

TRUST-DRIVEN ADOPTION OF AI-POWERED TRANSLATION TOOLS AMONG ARABIC LANGUAGE STUDENTS IN MALAYSIAN HIGHER EDUCATION

Nik Muhammad Najib Nik Ab Aziz, Wan Ab Aziz Wan Daud

Faculty of Language Studies and Human Development, Universiti Malaysia Kelantan, Kelantan,
Malaysia

*Corresponding author email: abaziz.wd@umk.edu.my

ARTICLE HISTORY

Received: 02nd May 2026

Revised: 20th June 2026

Accepted: 21st June 2026

Published: 30th June 2026

KEYWORDS

Arabic language learning;

Artificial intelligence;

Behavioral intention;

Perceived risk;

Perceived trust;

Technology acceptance model

ABSTRACT - Generative artificial intelligence (GenAI) translation tools are increasingly embedded in language-learning practices, yet their adoption in Arabic-language education raises questions about reliability, opacity, and risk. This study examines the factors shaping Arabic-language undergraduates' behavioral intention to use AI-supported translation tools in Malaysian public universities. An extended Technology Acceptance Model was evaluated using survey data from 300 valid respondents across four institutions. The model incorporated perceived usefulness, perceived ease of use, perceived intelligence, perceived trust, and perceived risk. Partial least squares structural equation modelling showed that perceived trust was the strongest direct predictor of behavioral intention ($\beta = 0.299$, $p < 0.001$), followed by perceived risk ($\beta = 0.207$, $p < 0.001$) and perceived usefulness ($\beta = 0.163$, $p = 0.044$). Perceived ease of use and perceived intelligence had no significant direct effects on intention. However, perceived trust fully mediated the relationship between perceived intelligence and behavioral intention ($\beta = 0.143$, $p = 0.002$) and partially mediated the relationship between perceived usefulness and behavioral intention ($\beta = 0.065$, $p = 0.029$). The unexpected positive association between perceived risk and intention suggests a possible form of calculated pragmatism: students may remain willing to use AI translation tools while recognizing their limitations. The findings support trust calibration, critical AI literacy, and institutionally governed use of GenAI in Arabic-language education.

INTRODUCTION

Artificial intelligence (AI) has become a consequential feature of contemporary higher education. The expansion of generative artificial intelligence (GenAI) has accelerated this development because students can now access systems that generate, revise, translate, and explain text through natural-language interaction (Alabdullatif & Alsubaie, 2024). In language-learning contexts, these systems are especially attractive because they offer rapid assistance with vocabulary, comprehension, drafting, and translation. AI-supported translation tools may therefore function as learning aids rather than merely as automated substitutes for dictionaries or conventional machine-translation systems. Their educational value, however, cannot be assessed solely through technical performance. Students must decide whether the outputs are useful, sufficiently accurate, trustworthy, and appropriate for academic use.

The issue is particularly significant in Arabic-language education. Arabic is characterized by morphological richness, syntactic complexity, lexical variation, and diglossia. Translation quality may vary according to register, dialect, context, and the cultural or religious sensitivity of particular expressions. A fluent output is not necessarily an accurate output. Students who use AI-generated translations for coursework may therefore encounter a difficult evaluative task: they must benefit from the speed and accessibility of the tool while remaining alert to semantic inaccuracies, hallucinated information, overgeneralization, and context loss. The resulting adoption decision is not a simple matter of convenience. It involves a judgement about when an AI tool is sufficiently reliable to support learning and when independent verification remains essential.

The Technology Acceptance Model (TAM) remains one of the most influential frameworks for explaining technology adoption. Davis (1989) proposed perceived usefulness and perceived ease of use as central determinants of user acceptance. Subsequent research has repeatedly demonstrated the value of TAM across different technological settings (Venkatesh et al., 2003). Nevertheless, the emergence of GenAI presents a distinctive challenge. A generative system may be exceptionally easy to operate while remaining difficult to evaluate. Its apparent fluency can mask uncertainty. For this reason, adoption research increasingly needs to consider psychological and ethical factors that are not captured fully by the traditional TAM variables.

