Determinants of AI adoption for authentic assessment in open university systems

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ABSTRACT

Artificial intelligence (AI) is transforming higher education through personalized learning and innovative assessment methods. This study explores the factors influencing AI adoption for authentic assessment in open and distance learning environments. Using a survey of 185 instructors, an integrated framework based on the theory of planned behavior (TPB) and the technology acceptance model (TAM) was tested via structural equation modeling (SEM). Key constructs included attitude toward the behavior (ATT), subjective norm (SN), perceived behavioral control (PBC), self-efficacy (SE), and barriers to AI adoption (BAA), with intention to use AI (INT) and actual adoption behavior (AAB) as outcomes. Results showed that SE, ATT, PBC, and SN positively influenced INT, which in turn strongly predicted AAB. In addition, BAA had no significant effect on INT but showed a negative impact on AAB. The model demonstrated good fit and explained substantial variance (R^2=0.746 for INT; R^2=0.649 for AAB). These findings highlight the importance of enhancing instructors' confidence, control, and institutional support while reducing perceived barriers. Strategic investments in training, infrastructure, and leadership support are crucial to advancing AI-enabled authentic assessment in higher education.

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1. INTRODUCTION

Artificial intelligence (AI) has increasingly become a transformative technology across various sectors, including higher education. The emergence of generative AI tools has intensified global discourse on both the potential and the implications of AI in teaching and learning contexts. International trends indicate an accelerating integration of AI into education, driven by expectations that it can enhance educational quality, improve teaching and learning efficiency, and promote educational equity [1], [2]. AI has been recognized for its capacity to reduce instructors' administrative burdens and to facilitate personalized learning experiences for learners. Notably, international surveys have highlighted "testing and assessment" as the area in which AI is expected to exert the most significant influence, surpassing other domains such as language learning, corporate training, and higher education in general. This trend underscores the central role of learning assessment as a key area where AI can add considerable value [3].

In the context of AI-era education in Thailand, authentic assessment plays a crucial role in measuring learning outcomes aligned with 21st-century skills. This approach aligns with modern curriculum policies and competency-based learning frameworks. Authentic assessment refers to the process of evaluating learners through tasks or problem-solving activities that reflect real-life situations, thereby enabling learners to demonstrate knowledge, skills, and attributes that are genuinely applicable in practical contexts. Such assessment methods are especially critical in preparing learners for the demands of the future workforce in an increasingly digital world [4], [5]. It is anticipated that authentic assessment can address various challenges in higher education, including enhancing graduate competencies, preventing academic dishonesty, and fostering equity in learning [1].

Furthermore, integrating AI into assessment practices may also help mitigate concerns over academic misconduct related to learner access to AI tools. This can be achieved by shifting instructors' perspectives towards using AI as a learning aid and adapting assessment practices to emphasize higher-order thinking skills. Such a shift not only reduces concerns about plagiarism but also supports the development of learners' digital competencies [6], [7].

Despite its potential, the widespread adoption of AI in education remains in its early stages. Empirical evidence suggests that many educators have yet to incorporate AI into their teaching or assessment practices, and the integration of AI into learning platforms remains sluggish across numerous institutions [8]–[10]. In Thailand, the adoption of AI in higher education has begun to gain momentum across both public and private universities, though implementation levels vary significantly by institution have introduced AI-driven initiatives, including the use of learning analytics to track student engagement, AI-based plagiarism detection systems, and generative AI tools to support teaching and research. Several institutions have piloted AI-powered chatbots to assist students with registration and academic services, while others have integrated AI into science, technology, engineering, and mathematic (STEM) and medical education for simulation-based learning. At the national level, the Ministry of Higher Education, Science, Research and Innovation (MHESI) has promoted the digital university framework, encouraging institutions to adopt AI for teaching, assessment, and administration as part of Thailand's AI strategy (2022–2027). Nevertheless, challenges remain, including uneven access to digital infrastructure, limited faculty readiness, and ethical concerns surrounding AI usage. This indicates that while progress is being made, AI integration in Thai higher education is still in its early phase and requires stronger institutional policies, professional development, and investment to achieve large-scale impact. This phenomenon highlights the need for a thorough investigation into the factors influencing educators' acceptance and use of AI [11], [12].

