International Journal of Research and Innovation in Social Science (IJRISS) - Manuscript Draft Relationship of Technology Acceptance and Behavioural Intention Toward AI-Based Educational Assessment among Lecturers in Saudi Arabia

Fahdah Mansour Alzeer1, Prof. Madya Dr. Adibah Binti Abdul Latif2*

1 PhD Candidate, Faculty of Educational Sciences and Technology, Universiti Teknologi Malaysia, Malaysia

2 Faculty of Educational Sciences and Technology, Universiti Teknologi Malaysia, Malaysia

DOI: https://doi.org/10.47772/IJRISS.2026.100500095

Received: 06 May 2026; Accepted: 11 May 2026; Published: 23 May 2026

ABSTRACT

The increasing use of artificial intelligence (AI) in educational assessment has intensified the need to understand the factors that shape lecturers' willingness to adopt AI-supported assessment practices. While prior studies have widely examined technology acceptance in education, fewer studies have focused specifically on the relationship between technology acceptance and behavioural intention toward AI-based educational assessment among lecturers in Saudi higher education. This study examined the extent to which technology acceptance constructs predict lecturers' behavioural intention to use, continue using, and recommend AI-based educational assessment tools. A quantitative cross-sectional survey design was employed using an extended UTAUT-based questionnaire administered to lecturers in Saudi higher education institutions. The result was based on 412 usable responses. Descriptive statistics, Pearson correlation, and hierarchical multiple regression were used to examine the relationships among performance expectancy, effort expectancy, social influence, facilitating conditions, perceived trust in AI, perceived threat to professional autonomy, job security concern, and behavioural intention. The results indicated that performance expectancy, perceived trust in AI, facilitating conditions, effort expectancy, and social influence were positively associated with behavioural intention, while perceived threat to professional autonomy and job security concern were negatively associated with behavioural intention. The hierarchical regression model explained 65.2% of the variance in behavioural intention, with performance expectancy and perceived trust in AI emerging as the strongest positive predictors. The findings suggest that lecturers' intention to adopt AI-based assessment is shaped not only by perceived usefulness and institutional support, but also by trust and professional concerns related to academic judgment and job relevance. The study contributes to technology acceptance research by offering a relationship-focused explanation of AI-based assessment adoption in Saudi higher education.

Keywords: AI-based educational assessment; behavioural intention; higher education; Saudi Arabia; technology acceptance; UTAUT

INTRODUCTION

Artificial intelligence (AI) is increasingly influencing how assessment is designed, delivered, scored, and interpreted in higher education. AI-based assessment tools can support automated scoring, adaptive testing, intelligent feedback, learning analytics, and predictive monitoring of student performance. These developments are significant because assessment is not only an administrative process but also a core mechanism for supporting learning, certifying achievement, and informing instructional decision-making. In this context, AI-based educational assessment has the potential to improve feedback timeliness, reduce repetitive grading workload, and support more data-informed evaluation practices (Chen et al., 2020; Crompton & Burke, 2023; Wang et al., 2024).

However, the adoption of AI-based assessment depends on more than the availability of technology. Lecturers remain central actors in assessment because they design tasks, interpret evidence of learning, make evaluative judgments, and ensure fairness in assessment decisions. If lecturers perceive AI-based assessment systems as useful, manageable, trustworthy, and institutionally supported, they may be more likely to adopt them. Conversely, if they perceive AI as opaque, difficult to use, professionally threatening, or misaligned with academic values, their behavioural intention may be weakened. This makes the relationship between technology acceptance and behavioural intention a critical area of empirical inquiry.

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a strong theoretical foundation for examining such relationships. UTAUT proposes that performance expectancy, effort expectancy, social influence, and facilitating conditions influence behavioural intention and technology use (Venkatesh et al., 2003, 2016). These constructs are relevant to AI-based educational assessment because lecturers' adoption decisions may be shaped by beliefs about usefulness, ease of use, peer and leadership influence, and the availability of institutional support. At the same time, AI-based assessment introduces additional concerns that extend beyond conventional educational technologies, particularly issues of trust, autonomy, and job security (Kizilcec & Lee, 2022; Nazaretsky et al., 2022).

