10.0%) held postgraduate or doctoral qualifications. This reflects the academically credentialled character of Malaysian public higher education staff.

Organisationally, respondents were distributed across national-level bodies (n = 20, 33.3%), local-level institutions (n = 35, 58.3%), and regional or other settings (n = 4, 6.7%). Role composition comprised 14 leadership-position holders (23.3%), 38 non-leadership professional or support staff (63.3%), and 8 in other roles

(13.3%). AI usage frequency was substantial, with 35.0% reported using AI tools several times per week and 28.3% daily or multiple times daily, with the remaining 36.7% using AI tools at least a few times per month.

**Table 1. The Profile of Respondents**

| Characteristic | Category | n (%) |
|---|---|---|
| Gender | Male | 24 (40.0%) |
| | Female | 36 (60.0%) |
| Age (years) | Mean = 43.8, SD = 9.4 | |
| Public Sector Experience | Mean = 17.6 years, SD = 10.1 | |
| Education Level | Secondary vocational or lower | 1 (1.7%) |
| | Higher vocational | 4 (6.7%) |
| | Bachelor's degree | 28 (46.7%) |
| | Master's degree | 21 (35.0%) |
| | Postgraduate / PhD | 6 (10.0%) |
| Organisational Level | National | 20 (33.3%) |
| | Local | 35 (58.3%) |
| | Regional / Other | 4 (6.7%) |
| Role | Leadership position | 14 (23.3%) |
| | Non-leadership / Support | 38 (63.3%) |
| | Other | 8 (13.3%) |
| Key Institutions | Ministry of Education (Kementerian Pendidikan Malaysia) | 21 (35.0%) |
| | Ministry of Higher Education (Kementerian Pengajian Tinggi) | 11 (18.3%) |
| | Public Universities | 20 (33.3%) |
| | Colleges and Other Agencies | 8 (13.3%) |
| AI Usage Frequency | Several times per week | 21 (35.0%) |
| | Daily or multiple times daily | 17 (28.3%) |
| | A few times per month or less | 22 (36.7%) |

### Instrumentation

All constructs were operationalised using validated scales adapted from established TAM and technology adoption instruments, with all multi-item scales rated on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). Behavioural intention to adopt AI tools in ODL practice was measured with five items adapted from Davis et al. (1989) and Venkatesh et al. (2003), capturing future intention to use, continue using, and routinely integrate AI tools (Cronbach's $\alpha = 0.894$). Perceived usefulness was assessed with five items measuring AI tools' contributions to achieving educational goals, improving task speed and work quality, stimulating creative ideation, and general professional helpfulness ($\alpha = 0.910$). Perceived ease of use was measured with four items assessing ease of learning, ease of use in ODL work contexts, self-comprehension of AI system functioning, and confidence in developing AI proficiency ($\alpha = 0.913$). Proactive AI behaviour was measured with six items adapted from Liang et al. (2022) and Crant (2000), capturing self-initiated AI exploration in ODL contexts, efficiency-seeking experimentation, colleague encouragement, and enthusiasm for new AI possibilities ($\alpha = 0.942$). Institutional expectation and prior AI experience were each operationalised as validated single five-point Likert items.

### Analytical Strategy

Construct composite scores (item means) were computed, and descriptive statistics, Cronbach's alpha reliability, and average variance extracted (AVE) approximations were calculated for all multi-item constructs. AVE was approximated via the mean of squared item-composite correlations, with values above 0.50 confirming convergent validity (Fornell & Larcker, 1981). Bivariate Pearson correlations were computed for all construct pairs. Hypotheses H1–H5 were tested using ordinary least squares multiple regression with behavioural intention as the dependent variable and perceived usefulness, perceived ease of use, institutional expectation, proactive

AI behaviour, and prior AI experience as simultaneous predictors. Standardised beta coefficients, t-statistics, and two-tailed p-values are reported. The significance threshold was $p < 0.05$.

