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Artificial Intelligence Adoption in Authentic Online Assessments: A Study of Online Distance Learning Institutions

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Abstract

This study explores the factors influencing the adoption of artificial intelligence (AI) in authentic online assessments within open and distance learning (ODL) institutions. Using the Theory of Planned Behaviour (TPB) as the underlying framework, the research examines the roles of attitude, perceived behavioural control, subjective norms, and self-efficacy in shaping educators' intention to adopt AI, and how this intention affects actual adoption. Data were collected from 299 academic staff through an online survey, and the analysis was conducted using SmartPLS 4. The findings show that intention, perceived behavioural control, self-efficacy, and subjective norms significantly influence the adoption of AI. Among these, intention was the strongest predictor of adoption behaviour. In contrast, attitude did not have a significant effect on adoption. The study also confirmed the mediating role of intention between the independent variables and adoption behaviour. Additional analysis using PLSpredict and the cross-validated predictive ability test (CVPAT) demonstrated that the model has good predictive relevance. These findings suggest that building educators' confidence, ensuring access to necessary tools, and fostering a supportive institutional culture are more effective in promoting AI adoption than focusing solely on positive attitudes. The study contributes to the theoretical understanding of technology adoption in education and offers practical guidance for ODL institutions aiming to implement AI-driven assessment strategies.

Keywords: Artificial Intelligence, Authentic Assessment, Technology Adoption, Theory of Planned, Behaviour, Open and Distance Learning

Introduction

The adoption of artificial intelligence (AI) in authentic online assessments presents significant opportunities for open and distance learning (ODL) institutions. AI can enhance assessment processes through personalised feedback, automated grading, and secure proctoring tools, making it especially relevant in ODL contexts where face-to-face interaction is limited (Khlaif et al., 2024; Gundu, 2024). The use of AI in online assessments is gaining traction globally, with applications such as adaptive testing and natural language processing being employed to evaluate open-ended responses (Jin et al., 2025; Xia et al., 2024). These tools enable real-time analytics and support more tailored learning experiences, improving both assessment accuracy and learner engagement (Owan et al., 2023; Gamage et al., 2023). Despite these benefits, challenges remain. Concerns about data privacy, algorithmic fairness, and technical readiness continue to hinder widespread adoption (Maistry & Singh, 2025; Arise et al., 2024). Moreover, while AI offers opportunities for innovation, many educators struggle to adapt due to limited training and evolving job expectations. Professional development and digital literacy efforts are therefore essential to equip educators with the necessary skills (Sevnarayan & Potter, 2024; Chakabwata, 2025). This study responds to the limited research on the psychological drivers behind AI adoption in educational settings. To address this, it draws upon the Theory of Planned Behaviour (Ajzen, 1991), which highlights intention, attitude, subjective norms, perceived behavioural control, and self-efficacy as key predictors of behavioural outcomes. This study aims to examine how these constructs influence the adoption of AI in authentic online assessments within ODL institutions. The findings are expected to inform institutional policies, academic development initiatives, and broader strategies for integrating AI in assessment.

Literature Review

Underpinning Theory

The Theory of Planned Behaviour (TPB) by Ajzen (1991) offers a strong foundation for understanding how individuals decide whether to perform a particular behaviour, including adopting new technologies. TPB highlights four key constructs: attitude, subjective norms, perceived behavioural control, and self-efficacy. In the context of this study, attitude refers to an educator's overall evaluation of using AI in assessments, whether they see it as beneficial or not. Subjective norms involve the perceived social pressure from peers, students, or institutional leaders to use or not use AI. Perceived behavioural control reflects whether individuals feel they have the ability, resources, or opportunities to use AI tools effectively. Self-efficacy, though often discussed together with perceived control, refers more specifically to one's confidence in their ability to carry out a task, in this case, using AI in online assessment. Intention is seen as the immediate factor leading to actual behaviour. When all these constructs are favourable, TPB suggests that a person is more likely to follow through with the behaviour. This theory fits well with the aim of the study, which is to explore what drives AI adoption in ODL institutions, especially when authentic online assessments are involved.

