ASEAN Journal of Open and Distance Learning (AJODL)
https://ajodl.oum.edu.my/
Vol. 17, No. 2, 2025, pp. 109 – 120

Determinants of Artificial Intelligence Adoption in Authentic Online Assessments: Lessons from Malaysia for ASEAN Open and Distance Learning

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Paper Info:
Received: 25 Sept 2025 | Revised: 17 Dec 2025
| Accepted: 26 Dec 2025 | Available Online: 31 Dec 2025

DOI: https://doi.org/10.64233/SGKA1046

Citation:
Omar, R., Osman, Z., & Hsien, O. L. (2025). Determinants of artificial intelligence adoption in authentic online assessments: Lessons from Malaysia for ASEAN open and distance learning. *ASEAN Journal of Open and Distance Learning, 17*(2), 109-120, https://doi.org/10.64233/SGKA1046

Abstract

This study investigates the adoption of artificial intelligence in authentic online assessments among academics in open and distance learning higher education institutions, with particular relevance to the ASEAN region. The integration of artificial intelligence has the potential to transform assessment practices by improving accuracy, enabling personalised feedback, and strengthening the quality of large-scale teaching and learning. Guided by the Theory of Planned Behaviour, the study examined the relationships between attitude and subjective norms, with intention acting as mediator of adoption. A structured survey was distributed to 420 academics, producing 299 valid responses. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The findings revealed that subjective norms exerted a strong positive influence on both intention and adoption, while attitude showed a moderate effect on intention. Intention was confirmed as a significant mediator between psychological and social factors and adoption. These results emphasise the importance of institutional culture, professional collaboration, and peer influence in shaping readiness for technology use in open and distance learning, particularly in large-scale assessment environments. The study suggests that professional development, policy support, and educator engagement are critical to promoting wider adoption of artificial intelligence in authentic online assessments. By positioning artificial intelligence as a driver of innovation, this research contributes to the body of knowledge on technology-enhanced learning and *offers practical implications for strengthening the assessment practices across ASEAN open and distance learning institutions.*

Keywords: adoption, artificial intelligence, ASEAN, authentic online assessment, higher education, Innovation, open and distance learning

1. Introduction

Artificial Intelligence (AI) is rapidly changing higher education worldwide, particularly in assessment, where issues of fairness, efficiency, and authenticity are critical in open and distance learning (ODL). Applications such as automated grading, adaptive testing, and personalised feedback can improve accuracy, enhance learner engagement, and reduce educators' workload. In the ASEAN region, where ODL plays a key role in expanding access to higher education, integrating AI into authentic online assessments presents a significant opportunity to strengthen teaching quality and encourage innovation. In this study, authentic online assessment is defined as evaluative tasks that require learners to apply knowledge to realistic and complex scenarios, rather than relying on simple digitised quizzes (Wiggins, 1990). While traditional ODL struggles to scale such assessments, AI now enables the automation of complex tasks, such as grading case studies or generating real-time scenarios, making authentic assessment viable at scale.

Despite this potential, the adoption of AI remains uneven, constrained by ethical concerns, data privacy, and varying levels of readiness among educators. Research on technology adoption highlights the importance of psychological and social determinants; however, limited attention has been given to how these factors operate specifically within ODL assessment contexts. Using the Theory of Planned Behaviour (TPB) as a framework, this study investigates the influence of attitude, subjective norms, and intention on academics' adoption of AI for authentic online assessment. By focusing on these determinants, the study contributes to understanding how institutional culture, peer influence, and professional values shape technology integration in ASEAN ODL institutions.

Based on the gaps identified in the literature, this study is guided by the following Research Objectives (RO):

- RO1: To examine the relationship between attitude and the intention to adopt AI in authentic online assessments.
- RO2: To determine the influence of subjective norms on both the intention and actual adoption of AI.
- RO3: To analyse the mediating role of intention in translating psychological and social factors into adoption behaviour.
- Correspondingly, the study seeks to answer the following Research Questions (RQ):
- RQ1: Does attitude significantly influence the intention to adopt AI in authentic online assessments?
- RQ2: How do subjective norms influence the intention and adoption of AI among ODL academics?
- RQ3: Does intention mediate the relationship between attitude, subjective norms, and the actual adoption of AI?