## RESULTS

### Descriptive Statistics and Measurement Quality

Table 2 presents descriptive statistics, reliability, and convergent validity for all study constructs. All multi-item constructs demonstrated excellent internal consistency whereby proactive AI behaviour had the highest reliability ($\alpha = 0.942$), followed by perceived ease of use (0.913), perceived usefulness (0.910), and behavioural intention (0.894). AVE approximations exceeded the Fornell and Larcker (1981) threshold of 0.50 for all multi-item constructs for example, perceived ease of use (0.793), proactive AI behaviour (0.781), perceived usefulness (0.745), and behavioural intention (0.704), confirming that each construct accounts for the majority of variance in its indicators.

Mean scores across constructs were uniformly high. Perceived usefulness registered the highest mean (M = 4.42, SD = 0.68), followed closely by behavioural intention (M = 4.42, SD = 0.62) and perceived ease of use (M = 4.39, SD = 0.64). Proactive AI behaviour showed a slightly lower mean (M = 4.24, SD = 0.77) and greater variability, which is consistent with variation in proactive disposition across a sample that includes both digitally pioneering academic staff and more administratively-oriented support personnel. Institutional expectations had the widest distribution (M = 3.25, SD = 0.91), reflecting heterogeneity in the degree of institutional AI endorsement across the sample's range of organisations with 15.0% reported low institutional expectation (levels 1–2), 46.7% moderate (level 3), and 38.3% high (levels 4–5). Prior AI experience was predominantly positive (M = 4.08, SD = 0.74; 80.0% rated their experience as 4 or 5 out of 5).

Table 3 describes AI tool usage patterns within the education subsample. The adoption gap between conversational AI tools and pedagogically transformative ODL applications is stark. Chatbots and AI assistants are found as tools which are primarily used for personal productivity and communication which were adopted by 59 of 60 respondents (98.3%). By contrast, knowledge management systems were used by 33.3%, cybersecurity tools by 18.3%, and speech/transcription tools by 13.3%. Pedagogically transformative ODL applications which include recommendation systems (8.3%), predictive analytics (5.0%), and robots/autonomous systems (3.3%) were adopted by very few respondents. This pattern reveals that Malaysian ODL practitioners have broadly embraced basic AI productivity tools while remaining substantially disengaged from the AI applications most directly relevant to improving ODL learner outcomes.

**Table 2. Construct Descriptive Statistics, Reliability, and Convergent Validity**

| Construct | k | n | M | SD | Min | Max | α | AVE |
|---|---|---|---|---|---|---|---|---|
| Behavioural Intention (BI) | 5 | 60 | 4.423 | 0.616 | 2.00 | 5.00 | 0.894 | 0.704 |
| Perceived Usefulness (PU) | 5 | 60 | 4.417 | 0.677 | 2.00 | 5.00 | 0.910 | 0.745 |
| Perceived Ease of Use (PEOU) | 4 | 59 | 4.394 | 0.635 | 2.00 | 5.00 | 0.913 | 0.793 |
| Proactive AI Behaviour (PAB) | 6 | 57 | 4.237 | 0.769 | 2.00 | 5.00 | 0.942 | 0.781 |
| Institutional Expectation (IE) | 1 | 60 | 3.250 | 0.914 | 1.00 | 5.00 | — | — |
| Prior AI Experience (AE) | 1 | 60 | 4.083 | 0.743 | 2.00 | 5.00 | — | — |

**Table 3. AI Tool Types Used by ODL Education Sector Respondents**

| AI Tool Type | n | % Adopted |
|---|---|---|
| Chatbots and AI assistants (e.g., ChatGPT, Copilot, Gemini) | 59 | 98.3% |
| Knowledge management and intelligent search systems | 20 | 33.3% |
| Cybersecurity and threat detection tools | 11 | 18.3% |
| Digital assistants (e.g., Siri, calendar AI) | 14 | 23.3% |
| Speech recognition and transcription tools | 8 | 13.3% |
| Facial recognition and identity verification | 7 | 11.7% |
| Automation of administrative tasks | 6 | 10.0% |

| AI Tool Type | n | % Adopted |
|---|---|---|
| AI-powered recommendation systems | 5 | 8.3% |
| Predictive and forecasting analytics | 3 | 5.0% |
| Autonomous robots and smart systems | 2 | 3.3% |

Note: Multiple responses permitted. Percentages represent proportions of all n = 60 respondents using each tool type.

