Korean Journal of English Language and Linguistics, **Vol 26, March 2026, pp. 486-508**
DOI: 10.15738/kjell.26..202603.486

KOREAN JOURNAL OF ENGLISH LANGUAGE AND LINGUISTICS

ISSN: 1598-1398 / e-ISSN 2586-7474

http://journal.kasell.or.kr

Exploring Vietnamese English Majors' Acceptance and Use of Generative AI in a Basic Translation Course

Bao Dinh Lu & Hung Dieu Luu (Ho Chi Minh City Open University)

Received: January 19, 2026
Revised: February 20, 2026
Accepted: March 9, 2026

Lu, Bao Dinh (First author, Corresponding author)
Lecturer, Faculty of Foreign Languages
Ho Chi Minh City Open University
35-37 Ho Hao Hon Street, Cau Ong Lanh Ward
Ho Chi Minh City, Vietnam
Tel: +84-28-3838-6606
Email: bao.ld@ou.edu.vn

Luu, Hung Dieu (Second author)
Student, Faculty of Foreign Languages
Ho Chi Minh City Open University
Email: 2157013035hung@ou.edu.vn

ABSTRACT

Lu, Bao Dinh and Hung Dieu Luu. 2026. Exploring Vietnamese English majors' acceptance and use of generative AI in a basic translation course. *Korean Journal of English Language and Linguistics 26*, 486-508.

The rise of generative AI (GenAI) has disrupted traditional product-oriented translation pedagogy in EFL contexts such as Vietnam, yet despite students' widespread use of GenAI tools, few studies have examined what shapes their acceptance and use in translation learning. Existing AI research has largely used conventional technology acceptance models that overlook GenAI's unique traits. To address this, this study adopts the recently developed AI Device Use Acceptance (AIDUA) model, which provides a three-phase appraisal framework for evaluating AI acceptance. This sequential explanatory mixed-method study examined GenAI acceptance and use among 362 English-major undergraduates in a basic translation course at a private Vietnamese university. Using AIDUA-based questionnaires and semi-structured interviews, the study found a high level of GenAI acceptance. Novelty value and perceived humanness of GenAI influenced both performance expectancy (PE) and effort expectancy, while hedonic motivation and social influence affected only PE. PE predicted cognitive but not affective attitude, and cognitive attitude was the strongest predictor of students' willingness to accept GenAI. ChatGPT was the most frequently used tool, mainly for translation and revision, but students' intuitive use raised concerns about academic integrity and over-reliance on GenAI. The findings emphasise the need to officially integrate GenAI into translation courses and provide proper training for both students and lecturers. The study recommends customising GenAI, underpinned by parallel corpora, to mitigate hallucinated outputs. Finally, a pedagogical framework for student-GenAI cooperation is put forward, along with diversified assessments, to ensure ethical and effective AI implementation in a translation course.

KEYWORDS

Generative AI, translation learning, AIDUA, technology acceptance, EFL learners

1. Introduction

As an integral component of language education, translation is taught formally as both an academic subject and a professional skill in universities worldwide (Sofyan and Tarigan 2023). Accordingly, basic translation courses are compulsory for English-major undergraduates in many English as a Foreign Language (EFL) contexts, such as China (Song 2022), Indonesia (Sulistiyo et al. 2019), and Vietnam (Nguyen 2017). However, the recent prevalence of generative AI (GenAI) chatbots has shaken up the field of translation, posing both challenges and opportunities for translation education (Li et al. 2023). While GenAI sparks concerns about its use in teaching and learning translation among educators, students readily use this technological advancement in their translation courses (Li et al. 2023, Zhang et al. 2025).

In Vietnam, translation-interpretation is not established as a standalone Bachelor's programme but is introduced as a specialisation within undergraduate language programmes (Do 2019). Despite the growing global academic attention to GenAI, translation teaching in Vietnam remains largely traditional, emphasising product-oriented assessment (Hoang 2020, Nguyen 2017, Nguyen 2023). This situation raises ethical concerns, as students could rely on GenAI without cognitively engaging in the actual translation process, posing threats to students' translation skill development. Due to the potential benefits of AI-driven tools in language education, it is unjustifiable to ban AI in translation teaching and learning; instead, educators should make use of human-AI collaboration (Fu and Liu 2024, Zubaidi et al. 2025). Therefore, understanding students' current acceptance and use of GenAI when learning translation is essential, as the findings could inform translation pedagogy through meaningful GenAI adoption to enhance learning outcomes. It is especially critical in the Vietnamese context, where AI adoption is uneven and lacks institutional readiness, and pedagogical innovation often outpaces policy development (Nguyen and Pham 2025).

2. Literature Review

2.1 Translation Teaching and Technology

Translation is a complex process that extends beyond the simple replacement of words between the source and target languages. Effective translation teaching equips students with essential skills in analysing text types, identifying communicative goals, and selecting suitable translation strategies based on linguistic and cultural considerations (House 2023, Sofyan and Tarigan 2023). However, in many undergraduate English language programs in Vietnam, professional translation courses are still conducted using a traditional approach with a sole emphasis on product-oriented assessment. Translation classes are typically taught in a teacher-centred format. Students sit in silence and translate printed documents with limited technological assistance, while lecturers elaborate on translation methods and evaluate students' work by comparing it to available answer keys (Hoang 2020, Nguyen 2023). Such instruction provides limited opportunities for students to develop translation skills, including problem-solving, and constrains the lecturers' ability to evaluate students' development because it overlooks the assessment of students' translation process. This issue becomes more critical when students can utilise technology to outsource translation tasks, thereby meeting the lecturers' requirements.

Technological advancements have substantially influenced the field of translation education. Computer-assisted translation tools, primarily functioning as a support mechanism for translators, are widely adopted in translation classrooms and professional workplaces (House 2023, Sofyan and Tarigan 2023). Meanwhile, technologies allowing the automatic generation of translated documents pose concerns for translation teaching. The advent of machine translation (MT), however, did not pose many obstacles to the traditional, product-oriented assessment in translation courses. Early versions of MT were incapable of providing natural translation, so lecturers' concerns over academic dishonesty were limited (Li et al. 2023). In contrast, powerful GenAI tools such as ChatGPT outperform conventional MT since they can produce translations with a high level of human-likeness (Cai and Tian 2025, Gao et al. 2024), posing challenges for lecturers in verifying students' translation authorship (Li et al. 2023).

Due to the absence of institutional policies on AI usage and academic integrity in Vietnamese tertiary education, lecturers are not provided with clear guidelines or tools to determine whether students' translated products are AI-generated. As a result, traditional instruction focusing solely on end products is no longer reliable in evaluating students' learning progress. The lack of supervision of students' translation process also increases the risks of their overreliance on GenAI, leading to deficiencies in translation skills. More importantly, as AI technology uses algorithms to provide answers, its translation output may be biased or culturally insensitive (Hockly 2024), which could distort students' perception of effective translation. These concerns underline the need to examine how students accept and use GenAI in their translation course.

2.2 AI Device Use Acceptance Model

Technology acceptance refers to the willingness of users to adopt and continue utilising a specific technology (Davis 1989). According to Gursoy et al. (2019), current studies on AI acceptance mostly use expectancy-based theoretical frameworks, such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT).

In translation studies, extended TAM and UTAUT have also been adopted for the investigation of AI acceptance. Using extended TAM, Salloum et al. (2024) explored the ChatGPT acceptance of 257 students in the United Arab Emirates in translation practices, and Ren (2025) investigated the acceptance of ChatGPT in translation practice among 385 English majors across several Chinese universities. The two studies revealed a high level of acceptance of ChatGPT, with perceived usefulness being the strongest factor. However, while perceived ease of use had a significant influence in Salloum et al.'s (2024) research, Ren (2025) found that this construct was not significant, which may be because of the differences in platform accessibility. As Ren (2025) shared, since ChatGPT is restricted in mainland China, students using this tool already have some technical competence, such as using VPN access. This issue implies that usability perceptions may vary across educational contexts. Adopting an extended UTAUT model, Wang et al. (2025) examined students' acceptance of ChatGPT as a tool for translation in Hong Kong. An online questionnaire was used to collect data from 148 student-translators and 160 non-translation students. The analysed data revealed that performance expectancy was the strongest factor in acceptance. The study also found that students with less experience using ChatGPT were more likely to be influenced by social factors and facilitating conditions when adopting the tool.

