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What Drives University Students to Use ChatGPT for Translation? Disciplinary and Experiential Influences

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ABSTRACT

The increasing use of large language models like ChatGPT has sparked interest in their potential for translation tasks. However, little is known about what drives university students to adopt these tools or how disciplinary background and prior experience shape their decisions. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), this study explores the adoption of ChatGPT for translation tasks among university students in Hong Kong. Survey responses from 308 students, including translation and non-translation majors, were analyzed using structural equation modeling. Results show that performance expectancy is the strongest determinant of adoption intention, followed by facilitating conditions, while effort expectancy and social influence were less significant. Experience level emerged as an important moderating factor: novice users relied on both social influence and performance expectations, whereas experienced users prioritized performance alone. Disciplinary differences were also pronounced. Translation students primarily valued performance benefits and used their technical expertise to evaluate ChatGPT independently. Non-translation students, however, were influenced by both performance expectations and facilitating conditions, suggesting a greater need for institutional support. These findings highlight the importance of tailored educational approaches that address the specific motivations of different student populations. For translation students, this means emphasizing advanced features and critical evaluation, while for non-translation students, it involves providing stronger support systems and guidance. The study also offers insights for LLM developers, underscoring the need for user-centered design that accommodates the diverse needs, experiences, and expectations of different student groups.

摘要

ChatGPT等大语言模型日益普及, 使其在翻译领域的应用潜力备受学界和业界关注。然而, 关于大学生为何使用此类工具, 以及学科背景与ChatGPT使用经验如何影响决策, 尚缺乏系统研究。本研究以整合技术接受模型 (UTAUT) 为框架, 调查香港地区308名大学生 (涵盖翻译与非翻译专业) 在翻译任务中使用ChatGPT的动因, 并采用结构方程模型进行分析。研究结果表明, 绩效期望是影响行为意向的最关键因素, 便利条件次之;努力期望与社会影响的作用则相对较小。进一步分析显示, 使用经验是重要的调节因素, 新手的行为意向受到社会影响与绩效期望的共同驱动, 而有经验的用户则更看重绩效因素。学科背景的差异同样显著, 翻译专业学生更重视ChatGPT的任务表现且更倾向于自行评估;相比之下, 非翻译专业学生不仅关注任务表现, 还受到便利条件影响, 因此更需要院校支持。研究结果凸显了教育策略须根据学生动因的差异作精准调整, 对翻译专业可强化高

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阶功能与批判性评估训练, 对非翻译专业则完善配套支持与使用指导。此外, 本研究也为大型语言模型的开发者提供了重要启示, 即应秉承以用户为中心的设计理念, 充分考虑不同学生群体的多元化需求、经验与期望。

1 | Introduction

AI chatbots powered by large language models have created new opportunities in translation education (Sun and Muñoz 2025; Xu et al. 2025). ChatGPT, in particular, has shown remarkable potential as a translation tool, often rivaling or surpassing state-of-the-art neural machine translation (NMT) systems such as Google Translate in terms of coherence, consistency, and precision (Calvo-Ferrer 2023; Gao et al. 2024). In some cases, its output quality approaches human parity for specific tasks (Calvo-Ferrer 2023). However, the use of ChatGPT for translation also raises concerns about information privacy, output bias, and its reliance on effective prompt design, which can present challenges for students (O'Brien 2023). These limitations underscore the need for informed use, making it essential for translation training to address both the strengths and constraints of these tools.

Integrating technology into translation workflows and educational contexts has long been recognized as essential (O'Brien 2012; O'Hagan 2013). The advent of powerful generative AI has spurred renewed scholarly discussion. Recent works have begun to explore how to integrate generative AI into translator training (Kornacki and Pietrzak 2021; Sun et al. 2025) and how to augment language skills for both translation specialists and general language learners (Pym and Hao 2024). These studies have addressed crucial pedagogical strategies, the evolving professional identity of translators, and the psychological impacts of automation, including technological anxiety (Kornacki and Pietrzak 2021).

However, while these studies outline pedagogical frameworks and professional challenges, there remains a lack of focused research that quantitatively measures the specific factors driving students' adoption of generative AI tools for translation. Existing studies on ChatGPT adoption have focused on general academic use (e.g., Liu and Ma 2023; Romero-Rodríguez et al. 2023). The determinants of adoption are further complicated by two key variables: students' academic backgrounds and their level of experience. Non-specialists—who constitute the largest user group for these tools (Bowker 2023)—likely have different motivations than trained translation students. Additionally, users' perceptions of a tool's utility naturally evolve with continued use (Venkatesh et al. 2003).

To systematically investigate these factors, this study applies the Unified Theory of Acceptance and Use of Technology (UTAUT), a well-established framework for understanding technology acceptance that incorporates both individual and contextual moderators (Venkatesh et al. 2003). The aim is to provide granular insights into the factors influencing students' adoption of ChatGPT as a translation tool, with particular attention to how these drivers are moderated by students' academic discipline and prior use experience. This comparative approach is essential for capturing the full spectrum of user behavior and for developing tailored pedagogical strategies that serve the diverse university student population.

To guide this investigation, this study addresses the following research questions:

RQ1: What factors influence students' intention to use ChatGPT as a translation tool?
RQ2: How do prior experience and academic background moderate these factors?