### Bivariate Correlations

Table 4 presents Pearson correlations among the study constructs. Behavioural intention was most strongly correlated with proactive AI behaviour ($r = 0.831$, $p < 0.001$) and perceived usefulness ($r = 0.830$, $p < 0.001$) which is virtually equal in zero-order magnitude, confirming that proactive disposition and utility perception are co-equally powerful antecedents of AI adoption intention at the bivariate level. Perceived ease of use showed a more moderate correlation with behavioural intention ($r = 0.595$, $p < 0.001$), substantially attenuated relative to the full Malaysian sample ($r = 0.779$), which is consistent with the experienced user profile. Prior AI experience demonstrated a moderate positive association with behavioural intention ($r = 0.541$, $p < 0.001$). Institutional expectation showed a weaker but statistically significant correlation with behavioural intention ($r = 0.378$, $p = 0.004$), reflecting its structural independence from cognitive belief constructs.

The strong correlation between perceived usefulness and proactive AI behaviour ($r = 0.848$) warrants attention in interpreting the regression model. These constructs share substantial variance, and both attenuates each other's beta coefficients in the controlled model. The moderate and structurally independent correlations of institutional expectation with other constructs confirm its conceptual distinctiveness.

**Table 4. Bivariate Pearson Correlations Among Constructs**

| Construct | 1. BI | 2. PU | 3. PEOU | 4. IE | 5. PAB | 6. AE |
|---|---|---|---|---|---|---|
| 1. Behavioural Intention (BI) | — | 0.830*** | 0.595*** | 0.378** | 0.831*** | 0.541*** |
| 2. Perceived Usefulness (PU) | | — | 0.757*** | 0.331* | 0.848*** | 0.566*** |
| 3. Perceived Ease of Use (PEOU) | | | — | 0.268* | 0.702*** | 0.591*** |
| 4. Institutional Expectation (IE) | | | | — | 0.279* | 0.264* |
| 5. Proactive AI Behaviour (PAB) | | | | | — | 0.535*** |
| 6. Prior AI Experience (AE) | | | | | | — |

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Correlations computed pairwise on available data; regression uses n = 56 (listwise deletion).

### Hypothesis Testing

Table 5 presents multiple regression results with behavioural intention as the dependent variable. The overall model was highly significant and explained 77.4% of the variance in behavioural intention ($R^2 = 0.774$; Adjusted $R^2 = 0.752$), confirming the extended TAM framework's robustness for predicting ODL AI adoption intention.

Hypothesis 1 (Perceived usefulness will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners) was supported. Perceived usefulness was the strongest significant predictor ($\beta = 0.425$, $B = 0.425$, $t = 3.329$, $p = 0.002$). For Malaysian ODL practitioners, the belief that AI tools will enhance professional effectiveness by improving educational goal attainment, work quality, task speed, and creative capacity, which formed as the dominant driver of adoption intention. This finding replicates the dominant pattern in TAM literature and confirms that ODL-specific AI utility, and not mere digital familiarity, is found as the principal cognitive gateway to adoption.

Hypothesis 2 (Perceived ease of use will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners) was not supported in the controlled model ($\beta = -0.167$, $t = -1.720$, $p = 0.091$). The non-significant and negative unstandardised coefficient reflects multicollinearity between

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perceived ease of use and perceived usefulness ($r = 0.757$) and prior AI experience ($r = 0.591$). Perceived ease of use's variance is substantially shared with these predictors, leaving insufficient independent residual to reach significance. This is theoretically consistent with Venkatesh and Morris (2000) whereby for experienced samples, perceived ease of use was found to operate indirectly through perceived usefulness rather than as a direct antecedent of behavioural intention. The very high perceived ease of use's mean ($M = 4.39$) and limited variance further reduce perceived ease of use's discriminating capacity across respondents.