Together, these studies demonstrate the dominant role of expectancy constructs in explaining AI acceptance in translation practice, with the perception of AI performance as the central factor. Although TAM and UTAUT have contributed valuable insights into users' willingness and attitudes towards AI adoption, they were initially developed for technologies earlier than AI-powered ones, and they present acceptance as a single-stage appraisal of evaluation. Consequently, researchers in these studies tend to extend the original models to accommodate the complexities of AI acceptance. However, unique characteristics of GenAI, such as human-likeness, were not specified in these models.

In contrast, the AI device use acceptance (AIDUA) model has been specifically developed to investigate the acceptance of AI technology (Gursoy et al. 2019, Ma and Huo 2023). Gursoy et al. (2019) argue that AIDUA, which evaluates the acceptance through multi-stage appraisals, can capture the complex evolution of human behavioural intentions for AI acceptance better than TAM or UTAUT, which evaluate all constructs as independent factors in a single appraisal stage. Moreover, Ma and Huo (2023) incorporate new constructs into Gursoy et al.'s AIDUA model to address frequently overlooked aspects of AI tools, including novelty value, perceived humanness and affective attitude, to further capture the unique dimensions of AI acceptance. This is especially relevant in translation studies, where students' perceptions, such as whether an AI tool is interesting, feels human-like, and evokes comfort in use, are crucial for the adoption.

Figure 1 depicts Ma and Huo's (2023, p.5) AIDUA model, comprising three stages of appraisal. The primary appraisal targets social influence (SI), hedonic motivation (HM), novelty value (NV) and perceived humanness (PH). These directly influence users' performance expectancy (PE) and effort expectancy (EE). In the secondary appraisal, PE and EE drive users' cognitive attitude (CA) and affective attitude (AA), which in turn lead to the willingness to accept (WA) or objections to the use (OU) of GenAI tools in the outcome stage.

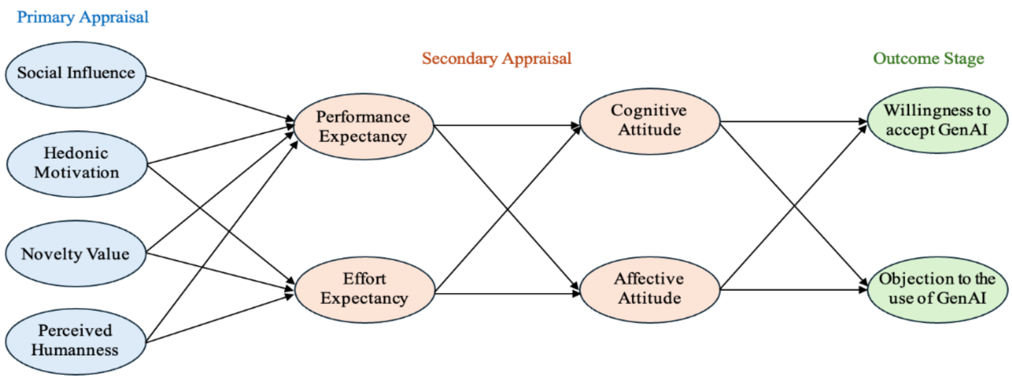

Figure 1. AIDUA Model

The AIDUA model proposed by Ma and Huo (2023) was employed as the theoretical framework for the study to capture the constantly evolving features of AI-based technologies in the context of translation education. This study aims to bridge the gap in research on GenAI acceptance by using an up-to-date framework to comprehensively describe factors influencing students' acceptance and use of available AI-powered chatbots in their translation practice.

3. Research Questions and Hypothesis Development

This study sought to answer two research questions:

1. What is the Vietnamese English-major students' acceptance of using GenAI in learning translation?
2. How do Vietnamese English-major students use GenAI in learning translation?

The hypotheses for research question 1 are presented in Figure 2.

3.1 Primary Appraisal Hypotheses

Social influence (SI) refers to the outside influences on an individual's belief in the importance of technology acceptance (Venkatesh et al. 2012). In a translation course, SI is understood as the influence of significant figures, such as lecturers and peers, on students' decisions to use GenAI chatbots. It is noted that the strength of an AI-powered chatbot lies in its ability to generate translations with high accuracy (Cai and Tian 2025, Gao et al. 2024). Accordingly, peer and instructor recommendations about the performance of GenAI tools may significantly influence students' acceptance. Hence, the hypothesis is presented as follows:

H1. Social influence positively influences students' performance expectancy of GenAI.

Hedonic motivation (HM) is described as the pleasure or enjoyment individuals experience when utilising technology (Venkatesh et al. 2012). Ma and Huo (2023) argue that when users have pleasant experiences interacting with ChatGPT, they will form favourable beliefs about its ease of use and its effectiveness in completing tasks. In an educational context, Yadegaridehkordi et al. (2025) also found significant effects of HM on academic staff's expectancies regarding ChatGPT's performance and the effort required to use it. Accordingly, in translation education, if students find using GenAI for learning translation enjoyable, they may perceive it as easy to use (effort expectancy), and it will assist them effectively during the translation process (performance expectancy). Therefore, the hypotheses were developed as follows:

H2a. Hedonic motivation positively influences students' performance expectancy of GenAI.
H2b. Hedonic motivation positively influences students' effort expectancy of GenAI.

Novelty value reflects how distinctly AI differs from existing technological advancements (Ma and Huo 2023). In translation practice, Gao et al. (2024) praise the distinct performance of ChatGPT over other translation technologies for its ability to understand the language, reason, and adjust the output through conversational prompting. Accordingly, students may find that these novel experiences with GenAI positively affect their translation performance expectancy. Moreover, the conversational prompting and follow-up interaction with GenAI could have a significant influence on effort expectancy. The hypotheses were presented as follows:

H3a. Novelty value positively influences students' performance expectancy of GenAI.
H3b. Novelty value positively influences students' effort expectancy of GenAI.

Perceived humanness refers to how AI-generated outputs and interactions resemble human-like production (Ma and Huo 2023). In translation, students perceiving GenAI's translation as close to human would have positive perceptions of its performance (Gao et al. 2024). Likewise, those who advocate for human-like responses from GenAI may perceive less effort required to interact with it (Cai and Tian 2025). The hypotheses were developed as follows:

H4a. Perceived humanness positively influences students' performance expectancy of GenAI.
H4b. Perceived humanness positively influences students' effort expectancy of GenAI.

3.2 Secondary Appraisal Hypotheses

Performance expectancy relates to how users perceive a technology can help them complete expected tasks (Venkatesh et al. 2012). Ma and Huo (2023) state that when users perceive the valuable contribution of an AI-driven tool in their work, they will highly accept it. Thus, students who recognise the usefulness of ChatGPT will have positive attitudes toward its usage. Accordingly, the hypotheses were formed as follows:

H5a. Performance expectancy positively influences students' cognitive attitudes toward GenAI.
H5b. Performance expectancy positively influences students' affective attitudes toward GenAI.

Venkatesh et al. (2012) define effort expectancy as the extent to which users perceive the ease of using a technology. Therefore, when students in a translation class find a GenAI chatbot easy to use, they also find it useful for their learning and form positive attitudes. The hypotheses are developed as follows:

H6a. Effort expectancy positively influences students' cognitive attitudes toward GenAI.
H6b. Effort expectancy positively influences students' affective attitudes toward GenAI.