2. Literature Review

2.1. Underpinning Theory

The TPB provides a widely applied framework for examining behavioural adoption of technology in educational contexts. Developed as an extension of the Theory of Reasoned Action (Ajzen & Fishbein, 1980; Ajzen, 1985), TPB posits that attitudes, subjective norms, and perceived behavioural control shape intention, which subsequently predicts actual behaviour. Attitude reflects an individual's evaluation of a behaviour, subjective norms capture perceived social pressure, and perceived behavioural control relates to the ease or difficulty of performing the behaviour (Ajzen, 2011). In higher education, TPB has been used to examine the adoption of innovations such as e-learning, online teaching, and educational technologies (Sangeeta & Tandon, 2021; Neves et al., 2022). Its strength lies in recognising both psychological determinants and the influence of institutional or social environments, making it particularly relevant for investigating artificial intelligence adoption in open and distance learning. Despite its wide application, TPB has been critiqued for its limited consideration of contextual and structural constraints, such as organisational policy, technological infrastructure, and governance mechanisms, which may also shape technology adoption behaviours (Ajzen, 2011).

2.2. Artificial Intelligence in Higher Education and ODL

Artificial intelligence has been increasingly recognised as a transformative force in higher education, particularly in enhancing teaching, learning, and assessment. In Malaysia, studies show that academics' adoption of AI depends strongly on factors such as trust, perceived behavioural control, and attitude (Osman et al., 2023). Students' perspectives similarly highlight satisfaction and perceived utility as key drivers of acceptance, while content quality and credibility play smaller roles (Yusoff et al., 2025). Within open and distance learning, AI has been identified as both an opportunity and a challenge, with issues of digital readiness, ethical use, and infrastructure limitations requiring careful institutional planning (Amin et al., 2025). Recent ODL-focused research has also shown that teaching, learning, and assessment practices were forced to adapt rapidly during the pandemic, underscoring the importance of institutional readiness in adopting emerging technologies (Chiew et al., 2022). These findings suggest that while AI can strengthen assessment and learning in ODL, its adoption is mediated by complex psychological and institutional dynamics.

2.3. Attitude, Intention, and Adoption

Within the framework of this study, it is essential to distinguish between the constructs of intention and adoption. Intention is defined as the psychological readiness and conscious plan to perform a specific behaviour, serving as the immediate antecedent to action. In contrast, adoption refers to the actual, sustained utilization of the tool in daily professional practice. While intention captures the willingness to use AI, adoption captures the execution of that willingness in real-world assessment scenarios. Attitude towards AI adoption reflects academics' evaluation of its usefulness, efficiency, and ability to improve the quality of assessments. Positive attitudes, such as recognising AI's potential to deliver timely feedback and reduce workload, are consistently linked to stronger intentions to adopt (Sangeeta & Tandon, 2021; Neves et al., 2022). Conversely, concerns over reliability, ethics, and bias can hinder adoption even when institutional support exists (Fischer & Karl, 2022). In Malaysia, Razak et al. (2024) found that postgraduate students' AI acceptance was shaped by factors beyond TPB, including habit and hedonistic motivations, suggesting that academics' attitudes may also interact with contextual influences in shaping adoption behaviour. Complementing this, research on digital tool acceptance among ODL students shows that readiness and perceptions significantly influence technology use, pointing to the critical role of institutional support in shaping adoption (Raju et al., 2021).

2.4. Subjective Norms, Intention, and Adoption

Subjective norms play a pivotal role in technology adoption within collectivist and institutionally guided environments such as ASEAN. Norms may derive from colleagues, administrators, students, or wider professional networks, creating pressures to align with expected behaviours (Rivis & Sheeran, 2003). Studies demonstrate that when academics perceive strong endorsement from peers and leadership, they are more likely to adopt AI tools in assessment (Khlaif et al., 2024; Mao et al., 2024). Recent regional scholarship highlights that governance frameworks and institutional culture in Southeast Asia significantly shape adoption patterns, with norms often carrying more weight than individual preferences (Putra, 2024). In ODL contexts, where technology-mediated learning is central, subjective norms may, therefore, carry heightened importance, reinforcing the collective responsibility of academics to engage with innovative assessment practices. These findings are particularly salient in the ASEAN context, where hierarchical institutional structures and collectivist professional cultures amplify the role of social norms in shaping academic behaviour.