Hypothesis 3 (Institutional expectation will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners) was not supported at $p < 0.05$ in the controlled model ($\beta = 0.074$, $t = 1.563$, $p = 0.124$). However, the directional finding is consistent with theory, and descriptive analysis reveals a practically meaningful pattern. Respondents in low institutional expectation environments (levels 1–2) reported mean for behavioural intention of 3.87 ($SD = 0.71$, $n = 9$), compared to 4.33 ($SD = 0.61$, $n = 28$) in moderate (level 3) and 4.76 ($SD = 0.35$, $n = 23$) in high-expectation environments with a total range of 0.89 points on the 5-point scale. The non-significance in the multivariate model reflects the small low-IE cell ($n = 9$) and associated power constraints rather than the absence of a substantive effect.

Hypothesis 4 (Proactive AI behaviour will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners) was strongly supported ($B = 0.377$, $t = 3.686$, $p = 0.001$). Proactive AI behaviour was the second largest significant independent predictor, virtually matching perceived usefulness in standardised effect size (proactive AI behaviour's $\beta = 0.377$ vs. perceived usefulness's $\beta = 0.425$). ODL practitioners who proactively explore, experiment with, and advocate for AI tools demonstrated substantially higher adoption intentions after controlling for utility, ease-of-use, and experience and the results confirmed that dispositional orientation toward AI is not merely a correlate of TAM constructs but an independent motivational pathway to adoption.

Hypothesis 5 (Prior AI experience will have a significant positive effect on behavioural intention to adopt AI tools among Malaysian ODL practitioners) was not supported at $p < 0.05$ in the controlled model ($\beta = 0.076$, $t = 1.145$, $p = 0.258$). While prior AI experience correlates moderately with behavioural intention ($r = 0.541$) and is clearly a relevant factor at the zero-order level, its independent contribution after controlling for perceived usefulness and proactive AI behaviour is absorbed by these constructs.

**Table 5. Multiple Regression Results**

| Predictor | B | β | SE | t | p |
|---|---|---|---|---|---|
| Perceived Usefulness (PU) | 0.425 | 0.467 | 0.128 | 3.329 | 0.002** |
| Perceived Ease of Use (PEOU) | -0.167 | -0.172 | 0.097 | -1.720 | 0.091 (n.s.) |
| Institutional Expectation (IE) | 0.074 | 0.109 | 0.047 | 1.563 | 0.124 (n.s.) |
| Proactive AI Behaviour (PAB) | 0.377 | 0.470 | 0.102 | 3.686 | 0.001** |
| Prior AI Experience (AE) | 0.076 | 0.092 | 0.066 | 1.145 | 0.258 (n.s.) |

Note: $R^2 = 0.774$; Adjusted $R^2 = 0.752$; $n = 56$ (listwise). ** $p < 0.01$; *** $p < 0.001$; n.s. = not significant at $p < 0.05$. β = standardised beta coefficient.

# DISCUSSION

### Perceived Usefulness

The finding that perceived usefulness is the dominant significant predictor of AI adoption intention replicates and extends a robust pattern established across TAM literature. Davis et al. (1989) first demonstrated PU's primacy over perceived ease of use, a result confirmed by Scherer et al.'s (2019) meta-analysis across 114 educational technology studies and by Zawacki-Richter et al.'s (2019) systematic review specifically targeting AI in higher education. The high perceived usefulness's mean in this sample indicates that Malaysian ODL practitioners broadly perceive AI tools as genuinely valuable and not merely mandated novelties or productivity toys. This is particularly significant given documented educator scepticism about AI's educational legitimacy

(Selwyn, 2019), suggesting the Malaysian public education practitioner cohort has moved beyond initial resistance toward constructive utility assessment.