Trust and risk are especially relevant in this context. Perceived trust concerns users' beliefs that an AI-supported translation tool is dependable, sufficiently accurate, and suitable for the intended task. Perceived risk concerns anticipated adverse consequences, including inaccurate translations, weakened language-learning habits, academic-integrity problems, privacy concerns, and excessive dependence on generated outputs. Earlier work in digital adoption has shown that perceived risk can influence users' willingness to engage with online services (Featherman & Pavlou, 2003), while emerging AI literature highlights trust as a central condition for sustained reliance on generative systems (Shahzad et al., 2024; Balaskas et al., 2025).

Malaysian universities provide an important setting for examining these issues. The higher-education sector is advancing digitalization initiatives, while students increasingly encounter AI tools in everyday academic practice (Ministry of Higher Education Malaysia, 2025; Mizan & Norman, 2024). However, evidence remains limited regarding Arabic-language undergraduates who use AI-supported translation tools in a linguistically sensitive learning environment. This study addresses that gap by testing an extended TAM that incorporates perceived intelligence, perceived trust, and perceived risk. The article focuses on the direct structural relationships and the most consequential mediation mechanisms identified in the thesis. It asks whether trust functions as a gatekeeper that converts students' perceptions of technical intelligence and usefulness into behavioral intention, and whether perceived risk necessarily suppresses adoption in this specific educational setting.

RESEARCH BACKGROUND

The rapid integration of generative artificial intelligence (GenAI) in higher education has fundamentally altered traditional learning paradigms, particularly within specialized language disciplines. While initial technological adoptions focused primarily on ease of operation and system interface, the deployment of advanced AI tools demands a deeper understanding of human-technology interaction, psychological trust, and risk evaluation among specialized learners. Therefore, establishing a comprehensive theoretical background that connects technology acceptance with the unique linguistic nuances of Arabic-language education is critical to contextualizing current student adoption behaviors.

AI-Supported Translation Tools In Arabic-Language Learning

The development of neural machine translation and GenAI has changed the nature of translation assistance. Earlier systems were often evaluated primarily through output quality and linguistic equivalence. Current systems are also interactive. They can explain lexical choices, reformulate sentences, propose alternatives, and respond to follow-up prompts. These features create educational opportunities because students may use the tools to explore meaning, compare registers, and identify possible translations. Bowker (2025) refers to the importance of machine-translation literacy: users

require the ability to interpret, verify, and responsibly integrate machine-generated outputs rather than treating them as unquestionable answers.

Arabic-language learning makes this literacy particularly important. Students may work with Modern Standard Arabic, specialized academic language, religious registers, or colloquial varieties. An output that appears grammatically polished can still misrepresent nuance. Al-Owaidi and Al-Ahdal (2023) illustrate the limits of AI-based translation when culturally and aesthetically complex Arabic texts are compared with human translation. The educational question is therefore not whether AI translation tools should be used without restriction or prohibited entirely. The more productive question concerns how learners evaluate and govern their use.

In Malaysia, the relevance of this question is intensified by the multilingual educational context and the increasing normalization of digital learning. Students may use AI-supported translation tools to save time, clarify vocabulary, understand difficult passages, and produce initial drafts. Such practices can support learning when accompanied by verification and reflection. They can also weaken independent linguistic judgement when students accept outputs uncritically. Adoption should consequently be examined as a negotiated process involving both perceived benefits and perceived limitations.

Extending TAM For Genai Adoption

TAM proposes that perceived usefulness and perceived ease of use influence a user's intention to adopt a system (Davis, 1989). Perceived usefulness refers to the belief that a technology improves task performance, while perceived ease of use refers to the belief that the system can be used without excessive effort. These constructs remain relevant to AI-supported translation tools. Students are more likely to use a tool if it accelerates comprehension, assists academic work, and is easy to operate. However, conversational GenAI interfaces have reduced the effort required to obtain an output. As a result, ease of use may be less discriminating than it was for earlier technologies.

The present study extends TAM through perceived intelligence, perceived trust, and perceived risk. Perceived intelligence refers to the user's assessment that the tool demonstrates relevant cognitive capabilities, such as producing coherent and context-sensitive responses. For AI-supported translation tools, perceived intelligence may include the ability to generate plausible translations, explain terminology, and respond flexibly to prompts. Yet perceived intelligence is not equivalent to trustworthiness. A system can appear intelligent while producing inaccurate, unverifiable, or contextually inappropriate outputs. This distinction is central to the proposed gatekeeper interpretation.

