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Factors Affecting Acceptance of Cloud-Based Computer-Assisted Translation Tools Among Translation Students

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***Abstract*—Translation technology is a fundamental aspect of the translation profession. Cloud-based computer-assisted translation (CAT) tools are becoming popular among translators because of their simplicity and usability. However, studies on the factors affecting the use of cloud-based CAT tools by translators and translation students are scarce. Therefore, this study explores the factors that influence the acceptance and use of such tools among translation students using the technology acceptance model (TAM). The hypothesized model is empirically validated using a survey of 181 participants. Using structural equation modeling, data analysis suggests that translation students' intention to use cloud-based CAT tools and their perceived usefulness are key adoption factors, while actual use is less significant. The simplicity of cloud-based CAT tools is also an important consideration, particularly for translation students with limited information technology experience. The implications for tool developers and translation instructors are discussed considering these findings.**

***Index Terms*—Cloud-based CAT, TAM, technology acceptance, translation technologies, translation training**

I. Introduction

Computer-assisted translation (CAT) tools can be defined as “any type of computerized tool that translators use to help them perform their jobs” (Bowker, 2002, p. 6). These tools were developed to aid translators during the translation process. The first commercial CAT software was launched in the early 1980s by a U.S.-based company, Automated Language Processing Systems (ALPS). That system included multilingual word processing, electronic dictionaries, and a terminology tool (Hutchins, 2007). This software was followed by more advanced packages offering sophisticated functions and tools. With new advances, we are witnessing a shift toward cloud-based translation technologies to expedite the translation process and enhance collaboration (Rothwell et al., 2023; Tarasenko et al., 2022).

Although some studies have discussed the potential of cloud-based CAT tools (Malenova, 2019; Alotaibi, 2020; Han, 2020; Tarasenko et al., 2022) and explored attitudes toward their use (e.g., Tian et al., 2023; Lui et al., 2022; Rico & González Pastor, 2022), research exploring the factors influencing translators’ acceptance and use of such technologies is limited (Moorkens, 2018; Olohan, 2011). According to Cheung and Vogel (2013), technology acceptance is a prerequisite for integration, particularly in teaching and learning. Hence, we must explore the factors that may influence students’ intentions to use cloud-based CAT tools before incorporating them into translation training. Thus, this study aims to identify the factors that influence the acceptance and use of cloud-based CAT tools among translation students by employing the technology acceptance model (TAM) (Davis et al., 1989). The TAM is a well-established model used to predict the intention to adopt and use any new technology. The model is based on reasoned action theory (RAT) to explain computer usage behaviors (Fishbein & Ajzen, 1975) which was developed by Davis (1989). Since then, the model has been used in numerous studies conducted in instructional settings (Jeyaraj, 2022; Kim & Song, 2022; Luo et al., 2022; Şahin et al., 2022; Lu et al., 2019; Rossi & Chevrot, 2019).

For translator training, most TAM studies have focused on machine translation (MT) (e.g., Yang & Wang, 2019; Al-Maroof et al., 2020; Yang & Mustafa, 2022; Robert, 2021). However, few studies have examined cloud-based translation tools from an MT perspective. Thus, this study aimed to answer the following research questions: What factors influence the acceptance of cloud-based CAT tools?

Understanding the factors that influence translation students’ acceptance and use of cloud-based CAT tools is essential to enhance their technological skills and prepare them for the demands of the translation industry. By identifying the factors that affect the perceived usefulness (PU) and perceived ease of use (PEU) of training programs, such programs can be developed to address barriers to adoption and more effective use of these tools can be promoted. The findings of this study can inform the development of more user-friendly and effective cloud-based CAT tools to meet the needs of translation students and professionals.

The following section presents a literature review of cloud-based CAT tools, the concept of technology acceptance, and relevant models.

II. Literature Review

A. *Cloud-Based CAT Tools*

Recent advances in translation technology have led to the effective integration of cloud-based CAT tools into the translation process, and there has been an increased demand for proficient translators with high-tech skills. Therefore, CAT courses are becoming an essential part of translation training programs at most universities (Bowker, 2002; Olohan, 2011). As cloud technologies gain popularity, there's been a rise in the use of cloud-based CAT tools among translators and translation trainees. These tools are more practical than computer-based systems because they do not require installation or work on multiple platforms. These tools also facilitate greater collaborative opportunities with various flexible licensing options (Tarasenko et al., 2022).