The pedagogical implications of this perceived usefulness dominance are specific to ODL design. ODL practitioners who believe AI will improve their educational goal achievement, work quality, and creative capacity are most likely to adopt. This implies that AI implementation strategies should foreground the ODL-specific value proposition for examples on the way AI-powered chatbots reduce the student support burden in large asynchronous cohorts, the way automated feedback tools compensate for the real-time feedback absence inherent in asynchronous learning, and the way predictive analytics enable the proactive tutor outreach that face-to-face instructors exercise naturally. Promoting AI merely as a general productivity tool is insufficient, as adoption can be accelerated more effectively when its usefulness is framed specifically within ODL context.

**Proactive AI Behaviour**

The near parity between proactive AI behaviour ($\beta = 0.377$) and perceived usefulness ($\beta = 0.425$) as predictors of behavioural intention is the most theoretically significant finding of this study. The standardised beta coefficients differ by only 0.048, establishing that for Malaysian ODL practitioners, dispositional orientation toward AI exploration is approximately as powerful a predictor of adoption intention as utility belief, even after controlling for perceived ease of use, institutional expectation, and prior AI experience. This represents a substantive extension of TAM, which positions adoption as a cognitive utility calculation, by demonstrating that a dispositional-behavioural pathway operates independently alongside the cognitive pathway.

This finding has particular resonance for ODL contexts. Distance education, by its structural character, demands self-directed competencies from practitioners i.e. the ability to independently navigate ambiguous digital environments, discover pedagogical applications without immediate collegial validation, and adapt instructional approaches without the scaffolding of shared physical space. The ODL practitioner who is proactively oriented toward AI exploration, who seeks out new tools, experiments with AI for course design, encourages colleagues, and is excited by AI's pedagogical possibilities is better positioned for the sustained, iterative AI integration that effective ODL delivery requires. A single adoption decision is insufficient because improving the quality of Open and Distance Learning through AI requires continuous exploration and refinement.

Rogers' (2003) diffusion of innovations framework provides theoretical grounding for the policy relevance of this finding. In educational technology diffusion, innovators and early adopters are characterised precisely by proactive orientation which disproportionately influence institutional adoption trajectories through modelling and peer advocacy. Identifying, empowering, and connecting proactively AI-oriented ODL practitioners across Malaysia's public education system may therefore yield institutional adoption dividends far exceeding what their individual behaviour directly produces.

**Institutional Expectation**

The non-significance of IE in the controlled model must be interpreted alongside the descriptive evidence, which reveals a practically meaningful pattern. Respondents in low institutional expectation environments (levels 1–2) reported a mean for behavioural intention of 3.87, compared to 4.76 in high institutional expectation environments (levels 4–5) which formed a gap of 0.89 points on a 5-point scale that corresponds to qualitatively different levels of adoption commitment. The regression non-significance reflects statistical power constraints of the small low-institutional expectation cell ($n = 9$) rather than the absence of a substantive effect.

The policy implications are direct and consequential for the DEP implementation context. Malaysian ODL institutions, including universities, colleges, and the Ministries of Education and Higher Education that actively and visibly signal their endorsement of AI integration create institutional environments that appear to substantially amplify practitioner adoption intention. This aligns with Oliver's (2001) institutional theory perspective and with the broader finding from the AWS/TechWireAsia (2025) survey that 71% of Malaysian businesses are more likely to adopt AI when the government leads by example. In the ODL context, the equivalent signal comes from institutional leadership comprising vice-chancellors and deans who model AI use, universities that integrate AI tools into official programmes and quality assurance frameworks.

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On the other hand, the Malaysian Qualifications Agency's Code of Practice for Programme Accreditation Open and Distance Learning (COPPA-ODL) Second Edition does not currently provide explicit standards or evaluation criteria related to AI integration readiness, either in terms of institutional resource adequacy or practitioner digital competency requirements. The institutional expectation findings of this study suggest that incorporating AI integration expectations into the COPPA-ODL framework could function as a structural institutional signal that positively influences practitioners' intention to adopt AI technologies across the ODL sector.