3.3 Outcome Stage Hypotheses

Cognitive attitude (CA) refers to whether the use of AI tools leads to desirable outcomes, while affective attitude (AA) is formed by emotions and sentiments deriving from such experience (Ma and Huo 2023). Thus, in this study, CA captures students' evaluation of the effectiveness of GenAI chatbots in learning translation, and AA comprises the extent to which students feel satisfied or joyful with GenAI adoption. The overall attitudes towards AI-powered tools would affect users' decisions on willingness to accept GenAI or objection to the use of GenAI (Ma and Huo 2023). The hypotheses were put forward as follows:

H7a. Cognitive attitude positively influences students' willingness to accept GenAI.
H7b. Cognitive attitude negatively influences students' objections to the use of GenAI.
H8a. Affective attitude positively influences students' willingness to accept GenAI.
H8b. Affective attitude negatively influences students' objections to the use of GenAI.

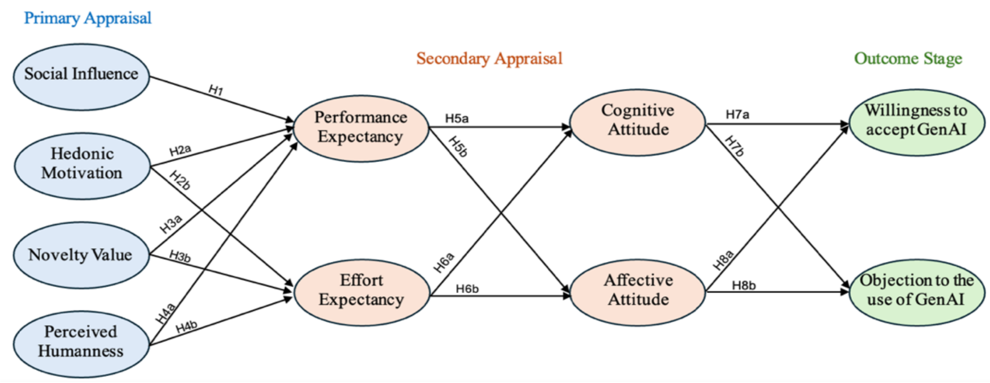

Figure 2. Hypothesis Development

4. Methodology

Given the novelty of research on GenAI acceptance in translation education, this study employed a sequential explanatory mixed-methods design to gain deeper insights from both quantitative and qualitative data (Creswell and Creswell 2022). The design involved two phases: the initial quantitative phase using a questionnaire, followed by a qualitative phase using semi-structured interviews.

4.1 Settings and Participants

The study was conducted at the Faculty of Foreign Languages at a private university in southern Vietnam. English-major undergraduates specialising in translation-interpretation take the first basic Translation Practice course in the second year of a four-year bachelor's programme. This 15-week course aims to build foundational translation skills between English and Vietnamese. The instruction includes both lectures on translation theory and hands-on practice using internal materials. Apart from a participation component (10%), students are assessed mostly through a product-oriented approach with weekly take-home assignments (30%), a midterm exam (20%) and a final exam (40%). The two exams are paper-based, requiring students to translate short passages from English to Vietnamese and vice versa.

At the time of data collection, there were no formal guidelines on GenAI adoption provided, so the use of AI depended on lecturers' decisions. The current product-based assessment and the absence of AI policies may raise concerns about academic integrity and students' cognitive engagement in the translation process.

The participants were students aged between 19 and 23 years. An invitation was sent to all students who had completed the course, resulting in 362 confirmed participants. All participants reported their use of GenAI tools during the course. Table 1 presents the demographics of participants. The percentage of male and female participants was 41.4% and 53.6%, respectively, while 5% of respondents preferred to conceal their gender identity.

Table 1. Participants

Gender	Frequency	Percentage
Male	150	41.4
Female	194	53.6
Preferred not to say	18	5.0
Total	362	100

4.2 Instruments

There are two research instruments (Appendix A): a questionnaire and a set of semi-structured interview questions presented in Table 2. The questionnaire comprises two parts with a total of 40 questions. The first part, adapted from the AIDUA model of Ma and Huo (2023), includes 38 five-point Likert scale items targeting students' acceptance of GenAI in learning translation. The second part contains two open-ended items asking about the GenAI tool used most and the types of functions used most. The interview questions, comprising 11 items, were also developed in alignment with the constructs of the questionnaire to provide more consistent results for the report.

Both instruments were sent to four experts in the field of EFL for evaluation using the item-objective congruence index. Accordingly, items with an index under 0.75 were removed to ensure content validity (Turner and Carlson 2003). As suggested by those experts, some items of the instruments were revised for wording, and the total number of items remained unchanged. To avoid unintended language barriers, the validated instruments were then translated into Vietnamese using back-translation conducted by two experienced translators. Subsequently, a pilot study was conducted before the official data collection.

Table 2. Research Instruments

	Constructs	Questionnaire	Semi-structured Interview Questions
Part 1: Students' GenAI acceptance	Social influence	Items 01 – 04	Question 01
	Hedonic motivation	Items 05 – 07	Question 02
	Novelty value	Items 08 – 11	Question 03
	Perceived humanness	Items 12 – 15	Question 04
	Performance expectancy	Items 16 – 19	Question 05
	Effort expectancy	Items 20 – 23	Question 06
	Cognitive attitude	Items 24 – 27	Question 07
	Affective attitude	Items 28 – 31	Question 08
	Willingness to accept	Items 32 – 34	Question 09
	Objection to use	Items 35 – 38	
Part 2: Students' GenAI use	The most used GenAI tool	Item 39	Question 10
	The most used functions	Item 40	Question 11

4.3 Ethical Considerations

This study complied with the ethical guidelines of the American Psychological Association (APA 2017). Participation was voluntary, and participants were informed of the study's aims, procedures and possible risks and benefits through a consent form presented in the Vietnamese language. Participants' confidentiality was assured. They hold the right to withdraw from the study at any time without consequence. The digital data was securely stored in a computer with a password, and access was restricted to the research team. The data were destroyed upon the publication of this study.

4.4 Data Collection

Quantitative data were collected through the online questionnaire administered to 362 participants via Google Forms. Based on the quantitative results, the second phase of the interview was conducted to further explain the quantitative findings. To gain insight into a group's experiences of a certain phenomenon, the interviews could range from 5 to 25 participants (Creswell and Poth 2017). Thus, five initial students were randomly selected for the interview. The process continued until data saturation was reached at the 11th student. The details of the interviewees are displayed in Table 3.

Table 3. Interviewees

Interviewee	Gender
Student 1	Male
Student 2	Male
Student 3	Female
Student 4	Female
Student 5	Male
Student 6	Female
Student 7	Female
Student 8	Male
Student 9	Female
Student 10	Male
Student 11	Female

4.5 Data Analysis

SmartPLS 3 software was utilised to analyse the quantitative data from the questionnaire. For part 1 of the questionnaire, partial least squares structural equation modelling (PLS-SEM) was used to analyse factors influencing students' acceptance of using GenAI through three appraisal stages of the AIDUA framework. The measurement model was first assessed before the evaluation of the structural model (Hair et al. 2022). Data from the second part of the questionnaire were analysed using descriptive statistics.

The interview recordings were transcribed and analysed using the thematic analysis procedure of Braun and Clarke (2006), consisting of six phases, as illustrated in Figure 3. To enhance trustworthiness, two researchers conducted the analysis independently; discrepancies in coding were reviewed and resolved to maintain consistency, as suggested by Creswell and Poth (2017). Examples of the coding process are presented in Appendix B to demonstrate the connection between interview excerpts, initial codes, subthemes, and themes.

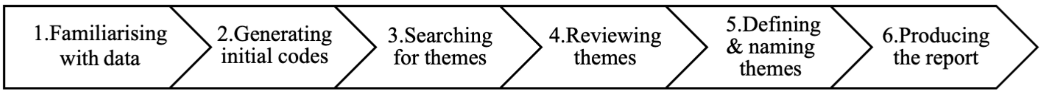

Figure 3. Braun and Clarke's (2006) Thematic Analysis Phases

5. Findings

Because of the sequence of the QUAN-qual studies, quantitative findings were presented first, followed by qualitative findings, reflecting the explanatory purpose of the design. From the qualitative data analysis, there were 43 initial data-driven codes, which were then refined into 15 subthemes and five main themes, as presented in two thematic maps in Figures 5 and 6, following Braun and Clarke's (2006) recommendations.

