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From innovativeness to insecurity: unveiling the facets of translation technology use behavior among EFL learners using TRI 2.0

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Translation technologies are essential in supporting English as a Foreign Language (EFL) students by overcoming language barriers and enhancing academic performance. Despite their potential benefits, the actual use behavior of these technologies is underexplored in the existing literature. This study investigates the drivers and inhibitors of translation technology use behavior among college EFL students by pioneering the application of the Technology Readiness Index (TRI) 2.0 framework. A structured questionnaire was administered to 554 junior and senior EFL students across six Chinese universities. Data were analyzed utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate the measurement and structural models and a multigroup analysis (MGA) to examine potential differences based on socioeconomic background. The results showed that optimism positively influenced behavioral intention ($\beta = 0.251$, $p < 0.001$) and use behavior ($\beta = 0.189$, $p < 0.001$) regarding translation technologies. The innovation demonstrated a significant positive effect on behavioral intention ($\beta = 0.113$, $p < 0.01$) but not on use behavior. Discomfort negatively impacted behavioral intention ($\beta = -0.276$, $p < 0.001$) but did not significantly affect use behavior. Insecurity negatively influenced both behavioral intentions ($\beta = -0.319$, $p < 0.001$) and use behavior ($\beta = -0.254$, $p < 0.001$). Behavioral intention was a strong predictor of use behavior ($\beta = 0.372$, $p < 0.001$). MGA showed no statistically significant differences between rural and urban students in the proposed relationships. By identifying optimism and insecurity as key determinants of intention and actual usage, this study underscores the importance of cultivating technology readiness and providing targeted support to promote translation technology adoption in higher education, ultimately strengthening language-learning outcomes for EFL students.

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Introduction

The landscape of education is rapidly transforming in the contemporary era, propelled by the integration of advanced technologies (Bygstad et al., 2022; Escueta et al., 2020; F. Huang et al., 2024; Y. Wang & Xue, 2024). Among these innovations, translation technologies have emerged as crucial tools, particularly for college EFL students. These technologies, which include machine translation (MT) systems, translation apps, and computer-assisted translation tools (Li et al., 2023), provide students with the means to overcome language barriers, facilitating more effective learning and communication in academic settings. The significance of translation technologies lies in their ability to support multilingual education, promote linguistic diversity, and improve translation performance among EFL students (Kalocsányiová, 2017; Muñoz-Basols, 2019). These tools not only facilitate immediate comprehension of unfamiliar vocabulary and complex expressions but also serve as scaffolding mechanisms that help students gradually build their language proficiency through exposure to accurate translations and linguistic patterns (Muñoz-Basols et al., 2023).

The evolution of translation technologies is deeply intertwined with the advancements in artificial intelligence (AI) and natural language processing (NLP). Early systems, such as rule-based machine translation (RBMT), have been superseded by more sophisticated models like neural machine translation (NMT), which can produce more accurate and contextually appropriate translations (Mondal et al., 2023). The widespread availability of mobile devices and internet connectivity has further democratized access to these tools (Vieira et al., 2021), making them readily available to students worldwide. This technological progress is critical in supporting the academic endeavors of EFL students, who often face significant challenges in understanding and producing academic content in English. Translation technologies hold transformative potential for them by assisting in various academic tasks, including reading comprehension (Klimova et al., 2023), writing assignments (Lee, 2020), and participating in discussions (Pituxcoosuvarn & Ishida, 2018). They offer multiple advantages, such as increased translation speed, improved accuracy, and the capability to handle large volumes of foreign text efficiently (Chen et al., 2022; X. Wang et al., 2021). By providing real-time translations and language assistance, these technologies can reduce the cognitive load on students, enabling them to better understand and engage with both the content and language simultaneously. This dual engagement, supported by translation technologies, enhances the efficiency and effectiveness of learning processes, ultimately contributing to improved academic outcomes for EFL students (Daelemans & Hoste, 2009; Shadiev & Sun, 2020).

Despite the apparent benefits, the actual use behavior of translation technologies among college EFL students varies widely. Multiple factors, including personal attitudes, technological readiness, and perceived usefulness, could influence students' willingness to engage with these tools. This study adopts the TRI 2.0 framework to explore the factors that drive or inhibit the use of these technologies. TRI 2.0, an evolution of the original TRI 1.0, assesses individuals' propensity to adopt and utilize new technologies through four dimensions: optimism, innovativeness, discomfort, and insecurity (Parasuraman & Colby, 2015). By identifying the factors that encourage or discourage use, educators, and policymakers can formulate strategies to promote positive attitudes and behaviors toward translation technologies and address the barriers that hinder the adoption and effective utilization of these technologies. Additionally, investigating the drivers and inhibitors of translation technology use contributes to the broader literature on technology adoption in education. It provides empirical insights that can be applied to other educational technologies, complementing the knowledge of how to foster a technology-enhanced learning environment.

Previous research has extensively explored the factors influencing technology adoption across different contexts. For instance, the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) are frequently employed frameworks for examining technology adoption in education (Venkatesh et al., 2003). These models emphasize the importance of perceived usefulness, ease of use, and behavioral intention in predicting technology use. In terms of translation technologies, studies have highlighted the potential benefits for language learning and academic performance (Ducar & Schocket, 2018; Lee, 2023) and explored various aspects such as the effectiveness of MT tools in improving language skills, students' intention to utilize these technologies, and the pedagogical implications of their use (Kelly & Hou, 2022; Li et al., 2024; Y. Yang & Wang, 2019). For instance, Lee (2020) showed that MT contributed to reducing grammatical errors and enhancing student revisions in EFL writing. Similarly, Klimova et al. (2023) found that translation technologies, when utilized by an experienced instructor to offer specific guidance, can significantly enhance the communication abilities of novice students, aiding them in expressing themselves more effectively and with reduced effort. However, little research has been done explicitly focusing on the factors influencing the use behavior of translation technologies among college EFL students.

This study seeks to bridge the gap by applying the TRI 2.0 framework to investigate the drivers and inhibitors of translation technology use among this demographic for the first time to the best of our knowledge. The TRI framework, particularly in its updated TRI 2.0 form, has been widely utilized to assess readiness across various technology domains, including online learning technologies (Browning et al., 2023), e-commerce (Ramírez-Correa et al., 2019), smart home technology (Basarir-Ozel et al., 2023; Mulcahy et al., 2019), and mobile payment (Balakrishnan & Lay Gan, 2023). These studies have underscored the significant role of individual dimensions such as optimism and innovativeness in driving technology adoption, while discomfort and insecurity act as barriers. Despite the extensive application of the TRI framework, there is a notable lack of research specifically investigating the actual usage of translation technologies within this framework. By examining the individual dimensions of technology readiness, this study aims to offer a thorough understanding of the drivers and inhibitors that impact the adoption of these tools in academic settings. The investigation will be guided by these questions:

1. How do optimism, innovativeness, discomfort, and insecurity influence college EFL students' behavioral intention to use translation technologies?
2. How do these dimensions of technology readiness affect the actual use behavior of translation technologies?
3. What is the connection between behavioral intention and the actual use behavior of translation technologies?
4. Does socioeconomic background moderate the relationships between technology readiness dimensions, behavioral intention, and use behavior?

This study provides several novel contributions to educational technology and translation research by addressing these questions. It is the first to adopt the TRI 2.0 framework specifically to examine EFL students' use of translation technologies, thereby extending the applicability of TRI 2.0 into a previously underexplored domain. It also extends the theoretical application of TRI 2.0 by integrating it with actual use behavior measurement, moving beyond mere adoption intention to examine real-world technology utilization patterns. By considering both behavioral intention and actual use behavior, along with the moderating influence of socioeconomic factors, this work offers a more comprehensive understanding of the motivators and barriers simultaneously influencing technology adoption in language-learning contexts. These findings provide actionable recommendations for educators, policymakers, and technology developers to improve the educational experiences of EFL students and advance our understanding of technology adoption in educational contexts.