Relationship between Attitude & Adoption

Attitude has long been identified as a factor that influences whether someone decides to adopt a new technology. Previous research (Moxley et al., 2022; Sailer et al., 2021; Santini et al., 2020) has shown that a positive attitude towards technology can support its use in educational settings. When educators believe that AI tools are useful, easy to use, and can help them do their job better, they are more likely to try them out. Studies like those by Au and Enderwick (2000), Li et al. (2016), and Singh and Tewari (2021) found that attitude is shaped not only by how helpful the technology is, but also by past experiences and how confident users feel. Moxley et al. (2022), for example, found that users' willingness to adopt technology depends on whether they see value in it, how easy it is to use, and their belief that they can handle it. This shows that promoting positive experiences with AI, along with institutional support, can help improve attitudes—something that might be especially important in ODL environments where technology plays a central role.

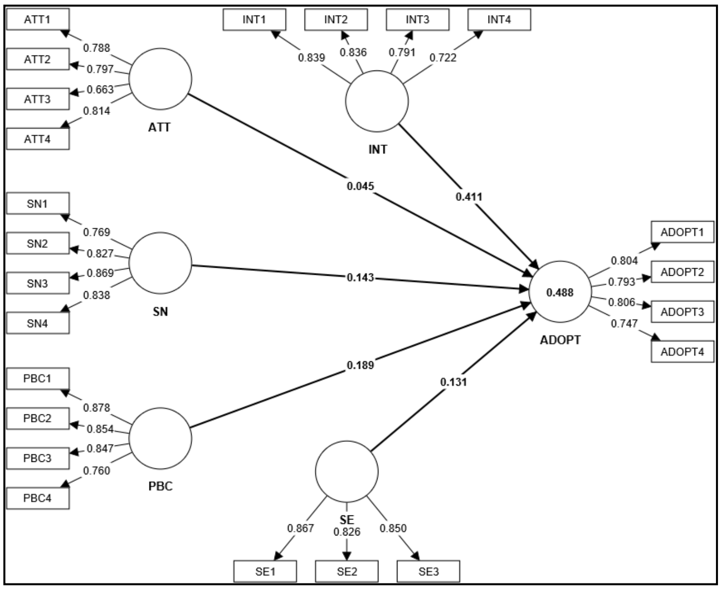
Relationship between Intention & Adoption
According to TPB, intention is the strongest predictor of whether someone will actually perform a behaviour (Ajzen, 1991). In other words, if an educator intends to use AI in assessment, they are more likely to do so. Several studies support this idea. For instance, Kabra et al. (2017), Roy et al. (2022), and Nazaretsky et al. (2022) found a strong link between intention and actual use of AI tools in education. The intention to adopt AI often comes from seeing its benefits, receiving support from the institution, or having prior exposure to AI-based assessment systems. More recently, Khlaif et al. (2024) noted that factors like performance expectations, ease of use, and social influence also play a role in shaping intention, especially when generative AI tools are involved. These findings underline the importance of building strong intentions among educators if institutions want to see meaningful AI adoption, especially in fully online environments like ODL.

Relationship between Perceived Behavioural Control & Adoption
Perceived behavioural control refers to how easy or difficult individuals believe it is to perform a certain behaviour. In this case, it relates to how capable educators feel when it comes to using AI tools for assessment. Ajzen (1991) argued that when people believe they have the necessary skills, time, and resources, they are more likely to follow through with their intention. This is supported by studies showing that educators are more open to adopting AI when they feel well-equipped and supported. For example, Lee (2022), Sánchez-Prieto et al. (2017), and Zhang and Hou (2024) found that technical support, training opportunities, and resource availability are major influences on adoption. On the other hand, when support is lacking or when there are concerns about the reliability of AI, educators may hesitate to use it (Lin & Chen, 2024). Almogren et al. (2024) also found that stronger perceived control increases intention, which then leads to higher adoption rates. For institutions that want to see more AI integration, especially in ODL settings, improving perceived behavioural control is a key area to focus on. This can be achieved through training, guidelines, and access to the right tools.

