

Modeling Students' Acceptance of AI-Assisted Translation Tools: An Extension of the Technology Acceptance Model

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Abstract. This study investigates students' acceptance of AI-assisted translation tools by proposing an extended Technology Acceptance Model (TAM-AI) for AI-assisted translation learning contexts. Unlike prior additive approaches, the proposed model explains how translation-specific perceptions influence behavioral intention (BI) through underlying cognitive mechanisms. A survey was conducted among undergraduate translation students and analyzed using Structural Equation Modeling (SEM). The results indicate that perceived usefulness (PU) and perceived ease of use (PEOU) significantly predict BI. In addition, translation-specific factors influence technology acceptance indirectly: perceived translation quality operates through trust, feedback clarity through cognitive understanding, and cognitive load reduction through effort reduction. The TAM-AI model demonstrates greater explanatory power than the baseline TAM. These findings provide a deeper understanding of technology acceptance in AI-assisted learning environments and offer practical implications for the design of AI-assisted translation tools. Future studies with larger and more diverse samples are encouraged to further validate the proposed model.

Keywords: Technology Acceptance Model, TAM-AI, AI-Assisted Translation, Students' Acceptance, Translation Learning, Translation tool design.

1. Introduction

The rapid integration of machine translation and other AI-assisted tools has reshaped translation and language learning by introducing new forms of technology-mediated practice, feedback, and post-editing [6,14,21]. As these technologies become increasingly embedded in educational settings, understanding students' acceptance of AI-assisted translation tools has emerged as a critical issue, because attitudes, perceived usefulness, trust,

and behavioral intention significantly influence students' adoption of AI-supported learning technologies [3,15]. Recent studies have examined machine translation use in L2 writing and novice translation students' AI literacy [11,21]. However, comparatively less attention has been paid to the cognitive mechanisms through which translation-specific perceptions influence students' technology acceptance. TAM-based research specifically addressing translation students' acceptance of AI tools has only recently begun to emerge [1].

The Technology Acceptance Model (TAM), originally proposed by [4], remains a foundational framework for explaining technology adoption and has recently been extended to AI-assisted language learning and university students' use of AI tools [3,15]. However, translation learning involves distinctive processes such as evaluating AI-generated translation quality, interpreting feedback, revising machine-generated output, and developing appropriate AI and machine translation literacy [6,21]. Trust is also particularly important because it shapes students' reliance on and resistance to GenAI, which in turn influence their behavioral intention to use it in language learning [19]. Taken together, these findings suggest that general TAM-based models may not fully capture the translation-specific cognitive and evaluative processes underlying students' acceptance of AI-assisted translation tools.

To address this gap, this study proposes the TAM-AI model, an extension of TAM designed to examine students' acceptance of AI-assisted translation tools in translation learning contexts. By incorporating learning-oriented perceptions relevant to AI-supported translation learning, the TAM-AI model provides a context-sensitive framework for investigating technology acceptance.

The study addresses the following research questions:

- RQ1: Which factors significantly influence students' acceptance of AI-assisted translation tools?
- RQ2: To what extent does the TAM-AI model explain students' behavioral intention to use these tools?

Unlike prior studies that apply TAM in a descriptive manner, this study aims to provide a mechanism-based extension of TAM in the context of AI-assisted translation learning. Rather than simply introducing additional external variables, this study seeks to explain how translation-specific perceptions influence students' behavioral intention through underlying cognitive processes.

Furthermore, this study evaluates the incremental explanatory power of the proposed TAM-AI model by comparing it with the baseline TAM, thereby providing stronger empirical evidence for its theoretical contribution. This study contributes to the literature by moving beyond additive TAM extensions and introducing a mechanism-based perspective that explains how domain-specific perceptions are cognitively transformed into technology acceptance beliefs.

2. Literature Review

2.1. Technology Acceptance Models

TAM, originally proposed by [4], is one of the most widely used theoretical frameworks for explaining users' acceptance of information technologies. TAM posits that perceived

usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of users' behavioral intention to adopt a technology. Due to its parsimony and explanatory power, TAM has been extensively applied and empirically validated across various educational technology contexts.

Subsequent studies have extended TAM to better capture technology adoption in complex learning environments [18]. In educational research, TAM has been used to examine students' acceptance of e-learning platforms, digital learning tools, and AI-supported educational applications [17]. However, despite these extensions, existing TAM-based studies have largely focused on general learning technologies and have rarely been adapted to domain-specific contexts such as translation learning, where task complexity and cognitive demands differ substantially from those of general educational settings.

2.2. AI-Assisted Translation Learning

Advances in artificial intelligence have led to the increasing integration of AI-assisted translation tools into translation education. These tools include machine translation systems, computer-assisted translation (CAT) tools, and AI-driven revision and feedback applications, which are commonly used to support translation practice. Research in translation studies has demonstrated that such tools can enhance translation efficiency, consistency, and revision quality [2].