Literature review and hypothesis development

TRI 2.0. The inception of TRI 1.0 (Parasuraman, 2000) introduced a comprehensive framework to assess technology readiness, defined as the propensity towards embracing and employing novel technologies for achieving personal and professional objectives. This model incorporated four core aspects of technology readiness: optimism and innovativeness as motivators and discomfort and insecurity as inhibitors. These dimensions were initially operationalized through a 36-item scale to measure individuals' overall readiness to engage with emerging technologies (Parasuraman, 2000). They were identified based on the theory that individuals' long-term attitudinal dispositions towards technology significantly influence their behavior concerning technology adoption and usage.

Over the years, the rapid pace of technological advancements necessitated an update to keep the TRI relevant. This led to the development of TRI 2.0, a more streamlined version with 16 items, retaining the original four dimensions but with a more concise set of items for each (Parasuraman & Colby, 2015). Of the 16 items in TRI 2.0, 11 were retained from TRI 1.0, and 5 are entirely new items (2 for optimism and 3 for insecurity). Several items from TRI 1.0 were reworded to be more technology-neutral, removing references to specific technologies like "computer programs" that could become outdated. Additionally, TRI 2.0 incorporated new items to reflect contemporary themes, such as the impact of technology on personal relationships, technology dependency, and social pressures, which were not as prevalent when TRI 1.0 was developed. This updated index was designed to capture the evolving technology environment, including the widespread adoption of e-commerce, social media, and cloud computing, which have become integral to people's lives since the publication of TRI 1.0.

The refinement process for TRI 2.0 was underpinned by a two-phase research project. The qualitative phase involved forum discussions with consumers to identify emerging technology themes, while the quantitative phase included mail and online surveys to validate the shortened scale. This rigorous approach ensured that TRI 2.0 maintained the robust psychometric properties of its predecessor and enhanced its applicability and relevance to contemporary technology contexts (Parasuraman & Colby, 2015). Furthermore, TRI 2.0's validity and reliability as a segmentation tool have been rigorously demonstrated, rendering it a valuable resource for understanding and predicting technology adoption behaviors across various user demographics. For instance, its application in assessing the readiness and adoption of home tele-monitoring services (Crundall-Goode et al., 2017), contactless hospitality services (Hao & Chon, 2021), and connected and autonomous vehicles (O'Hern & St. Louis, 2023) highlights its utility in diverse technological domains. Moreover, the individual dimensions of TRI 2.0 have been independently associated with significant effects on the adoption of technologies in mobile payments (Balakrishnan & Eesan, 2024; S. A. Rahman et al., 2017), underscoring the index's multifaceted applicability.

TRI 2.0 offers a refined and empirically validated framework for assessing technology readiness, capturing the sophisticated interplay of motivators and inhibitors that shape individuals' engagement with new technologies. Given the proven efficacy of TRI 2.0 in gauging technology readiness and its impact on technology adoption decisions, integrating this model with the constructs of behavior intention and use behavior from classic technology acceptance models will generate a comprehensive framework for comprehending college students' acceptance and use of translation technologies. This pioneering integration allows for a detailed examination of the motivators and inhibitors influencing students' intention and behavior, providing critical insights into strategies for promoting the adoption of translation technologies in academic settings.

Hypothesis development

Optimism. Optimism is identified as a general construct capturing positive feelings toward technology and the belief that technology enables control, efficiency, and flexibility in achieving goals (Parasuraman, 2000). As a personality trait (King & Caleon, 2021), optimism positively influences individuals' receptiveness to new technologies by alleviating fears and promoting positive responses (Sing et al., 2022). This trait plays an essential role in shaping undergraduates' intentions to utilize translation technologies, as it can help mitigate the apprehension or skepticism they might have toward this relatively new form of academic aid. Moreover, optimism captures the general attitude that technology is beneficial (Tsikriktsis, 2004), suggesting that students who are optimistic about translation technologies tend to exhibit positive use behavior as they approach the technologies with a hopeful and constructive attitude. Davidson and Prkachin (1997) define dispositional optimism as an innate tendency towards hopeful thinking frequently linked with favorable behavioral outcomes. Heger and Papageorge (2018) note that optimism involves underestimating task difficulty, which can be beneficial in the context of using translation technologies, as students with this optimistic bias may be more inclined to engage with the technologies, anticipating fewer difficulties and thus exhibiting more persistent use behavior. An optimistic outlook toward technologies is likely to positively influence various dimensions of use behavior among college students, including frequency, duration, and patterns of usage (Marikyan et al., 2023; Strzelecki, 2024; Venkatesh et al., 2003). Therefore, we hypothesized that:

H1: Optimism positively impacts behavioral intention to utilize translation technologies among EFL students.

H2: Optimism positively impacts the use behavior of translation technologies among EFL students.

Innovativeness. Innovativeness pertains to an individual's propensity to embrace novel ideas before others within their social environment (Rogers, 2003) and is characterized by a tendency for novel and diverse experiences (Hirschman, 1980; J. Kim & Forsythe, 2008). In the realm of information systems, personal innovativeness is seen as a driving force behind the willingness to engage with new IT applications (Lu, 2014; Pitafi & Ali, 2023) and is specifically defined as individuals' readiness to experiment with new technologies (Robinson et al., 2005). Rogers (2003) describes the behavioral characteristics of highly innovative individuals, such as actively seeking information and being less dependent on others' evaluations. This proactive and independent approach to new technologies makes innovative students more likely to adopt and use translation technologies. Empirical research has shown that personal innovativeness is a significant factor in the adoption of diverse educational technologies such as e-learning platforms (Twum et al., 2022), mobile learning (Sitar-Taut & Mican, 2021), and online learning (M. K. Rahman et al., 2023). Agarwal and Prasad (1998) specifically associate this willingness with the acceptance and utilization of new technologies in everyday activities. The connection between innovativeness and technology adoption is further reinforced by the concept of use behavior as the tangible manifestation of technology adoption (Marikyan et al., 2023; Z. Zhang et al., 2022). In Rogers' framework (2003), innovativeness places individuals on a continuum regarding their readiness to adopt new ideas relative to their peers, suggesting that college students exhibiting greater innovativeness are more inclined to both intend to use and actually engage with translation technologies. Thus, we proposed that:

H3: Innovativeness positively impacts behavioral intention to utilize translation technologies among EFL students.

H4: Innovativeness positively impacts the use behavior of translation technologies among EFL students.

Discomfort. Discomfort is linked to a perception of insufficient control and a sense of being inundated by technological advancements (Hailey Shin et al., 2021; Sunny et al., 2019), which is viewed as a tangible component of adverse emotional effects (Ashkenazy & DeKeyser Ganz, 2019; Kamble et al., 2019; Parasuraman, 2000). The TRI 2.0 framework identifies discomfort as a dimension that reflects a lack of confidence in and unease with technology (Parasuraman & Colby, 2015). The essence of discomfort in the technological context is the user's perceived incapacity to effectively manage and understand the technology, leading to feelings of anxiety and overload.