According to the theory of planned behavior (TPB), the adoption of new technologies is influenced by three core components: attitudes toward the technology, subjective norm (SN) or social pressures, and perceived behavioral control (PBC) over its use. These components collectively shape intention to use AI (INT) technology, which in turn predicts actual usage behavior. Moreover, a substantial body of research on technology acceptance emphasized self-efficacy (SE), individuals' beliefs in their capabilities to successfully use technology, as a significant internal factor influencing adoption. Those who believe they can learn and effectively use AI tend to be more willing to engage with such technologies. In parallel, external factors such as access to reliable information about AI and institutional support also play vital roles in enhancing educators' awareness and confidence in applying AI in teaching and assessment.

To address the existing knowledge gap, this study aimed to examine the factors that promote the adoption of AI in authentic online assessment, with a particular focus on instructors at open universities. These educators operate within a distance education model, where learners are geographically dispersed across the country. The open university context is especially relevant, as assessment is typically conducted online or in blended formats, allowing learners to learn at any time and from anywhere. The relatively high learner-to-instructor ratio further necessitates the use of efficient assessment tools. This study adopted an integrated theoretical framework combining the TPB, emphasizing attitudinal, social, and control-related factors, and the technology acceptance model (TAM), which focuses on perceptions of technology use. The findings help to inform strategies and practices for effectively integrating AI into assessment processes, offering policy and practical implications for other educational institutions seeking to leverage AI to enhance teaching and learning quality in the future.

2. LITERATURE REVIEW

2.1. AI in higher education and online assessment

Artificial intelligence in education (AIEd) refers to technologies specifically designed to support both instructors and learners in educational contexts. AI can perform a wide range of functions, such as automating repetitive tasks, analyzing large datasets to generate actionable insights, and assisting in the planning of instruction and assessment with improved efficiency [6], [13], [14]. For instance, modern AI systems are capable of personalizing learning experiences based on individual needs and providing rapid grading for a large volume of assignments, thereby allowing instructors to focus more on interpersonal and advisory roles [10], [15], [16].

In the realm of learner assessment, AI plays a prominent role in enhancing both the effectiveness and scope of evaluation processes. Processes such as automatic scoring of open-ended or essay questions have been implemented, and learner performance has been analyzed through educational data mining to identify individual strengths and weaknesses. Predictive analytics has also been employed to forecast academic outcomes and identify at-risk learners based on their online learning behaviors [13], [17]. Previous research has emphasized several advantages of AIEd, such as improving instructor efficiency, reducing administrative workload, and facilitating quick resolution of classroom challenges [6], [17], [18]. Moreover, AI contributes to more engaging and interactive learning environments, such as through intelligent tutoring systems that can answer learners' questions around the clock, thereby supporting continuous learning outside the classroom [19]. As reported by Hazzan-Bishara *et al.* [20], AI holds significant potential to add value to the domain of assessment and evaluation, particularly in delivering more secure and fair online testing environments, as well as in offering timely, automated feedback to support learner development. Approximately one-third of educational leaders and service providers surveyed expected AI to have a "very high" positive impact on assessment and feedback shortly, with another 31% anticipating a "moderate" impact [19]. However, while many situations are beginning to plan, invest in, and implement AI solutions, a substantial number remain in the exploratory or pilot-testing phase, and some have yet to initiate any formal action [21]. This hesitation is partly due to the emerging nature of many AI technologies, the lack of adequate tools and personnel, and the fact that numerous AI applications for education are still undergoing adaptation to suit real-world educational contexts [22], [23].

2.2. Authentic assessment on digital platforms: opportunities and challenges with AI

The implementation of authentic assessment through digital platforms presents both opportunities and challenges when coupled with AI technologies. On the opportunities side, AI enables the creation of more realistic and varied assessment scenarios that are adaptable to specific course contexts. As Dolbin *et al.* [1] noted, such applications can foster creativity among both instructors and learners while helping to overcome limitations stemming from instructors' prior experiences or perspectives. AI can rapidly propose diverse ideas beyond human imagination within limited time frames.

Additionally, AI has the potential to assist in the analysis and feedback processes involved in authentic assessment. For example, in project-based courses where learners produce reports or video presentations, AI can be used to process a large number of submissions, identifying key strengths and weaknesses according to predefined rubrics. This allows instructors to provide timely and personalized feedback to individual learners. Some AI-based innovations, such as automated scoring systems, can now evaluate writing, analytical thinking, and even collaborative skills through natural language processing and social learning network analysis. The result is a more comprehensive assessment process that reduces human bias and provides valuable insights for instructional improvement.