In Saudi Arabia, this issue is particularly timely because higher education institutions are operating within a broader national digital transformation agenda. The adoption of AI in education is aligned with efforts to improve quality, efficiency, innovation, and data-informed governance. Yet, technological investment alone does not ensure adoption. Lecturers' acceptance and behavioural intention are essential for translating policy aspirations into meaningful practice. Understanding the predictors of behavioural intention can therefore help universities design more targeted professional development, institutional support systems, and responsible AI implementation strategies. This research examines the relationship between technology acceptance and behavioural intention toward AI-based educational assessment. Specifically, it investigates how core UTAUT constructs and AI-specific professional concerns are associated with lecturers' intention to use, continue using, and recommend AI-based assessment tools in Saudi higher education.

Research Objectives

1. To examine the level of technology acceptance and behavioural intention toward AI-based educational assessment among lecturers in Saudi higher education.

2. To determine the relationship between technology acceptance constructs and behavioural intention toward AI-based educational assessment.

3. To examine the extent to which core UTAUT constructs and AI-specific professional concerns predict behavioural intention toward AI-based educational assessment.

Research Questions

1. What is the level of technology acceptance and behavioural intention toward AI-based educational assessment among lecturers in Saudi higher education?

2. What is the relationship between technology acceptance constructs and behavioural intention toward AI-based educational assessment?

3. Which technology acceptance constructs significantly predict behavioural intention toward AI-based educational assessment?

Hypotheses

H1: Performance expectancy is positively related to behavioural intention toward AI-based educational assessment.

H2: Effort expectancy is positively related to behavioural intention toward AI-based educational assessment.

H3: Social influence is positively related to behavioural intention toward AI-based educational assessment.

H4: Facilitating conditions are positively related to behavioural intention toward AI-based educational assessment.

H5: Perceived trust in AI is positively related to behavioural intention toward AI-based educational assessment.

H6: Perceived threat to professional autonomy is negatively related to behavioural intention toward AI-based educational assessment.

H7: Job security concern is negatively related to behavioural intention toward AI-based educational assessment.

LITERATURE REVIEW

Behavioural Intention as an Outcome of AI-Based Assessment Adoption

Behavioural intention is a central construct in technology acceptance research because it reflects a user's motivational readiness to adopt, continue using, or recommend a technology. In higher education, behavioural intention is especially important because lecturers often exercise professional discretion in selecting assessment strategies and interpreting assessment evidence. In AI-based educational assessment, behavioural intention may involve willingness to experiment with automated scoring, use AI-supported feedback, rely on analytics dashboards, or recommend AI-based assessment tools to colleagues.

Unlike general educational technologies, AI-based assessment tools enter a high-stakes academic domain. Assessment outcomes can influence grades, feedback quality, student progression, and institutional accountability. Therefore, lecturers' behavioural intention is likely to be shaped by both instrumental beliefs and professional judgments. Recent AI-in-education literature emphasises that educator adoption is closely linked to perceived benefits, explainability, trust, ethical safeguards, and institutional readiness (European Commission, 2022; Miao & Holmes, 2023; U.S. Department of Education, 2023). This means that behavioural intention should be examined as a relational outcome influenced by multiple acceptance factors rather than as an isolated attitude.

Performance Expectancy and Behavioural Intention

Performance expectancy refers to the extent to which lecturers believe that AI-based assessment tools can improve their assessment performance. In the assessment context, performance expectancy may include beliefs that AI can reduce grading workload, improve scoring consistency, provide timely feedback, and support evidence-based evaluation of student learning. UTAUT research has consistently identified performance expectancy as one of the strongest predictors of behavioural intention (Venkatesh et al., 2003, 2016).

In AI-based assessment, performance expectancy is conceptually important because lecturers are more likely to adopt AI tools when they perceive clear academic value. If AI systems are viewed as improving accuracy, feedback quality, and assessment efficiency, lecturers may develop stronger intention to use them. However, performance expectancy alone may be insufficient if lecturers are not confident in the fairness or transparency of AI-generated outcomes. Therefore, while performance expectancy is expected to positively predict behavioural intention, its influence should be interpreted alongside trust and institutional support.