Relationship between Self-Efficacy & Adoption
Self-efficacy is closely related to perceived behavioural control but focuses more on a person's confidence in their own ability to use AI effectively. Tan et al. (2021) describe self-efficacy as the belief that one can perform specific tasks successfully. When educators believe in their ability to manage and apply AI tools in assessments, they are more likely to use them. Yentür (2023) suggested that individuals with high self-efficacy are more resilient when facing challenges and are more likely to embrace new technologies. Several studies have confirmed that educators who are confident in their tech skills are more inclined to adopt AI-driven assessment tools (Li et al., 2016; Sailer et al., 2021; Sánchez-Prieto et al., 2017). These findings suggest that building self-efficacy is an important part of increasing AI adoption. For ODL institutions, this means investing in professional development that allows educators to engage with AI in practical and supported ways. Confidence often grows through hands-on experience, peer learning, and structured training sessions.

Relationship between Subjective Norms & Adoption
Subjective norms refer to the influence of others on an individual's decision to adopt a new practice. In educational settings, this can include encouragement from colleagues, expectations from leadership, or trends within professional communities. Ahadzadeh et al. (2024) noted that when educators perceive strong support or expectation from their institutions or peers, they are more likely to adopt AI. Zhang and Hou (2024) also reported that subjective norms played an important role in shaping behavioural intention, alongside trust and perceived usefulness. In addition, professional learning communities and collaborative networks have been found to influence educators' perceptions and behaviours related to AI (Jin et al., 2024; Zheng et al., 2021). These findings point to the importance of cultivating a supportive community within ODL institutions. When educators see that others around them are exploring and benefiting from AI, they may feel more motivated to follow suit. Therefore, fostering positive norms around innovation and technology use is another strategic step institutions can take to encourage adoption.

Figure 1: Research Model



Notes: INT=Intention ATT=Attitude SN=Subjective Norms SE=Self-Efficacy
PBC=Perceived Behavioral Control ADOPT=Adoption

Methodology
This study aimed to examine the factors that influence the adoption of artificial intelligence (AI) in authentic online assessments among academic staff in open and distance learning (ODL) institutions. The research focused on four independent variables: attitude, perceived behavioural control, subjective norms, and self-efficacy. Intention was examined as a mediating variable, while AI adoption was the dependent variable.

To collect data, an online questionnaire was developed based on established instruments from prior studies. A purposive sampling method was used to identify participants, as there was no complete list of the population available. The survey was distributed via email to academic staff members, and 321 responses were received. After data screening and the removal of outliers, 299 valid responses were used for analysis. This response rate of 76.4% was considered acceptable for the purposes of structural equation modelling (SEM).

Each construct in the study was measured using multiple items drawn from prior validated scales. Attitude (four items) was adapted from Voon et al. (2011), subjective norms (four items) from Rivis and Sheeran (2003), perceived behavioural control (four items) from Li et al. (2020), and self-efficacy (three items) from Chen et al. (2001). The mediating variable, intention (four items), was based on Fu et al. (2016), while the adoption construct (four items) was measured using items from De Cannière et al. (2009). All items were rated on a five-point Likert scale ranging from “strongly disagree” to “strongly agree”.

For data analysis, the study used SmartPLS 4 software, which is widely applied in SEM research, particularly when working with complex models and small-to-moderate sample sizes. This tool enabled the researchers to test both the measurement and structural models. The choice of SmartPLS 4 was guided by its suitability for exploratory models and its ability to handle latent constructs effectively, as recommended by Ringle et al. (2022).

Data Analysis

Respondents’ Profiles

A total of 299 academic staff participated in this study. Among them, 59.5% were male (n = 178), and 40.5% were female (n = 121). In terms of age, 3.0% were under 30 years old, 23.1% were between 31 and 40, 40.5% were aged 41 to 50, 20.1% were in the 51 to 60 age group, and 13.4% were above 60. Regarding years of service, 5.7% had less than five years of experience, while 13.7% had between six and ten years. Another 15.7% had worked for 11 to 15 years, and 12.7% each had between 16 to 20 and 21 to 25 years. Additionally, 15.4% had served for 26 to 30 years, while 18.1% had more than 30 years of experience. In terms of designation, the majority were senior lecturers (75.6%), followed by associate professors (21.1%), professors (2.0%), and lecturers (1.3%). Notably, 97.7% of respondents expressed support for using AI in education, indicating a generally positive disposition toward technological adoption in assessments.