Furthermore, the time and effort required to learn new AI tools and integrate them into existing workflows have been reported as significant challenges. Ethical considerations and inequities in learners' access to technology have also been raised [6], [17], [24], [25]. These concerns align with previous international research, which has indicated that resistance or superficial use may occur when sufficient institutional training and support are not provided, or when AI tools are not aligned with clear instructional goals [26].

2.3. Theoretical frameworks for technology acceptance and related factors

Studies on the adoption of innovations and emerging technologies in education are often based on several classical theoretical frameworks. In addition to the TPB, which was introduced in the previous section, the TAM has been widely used to explain the factors influencing users' acceptance of technologies. The TAM [27] identifies two primary determinants of technology acceptance: perceived usefulness (PU) and perceived ease of use. These two constructs have been shown to influence users' attitudes and INT technologies within educational contexts. However, the input variables for behavioral INT differ between these two models. TAM emphasized users' direct perceptions of the technology itself, namely its utility and usability, whereas TPB focuses on psychosocial factors, including attitude toward the behavior (ATT), SN, and PBC, as illustrated in Table 1.

From this comparison, as in Table 1, it can be observed that TAM is more specifically oriented toward the "technology" dimension. At the same time, TPB provides a broader view that incorporates both the "user" and the "context". Therefore, when examining the adoption of AI for authentic online assessment in open universities, which involves both technological and human dimensions, it is appropriate to integrate both perspectives. In recent years, a growing number of studies have adopted integrative approaches, such as hybrid models combining TAM and TPB, or incorporating additional variables to explain the factors influencing AI adoption more comprehensively.

Table 1. A systematic comparison between the TAM and the TPB

Aspect	TAM	TPB
Origin/year developed	Developed from the theory of reasoned action [27].	An extension of the theory of reasoned action.
Key constructs	PU, SE, ATT, INT, AAB.	ATT, SN, PBC, INT, AAB.
Social factors	Not included in the original model (social influence was later added in TAM2).	SN is a core component of the model.
Control factors	Considered indirectly through perceived ease of use (users feel more in control if the system is easy to use)	PBC is explicitly included, covering both internal and external enabling factors.
Emphasis	Focuses on users' perceptions of the technology itself (e.g., usefulness and usability).	Emphasizes psychological and social-contextual factors influencing behavior.
Application in education	Commonly used to study the acceptance of educational tools or technologies based on PU and ease of use.	Used to predict AAB through the lens of attitude, social norms, and perceived control; often combined with other models to include technology-related variables.

For instance, proposed an integrated model to examine instructors' willingness to adopt generative AI technology. The model combined variables from TAM (such as perceived ease of use, PU, and perceived cost) with those from TPB (including ATT, SN, and PBC). The study found that this hybrid model effectively explained instructors' INT to adopt AI and confirmed that attitude, social norm, and perceived control positively influenced INT, while PU and ease of use, as highlighted in TAM, also played a crucial role.

In Thailand, policy initiatives and capacity-building efforts have also been undertaken to support the adoption of AIEd. Many universities have organized training programs to help instructors apply AI in assessment and evaluation practices. This indicates a growing recognition among educational institutions of AI's potential role, along with a concerted effort to prepare academic staff to effectively leverage the technology. At the same time, research and development agencies have increasingly focused on developing guidelines and standards to ensure that AI is used both ethically and effectively, which is expected to further facilitate long-term acceptance.

Based on the reviewed literature and theoretical foundations, it is evident that multiple dimensions influence AI acceptance in higher education. These include both technology-focused perceptual factors and psychosocial elements influencing behavioral INT. Therefore, this study adopts a comprehensive framework that integrates these dimensions in order to investigate real-world practices within the open university context, thus aligning with emerging international research trends and ensuring a more holistic understanding of AI adoption in educational assessment.

3. METHOD

3.1. Participants and context

The participants in this study were academic personnel from open universities in Thailand, where distance and online education are the primary modes of instruction. The target population consisted of 285 faculty members from various academic programs. Data was collected through an online questionnaire distributed to this population. A total of 185 completed responses were received, yielding a response rate of approximately 64.9%. Similarly, Creswell and Creswell [28] emphasized that response rates above 60% in educational research provide a reasonable level of confidence in the generalizability of findings.