By answering these research questions, this study seeks to improve training strategies for educators and inform the design of user-centered AI tools. It also provides evidence to guide institutional policy, promote ethical and effective integration of AI in the curriculum, and deepen our understanding of technology acceptance across disciplines and experience levels. In doing so, the research contributes to improved learning outcomes and the development of best practices for implementing AI-powered tools in academic contexts.

2 | Literature Review

2.1 | ChatGPT as a Translation Tool and Implications for Students

ChatGPT has attracted significant attention in academia for its advanced language capabilities and potential as a translation tool. Recent studies evaluating its translation performance have identified both strengths and limitations (Calvo-Ferrer 2023; Fu and Liu 2024). ChatGPT often outperforms traditional NMT systems in producing more natural and coherent translations, with some research suggesting that its results are comparable to those of human translators (Calvo-Ferrer 2023; Lee 2023). For example, Calvo-Ferrer (2023) found no significant difference in quality ratings between subtitles produced by ChatGPT and those translated by humans.

ChatGPT's key advantage lies in its flexibility for refining translations through interactive prompts—a feature not available in conventional NMT systems—with iterative prompting significantly improving output quality (Gao et al. 2023). Beyond translation, ChatGPT supports various tasks such as text comprehension, terminology generation, and translation editing, making it versatile for language learners and translators (Sahari et al. 2023). For students, it offers opportunities to enhance digital and AI literacy while providing hands-on experience with its capabilities and limitations (Kornacki and Pietrzak 2021; Kwok et al. 2025).

However, several challenges remain. ChatGPT sometimes fails to capture implied meanings and cultural nuances, which can affect

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translation accuracy. It also raises privacy concerns, especially when handling sensitive or confidential information (O'Brien 2023; Zhou et al. 2024). These privacy risks stem from the model's training on vast public datasets and its handling of user inputs (Wu et al. 2024). Notably, the free version may use user inputs for model training, a practice that conflicts with professional translation ethics regarding client confidentiality. Paid versions, including API and enterprise subscriptions, provide essential data-handling assurances by not using submitted data for training. This distinction is crucial in both professional and educational contexts and highlights the need for users to understand which version they are using. Additionally, ChatGPT's outputs can reflect training data biases, necessitating critical evaluation by users (Yu et al. 2023).

Despite growing evaluations of ChatGPT's translation capabilities (Fu and Liu 2024; Gao et al. 2024), little research has explored students' willingness to adopt ChatGPT for translation or the factors influencing their decisions. This gap limits educators' ability to design effective training programs, highlighting the need for further investigation.

2.2 | The Unified Theory of Acceptance and Use of Technology

UTAUT, developed by Venkatesh et al. (2003), is a widely used framework for understanding technology adoption. It integrates eight prior models and explains up to 70% of the variance in users' behavioral intentions (BI) to use technology. Its validity has been demonstrated across various technologies, user groups, and contexts (Williams et al. 2015; Wu et al. 2022).

UTAUT comprises four key constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These constructs influence BI and, subsequently, use behavior (UB). PE refers to the belief that using ChatGPT will enhance translation performance, and it is consistently identified as the strongest predictor of BI. EE reflects the perceived ease of using ChatGPT, with adoption increasing as the tool becomes easier to use. SI captures the influence of others, such as peers and teachers, in encouraging ChatGPT adoption for translation tasks, impacting BI through internalization and identification mechanisms (Venkatesh et al. 2003; Venkatesh and Morris 2000). FC denotes the availability of technical and organizational support for using ChatGPT, influencing both BI and actual usage (Venkatesh et al. 2012).

This study focuses on the four UTAUT constructs and their impact on students' BI to use ChatGPT for translation, while excluding UB. As BI strongly predicts UB, analyzing BI provides valuable insights into students' adoption of ChatGPT without requiring the more resource-intensive investigation of actual usage. This approach ensures the feasibility of this study while addressing its core research objectives.

Existing studies on AI tools in education indicate generally positive attitudes among students. For example, PE, EE, and SI have been shown to significantly influence BI for AI-assisted learning (Wu et al. 2022). However, findings are not always consistent. While PE is consistently a strong predictor, the effects of EE, SI, and FC vary across contexts. For instance, Romero-Rodríguez et al. (2023) observed that EE and SI did not significantly influence BI, while FC became more relevant as students gained experience. Similarly, Tiwari et al. (2023) found that technical challenges reduced the impact of EE on BI. These mixed results suggest that factors like user experience and task specificity may moderate the relationships between UTAUT constructs and BI.

Most prior studies focus on general educational uses of ChatGPT, leaving its application to professional tasks like translation underexplored (Lee et al. 2003). This study addresses this gap by applying the UTAUT framework to examine ChatGPT adoption in translation. The following hypotheses are proposed:

H1: PE positively correlates with BI.
H2: EE positively correlates with BI.
H3: SI positively correlates with BI.
H4: FC positively correlates with BI.

2.3 | Potential Moderating Effects of Use Experience and Academic Discipline

Venkatesh et al. (2003) suggested that user experience with a tool can influence the relationships between UTAUT constructs. With more experience, the effects of EE and SI on BI tend to weaken, while the impact of FC on UB grows stronger. This shift occurs as users become more familiar with the technology, making ease of use and external encouragement less critical to their intention to use it. Instead, practical considerations like technical support and resource compatibility become more important (Yang and Wang 2019).