5.1 Students' GenAI Acceptance

5.1.1 Measurement model assessment

Firstly, the measurement model was evaluated for its internal consistency, reliability and convergent validity, and outer loadings, as displayed in Table 4. The Cronbach's alpha values for all constructs exceed 0.7, confirming acceptable internal consistency among the measurement items (Hair et al. 2022). Moreover, the composite reliability (CR) value exceeds the recommended level of 0.7, and the average variance extracted (AVE) value surpasses the threshold of 0.5, indicating satisfactory convergent validity (Hair et al. 2022). Although the recommended threshold for indicator loadings is 0.7, Hair et al. (2022) note that indicators with loadings between 0.6 and 0.7 may be acceptable provided that the constructs demonstrate adequate internal consistency reliability and convergent validity. Accordingly, items SI4 (loading = 0.696) and PE1 (loading = 0.687) were retained in the model.

Table 4. Internal Consistency, Reliability and Convergent Validity

Constructs	Items	Outer loadings	VIF	Cronbach's α	CR	AVE
Social influence (SI)	SI1	0.836	2.592	0.848	0.893	0.678
	SI2	0.896	2.565			
	SI3	0.851	2.040			
	SI4	0.696	1.927			
Hedonic motivation (HM)	HM1	0.861	2.252	0.861	0.914	0.781
	HM2	0.899	2.276			
	HM3	0.890	2.070			
Novelty value (NV)	NV1	0.771	1.658	0.800	0.870	0.625
	NV2	0.802	1.736			
	NV3	0.765	1.546			
	NV4	0.824	1.838			
Perceived humanness (PH)	PH1	0.726	1.425	0.763	0.849	0.584
	PH2	0.796	1.550			
	PH3	0.789	1.644			
	PH4	0.745	1.403			
Performance expectancy (PE)	PE1	0.687	1.451	0.768	0.853	0.593
	PE2	0.846	1.961			
	PE3	0.821	1.844			
	PE4	0.715	1.612			
Effort expectancy (EE)	EE1	0.796	1.744	0.818	0.879	0.645
	EE2	0.843	2.224			
	EE3	0.824	2.099			
	EE4	0.748	1.372			
Cognitive attitude (CA)	CA1	0.845	2.124	0.768	0.849	0.586
	CA2	0.744	2.694			
	CA3	0.733	2.770			
	CA4	0.734	2.326			
Affective attitude (AA)	AA1	0.831	1.698	0.837	0.890	0.670
	AA2	0.780	1.589			
	AA3	0.812	1.255			
	AA4	0.849	1.992			
Willingness to accept (WA)	WA1	0.882	1.946	0.880	0.926	0.807
	WA2	0.910	1.784			
	WA3	0.902	2.067			
Objection to use (OU)	OU1	0.765	1.688	0.816	0.879	0.646
	OU2	0.865	2.253			
	OU3	0.829	1.994			
	OU4	0.750	1.460			

Secondly, Hair et al. (2022) suggest assessing discriminant validity (Table 5) with the Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT). In the Fornell-Larcker criterion section, the square root of the AVE of each construct is greater than its correlations with other constructs. Also, all HTMT values in Table 5 do not cross the threshold of 0.85 as recommended by Hair et al. (2022). These conditions confirm the satisfaction of discriminant validity. Taken together, the measurement model demonstrated acceptable reliability and validity, providing an adequate condition for the subsequent evaluation of the structural model.

Table 5. Discriminant Validity

Fornell-Larcker criterion										
	SI	HM	NV	PH	PE	EE	CA	AA	WA	OU
SI	0.823									
HM	-0.082	0.884								
NV	-0.140	0.539	0.791							
PH	-0.067	0.306	0.504	0.764						
PE	0.170	0.392	0.180	0.278	0.770					
EE	-0.053	0.318	0.566	0.566	0.251	0.803				
CA	0.091	0.531	0.48	0.516	0.443	0.454	0.766			
AA	-0.050	0.222	0.497	0.567	0.184	0.451	0.404	0.819		
WA	-0.037	0.399	0.703	0.648	0.317	0.567	0.571	0.473	0.898	
OU	0.013	-0.430	-0.594	-0.526	-0.267	-0.673	-0.533	-0.455	-0.561	0.804
Heterotrait-monotrait ratio										
	SI	HM	NV	PH	PE	EE	CA	AA	WA	OU
SI										
HM	0.147									
NV	0.214	0.665								
PH	0.132	0.359	0.637							
PE	0.197	0.466	0.278	0.37						
EE	0.146	0.362	0.676	0.697	0.344					
CA	0.169	0.653	0.552	0.618	0.577	0.522				
AA	0.115	0.254	0.594	0.707	0.256	0.528	0.463			
WA	0.138	0.452	0.831	0.779	0.416	0.647	0.634	0.542		
OU	0.146	0.510	0.733	0.662	0.336	0.833	0.657	0.543	0.659	

5.1.2 Structural model assessment

Collinearity among constructs was assessed using the variance inflation factor (VIF) values. All VIF values (Table 4) were below 3.0, indicating that multicollinearity was not a concern within the model (Hair et al. 2022). Table 6 and Figure 4 present the results of the structural model test.

For the primary appraisal, social influence (SI), hedonic motivation (HM), novelty value (NV), and perceived humanness (PH) were examined for their influence on performance expectancy (PE) and effort expectancy (EE). First, SI positively affected PE ($\beta = 0.201$, $p < 0.001$), supporting H1. Next, HM exhibited positive influences on PE ($\beta = 0.406$, $p < 0.001$), while it had no significant impact on EE ($\beta = -0.001$, $p = 0.984$). Thus, H2a was supported, but H2b was rejected. NV had a negative influence on PE ($\beta = -0.127$, $p < 0.05$), so H3a was not supported because it contradicted the hypothesis. NV had a positive influence on EE ($\beta = 0.377$, $p < 0.001$), supporting H3b. Last, H4a and H4b were supported as PH was a strong predictor of both PE ($\beta = 0.231$, $p < 0.001$) and EE ($\beta = 0.376$, $p < 0.001$).

In the secondary appraisal, both PE and EE were evaluated for their influence on cognitive attitude (CA) and affective attitude (AA). PE significantly predicted CA ($\beta = 0.351$, $p < 0.001$), but did not significantly influence AA ($\beta = 0.075$, $p = 0.178$), supporting H5a and rejecting H5b, respectively. Conversely, EE had a significant effect on CA ($\beta = 0.366$, $p < 0.001$) and AA ($\beta = 0.432$, $p < 0.001$), supporting H6a and H6b.

As for the outcome stage, both CA and AA significantly predicted the willingness to accept GenAI (WA) and objection to the use of GenAI (OU). CA had a strong positive effect on WA ($\beta = 0.454$, $p < 0.001$) and a strong negative effect on OU ($\beta = -0.418$, $p < 0.001$); thus, H7a and H7b were supported. Similarly, AA positively influenced WA ($\beta = 0.289$, $p < 0.001$) and negatively influenced OU ($\beta = -0.286$, $p < 0.001$), supporting H8a and H8b.