The negative emotional state induced by discomfort can be a significant barrier to the formation of positive behavioral intention and actual usage of technology. In the context of students engaging with translation technologies, an overwhelming sense of disempowerment and loss of control may act as a deterrent, undermining their willingness to utilize these tools due to the anticipation of a stressful and unmanageable experience. This observation aligns with the findings of Pang et al. (2017) and Akhtar et al. (2020), who found that discomfort can lead to decision deferral as individuals seek to avoid the negative emotional state by postponing technology adoption or seeking alternatives. Studies on similar technologies have shown that user discomfort can lead to resistance or reduced engagement. For instance, Scherer and Hatlevik (2017) found that discomfort experienced by students, whether due to psychological barriers, physical discomfort, or learning stress, negatively impacts their willingness and ability to use information and communication technology effectively. Similarly, Cohen-Lazry et al. (2023) demonstrated a negative correlation between discomfort and technology usage in intelligent autonomous systems. Extending this to the context of translation technologies, students experiencing discomfort might find these technologies overwhelming or challenging to harness, thereby impacting their usage behavior negatively. Hence, we hypothesized that:

H5: Discomfort negatively impacts behavioral intention to use translation technologies among EFL students.

H6: Discomfort negatively impacts the use behavior of translation technologies among EFL students.

Insecurity. Within the framework of TRI 2.0, insecurity refers to a deficiency in trust toward technology and skepticism concerning its functionality (Parasuraman & Colby, 2015). Individuals who feel insecure may doubt the technology's reliability and fear possible errors or misuse (Meuter et al., 2000). This distrust can be a significant barrier to technology adoption for college students since they may have less confidence in the technology's ability to meet their language learning or translation needs, potentially affecting both their intention to use and actual usage patterns. Insecurity is often categorized as an adverse driver for individuals' technology readiness (Parasuraman & Colby, 2015) because those with a heightened sense of technological insecurity are less inclined to engage with it (Blut & Wang, 2020). Factors incorporated in UTAUT2, such as performance expectancy, effort expectancy, and social influence, could be influenced by perceived insecurity (Venkatesh et al., 2012). For instance, if undergraduates perceive translation technologies as insecure, it could lower their performance expectancy (belief about the beneficial outcomes of using the technology), thus negatively affecting both their intention and usage behavior.

Empirical studies have found that perceived risk, including security concerns, can negatively affect the adoption of various technologies, including e-commerce (Gurung & Raja, 2016), home telehealth services (Cimperman et al., 2016), and real-time online classes (S. S. Kim, 2023) among various demographics. Similarly, Jarrar et al. (2020) found that insecurity has a negative influence on the intention to embrace new technology in terms of smartphone apps for tourism. Research in similar technology domains, like online learning platforms, has consistently shown that perceived security concerns can significantly affect user behavior and acceptance (Jiang et al., 2022; S. S. Kim, 2023). Applying this to translation technologies, it is plausible that students' concerns about the security and reliability of these tools could lead to both reduced intention to use and actual usage. Therefore, we proposed that:

H7: Insecurity negatively impacts behavioral intention to use translation technologies among EFL students.

H8: Insecurity negatively influences the use behavior of translation technologies among EFL students.

Behavioral intention and use behavior. Behavioral intention is fundamentally the extent to which individuals plan to utilize technology, reflecting their internal schema of beliefs and motivational factors (Venkatesh et al., 2003). This intention encompasses the user's readiness and willingness to engage with the technology. The concept is central to different technology acceptance models and predicts actual technology utilization. The relationship between behavioral intention and use behavior has been consistently validated across various technological contexts. For instance, the investigation on the use of DingTalk indicates a significant influence of behavioral intention on the technology's actual usage (Hou & Yu, 2023). This relationship is further supported by research on Learning Management Systems (Raza et al., 2021), e-government (Hooda et al., 2022), online labs (Bazelais et al., 2024), and interactive whiteboards (Tosuntaş et al., 2015), where the behavioral intention is linked to enhanced use behavior. These studies highlight the generalizability of this relationship across various technologies and user groups, which suggests that the intention to utilize technology like translation tools can significantly predict actual usage patterns among college EFL students. Thus, Hypothesis 9 was put forward:

H9: Behavioral intention positively impacts the use behavior of translation technologies among EFL students.

The overall research framework is shown in Fig. 1.

Methods

Participants. Participants were selected using convenience sampling from six Chinese universities, targeting junior and senior students enrolled in English-related majors (i.e., English, Business English, and Translation), a significant subset of EFL learners. This selection ensured that all participants possessed hands-on experience and familiarity with translation technologies through their school curriculum. In total, 554 students took part in the survey. The participants were primarily female (86.8%), with

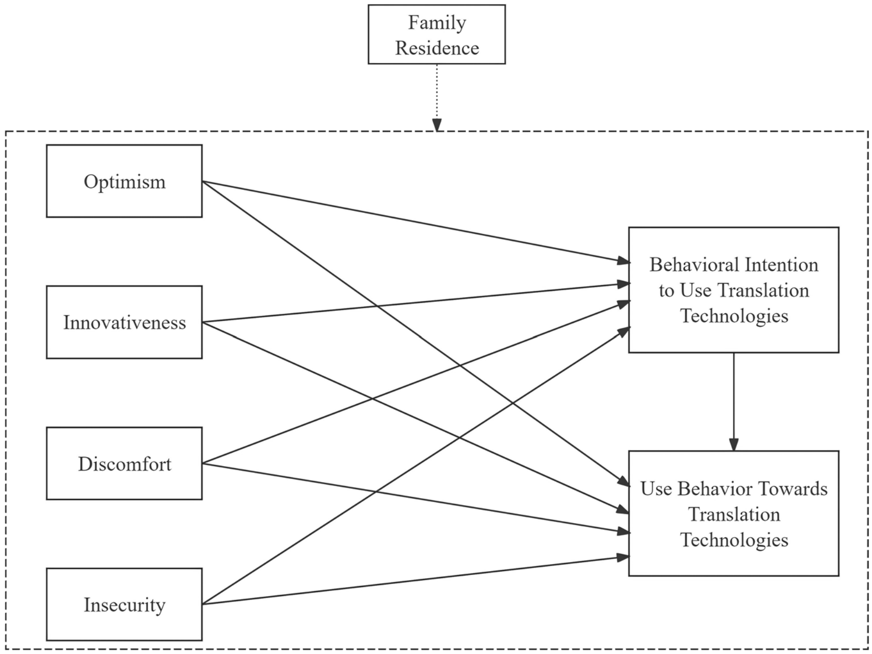

Fig. 1 Research framework.

males comprising 13.2% of the sample. The gender imbalance observed in this study reflects the demographic trends of English-related majors in Chinese universities, which traditionally exhibit higher female enrollment rates. This phenomenon is consistent with national data and other studies focusing on similar academic programs in China, where the female-to-male ratio in English-related disciplines is markedly skewed (S. Zhang & Lai, 2024). Most respondents were between 18 and 22 (93.1%), while a smaller percentage were older than 22 (6.9%). About 44.6% of the participants were from urban areas, and 55.4% were from rural areas. The participants' experience with translation technologies varied: 25.5% had less than one year of experience, 49.3% had between one and three years, 17.3% had between three and five years, and 7.9% had more than five years of experience.

This study constitutes a component of a broader research project conducted by our team, focusing on the adoption and use of translation technologies among undergraduate students. This paper explicitly investigates the actual use behavior of translation technologies by applying the TRI 2.0 framework, providing empirical insights into the drivers and inhibitors affecting this behavior.

Ethical considerations were duly observed throughout the study. Participation was voluntary. Participants were informed about the objective of the investigation and assured of the confidentiality of their responses, and their informed consent was obtained prior to participation. The research protocol received evaluation and subsequent approval from the institutional review board associated with the investigator's university.

Instruments. The study utilized a cross-sectional survey through a two-part questionnaire. The initial portion focused on collecting demographic information, including age, gender, family residence, and prior experience with translation technologies. This demographic information provided a comprehensive overview of the participants' backgrounds, essential for contextualizing the subsequent analysis.