In the context of machine translation, experience may also moderate the influence of performance expectancy. As users become more familiar with a tool, they can better identify its strengths and weaknesses, which may enhance their perceptions of its usefulness for improving translation efficiency and accuracy (Yang and Wang 2019; Vieira et al. 2022). However, increased use may also reveal limitations, such as privacy risks or biases, which are only noticeable after specific incidents, like the accidental sharing of sensitive data (Vieira et al. 2022). Since these dynamics have not yet been explored for ChatGPT as a translation aid, this study extends the inquiry by proposing the following hypotheses:

H5: Experience moderates the effect of PE on BI, such that the effect strengthens with more experience.
H6: Experience moderates the effect of EE on BI, such that the effect weakens with more experience.
H7: Experience moderates the effect of SI on BI, such that the effect weakens with more experience.
H8: Experience moderates the effect of FC on BI, such that the effect weakens with more experience.

In addition to user experience, academic discipline may also influence students' perceptions of ChatGPT for translation tasks. Non-translation students, who constitute a significant user base

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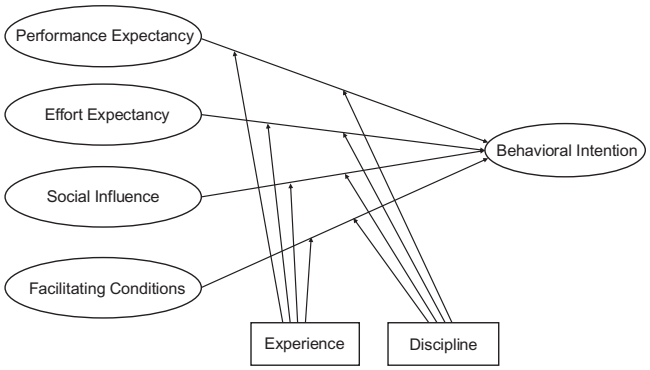

FIGURE 1 | Research model.

for machine translation, typically lack specialized training. Consequently, they often use a narrower range of tools, demonstrate less awareness of their limitations, and may find it challenging to critically evaluate translation quality (Bowker 2022, 2023; Yamada 2020). A small-scale survey by Sahari et al. (2023) highlighted this distinction. Translation students expressed a clear preference for Google Translate, while non-translation students chose ChatGPT. This contrast reflects the influence of academic background and task-specific expectations on users' selection of translation tools.

ChatGPT offers distinct advantages, such as producing idiomatic and precise translations in certain contexts. However, it supports fewer languages and processes long texts more slowly than specialized tools like Google Translate (Lee 2023). Such differences may lead non-translation students to hold more favorable attitudes toward ChatGPT, as they may prioritize ease of use. In contrast, translation students are likely to evaluate the tool more critically against professional standards. Based on these differences, this study investigates how students' academic backgrounds may moderate the relationships between the UTAUT constructs and their behavioral intention. The following hypotheses are proposed:

H9: The effect of PE on BI is stronger for translation students compared with non-translation students.
H10: The effect of EE on BI is weaker for translation students compared with non-translation students.
H11: The effect of SI on BI is stronger for translation students compared with non-translation students.
H12: The effect of FC on BI is weaker for translation students compared with non-translation students.

To visualize all the hypotheses outlined above, including the main effects and moderating relationships, the complete research model for this study is depicted in Figure 1.

3 | Method

3.1 | Sampling and Data Collection

This study employed a cross-sectional questionnaire survey to investigate the factors influencing students' adoption of ChatGPT as a translation tool. The target population consisted of translation and non-translation students enrolled in Hong Kong universities who had prior experience using ChatGPT for translation purposes.

To achieve a sufficient sample size, a priori power analysis was conducted using G*Power (Faul et al. 2007). The analysis, configured for a multiple regression model with four predictors and two moderators, indicated that a minimum of 149 participants were needed to detect an effect size of 0.2 with 80% statistical power at a significance level of $\alpha = 0.05$ (Memon et al. 2020).

Data were collected between December 2023 and February 2024 via an online questionnaire created with Google Forms. Participants were recruited from tertiary institutions across Hong Kong through convenience and snowball sampling techniques (Wagner 2015). An initial dataset of 323 responses was collected. To ensure data quality, the initial dataset was screened for non-engaged or incoherent responses. For instance, responses were removed if they exhibited "straight-lining" (i.e., the practice of selecting the same answer for all consecutive Likert-scale items) or contained logically inconsistent patterns. This screening process resulted in a final sample of 308 valid responses for analysis. The sample comprised 148 translation students and 160 non-translation students from diverse academic fields such as arts, humanities, engineering, and sciences. Demographically, the sample included 104 males and 204 females. Regarding technology usage, 33.1% of participants reported using ChatGPT 3.5, 13.3% used ChatGPT 4.0, and 53.6% used both versions. Additional demographic details are provided in Table 1.

All participants were informed of the study's objectives and assured of the complete anonymity of their responses, as no personally identifiable information was collected. They were also notified of their right to withdraw at any time. The submission of a completed questionnaire was taken as informed consent. As a token of appreciation, participants received a small incentive for their contribution.

3.2 | Instruments

The questionnaire consisted of three sections. It began with a screening question—"Have you used ChatGPT for translation?"—to ensure all respondents had relevant experience. Individuals who answered "No" were excluded from the final sample.