3.2. Research instrument

The research instrument was an online questionnaire developed based on the conceptual frameworks of the TAM and the TPB, as well as relevant literature. The questionnaire was designed to measure factors presumed to influence the adoption of AI in authentic assessment practices. It employed a 5-point Likert scale and included seven constructs, five independent variables: i) ATT, ii) SN, iii) PBC, iv) SE, and v) barriers to AI adoption (BAA); and two dependent variables: vi) INT and vii) AI actual adoption behavior (AAB).

The questionnaire underwent expert validation and pilot testing to ensure its psychometric soundness. Content validity was examined by five experts in educational technology and AIEd, yielding item–objective congruence (IOC) indices ranging from 0.80 to 1.00, which indicates a high degree of agreement among experts regarding the appropriateness and clarity of the items. The reliability of the instrument was assessed through internal consistency testing with a pilot sample, resulting in Cronbach's alpha coefficients ranging from 0.82 to 0.91 across the seven dimensions, demonstrating a high level of reliability.

3.3 Data analysis

To analyze the data, advanced statistical techniques were employed to test the relationships among the variables as proposed in the conceptual framework. structural equation modeling (SEM) was used, as it is well-suited for evaluating the fit between theoretical models and empirical data and allows for simultaneous analysis of both direct and indirect effects (IE) among multiple variables.

4. RESULTS

The quantitative data were analyzed using a SEM, which revealed the relationships among key variables, as shown in Figure 1. The results from the path analysis indicated that several had statistically significant positive effects on the INT. These included SE, ATT, SN, and PBC. In contrast, BAA exerted a negative but statistically non-significant influence on the INT. However, INT was found to significantly predict AAB. These findings suggest that enhancing internal factors and reducing barriers may facilitate the implementation of AI for authentic assessment on digital platforms in open university systems. The results are presented in Table 2.

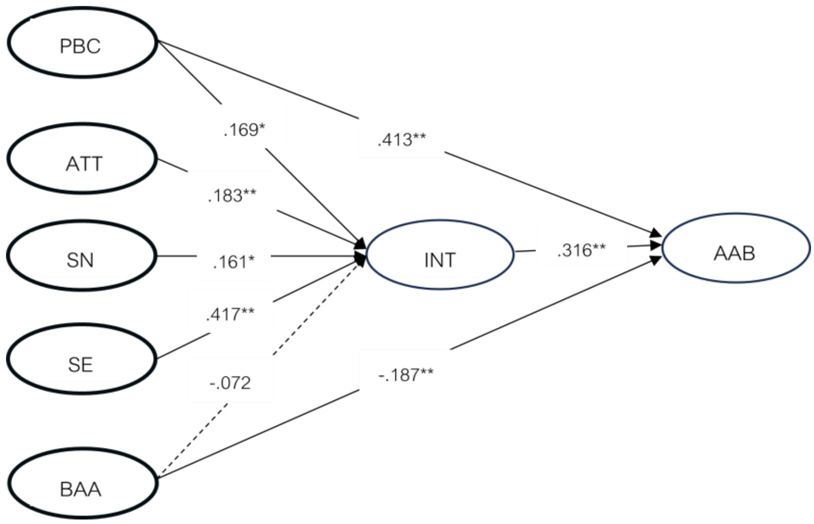

Figure 1. The model of factors influencing the adoption of AI in online authentic assessment

Table 2. Results of SEM

Path	Coefficient (β)	Relationship	Significance	Interpretation
PBC→INT	0.169	Positive	$p<0.05$	Individuals who perceive greater behavioral control tend to show higher INT.
ATT→INT	0.183	Positive	$p<0.01$	Individuals with a positive attitude toward AI are more likely to intend to use it.
SN→INT	0.161	Positive	$p<0.05$	Social norms positively influence the INT.
SE→INT	0.417	Positive	$p<0.01$	Individuals with higher SE are more likely to express an INT.
BAA→AAB	-0.187	Negative	$p<0.01$	Perceived barriers negatively impact actual AAB.
BAA→INT	-0.072	Not significant	–	Barriers do not have a direct effect on the INT.
INT→AAB	0.316	Positive	$p<0.01$	INT significantly predicts actual AI usage behavior.