Common Method Bias

To assess the presence of common method bias (CMB), the study followed the full collinearity test approach as proposed by Kock (2015). Variance inflation factor (VIF) values were examined for all constructs. The results, as shown in Table 1, indicated that all VIF values ranged between 1.409 and 1.945, which are well below the accepted threshold of 3.3. These findings suggest that multicollinearity is not a concern in this dataset, and CMB is unlikely to distort the results. The constructs measured in the study are therefore considered conceptually distinct and statistically sound.

Table 1
Full Collinearity

	ADOPT	ATT	SN	PBC	SE	INT
ADOPT		1.879	1.849	1.830	1.851	1.540
ATT	1.672		1.419	1.659	1.664	1.654
SN	1.945	1.677		1.980	1.792	1.956
PBC	1.506	1.534	1.548		1.337	1.548
SE	1.938	1.957	1.784	1.702		1.960
INT	1.409	1.701	1.702	1.722	1.713	

Measurement Model

The measurement model was assessed through three key indicators: internal consistency, convergent validity, and discriminant validity. Cronbach's alpha (CA) values for all constructs were above 0.7, ranging from 0.765 to 0.856, indicating acceptable internal consistency. Composite reliability (CR) values were also satisfactory, falling between 0.772 and 0.872. Average variance extracted (AVE) scores exceeded the recommended threshold of 0.5, with values between 0.589 and 0.719, confirming convergent validity. The detailed values for CA, CR, AVE, and item loadings are presented in Table 2.

Individual item loadings were mostly above 0.7. For instance, items such as SE1 (0.867) and PBC1 (0.878) demonstrated strong loadings, reinforcing the reliability of the measurement instruments. Discriminant validity was evaluated using the Heterotrait-Monotrait ratio (HTMT), with all values falling below 0.85, as recommended by Henseler et al. (2015). These results, along with the HTMT ratios, are further detailed in Table 3, supporting the distinctiveness of the constructs used.

Table 2
Construct Reliability and Validity & Item Loadings

Constructs	Items	Loadings	CA	CR	AVE
Adoption	ADOPT1	0.804	0.797	0.804	0.621
	ADOPT2	0.793			
	ADOPT3	0.806			
	ADOPT4	0.747			
Attitude	ATT1	0.788	0.765	0.772	0.589
	ATT2	0.797			
	ATT3	0.663			
	ATT4	0.814			
Intention	INT1	0.839	0.810	0.818	0.637
	INT2	0.836			
	INT3	0.791			
	INT4	0.722			
Perceived	PBC1	0.878	0.856	0.864	0.699
Behavioral Control	PBC2	0.854			
	PBC3	0.847			
	PBC4	0.760			
	SE1	0.867			
Self-Efficacy	SE2	0.826	0.805	0.806	0.719
	SE3	0.850			
Subjective Norms	SN1	0.769	0.847	0.872	0.683
	SN2	0.827			
	SN3	0.869			
	SN4	0.838			

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

Table 3
Hetrotrait-Monotrait (HTMT) Ratios

	ADOPT	ATT	INT	PBC	SE
ATT	0.541				
INT	0.754	0.534			
PBC	0.538	0.461	0.432		
SE	0.546	0.520	0.462	0.368	
SN	0.599	0.741	0.560	0.445	0.662

Structural Model
The structural model was evaluated using the approach recommended by Hair et al. (2017), which involves examining path coefficients (β), t-statistics, p-values, and the coefficient of determination (R^2). A bootstrapping procedure with 5,000 sub-samples was conducted using SmartPLS 4 to determine the significance of each path. The results are summarised in Table 4.

Among the hypotheses tested, only one was not supported. Hypothesis 1 (H1), which posited a relationship between attitude and AI adoption, showed a beta value of 0.045, a t-statistic of 0.758, and a p-value of 0.448. This indicates a non-significant effect, and the hypothesis was rejected. In contrast, intention (H2) showed a strong and significant positive relationship with adoption ($\beta = 0.411$, $t = 8.128$, $p < 0.001$), confirming that intention is a key predictor of AI adoption.