The first section assessed the UTAUT constructs: PE, EE, SI, FC, and BI. Each construct was measured using four items adapted from validated scales developed in prior technology acceptance research (Bernabei et al. 2023; Shroff and Keyes 2017; Venkatesh et al. 2003; Venkatesh et al. 2012) (see Appendix). All items were rated on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).

The second section examined students' use of translation tools and resources, including MT systems, search engines, dictionaries, corpora, grammar checkers, CAT tools, professional translation services, and ChatGPT (Gough 2017). Participants rated their usage frequency on a 5-point scale (1 = never to 5 = always). This

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TABLE 1 | Demographic characteristics of respondents (N = 308).

Demographic characteristic	*n*	%
Gender		
Male	104	33.8
Female	204	66.2
Age		
18–24	141	45.8
25–30	141	45.8
≥ 31	26	8.4
Education level		
Undergraduate	14	4.5
Master's	158	51.3
Doctoral	136	44.2
Discipline		
Translation	148	48.1
Non-translation	160	51.9
Versions of ChatGPT used		
GPT-3.5	102	33.1
GPT-4	41	13.3
Both	165	53.6
Institution		
The Hong Kong Polytechnic University	229	74.4
The University of Hong Kong	25	8.1
City University of Hong Kong	23	7.5
The Chinese University of Hong Kong	14	4.5
Hong Kong Baptist University	8	2.6
Lingnan University	4	1.3
The Education University of Hong Kong	1	0.3
Other Hong Kong Universities	4	1.3

section also explored students' purposes for translation and their experience with ChatGPT, providing data to address RQ2. The final section collected demographic information, including age, gender, level of education, institution, and field of study.

To ensure content validity, the questionnaire was reviewed by three experts in translation studies, and their feedback was incorporated to refine the items. The instrument, administered in English, was then pilot-tested with 10 translation and 10 non-translation students from the target population to identify and resolve any ambiguities, thereby enhancing its clarity and reliability.

3.3 | Data Analysis

Data analysis was conducted using SPSS 26 and AMOS 28. To prepare for the moderation analysis, participants were categorized into high-experience (n = 154) and low-experience (n = 154) groups. Experience was operationalized as a composite index reflecting both the duration and frequency of ChatGPT use for translation. This index was calculated by multiplying two values: (1) the length of use in months and (2) self-reported usage frequency, rated on a 3-point scale (3 = often (daily/weekly), 2 = sometimes (monthly), 1 = rarely). A median split was then applied to this index to create the two experience groups (Iacobucci et al. 2015).

First, a preliminary analysis was conducted to determine if data from users of different ChatGPT versions (GPT-3.5 and GPT-4) could be pooled. To examine potential bias from different versions, Mann-Whitney U tests were performed to compare the median scores of the core constructs (PE, EE, SI, and FC) between users of GPT-3.5 (n = 102) and GPT-4 (n = 41). The results indicated no statistically significant difference between users of GPT-3.5 (n = 102) and GPT-4 (n = 41): PE (U = 2344.5, p = 0.255, r = 0.09), EE (U = 2490.0, p = 0.074, r = 0.15), SI (U = 2148.0, p = 0.800, r = 0.02), and FC (U = 2180.0, p = 0.692, r = 0.03). These results validate treating the sample as a single cohort for the subsequent analyses.

Next, a confirmatory factor analysis (CFA) was performed to assess distribution normality, construct reliability, validity, and model fit. Composite reliability and Cronbach's alpha were used to evaluate internal consistency (Taber 2018), while convergent and discriminant validity were assessed to ensure construct validity (Hair et al. 2017).

Finally, we employed structural equation modeling (SEM) with maximum likelihood estimation to test the hypothesized relationships between the latent variables (Kline 2023). To investigate the moderating effects of use experience and academic discipline, a multi-group SEM analysis was conducted, comparing the structural models across the defined groups (Byrne 2004).

4 | Results

4.1 | Assessment of Measurement Model and Measurement Invariance

First, the measurement items were assessed for normality. Skewness and kurtosis values ranged from −1.36 to 0.29 and −0.95 to 2.32, respectively. These values fall within the acceptable thresholds of 2.0 and 7.0 (Finney and DiStefano 2006), confirming acceptable normality. The average ratings for all items exceeded the midpoint, suggesting generally positive attitudes toward using ChatGPT for translation.

A CFA was conducted to evaluate the measurement model. As shown in Table 2, all constructs demonstrated strong reliability and convergent validity. Cronbach's alpha value for all constructs exceeded 0.7, indicating high internal consistency (Taber 2018). Furthermore, composite reliability (CR) values were also above 0.7, and the average variance extracted (AVE) values surpassed 0.5, confirming reliability and convergent validity (Fornell and Larcker 1981; Hair et al. 2017). Additionally, all factor loadings were significant, further supporting the reliability of the measurement scale.

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TABLE 2 | Confirmatory factor analysis and reliability assessment (N = 308).