The model demonstrated a satisfactory fit with the empirical data (χ^2=4.781, df=3, p=0.189; GFI=0.993; AGFI=0.931; RMR=0.005; RMSEA=0.058), indicating that the proposed model did not significantly differ from the observed data, as shown in Tables 3 and 4. The INT was significantly influenced by three key factors: SE, ATT, and PBC. Among these, SE demonstrated the strongest effect (β=0.417, p<0.01), suggesting that favorable attitudes toward the usefulness and appeal of AI increased the INT to adopt it. PBC was similarly found to be significant (β=0.169, p<0.05), implying that when instructors perceived themselves to have control over the necessary conditions and resources, their interest in using AI also increased. In addition, SN had a significant positive impact on INT (β=0.161, p<0.05), meaning that perceived social pressure or support from colleagues, administrators, or the wider community influenced instructors' decisions regarding AI adoption. This may reflect the emerging nature of AIEd, where institutional policies and widespread adoption are not yet firmly established enough to form clear social norms.

Table 3. Statistical results of model analysis on factors promoting the use of AI in authentic assessment on digital platforms among open university educators

Dependent variables	INT			AAB		
Independent variables	TE	IE	DE	TE	IE	DE
ATT	0.183**	-	0.183**	0.058*	0.058*	-
	(0.059)	-	(0.059)	(0.028)	(0.028)	-
SN	0.161*	-	0.161*	0.051*	0.051*	-
	(0.060)	-	(0.060)	(0.026)	(0.026)	-
PBC	0.169*	-	0.169*	0.467**	0.053*	0.413**
	(0.070)	-	(0.070)	(0.080)	(0.031)	(0.085)
SE	0.417**	-	0.417**	0.132**	0.132**	-
	(0.078)	-	(0.078)	(0.050)	(0.050)	-
BAA	-0.072	-	-0.072	-0.210**	-0.023	-0.187**
	(0.040)	-	(0.040)	(0.059)	(0.017)	(0.058)
INT				0.316**	-	0.316**
				(0.090)	-	(0.090)
Statistics						
Chi-square=4.781, df=3, p=0.189, GFI=0.993, AGFI=0.931, RMR=0.005, RMSEA=0.058						
Structural equation	INT	AAB				
R-square	0.746	0.649				

Note: TE=total effect, IE=indirect effect, DE=direct effect.
*p<0.05, **p<0.01; Standard errors are provided in parentheses.

Table 4. Statistical results of correlation matrix among variables

Correlation matrix among variables	ATT	SN	PBC	SE	BAA	AAB
ATT	1.000					
SN	0.772**	1.000				
PBC	0.657**	0.661**	1.000			
SE	0.639**	0.689**	0.845**	1.000		
BAA	-0.456**	-0.567**	-0.494**	-0.478**	1.000	
AAB	0.718**	0.742**	0.784**	0.822**	-0.529**	1.000

*p<0.05, **p<0.01; Standard errors are provided in parentheses.

BAA had a significant negative effect of INT (β=–0.187, p<0.01). This indicated that instructors who perceived more barriers were significantly less likely to intend to use AI, supporting the hypothesis that barriers serve as obstacles to technology acceptance. Although the total effect (TE) of BAA on INT was relatively small and non-significant (–0.072, ns), its direct effect (DE) on AAB was substantial and statistically significant (TE=–0.210**, BAA→AAB). Thus, instructors who experienced more perceived obstacles tended to adopt AI less frequently than those who faced fewer challenges.

AAB, the results confirmed that PBC was the strongest predictor of actual AI usage (β=0.467, p<0.01). Instructors with a high level of control over relevant conditions were significantly more likely to implement AI in authentic assessment practices. PBC was also found to exert both DE and IE on AAB (DE≈0.413** via INT), aligning with the TPB, which posits that when individuals perceive high control over external factors, available resources, and opportunities can translate INT into AAB. Other variables, such as ATT and SN, had IE on AAB through INT (ATT TE=0.058*, SN TE=0.051*). Although neither ATT nor SN had direct paths to AAB in the model, their indirect contributions via INT highlighted their supportive roles. Instructors with positive attitudes and strong social support were more likely to act on their INT, as shown in Table 5.