Table 6. Hypothesis Testing

	Hypothesis	Path	Coefficients (β)	*Standard Error*	*t*-value	*p*-value	Result
Primary appraisal	H1	SI→PE	0.201	0.047	4.256	0.000	supported
	H2a	HM→PE	0.406	0.055	7.431	0.000	supported
	H2b	HM→EE	-0.001	0.042	0.020	0.984	*rejected*
	H3a	NV→PE	-0.127	0.055	2.330	0.020	*rejected*
	H3b	NV→EE	0.377	0.062	6.082	0.000	supported
	H4a	PH→PE	0.231	0.044	5.288	0.000	supported
	H4b	PH→EE	0.376	0.047	7.935	0.000	supported
Secondary appraisal	H5a	PE→CA	0.351	0.050	6.946	0.000	supported
	H5b	PE→AA	0.075	0.056	1.348	0.178	*rejected*
	H6a	EE→CA	0.366	0.044	8.364	0.000	supported
	H6b	EE→AA	0.432	0.050	8.695	0.000	supported
Outcome stage	H7a	CA→WA	0.454	0.061	7.407	0.000	supported
	H7b	CA→OU	-0.418	0.048	8.664	0.000	supported
	H8a	AA→ WA	0.289	0.067	4.304	0.000	supported
	H8b	AA→OU	-0.286	0.052	5.462	0.000	supported

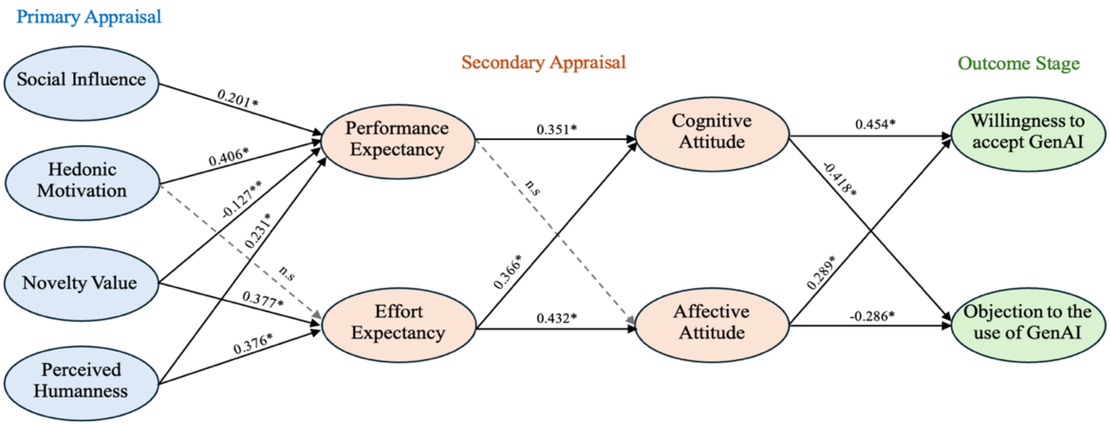

Figure 4. Results of Structural Model Assessment

Note. ** $p < 0.05$, * $p < 0.001$, n.s: not significant.

5.1.3 Factors shaping students' GenAI acceptance

Figure 5 displays a thematic map illustrating key factors shaping students' acceptance of GenAI from interview data. There are three main themes: lecturers as key drivers, efficiency–quality trade-offs, and ethical and dependency concerns.

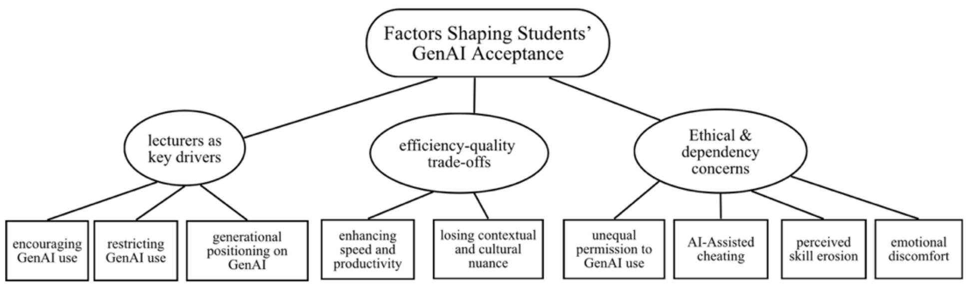

Figure 5. Factors Shaping Students' GenAI Acceptance

5.1.3.1 Lecturers as key drivers of GenAI adoption

All interviewed students agreed that, apart from their peers, the approval of lecturers in the translation course was the most influential factor in their adoption of GenAI when learning translation. However, this adoption was not always welcomed by all lecturers, as three interviewees noted that their senior lecturers tended to distance students from GenAI use. These views were shared as follows:

> *"Many lecturers encouraged us to use GenAI for translation because it's such a handy tool. But a few of the seniors, like my lecturer, were on the opposite side. So, I could only use it outside the classroom."* (Student 6)

> *"I found that young lecturers would welcome GenAI more than senior lecturers. My lecturer was young, so he was ok with the GenAI in his class, but I was not clear about the dos and the don'ts with an AI tool when learning translation."* (Student 2)

5.1.3.2 Efficiency-quality trade-offs

The interviewed students perceived GenAI usage as a new experience with rapid translation capabilities. Thus, they expressed strong agreement on the enhanced productivity.

> *"Since no person can translate a two-page document in a few seconds, GenAI definitely received ten marks for its speed. It greatly helped me in finishing my translation assignments."* (Student 8)

More importantly, 8 of the 11 interviewees highlighted the limitations of GenAI outputs. They noticed a lack of content retention and contextual sensitivity in AI-generated documents when it came to long texts and cultural topics.

> *"I found that the translation of GenAI was not so good when I put a long document into it. Sometimes, it ignored several sentences in the middle of the text."* (Student 11)

> *"Sometimes GenAI didn't quite meet my expectations, especially when it was translating content about culture. Compared to a human translator, the results often felt a bit robotic and didn't always flow smoothly."* (Student 1)

5.1.3.3 Ethical and dependency concerns

The qualitative data revealed a range of ethical and emotional concerns about the use of GenAI in learning translation. Three interviewees whose lecturers banned the use of GenAI raised concerns about fairness regarding traditional product-based assessments.

> *"If I hadn't used GenAI as my lecturer asked, but my peers used it for homework, it would have been unfair for me because the lecturer only looked at our output and marked."* (Student 10)

One student also described the strategic misuse of GenAI by a peer to work around the lecturer's ban on AI.

> *"I saw a peer use ChatGPT to do the translation, and then he asked AI to add a few mistakes. He told me that the final version wasn't perfect, but it looked just like something a student could do. Because the lecturer didn't allow AI, doing it this way meant he wouldn't get caught."* (Student 5)

More than half of the interviewees expressed a sense of guilt and concern about AI dependency. Regarding their interest in becoming translators in the future, they worried that while GenAI accelerated their translation speed, overusing it could reduce their motivation to develop necessary translation skills.

> *"Because it can make us feel lazy, I think that students shouldn't use it too much. The more we rely on GenAI, the more our thinking and translation skills could suffer. That would be a serious problem for me, especially because I want to become a professional translator."* (Student 6)

5.2 Students' GenAI Use

5.2.1 General use of GenAI in learning translation

To explore participants' choice of GenAI selection and the function usage, frequencies and percentages were computed as displayed in Table 7. ChatGPT (72.1%) was the most commonly used GenAI tool in translation classes, followed by Gemini (21.8%), while some unnamed tools accounted for a small portion of selection across the investigated students.

Students employed GenAI primarily during the while-translation and post-translation stages. Most respondents (83.4%) used the translation function of GenAI, while all of them used GenAI for revision. Additionally, 13.3 % of participants reported using GenAI for other functions, such as summarising documents or searching for appropriate lexical choices.

Table 7. Students' GenAI Use in Learning Translation

Measure	Items	Frequency	Percentage
The most used GenAI tool	ChatGPT	261	72.1
	Gemini	79	21.8
	Others	22	6.1
	Total	362	100
The most used functions	Translation	302/362	83.4
	Revision	362/362	100
	Others	48/362	13.3

5.2.2 Students' GenAI practices

Figure 6 illustrates the thematic map showing interview data on students' GenAI practices. It includes two themes: Human-AI collaboration models and prompting practices.

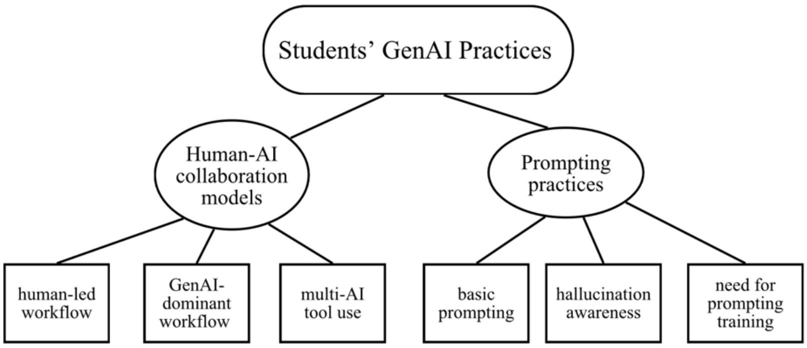

Figure 6. Students' GenAI Practices

5.2.2.1 Varied models of human-AI collaboration

The interview data elaborate on diverse approaches to human-AI collaboration in a translation course. While some students translated documents themselves and then used GenAI tools to refine their translation, others relied on GenAI for all stages.