Effort Expectancy and Behavioural Intention

Effort expectancy refers to the perceived ease associated with using a system. For lecturers, AI-based assessment tools may be viewed as easy to adopt when they have intuitive interfaces, clear workflows, manageable training requirements, and compatibility with existing teaching practices. Technologies perceived as overly complex may reduce intention to use, even when they are seen as potentially useful.

In AI-based educational assessment, effort expectancy is especially relevant because lecturers may vary in their digital competence and prior exposure to AI tools. If lecturers believe that AI-based assessment systems are difficult to learn or require extensive technical assistance, behavioural intention may decline. Conversely, when tools are perceived as user-friendly and easy to integrate into existing assessment routines, lecturers may be more willing to experiment with and sustain AI use.

Social Influence and Behavioural Intention

Social influence captures the extent to which lecturers perceive that important others encourage or expect them to use AI-based assessment. In universities, these referents may include colleagues, department heads, academic leaders, professional networks, and institutional policy directions. Social influence may be particularly relevant in organisational contexts where innovation is shaped by leadership expectations, peer modelling, and strategic digital transformation agendas.

For Saudi higher education, social influence may operate through both formal and informal channels. Formal influence may arise from institutional policies, quality assurance initiatives, or national digital transformation priorities. Informal influence may emerge from colleagues' practices, departmental culture, or professional communities. When lecturers observe respected peers using AI-based assessment effectively, their behavioural intention may increase. However, social influence may be weaker if institutional expectations are unclear or if lecturers perceive AI adoption as imposed rather than professionally meaningful.

Facilitating Conditions and Behavioural Intention

Facilitating conditions refer to lecturers' perceptions that institutional, technical, and organisational resources are available to support AI adoption. These conditions may include reliable infrastructure, technical support, professional development, data governance policies, ethical guidelines, and integration with learning management systems. UTAUT positions facilitating conditions as important for technology use because users are more likely to adopt a system when they believe that adequate support exists (Venkatesh et al., 2003, 2016).

In AI-based assessment, facilitating conditions are particularly important because lecturers may require support not only in technical operation but also in interpreting AI outputs, evaluating algorithmic fairness, and aligning AI-supported decisions with assessment validity principles. Institutional support can therefore reduce uncertainty and strengthen behavioural intention. Without adequate support, lecturers may be reluctant to use AI-based assessment even when they recognise its potential benefits.

Perceived Trust in AI and Behavioural Intention

Perceived trust in AI refers to lecturers' confidence that AI systems can produce accurate, fair, transparent, and ethically acceptable assessment outputs. Trust is a critical construct because AI-based assessment involves algorithmic processes that may not be fully visible to users. In assessment contexts, lecturers must be able to justify decisions, protect student rights, and maintain confidence in the validity and fairness of evaluation processes.

Previous research on AI-powered educational technology has shown that teachers' trust can influence their willingness to use AI tools (Nazaretsky et al., 2022). Trust is also closely related to explainability, transparency, and perceived fairness (Huggins-Manley et al., 2022; Kizilcec & Lee, 2022). In the present study, perceived trust is expected to positively predict behavioural intention because lecturers are more likely to adopt AI-based assessment when they believe the technology can support, rather than compromise, fair and defensible evaluation.

Professional Autonomy, Job Security, and Behavioural Intention

AI-based educational assessment may also generate professional concerns. Perceived threat to professional autonomy refers to lecturers' concern that AI may reduce their control over assessment design, grading, feedback, and academic judgment. Job security concern refers to anxiety that AI automation may reduce the relevance of human evaluators or devalue academic roles. These concerns are not merely emotional reactions; they are connected to the professional identity of lecturers as assessment designers, evaluators, and interpreters of student learning.

Current discussions on AI in education emphasise the need for human oversight, educator agency, and responsible implementation (Kasneci et al., 2023; Miao & Holmes, 2023). If lecturers perceive AI as replacing their judgment or weakening their professional role, behavioural intention may decline. Therefore, perceived threat to professional autonomy and job security concern are expected to have negative relationships with behavioural intention. Examining these relationships allows the study to move beyond conventional technology acceptance constructs and address the human-professional dimension of AI adoption.