Table 5. Standardized coefficients of the effects of factors on INT and AAB in the SEM

Factor	Effect on INT (β)	Effect on AAB (β)
ATT	+0.183** (significant)	+0.058* (IE via INT)
SN	+0.161 (not significant)	+0.051* (IE via INT)
PBC	+0.169* (significant)	+0.467** (TE; DE +0.413**, IE+0.053*)
SE	+0.417** (significant)	+0.132** (IE via INT)
BAA	–0.072 (significant)	–0.210** (TE; DE –0.187**, IE–0.023)
INT	–	+0.316** (DE)
R^2 (explained variance)	0.746 (74.6%)	0.649 (64.9%)

Note: *p<0.05, **p<0.01)

Table 5 summarizes the statistical influence of various factors on both the INT and actual AAB. The model explained 74.6% of the variance in INT and 64.9% of the variance in AAB, demonstrating strong explanatory power. Among the predictors of INT, SE emerged as the most influential factor, followed by ATT and PBC. SN and BAA also contributed to the model, although BAA had a negative effect on INT. With regard to AAB, PBC was found to be the strongest determinant, followed by INT and BAA. The direct inhibitory effect of BAA on AAB underscored the importance of addressing perceived obstacles in order to facilitate the integration of AI into authentic assessment practices within higher education contexts.

The structural model revealed that PBC and SE were the most influential predictors of AI adoption among instructors. Educators who felt confident in their technological competencies and had access to necessary resources were significantly more likely to engage in AI-integrated assessment practices. These internal enablers also contributed to increased INT, which served as a proximal determinant of actual usage behavior. Interestingly, while ATT and SN did not exhibit a direct impact on AAB, their indirect influence through INT was significant. This finding underscores the importance of fostering a positive institutional culture and encouraging peer influence to shape instructors' motivation. Institutional support, in the form of leadership endorsement and peer-led success stories, can catalyze the conversion of favorable attitudes into action.

Conversely, BAA significantly impeded AAB, even when INT were present. These obstacles—ranging from limited time and training to technical uncertainties—may inhibit instructors from implementing AI despite recognizing its value. Thus, any strategy aiming to promote AI use in assessment must address these practical and psychological impediments.

5. DISCUSSION

The findings of this study confirmed the theoretical foundations and aligned with several international studies on instructors' attitudes and readiness. Regarding instructors' attitudes and readiness, it was found that instructors in open universities generally held positive attitudes and demonstrated strong interest in adopting AI for online assessment. This observation was consistent with a global trend where instructors increasingly recognized the benefits of AI in supporting their teaching, particularly in assessment and feedback. The survey results indicated that approximately two-thirds of educational leaders and practitioners had a positive view of AI's potential to improve the quality of assessment and firmly believed that AI could improve learner learning experiences when implemented appropriately [29]. The results, which indicated a high interest in using AI even among instructors who had never used it before, highlighted the "latent motivation" that could be aroused when given the opportunity, meaning that appropriate policies or initiatives could easily turn such interest into real-world use.

In terms of influencing factors, both intrinsic and extrinsic variables were emphasized, supporting previous research [19], which identified that SE and institutional support are important drivers of AI adoption. In the case of the instructors in the open universities studied, the sample showed relatively high SE, likely due to their extensive teaching experience and subject-area expertise. Therefore, it was not surprising that SE emerged as one of the most important predictors of interest in AI. When instructors believed they could easily handle new technologies, their hesitation decreased, making them more willing to experiment with AI in their work. This was consistent with the TPB and research by Ryan and Deci [10], which emphasized that SE was a key factor in educators' acceptance of new digital tools. Conversely, instructors who lacked confidence, such as fear of inadequate skills or inability to learn, tended to express hesitation or reject such innovations. Thus, developing digital skills was deemed essential to enhance SE, which in turn increases acceptance of AI.

Attitudes and PU were also validated as key influencing factors. Several studies [16], [30] reported that when users perceived a technology as beneficial or compatible with their work, positive attitudes and willingness to use it were promoted. The majority of respondents in our study viewed AI-based assessment as a "good and smart idea", indicating that they were aware of the potential benefits of AI, such as faster and more efficient assessments and reduced workload. This corresponded with the literature suggesting that AI could allow instructors to allocate more time to crucial teaching tasks, while delegating certain assessment duties to AI. Positive attitudes may have also been driven by instructors' awareness that AI aligned with modern educational trends and something they should learn to avoid becoming obsolete.