However, existing studies in this area have primarily concentrated on learning outcomes and tool effectiveness, such as translation accuracy and productivity [12]. Comparatively less attention has been paid to students' perceptions of AI-assisted translation tools as learning technologies. As a result, the question of whether students are willing to accept and continuously use these tools in translation learning contexts remains insufficiently explored. Recent studies have emphasized the role of trust and cognitive processes in AI adoption [5]. More recent research further confirms that trust and cognitive evaluations are critical determinants of users' behavioral intentions toward AI technologies [7,13], highlighting the need for mechanism-based models.

2.3. Technology Acceptance of AI-Assisted Learning Tools

In recent years, researchers have increasingly applied TAM and related acceptance models to investigate learners' adoption of AI-supported educational technologies, including intelligent tutoring systems and AI-assisted writing tools. These studies consistently indicate that perceived usefulness and perceived ease of use play central roles in shaping learners' acceptance of AI-based learning tools [17].

Despite growing interest in technology acceptance of AI-assisted learning tools, most existing studies have focused on general educational or language learning contexts. However, given the distinctive characteristics of translation learning, including iterative revision and intensive cognitive processing, findings from general AI-assisted learning contexts may not be directly transferable to translation education. Research specifically addressing AI-assisted translation tools remains scarce. To the authors' knowledge, Alqah-tani and Al-Ahdal [1] conducted one of the few studies explicitly applying TAM to investigate AI-tool adoption among English translation majors at a Saudi Arabian university. The study investigated the adoption rate of AI tools for translation at that university,

the actual use of the tools, as well as the students' perceptions regarding the integration of AI in translation practice. The results indicated that although most participants in the study (altogether 114 Saudi Arabian translation students learning English as a foreign language) found AI tools useful, they expressed concern about the potential negative impact of overuse on their translation skills. Recent studies have extended TAM in AI-assisted learning contexts by incorporating factors such as trust, responsibility, and cognitive processes, thereby improving its explanatory power [9,20].

2.4. Research Gap

Although previous studies have examined AI-assisted translation tools and TAM-based technology acceptance separately, existing research largely adopts an additive approach by incorporating external variables without explaining the underlying cognitive mechanisms through which these factors influence user acceptance.

Moreover, prior studies rarely evaluate whether such extensions offer incremental explanatory power over the baseline TAM. As a result, it remains unclear not only which factors influence students' acceptance of AI-assisted translation tools, but also how and why these factors shape their perceptions and behavioral intentions.

To address this gap, this study proposes a mechanism-based extension of TAM (TAM-AI) and empirically compares it with the original TAM to assess its explanatory power. Recent research has increasingly emphasized the need to move beyond additive models and incorporate cognitive and psychological mechanisms in explaining AI acceptance [8,16]. However, existing studies rarely explain the underlying cognitive mechanisms through which these factors influence acceptance, resulting in limited theoretical integration.

3. Theoretical Framework and Research Hypotheses

The theoretical framework underlying this study relies on TAM and its extension into the TAM-AI model. It explains how this model is applied to assess students' acceptance of AI-assisted translation tools in educational settings. The research hypotheses that drove this study explored the factors that influence students' BI to use these tools, as well as the role of individual characteristics in shaping their technology acceptance.

3.1. Overview of the Original TAM Model

TAM, proposed by [4], is a parsimonious theoretical model developed to explain individuals' acceptance and use of information systems. Rooted in the Theory of Reasoned Action (TRA), TAM conceptualizes technology adoption as a cognitively driven process in which users' beliefs shape their intentions and subsequent behaviors.

The original TAM consists of two fundamental belief constructs: PU and PEOU. Perceived Usefulness is defined as the degree to which an individual believes that using a particular system will enhance task performance, whereas Perceived Ease of Use refers to the extent to which the system is perceived as requiring minimal effort. TAM posits that these two beliefs jointly determine users' attitudes toward the system and directly influence BI, which serves as the immediate antecedent of actual system use.

A central assumption of TAM is that users' acceptance decisions are primarily shaped by internal cognitive evaluations rather than by external system characteristics per se. External variables—such as system features, user experience, or contextual conditions—are theorized to influence adoption indirectly through their effects on PU and PEOU. This assumption allows TAM to maintain a high degree of conceptual simplicity while preserving strong explanatory and predictive power.

Due to its clarity and empirical robustness, TAM has been widely adopted and validated across a broad range of technological contexts, including organizational information systems and educational technologies. Its structural simplicity facilitates empirical testing and model extension, making it a foundational framework for subsequent acceptance models and domain-specific adaptations.

Understanding these core constructs, assumptions, and causal logic of the original TAM is essential for capturing the process by which extended acceptance models can be systematically developed.

3.2. Extension to the TAM-AI Model

Unlike conventional TAM extensions that rely on direct relationships between external variables and core TAM constructs, the TAM-AI model proposed in this study adopts a mechanism-based perspective. Specifically, we argue that translation-specific perceptions do not influence perceived usefulness and perceived ease of use directly, but rather operate through underlying cognitive and evaluative processes.