Conceptual Framework of the Present Study

The conceptual framework of this study positions behavioural intention as the dependent variable and technology acceptance constructs as predictors. The predictors include four core UTAUT constructs, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, together with three AI-specific constructs, namely perceived trust in AI, perceived threat to professional autonomy, and job security concern. The framework assumes that positive acceptance beliefs strengthen behavioural intention, while professional threat concerns weaken it. This relationship-focused approach differs from the first validation paper by examining predictive pathways rather than instrument development evidence.

METHODOLOGY

Research Design

This study employed a quantitative cross-sectional survey design to examine the relationship between technology acceptance and behavioural intention toward AI-based educational assessment among lecturers in Saudi higher education. The design was appropriate because the study sought to determine the strength and direction of relationships among measured constructs and to identify significant predictors of behavioural intention.

Population and Sample

The target population comprised lecturers working in Saudi higher education institutions. A total of 500 questionnaires were distributed, and 412 usable responses were retained after data screening. This sample size was considered adequate for correlation and multiple regression analysis involving seven predictor constructs and one dependent variable.

Instrumentation

The study used an extended UTAUT-based questionnaire designed to measure lecturers' perceptions of AI-based educational assessment. The questionnaire contained demographic items and 10 measurement constructs: performance expectancy, effort expectancy, social influence, facilitating conditions, perceived trust in AI, perceived threat to professional autonomy, job security concern, intention to use, intention to continue use, and intention to recommend AI-based assessment tools. Items were measured using a four-point Likert scale ranging from 1 = Strongly Disagree to 4 = Strongly Agree. The behavioural intention score was computed as the composite mean of intention to use, intention to continue use, and intention to recommend.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

Data Analysis

Data analysis was conducted using descriptive statistics, reliability analysis, Pearson product-moment correlation, and hierarchical multiple regression. Descriptive statistics were used to determine the level of each construct. Mean scores were interpreted using three levels based on the four-point Likert scale: low = 1.00–1.99, moderate = 2.00–2.49, moderately high = 2.50–2.99, and high = 3.00–4.00. Cronbach's alpha was used to examine internal consistency. Internal consistency reliability was assessed using Cronbach's alpha. Alpha values of .70 and above were considered acceptable for research purposes, while values above .80 indicated good internal consistency. In this study, all constructs demonstrated acceptable to excellent reliability, with Cronbach's alpha values ranging from .87 to .94. Pearson correlation was used to examine bivariate relationships between technology acceptance constructs and behavioural intention. The hierarchical approach was used to determine whether AI-specific constructs added explanatory value beyond the conventional UTAUT constructs. Hierarchical multiple regression was conducted in two steps. In Model 1, the four core UTAUT constructs were entered as predictors. In Model 2, the three AI-specific constructs were added to determine whether they explained additional variance in behavioural intention. Statistical significance was interpreted at $p < .05$.

Ethical Considerations

Participation was voluntary and anonymous. Respondents were informed about the academic purpose of the study, confidentiality of responses, and their right to withdraw. Data were analysed in aggregate form, and no personally identifiable information was reported.

RESULTS

Respondent Profile

A total of 412 usable responses were included in the analysis. The demographic distribution showed adequate representation across gender, age, academic rank, teaching experience, and academic discipline.

Table 1. Demographic Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	235	57.0
	Female	177	43.0
Age	Below 30 years	48	11.7
	31-40 years	151	36.7
	41-50 years	142	34.5
	Above 50 years	71	17.2
Academic Rank	Lecturer	104	25.2
	Assistant Professor	166	40.3
	Associate Professor	98	23.8
	Professor	44	10.7
Teaching Experience	Less than 5 years	63	15.3
	5-10 years	143	34.7
	11-15 years	124	30.1
	More than 15 years	82	19.9
Academic Discipline	Social Sciences	151	36.7

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue V May 2026

	Science and Technology	116	28.2
	Engineering	145	35.2
AI Training	Yes	192	46.6
	No	220	53.4
Previous AI Tool Use	Yes	229	55.6
	No	183	44.4

The descriptive statistics indicated that lecturers reported moderately high perceptions of AI-based educational assessment across most technology acceptance constructs. Performance expectancy recorded the highest mean score, followed by behavioural intention and perceived trust in AI. Professional concern constructs, namely perceived threat to professional autonomy and job security concern, recorded lower mean scores, indicating that while concerns existed, they were not dominant among the respondents.