Perceived trust captures the user's willingness to rely on the tool under conditions of uncertainty. In GenAI adoption, trust is neither blind acceptance nor general enthusiasm for technology. Appropriate trust requires calibration: confidence should correspond to the tool's actual limitations and the consequences of error. Trust is therefore expected to influence behavioral intention directly and to mediate the effects of perceived usefulness and perceived intelligence. Students may recognize that a system is capable or efficient, but these perceptions may translate into adoption only when the system is judged sufficiently dependable for academic tasks.

Perceived risk introduces a complementary perspective. Conventional adoption models often assume that risk reduces intention. This expectation is reasonable when users can avoid the technology without losing meaningful benefits. In higher education, however, students may continue to use AI-supported tools while remaining conscious of their weaknesses. Such a pattern would not imply that risk is desirable. It would instead indicate a pragmatic form of adoption in which users recognize possible harms but continue to engage because the perceived academic utility remains substantial. The study therefore tests the hypothesized direct and indirect relationships while interpreting any unexpected direction cautiously.

RESEARCH OBJECTIVE

The objective of this article is to examine the direct and mediating relationships that shape Arabic-language undergraduates' behavioral intention to adopt AI-supported translation tools in Malaysian public universities. The tested model includes perceived usefulness (PU), perceived ease of use (PEOU), perceived intelligence (PI), perceived trust (PT), perceived risk (PR), and behavioral intention

(BI). Particular attention is given to the possibility that perceived trust acts as a gatekeeper between perceived intelligence and behavioral intention.

METHODS AND MATERIALS

Research Design and Participants

This study employed a quantitative, post-positivist, cross-sectional survey design. The primary population comprised undergraduates studying Arabic or enrolled in Arabic-proficiency courses at Malaysian public universities. A multi-stage sampling procedure was used. First, eligible public universities in Peninsular Malaysia were stratified into four geographical regions: northern, southern, eastern, and central. Second, one public university was randomly selected from each region. Third, relevant Arabic-language classes were selected purposively to ensure that the sample represented students at different academic levels. Finally, students were selected from the identified classes through institutional academic channels. This procedure balanced geographical coverage with the practical need to reach students who were directly relevant to the research questions.

The four participating institutions were Universiti Sains Islam Malaysia (USIM), International Islamic University Malaysia (IIUM), Universiti Malaysia Kelantan (UMK), and Universiti Pendidikan Sultan Idris (UPSI). A total of 400 questionnaires were distributed and 379 responses were received. Data screening excluded 79 responses because of ineligibility, substantial missing data, or low-quality response patterns such as straight-lining. The final structural-model sample consisted of 300 valid cases. Of these respondents, 55.0% were women and 45.0% were men. More than 73% reported using AI-supported translation tools daily or several times per day, indicating that most respondents had sufficient practical exposure to evaluate the tools.

Instrument Development

The questionnaire measured six reflective constructs: perceived usefulness, perceived ease of use, perceived intelligence, perceived trust, perceived risk, and behavioral intention. Each construct was measured using 10 items, producing a total of 60 items. Responses were recorded on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The measurement items were adapted from established technology-adoption and trust literature and contextualized for AI-supported translation tools used in Arabic-language learning. The use of multiple indicators was intended to capture the breadth of each construct while maintaining consistency with the extended TAM framework.

Instrument development was conducted in two stages. Before the main study, an exploratory factor analysis (EFA) was performed using a separate sample of 253 Arabic-language students from Malaysian private universities. Principal axis factoring with Promax rotation was used because the psychological constructs were expected to correlate. The Kaiser-Meyer-Olkin measure was 0.971 and Bartlett's test of sphericity was significant, $\chi^2(1770) = 24870.433$, $p < 0.001$. Six factors were retained, collectively accounting for 83.46% of the cumulative common variance. Cronbach's alpha values in the exploratory phase ranged from 0.976 to 0.985. The results supported the dimensional structure of the adapted instrument before its administration to the main sample.

Data Analysis

The main dataset was analysed using SmartPLS 4. The analysis followed the two-stage procedure recommended for partial least squares structural equation modelling (PLS-SEM): assessment of the reflective measurement model followed by assessment of the structural model (Hair et al., 2019). The measurement model was evaluated through indicator loadings, Cronbach's alpha, rho_A, composite reliability, average variance extracted (AVE), the heterotrait-monotrait ratio of correlations (HTMT), and the Fornell-Larcker criterion. The structural model was evaluated through inner variance inflation factor (VIF) values, coefficients of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), path coefficients, bias-corrected confidence intervals, and specific indirect effects.