Constructs	Items	Mean	SD	Standardized factor loading	Cronbach's alpha	CR	AVE
Performance expectancy (PE)	PE1	5.75	1.19	0.85	0.90	0.90	0.69
	PE2	5.83	1.30	0.83			
	PE3	5.69	1.24	0.85			
	PE4	5.62	1.26	0.78			
Effort expectancy (EE)	EE1	5.77	1.26	0.76	0.85	0.85	0.59
	EE2	5.37	1.22	0.73			
	EE3	5.60	1.29	0.83			
	EE4	5.34	1.32	0.75			
Social influence (SI)	SI1	4.94	1.62	0.88	0.82	0.83	0.63
	SI2	4.77	1.63	0.86			
	SI3	4.92	1.62	0.61			
Facilitating conditions (FC)	FC1	5.51	1.44	0.70	0.76	0.77	0.53
	FC2	5.36	1.34	0.81			
	FC3	5.33	1.37	0.66			
Behavioral intention (BI)	BI1	5.01	1.59	0.84	0.89	0.90	0.68
	BI2	5.21	1.47	0.83			
	BI3	4.85	1.65	0.82			
	BI4	5.59	1.56	0.82			

Note. Items SI4 and FC4 were removed due to low factor loadings (< 0.5), which reduced their explanatory power and negatively impacted composite reliability and model fit. The remaining items were sufficient to maintain the statistical identification of the constructs SI and FC (Hair et al. 2017).

TABLE 3 | HTMT ratio of correlations.

	PE	EE	SI	FC	BI
Performance expectancy (PE)					
Effort expectancy (EE)	0.74				
Social influence (SI)	0.26	0.22			
Facilitating conditions (FC)	0.56	0.68	0.33		
Behavioral intention (BI)	0.74	0.61	0.30	0.58	

TABLE 4 | Correlation matrix and discriminant validity.

	PE	EE	SI	FC	BI
PE	0.83				
EE	0.74	0.77			
SI	0.26	0.22	0.79		
FC	0.56	0.68	0.33	0.73	
BI	0.73	0.61	0.30	0.58	0.83

Note. The numbers along the diagonal represent the square roots of AVEs. Other numbers in the table are the correlation coefficients between the UTAUT constructs.

Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al. 2015) and the Fornell-Larcker criterion (Fornell and Larcker 1981). All HTMT ratios were below 0.85 (Table 3), and the square roots of the AVEs for each construct exceeded their correlations with other constructs (Table 4). These results confirm strong discriminant validity for the measurement model (Table 5).

We evaluated the fit of the measurement model using several indices: Comparative Fit Index (CFI > 0.90), Tucker-Lewis Index (TLI > 0.90), Root Mean Square Error of Approximation (RMSEA < 0.08), and Standardized Root Mean Square Residual (SRMR < 0.08) (Hair et al. 2017; Kline 2023). As shown in Table 5, the model demonstrated good fit, $\chi^2(125) = 286.81$, $\chi^2/df = 2.30$, CFI = 0.95, TLI = 0.94, RMSEA = 0.07, 90% CI [0.06, 0.08], SRMR = 0.05.

Before performing multigroup SEM, we assessed measurement invariance across groups using multigroup CFA, following Byrne's (2004, 2008) guidelines. The CFA model, with experience as the grouping variable, exhibited good fit, indicating configural equivalence across students with varying levels of ChatGPT experience (Byrne 2004; Hair et al. 2017). Next, metric invariance was tested by constraining the factor loadings to be equal across groups. Results showed no significant decrease in fit ($\Delta\chi^2 = 20.03$, $\Delta df = 16$, $p = 0.219$), confirming that the items were interpreted consistently across experience levels.

Similarly, the unconstrained model with discipline as the grouping variable demonstrated acceptable fit, confirming configural invariance across translation and non-translation students. When

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TABLE 5 | Comparison of fit between unconstrained and constrained measurement models.

Models	$\chi^2(df)$	CFI	TLI	RMSEA	SRMR
Baseline	286.81(125)	0.95	0.94	0.065 [0.055, 0.075]	0.05
Experience-grouped	443.86(250)	0.94	0.93	0.05 [0.043, 0.058]	0.05
Constrained experience-grouped	462.64(263)	0.94	0.93	0.05 [0.042, 0.057]	0.06
Discipline-grouped	480.12(250)	0.93	0.91	0.055 [0.047, 0.062]	0.06
Constrained discipline-grouped	492.34(263)	0.93	0.91	0.053 [0.046, 0.061]	0.06

Note. Baseline: model tested on the entire sample ($N = 308$). Experience-grouped models compare high versus low experience groups. Discipline-grouped models compare translation versus non-translation students. Constrained models test measurement invariance by constraining factor loadings to equality across groups.

TABLE 6 | Hypothesis testing with the entire sample.

Paths	Standardized regression coefficients	*t*	*p*	Result
H1: PE → BI	0.59	6.90	< 0.001***	Supported
H2: EE → BI	0.01	0.13	0.894	Rejected
H3: SI → BI	0.07	0.18	0.183	Rejected
H4: FC → BI	0.22	2.76	0.006**	Supported

Note. *$p < 0.05$,
**$p < 0.01$,
***$p < 0.001$.

factor loadings were constrained across these groups, no significant decrease in model fit was observed ($\Delta\chi^2 = 12.23$, $\Delta df = 13$, $p = 0.509$).

4.2 | Structural Model

The structural model demonstrated good fit, $\chi^2(125) = 286.81$, $\chi^2/df = 2.30$, CFI = 0.95, TLI = 0.94, RMSEA = 0.07, 90% CI [0.06, 0.08], SRMR = 0.05 (Hair et al. 2017; Kline 2023). Table 6 presents the path coefficient estimates of the structural model ($N = 308$). Specifically, BI was positively influenced by PE ($\beta = 0.59$, $p < 0.001$) and FC ($\beta = 0.22$, $p = 0.006$), but was non-significantly influenced by EE ($\beta = 0.01$, $p = 0.894$) and SI ($\beta = 0.07$, $p = 0.183$). The four predictors together explained 58.9% of the variance of BI. Based on these results, H1 and H4 were supported, while H2 and H3 were rejected.