In relation to the demographic profile, two descriptive trends were observed before the main correlation and regression analyses were conducted. First, lecturers who had attended AI-related training appeared to report slightly higher behavioural intention than those without such training.

This suggests that prior exposure to AI training may be associated with greater confidence and willingness to adopt AI-based educational assessment tools. Second, lecturers who had previously used AI tools for teaching or assessment showed slightly higher mean scores in performance expectancy, perceived trust in AI, and behavioural intention compared with those who had no prior AI tool use.

These descriptive patterns indicate that training and prior AI experience may play a supportive role in shaping lecturers' acceptance of AI-based assessment. However, these differences were treated as descriptive trends only and were not used as the main basis for hypothesis testing. The main analysis focused on the relationships between technology acceptance constructs and behavioural intention.

Table 2. Descriptive Statistics and Reliability of Study Constructs

Construct	Mean	SD	Interpretation	Cronbach alpha
Performance Expectancy	3.18	0.48	High	0.93
Effort Expectancy	3.02	0.51	High	0.91
Social Influence	2.82	0.56	Moderately High	0.89
Facilitating Conditions	2.76	0.58	Moderately High	0.90
Perceived Trust in AI	2.91	0.53	Moderately High	0.92
Perceived Threat to Professional Autonomy	2.34	0.61	Moderate	0.88
Job Security Concern	2.21	0.64	Moderate	0.87
Behavioural Intention	2.96	0.50	Moderately High	0.94

Pearson correlation analysis was conducted to examine the relationships between technology acceptance constructs and behavioural intention.

The results showed significant positive correlations between behavioural intention and performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived trust in AI. In contrast, perceived threat to professional autonomy and job security concern were negatively correlated with behavioural intention.

Table 3. Pearson Correlations Between Technology Acceptance Constructs and Behavioural Intention

Predictor Construct	r with Behavioural Intention	p-value	Interpretation
Performance Expectancy	0.68	< .001	Strong positive
Effort Expectancy	0.55	< .001	Moderate positive
Social Influence	0.49	< .001	Moderate positive
Facilitating Conditions	0.58	< .001	Moderate positive
Perceived Trust in AI	0.63	< .001	Strong positive
Perceived Threat to Professional Autonomy	-0.41	< .001	Moderate negative
Job Security Concern	-0.33	< .001	Moderate negative

Hierarchical multiple regression was conducted to examine the predictive contribution of the core UTAUT constructs and AI-specific constructs. In Model 1, performance expectancy, effort expectancy, social influence, and facilitating conditions explained 56.1% of the variance in behavioural intention.

In Model 2, perceived trust in AI, perceived threat to professional autonomy, and job security concern were added, increasing the explained variance to 65.2%. The change in R-squared was statistically meaningful, suggesting that AI-specific constructs contributed additional explanatory value beyond conventional UTAUT variables.

Table 4. Hierarchical Regression Model Summary

Model	R	R2	Adjusted R2	F	p-value	Delta R2
Model 1: Core UTAUT Constructs	0.749	0.561	0.557	132.41	< .001	-
Model 2: Extended Model	0.807	0.652	0.646	108.17	< .001	0.091

Table 5. Multiple Regression Coefficients Predicting Behavioural Intention

Predictor	Standardized beta	t-value	p-value	Interpretation
Performance Expectancy	0.31	6.84	< .001	Significant positive predictor
Effort Expectancy	0.10	2.37	.018	Significant positive predictor
Social Influence	0.12	2.98	.003	Significant positive predictor
Facilitating Conditions	0.17	4.02	< .001	Significant positive predictor
Perceived Trust in AI	0.25	5.61	< .001	Significant positive predictor

Perceived Threat to Professional Autonomy	-0.15	-3.76	< .001	Significant negative predictor
Job Security Concern	-0.08	-2.14	.033	Significant negative predictor

The strongest positive predictor of behavioural intention was performance expectancy, followed by perceived trust in AI and facilitating conditions. This indicates that lecturers were more likely to intend to adopt AI-based assessment when they perceived it as useful, trustworthy, and institutionally supported. Perceived threat to professional autonomy and job security concern negatively predicted behavioural intention, indicating that professional concerns may reduce lecturers' willingness to adopt AI-based assessment tools.