2.5. Gaps and Research Direction

Although prior studies have established the significance of attitudes and subjective norms in shaping AI adoption, little attention has been given to the specific context of authentic online assessment in open and distance learning. Much of the existing work in Malaysia and ASEAN focuses on teaching, curricula, or student acceptance (Osman et al., 2023; Yusoff et al., 2025; Razak et al., 2024), leaving a gap in understanding how academics in ODL institutions approach assessment innovation. While prior studies have examined AI adoption in teaching and learning, they rarely distinguish between psychological readiness (intention) and enacted behaviour (adoption) within assessment-driven ODL environments, limiting their explanatory power for institutional practice. Furthermore, while global studies recognise ethical and cultural factors influencing AI adoption, few have systematically applied TPB to explore the mediating role of intention in ODL assessment contexts. Addressing this gap, the present study examines the relationships between attitude, subjective norms, and intention in the adoption of artificial intelligence for authentic online assessments in Malaysia, with implications for open and distance learning across ASEAN.

2.6. Hypotheses Development

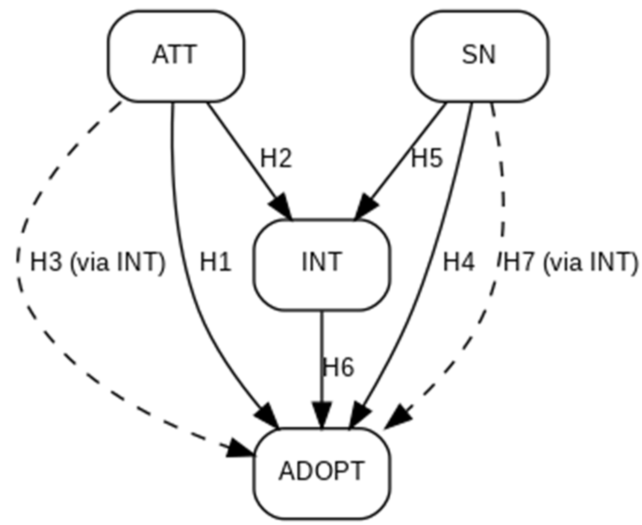
Drawing from the TPB and prior empirical findings, this study proposes a model linking attitude, subjective norms, intention, and adoption of artificial intelligence in authentic online assessments. Attitude is expected to influence both intention and adoption, while subjective norms are anticipated to shape intention directly and adoption both directly and indirectly. Intention is positioned as a mediator that translates these psychological and social determinants into actual adoption behaviour.

Based on this framework, the following hypotheses are formulated and illustrated in the proposed conceptual research model (see Figure 1):

- H1: Attitude has a positive relationship with the adoption of artificial intelligence in authentic online assessments.
- H2: Attitude has a positive relationship with intention to adopt artificial intelligence in authentic online assessments.
- H3: Intention mediates the relationship between attitude and adoption of artificial intelligence in authentic online assessments.
- H4: Subjective norms have a positive relationship with the adoption of artificial intelligence in authentic online assessments.

- H5: Subjective norms have a positive relationship with intention to adopt artificial intelligence in authentic online assessments.
- H6: Intention has a positive relationship with the adoption of artificial intelligence in authentic online assessments.
- H7: Intention mediates the relationship between subjective norms and adoption of artificial intelligence in authentic online assessments.

Figure 1
Conceptual Research Model of the Study



Note. ATT = Attitude; SN = Subjective Norms; INT = Intention; ADOPT = Adoption. Dashed arrows represent mediation hypotheses (H3 and H7).

3. Research Method

This study employed a quantitative design to examine the determinants of artificial intelligence adoption in authentic online assessments within open and distance learning institutions in Malaysia. Guided by the TPB, the proposed conceptual research model (see Figure 1) tested the relationships between attitude, subjective norms, intention, and adoption. The model also examined the mediating role of intention in linking psychological and social determinants to adoption behaviour.

3.1. Sampling and Data Collection

The respondents comprised 299 academics from ODL institutions. The gender distribution was 59.5% male and 40.5% female. In terms of age, the majority were between 41–50 years old (40.5%), followed by 31–40 years (23.1%). Regarding academic position, the sample included Senior Lecturers (75.6%), Associate Professors (21.1%), Professors (2.0%), and Lecturers (1.3%).

Data collection was conducted between January and March 2025 at Open University Malaysia and Wawasan Open University. While the survey was distributed via institutional email to the broad academic community, the target population was restricted to active Course Coordinators and Programme Directors directly responsible for designing authentic online assessments, estimated at 420 distinct academic roles across both institutions.