The second section comprised the main items of interest, organized into six constructs relevant to the research objective. A total of 23 questions were included in this part, each measured on a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The items were adapted from established scales originally designed to measure technology readiness and acceptance in general contexts. To ensure their relevance for evaluating translation technologies among EFL students, modifications were made to reflect the specific context of using translation tools. These adaptations aimed to maintain the reliability and validity of the original scales while aligning them with the study's focus. A significant part of this section was dedicated to assessing technology readiness using the TRI 2.0 framework (Parasuraman & Colby, 2015), which includes 16 items to evaluate four dimensions. Unlike those studies that compute a composite TRI 2.0 score of these four dimensions, this study treats each dimension as an independent variable. This approach facilitates a thorough examination of how individual dimensions of technology readiness impact behavioral intention and use behavior of translation technologies among the participants. Such an approach echoes the empirical studies by Ramírez-Correa et al. (2019), who employed the four constructs as independent variables to predict online hedonic and utilitarian purchases, and Rahman et al. (2017), who investigated the effect of these four variables on perceived ease of use and perceived usefulness of mobile money service technology.

Furthermore, behavioral intention and use behavior were assessed through items adapted from the UTAUT2 model (Venkatesh et al., 2012). Specifically, three items assessed behavioral intention, and four items evaluated actual use behavior of translation technologies. The integration of the UTAUT2 model provides a robust framework for understanding the factors driving and inhibiting the adoption and usage of translation technologies among college EFL students.

Data collection. The data collection process for this study was conducted in collaboration with educators who had direct access to junior and senior students majoring in English-related disciplines across the six targeted universities. These instructors served as intermediaries to facilitate the distribution of the survey. An electronic version of the questionnaire was shared with the teachers, who then forwarded it to their students. The survey was

Table 1 Descriptive and measurement model analysis.

Construct	Item	Mean	SD	Factor loading	VIF	Cronbach's α	CR	AVE
BI	BI1	3.966	0.524	0.864	2.108	0.875	0.923	0.801
	BI2	3.892	0.572	0.930	3.096			
	BI3	3.921	0.583	0.889	2.469			
DIS	DIS1	2.036	0.487	0.886	2.851	0.927	0.948	0.821
	DIS2	2.128	0.537	0.917	3.524			
	DIS3	2.047	0.467	0.914	3.534			
	DIS4	2.054	0.510	0.907	3.200			
INN	INN1	3.271	0.550	0.891	3.086	0.892	0.925	0.756
	INN2	3.242	0.533	0.825	2.137			
	INN3	3.283	0.564	0.831	2.235			
	INN4	3.186	0.480	0.926	3.629			
INS	INS1	1.966	0.462	0.907	3.481	0.936	0.954	0.839
	INS2	1.984	0.471	0.941	4.950			
	INS3	2.011	0.488	0.909	3.375			
	INS4	2.036	0.523	0.905	3.399			
OPT	OPT1	3.845	0.596	0.902	3.399	0.942	0.959	0.853
	OPT2	3.884	0.561	0.939	4.744			
	OPT3	3.906	0.578	0.921	3.892			
	OPT4	3.897	0.569	0.931	4.242			
UB	UB1	3.975	0.527	0.906	3.146	0.921	0.944	0.808
	UB2	3.937	0.565	0.910	3.305			
	UB3	4.007	0.506	0.919	3.607			
	UB4	3.881	0.589	0.859	2.473			

BI behavioral intention, *DIS* discomfort, *INN* innovativeness, *INS* insecurity, *OPT* optimism, *UB* use behavior.

hosted on "Wenjuanxin," a widely recognized online platform in China. Students were invited to complete the questionnaire during the data collection period, which spanned two months, from December 26, 2023, to February 26, 2024. This approach allowed for efficient and broad participation while ensuring the anonymity and confidentiality of the respondents.

Data analysis and procedure. This study employed PLS-SEM to test the proposed hypotheses by SmartPLS 4, a comprehensive software for PLS-SEM that facilitates complex model testing with high precision (Becker et al., 2023).

The first step was evaluating the measurement model. This involved assessing the reliability and validity of the constructs. Indicator reliability was examined by each indicator's outer loadings. Internal consistency reliability was assessed through composite reliability (CR) and Cronbach's α. Convergent validity was measured using the average variance extracted (AVE). Discriminant validity was evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio.

Following the establishment of validity and reliability in the measurement model, the structural model was evaluated. The variance inflation factor (VIF) values were checked to ensure the absence of multicollinearity issues. The overall model fit and quality were assessed using several indices. The standardized root mean square residual (SRMR) was calculated, with values below 0.08 indicating a good fit. The normed fit index (NFI) was also evaluated, with values close to 1 suggesting a good model fit.

Subsequently, the significance of the hypothesized relationships was tested through bootstrapping with 5000 resamples to obtain standard errors, p values, and t values. The model's explanatory power was assessed by examining the R^2 values for the endogenous constructs. f^2 was calculated to determine the effect of each predictor construct on the dependent construct. Q^2 was also evaluated using the blindfolding procedure to test the predictive relevance.

Additionally, MGA was performed to examine potential differences in the structural relationships between participants from rural and urban family backgrounds. MGA within SmartPLS 4 compared the path coefficients across the two subgroups, highlighting any significant differences that could provide insights into the varying factors affecting the actual use behavior of translation technologies. The procedure followed involved assessing measurement invariance across the groups before comparing structural paths, ensuring that any observed differences were due to genuine variations in the effects of translation technologies among these demographics.

Results

Measurement model assessment. High factor loadings indicate that the items effectively represent the latent construct. According to Table 1, all factor loadings exceed the threshold of 0.7, suggesting that each item is a good indicator of its respective construct.

Internal consistency reliability assesses the extent to which items of a construct are consistent with one another. This is evaluated using Cronbach's α and CR. Generally, values above 0.7 indicate acceptable reliability. According to Table 1, all constructs exhibit high Cronbach's α and CR values, indicating strong internal consistency reliability. Convergent validity refers to the degree to which measures of a construct exhibit a strong correlation. As shown in Table 1, all constructs have AVE values well above 0.5, demonstrating adequate convergent validity. Discriminant validity examines whether constructs that should be unrelated are distinct. This is evaluated using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio in this study. According to Table 2, the square root of each variable's AVE is greater than its highest correlation with any other construct, indicating adequate discriminant validity (Fornell & Larcker, 1981). Table 3 shows HTMT values range from 0.511 to 0.811, all below the threshold of 0.9, which further supports the validation of discriminant validity.

Results of the structural model. We calculated the VIF values to examine the presence of multicollinearity in the dataset. The

Table 2 Fornell–Larcker criterion.

	BI	DIS	INN	INS	OPT	UB
BI	0.895					
DIS	−0.656	0.906				
INN	0.567	−0.468	0.869			
INS	−0.700	0.613	−0.584	0.916		
OPT	0.643	−0.524	0.552	−0.578	0.923	
UB	0.733	−0.574	0.535	−0.684	0.629	0.899

Table 3 HTMT.

	BI	DIS	INN	INS	OPT	UB
BI						
DIS	0.728					
INN	0.639	0.511				
INS	0.772	0.659	0.635			
OPT	0.707	0.560	0.599	0.616		
UB	0.811	0.617	0.587	0.733	0.673	

threshold commonly cited in the literature for VIF values is 10, above which multicollinearity is considered problematic (Hair et al., 2009). However, the more conservative threshold of 5 has also been recommended (O'brien, 2007). As shown in Table 1, all VIF values are below 5, suggesting that multicollinearity is not a significant issue in this study.

The structural model evaluation was conducted using PLS-SEM to examine the hypothesized relationships among the constructs. The model indices demonstrated a satisfactory fit, with the SRMR at 0.039 and the NFI at 0.902. The d_ULS and d_G metrics also yielded insignificant values (0.414 and 0.345, respectively), further indicating a good fit (Dash & Paul, 2021).