Social norms were found to moderately affect INT, in line with previous research [19], which highlighted the role of credible sources and organizational support in promoting awareness and acceptance of AI. Among instructors at the open universities, mixed signals were perceived. On the one hand, some felt that administrators or departments had begun to value AI, while on the other hand, colleagues or staff were perceived as indifferent or unsupportive. This indicated inconsistencies in institutional support, possibly stemming from differences among departments or hierarchy levels. For example, while senior leaders may support AI, operational staff might not be as adaptive. As a result, the average score on SN was approximately 3.9, which was lower than other factors. It was argued that for AI adoption to be successful, an organizational culture that actively promotes AI usage should be established, which would require a shared understanding at all levels, from leaders to faculty and staff, that AI is a valuable educational tool, along with promoting effective internal communication.

The gap between INT and behaviors identified in this study reflects a common scenario addressed in technology acceptance theory: even when interest exists, action is not guaranteed. External obstacles such as a lack of opportunity, resources, or last-minute difficulties often intervene. Despite a high mean INT score (4.05), actual use was significantly lower (3.79), which was directly linked to the barriers reported by respondents. Those new to AI often cited "lack of time to explore" or "uncertainty about the tools" as reasons for this. Some were waiting for clearer policy and institutional support, taking a "wait and see" attitude. Thus, unless supportive measures were implemented to reduce barriers, motivation could gradually decline. Gartner and Krašna [22] indicated that from 2019 to 2022, many institutions were still in the "planning" or "exploring" phase of AI integration, with real-world AI adoption set to increase significantly after 2023. What triggered the implementation were successful case studies and the availability of suitable tools. In the context of the Thai Open University, a "spark" might be needed, such as pilot projects in AI-based assessments or institutional change agents that could demonstrate tangible benefits. These initiatives could transform accumulated interest into actual practice.

Barriers and concerns were consistent with global findings, ranging from time constraints, ethics, and accuracy to fears of replacement. Previous studies [6], [15] highlighted widespread uncertainty among educators about the effectiveness of AI, and concerns that it could diminish instructors' roles or interfere with the instructor-learner relationships. Security and data privacy risks, particularly when AI tools require learner input, have also been highlighted as significant global barriers. As noted by Abulail *et al.* [31], AI adoption is often hampered by budget constraints, skills gaps, and a lack of awareness. Although budget was not a primary concern in the study, respondents did mention the cost of AI tools, reflecting financial concerns. Skills shortages and a lack of knowledge about AI were also noted. These findings pointed to the urgent need for training and skills development to reduce barriers, echoing Feuerriegel *et al.* [19] recommendation that AI professional development programs for educators would be a key strategy to promote technology adoption.

6. CONCLUSION

The study examined the factors influencing the adoption of AI for authentic assessment in an open university context. Drawing on the TPB and the TAM, the research confirmed that attitudes, SN, PBC, and SE significantly shaped instructors' INT to adopt AI. These INT, in turn, were the strongest predictors of AAB. Despite high levels of interest, the findings revealed a persistent gap between INT and action, attributed primarily to perceived barriers such as time constraints, lack of institutional clarity, and insufficient access to resources. Addressing these barriers through institutional policies, professional development programs, and access to user-friendly AI tools is critical to promoting successful and sustainable integration. Ultimately, instructors at the open university exhibited readiness and openness to leveraging AI in assessment, signaling a favorable climate for innovation. Institutions are encouraged to capitalize on this momentum by implementing comprehensive strategies that support and scale AI-driven educational practices in ways that align with both pedagogical objectives and institutional capacities.

Future research could extend beyond the open university context to compare AI adoption across different types of higher education institutions in Thailand and internationally. Such comparative studies would provide deeper insights into institutional readiness, cultural influences, and policy environments that shape AI integration. In addition, further studies could explore the long-term impact of AI-driven authentic assessment on student learning outcomes, equity in education, and academic integrity. Investigating emerging technologies such as generative AI and adaptive learning systems may also offer valuable directions for enhancing assessment practices and aligning them with future workforce competencies.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest regarding this research article.

ETHICAL APPROVAL

The authors declare no conflict of interest. Research ethics, this research is allowed to conduct research according to the announcement of Nakhonratchasima Rajabhat University: No. HE-109-2568 on May 16, 2025.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [KM], upon reasonable request.

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