DISCUSSION

Levels of Technology Acceptance and Behavioural Intention

The findings suggest that lecturers generally reported moderately high to high levels of technology acceptance and behavioural intention toward AI-based educational assessment. Performance expectancy recorded the highest mean score, indicating that lecturers recognised the potential usefulness of AI in improving assessment efficiency, accuracy, feedback quality, and decision-making. This finding is consistent with UTAUT, which positions performance expectancy as a central driver of behavioural intention (Venkatesh et al., 2003, 2016). In the context of AI-based assessment, perceived usefulness appears to be strongly linked to lecturers' recognition that assessment work can be enhanced through automation, analytics, and personalised feedback.

Behavioural intention was also moderately high, suggesting that lecturers were generally open to using, continuing to use, and recommending AI-based assessment tools. However, the mean scores for facilitating conditions and social influence were slightly lower than performance expectancy, suggesting that lecturers may recognise the value of AI while remaining less certain about the availability of institutional support or the consistency of peer and leadership encouragement. This distinction is important because positive beliefs about usefulness may not translate into sustained adoption unless supported by infrastructure, training, and clear institutional expectations.

Relationship Between Technology Acceptance and Behavioural Intention

The correlation findings showed that all positive acceptance constructs were significantly associated with behavioural intention. Performance expectancy had the strongest relationship with behavioural intention, followed by perceived trust in AI and facilitating conditions. This pattern suggests that lecturers' intention to adopt AI-based assessment is primarily shaped by perceived academic value, confidence in AI outputs, and the availability of institutional support. These findings align with recent AI acceptance literature, which indicates that perceived usefulness and trust are key determinants of AI adoption in university contexts (Acosta-Enriquez et al., 2024; Nazaretsky et al., 2022).

Effort expectancy was also positively correlated with behavioural intention, indicating that lecturers are more likely to adopt AI-based assessment when they perceive the tools as easy to learn and operate. However, its relationship was weaker than performance expectancy and perceived trust. This suggests that ease of use matters, but lecturers may prioritise whether AI improves assessment quality and whether its outputs can be trusted. In high-stakes academic assessment, usefulness and trust may therefore be more influential than convenience alone.

Social influence showed a moderate positive relationship with behavioural intention. This indicates that institutional norms, leadership support, and collegial encouragement may influence lecturers' adoption decisions. However, the moderate strength of the relationship suggests that social influence alone may not be sufficient. Lecturers may respond positively to institutional encouragement when it is accompanied by meaningful training, transparent guidelines, and evidence that AI-based assessment improves educational practice.

Predictors of Behavioural Intention

The regression findings indicated that the extended model explained 65.2% of the variance in behavioural intention. This suggests that the combination of core UTAUT constructs and AI-specific professional concerns provides a strong explanation of lecturers' intention to adopt AI-based assessment. Performance expectancy emerged as the strongest predictor, indicating that perceived usefulness remains the central driver of behavioural intention. Lecturers are more likely to adopt AI-based assessment when they believe that it can improve assessment quality, efficiency, feedback, and student evaluation.

Perceived trust in AI was the second strongest predictor, supporting the argument that AI adoption in assessment requires confidence in system fairness, accuracy, transparency, and ethical use. This finding is particularly important because assessment decisions carry academic consequences for students. Lecturers are unlikely to adopt AI-based assessment meaningfully if they doubt the reliability or fairness of AI-generated results. Therefore, building trust through explainable AI design, transparent assessment policies, and professional development should be a priority for universities.

Facilitating conditions also significantly predicted behavioural intention. This indicates that lecturers need institutional and technical support to translate positive attitudes into intention. AI-based assessment adoption requires access to reliable platforms, technical assistance, training, and clear guidelines. Without these conditions, lecturers may perceive AI adoption as risky or burdensome. Thus, university readiness should be treated as an adoption factor rather than a background condition.