Bootstrapping with 5,000 subsamples was used to determine statistical significance. PLS-SEM does not require multivariate normality; nevertheless, item-level skewness and kurtosis were examined descriptively to identify serious anomalies. In addition, common-method bias was addressed

procedurally through careful questionnaire design and statistically through a full-collinearity assessment (Podsakoff et al., 2003). All factor-level VIF values remained below the conservative threshold of 3.3, suggesting that common-method bias was not a dominant concern.

FINDING

Measurement Model Assessment

The reflective measurement model demonstrated satisfactory reliability and validity. All indicator loadings exceeded 0.708, ranging from 0.722 to 0.905. Cronbach's alpha values ranged from 0.943 to 0.963, rho_A values ranged from 0.945 to 0.964, and composite reliability values ranged from 0.952 to 0.968. The AVE values ranged from 0.663 to 0.773, exceeding the recommended minimum value of 0.500. These results provide evidence of indicator reliability, internal-consistency reliability, and convergent validity.

Discriminant validity was assessed using HTMT and the Fornell-Larcker criterion (Henseler et al., 2015). All HTMT values were below 0.85, with the highest value recorded between perceived usefulness and perceived ease of use (HTMT = 0.721). The square roots of the AVE values also exceeded the corresponding inter-construct correlations. The constructs were therefore empirically distinct.

Table 1: Measurement model assessment

Construct	Loading range	Cronbach's α	rho_A	Composite reliability	AVE
Behavioural intention (BI)	0.722-0.849	0.943	0.945	0.952	0.663
Perceived ease of use (PEOU)	0.728-0.886	0.952	0.955	0.959	0.701
Perceived intelligence (PI)	0.798-0.857	0.954	0.954	0.960	0.706
Perceived risk (PR)	0.749-0.876	0.944	0.950	0.952	0.664
Perceived trust (PT)	0.805-0.848	0.949	0.949	0.956	0.684
Perceived usefulness (PU)	0.845-0.905	0.963	0.964	0.968	0.773

Note. All constructs were measured reflectively. Results were generated using SmartPLS 4.

Table 2: Heterotrait-monotrait ratio of correlations (HTMT)

Construct	BI	PEOU	PI	PR	PT	PU
BI	-					
PEOU	0.508	-				
PI	0.467	0.591	-			
PR	0.392	0.254	0.187	-		
PT	0.571	0.509	0.660	0.286	-	
PU	0.524	0.721	0.550	0.271	0.538	-

Note. All HTMT values were below the conservative threshold of 0.85.

Structural Model Assessment

All inner VIF values were below the conservative threshold of 3.0, ranging from 1.115 to 2.171. Collinearity was therefore not a concern in the structural model. The model explained 41.6% of the variance in behavioural intention ($R^2 = 0.416$), 44.4% of the variance in perceived trust ($R^2 = 0.444$), and 7.9% of the variance in perceived risk ($R^2 = 0.079$). Following Geisser (1974) and Stone (1974), predictive relevance was assessed using Q^2 . The Q^2 values were above zero for all endogenous constructs: 0.350 for behavioural intention, 0.386 for perceived trust, and 0.041 for perceived risk. The model therefore demonstrated predictive relevance, although the explanatory and predictive power for perceived risk remained limited. The estimated model produced an SRMR value of 0.051, below the conventional threshold of 0.08 (Hu & Bentler, 1999).

The direct-effects results are reported in Table 4. Perceived trust had the strongest significant direct effect on behavioural intention ($\beta = 0.299$, $t = 4.057$, $p < 0.001$), supporting H8. Perceived usefulness also had a significant positive effect on behavioural intention ($\beta = 0.163$, $t = 2.016$, $p = 0.044$), supporting H9. In contrast, perceived ease of use did not significantly predict behavioural intention ($\beta = 0.147$, $t = 1.414$, $p = 0.157$), and perceived intelligence had no significant direct effect on behavioural intention ($\beta = 0.051$, $t = 0.644$, $p = 0.520$).

Perceived intelligence strongly predicted perceived trust ($\beta = 0.478$, $t = 6.486$, $p < 0.001$), with a medium effect size ($f^2 = 0.265$). Perceived usefulness also positively predicted perceived trust ($\beta = 0.218$, $t = 2.552$, $p = 0.011$), although the effect size was small ($f^2 = 0.042$). The remaining antecedent paths to perceived trust and perceived risk were not statistically significant.