Cloud-based CAT tools typically integrate various features and functionalities designed to make the translation process more efficient and productive (Rothwell et al., 2023). Common features of cloud-based CAT tools include a translation memory (TM), that is, a database of previously translated segments that can be reused to improve consistency and efficiency; a terminology management system for managing and storing terminology to ensure consistency and accuracy in translations; an MT engine to provide suggestions for translations that can be edited and refined by human translators; collaboration tools to manage and share translation projects, including real-time collaboration, communication, and version control; quality assurance tools to ensure the quality and accuracy of translations, including spelling and grammar checkers, a consistency checker, and error detection; project management tools for managing translation projects, including scheduling, budgeting, and resource allocation; and reporting and analytics for tracking project progress, productivity, and quality metrics (Amelina et al., 2018; Alotaibi, 2020; Han, 2020; Mitchell-Schuitevoerder, 2020; Tarasenko et al., 2022).

Cloud-based CAT tools have the following advantages over computer-based tools.

- Accessibility: They can be accessed anywhere through an Internet connection, whereas computer-based CAT tools require software to be installed on a specific computer.
- Collaboration: This allows multiple users to simultaneously work on the same project, making collaboration easier and more efficient.
- Scalability: These tools can be easily scaled up or down based on project needs, whereas computer-based CAT tools are limited by the processing power of the computers on which they are installed.
- Automatic updates: These tools are automatically updated with the latest features and updates, whereas computer-based CAT tools require manual updates to be installed.
- Cost: They typically have a lower upfront cost as they do not require the purchase of hardware or software licenses. In addition, they are often subscription-based, allowing users to pay only for the features and services they require.

However, some of these advantages can be perceived as drawbacks (O'Brien et al., 2017; Gamal, 2020; Malenova, 2019). Cloud-based CAT tools require a stable internet connection to function properly. Slow or unreliable Internet connections can affect translators' performance and productivity. Security and privacy are other issues that might raise concerns, particularly with sensitive data because data are stored on external servers and accessed through the Internet. Another concern is related to cost. While cloud-based CAT tools can be cost-effective for smaller projects or occasional use, they can become more expensive for larger or ongoing projects, as users typically pay for monthly or annual subscriptions. Customizability is another drawback, as users may find cloud-based CAT tools less customizable than computer-based CAT tools because they are typically designed to be used by various users (O'Brien et al., 2017).

These issues must be considered when deciding whether to use cloud- or computer-based CAT tools. When deciding, it is important to weigh the advantages and disadvantages and consider various factors such as project size, budget, and security concerns.

Several recent studies have investigated the adoption of CAT tools by translators, whether computer- or cloud-based. The next section explores these studies to highlight the models used and the main findings.

B. *Studies on CAT Tools Acceptance and Adoption*

Translators can use several theoretical models to investigate the adoption and use of cloud-based CAT tools. The unified theory of acceptance and use of technology (UTAUT) is one of the models that identify four key factors affecting technology adoption: performance expectancy (PE), effort expectancy, social influence, and facilitating conditions. It has been applied to investigate the adoption of technologies such as e-banking and government services. However, the use of this model to evaluate translation technology adoption is limited. In one of the few studies that addressed this area, Hui and Selamat (2023) investigated the individual adoption of a crowdsourcing translation platform. This study adds variables specific to crowdsourcing translation such as perceived value, individual innovation, network learning adaptability, and perceived risk. The results indicate that both crowdsourcing professionals and nonprofessionals have a strong willingness to use a highly integrated crowdsourcing platform.

Daems (2022) used UTAUT to study 155 Dutch literary translators. A survey was distributed among the participants to collect data on their background, education, and use and awareness of technology for translation, including both general technology and technology specifically developed for translation. This study investigated whether demographic factors such as date of birth, years of experience and education impact translators' use of technology. The findings revealed that, although most translators were aware of common translation technologies, they lacked awareness of recent advances and the integration of functionalities into translation environment tools. In Daems's 2022 study, while 99% of respondents used general technology, only 18% utilized translation technology for literary translation; those trained in technology were more inclined to use it. Termbases and TM systems were perceived as more useful than MT. Respondents suggested that ideal translation technology should include a database of literary translations, easy access to resources, and ways to move beyond the sentence level. Existing technology limitations can hinder inspiration, and creativity, and relegate translators to a passive role. This study emphasized the need for personalized translation technologies and ongoing education in translation technology.