Perceived behavioural control (H3) also had a significant effect on adoption ($\beta = 0.189$, $t = 3.453$, $p = 0.001$), suggesting that individuals who feel they have control over using AI are more likely to adopt it. Similarly, self-efficacy (H4) showed a positive effect ($\beta = 0.131$, $t = 2.172$, $p = 0.030$), indicating that confidence in one's own ability contributes to adoption behaviour. Subjective norms (H5) were also significant ($\beta = 0.143$, $t = 2.263$, $p = 0.024$), reinforcing the importance of social influence in shaping educators' adoption decisions.

These findings highlight that intention, perceived behavioural control, self-efficacy, and subjective norms all play important roles in influencing the adoption of AI in online assessment. However, attitude alone does not appear to drive adoption directly in this context.

Table 4
Hypotheses Testing Results

Hypotheses	Beta	T statistics	P values	2.50%	97.50%	Decision
H1: ATT -> ADOPT	0.045	0.758	0.448	-0.072	0.164	*Rejected*
H2: INT -> ADOPT	0.411	8.128	0.000	0.309	0.504	*Accepted*
H3: PBC -> ADOPT	0.189	3.453	0.001	0.081	0.296	*Accepted*
H4: SE -> ADOPT	0.131	2.172	0.030	0.018	0.251	*Accepted*
H5: SN -> ADOPT	0.143	2.263	0.024	0.019	0.270	*Accepted*

Note: Significant at p<0.05, t-value>1.96

Effect Sizes (f^2)

To understand the impact of each predictor on AI adoption more precisely, the study examined effect sizes (f^2) as proposed by Cohen (1992). Effect size helps determine the practical significance of each construct beyond its statistical significance. According to Cohen's guidelines, f^2 values are interpreted as small (0.02), medium (0.15), or large (0.35).

As shown in Table 5, the construct with the largest effect size on adoption was intention (f^2 = 0.233), which falls within the medium range. This suggests that intention plays a meaningful role in explaining variance in adoption behaviour. Perceived behavioural control (f^2 = 0.055) had a small but notable effect, while self-efficacy (f^2 = 0.022) also contributed modestly. Subjective norms (f^2 = 0.019) and attitude (f^2 = 0.002) had minimal effects. The low effect size for attitude is consistent with the earlier finding that its relationship with adoption was statistically non-significant.

These results support the importance of focusing on constructs such as intention and perceived behavioural control when designing strategies to promote AI adoption in assessment practices.

Table 5
Effect Sizes (f^2)

Constructs	ADOPT
ATT	0.002
INT	0.233
PBC	0.055
SE	0.022
SN	0.019

PLSpredicts & Cross-Validated Predictive Ability Test (CVPAT)

To assess the model's predictive relevance beyond the sample used in the study, the PLSpredict procedure was conducted, as recommended by Shmueli et al. (2016, 2019). This technique examines how well the model predicts new or unseen data, which is an important step in evaluating its practical usefulness. Table 6 presents the results of the PLSpredict analysis.

All Q^2 values were above zero, indicating that the model has predictive relevance. In addition, the root mean squared error (RMSE) values for all four adoption indicators were lower in the PLS model compared to the linear regression (LM) benchmark. These results suggest that the model is not only statistically significant but also has good out-of-sample predictive power.

To support these findings further, the Cross-Validated Predictive Ability Test (CVPAT) was conducted, following the method outlined by Hair et al. (2022) and Liengaard et al. (2021). The CVPAT compares the predictive accuracy of the model with a naïve benchmark by calculating average loss. As shown in Table 7, the negative average loss difference and the significant t-value (6.448) with a p-value of 0.000 indicate that the model performs better than the benchmark. This provides additional support for the robustness of the model's predictive capability.

Taken together, the results of PLSpredict and CVPAT demonstrate that the model is not only theoretically sound but also practically useful for forecasting adoption behaviour in similar contexts.