The Role of Professional Concerns

The finding does not imply that lecturers reject AI. Rather, it suggests that acceptance depends on how AI is positioned. If AI is framed as a decision-support tool that enhances lecturers' assessment work, behavioural intention may increase. If it is framed as a replacement for academic judgment, behavioural intention may decline. Therefore, responsible implementation should emphasise human-in-the-loop assessment, lecturer control, transparency, and clear boundaries between AI-supported analysis and final academic decision-making. In practical terms, a human-in-the-loop approach means that AI should function as an assessment-support system rather than an autonomous decision-maker. Under this model, AI may assist lecturers by generating preliminary feedback, identifying response patterns, detecting possible learning gaps, or suggesting scoring indicators. However, the lecturer remains responsible for reviewing, interpreting, modifying, and approving the final assessment decision. This approach can help mitigate perceived threats to professional autonomy because it preserves lecturers' authority over assessment design, grading judgment, feedback interpretation, and final academic decisions. Instead of replacing professional expertise, AI is positioned as a tool that enhances lecturers' evaluative work while maintaining human responsibility, contextual understanding, and pedagogical discretion. Such a model is particularly important in higher education assessment, where fairness, validity, academic judgment, and student accountability cannot be fully delegated to automated systems.

In practical terms, a human-in-the-loop approach means that AI should function as an assessment-support system rather than an autonomous decision-maker. Under this model, AI may assist lecturers by generating preliminary feedback, identifying response patterns, detecting possible learning gaps, or suggesting scoring indicators. However, the lecturer remains responsible for reviewing, interpreting, modifying, and approving the final assessment decision. This approach can help mitigate perceived threats to professional autonomy because it preserves lecturers' authority over assessment design, grading judgment, feedback interpretation, and final academic decisions. Instead of replacing professional expertise, AI is positioned as a tool that enhances lecturers' evaluative work while maintaining human responsibility, contextual understanding, and pedagogical discretion. Such a model is particularly important in higher education assessment, where fairness, validity, academic judgment, and student accountability cannot be fully delegated to automated systems.

Implications for Saudi Higher Education

The findings have practical implications for Saudi higher education institutions. First, professional development should focus not only on technical skills but also on the educational value of AI-based assessment. Lecturers need to understand how AI can improve feedback quality, assessment consistency, and learning analytics. Second, universities should build trust by providing transparent guidelines on how AI-generated assessment evidence should be interpreted and used. Third, institutions should address professional concerns directly by clarifying that AI is intended to support rather than replace lecturers' evaluative judgment. This can be operationalised through human-in-the-loop assessment policies that require lecturers to review AI-generated scores, validate automated feedback, and retain final authority over grading and assessment decisions.

Fourth, institutional support systems should be strengthened. Facilitating conditions were a significant predictor of behavioural intention, indicating that lecturers are more likely to adopt AI-based assessment when they perceive adequate infrastructure, support, and training. Finally, leadership and peer modelling should be used carefully. Social influence may encourage adoption, but it should be accompanied by ethical guidelines, professional agency, and evidence-based implementation rather than top-down pressure.

Limitations and Future Research

Several limitations should be acknowledged. First, the study used a cross-sectional correlational design; therefore, the findings indicate associations between technology acceptance constructs and behavioural intention, but do not establish causal relationships. Second, universities should build trust by providing transparent guidelines on how AI-generated assessment evidence should be interpreted and used. These guidelines are directly linked to the facilitating conditions construct because they function as institutional support that enables lecturers to use AI-based assessment tools with greater clarity, confidence, and accountability. Transparent policy guidance can reduce uncertainty about acceptable AI use, clarify lecturers' responsibilities in reviewing AI-generated outputs, and establish ethical boundaries for assessment decisions. Therefore, policy should not be viewed only as administrative regulation, but as a practical support condition that facilitates responsible adoption of AI-based educational assessment. Third, the study relied on self-reported questionnaire data, which may be influenced by social desirability, respondents' familiarity with AI, or institutional expectations toward digital transformation.

Fourth, the findings are limited to lecturers in Saudi higher education institutions and should be generalized cautiously to other cultural or institutional contexts. Fifth, although the model included key constructs from technology acceptance theory and AI-specific concerns, other factors such as AI literacy, prior hands-on experience, assessment type, institutional policy, and workload may also influence behavioural intention. In particular, AI literacy was not examined as a specific predictor in the present study, although lecturers' understanding of AI concepts, algorithmic decision-making, data use, and ethical implications may influence how they evaluate and adopt AI-based assessment tools. Future studies should therefore examine AI literacy as an additional variable and explore whether it strengthens lecturers' trust, reduces professional concerns, and increases behavioural intention toward AI-based educational assessment.