Estelles and Monzó (2015) argued that translation technologies are often imposed on translators by companies, institutions, agencies, or the market’s demand which might, among other factors, explain why CAT tools are unevenly used and appreciated by professionals. The researchers used the UTAUT to evaluate the acceptance of CAT tools among translators and language specialists, measured using behavioral intention (BI) as a dependent variable. They found that the actual use (AU) of CAT tools was the most significant factor influencing translators’ acceptance, with PE being the highest predictor of acceptance. Ease of use, academic partnerships, and training programs were significant in determining BI to use CAT tools. Self-determination (SD) is an important construct in this model, with extrinsic motivators being more important than intrinsic motivators. The communication capabilities of CAT tools improve relationships with other agents; however, playfulness was not considered a significant factor. This study suggests that software developers should focus on productivity and ease of use to better cater to the needs and wants of professional translators. The significance of SD for translators also highlights the need for further research into managerial styles and techniques that can improve motivation and autonomous behavior (Estelles & Monzó, 2015).

The TAM (Davis, 1989; Davis et al., 1989) is a popular approach for exploring factors affecting technology adoption to understand user behavior toward a particular technology. The model indicates that, when a user is presented with a new system or tool, several factors influence their decisions regarding the manner and when to use it. The TAM focuses on several factors, such as:

- A PU is a potential user’s belief that the use of a certain technology will enhance their performance.
- The PEU is the extent to which a potential user expects the target technology to be easy to use.
- BI, namely, the user’s intention or willingness to use technology, is influenced by their attitude (AT) toward use and PU.
- AU, namely, users’ actual behavior in using technology, is influenced by their BI and external factors such as the availability of resources and support.

Several studies have used TAM to evaluate translation technologies with a focus on MT (Yang & Wang, 2019; Al-Maroof et al., 2020; Yang & Mustafa, 2022; Robert, 2021). Few studies have examined the adoption of CAT tools from the TAM perspective.

Sam et al. (2015) investigated the adoption of CAT tools by government translators using the TAM with two antecedents: perceived efficiency requirements (PER) and perceived repetition rate (PRR). This study found that PRR had a significant positive impact on the PU of the CAT tools, whereas PER did not. The PEOU of CAT systems was also found to have a significant positive impact on the PU of the systems, which in turn had a significant positive impact on the BI to adopt these tools. However, the BI’s adoption of CAT systems has a significantly negative impact on the AU of such systems. The study also found that experience had a significant negative impact on translators’ BI in adopting CAT tools. However, because of the study’s limited sample size and focus on government translators, it is difficult to generalize these findings.

In the academic context, Sil-Hee (2019) investigated the acceptance of CAT tools by instructors and students in a postgraduate translation and interpreting (T&I) program in Korea. This study involved redesigning a training program to incorporate CAT technology into translation classrooms. The researcher also explored the students’ and instructors’ perceptions of CAT tools and their technological acceptance. The overall findings indicated positive responses from students; however, their responses to IU and PU were higher than those of PEU and AT toward CAT tools. The researcher linked these findings to students’ technical competence and encouraged CAT tool designers to consider varying levels of IT skills among translators and to design tools that are user-friendly and accessible to all users, regardless of their IT proficiency.

Dianati et al. (2022) used TAM to examine the factors contributing to the adoption of T&I technologies by 21 university instructors in Australia. Despite the small sample size, researchers found that the frequency of technology use among instructors has a significant impact on their intention to use such technologies in the future. However, their experience in teaching and using these technologies did not significantly affect their future use. Instructors who held favorable views of T&I technologies tended to recommend them to others because they believed that these tools improved job performance accuracy, job security, and overall employment market advantages. Nonetheless, the instructors in this study encountered certain difficulties when using T&I technologies, such as output accuracy and software lifespan. Despite these challenges, instructors who perceived T&I technologies as useful expressed their intentions to continue using them. Despite these interesting findings, the researchers acknowledged several limitations, including the small sample size, caution in generalizing the results outside Australia, the use of non-uniform ranking scales, and a lack of clear distinction between T&I technologies in the research design.

Few studies have attempted to evaluate the usefulness and usability of cloud-based CAT tools among translators and translation students (e.g., Tarasenko et al., 2022; Alotaibi, 2020; Herget, 2020).

Alotaibi (2020) examined the usability of cloud-based CAT tools among Arab translators using a software usability measurement inventory (SUMI) survey. The elements of efficiency, affect, usefulness, control, and learnability were evaluated by 42 translators. The researcher found that global usability was above average. Affect and efficiency received the highest scores, whereas helpfulness and learnability received the lowest. The researcher advised developers to improve the usability and learnability of cloud-based CAT tools and emphasized the need for enhanced Arabic language support. This study also emphasizes the need to prioritize ease of use and intuitive interfaces with clear instructions and access to support resources. In addition, designers should consider incorporating features that can help bridge the gap between varying IT skill levels, such as interactive tutorials and contextual help features. Designing accessible and user-friendly CAT tools will increase their adoption, ultimately improving the efficiency and quality of the translation process.