> "*I usually start by quickly scanning the passage and doing a rough translation myself. Then, I let ChatGPT proofread it, since it might catch mistakes I missed, especially word choice or phrasing*." (Student 2)

> "*I learned translation with ChatGPT. I mostly used it to translate and refine the language to improve the overall quality of the translation*." (Student 5)

Most interviewees used one GenAI tool, but some incorporated two types of GenAI tools for various purposes, including refining translated documents and learning by comparing different versions. The main highlight was the lexical benefits from GenAI. These are excerpts from the interviews.

> "*After using Gemini for a rough translation, I turned to ChatGPT to fix any small errors, like incorrect word choices, that were still in Gemini's version*." (Student 1)

> "*I created translation drafts with both ChatGPT and Gemini, and I compared the two to see which one was better. This helped me come up with new ideas for word choices and taught me different ways to translate sentences*." (Student 8)

5.2.2.2 Prompting practices

Regarding GenAI prompting, seven interviewees shared that they only use a single round with a simple prompt to ask GenAI to perform translation or grammar correction, citing their lack of prompting knowledge, as one student shared:

> "*I just typed a command for AI, like please translate into English or please correct errors…Things like that. I didn't know much about prompting*." (Student 2)

The other four students shared that they usually interacted with GenAI for a few rounds, but found a sense of hallucination in the generated output, especially when doing English-Vietnamese translation.

> "*Normally, I would chat for a few rounds with GenAI, but not too many. Because I felt that the more I asked AI to revise the translation over many rounds, the more the output drifted further away from the original meaning. It usually happened with English-Vietnamese translation. When I read the modified output of Vietnamese from AI, its meaning sometimes sounded strange.*" (Student 3)

All interviewees expressed a willingness to embrace GenAI in learning translation and asked for official training from the schools or lecturers. One student argued that:

> *"I hope the lecturers will officially allow us to use GenAI in their translation courses. I mean, there should be training time to show us how to use the tool effectively and ethically."* (Student 4)

6. Discussion

6.1 Determinants of Students' GenAI Acceptance

The factors influencing students' GenAI acceptance in this study generally align with previous studies using the AIDUA model of Gursoy et al. (2019) and Ma and Huo (2023). More importantly, novelty value and perceived humanness, the two essential features of GenAI proposed by Ma and Huo (2023), have proved their significant influence on both performance expectancy (PE) and effort expectancy (EE). However, there are also discrepancies emerging.

Social influence (SI) significantly influenced the PE of GenAI for generating translation, aligning with findings in studies of Gursoy et al. (2019) and Ma and Huo (2023). However, the path coefficient indicates that this influence is not strong. This may be explained by evidence from the interviews that young lecturers were more open to GenAI use, whereas senior lecturers tended to oppose this technological development. This interpretation echoes that of Ma and Huo (2023), indicating that younger users are generally more willing to embrace GenAI than their older counterparts. Sun and Martín (2025) note a similar generational difference as young translators, who are mostly digital natives, are more open to technological advancements. Conservative views of senior experts on AI in translation may also derive from concerns about skill development and professional ethics (Shi et al. 2025, Sun and Martín 2025). These mixed perspectives may influence SI. More importantly, even though students had approval for GenAI use from their teachers, they also expressed confusion about the dos and don'ts of this technology, due to the lack of clear instructions. Thus, these consequences might contribute to the weak influence of SI on PE.

Hedonic motivation (HM) did not significantly affect EE, which is contrary to previous studies of Gursoy et al. (2019) and Ma and Huo (2023). The results of this study suggest that simply feeling joyful did not make students see GenAI as an easy tool to use in translation. A possible explanation could be noticed from the qualitative data. The interview analysis showed that students often used AI haphazardly, causing confusion in their translation learning, with prompting as the most frequently mentioned obstacle. This finding aligned with Zhang et al. (2025), who found that student-translators without adequate prompting training can solely interact with AI with very simple and sometimes vague prompts with abstract terms. This may explain the unsupported HM-EE relationship in this study.

Novelty value positively influenced performance expectancy in studies of Gursoy et al. (2019) and Ma and Huo (2023), yet this study confirmed the opposite. This finding suggests that students who perceived GenAI as introducing overly novel values may be sceptical about its translation quality. Sofyan and Tarigan (2023) argue that the quality of a translation-assisted technology lies in its fast, accurate and consistent performance. However, due to the lack of training in AI use, students can only enjoy the speed of GenAI, whereas the issues with accuracy and hallucination still exist. Therefore, excessive novelty in GenAI without sufficient training could determine students' perception of its performance.

While Gursoy et al. (2019) and Ma and Huo (2023) found the influence of performance expectancy on affective attitude, this path was not supported in this study. This finding shows that students' high appreciation of GenAI performance does not lead to their positive feelings when using it. Given the context of a translation course, the findings are linked to ethical concerns and a sense of guilt for GenAI dependency emerging from the interview data, which were also recorded in Zhang et al.'s (2025) study.

In short, the three-stage appraisal investigation of the AIDUA model, accompanied by interview data, sheds more light on Vietnamese students' acceptance of GenAI in the basic translation course. Although participants expressed a willingness to adopt GenAI, its performance, the lack of AI training and AI usage policies pose concerns about the acceptance.

6.2 Implications for GenAI Use

The findings showed that students adopted GenAI based on their intuition, resulting in haphazard human-AI collaboration with ineffective prompting. While many studies on GenAI use in translation recognised the use of a single GenAI tool, mostly ChatGPT (Cai and Tian 2025, Gao et al. 2024, Zhang et al. 2025), several participants shared their adoption of two AI tools for separate functions of translating or revising, instead of using different prompts to control a single AI tool. Regarding the GenAI interaction, most interviewees shared their single round of GenAI interaction with a simple prompt, whereas a few interviewees could interact with GenAI for many rounds to process the translation, but still faced obstacles, such as a lack of content retention or cultural sensitivity. This resonates with the findings of Zhang et al. (2025) for students' lack of prompting skills for using vague, abstract terms without contextual cues in prompts.

Interviewees looked forward to a training session on AI use in learning translation. This aligns with the advocacy for human-GenAI cooperation proposed in the current literature (Cai and Tian 2025, Fu and Liu 2024, Gao et al. 2024, Zhang et al. 2025, Zubaidi et al. 2025). In such cooperation, students play a key role in directing, validating and making decisions on GenAI output (Fu and Liu 2024, Zubaidi et al. 2025). However, due to the lack of translation theory and linguistic and cultural knowledge, students find it hard to play this leading role in this coexistence, resulting in GenAI reliance. This required the role of the lecturer as the utmost social influence shared by interviewees. Nevertheless, students shared that several lecturers, especially seniors, tend to resist GenAI for translation classes. Beyond concerns about ethics, Herzallah and Makaldy (2025) find that teachers' objections to AI are largely due to the lack of AI literacy skills and training. Therefore, the integration of AI in the translation syllabus should prioritise professional development in AI and accessible support systems for lecturers.

To ease students' concerns about the academic integrity of GenAI usage, Hockly (2024) suggests that educational institutions should adopt or regulate their policies with existing frameworks and policy guidelines on AI adoption, such as UNESCO's guidelines on GenAI usage in research and education, the EU's Artificial Intelligence Act, and the Australian Framework for Generative Artificial Intelligence in Schools. On that basis, discussions about GenAI could be conducted with students at the beginning of the course, with a focus on principles, ethics, pros and cons of AI, to enhance students' development with AI-assistance.