A notable result concerned perceived risk. The hypothesised negative effect of perceived risk on behavioural intention was not supported. Instead, the relationship was positive and statistically significant ($\beta = 0.207$, $t = 3.679$, $p < 0.001$). A subsequent coding review confirmed that the perceived-risk items had not been reverse-coded incorrectly: higher scores represented greater perceived risk. The positive coefficient should therefore be interpreted cautiously as an empirical association rather than as evidence that students prefer risk.

Table 3: Explanatory and predictive relevance of the model

Endogenous construct	R ²	Adjusted R ²	Q ²	Interpretation
Behavioural intention (BI)	0.416	0.406	0.350	Moderate explanatory and predictive relevance
Perceived trust (PT)	0.444	0.439	0.386	Moderate explanatory and predictive relevance
Perceived risk (PR)	0.079	0.069	0.041	Limited explanatory and small predictive relevance

Note. Q² values above zero indicate predictive relevance.

Table 4: Direct effects and hypothesis testing

Hypothesis	Path	β	SE	t	p	95% BC CI	Decision
H1	PEOU -> BI	0.147	0.104	1.414	0.157	[-0.048, 0.359]	Not supported
H2	PEOU -> PR	0.111	0.096	1.153	0.249	[-0.073, 0.297]	Not supported
H3	PEOU -> PT	0.064	0.082	0.783	0.434	[-0.094, 0.225]	Not supported
H4	PI -> BI	0.051	0.079	0.644	0.520	[-0.100, 0.207]	Not supported
H5	PI -> PR	0.025	0.075	0.336	0.737	[-0.122, 0.170]	Not supported
H6	PI -> PT	0.478	0.074	6.486	< 0.001	[0.332, 0.616]	Supported
H7	PR -> BI	0.207	0.056	3.679	< 0.001	[0.097, 0.316]	Not supported: opposite direction
H8	PT -> BI	0.299	0.074	4.057	< 0.001	[0.157, 0.440]	Supported
H9	PU -> BI	0.163	0.081	2.016	0.044	[0.003, 0.318]	Supported
H10	PU -> PR	0.176	0.101	1.747	0.081	[-0.019, 0.370]	Not supported
H11	PU -> PT	0.218	0.086	2.552	0.011	[0.050, 0.382]	Supported

Note. BC CI = bias-corrected confidence interval. A p-value reported as < 0.001 replaces SmartPLS output displayed as 0.000. H7 was not supported because the significant coefficient was opposite to the hypothesised negative direction.

Mediation Analysis

Table 5 reports the specific indirect effects. Perceived trust fully mediated the relationship between perceived intelligence and behavioural intention ($\beta = 0.143$, $t = 3.132$, $p = 0.002$, 95% CI [0.069, 0.249]). The direct PI-to-BI path was not significant, while the indirect path through trust was significant. This result supports the gatekeeper interpretation: students' perceptions that an AI translation tool is intelligent do not translate directly into intention unless the perceived capability is accompanied by trust.

Perceived trust also partially mediated the relationship between perceived usefulness and behavioural intention ($\beta = 0.065$, $t = 2.189$, $p = 0.029$, 95% CI [0.015, 0.134]). Perceived usefulness influenced

behavioural intention both directly and indirectly through trust. In contrast, the indirect effects involving perceived risk were not significant, and perceived ease of use did not produce significant indirect effects through either mediator.

Table 5: Specific indirect effects and mediation results

Hypothesis	Indirect path	β	SE	t	p	95% BC CI	Result
H12	PU -> PT -> BI	0.065	0.030	2.189	0.029	[0.015, 0.134]	Partial mediation
H13	PU -> PR -> BI	0.036	0.024	1.489	0.136	[-0.001, 0.098]	Not supported
H14	PEOU -> PT -> BI	0.019	0.025	0.773	0.439	[-0.028, 0.071]	Not supported
H15	PEOU -> PR -> BI	0.023	0.021	1.095	0.274	[-0.012, 0.071]	Not supported
H16	PI -> PT -> BI	0.143	0.046	3.132	0.002	[0.069, 0.249]	Full mediation
H17	PI -> PR -> BI	0.005	0.017	0.315	0.753	[-0.023, 0.042]	Not supported

Note. BC CI = bias-corrected confidence interval. Mediation was interpreted by considering the significance of the indirect effect and the corresponding direct path.