**Perceived Ease of Use**

The non-significant perceived ease of use's effect ($\beta = -0.167$, $p = 0.091$) in the controlled model reflects the digital maturity of the Malaysian ODL practitioner cohort rather than the irrelevance of ease-of-use to adoption. With a perceived ease of use mean score of 4.39 and a sample profile characterised by extensive experience with digital platforms, including a mean service duration of 17.6 years, 80 percent of respondents holding at least a bachelor's degree, and the post pandemic normalisation of online teaching and learning, ease of use for the currently dominant category of AI tools, namely conversational chatbots, has effectively ceased to function as a significant barrier to adoption. Practitioners who have managed LMS platforms, video conferencing systems, and digital assessment tools for years do not find ChatGPT or Copilot difficult to use.

However, this finding should not be generalised to conclude that perceived ease of use is irrelevant to AI adoption. The tool types that remain underutilised for examples learner analytics dashboards (5.0%), adaptive learning systems, and AI-powered recommendation engines (8.3%) are precisely those that demand higher technical fluency and involve greater integration complexity with existing ODL infrastructure. For these pedagogically transformative applications, perceived ease of use may reemerge as a significant adoption barrier. This distinction suggests a phased ODL AI strategy which consolidate the chatbot foundation (where perceived ease of use is no longer a constraint) and then deliberately bridge to analytics and adaptive tools (where perceived ease of use-targeted training support will be needed).

**Prior AI Experience**

The non-significant effect of prior AI experience on behavioural intention ($\beta = 0.076$, $t = 1.145$, $p = 0.258$) warrants careful interpretation rather than dismissal. Although prior AI experience correlated positively with BI at the bivariate level ($r = 0.541$, $p < 0.001$), its independent contribution was fully absorbed once perceived usefulness and proactive AI behaviour were simultaneously controlled. This pattern is consistent with a well-established mechanism in TAM-based research: experience functions as a distal antecedent of BI, exerting its influence through proximal cognitive and dispositional mediators rather than independently (Venkatesh & Morris, 2000; Taylor & Todd, 1995). Venkatesh and Davis (2000) theorised in TAM2 that as experience accumulates, perceived usefulness crystallises into the dominant and stable adoption driver, leaving experience without an independent residual contribution. Taylor and Todd (1995) similarly reported that the PU–BI relationship was stronger for inexperienced users, implying that experienced users draw on internalised adoption dispositions rather than raw experiential input when forming behavioural intentions.

The contrarian evidence reviewed in the literature adds further nuance. Jiao and Cao (2024) found that designers with higher AI knowledge displayed lower adoption intention, as familiarity with AI limitations induced greater scepticism toward AI-generated outputs. A comparable dynamic may operate within this ODL sample at the tool-category level: practitioners who are highly experienced with conversational AI chatbots may have simultaneously developed reservations about the reliability and pedagogical appropriateness of more complex AI applications, contributing to the adoption depth gap documented in this study (chatbot adoption at 98.3% versus learner analytics at 5.0%). The aggregate experience measure captures this dynamic imprecisely, which further suppresses its predictive power. The relationship between prior AI experience and the significant relationship is also inconsistently reported across contexts (Gursoy et al., 2019), and the present finding is consistent with this broader pattern of conditional rather than universal experience effects.

For Malaysian ODL policy, this finding implies that professional development programmes that merely accumulate AI exposure are likely insufficient to shift adoption trajectories. What matters is whether experience

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is structured to build task-relevant perceived usefulness and proactive exploration dispositions in ODL practice. Future research should investigate whether experience with pedagogically specific AI tools, such as learner analytics or adaptive learning systems, functions as a significant independent predictor of BI in contexts where experiential variance is preserved across adopter stages.