The findings presented in Fig. 2 and Table 4 show that optimism had a positive and significant effect on both behavioral intention (β = 0.251, $p < 0.001$, CI [0.173, 0.332]) and use behavior (β = 0.189, $p < 0.001$, CI [0.107, 0.268]) of translation technologies among college students, thus supporting H1 and H2. This indicates that higher levels of optimism among college students positively influence their intention to use translation technologies and their actual usage. Similarly, innovativeness also positively and significantly affected behavioral intention (β = 0.113, $p < 0.01$, CI [0.034, 0.192]), supporting H3, implying that more innovative students tend to have a higher intention to utilize translation technologies. However, its influence on use behavior was not significant (β = 0.047, $p > 0.05$, CI [−0.036, 0.128]), leading to the rejection of H4. Thus, innovativeness did not significantly predict the actual use of translation technologies. The discomfort had a negative and significant impact on behavioral intention (β = −0.276, $p < 0.001$, CI [−0.364, −0.190]), supporting H5, indicating that students who experience higher discomfort are less likely to intend to use translation technologies. However, its impact on use behavior was not significant (β = −0.053, $p > 0.05$, CI [−0.143, 0.041]), resulting in the rejection of H6, suggesting that discomfort did not significantly affect the actual use of translation technologies. Insecurity had a negative and significant impact on behavioral intention (β = −0.319, $p < 0.001$, CI [−0.416, −0.223]), supporting H7, indicating that students with higher insecurity are less inclined to intend to use translation technologies. Additionally, the path from insecurity to use behavior was negative and significant (β = −0.254, $p < 0.001$, CI [−0.365, −0.149]), supporting H8, indicating that insecurity significantly reduces the actual usage of translation technologies among students. Lastly, the analysis confirmed that behavioral intention positively and significantly affected use behavior (β = 0.372, $p < 0.001$, CI [0.272, 0.471]), supporting H9, indicating that students' intentions to utilize translation technologies strongly predict their actual use. Although the results show that behavioral intention is a robust predictor of use behavior, it is noteworthy that only optimism and insecurity had direct and significant effects on actual usage. In contrast, innovativeness and discomfort, while significantly related to behavioral intention, did not translate into significant direct effects on use behavior. This finding suggests that for students who score high on innovativeness or discomfort, their decision to actually use translation technology depends more on their formed intention rather than the trait itself exerting a direct impact.

Overall, these results indicate that optimism significantly influences the behavioral intention to utilize and the actual usage of translation technologies among EFL students. Innovativeness influences behavioral intention but does not significantly affect actual use behavior. Discomfort significantly affects behavioral intention but not actual use, whereas insecurity negatively influences both behavioral intention and use behavior. Behavioral intention significantly impacts college EFL students' use behavior, though the pattern of direct effects shows that only optimism and insecurity influence both behavioral intention and actual use, while innovativeness and discomfort only affect behavioral intention.

According to Cohen (1988), f^2 values can be classified as small (0.02), medium (0.15), and large (0.35). As shown in Table 4, the f^2 effect sizes reveal that optimism has an effect size of 0.097 on behavioral intention and 0.049 on use behavior, indicating a small influence. In contrast, innovativeness exhibits an effect size of 0.020 on behavioral intention, which is at the threshold of a small effect, and 0.003 on use behavior, which is negligible. Discomfort exhibits an effect size of 0.119 on behavioral intention and 0.004 on use behavior, indicating a small effect on behavioral intention but a negligible effect on use behavior. Similarly, insecurity shows an effect size of 0.132 on behavioral intention, which is small to medium, and 0.072 on use behavior, representing a small effect. Finally, behavioral intention has an effect size of 0.135 on use behavior, indicating a small to medium effect. These results highlight that the independent variables have a range of effects, mostly small, on behavioral intention and use behavior, depending on the individual variable.

The structural model assessment for this study reveals substantial explanatory power and predictive relevance. Table 5 shows that the R^2 value is 0.630 for behavioral intention, meaning the model explains 63% of the variance in behavioral intention. Similarly, the R^2 value is 0.621 for use behavior, indicating that the model explains 62.1% of the variance in use behavior. These values demonstrate a substantial level of explanatory power for both constructs. According to Table 5, the Q^2 values for behavioral intention and use behavior are 0.623 and 0.559, respectively. Both values are well above zero, demonstrating that the model possesses strong predictive relevance for both constructs. These findings confirm that the model is not only explanatory but also predictive in nature.

Multigroup analysis. A PLS-MGA was conducted to compare rural and urban sub-samples of college EFL students, aiming to investigate the effect of family residence on the proposed relationships. Before performing the multigroup analysis, the measurement invariance of composite models (MICOM) procedure was utilized to ensure the validity of the comparisons. The MICOM approach involves three steps: assessment of configurational invariance, compositional invariance, and the

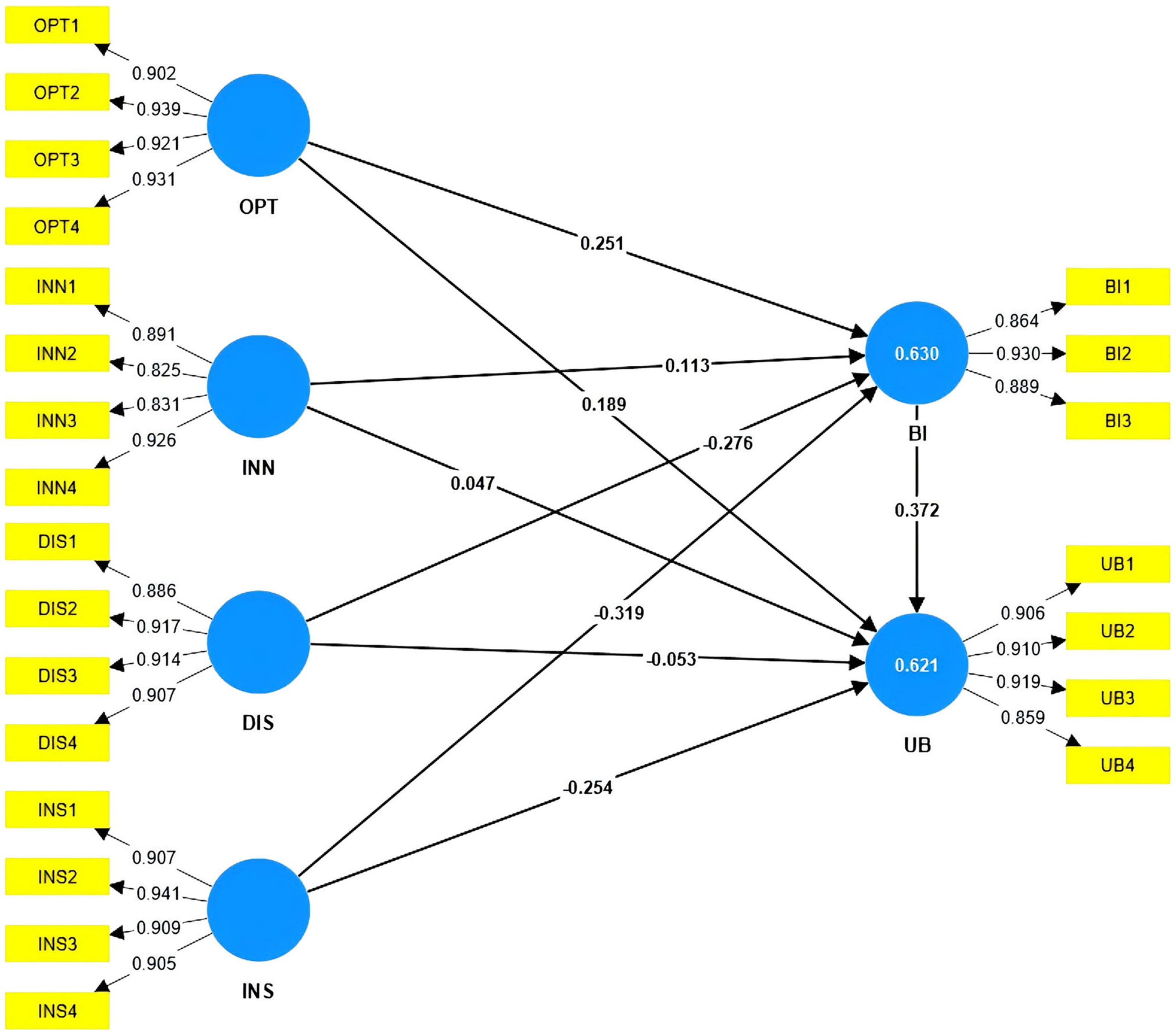

Fig. 2 PLS-SEM results.