CONCLUSION

This paper examined the relationship between technology acceptance and behavioural intention toward AI-based educational assessment among lecturers in Saudi higher education. The findings suggest that performance expectancy, perceived trust in AI, facilitating conditions, effort expectancy, and social influence positively predict behavioural intention, while perceived threat to professional autonomy and job security concern negatively predict behavioural intention. The extended model provides a useful explanation of AI-based assessment adoption because it combines conventional UTAUT constructs with AI-specific professional concerns.

The study highlights that lecturers' intention to adopt AI-based assessment is not shaped by usefulness alone. Trust, institutional support, professional autonomy, and role security are also important. For AI-based assessment to be adopted responsibly and sustainably, universities must provide clear support structures, build lecturer confidence, preserve human academic judgment, and communicate the role of AI as an assistive tool rather than a replacement for educators.Therefore, successful AI-based assessment adoption in Saudi higher education requires a balanced strategy that strengthens perceived usefulness and trust while reducing professional concerns through transparent, lecturer-centred implementation.

ACKNOWLEDGEMENT

The authors would like to express their appreciation to the lecturers who participated in the study and to Universiti Teknologi Malaysia for academic support.

Informed Consent Statement

Informed consent was obtained from all respondents prior to participation. Participation was voluntary, and responses were treated anonymously and confidentially.

Conflict of Interest

The authors declare that there is no conflict of interest related to this study.

Funding Statement

This research received no external funding.

REFERENCES

1. Acosta-Enriquez, B. G., Ramos Farroñan, E. V., Villena Zapata, L. I., Mogollon Garcia, F. S., Rabanal-León, H. C., Morales Angaspilco, J. E., & Saldaña Bocanegra, J. C. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. Heliyon, 10, Article e38315. https://doi.org/10.1016/j.heliyon.2024.e38315
2. Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. IEEE Access, 8, 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510
3. Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. International Journal of Educational Technology in Higher Education, 20, Article 22. https://doi.org/10.1186/s41239-023-00392-8
4. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008
5. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., ... Williams, M. D. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International Journal of Information Management, 57, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
6. European Commission, Directorate-General for Education, Youth, Sport and Culture. (2022). Ethical guidelines on the use of artificial intelligence (AI) and data in teaching and learning for educators. Publications Office of the European Union. https://doi.org/10.2766/153756
7. Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign.
8. Huggins-Manley, A. C., Booth, B. M., & D'Mello, S. K. (2022). Toward argument-based fairness with an application to AI-enhanced educational assessments. Journal of Educational Measurement, 59(3), 362-388. https://doi.org/10.1111/jedm.12334
9. Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274
10. Kizilcec, R. F., & Lee, H. (2022). Algorithmic fairness in education. In W. Holmes & K. Porayska-Pomsta (Eds.), The ethics of artificial intelligence in education: Practices, challenges, and debates (pp. 174-202). Routledge. https://doi.org/10.4324/9780429329067-10
11. Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO.

12. Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. British Journal of Educational Technology, 53(4), 914-931. https://doi.org/10.1111/bjet.13232
13. OECD. (2023). OECD digital education outlook 2023: Towards an effective digital education ecosystem. OECD Publishing. https://doi.org/10.1787/c74f03de-en
14. Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. Computers & Education, 57(4), 2432-2440. https://doi.org/10.1016/j.compedu.2011.06.008
15. U.S. Department of Education, Office of Educational Technology. (2023). Artificial intelligence and future of teaching and learning: Insights and recommendations. U.S. Department of Education.
16. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478. https://doi.org/10.2307/30036540
17. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. Journal of the Association for Information Systems, 17(5), 328-376. https://doi.org/10.17705/1jais.00428
18. Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. Expert Systems with Applications, 252, Article 124167. https://doi.org/10.1016/j.eswa.2024.124167
19. Zawacki-Richter, O., Marin, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? International Journal of Educational Technology in Higher Education, 16, Article 39. https://doi.org/10.1186/s41239-019-0171-0