4.2.1 | Multigroup Analysis by Experience

The unconstrained structural model with experience as the grouping variable showed good fit, $\chi^2(250) = 443.86$, $\chi^2/df = 1.78$, CFI = 0.94, TLI = 0.93, RMSEA = 0.05, 90% CI [0.04, 0.06], SRMR = 0.06. Constraining structural weights across groups did not significantly affect fit, $\Delta\chi^2 = 24.17$, $\Delta df = 17$, $p = 0.115$.

For high-experience students, PE was a stronger predictor of BI ($\beta = 0.63$, $t = 5.60$, $p < 0.001$) compared to low-experience students ($\beta = 0.42$, $t = 2.92$, $p = 0.004$). Conversely, SI significantly predicted BI only for low-experience students ($\beta = 0.25$, $t = 2.89$, $p = 0.004$). EE and FC were not significant predictors for either group. These results support H5 and H7 but reject H6 and H8. Overall, the model accounted for 56.9% of experienced students' and 60% of less-experienced students' intention to use ChatGPT for translation purposes.

4.2.2 | Multigroup Analysis by Discipline

With students' discipline as the grouping variable, the unconstrained structural model demonstrated good fit, $\chi^2(250) = 480.12$, $\chi^2/df = 1.92$, CFI = 0.93, TLI = 0.91, RMSEA = 0.06, 90% CI [0.05, 0.06], SRMR = 0.06. We then compared the path coefficients between the two groups (see Table 7). PE was a stronger predictor of BI for translation students ($\beta = 0.70$, $t = 5.12$, $p < 0.001$) than for non-translation majors ($\beta = 0.56$, $t = 4.74$, $p < 0.001$), supporting H9. EE and SI were not significant predictors for either group, thus rejecting H10 and H11. FC significantly predicted BI only for non-translation students ($\beta = 0.29$, $t = 2.66$, $p = 0.008$) and not for translation students' BI ($\beta = 0.06$, $t = 0.44$, $p = 0.663$), which supported H12. Overall, the model explained 58.1% of the variance in BI among translation students and 61.1% among non-translation students.

4.3 | Students' Ratings of Translation Tool Usage Frequency

As shown in Figure 2, MT tools were the most frequently used translation aids, surpassing ChatGPT. A Wilcoxon signed-rank test confirmed this difference, with $z = -4.06$, $p < 0.001$ for

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TABLE 7 | Comparison of standardized path coefficients by experience and discipline.

	Experience groups		Discipline groups	
Path	**Low experience**	**High experience**	**Non-translation**	**Translation**
PE → BI	0.42***	0.63***	0.56***	0.70***
EE → BI	0.20	−0.13	0.02	−0.02
SI → BI	0.25**	0.02	0.07	0.08
FC → BI	0.10	0.29	0.29**	0.06
R^2	60.0%	56.9%	61.1%	58.1%

Note. *$p < 0.05$,
**$p < 0.01$,
***$p < 0.001$.

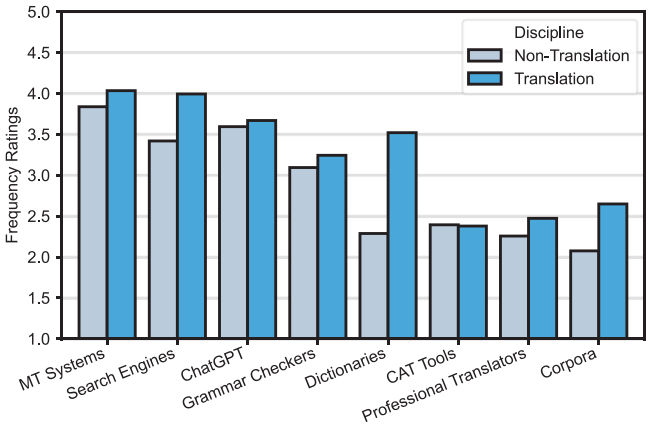

FIGURE 2 | Frequency ratings for translation tool and resource usage among translation and non-translation students. [Color figure can be viewed at wileyonlinelibrary.com]

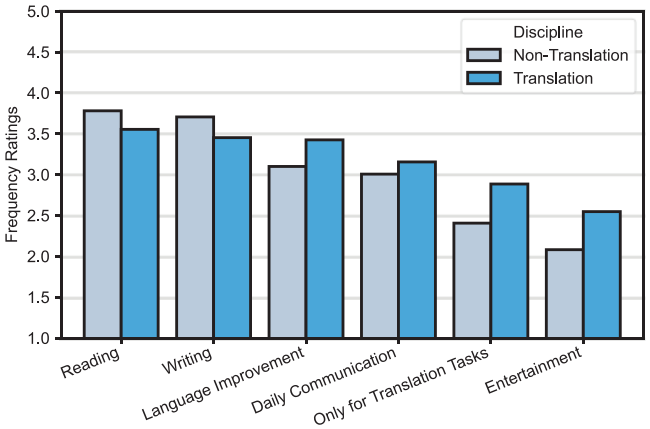

FIGURE 3 | Frequency ratings of translation purposes among translation and non-translation students. [Color figure can be viewed at wileyonlinelibrary.com]

translation students and $z = -2.59$, $p = 0.009$ for non-translation students. Despite this, ChatGPT ranked among the top three preferred translation tools.