Table 4 Results of structural path analysis.

Hypothesis	Path	β	SD	T values	P values	CI (2.5%)	CI (97.5%)	Decision	f^2
H1	OPT - > BI	0.251	0.041	6.118	0.000	0.173	0.332	Supported	0.097
H2	OPT - > UB	0.189	0.041	4.564	0.000	0.107	0.268	Supported	0.049
H3	INN - > BI	0.113	0.040	2.795	0.005	0.034	0.192	Supported	0.020
H4	INN - > UB	0.047	0.041	1.131	0.258	−0.036	0.128	Rejected	0.003
H5	DIS - > BI	−0.276	0.044	6.239	0.000	−0.364	−0.190	Supported	0.119
H6	DIS - > UB	−0.053	0.047	1.118	0.264	−0.143	0.041	Rejected	0.004
H7	INS - > BI	−0.319	0.049	6.469	0.000	−0.416	−0.223	Supported	0.132
H8	INS - > UB	−0.254	0.054	4.668	0.000	−0.365	−0.149	Supported	0.072
H9	BI - > UB	0.372	0.051	7.373	0.000	0.272	0.471	Supported	0.135

evaluation of equal means and variances (Cheah et al., 2023). As shown in Table 6, configurational invariance was confirmed for all constructs, indicating that the basic configuration of the measurement model is identical across both groups. Compositional invariance was also achieved for all constructs, as indicated by an original correlation of 1.000 or close to 1.000 and non-significant differences in the permutation tests. This step ensures that the composite scores are comparable across groups. Despite establishing compositional invariance, full measurement invariance was not achieved for all constructs. Specifically, the equal mean assessment failed for optimism, and the equal variance assessment failed for discomfort and use behavior. As such, partial measurement invariance was confirmed, which is sufficient for conducting multigroup analysis.

The multigroup analysis (Table 7) highlights the differences in path coefficients between rural and urban participants. For the

Table 5 R^2 and Q^2.

Endogenous factor	R^2	R^2 adjusted	Q^2
BI	0.630	0.628	0.623
UB	0.621	0.618	0.559

relationship between behavioral intention and use behavior, the path coefficient was significant for rural (β = 0.324, $p < 0.001$) and urban (β = 0.452, $p = 0.001$) samples separately. However, the difference between the coefficients (β = −0.128) was not statistically significant ($p > 0.05$). Similarly, the relationship between discomfort and behavioral intention showed significant negative path coefficients for both rural (β = −0.270, $p < 0.001$) and urban (β = −0.267, $p < 0.001$) samples, with no significant difference between the groups ($p > 0.05$). The path from discomfort to use behavior was not significant for either group, and the difference in path coefficients (β = −0.123) was also not significant ($p > 0.05$).

The analysis further revealed that the path from innovativeness to behavioral intention was significant only for the urban sample (β = 0.174, $p < 0.01$), while it was insignificant for the rural sample (β = 0.070, $p > 0.05$). Nevertheless, the difference in path coefficients (β = −0.103) was not significant ($p > 0.05$). The path from innovativeness to use behavior was not significant for either group, with an insignificant difference in path coefficients ($p > 0.05$). Insecurity to behavioral intention showed significant negative paths for both rural (β = −0.321, $p < 0.001$) and urban (β = −0.317, $p < 0.001$) samples, with no significant difference between the groups ($p > 0.05$). The same pattern was observed for the path from insecurity to use behavior, which showed significant negative paths for both rural (β = −0.249, $p < 0.01$) and urban (β = −0.252, $p < 0.01$) samples, with no significant difference between the groups ($p > 0.05$).

Optimism to behavioral intention revealed significant positive paths for both rural (β = 0.259, $p < 0.001$) and urban (β = 0.236, $p < 0.001$) samples, with no significant difference between the groups ($p > 0.05$). Similarly, the path from optimism to use behavior was significant for both rural (β = 0.207, $p < 0.001$) and urban (β = 0.167, $p < 0.05$) samples, with no significant difference between the groups ($p > 0.05$).

Overall, the results indicate that family residence (rural vs. urban) does not significantly moderate the proposed relationships, which suggests that the drivers and inhibitors of translation technology use behavior are similar regardless of family socioeconomic backgrounds. This finding underscores the uniformity in the influence of technological readiness across different family residence contexts among college EFL students.

Discussion

The following discussions interpret the study's findings by analyzing how key constructs of TRI 2.0 influence translation technology use behavior among EFL students. It examines the role of optimism and innovativeness in shaping behavioral intention and actual use, emphasizing their implications for technology adoption. The section also addresses the negative effects of discomfort and insecurity, exploring how these factors impact intention and use behavior differently. Additionally, the relationship between behavioral intention and use behavior is discussed, highlighting its broader theoretical and practical significance. The findings from the multigroup analysis are then considered, shedding light on the consistent applicability of the proposed relationships across diverse socioeconomic backgrounds and their implications for fostering inclusive technology adoption strategies.

Table 6 Results of invariance measurement testing using permutation.

Constructs	Configurational invariance (Step 1)	Compositional invariance (Step 2)		Partial measurement invariance	Equal mean assessment (Step 3a)			Equal variance assessment (Step 3b)			Full measurement invariance
		Original correlation	5.0%		Original differences	Confidence interval	Equal	Original differences	Confidence interval	Equal	
BI	Yes	1.000	1.000	Yes	−0.077	[−0.169,0.157]	Yes	−0.255	[−0.274,0.262]	Yes	Yes
DIS	Yes	1.000	1.000	Yes	0.043	[−0.175,0.159]	Yes	−0.383	[−0.343,0.329]	No	No
INN	Yes	1.000	0.999	Yes	−0.054	[−0.172,0.175]	Yes	−0.022	[−0.471,0.482]	Yes	Yes
INS	Yes	1.000	1.000	Yes	0.159	[−0.169,0.157]	Yes	−0.338	[−0.337,0.351]	Yes	Yes
OPT	Yes	1.000	1.000	Yes	−0.173	[−0.163,0.167]	No	−0.121	[−0.264,0.264]	Yes	No
UB	Yes	1.000	1.000	Yes	−0.136	[−0.157,0.157]	Yes	−0.398	[−0.292,0.290]	No	No

Table 7 Results of multigroup analysis.