DISCUSSION

Trust As A Gatekeeper

The results indicate that perceived trust occupies a central position in the adoption of AI-supported translation tools among Arabic-language undergraduates. Trust emerged as the strongest direct predictor of behavioural intention, and it fully mediated the effect of perceived intelligence on intention. This finding is theoretically important because it clarifies the difference between perceived capability and dependable adoption. Students may recognise that an AI tool can produce fluent, fast, and apparently sophisticated translations. Nevertheless, the perception of intelligence does not automatically result in a stable intention to use the tool. The capability must first be translated into trust.

This pattern is understandable in a high-stakes language-learning context. A generated translation may appear persuasive while remaining difficult to verify. For Arabic learners, inaccuracies can affect morphology, register, meaning, and cultural appropriateness. The system's opacity intensifies the problem because students may not know why a particular translation has been produced or whether an apparently coherent answer is supported by reliable information. Trust therefore functions as a psychological gatekeeper. It does not merely increase positive attitudes; it regulates whether perceived technical intelligence becomes behaviourally consequential.

The finding is consistent with recent studies that place trust at the centre of AI adoption in higher education. Shahzad et al. (2024) highlighted trust as a cornerstone of ChatGPT acceptance, while Balaskas et al. (2025) demonstrated the value of extending TAM through trust and risk. Đerić et al. (2025) likewise showed that trust in GenAI tools remains a consequential issue among students, educators, and researchers. The present study adds a language-specific interpretation: trust becomes especially salient when learners must rely on outputs that are linguistically plausible but potentially difficult to authenticate.

Usefulness Remains Relevant, While Ease Of Use Recedes

Perceived usefulness remained a significant predictor of behavioural intention and also influenced intention indirectly through perceived trust. This finding preserves an important element of TAM. Students adopt AI-supported translation tools partly because they believe the tools help them complete academic tasks, understand difficult texts, and access rapid translation support. However, usefulness operates through more than one route. Students may value efficiency directly, while also treating consistent usefulness as evidence that a tool deserves a degree of trust.

By contrast, perceived ease of use did not significantly predict behavioural intention. This result should not be interpreted as evidence that usability no longer matters. A difficult or inaccessible tool may still discourage engagement. Instead, ease of use may have become a baseline expectation. Natural-language interfaces reduce the effort required to interact with GenAI systems: students can ask questions in ordinary language and obtain immediate responses without specialised technical knowledge. When nearly all users regard the interface as easy, ease of use has limited capacity to

distinguish those with stronger adoption intentions from those with weaker intentions. In this setting, ease of use resembles a hygiene factor: necessary for a satisfactory experience but insufficient as a primary motivational driver.

Interpreting The Positive Perceived-Risk Association

The positive association between perceived risk and behavioural intention is the most counter-intuitive direct effect in the model. The original hypothesis anticipated that perceived risk would reduce intention. That hypothesis was not supported because the coefficient was positive. The result does not imply that risk is beneficial or that students seek risk. Nor does the cross-sectional design justify a causal claim that risk increases adoption. A more cautious interpretation is that frequent or committed users may become more aware of the limitations of AI-supported translation tools while continuing to use them because the perceived utility remains substantial.

This pattern may be described as calculated pragmatism. Students who use GenAI translation tools intensively can recognise the possibility of inaccurate outputs, privacy concerns, over-reliance, and weakened independent language practice. Nevertheless, they may continue to use the tools selectively because the tools remain valuable for specific academic tasks. Risk awareness and adoption intention can therefore coexist. The implication is not that universities should normalise unsafe use. Rather, institutions should help students develop practices that match the level of trust to the consequences of error.

The result also helps explain why perceived risk did not function as a mediator in the proposed paths. Perceived risk appears to operate as a parallel evaluative consideration rather than as the mechanism through which usefulness, ease of use, or intelligence influence intention. Students may evaluate usefulness and trust on one track while simultaneously monitoring risk on another. Future longitudinal and qualitative research is needed to examine whether risk awareness grows after repeated use, whether more experienced users verify outputs more carefully, and whether disciplinary expectations alter the relationship.