A Mann-Whitney U test was conducted to compare the usage frequency of other translation tools between the two groups. Translation students used search engines ($z = -4.59$, $p < 0.001$), dictionaries ($z = -7.93$, $p < 0.001$), and corpora ($z = -4.24$, $p < 0.001$) significantly more than non-translation students. These findings suggest that translation students rely on a broader range of resources.

4.4 | Students' Purposes for Translation Practices

To understand students' acceptance of ChatGPT as a translation tool, we compared the purposes of translation activities between translation and non-translation students (see Figure 3). Both groups primarily use translation for reading comprehension, writing, and language improvement, while translating solely for translation tasks was less common.

Non-translation students reported translating more frequently for reading comprehension ($z = -1.95$, $p = 0.05$) and writing tasks ($z = -2.21$, $p = 0.027$). In contrast, translation students were more likely to translate for language improvement ($z = -2.45$, $p = 0.014$), translation-specific tasks ($z = -3.34$, $p = 0.001$), and entertainment ($z = -3.88$, $p < 0.001$). These findings suggest that non-translation students use translation as a means to achieve other goals, while translation students view translation as an end in itself.

4.5 | Summary of Hypothesis Testing

In summary, the results of our hypothesis testing address our two research questions as follows. For RQ1, which examines the main drivers of adoption, performance expectancy (H1), and facilitating conditions (H4) were significant predictors of behavioral intention, and both hypotheses were supported. Effort expectancy (H2) and social influence (H3) were not significant and were therefore rejected. Regarding RQ2, which investigates moderating effects, prior use experience strengthened the effect of performance expectancy (H5), and weakened the effect of social influence (H7), supporting both hypotheses. Experience did not significantly moderate the effects of effort expectancy (H6) or facilitating conditions (H8), which were rejected. Finally, academic discipline also acted as a moderator, strengthening the

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effect of performance expectancy (H9) and showing the effect of facilitating conditions to be weaker for translation students (H12); therefore, H9 and H12 were supported. Discipline did not moderate the effects of effort expectancy (H10) or social influence (H11), which were rejected.

5 | Discussion

This study applied the UTAUT model to examine the factors influencing Hong Kong university students' intention to use ChatGPT for translation, exploring the moderating roles of experience and academic discipline. The findings reveal a pragmatic student body whose adoption of ChatGPT is driven more by practical utility than by social trends, with significant nuances emerging based on their academic background and experience.

5.1 | Performance and Support: The Pragmatic Drivers of Student Adoption

In response to our first research question, this study found that the intention to use ChatGPT for translation is overwhelmingly driven by its perceived utility and the support systems available. PE was the strongest predictor of adoption, while FC also exerted a significant positive influence. In contrast, EE and SI were non-significant. Taken together, these results suggest that for university students in Hong Kong, the decision to use ChatGPT is less a matter of ease or peer pressure and more a pragmatic calculation of its ability to deliver better, faster results within a supportive environment.

A noteworthy finding of this study is the non-significance of EE and SI, which diverges from the traditional UTAUT model (Venkatesh et al. 2003). This divergence does not suggest that ease of use and social influence are unimportant in technology adoption universally; rather, it is likely attributable to the specific characteristics of our user group and the technology itself. The negligible effect of EE can be explained by the high digital literacy of the university student population and the inherent usability of ChatGPT. For these digitally native participants, accustomed to rapidly learning new technologies, the effort required to use ChatGPT is minimal. The tool's intuitive, conversational interface further diminishes the cognitive load, making ease of use a baseline expectation rather than a primary driver of adoption. Similarly, the non-significant influence from SI suggests that while peers or instructors might introduce students to the tool, this user group tends to rely on independent evaluation for sustained use. Once they have personally verified the tool's performance, the influence of external opinion wanes. In a context where a technology's utility is apparent and individually verifiable, the need for social reinforcement appears to be less critical.

These findings yield direct implications for both pedagogy and institutional policy. The prominence of PE means that to foster informed adoption, translation training programs should emphasize both the benefits and potential risks of using AI tools, ensuring students develop critical skills while leveraging the technology effectively. Simultaneously, the significance of FC points directly to the university's responsibility to provide a secure and supportive infrastructure. This extends beyond simple technical assistance to address the paramount issue of data privacy. Given that the free version of ChatGPT may not guarantee data privacy and is unsuitable for academic exercises that simulate professional practice (Wu et al. 2024), a key facilitating condition for ethical and effective integration is institutional provision of the secure, paid version (e.g., via API or an enterprise license). The findings suggest that effective AI integration in translation training depends on two key factors. First, educational programs should help students critically assess both the benefits and limitations of AI tools. Second, institutions can support this integration by providing secure, paid platforms that address the data privacy concerns associated with free versions.

5.2 | The Moderating Roles of Experience and Academic Discipline

Our second research question investigated how experience and academic discipline moderate the factors influencing students' intention to use ChatGPT for translation. The findings reveal that a one-size-fits-all approach to AI pedagogy is insufficient. Instead, students' motivations are shaped by their specific user profiles. This underscores the need for tailored educational and developmental strategies that respond to diverse learner needs.