Regarding students' reports of hallucinations in GenAI output, this is noted by Hockly (2024) as an instinctive downside of current AI technology. For languages with limited digital resources, AI could create translations with grammatical errors, incoherence or made-up vocabulary (Cai and Tian 2025, Zubaidi et al. 2025). To alleviate translation biases, parallel corpora are recommended in teaching translation (Vaupot 2021). However, while Vaupot required master's students to construct their bilingual corpora, this is quite challenging for beginner EFL students without technical skills and limited linguistic awareness. Indeed, there are several existing parallel corpora of English and Vietnamese (Dang and Ho 2007, Doan et al. 2021, Ngo et al. 2014). Therefore, it is suggested that training sessions with a customised GenAI powered by parallel corpora could benefit students in translation courses. The fine-tuned chatbots could provide students with authentic examples and more accurate translation suggestions stemming from parallel corpora.

Regarding pedagogical concerns, this study proposes a structured approach to incorporate AI into a translation lesson, as shown in Figure 7. The framework is informed by Hockly's (2024) recommendations on human-AI cooperation in education. First, students analyse the source text and draft their own translations. Next, the draft is refined using a GenAI tool powered by parallel corpora to reduce the risk of hallucinations. At this stage, the teacher could provide students with guidance on effective prompting. With AI suggestions, students then finalise the translation, making their own decisions to settle issues arising during redrafting. This emphasis on human post-editing is based on Gao et al. (2024), who argue that such intervention is necessary for ensuring high-quality translation, rather than relying solely on AI-generated output. Following the translation and post-editing stages, there should be opportunities for students to reflect on what and how they have learned during that process, since reflection is essential to creating significant learning experiences for students (Fink 2013). In the context of this study, students expressed ethical issues with the existing product-based assessment, indicating a misalignment between assessment practices and GenAI adoption. To tackle this, process-based assessment should be incorporated (Hockly 2024). Accordingly, the lecturer should evaluate both the final translation and the AI-assisted process by having students submit their initial draft, screenshots of their GenAI interactions, and the final product. By only employing GenAI for the redrafting stage, the framework provides more space for students' cognitive engagement in fundamental analytical and translation skills. Moreover, the teacher could regulate the GenAI usage at the second stage by limiting the number of prompts students can interact with GenAI.

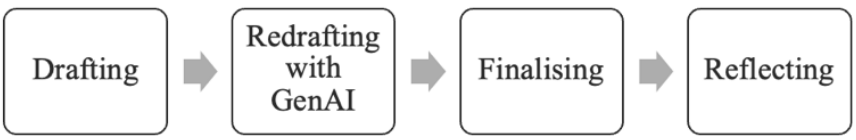

Figure 7. A GenAI-integrated Teaching Approach

7. Conclusion

Currently, GenAI has significantly influenced translation studies. However, there is a very narrow understanding of how students accept and use AI-powered tools in their translation classes. Moreover, studies on AI acceptance mostly employ TAM or UTAUT models, which were designed for technologies earlier than the AI era, whereas AIDUA is purposefully designed to investigate the AI-driven tool acceptance through three interrelated stages.

This mixed-method study employed AIDUA to examine Vietnamese English-major students' acceptance and use of GenAI in a basic translation course. The findings confirmed the overall influences of most AIDUA factors on students' willingness to accept GenAI. While novelty value and perceived humanness affected both performance expectancy (PE) and effort expectancy (EE), hedonic motivation and social influence only influenced PE. Moreover, GenAI PE did not influence affective attitude (AA) but cognitive attitude (CA). CA had more influence on students' willingness to accept GenAI than AA. For GenAI use, ChatGPT continued to be students' preferred tool, and translation and revision were the two most frequently used functions. In addition, the data showed students' intuitive, haphazard use of GenAI and the lack of AI training. Apart from lecturers' polarised opinion on GenAI, participants also raised ethical considerations and the downside of AI for their translation skill development.

Given these issues, this study put forward pedagogical implications for human-AI cooperation in translation classes. It recommends adapting AI usage policies, providing training on AI usage for both students and lecturers, and customising GenAI tools powered by parallel corpora. Students play the primary role in drafting, redrafting, and finalising the translation, while GenAI can be employed for the redrafting stage with the facilitation of the lecturer. More importantly, students' reflection is essential for consolidating the significant learning experience with AI assistance. Accordingly, both product-based and process-based assessments should be employed to fully evaluate student-AI translation performance.

This study theoretically contributes to the body of research on technology acceptance. While the AIDUA model has been used mainly in fields other than education, its application in this study demonstrates the model's suitability for investigating AI acceptance in educational settings, providing a multi-stage alternative to TAM or UTAUT.

The study was limited by its focus on a single stakeholder (i.e., students) in the translation course. The participants' levels of GenAI use or experience were also not stratified during sampling. Moreover, students could be classified based on their academic records to yield more in-depth findings, as those with different achievements and varying levels of AI proficiency may bring distinct perspectives on GenAI acceptance. Hence, future research could include relevant stakeholders, such as lecturers and course administrators, and apply more detailed sampling strategies.

References

APA. 2017. Ethical principles of psychologists and code of conduct. *American Psychological Association.* Available online at https://www.apa.org/ethics/code

Braun, V., and V. Clarke. 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology* 3(2), 77-101.

Cai, Y. and S. Tian. 2025. Student translators' web-based vs. GenAI-based information-seeking behavior in the translation process: A comparative study. *Education and Information Technologies* 30(13), 18997-19025.

Creswell, J. W. and C. N. Poth. 2017. *Qualitative Inquiry and Research Design: Choosing Among Five Approaches* (4th edition). Thousand Oaks, CA: Sage.

Creswell, J. W. and J. D. Creswell. 2022. *Research Design Qualitative, Quantitative, and Mixed Methods Approaches* (6th edition). Thousand Oaks, CA: Sage.

Dang, V. B. and B. Q. Ho. 2007. Automatic construction of English-Vietnamese parallel corpus through web mining. In *Proceedings of the 2007 IEEE International Conference on Research, Innovation and Vision for the Future,* 261-266.

Davis, F. D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13(3), 319-340.

Do, T. T. Q. 2019. Pedagogical and professional perspectives on developing graduates' employability: The case of university translation programs in Vietnam. In R. Chowdhury, ed., *Transformation and Empowerment through Education: Reconstructing Our Relationship with Education* (1st edition), 95-116. Abingdon, UK: Routledge.

Doan, L., L. T. Nguyen, N. L. Tran, T. Hoang and D. Q. Nguyen. 2021. PhoMT: A high-quality and large-scale benchmark dataset for Vietnamese-English machine translation. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, 4495-4503.

Fink, L. D. 2013. *Creating Significant Learning Experiences: An Integrated Approach to Designing College Courses* (2nd edition). San Francisco, CA: Jossey-Bass.

Fu, L. and L. Liu. 2024. What are the differences? A comparative study of generative artificial intelligence translation and human translation of scientific texts. *Humanities and Social Sciences Communications* 11, 1-12.

Gao, R., Y. Lin, N. Zhao and Z. G. Cai. 2024. Machine translation of Chinese classical poetry: A comparison among ChatGPT, Google Translate, and DeepL Translator. *Humanities and Social Sciences Communications* 11, 1-10.

Gursoy, D., O. H. Chi, L. Lu and R. Nunkoo. 2019. Consumers acceptance of artificially intelligence (AI) device use in service delivery. *International Journal of Information Management* 49, 157-169.

Hair, J. F., G. T. M. Hult, C. M. Ringle and M. Sarstedt. 2022. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)* (3rd edition). Thousand Oaks, CA: Sage.

Herzallah, A. M. and R. Makaldy. 2025. Technological self-efficacy and sense of coherence: Key drivers in teachers' AI acceptance and adoption. *Computers and Education: Artificial Intelligence* 8, 1-11.

Hoang, L. B. 2020. Translation profession status in Vietnam: Document and empirical analyses. *International Journal of Translation and Interpreting* 1(4), 99-123.

Hockly, N. 2024. *Nicky Hockly's 30 Essentials for Using Artificial Intelligence*. Cambridge: Cambridge University Press.

House, J. 2023. *Translation: The Basics* (2nd edition). Abingdon, UK: Routledge.