Based on this eligible target population, the study received 321 responses, yielding an effective response rate of 76.4%. This high engagement is attributed to the timeliness of the AI topic, which generated significant professional interest among the respondents, alongside the effectiveness of the systematic reminder protocol. Following data screening (removing 22 incomplete or straight-lined responses), the final sample consisted of 299 valid responses.

3.2. Measurement Instruments

The survey instrument consisted of four constructs: attitude, subjective norms, intention, and adoption. Each construct was measured with four items adapted from established TPB scales: attitude (Voon et al., 2011; Taylor & Todd, 1995), subjective norms (Taylor & Todd, 1995), intention (Taylor & Todd, 1995), and adoption/behaviour (De Cannière et al., 2009). All items were rated on a five-point Likert scale ranging from “strongly disagree” to “strongly agree.”

To ensure content validity within the local context, the items underwent a qualitative expert review by three senior academics in ODL and educational technology. Based on their feedback, minor linguistic adjustments were made to ensure clarity for Malaysian respondents. Construct validity was subsequently confirmed statistically, with all item loadings exceeding the 0.708 threshold (Hair et al., 2017).

3.3. Data Analysis

The data were analysed using PLS-SEM with SmartPLS 4, which is well-suited for testing complex models with multiple mediating relationships. This approach allowed the simultaneous assessment of measurement properties and structural paths. The analysis followed a two-stage process: first, the measurement model was evaluated for reliability and validity using Cronbach’s alpha, Composite Reliability, and Heterotrait-Monotrait (HTMT) ratios. Second, the structural model was assessed, where bootstrapping procedures with 5,000 subsamples were applied to test the significance of the path coefficients. Finally, Common Method Bias (CMB) was examined using the full collinearity assessment approach to ensure the robustness of the findings.

4. Findings and Discussion

4.1. Findings

Prior to assessing the structural model, CMB was examined since data were collected using a single survey instrument. Following the full collinearity assessment approach recommended by Kock (2015), the Variance Inflation Factor (VIF) values for all constructs were calculated. The analysis yielded VIF values of 1.733 for Adoption, 1.614 for Attitude, 1.692 for Subjective Norms, and 1.327 for Intention. As all VIF values remained consistently below the threshold of 3.3, the model is considered free from significant common method bias.

The analysis using Structural Equation Modelling confirmed significant relationships among the constructs of the research model (see Figure 1). Attitude was found to exert a positive influence on intention, which in turn mediated its effect on adoption. Subjective norms showed a strong positive impact on both intention and adoption, while intention itself demonstrated the largest direct effect on adoption.

To assess the reliability and validity of the constructs, the measurement model was first examined. As shown in Table 1, Cronbach’s alpha and composite reliability values exceeded

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recommended thresholds, while average variance extracted values were above 0.50. Item loadings ranged from 0.68 to 0.87, and HTMT ratios were below 0.85, confirming adequate convergent and discriminant validity.

Table 1

Construct Reliability and Validity

Construct	Item	Loading Range	Cronbach's Alpha	Composite Reliability	AVE	HTMT (highest)
Adoption	ADOPT1–ADOPT4	0.74–0.81	0.797	0.806	0.620	0.54
Attitude	ATT1–ATT4	0.68–0.82	0.765	0.770	0.588	0.54
Intention	INT1–INT4	0.72–0.84	0.810	0.819	0.638	0.75
Subjective Norms	SN1–SN4	0.77–0.87	0.847	0.872	0.684	0.74

Note. ADOPT=Adoption; ATT=Attitude; INT=Intention; SN=Subjective Norms; AVE = Average Variance Extracted; HTMT = Heterotrait-Monotrait ratio.

Having established reliability and validity, the structural model was tested to examine the hypothesised relationships. The results, presented in Table 2, indicate that intention had the strongest direct effect on adoption ($\beta = 0.463$, $p < 0.001$), confirming its role as a central mediator. Subjective norms significantly influenced both intention ($\beta = 0.348$, $p < 0.001$) and adoption ($\beta = 0.240$, $p < 0.001$). Attitude significantly affected intention ($\beta = 0.217$, $p < 0.01$), but its direct effect on adoption was not significant. Bootstrapping with 5,000 subsamples was applied to generate t-statistics and confidence intervals. As presented in Table 2, the analysis confirmed six out of the seven proposed hypotheses.