Tarasenko et al. (2022) asked 67 translation students to evaluate the usefulness of the individual functions of a cloud-based CAT tool using a 5-point scale. The results indicated highly favorable rates for all functions, such as source text review during translation, display of full matches, display of fuzzy matches, and integration with the MT system. Researchers have recommended the use of these tools as core components of cloud-based environments to enhance translation training. However, this study overlooked the factors affecting the adoption of these tools among students and how these factors affected students' intentions to use them in the future and after graduation.

Herget (2020) also investigated cloud-based CAT tools, and Memsource and MemoQ were utilized among master's students to facilitate collaborative and problem-solving strategies in real-world scenarios. The researcher explored the implementation of these systems in a language classroom, using a problem-based learning (PBL) approach. According to Herget (2020), the project management activities provided by these tools provide students with hands-on experience and an understanding of a translation project's workflow. He suggested that using CAT tools in a language classroom with PBL teaching approaches could improve students' linguistic proficiency and create transversal competencies. However, the factors that affect students' adoption of CAT tools have not yet been discussed.

This review highlights a clear gap in the literature, particularly regarding the acceptance of cloud-based CAT tools. Thus, this study is significant because it aimed to identify the factors that influence the acceptance and use of cloud-based CAT tools among translation students. Understanding these factors is crucial to enhancing students' technological skills and preparing them for the demands of the translation industry. Addressing barriers to the adoption and promoting the effective use of these tools through targeted training programs can help students gain confidence in using CAT tools. The findings of this study can inform the development of effective cloud-based CAT tools that cater to the needs of translation students and professionals.

III. MATERIALS AND METHODS

A. Research Model and Hypotheses

This study analyzed the factors influencing the intention to use and acceptance of cloud-based CAT tools among translation students. The TAM was used as the research model and included the following variables:

- BI is an individual's willingness to use a cloud-based CAT tool.
- PU is the extent to which a cloud-based CAT tool is perceived to be beneficial.
- The PEU is the degree to which a cloud-based CAT tool is perceived as easy to use.
- AU, the extent to which a cloud-based CAT tool is used,
- Subjective norm (SN), namely, the extent to which translation students perceive that others, such as instructors, support the use of cloud-based CAT tools.
- IT skills, namely, translation student expertise in IT.

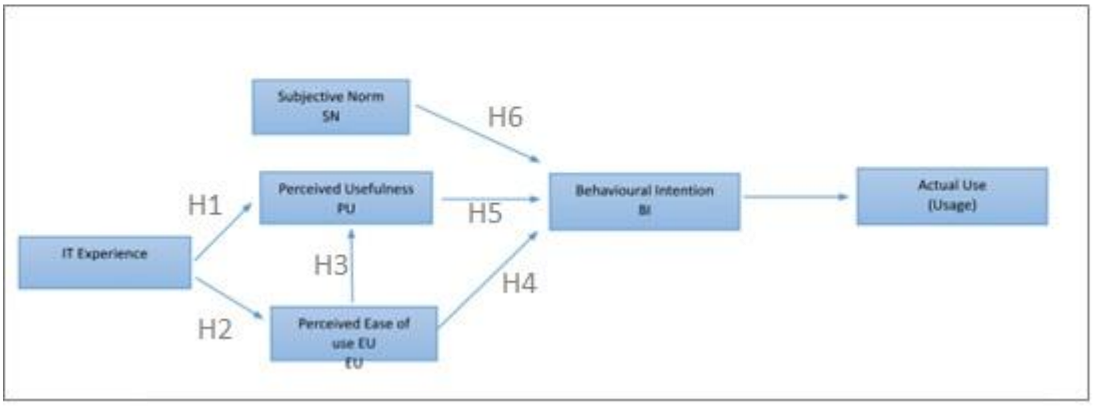

Figure 1. Depicts the Research Model and the Research Hypotheses

- H1: IT experience has a positive and substantial effect on the PU of cloud-based CAT tools.
- H2: IT experience has a positive and substantial effect on the PEU of cloud-based CAT tools.
- H3: PEU has a positive and substantial effect on the PU of cloud-based CAT tools.
- H4: PEU has a positive and significant effect on BI when cloud-based CAT tools are used.
- H5: PU has a positive and significant effect on BI when cloud-based CAT tools are used.
- H6: SN has a positive effect and significant impact on BI when using cloud-based CAT tools.