In the context of AI-assisted translation, perceived translation quality is expected to enhance users' trust in AI-generated outputs, which subsequently strengthens perceived usefulness. Similarly, feedback clarity facilitates users' cognitive understanding of translation errors and corrections, thereby reinforcing their perception of the tool's value.

In addition, cognitive load reduction lowers the mental effort required during translation tasks, which contributes to the perception that the system is easy to use. By incorporating these cognitive mechanisms, the TAM-AI model moves beyond a purely additive structure and provides a process-oriented explanation of technology acceptance.

Furthermore, to validate the theoretical contribution of the proposed model, this study compares TAM-AI with the baseline TAM to assess its incremental explanatory power.

3.3. Research Hypotheses

Based on the TAM-AI model, the following hypotheses are proposed to examine the factors influencing students' acceptance of AI-assisted translation tools.

PU, PEOU, and BI relationships

H1: Perceived usefulness (PU) of AI-assisted translation tools will have a significant positive effect on students' behavioral intention (BI) to use these tools.

H2: Perceived ease of use (PEOU) of AI-assisted translation tools will have a significant positive effect on students' behavioral intention (BI) to use these tools.

Mechanism-based relationships

H3: Perceived translation quality (PTQ) positively influences trust in AI-assisted translation tools.

H4: Trust in AI-assisted translation tools positively influences perceived usefulness (PU).

H5: Feedback clarity (FC) positively influences students' cognitive understanding of translation processes.

H6: Cognitive understanding positively influences perceived usefulness (PU).

H7: Cognitive load reduction (CLR) positively influences perceived effort reduction.

H8: Effort reduction positively influences perceived ease of use (PEOU).

Individual characteristics

H9: Prior experience with AI tools positively influences perceived usefulness (PU) and perceived ease of use (PEOU).

H10: Translation proficiency positively influences perceived usefulness (PU) and behavioral intention (BI).

H11: Learning preferences aligned with technology-based learning positively influence behavioral intention (BI).

These hypotheses aim to examine not only the direct effects of TAM constructs, but also the underlying cognitive mechanisms through which AI-related perceptions influence students' acceptance of AI-assisted translation tools.

4. Methodology

These factors include both the core constructs of the Technology Acceptance Model (TAM), namely perceived usefulness (PU) and perceived ease of use (PEOU), as well as AI-specific variables such as feedback clarity (FC), perceived translation quality (PTQ), and cognitive load reduction (CLR).

Importantly, the study also incorporates mediating constructs—trust in AI-assisted translation tools (TR), cognitive understanding (CU), and effort reduction (ER)—to capture the underlying cognitive mechanisms through which AI-specific perceptions influence technology acceptance.

To assess the incremental explanatory power of the proposed TAM-AI model, a baseline TAM model including only perceived usefulness and perceived ease of use was estimated. The results were compared in terms of explained variance (R^2) and model fit indices to determine whether TAM-AI provides superior explanatory power.

4.1. Research Design

This study adopted a quantitative research design using a cross-sectional survey to assess students' acceptance of AI-assisted translation tools. The research focused on measuring students' behavioral intention (BI) to use AI tools for translation learning and aimed to identify the factors influencing their acceptance.

These factors include both the core constructs of the Technology Acceptance Model (TAM), namely perceived usefulness (PU) and perceived ease of use (PEOU), as well as AI-specific variables such as feedback clarity (FC), perceived translation quality (PTQ), and cognitive load reduction (CLR).

Importantly, the study also incorporates mediating constructs—trust in AI-assisted translation tools (TR), cognitive understanding (CU), and effort reduction (ER)—to capture the underlying cognitive mechanisms through which AI-specific perceptions influence technology acceptance.

4.2. Participants

The participants were 120 undergraduate translation students enrolled in translation-related programs, and the data were collected from undergraduate students at Shandong Jiaotong University in China. All participants had at least some prior exposure to AI-powered translation tools, while 33.3% reported frequent or multi-tool usage experience.

In addition to AI tool experience, demographic information was collected to assess individual characteristics such as translation proficiency, which was operationalized using students' self-reported academic performance in translation-related courses and categorized as Top 10%, Top 11–30%, Middle 31–70%, and Bottom 30%, prior exposure to AI technology (measured by how often students have used AI tools), and learning preferences (e.g., preference for interactive feedback or autonomous learning). This allowed for subgroup analysis to examine how these characteristics influence students' acceptance of AI-assisted translation tools. The demographic characteristics of the participants are summarized in Table 1.

Table 1. Demographic information of participants.

Demographic Profile	Classification	Number	Percent
Grade	Junior 1	29	24.17%
	Junior 2	30	25%
	Junior 3	31	25.83%
	Junior 4	30	25%
Frequent or Multi-Tool Experience	AI Google Translate, DeepL, Grammarly	40	33.3%
Translation Proficiency	Self-reported translation performance categories	120	100%
Prior Exposure to AI Technology	Frequency of AI tool usage	56	46.7%
Learning Preferences	Interactive feedback, autonomous learning	60	50%

4.3. Instruments

A structured self-report questionnaire was used to collect data from participants. The questionnaire included items designed to measure the core constructs of the TAM, namely PU, PEOU, and BI.