Table 2

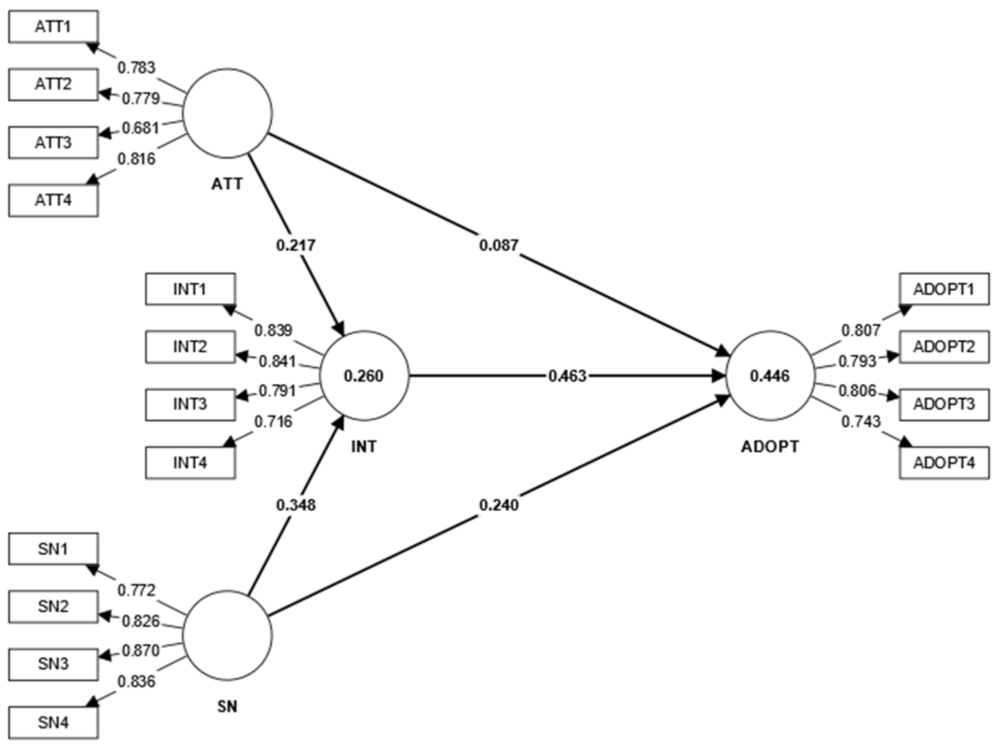
Hypotheses Testing Results, Confidence Intervals, and Decisions

Hypothesis	Path	β	t-value	p-value	95% Confidence Interval (BC)	Decision
H1	Attitude → Adoption	0.087	1.394	0.163	[-0.034, 0.210]	Rejected
H2	Attitude → Intention	0.217	3.312	0.001	[0.079, 0.338]	Accepted
H3	Attitude → Intention → Adoption	0.100	3.034	0.002	[0.037, 0.165]	Accepted
H4	Subjective Norms → Adoption	0.240	4.062	0.000	[0.126, 0.358]	Accepted
H5	Subjective Norms → Intention	0.348	5.339	0.000	[0.219, 0.473]	Accepted
H6	Intention → Adoption	0.463	8.792	0.000	[0.356, 0.560]	Accepted
H7	Subjective Norms → Intention → Adoption	0.161	4.498	0.000	[0.096, 0.237]	Accepted

Note. Significant at $p < 0.05$, $t > 1.96$.

Figure 2

Structural Model Assessment with Path Coefficients and R^2 Values



Note. Values on arrows represent path coefficients (β). Values inside circles represent the coefficient of determination (R^2)

The results indicate that Intention had the strongest direct effect on Adoption (β = 0.463, t =8.792), confirming its critical role as a mediator. Subjective Norms also exerted a significant influence on both Intention (β = 0.348) and directly on Adoption (β = 0.240). Conversely, Attitude did not have a significant direct effect on Adoption (H1 rejected, $p > 0.05$), as the confidence interval included zero [-0.034, 0.210].

Taken together, these results show that: (a) H1 was not supported, indicating attitudes alone do not drive adoption; (b) H2 and H3 were supported, showing attitudes influence adoption indirectly via intention; (c) H4 and H5 were supported, confirming the strong role of subjective norms in shaping both intention and adoption; (d) H6 was the strongest path, establishing intention as the central driver of adoption; and (e) H7 was supported, highlighting intention's mediating role in translating social and institutional pressures into adoption behaviour.