**AI Adoption Gap and Consequences**

Perhaps the most practically urgent finding of this study is the profound gap between the AI tools currently adopted by Malaysian ODL practitioners and those with greatest potential to improve ODL outcomes. The 98.3 percent chatbot adoption rate represents a genuine achievement because the normalisation of conversational AI for productivity and communication serves as a necessary foundation for broader AI integration. However, the tools documented by ODL research as most transformative for learner retention and success remain almost entirely absent from practitioners' AI repertoires which comprised predictive analytics (5.0%), adaptive learning (not separately quantified but similarly negligible), and recommendation systems (8.3%).

This gap has direct consequences for Malaysia's ability to address its ODL quality challenges. The 21,316 students who dropped out during the COVID-19 MCO period (Izzaty et al., 2023), and the structural ODL dropout risk of 20–50% globally (Frankola, 2001), cannot be meaningfully addressed by chatbot adoption alone. Early warning systems that identify disengaging students before dropout materialises, adaptive content systems that respond to individual learning trajectories, and personalised support systems that maintain learner motivation in the absence of face-to-face interaction are among the AI applications seemed to remain far from realised. Bridging practitioners from chatbot comfort to analytics engagement is therefore not merely a technology training question but a strategic ODL quality imperative.

**Implications for Policy and Practice**

The study's combined findings generate four concrete recommendations for Malaysian ODL stakeholders. First, AI professional development programmes should move beyond tool-specific training toward ODL-specific utility demonstration. Programmes that show ODL practitioners concretely how learner analytics reduce dropout risk, how automated feedback scales personalisation, and how AI-powered support systems maintain learner engagement in asynchronous contexts are more likely to shift perceived usefulness perceptions than generic AI literacy modules.

Second, cultivating proactive AI orientation should be treated as a faculty development priority equivalent in importance to technical skill training. AI sandboxes, the structured spaces for low-stakes experimentation which comprise AI teaching portfolio components, innovation micro-grants, and peer coaching networks that connect proactive AI practitioners across institutions can build the dispositional readiness that this study identifies as a co-equal adoption driver.

Third, institutional leadership endorsement should be made explicit and sustained. University-level AI integration policies that go beyond general digital transformation rhetoric such as specific AI tools, use cases, and quality standards in ODL delivery could create the institutional expectation signal that substantially amplifies practitioner adoption intention.

Fourth, the COPPA-ODL by the Malaysian Qualifications Agency might be enhanced to explicitly incorporate AI integration readiness within institutional and programme quality assurance requirements. Within the COPPA-ODL context, this may include institutional provisions such as access to licensed AI applications, structured AI-related professional development, technical and instructional support mechanisms, and governance guidelines for ethical AI usage in teaching and assessment. At the practitioner level, the framework may also emphasise evidence of competency in applying at least one pedagogically relevant AI tool for learner support, assessment, feedback, or instructional design. Consistent with the descriptive institutional expectation patterns observed in this study, such structural reinforcement is expected to strengthen practitioners' intentions to adopt AI in ODL practice.

### Limitations And Directions for Future Research

Several limitations qualify the scope of this study's conclusions. Given that this study is just a preliminary, the most significant is the modest education-sector sample size of 60. While sufficient to detect large effects, this sample constrains power to detect medium effects which likely contributing to the non-significance of institutional expectation, perceived ease of use, and prior AI experience. Future research should target larger, purposively sampled cohorts of ODL practitioners, using stratified by institution type, academic discipline, and role type, with a minimum sample size of 200 would enable PLS-SEM with full structural model testing, bootstrapped confidence intervals, and mediation analysis to examine whether proactive AI behaviour mediates the relationship between perceived usefulness and behavioural intention or whether institutional expectation moderates the relationship between proactive AI behaviour and behavioural intention.

Second, the cross-sectional design precludes causal inference. Longitudinal panel designs tracking ODL practitioners as the DEP implementation proceeds would allow causal claims and would capture the way perceived usefulness and proactive AI behaviour evolve as institutional AI integration deepens. Experience sampling methods that capture actual AI use episodes alongside intention and belief data would further bridge the intention–behaviour gap identified in technology adoption research (Sheeran, 2002).