In addition, the questionnaire incorporated translation-specific variables, including FC, PTQ, and CLR.

To capture the underlying cognitive mechanisms proposed in the TAM-AI model, three additional constructs were included: trust in AI-assisted translation tools, CU, and ER. These constructs were designed to reflect the mediating processes through which AI-specific perceptions influence students' acceptance of AI-assisted translation tools.

All items were measured using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The measurement items were adapted from prior TAM and AI acceptance studies and refined to fit the context of AI-assisted translation learning.

The complete questionnaire is provided in Appendix A.

4.4. Data Collection and Procedure

The data were collected through the Google Forms online survey platform, and the key characteristics of the data collection process are summarized in Table 2. Participants received an invitation to complete the survey, along with an explanation of the study's purpose, ethical considerations, and instructions for completing the questionnaire. The survey took approximately 15–20 minutes to complete, and students were informed that participation is voluntary and anonymous.

The survey was distributed to students via email or online learning platforms, ensuring that it reached the intended participants. The data collection period lasted two weeks, allowing sufficient time for participants to respond. After the completion of the survey, responses were collected, anonymized, and stored securely for analysis.

Table 2. Data collection.

Data Collection Characteristics	Information
Platform	Online survey platform (Google Forms)
Survey Duration	15–20 minutes to complete
Survey Distribution	Distributed via email or online learning platforms
Data Collection Period	Two weeks
Data Handling	Responses were anonymized and securely stored for analysis

4.5. Data Analysis

The data were analyzed using Structural Equation Modeling (SEM) with AMOS software⁵. The analysis consisted of two main stages: assessment of the measurement model and evaluation of the structural model.

First, Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and validity of the measurement model. Convergent validity was evaluated using factor loadings, composite reliability (CR), and average variance extracted (AVE). Discriminant validity was assessed using the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT).

Second, the structural model was examined to test the hypothesized relationships among constructs. Path coefficients, significance levels, and coefficients of determination (R^2) were reported.

To examine the mediating effects proposed in the TAM-AI model, bootstrapping with 5000 resamples was employed to estimate indirect effects and their confidence intervals.

Finally, to evaluate the incremental explanatory power of the proposed TAM-AI model, a baseline TAM model including only PU and PEOU was estimated and compared with the TAM-AI model in terms of explained variance (R^2) and model fit indices.

⁵ IBM SPSS AMOS software, available at: <https://www.ibm.com/products/structural-equation-modeling-sem>

To assess potential common method bias, Harman's single-factor test was conducted. The results showed that the first factor accounted for less than 50% of the total variance, indicating that common method bias was unlikely to be a serious concern. The main data analysis procedures and statistical techniques used in this study are summarized in Table 3.

Table 3. Data analysis.

Data Analysis Characteristics	Details
Analysis Method	SEM
Key Constructs Tested	PU, PEOU, FC, PTQ, CLR, TR, CU, ER, BI
Subgroup Analysis	Individual characteristics and exploratory subgroup differences
Software Used	SPSS AMOS

4.6. Ethical Considerations

This study adhered to ethical standards regarding participant rights, informed consent, and confidentiality. Informed consent was obtained from all participants prior to their participation in the study. They were informed about the study's purpose, the voluntary nature of their participation, and the confidentiality of their responses.

All data were anonymized to ensure that participants' identities were protected. The responses were stored securely and were only used for research purposes. This study was reviewed and approved by the Ethics Committee of Shandong Jiaotong University prior to data collection. All participants provided informed consent, and their responses were collected anonymously. All procedures performed in this study were in accordance with institutional ethical standards.

5. Results

5.1. Measurement Model

Confirmatory Factor Analysis (CFA) was conducted to evaluate the measurement model. The results indicate that all constructs demonstrate satisfactory reliability and validity.

Convergent validity was confirmed as all factor loadings exceeded 0.70, composite reliability (CR) values were above 0.70, and average variance extracted (AVE) values exceeded the recommended threshold of 0.50.

Discriminant validity was assessed using both the Fornell–Larcker criterion and the HTMT ratio. The square root of AVE for each construct was greater than its correlations with other constructs, and all HTMT values were below the threshold of 0.85, indicating adequate discriminant validity.

These results suggest that the measurement model is reliable and valid. The detailed results are presented in Table 4. All factor loadings exceeded 0.70. Composite reliability

(CR) values ranged from 0.84 to 0.89, and AVE values exceeded 0.50. HTMT values were below 0.85, indicating satisfactory discriminant validity.

Table 4. Measurement model results.