Path	Rural			Urban			Path coefficient differences	p Value Henseler's MGA	p Value Permutation Test	Decision
	Path Coefficient	CI (95%)	p value	Path Coefficient	CI (95%)	p value				
BI- > UB	0.324	[0.201,0.447]	0.000	0.452	[0.292,0.604]	0.000	−0.128	0.215	0.218	Reject
DIS- > BI	−0.270	[−0.400,-0.146]	0.000	−0.267	[−0.397,−0.154]	0.000	−0.004	0.962	0.974	Reject
DIS- > UB	−0.115	[−0.238,0.010]	0.071	0.009	[−0.124,0.155]	0.904	−0.123	0.194	0.211	Reject
INN- > BI	0.070	[−0.048,0.187]	0.235	0.174	[0.068,0.269]	0.001	−0.103	0.189	0.197	Reject
INN- > UB	0.087	[−0.007,0.187]	0.081	−0.007	[−0.153,0.130]	0.922	0.094	0.284	0.289	Reject
INS- > BI	−0.321	[−0.461,-0.173]	0.000	−0.317	[−0.436,-0.181]	0.000	−0.004	0.974	0.977	Reject
INS- > UB	−0.249	[−0.396,-0.106]	0.001	−0.252	[−0.422,−0.095]	0.002	0.003	0.981	0.981	Reject
OPT- > BI	0.259	[0.147,0.372]	0.000	0.236	[0.126,0.353]	0.000	0.023	0.775	0.777	Reject
OPT- > UB	0.207	[0.115,0.304]	0.000	0.167	[0.035,0.298]	0.014	0.040	0.634	0.663	Reject

Our findings confirm that optimism significantly influences both behavioral intention and actual use behavior of translation technologies among college EFL students. Optimism positively affects students' perceptions of translation technologies, which aligns with the established view that optimism, as a positive disposition towards technology, encourages greater engagement and frequent use (King & Caleon, 2021; Tsikriktsis, 2004). Optimistic students perceive translation technologies as beneficial and user-friendly, which reduces anxiety and enhances their willingness to integrate these tools into their academic activities. These results resonate with prior studies such as Singh et al. (2022), who noted that optimism mitigates fears and fosters positive reactions toward new technologies. By comparing our findings with the studies that underscored the role of optimism in the adoption of e-learning platforms (Álvarez-Marín et al., 2023; El Alfy et al., 2017), we reinforce the notion that optimism is a critical driver of translation technology acceptance and usage among EFL students. Further, we support the assertion that an optimistic outlook correlates with higher intensity and diverse patterns of technology use even after first adoption (Son & Han, 2011). Therefore, enhancing students' optimistic perspectives toward translation technologies could be a strategic focus for educators and policymakers aiming to increase the adoption of these tools. The Practical Implications section provides detailed strategies for fostering optimism and ensuring its integration into policy and curriculum design.

The study reveals that innovativeness significantly affects behavioral intention but does not significantly influence actual use behavior. This partial support indicates that although innovative students are more inclined to express intent to use translation technologies, this does not necessarily translate into actual usage. Our findings align with those of Yi et al. (2006) and Huang and Liao (2015), who found that while innovativeness fosters initial acceptance, it might not always lead to sustained use of technologies. Innovativeness might drive the initial curiosity and intent but may not sustain long-term engagement without additional facilitating factors. Although innovativeness is a precursor to adoption intention, other factors such as ease of use, support, financial cost, and contextual relevance ultimately determine continued usage (Dajani & Abu Hegleh, 2019; Twum et al., 2022). While innovative students intend to use these tools, practical barriers might inhibit consistent and effective use, suggesting that additional support might be necessary to convert intentions into consistent usage. As Nyoni and Goddard (2021) and Hodge and Turner (2016) indicated, innovators are quick to adopt but do not always sustain long-term use without appropriate support mechanisms. This difference may be attributed to the context-specific nature of translation technologies, which require not only initial interest but also continuous practical utility and integration into academic workflows. Therefore, supporting innovative students with training and continuous engagement strategies could bridge the gap between intention and actual use.

Discomfort was identified to impact behavioral intention negatively but not actual use behavior. This finding suggests that while discomfort reduces the likelihood of students intending to use translation technologies, it does not necessarily impede those who have already decided to use these technologies from actual usage. Discomfort, or the perception of technology being overwhelming and challenging to use, can deter individuals from forming a positive intention towards its use (Pang et al., 2017; Sunny et al., 2019). Our findings are consistent with the research by Parasuraman (2000) and Hailey Shin et al. (2021), who highlighted discomfort as a barrier to technology adoption due to a perceived lack of control and overwhelming feelings. Kocur and Jach (2024) also identified a negative correlation between discomfort and technology usage in digital learning tools in a synchronous online scenario, supporting our results regarding behavioral intention. However, the non-significant effect on actual use behavior might be explained by students' adaptation over time. Once students overcome initial barriers and decide to use the technology, their actual usage may not be as adversely affected by discomfort. They might continue to use the technology due to perceived benefits or necessity. This phenomenon could be interpreted by the adaptation and learning processes described by Jensen and Konradsen (2018), where initial discomfort is mitigated through experience and familiarity with the technology, reducing its impact on actual use. This insight extends the work of Lakhal et al. (2021), indicating that interventions targeting discomfort can effectively boost initial acceptance, even if long-term use behavior requires additional factors. The Practical Implications section outlines strategies for reducing discomfort, such as training programs and user-friendly design, to enhance adoption.

Insecurity negatively influenced behavioral intention and actual use behavior. This supports the TRI 2.0 framework's assertion that insecurity, characterized by distrust and skepticism, impedes technology adoption (Parasuraman & Colby, 2015). Students with higher insecurity levels doubted the reliability and efficacy of translation technologies, which significantly decreased both their intention to use and actual usage. This finding is in line with Jarrar et al. (2020), who confirmed that insecurity significantly influences the intention to adopt mobile tourism apps. Further, the negative impact of insecurity on use behavior corroborates Kim (2023) and Zhai et al. (2020), who observed that perceived security concerns significantly reduce user engagement with real-time virtual classes and online collaborative learning. The significant negative relationship between insecurity and use behavior highlights the critical role of trust and reliability perceptions in technology adoption. Addressing these insecurities through improved communication about data protection and reliability could enhance the intention to use and actual usage among students. Specific interventions for mitigating insecurity are detailed in the Practical Implications section, including recommendations for technology developers and institutional policymakers.

While our findings generally support the relationship between behavioral intention and use behavior, they reveal a more complex pattern than previously documented in technology adoption literature. The positive correlation between these constructs confirms the core premise of UTAUT (Venkatesh et al., 2003) and underscores the significance of fostering strong behavioral intentions to drive actual usage, but importantly, our results show that this relationship varies across technology readiness dimensions. Specifically, while behavioral intention significantly predicts use behavior overall, only optimism and insecurity demonstrated significant direct effects on actual use behavior. In contrast, innovativeness and discomfort did not show significant direct effects on use behavior despite their influence on behavioral intention. This detailed finding differs from previous studies of web-based education technologies (Raza et al., 2021), social network sites (Liu et al., 2016), and online labs (Bazelais et al., 2024), which typically reported more uniform relationships. These results extend our understanding of technology adoption among undergraduates by highlighting how different psychological dispositions towards technology can lead to varying patterns in actual usage behavior (Efiloğlu Kurt & Tingöy, 2017; Hooda et al., 2022). Consequently, strategies to promote translation technology adoption should consider behavioral intentions and how different technology readiness dimensions directly influence actual usage in the EFL learning context.

The multigroup analysis revealed no significant moderating effect of socioeconomic background on the proposed relationships. This finding suggests that the factors influencing the use behavior of translation technologies among college EFL students are consistent regardless of whether they come from rural or urban backgrounds. This uniformity aligns with previous research indicating the pervasive influence of technology readiness factors across different demographic groups (Browning et al., 2023; Rahmat et al., 2022). This consistency highlights the universal applicability of TRI 2.0 and UTAUT models in understanding technology adoption behaviors among diverse student populations. It also underscores the importance of creating inclusive technological environments that cater to the needs of all students, irrespective of their socioeconomic backgrounds.