Table 6
PLSpredicts

	Q^2predict	PLS-RMSE	LM-RMSE	PLS-LM
ADOPT1	0.372	0.576	0.599	-0.023
ADOPT2	0.249	0.602	0.620	-0.018
ADOPT3	0.274	0.652	0.677	-0.025
ADOPT4	0.209	0.700	0.722	-0.022

Table 7
Cross-Validated Predictive Ability Test (CVPAT)

	Average loss difference	t-value	p-value
ADOPT	-0.152	6.448	0.000
Overall	-0.152	6.448	0.000

Importance-Performance Map Analysis (IPMA)
To gain deeper insights into which factors should be prioritised for improving AI adoption, the Importance-Performance Map Analysis (IPMA) was carried out. This technique, recommended by Ringle and Sarstedt (2016) and Hair et al. (2018), helps identify constructs that are not only important for predicting the outcome but also show room for performance improvement.

As shown in Table 8, the construct with the highest importance was intention (importance = 0.411), although its performance level (61.509) was comparatively lower than other constructs. This suggests that intention plays a key role in driving adoption, yet it may not be fully optimised among respondents. On the other hand, attitude showed the lowest importance (0.045) but had a relatively higher performance score (66.555), which aligns with earlier findings that attitude does not significantly influence adoption in this context.

Other constructs such as perceived behavioural control (importance = 0.189), self-efficacy (0.131), and subjective norms (0.143) had moderate importance and satisfactory performance levels. These results suggest that while they are not the top predictors, they still contribute meaningfully to AI adoption and should be supported through targeted interventions.

Overall, the IPMA highlights intention as the most strategic leverage point. Institutions should focus on strengthening intention through professional development, hands-on exposure to AI tools, and supportive peer environments. This can enhance adoption outcomes more effectively than focusing solely on attitude, which shows limited predictive value.

Table 8
Importance-Performance Map Analysis (IPMA)

	Importance	Performance
ATT	0.045	66.555
INT	0.411	61.509
PBC	0.189	67.426
SE	0.131	66.744
SN	0.143	67.147

Discussion & Conclusion

Discussion

The results of this study offer important insights into the psychological factors that influence the adoption of artificial intelligence (AI) in authentic online assessment, particularly within open and distance learning (ODL) environments. The findings confirm that intention plays the most significant role in predicting actual adoption behaviour, which is consistent with the Theory of Planned Behaviour (Ajzen, 1991). This reinforces the idea that, regardless of external or personal factors, educators must first form a clear intention before engaging with new technologies like AI.

Perceived behavioural control and self-efficacy also emerged as significant predictors, highlighting the importance of confidence, capability, and access to resources. Educators are more likely to adopt AI tools when they feel they have the knowledge, skills, and institutional support to use them effectively. This finding supports the argument that capability-related factors are just as important as motivational factors when it comes to adopting educational technologies.

Interestingly, while previous studies have highlighted attitude as a strong predictor of technology adoption (Moxley et al., 2022; Sailer et al., 2021), this study did not find a significant relationship between attitude and adoption. This suggests that even if educators view AI positively, they may not act on that attitude unless they also have the intention, ability, and encouragement to do so. In an ODL setting, where practical challenges often outweigh personal preference, this finding offers a more nuanced understanding of what drives technology use.

Subjective norms also had a moderate but meaningful influence on adoption, indicating that social and professional expectations can shape educators' decisions. When peers, supervisors, or institutional policies encourage the use of AI, educators are more likely to adopt it, even if other factors are neutral.

Overall, these findings suggest that strategies aimed at increasing AI adoption in assessment should focus less on changing attitudes and more on strengthening intention, building confidence, and creating supportive professional environments.

Theoretical Implications

This study strengthens the application of the Theory of Planned Behaviour (TPB) in understanding the adoption of artificial intelligence (AI) in authentic online assessment within open and distance learning (ODL) institutions. It supports TPB's core assumption that intention is the most direct predictor of actual behaviour (Ajzen, 1991). The significant roles of perceived behavioural control and self-efficacy also confirm that when educators feel confident and capable, they are more likely to adopt AI tools for assessment purposes. These findings are consistent with previous research that emphasises psychological readiness and individual agency as key drivers in technology adoption (Li et al., 2016; Sánchez-Prieto et al., 2017).