Construct	Loading Range	CR	AVE	HTMT (max)
PU	0.74–0.86	0.86	0.68	0.78
PEOU	0.72–0.84	0.84	0.64	0.80
PTQ	0.71–0.85	0.85	0.66	0.76
FC	0.73–0.87	0.86	0.67	0.79
CLR	0.75–0.88	0.87	0.69	0.77
TR	0.76–0.89	0.88	0.71	0.74
CU	0.74–0.86	0.86	0.68	0.76
ER	0.73–0.85	0.85	0.66	0.78
BI	0.78–0.90	0.89	0.73	—

Note 1. Discriminant validity was assessed using the Fornell–Larcker criterion and inter-construct correlations.

Note 2. AVE > 0.50 and CR > 0.70 indicate acceptable convergent validity and reliability [10].

5.2. Structural Model (H1–H8)

Following the validation of the measurement model, the SEM was conducted to test the relationships between the key constructs in the TAM-AI model. The results of the structural model and hypothesis testing are summarized in Table 5.

The structural model demonstrated a good fit to the data (CFI = 0.95, TLI = 0.93, RMSEA = 0.048).

Perceived usefulness (PU) had a significant positive effect on behavioral intention (BI) ($\beta = 0.41$, $p < 0.001$), supporting H1. Perceived ease of use (PEOU) also positively influenced BI ($\beta = 0.29$, $p < 0.01$), supporting H2.

Perceived translation quality (PTQ) significantly influenced trust ($\beta = 0.52$, $p < 0.001$), supporting H3. Trust, in turn, had a significant effect on perceived usefulness ($\beta = 0.36$, $p < 0.001$), supporting H4.

Feedback clarity (FC) positively affected cognitive understanding ($\beta = 0.48$, $p < 0.001$), supporting H5. Cognitive understanding significantly influenced perceived usefulness ($\beta = 0.33$, $p < 0.01$), supporting H6.

Cognitive load reduction (CLR) significantly influenced effort reduction ($\beta = 0.50$, $p < 0.001$), supporting H7. Effort reduction significantly affected perceived ease of use (PEOU) ($\beta = 0.35$, $p < 0.01$), supporting H8.

The model explained 58% of the variance in BI ($R^2 = 0.58$).

These results provide strong evidence that PU and PEOU are critical factors in determining students' BI to use AI-assisted translation tools.

Table 5. Hypothesis testing.

Hypothesis	Path	Standardized Coefficient (β)	p -value	Result
H1	PU $\rightarrow$ BI	0.41	< 0.001	Supported
H2	PEOU $\rightarrow$ BI	0.29	< 0.01	Supported
H3	PTQ $\rightarrow$ TR	0.52	< 0.001	Supported
H4	TR $\rightarrow$ PU	0.36	< 0.001	Supported
H5	FC $\rightarrow$ CU	0.48	< 0.001	Supported
H6	CU $\rightarrow$ PU	0.33	< 0.01	Supported
H7	CLR $\rightarrow$ ER	0.50	< 0.001	Supported
H8	ER $\rightarrow$ PEOU	0.35	< 0.01	Supported

5.3. Additional Hypothesis Testing Results (H9–H11)

Bootstrapping analysis (5000 resamples) was conducted to examine the mediating effects proposed in the mechanism-based TAM-AI model. The results showed that trust significantly mediated the relationship between PTQ and PU (indirect effect $\beta = 0.19$, 95% CI [0.11, 0.28]). Cognitive understanding significantly mediated the relationship between FC and PU ($\beta = 0.16$, 95% CI [0.08, 0.24]). Effort reduction significantly mediated the relationship between CLR and PEOU ($\beta = 0.18$, 95% CI [0.10, 0.27]). These results support the mechanism-based structure of the TAM-AI model.

In addition, further analyses were conducted to test hypotheses H9–H11 concerning individual characteristics. Specifically, prior AI tool experience significantly influenced PU and PEOU, translation proficiency significantly influenced PU and BI, and learning preferences significantly influenced BI. The results of these additional hypothesis tests are summarized in Table 6.

Table 6. Additional hypothesis testing results (H9–H11).

Hypothesis	Path Coefficient (β)	p -value	Result
H9a: Prior AI Tool Experience $\rightarrow$ PU	0.34	< 0.001	Supported
H9b: Prior AI Tool Experience $\rightarrow$ PEOU	0.29	< 0.01	Supported
H10a: Translation Proficiency $\rightarrow$ PU	0.31	< 0.01	Supported
H10b: Translation Proficiency $\rightarrow$ BI	0.26	< 0.05	Supported
H11: Learning Preferences $\rightarrow$ BI	0.28	< 0.01	Supported

5.4. Subgroup Analysis

It should be noted that the coefficients reported in the subgroup analysis differ from those in the main structural model, as they are derived from separate analyses. The coefficients reported in Table 6 represent the additional hypothesis testing results for H9–H11, whereas the subgroup coefficients reported below reflect variations across specific participant groups and are therefore not directly comparable.

Subgroup analysis was performed to examine the effect of individual student characteristics, such as AI tool experience, translation proficiency, and learning preferences, on their BI to use AI-assisted translation tools. The results are summarized below.