Li, F., Z. Cao and X. Li. 2023. College translation teaching in the era of Artificial Intelligence: Challenges and solutions. *Journal of Higher Education Theory and Practice* 23(19), 39-49.

Ma, X. and Y. Huo. 2023. Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society* 75, 1-13.

Ngo, Q. H., D. Dien and W. Winiwarter. 2014. Building English-Vietnamese named entity corpus with aligned bilingual news articles. In *Proceedings of the Fifth Workshop on South and Southeast Asian Natural Language Processing*, 85-93.

Nguyen, H. 2023. The application of consciousness-raising in teaching translation in a Vietnamese tertiary English language program. *Translation & Interpreting* 15(1), 200-215.

Nguyen, T. P. N. and T. H. Pham. 2025. Challenges and opportunities for digital learning resource development: An analysis of AI application in Vietnamese general education. *Advances in Artificial Intelligence and Machine Learning* 5(3), 4292-4307.

Nguyen, T. T. K. 2017. A survey of translation evaluation at tertiary level in Vietnam. *VNUHCM Journal of Social Sciences and Humanities* 1(1), 83-90.

Ren, X. 2025. We want but we can't: Measuring EFL translation majors' intention to use ChatGPT in their translation practice. *Humanities and Social Sciences Communications* 12*,* 1-11.

Salloum, S. A., R. A. Aljanada, A. M. Alfaisal, M. R. Al-Saidat and R. Alfaisal. 2024. Exploring the acceptance of ChatGPT for translation: An extended TAM model approach. In A. Al-Marzouqi, S. A. Salloum, M. R. Al-Saidat, A. Aburayya and B. Gupta, eds., *Artificial Intelligence in Education: The Power and Dangers of ChatGPT in the Classroom*, 527-542. Cham, Switzerland: Springer.

Shi, Y., H. Xu, H. L. Kwok and K. Liu. 2025. ChatGPT in professional translation: A double-edged sword, insights from Chinese translators on capabilities, concerns, and future prospects. In S. Sun, K. Liu and R. Moratto, eds., *Translation Studies in the Age of Artificial Intelligence* (1st edition), 125-149. Abingdon, UK: Routledge.

Sofyan, R. and B. Tarigan. 2023. Becoming professional translators: Developing effective TAP course for undergraduate students. *Indonesian Journal of Applied Linguistics* 12(3), 765-776.

Song, X. 2022. College English curriculum setting and evaluation based on language curriculum design model-taking English translation course as an example. *Frontiers in Educational Research* 5(2), 47-51.

Sulistiyo, U., M. Wiryotinoyo and R. Wulan. 2019. Examining an English as a foreign language teacher education program (EFLTEP)'s curriculum: A case study in an Indonesian university. *European Journal of Educational Research* 8(4), 1323-1333.

Sun, S. and R. M. Martín. 2025. Reframing translation expertise for the AI era. In S. Sun, K. Liu and R. Moratto, eds., *Translation Studies in the Age of Artificial Intelligence* (1st edition), 42-62. Abingdon, UK: Routledge.

Turner, R. C. and L. Carson. 2003. Indexes of item-objective congruence for multidimensional items. *International Journal of Testing* 3(2), 163-171.

Vaupot, S. 2021. Creating a bilingual dictionary of collocations: A learner-oriented approach. *Indonesian Journal of Applied Linguistics* 10(3), 762-770.

Venkatesh, V., J. Y. L. Thong and X. Xu. 2012. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly* 36(1), 157-178.

Wang, L., S. Xu and K. Liu. 2025. What drives university students to use ChatGPT for translation? Disciplinary and experiential influences. *International Journal of Applied Linguistics* 1, 1-19.

Yadegaridehkordi, E., B. Foroughi and M. Ghobakhloo. 2025. Factors affecting academic staff's willingness to use ChatGPT for teaching and learning: A PLS-SEM and ANN approach. *Innovative Higher Education* 51, 1-28.

Zhang, J., X. Zhao and S. Doherty. 2025. Prompt engineering in translation: How do student translators leverage GenAI tools for translation tasks?. In *Proceedings of Machine Translation Summit XX*, 420-431.

Zubaidi, A., A. Munip, S. Widodo and T. Zerrouki. 2025. Enhancing Arabic writing skills using Chat GPT-based AI learning models: A tridimensional human-AI collaboration framework. *Indonesian Journal of Applied Linguistics* 15(1), 87-101.

Examples in: English
Applicable Languages: English
Applicable Level: Tertiary

Appendix A. Instruments

Questionnaire	Interview questions
Social influence (SI) *When learning translation, …*	
SI1 people who influence my behavior would want me to utilize GenAI. SI2 people whose opinions I value would prefer that I utilize GenAI. SI3 people who are important to me would encourage me to utilize GenAI. SI4 people in my social networks who would utilise GenAI have more prestige than those who don't.	1.Who encouraged or inspired you to use GenAI to learn translation?
Hedonic motivation (HM) *When learning translation, …*	
HM1 interacting with GenAI is fun. HM2 interacting with GenAI is entertaining. HM3 interacting with GenAI is enjoyable.	2. Do you find using GenAI for learning translation enjoyable or fun? If so, in what ways?
Novelty value (NV) *When learning translation, …*	
NV1 I found using GenAI to be a novel experience. NV2 using GenAI is new and refreshing. NV3 using GenAI satisfied my curiosity. NV4 GenAI made me feel like I was exploring a new world.	3. What novel or unique value does GenAI offer in the process of learning translation?
Perceived humanness (PH)	
PH1 GenAI's translations feel natural. PH2 GenAI has a humanlike response. PH3 GenAI's translations do not feel machine-like. PH4 GenAI reacts in a human way.	4. How human-like does GenAI seem to you when you use it to learn translation?
Performance expectancy (PE) *When learning translation, …*	
PE1 I would find GenAI useful. PE2 using GenAI would help me accomplish translation tasks more quickly. PE3 using GenAI has increased my productivity. PE4 GenAI would increase my chances of achieving things that are important to me.	5. How would you describe GenAI's performance when using it to learn translation?
Effort expectancy (EE) *When learning translation, …*	
EE1 learning how to use GenAI would be easy for me. EE2 my interaction with GenAI would be clear and understandable. EE3 I find it is easy to use GenAI. EE4 it would be easy for me to become skillful using GenAI.	6. How would you describe the level of effort required when using GenAI to learn translation?
Cognitive attitude (CA) *When learning translation, …*	
CA1 using GenAI is effective. CA2 using GenAI is helpful. CA3 GenAI is practical. CA4 GenAI is valuable.	7. How do you evaluate the usefulness or value of GenAI when using it to learn translation?
Affective attitude (AA) *Using GenAI in learning translation is …*	
AA1 happy. AA2 positive. AA3 pleasing. AA4 satisfactory.	8. What kinds of feelings do you experience when you use GenAI for learning translation?
Willingness to accept (WA) *When learning translation, …*	9. Are you open to accepting GenAI when learning translation, or do you prefer to avoid using it? Why?
WA1 I am willing to receive GenAI. WA2 I feel happy to interact with GenAI. WA3 I am likely to interact with GenAI.	
Objection to use (OU) *When learning translation, …*	
OU1 the information is processed in a less humanized manner. OU2 the existing problems with GenAI make me take a wait-and-see approach to GenAI. OU3 I do not plan to continue using GenAI. OU4 I prefer human translation to GenAI translation.	
List ONE GenAI tool you used most often when learning translation.	10. What type of GenAI tool did you use most frequently when learning translation? Please explain your choice.
List ALL GenAI functions you used most often when learning translation.	11. How did you use GenAI when learning translation?

Appendix B. Examples of the Coding Process

Example Quote	Initial code	Subtheme	Theme
"Our lecturer told us not to use AI too much because we still need to develop our own translation skills."	Limiting GenAI use	Lecturers as key drivers	Factors shaping students' GenAI acceptance
"When I translate long texts, GenAI helps me create a draft quickly."	Enhancing speed	Efficiency–quality trade-offs	
"I usually type something like 'translate this paragraph into English and make it sounds natural'."	Basic prompting	Prompting practices	Students' GenAI practices