First, a student's level of experience clearly shapes a developmental trajectory in their adoption of AI tools. Novice users relied on both PE and SI, with their decisions influenced by trusted individuals like teachers and peers. This aligns with classic technology acceptance models where social cues are critical in early stages (Venkatesh et al. 2003; Venkatesh and Morris 2000). However, as students gained direct experience, the impact of SI diminished, and PE became the dominant factor. This shift suggests that while social encouragement is key to overcoming initial hesitation, sustained use ultimately depends on the tool's proven, practical benefits, which users learn to evaluate independently over time.

Second, academic discipline appeared to be a critical moderator, creating a clear divide between specialist and non-specialist users. For translation students, PE was the sole significant driver. As emerging experts trained in a variety of translation technologies, they evaluate ChatGPT with a professional lens, focusing exclusively on its capacity to improve their workflow and output quality. This finding supports the vision of the translator as an "AI-assisted language specialist" (Kornacki and Pietrzak 2021), who is more focused on how technology can augment their expertise than on basic support. In contrast, non-translation students were influenced by both PE and FC. Lacking specialized training, they understandably depend more on institutional resources to use AI tools effectively and responsibly. Their reliance on FC provides empirical weight to arguments for integrating foundational technology training into general language education (Pym and Hao 2024).

These divergent user profiles—the experienced specialist versus the supported novice—carry direct implications for both pedagogy and platform development. Educators must move beyond a one-size-fits-all model: translation students require training focused on advanced features that enhance efficiency, while

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non-translation students need stronger institutional support and foundational AI literacy to build confidence and competence. This educational need is directly linked to the responsibilities of developers. To serve both groups, platforms must not only offer advanced features but also address the core need for a supportive environment, particularly regarding data security. By making privacy controls more transparent and demystifying the "black box" of data management (Wu et al. 2024), developers can build the user trust that is essential for deep adoption in professional and academic fields (Ayvazyan et al. 2024; Pym 2025).

6 | Conclusion

This study provides crucial empirical evidence on the adoption of ChatGPT for translation in higher education, revealing that student choices are driven by pragmatic assessments of performance and moderated by experience and academic discipline. Our research contributes to GenAI translation pedagogy by demonstrating that while performance benefits are universally valued, the path to effective and ethical adoption differs significantly between user groups. Translation students act as expert evaluators focused on efficiency, whereas their non-translation peers rely more heavily on institutional support. This distinction highlights the need for tailored pedagogical strategies. Ultimately, this study argues that to prepare students for an AI-assisted future, universities must not only teach critical evaluation skills but also provide the secure, professional-grade tools necessary for ethical practice.

While these findings offer valuable insights, the study includes several limitations that point to possible directions for future research. First, the use of convenience and snowball sampling, although efficient, may reduce the generalizability of the results. Future studies can adopt stratified random sampling across a wider set of universities to improve the external validity of the conclusions. Second, the research relies on self-reported data, which reflects intended behavior rather than actual usage. Although behavioral intention serves as a strong predictor of usage in the UTAUT framework (Venkatesh et al. 2003), a gap may still exist between intention and action. Studies that follow a defined group of students over time or that apply in-depth qualitative methods can offer a clearer view of how usage patterns shift and what factors drive these changes. Finally, while the UTAUT model offers a sound theoretical base, it may not address certain aspects that are central to AI translation, such as ethical concerns, data security, or the complexity of intercultural communication. Future research should expand or adjust the UTAUT framework by introducing constructs that reflect these critical issues, in order to build a more complete view of AI adoption in this fast-developing area.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data concerning the study are publicly available on Open Science Framework (https://osf.io/yh8p3/).

Peer Review

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Appendix

UTAUT Questionnaire Items

Constructs	Items	Source
Performance expectancy	I find ChatGPT useful for translation.	Venkatesh et al. 2003
	Using ChatGPT enables me to accomplish translation tasks more quickly.	
	Using ChatGPT increases my translation productivity.	
	Using ChatGPT increases my chances of achieving my goals.	
Effort expectancy	Learning to use ChatGPT is easy for me.	Venkatesh et al. 2003
	My interaction with ChatGPT is clear and understandable.	
	I find ChatGPT easy to use for translation.	
	It is easy for me to become skillful at using ChatGPT for translation.	
Social influence	I use ChatGPT for translation because people around me have mentioned it.	Bernabei et al. 2023
	I use ChatGPT for translation because people around me use it.	
	I use ChatGPT for translation because I heard about it from lectures/social networks/newspapers.	
	I use ChatGPT for translation to stay updated. (Removed)	
Facilitating conditions	I have the resources necessary to use ChatGPT for translation (e.g., access permission).	Venkatesh et al. 2003
	I have the knowledge necessary to use ChatGPT for translation (e.g., knowledge of ChatGPT's capabilities).	
	ChatGPT is compatible with other translation tools and resources I use.	
	I can get help from others when I have difficulties using ChatGPT for translation. (Removed)	
Behavioral intention to use	I intend to use ChatGPT frequently for my translation tasks.	Shroff and Keyes 2017
	I intend to increase my use of ChatGPT for translation tasks.	
	Whenever possible, I intend to use ChatGPT for translation as often as needed.	
	I expect to continue using ChatGPT as a translation tool in the future.	

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