– AI Tool Experience:

Students with prior experience using AI translation tools (e.g., Google Translate, DeepL) reported higher levels of PU ($\beta = 0.40$, $p < 0.01$) and PEOU ($\beta = 0.35$, $p < 0.01$) compared to students with little or no prior experience. They also showed a higher BI to use these tools.

– Translation Proficiency:

Students with higher translation proficiency demonstrated a stronger perception of PTQ ($\beta = 0.30$, $p < 0.05$) and were more likely to use AI-assisted translation tools to aid in their translation work. These results indicate differences across proficiency levels rather than statistically tested moderation effects.

– Learning Preferences:

Students who preferred interactive feedback and autonomous learning had higher BI to use AI tools ($\beta = 0.33$, $p < 0.01$). These students valued tools that provided personalized feedback and allowed them to take ownership of their learning process.

5.5. Qualitative Findings

In addition to the quantitative survey, open-ended responses were collected from participants to capture their personal experiences and insights regarding AI translation tools. A total of 120 valid qualitative responses were analyzed using thematic analysis. Two researchers independently coded the data, and discrepancies were resolved through discussion to ensure consistency. A thematic analysis of these responses revealed several key themes:

- Tool Usability: Students emphasized the importance of ease of use, with many expressing satisfaction with tools like Google Translate and DeepL due to their user-friendly interfaces. However, some students with more advanced translation experience mentioned the need for tools with more advanced features like contextual translation.
- Feedback and Improvement: Many students reported that real-time feedback helped them improve their translations. Tools that provided detailed explanations of corrections were especially appreciated by students who valued self-directed learning.
- Translation Quality Concerns: A significant portion of students expressed concerns about the accuracy of AI translations. They often felt that the tools were not sufficiently accurate for context-sensitive translations, especially in specialized fields such as legal or medical translation. One student noted, “AI tools are helpful, but sometimes they fail to capture the exact meaning in specialized contexts.”

These qualitative findings further support the quantitative results and provide deeper insights into the factors that influence students’ acceptance and use of AI translation tools.

5.6. Robustness Checks

To ensure the robustness of the findings, several additional tests were conducted. First, a baseline TAM model including only perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI) was estimated and compared with the proposed TAM-AI model. The TAM-AI model demonstrated higher explanatory power and improved model fit indices.

Second, alternative structural specifications excluding the mediating constructs were tested. The results showed a reduction in explanatory power, supporting the importance of the proposed cognitive mechanisms.

Specifically, the alternative models excluded the mediating constructs (TR, CU, and ER) and directly linked translation-specific variables to PU and PEOU, representing an additive specification. Compared with these alternative models, the proposed mechanism-based TAM-AI model demonstrated stronger explanatory power and better model fit. This supports the theoretical importance of the mediating mechanisms and suggests that the findings are not merely a result of adding more predictors to the baseline TAM.

5.7. Summary of Results

The results of this study confirm that perceived usefulness (PU) and perceived ease of use (PEOU) are significant predictors of students' behavioral intention (BI) to use AI-assisted translation tools.

More importantly, the findings demonstrate that translation-specific perceptions influence students' acceptance of AI tools indirectly through cognitive mechanisms. Specifically, perceived translation quality operates through trust, feedback clarity operates through cognitive understanding, and cognitive load reduction operates through effort reduction.

These results provide strong support for the mechanism-based TAM-AI model and highlight the importance of cognitive processes in shaping technology acceptance in AI-assisted translation learning. Regarding RQ1, the results indicate that both TAM constructs and translation-specific factors influence students' acceptance of AI-assisted translation tools, either directly or indirectly through cognitive mechanisms. Regarding RQ2, the TAM-AI model demonstrates greater explanatory power than the baseline TAM model in explaining students' behavioral intention.

6. Discussion

6.1. Interpretation of Key Findings

Building on the empirical results reported in Section 5, this study provides a mechanism-based interpretation of students' acceptance of AI-assisted translation tools. This mechanism-based perspective offers a more theoretically grounded explanation of technology acceptance in AI-assisted learning environments and advances TAM research by shifting from variable inclusion to process explanation.

First, the results confirm that perceived usefulness (PU) and perceived ease of use (PEOU) remain the key determinants of students' behavioral intention (BI), which is consistent with the core assumptions of the Technology Acceptance Model (TAM). This

finding reinforces the continued relevance of TAM in explaining technology adoption in AI-supported learning environments.

More importantly, the findings reveal that translation-specific factors influence technology acceptance through underlying cognitive mechanisms rather than through direct effects. Specifically, perceived translation quality (PTQ) affects perceived usefulness indirectly through trust in AI-assisted translation tools. This suggests that students' evaluation of AI-generated translations depends not only on output quality but also on their confidence in the reliability of the system.

Similarly, feedback clarity (FC) influences perceived usefulness through cognitive understanding. Clear and interpretable feedback enables students to better understand translation errors and revision strategies, which enhances their perception of the tool's usefulness. This finding highlights the importance of cognitive processing in AI-assisted learning environments.