However, the non-significant influence of attitude on AI adoption in this study suggests that having a positive perception alone may not be enough to motivate actual use. While earlier studies reported a positive relationship between attitude and technology adoption (Moxley et al., 2022; Sailer et al., 2021), this result shows that intention and perceived control may carry more weight, especially in digitally mediated environments where AI tools are still new to many educators. This highlights a potential limitation in TPB when applied to emerging and complex technologies, and it raises the need for further research to examine under what conditions attitude exerts greater or lesser influence.

Overall, the study reaffirms TPB's relevance in guiding research on AI adoption in education, while also offering new insights about the relative influence of its components in the context of ODL.

Practical Implications

For institutions aiming to integrate AI into online assessment, the findings point to clear areas for action. First, efforts should focus on building educators' intention to adopt AI. This can be done through exposure, awareness programmes, and opportunities for hands-on use that help staff see AI as both useful and manageable.

Second, strengthening perceived behavioural control and self-efficacy is essential. This includes offering consistent training, peer mentoring, and easy access to reliable AI tools and technical support. When educators feel confident and in control, they are more likely to embrace AI as part of their assessment strategy.

Creating a culture where AI adoption is viewed positively by colleagues and leadership can also influence subjective norms. Institutions can support this by showcasing success stories, encouraging open discussions about AI tools, and recognising staff who innovate in their assessment practices.

Beyond institutional strategies, this study offers practical insights for policymakers working to promote innovation while ensuring ethical oversight. The findings may inform the development of national guidelines or funding frameworks that support responsible AI use in education.

Educators, on the other hand, can benefit from reduced administrative workload and more efficient assessment delivery, allowing them to focus on instructional quality and student engagement. Meanwhile, students stand to gain from more personalised feedback, fairer assessments, and learning experiences that are responsive to their needs.

Suggestions for Future Studies

This study opens up several avenues for future research. First, qualitative methods such as interviews or focus groups can be used to explore the underlying reasons why attitude may not lead directly to adoption in some settings. These insights could reveal emotional, cultural, or institutional barriers that were not captured through the survey.

Second, a longitudinal study would allow researchers to observe changes in intention and adoption over time, especially before and after training or AI implementation initiatives. Third, the study could be expanded to include multiple institutional types or countries, which would help determine whether these findings hold in other contexts or are influenced by specific educational cultures.

Lastly, future studies could also examine the impact of AI tools on student learning outcomes. This would help bridge the gap between adoption decisions and educational effectiveness, providing a more complete picture of AI integration in assessment.

Conclusion

This study identified key psychological factors that influence the adoption of AI in authentic online assessments in ODL institutions. Intention, perceived behavioural control, self-efficacy, and subjective norms were found to be significant predictors, while attitude did not show a direct effect. These findings offer valuable insights for educators, policymakers, and institutional leaders seeking to promote the effective use of AI in education. By focusing on practical strategies that build intention, confidence, and social support, institutions can create environments where AI adoption becomes both achievable and meaningful. As AI continues to shape the future of education, understanding these human-centred factors remains essential for its responsible and impactful integration.

This study makes a significant theoretical contribution by extending the Theory of Planned Behaviour (TPB) to the context of artificial intelligence (AI) adoption in authentic online assessments within open and distance learning (ODL) institutions. While previous studies have confirmed the predictive strength of attitude toward technology adoption, this research notably highlights that attitude alone does not significantly drive adoption in the specialized context of AI-driven assessments. This suggests a critical contextual nuance: in technology-intensive educational environments like ODL, intention, self-efficacy, perceived behavioural control, and subjective norms are more crucial determinants than mere positive attitudes. Contextually, this study provides empirical evidence specific to Malaysian ODL institutions, addressing a critical gap in understanding how academic staff perceptions and institutional dynamics influence the adoption of AI-based assessment tools. Practically, these insights guide policymakers and institutional leaders to strategically prioritize capacity-building, supportive institutional culture, and confidence enhancement, thereby facilitating smoother integration and sustained adoption of innovative assessment practices.

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