Implications

Theoretical implications. This research extends the TRI 2.0 framework by validating its dimensions as critical factors influencing both behavioral intention and actual use behavior in the specific context of translation technologies. It reinforces the relevance and robustness of TRI 2.0 in a technological setting that has not been previously investigated, confirming its utility beyond general technology readiness and into specialized translation tools in higher education. Furthermore, the findings demonstrate the intricate interplay between these dimensions, highlighting that while optimism and innovativeness positively impact behavioral intention, only optimism significantly translates into actual use, underscoring the complex nature of technology adoption processes. The significant negative influence of discomfort and insecurity on behavioral intention also provides deeper insights into the barriers to technology acceptance, suggesting that emotional and trust-related factors play pivotal roles. Moreover, the consistent findings across rural and urban student populations affirm the robustness and generalizability of the TRI 2.0 framework in diverse demographic contexts, suggesting its broad applicability in educational technology research. These theoretical implications validate the TRI 2.0 model in a new context and offer a more integrated understanding of the interplay between technology readiness dimensions and use behaviors, offering an integrated framework for future research on technology adoption in educational settings.

Practical implications. Higher education institutions and policymakers are crucial in cultivating a supportive environment for adopting and using translation technologies among college EFL students. Given the significant effect of optimism and insecurity on both behavioral intention and actual use, institutions should focus on building a positive technological outlook while addressing security concerns. This can be achieved through comprehensive training programs highlighting the benefits and ease of use of translation technologies. For example, Yang et al. (2016) demonstrated that online collaborative translation significantly increased EFL students' enthusiasm and self-efficacy in specialized English translation, indicating that well-designed training programs can boost students' confidence and engagement. Additionally, institutions should invest in robust cybersecurity measures and transparent data protection policies to mitigate students' insecurity and build trust in these technologies. They can implement GDPR-compliant data protection policies, ensuring that students' personal information is handled with the highest level of security (Voigt & Von dem Bussche, 2017). Communicating these policies clearly to students can mitigate insecurity and encourage the use of translation technologies. Policymakers should also consider integrating technology readiness assessments into educational frameworks through measures such as pre-semester technology readiness surveys, periodic digital literacy evaluations, and structured feedback mechanisms on technology usage patterns. These assessments can help design targeted interventions, such as personalized training modules for students with low technology readiness scores, peer mentoring programs for technology adoption, and adaptive learning platforms that match students' technological proficiency levels. As Blut and Wang (2020) found, technology readiness, particularly optimism and innovativeness, significantly influences the usage of cutting-edge technologies.

Educators and curriculum designers have a direct influence on students' engagement with translation technologies. Integrating these technologies into the curriculum can significantly boost students' familiarity and comfort with their use. Educators can design assignments and activities that require the use of translation tools, thereby making their use a part of regular academic practice. For instance, Garcia and Pena (2011) highlighted that when students regularly used translation tools as part of their assignments, their language proficiency and comfort with the technology significantly improved. Curriculum designers should ensure that the integration of translation technology is not merely supplementary but is systematically embedded within the learning objectives and intended outcomes of relevant courses. For example, using machine translation for revising student writing significantly decreased lexico-grammatical errors and improved students' writing strategies, helping them view writing as a less daunting process (Lee, 2020). By doing so, they can enhance students' technology readiness, particularly in terms of optimism and innovativeness, which are critical drivers of behavioral intention and use behavior. Moreover, training sessions and hands-on workshops can help students overcome initial discomfort, reduce their feelings of insecurity, and build a more optimistic attitude toward these tools. For instance, workshops that simulate real-life translation tasks can assist students in comprehending the practical benefits and applications of these technologies (Konttinen et al., 2020).

Technology developers have a critical role in creating user-friendly and secure translation technologies that cater to the needs of college EFL students. Understanding the drivers and inhibitors identified in this study, developers should prioritize improving the user experience by designing intuitive interfaces that reduce discomfort and make the technology more accessible. Addressing insecurity through robust security features and transparent data handling practices is essential, including clear privacy policies and data usage explanations, thereby building trust and fostering a positive outlook toward using the technology (Cenfetelli & Schwarz, 2011). This can also be achieved by employing advanced encryption methods and regularly updating security protocols to protect user data (Panayiotou et al., 2019). Meanwhile, developers can focus on building features that demonstrate the tangible benefits of translation technologies. For example, introducing collaborative features, where students can work together and share translations in real-time, can demonstrate the practical benefits of the technology (Chang & Hsu, 2011). Integrating features showing real-time improvement in language proficiency, such as interactive feedback and progress tracking, can make the benefits more evident (Lai & Zheng, 2018). Additionally, collaboration with educational institutions can provide developers with valuable insights into the specific needs and challenges faced by students, enabling the creation of more tailored and effective translation tools. For instance, involving educators in the design process can ensure that the tools support pedagogical goals and enhance learning outcomes (Jeong, 2017).

Conclusion

This study investigates the drivers and inhibitors affecting the use behavior of translation technologies among EFL undergraduates through the lens of the TRI 2.0 framework. The findings identify the critical roles of optimism and insecurity in affecting both behavioral intention and use behavior, highlighting the importance of fostering a positive outlook and addressing security concerns to enhance technology adoption. While innovativeness positively impacts behavioral intention, its influence on actual use is less pronounced, suggesting that initial enthusiasm must be supported by practical usability. Discomfort significantly deters behavioral intention but does not necessarily impede actual use, indicating that initial training and continuous support are essential to overcome early barriers. Additionally, the strong connection between behavioral intention and use behavior reaffirms the importance of fostering robust intentions to ensure sustained technology use. The study's results are consistent across rural and urban populations, demonstrating the universal applicability of the TRI 2.0 model in diverse educational settings. This research enriches the understanding of technology acceptance in EFL education and provides a robust theoretical and practical foundation for enhancing technology readiness and adopting translation tools among students.

Despite its contributions, this study has several limitations that warrant consideration for future research. First, the investigation was conducted across six Chinese universities, focusing on junior and senior students in English-related majors. While these universities encompass diverse socioeconomic backgrounds, the findings may still be context-specific and not entirely generalizable to global EFL populations. Cultural, educational, and technological factors unique to China could influence the results, limiting their applicability to other countries or regions. Future research should consider replicating this study in different cultural and geographical contexts to validate the generalizability of the findings. Second, the cross-sectional approach captures the relationships at a single point, which may not account for changes in technology use behavior over time. Longitudinal studies are recommended to understand how these behaviors and attitudes evolve. Additionally, while the study identifies key factors influencing use behavior, it does not delve into the potential mediating and moderating roles of other psychological and contextual variables, such as technological self-efficacy or institutional support. Future research could explore additional variables to enhance the comprehensive understanding of technology adoption dynamics.

Data availability

The dataset generated and analyzed during the current study is provided in the supplementary file.

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Author contributions

JZ: Conceptualization, funding acquisition, investigation, project administration, validation, and writing—review and editing. XL: Data curation, formal analysis, funding acquisition, methodology, software, visualization, and writing—original draft. ZG: Data curation, investigation, resources, supervision, and writing—review and editing.

Competing interests

The authors declare no competing interests.

Ethical approval

This study received ethical approval from the Institutional Ethics Committee of the School of Foreign Languages and Cultures at Panzhihua University (Approval No.: HRECA23-006-3). Approval was granted on December 26, 2023, prior to the commencement of the research. All research procedures were conducted in strict accordance with the principles of the Declaration of Helsinki. The ethical approval covers all aspects of the study, including participant recruitment, questionnaire administration, and data analysis. The investigation period spanned from December 26, 2023 to February 26, 2024.

Informed consent

Informed consent was obtained in electronic written form from all participants prior to their participation in the questionnaire survey. The consent process clearly informed participants about the purpose of the research, how their data would be used, and assured them of confidentiality and anonymity. Participants were informed that their participation was entirely voluntary, and they could withdraw from the study at any time without consequences. All participants were adults (above 18 years of age). The informed consent covered participation, data use, and consent to publish anonymized results.

Additional information

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