In addition, cognitive load reduction (CLR) affects perceived ease of use through effort reduction. When AI tools reduce the mental effort required for translation tasks, students are more likely to perceive these tools as easy to use.

Overall, these findings support the mechanism-based extension of TAM proposed in this study, demonstrating that AI-specific perceptions shape technology acceptance through cognitive and evaluative processes rather than through direct relationships. These findings are consistent with recent studies on AI-assisted learning and technology acceptance, which highlight the importance of trust, cognitive mechanisms, and contextual factors in shaping users' behavioral intentions [7,13,16].

6.2. Theoretical Contributions

This study contributes to the TAM literature by proposing a mechanism-based extension of the Technology Acceptance Model in the context of AI-assisted translation learning. This aligns with recent efforts to extend TAM in AI-driven learning environments by incorporating cognitive and affective mechanisms [20].

Unlike prior TAM-based studies that primarily adopt an additive approach by introducing external variables as direct predictors, this study explains how AI-specific perceptions influence technology acceptance through underlying cognitive mechanisms, including trust, cognitive understanding, and effort reduction. This mechanism-based perspective provides a deeper and more process-oriented explanation of technology acceptance.

Furthermore, this study empirically demonstrates that the TAM-AI model provides greater explanatory power than the baseline TAM model. By incorporating cognitive mechanisms, the proposed model better captures the complexity of students' interactions with AI-assisted translation tools.

In addition, this study extends TAM to a domain-specific context—translation learning—where cognitive processing and feedback interpretation play a critical role. This contributes to the growing body of research on AI-assisted learning and highlights the importance of adapting technology acceptance models to specific learning environments. The findings contribute to AI acceptance research by demonstrating that domain-specific perceptions influence behavioral intention through identifiable cognitive mechanisms rather than direct effects alone.

6.3. Practical Implications

The findings from this study have several practical implications for the design and implementation of AI-assisted translation tools. First, the significant impact of PU and PEOU suggests that AI translation tools must prioritize usability and utility. Developers should focus on creating tools that are not only user-friendly but also provide value in enhancing students' translation skills. Clear, context-aware feedback and accurate translations should be central to the design process.

The study also underscores the importance of aligning AI tools with students' learning preferences. Students who prefer interactive feedback and autonomous learning reported higher BI, suggesting that tools incorporating these features will have greater success in engaging users. Educational practitioners should consider these preferences when integrating AI tools into translation curricula to ensure greater adoption and effectiveness.

Furthermore, since prior AI tool experience and translation proficiency were significant factors in tool adoption, it is crucial for educators to provide targeted support to students with limited experience using AI tools. Offering training sessions or introductory workshops on how to effectively use these tools may help increase their acceptance and encourage more widespread usage.

6.4. Limitations

While this study provides valuable insights, there are several limitations that should be considered. First, the sample consisted of undergraduate translation students from a single institution, which may limit the generalizability of the findings. The results may not be applicable to students from other academic backgrounds or institutions. Future studies could expand the sample to include a broader range of students from different universities or countries, which would enhance the external validity of the findings.

Second, the study relied on self-reported data, which can be subject to response biases. Students may have provided socially desirable answers, especially when reporting their AI tool usage or translation proficiency. Future research could incorporate objective measures, such as system-generated usage logs (e.g., frequency and duration of AI tool use), performance-based translation assessments evaluated by instructors or experts, or automated translation quality indicators, to reduce the risk of bias and provide a more accurate assessment of students' engagement with AI tools.

Lastly, this study focused exclusively on AI-assisted translation tools, and its findings may not be directly applicable to other types of AI tools in education. Future research could explore the application of the TAM-AI model in other educational contexts, such as AI-powered language learning tools or AI-driven tutoring systems, to examine the broader applicability of the model.

Although the sample size ($N = 120$) satisfied commonly accepted minimum requirements for covariance-based SEM and yielded stable model estimates, the relatively modest sample may still limit the generalizability of the findings. Future research should validate the proposed TAM-AI model using larger and more diverse samples across different universities, disciplines, and educational settings. Such efforts would help further examine the robustness and broader applicability of the model.

6.5. Future Research Directions

This study opens several avenues for future research. First, it would be valuable to explore the long-term effects of using AI translation tools on students' learning outcomes. Longitudinal studies could track changes in students' PU, PEOU, and BI over time, and assess how these factors impact students' translation proficiency and engagement with AI tools in the long run.

Second, research could investigate cross-cultural differences in the acceptance of AI tools. Students from different cultural backgrounds may have different attitudes towards technology and education, which could affect their willingness to adopt AI-assisted translation tools. Future studies could compare students' perceptions and behavioral intentions in different cultural contexts to better understand how cultural factors influence technology acceptance.

Finally, future research could examine the impact of AI translation tools on professional translators. While this study focused on students, it would be insightful to explore how AI tools affect the workflow of professional translators, particularly with regard to efficiency and quality of translation. Understanding how AI tools are integrated into professional practices could provide valuable insights for the design of future tools aimed at both learners and professionals.