To further interpret the strength of these relationships, effect size analysis was conducted. As shown in Table 3, intention had a large effect on adoption ($f^2 = 0.286$), while subjective norms had smaller but meaningful effects on both adoption and intention. Attitude, in contrast, showed negligible direct influence on adoption.

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Table 3

Effect Sizes (f^2)

Relationship	f^2	Effect size
Attitude → Adoption	0.008	Negligible
Intention → Adoption	0.286	Large
Subjective Norms → Adoption	0.059	Small
Subjective Norms → Intention	0.103	Small–Moderate

Note. Effect size interpretation follows Cohen (1992).

4.2. Discussion

The findings of this study provide critical insights into the determinants of AI adoption in authentic online assessments within ODL institutions. By applying the TPB, the results clarify how psychological and social factors interact in this unique educational context.

Contrary to initial expectations, Hypothesis 1 is rejected, indicating that a positive attitude towards AI does not directly lead to adoption ($\beta = 0.087$, $p > 0.05$). This finding contrasts with earlier Western-centric studies where individual preference often drives behaviour directly (Sangeeta & Tandon, 2021). However, Hypothesis 2 confirms that attitude significantly builds intention ($\beta = 0.217$). This suggests that while ODL academics may recognize the benefits of AI (such as efficiency and feedback quality), this "internal" approval is insufficient to drive actual usage without the "external" push of institutional readiness. This aligns with Fischer and Karl (2022), who note that concerns over reliability and ethics can stall adoption even when attitudes are positive. In the Malaysian ODL context, an academic's personal willingness (attitude) effectively remains latent until it is activated by formal intent or organizational sanction.

A key finding is the powerful influence of Subjective Norms, which significantly impacts both intention (H5) and adoption (H4). This supports recent scholarship on the collectivist nature of the ASEAN educational context, where professional behaviour is heavily shaped by peer expectations and institutional directives (Putra, 2024). The fact that subjective norms drive adoption directly ($\beta = 0.240$), bypassing intention, implies that academics often adopt AI tools to align with departmental culture or key performance indicators (KPIs), regardless of their personal psychological readiness. This confirms the work of Khlaif et al. (2024), who find that leadership endorsementis a decisive factor in technology integration.

The study confirms that Intention is the strongest predictor of adoption (H6, $\beta = 0.463$) and acts as a vital mediator (H3, H7). This reinforces the core tenet of the TPB: that psychological readiness must be solidified into a conscious plan before action occurs (Ajzen, 2011).

Practically, these results suggest that ODL institutions should move beyond merely "promoting" AI benefits. Instead, they must encourage a collaborative culture where AI usage is normalized through peer mentoring and visible leadership endorsement. Future research should consider longitudinal designs to track how these norms evolve as AI tools become commonplace. Additionally, qualitative inquiries can deepen the understanding of specific barriers, like lack of technical training or ethical uncertainty, that prevent positive attitudes from translating directly into action.

5. Conclusion

This study examined the determinants of artificial intelligence adoption in authentic online assessments among academics in Malaysia's open and distance learning institutions. Underpinned by the TPB, the research model tested the influence of attitude and subjective norms on adoption, with intention as a mediator. Using survey data from 299 academics and structural equation modelling, the results showed that subjective norms strongly influenced both intention and adoption, while attitude shaped intention but did not directly predict adoption. Intention emerged as the most powerful driver of adoption, mediating the relationships between both psychological and social factors and actual use. These findings extend the theoretical framework by demonstrating the central role of intention in authentic online assessment contexts, while also highlighting that institutional culture and peer influence are more decisive than individual attitudes in ODL settings. The study contributes theoretically by advancing understanding of technology adoption in authentic online assessment, and practically by showing that professional development, policy frameworks, and collaborative networks are critical for normalising the use of artificial intelligence in higher education. By situating artificial intelligence adoption within authentic online assessment, this study underscores the importance of aligning technological innovation with institutional support to enhance learning and assessment quality in ODL.

Funding*:* This research was funded by the Open University Malaysia Internal Research Fund under Grant No. OUM-IRF-2025-010.

Acknowledgement: The authors would like to acknowledge the support of the Centre for Research and Innovation, Open University Malaysia, for facilitating the conduct of this project and providing guidance throughout the research process.

Conflict of Interest Statement: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Ethics Statement: The study was conducted in accordance with the ethical guidelines of the Open University Malaysia Research Ethics Committee. Informed consent was obtained from all subjects involved in the study.

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