Implications For Arabic-Language Education

The findings have direct implications for Arabic-language educators and university administrators. First, AI literacy should be framed as critical AI literacy rather than merely operational proficiency. Students already know how to enter prompts. They require guidance on how to verify lexical choices, compare translations, evaluate registers, identify hallucinated explanations, and recognise when a human expert or authoritative source is necessary. Arabic-language programmes should embed verification exercises into coursework so that students learn to treat AI outputs as provisional resources rather than final answers.

A practical implementation strategy is to design assessment tasks that require transparent comparison between an AI-generated translation and a student-verified version. Students can be asked to annotate lexical, syntactic, and register-related differences; justify revisions using authoritative sources; and explain the conditions under which the generated output may be misleading. Such activities shift AI use from passive consumption to reflective language learning. They also create a clearer academic-integrity boundary: the educational objective is not to conceal the use of AI assistance, but to demonstrate the student's capacity to evaluate and improve the output. Instructors can further differentiate low-risk activities, such as vocabulary exploration, from higher-risk activities, such as translating culturally sensitive passages or submitting assessed work. This tiered approach enables students to benefit from the efficiency of AI tools while preserving independent linguistic judgement and accountability.

Second, institutional governance should move beyond binary positions of unrestricted use or blanket prohibition. A calibrated approach is more appropriate. Universities can define permissible uses for translation support, require disclosure where AI assistance materially affects submitted work, and provide guidance on academic integrity. Secure, institutionally governed AI environments may also be considered where privacy, access equity, and monitoring are important. Such environments should not be presented as technological solutions to every pedagogical problem; their value lies in enabling accountable use.

Third, developers of AI-supported translation tools should improve transparency and explainability. Arabic learners benefit when tools provide alternatives, indicate uncertainty, distinguish Modern Standard Arabic from dialectal forms, and encourage verification. Explainable features can support appropriate reliance by helping learners understand the conditions under which an output is more or less dependable. In this sense, the educational goal is not maximal trust. It is well-calibrated trust.

Limitations And Future Research

Several limitations should be considered. The study used a cross-sectional design, so the reported relationships are predictive associations rather than definitive causal effects. The multi-stage sampling procedure included purposive selection at the class level and was limited to four Malaysian public universities. The findings should therefore be interpreted within the boundaries of the selected institutions and the Arabic-language undergraduate population. The study measured behavioural intention rather than verified long-term usage behaviour. In addition, the positive perceived-risk association requires further investigation through longitudinal, experimental, and qualitative designs. Future studies should examine how students verify translations in practice, whether trust calibration changes with experience, and whether different AI tools produce distinct adoption patterns. Comparative research across languages, institutions, and student groups would also clarify the extent to which the gatekeeper role of trust is context-specific.

CONCLUSIONS AND RECOMMENDATION

This study examined the adoption of AI-supported translation tools among Arabic-language undergraduates in Malaysian public universities through an extended TAM. The results show that adoption is not driven by technical ease alone. Perceived trust emerged as the strongest direct predictor of behavioural intention and fully mediated the relationship between perceived intelligence and intention. Perceived usefulness remained important through both direct and indirect routes. Perceived ease of use, however, did not significantly explain behavioural intention in this context.

The positive relationship between perceived risk and behavioural intention requires a careful interpretation. Students may continue to use AI translation tools while recognising their limitations, reflecting a possible pattern of calculated pragmatism. This finding reinforces the need for responsible institutional governance. Arabic-language programmes should integrate critical AI literacy, translation verification, and academic-integrity guidance into their curricula. Universities should support students in developing calibrated trust: neither uncritical dependence nor indiscriminate rejection, but informed use that is proportionate to the risks and benefits of the task.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the participating universities and students for their cooperation and valuable contributions to this study.

FUNDING

This study was not supported by any grants from funding bodies in the public, private, or not-for-profit sectors.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

AUTHORS CONTRIBUTION

Nik Muhammad Najib Nik Ab Aziz: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Writing - original draft preparation. **Wan Ab Aziz Wan Daud:** Supervision, Validation, Writing - review and editing. Both authors approved the final manuscript and agreed to be accountable for its content.

AVAILABILITY OF DATA AND MATERIALS

The data used in this study are confidential. De-identified data may be made available by the corresponding author upon reasonable request, subject to ethical and institutional restrictions.