Third, the single-item operationalisation of institutional expectation and prior AI experience limits psychometric depth. A validated multi-item of institutional expectation scale specific to Malaysian higher education, encompassing policy clarity, leadership modelling, resource provision, and collegial norms around AI use would enable more precise measurement and structural modelling. Development of such an instrument tailored to the ODL accreditation context would be a valuable methodological contribution.

Fourth, the study does not distinguish between AI tools used for administrative or productivity purposes (dominant at 98.3% chatbot adoption) and those used for learner-facing ODL functions (analytics, adaptive learning, assessment). Future research should disaggregate adoption intentions by tool category, as the determinants of intent to deploy AI-powered learner analytics likely differ from those governing chatbot adoption, with different implications for professional development design and policy intervention.

Fifth, student perspectives on AI adoption in Malaysian ODL are entirely absent from this study. Practitioner adoption intention is shaped partly by perceived student readiness, data privacy obligations, and anticipated learning outcome effects. Integrating dual-level (practitioner and student) perspectives in a multi-level model would provide a more comprehensive understanding of AI adoption dynamics in Malaysian ODL systems and would align with the growing student-facing AI adoption literature (JONUS, 2025).

Sixth, the model does not incorporate AI-specific constructs increasingly identified as relevant in educational contexts which consists of AI transparency and explainability perceptions, algorithmic fairness concerns, data privacy risk assessments, and academic integrity implications of generative AI in assessment design. These constructs may moderate the relationship between perceived usefulness and behavioural intention and the relationship between institutional expectation and behavioural intention in ways particularly salient to the ODL context, where learner data use and automated assessment are more central than in face-to-face settings.

Since the study provides a preliminary understanding of the AI adoption among ODL practitioners in Malaysia, future study may increase the sample size and including participants from a wider range of higher education institutions to improve representativeness and generalisability. Future studies should also consider longitudinal or mixed-methods approaches to examine the way AI adoption behaviours evolve over time and to gain deeper insight into practitioners' experiences with AI tools. Providing clearer theoretical differentiation between proactive AI behaviour and other motivational or behavioural constructs would further strengthen the conceptual framework.

## CONCLUSION

This study has demonstrated that an extended TAM framework, incorporating proactive AI behaviour and institutional expectation alongside core TAM constructs, provides a robust and highly explanatory model of AI adoption intention among Malaysian ODL practitioners in the public education sector. Accounting for 77.4% of variance in behavioural intention from a domain-specific sample of n = 60 confirmed AI users, the model establishes that both perceived usefulness and proactive AI behaviour are primary, approximately co-equal determinants of AI adoption intention signifies a finding that substantially extends standard TAM by introducing a dispositional-behavioural pathway alongside the cognitive utility pathway.

The near parity between proactive AI behaviour and perceived usefulness as adoption predictors in the ODL context is this study's primary theoretical contribution. It establishes that in self-directed, technology-mediated educational environments where practitioners must independently navigate rapidly evolving AI capabilities, dispositional orientation toward exploration is not merely associated with adoption intention but functions as an independent determinant. The findings provide implications for the way technology acceptance theory is conceptualised in distance education research. Future theoretical development should examine whether proactive AI behaviour mediates or moderates TAM relationships in ODL contexts, and whether it can be cultivated through structured professional development interventions.

The AI adoption depth gap with the near-universal chatbot use coexisting with near-zero uptake of learner analytics and adaptive learning tools is the most pressing practical finding. It reveals that Malaysian ODL practitioners are digitally engaged with AI but have not bridged to the applications most directly relevant to ODL quality, reflected by early warning dropout systems, personalised learning pathways, and scaled automated feedback. As Malaysia's DEP implementation proceeds and evolves, closing this gap should be understood not merely as a training challenge but as a strategic quality imperative for the hundreds of thousands of Malaysian learners whose educational trajectories depend on the willingness and capacity of their ODL practitioners to harness AI's fullest potential.

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