7. Conclusion

This study provides a comprehensive examination of students' acceptance of AI-assisted translation tools by proposing a mechanism-based extension of the Technology Acceptance Model (TAM-AI).

The findings indicate that students' behavioral intention to use AI-assisted translation tools is primarily driven by perceived usefulness and perceived ease of use. More importantly, the study demonstrates that translation-specific perceptions influence technology acceptance indirectly through cognitive mechanisms, including trust in AI tools, cognitive understanding of feedback, and effort reduction during translation tasks.

By incorporating these mechanisms, the TAM-AI model offers a more nuanced and process-oriented understanding of how students evaluate and adopt AI-assisted translation tools. This highlights the importance of considering cognitive and evaluative processes in modeling technology acceptance in AI-supported learning environments.

The study provides practical insights for the design of AI-assisted translation tools, emphasizing the need to enhance trust, improve feedback clarity, and reduce cognitive effort. Future research can further explore the applicability of the TAM-AI model in other AI-supported educational contexts and investigate its long-term impact on learning outcomes.

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Appendix

A. Questionnaire

Instructions

This questionnaire aims to examine students' acceptance of AI-assisted translation tools used for translation learning. Please answer all questions based on your actual experience with AI-assisted translation tools (e.g., Google Translate, DeepL, Grammarly).

All items in Sections C–K are measured on a 5-point Likert scale:

1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree.

Participation is voluntary and anonymous. All responses will be used for research purposes only.

Section A. Demographic Information

A1. Grade

- ☐ Junior 1
- ☐ Junior 2
- ☐ Junior 3
- ☐ Junior 4

A2. Major / Program

- ☐ Translation
- ☐ English
- ☐ Other: _____

Section B. Background Information

Prior AI Tool Experience

B1. Which AI-assisted translation tools have you used? (Multiple choice)

- ☐ Google Translate
- ☐ DeepL
- ☐ Grammarly
- ☐ Other AI-based tools (e.g., ChatGPT): _____

B2. How often do you use AI-assisted translation tools for translation-related tasks?

- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Very often

Translation Proficiency

B3. How would you describe your academic performance in translation-related courses?

- ☐ Top 10%
- ☐ Top 11–30%
- ☐ Middle 31–70%
- ☐ Bottom 30%

Learning Preferences

B4. I prefer learning activities that involve technology-supported interaction and feedback.

B5. I prefer autonomous learning environments where I can control my learning pace.

B6. I feel comfortable learning with digital tools rather than only traditional materials.

Section C. Perceived Usefulness (PU)

PU1. Using AI-assisted translation tools improves my performance in translation learning.

PU2. AI-assisted translation tools help me complete translation tasks more efficiently.

PU3. AI-assisted translation tools enhance the overall effectiveness of my translation learning.

Section D. Perceived Ease of Use (PEOU)

PEOU1. Learning to use AI-assisted translation tools is easy for me.

PEOU2. I find AI-assisted translation tools easy to use for translation tasks.

PEOU3. Using AI-assisted translation tools does not require much mental effort.

Section E. Feedback Clarity (FC)

FC1. The feedback provided by AI-assisted translation tools is clear and easy to understand.

FC2. The feedback clearly indicates what aspects of my translation need improvement.

FC3. The feedback helps me understand how to revise or refine my translation.

Section F. Perceived Translation Quality (PTQ)

PTQ1. The translations generated by AI-assisted translation tools are generally accurate.

PTQ2. The translations produced by AI-assisted translation tools are reliable across different texts.

PTQ3. The translations are appropriate in meaning and wording.

Section G. Cognitive Load Reduction (CLR)

CLR1. Using AI-assisted translation tools reduces the mental effort required for translation tasks.

CLR2. AI-assisted translation tools help me handle complex translation tasks with less cognitive strain.

CLR3. Using AI-assisted translation tools makes translation learning mentally easier.

Section H. Trust in AI-Assisted Translation Tools (TR)

TR1. I trust the translations generated by AI-assisted translation tools.

TR2. AI-assisted translation tools provide reliable translation outputs.

TR3. I feel confident relying on AI-assisted translation tools during translation learning.

Section I. Cognitive Understanding (CU)

CU1. The feedback provided by AI-assisted translation tools helps me better understand my translation errors.

CU2. AI-assisted translation tools improve my understanding of how to revise and refine translations.

CU3. By using AI-assisted translation tools, I gain a clearer understanding of the translation process.

Section J. Effort Reduction (ER)

ER1. AI-assisted translation tools reduce the amount of effort I need to complete translation tasks.

ER2. Using AI-assisted translation tools makes translation tasks less demanding for me.

ER3. AI-assisted translation tools simplify the process of completing translation work.

Section K. Behavioral Intention (BI)

BI1. I intend to continue using AI-assisted translation tools for translation learning.

BI2. I plan to use AI-assisted translation tools frequently in the future.

BI3. I am willing to recommend AI-assisted translation tools to others for translation learning.

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