DECLARATION OF GENERATIVE AI

During the preparation of this work, the author(s) used Gemini to enhance the clarity and readability of the writing. After using the tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

ETHIC STATEMENTS

This study involved human subjects in the form of an anonymous questionnaire survey among university students. Formal institutional ethical approval was not required as the study posed minimal risk to participants and did not collect highly sensitive personal data. However, the study strictly adhered to academic research ethics, and informed consent was obtained from all respondents prior to data collection, ensuring confidentiality and voluntary participation.

REFERENCES

- Alabdullatif, A. M., & Alsubaie, M. A. (2024). ChatGPT in learning: Assessing students' use intentions through the lens of perceived value and the influence of AI literacy. *Behavioral Sciences, 14*(9), Article 845. <https://doi.org/10.3390/bs14090845>
- Al-Owaidi, N., & Al-Ahdal, A. A. M. H. (2023). Artificial intelligence-based machine translation from Arabic to English versus human translation of poetry: An analytical study of the outcomes. *Journal of Namibian Studies: History Politics Culture, 33*(S1), 800-823. <https://doi.org/10.59670/jns.v33i.800>
- Al-Ziyoud, M., Al-Shnabelah, N., Al-Ammar, S., Al-Nasser, A. S., Mustafa, A. A., Al-Momani, A. M., & Al-Hawari, S. I. S. (2024). Artificial intelligence in Jordanian education: Assessing acceptance through perceived cybersecurity, novelty value, and perceived trust. *International Journal of Data and Network Science, 8*(2), 823-834. <https://doi.org/10.5267/j.ijdns.2023.12.022>
- Amin, M. A., Kim, Y. S., & Noh, M. (2025). Unveiling the drivers of ChatGPT utilization in higher education sectors: The direct role of perceived knowledge and the mediating role of trust in ChatGPT. *Education and Information Technologies, 30*(6), 7265-7291. <https://doi.org/10.1007/s10639-024-13095-y>
- Balaskas, S., Tsiantos, V., Chatzifotou, S., & Rigou, M. (2025). Determinants of ChatGPT adoption intention in higher education: Expanding on TAM with the mediating roles of trust and risk. *Information, 16*(2), Article 82. <https://doi.org/10.3390/info16020082>
- Bowker, L. (2025). Machine translation literacy. In L. McCallum & D. Tafazoli (Eds.), *The Palgrave encyclopedia of computer-assisted language learning*. Springer. https://doi.org/10.1007/978-3-031-51447-0_258-1
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.
- Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.
- 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>
- Đerić, I., Franc, D., & Milković, M. (2025). Trust in generative artificial intelligence tools: A comparative study of higher education students, teachers, and researchers. *Information, 16*(7), Article 622. <https://doi.org/10.3390/info16070622>
- Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human-Computer Studies, 59*(4), 451-474. [https://doi.org/10.1016/S1071-5819\(03\)00111-3](https://doi.org/10.1016/S1071-5819(03)00111-3)
- Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika, 61*(1), 101-107. <https://doi.org/10.1093/biomet/61.1.101>
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. <https://doi.org/10.1108/EBR-11-2018-0203>

- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115-135. <https://doi.org/10.1007/s11747-014-0403-8>
- Hu, L.-T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55. <https://doi.org/10.1080/10705519909540118>
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15-25. <https://doi.org/10.1016/j.bushor.2018.08.004>
- Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.
- Ministry of Higher Education Malaysia. (2025). *Dasar Pendigitalan Pendidikan Tinggi 2025-2030* [Higher Education Digitalisation Policy 2025-2030]. <https://www.mohe.gov.my>
- Mizan, N., & Norman, H. (2024). Pre-university students' perception of using generative artificial intelligence: A study in a Malaysian private university. *International Journal of Academic Research in Business and Social Sciences*, 14(8), 2292-2308. <https://doi.org/10.6007/IJARBS/v14-i8/22455>
- Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903. <https://doi.org/10.1037/0021-9010.88.5.879>
- Raba, A. A., Saja, I., & Azmi, A. (2024). The use of artificial intelligence translation tools: Implications for third-language proficiency. *International Journal of Research and Innovation in Social Science*, 8(9), Article IJRIS.2024.8090161. <https://doi.org/10.47772/IJRIS.2024.8090161>
- Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, 21, Article 46. <https://doi.org/10.1186/s41239-024-00478-x>
- Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society: Series B (Methodological)*, 36(2), 111-133. <https://doi.org/10.1111/j.2517-6161.1974.tb00994.x>
- 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>