B. Data Collection

An online survey was distributed through social media channels to undergraduate students from several Saudi universities (N = 181). The first section of the survey gathered the necessary data on the participants' demographic information such as age, level, and familiarity with cloud-based CAT tools. The second section includes statements related to the constructs of the TAM and hypotheses. The participants were instructed to indicate their agreement using a 5-point Likert scale. The questionnaire was reviewed by an expert with over ten years of experience in a related field. The questionnaire was administered to a group of translation students (20 participants). The clarity and readability of the questions were tested, the time required to complete the survey was assessed, and any potential biases or sources of confusion were eliminated.

IV. Data Analysis and Results

SPSS 19 statistical tool was used to perform a missing value analysis test on the dataset. Table 1 displays the results of the univariate statistics generated, which indicated that there were missing cases among the 181 cases analyzed; with IT experience and AU, however, there were no missing cases. In addition, the dataset was free of outlying responses, which are responses that are either inconsistent or particularly dissimilar to the rest of the dataset and have notably larger or smaller values. A test for detecting univariate outliers was also conducted using the SPSS 19 statistical tool, and Z-scores were derived by interpreting the presence of probable outliers. The Z-scores for all attributes were lower than four, indicating that there were no outlying responses. Consequently, the dataset was approved for the next stage of analysis.

Table 1
Univariate Statistics

	N	Mean	SD	Missing		No. of Extremes	
				Count	Per cent	Low	High
PUS1	177	4.1299	.93545	4	2.2	8	0
PUS2	177	3.9209	.96793	4	2.2	0	0
PUS3	177	4.1638	.97190	4	2.2	8	0
PUS4	177	4.0000	.80482	4	2.2	10	4
PUS5	177	3.7006	.89547	4	2.2	4	0
PUS6	177	3.4859	.88618	4	2.2	3	0
PUS7	177	3.7571	.86127	4	2.2	3	0
PEU1	177	3.6441	1.00729	4	2.2	4	0
PEU2	177	3.3898	1.02830	4	2.2	4	0
PEU3	177	3.8136	.97947	4	2.2	0	0
PEU4	177	3.6271	.90889	4	2.2	2	0
SN1	177	4.1073	.96224	4	2.2	7	0
SN2	177	4.1017	1.01738	4	2.2	7	0
SN3	177	4.1582	.95813	4	2.2	8	0
BI1	177	4.2260	.91998	4	2.2	5	0
BI2	177	4.2260	.91998	4	2.2	5	0
BI3	177	4.0339	.94085	4	2.2	6	0
ITE	181	3.3370	.76899	0	2.2	3	0
AU	181	2.8287	.72146	0	2.2	0	2

A. Normality Tests of Variables

Table 2 presents the results of testing the dataset for a non-normal distribution, which involved computing the Kolmogorov–Smirnov statistics, kurtosis, and skewness values to interpret the distribution type. The test revealed statistically significant Kolmogorov–Smirnov values for all attribute items.

TABLE 2
ONE-SAMPLE KOLMOGOROV–SMIRNOV TEST

Items	N	Normal parameters		Most extreme differences			K–S	Sig
		Mean	SD	Absolute	Positive	Negative		
PUS1	177	4.1299	.93545	3.1299		-3.1299	.292	.000
PUS2	177	3.9209	.96793				.278	.000
PUS3	177	4.1638	.97190	2.9209		-2.9209	.257	.000
PUS4	177	4.0000	.80482	3.0000		-3.0000	.308	.000
PUS5	177	3.7006	.89547	2.7006	1.2994	-2.7006	.219	.000
PUS6	177	3.4859	.88618	2.4859		-2.4859	.279	.000
PUS7	177	3.7571	.86127	2.7571		-2.7571	.221	.000
PEU1	177	3.6441	1.00729	2.6441		-2.6441	.231	.000
PEU2	177	3.3898	1.02830	2.3898		-2.3898	.198	.000
PEU3	177	3.8136	.97947				.231	.000
PEU4	177	3.6271	.90889	2.6271		-2.6271	.230	.000
SN1	177	4.1073	.96224	3.1073		-3.1073	.252	.000
SN2	177	4.1017	1.01738	3.1017		-3.1017	.257	.000
SN3	177	4.1582	.95813	3.1582		-3.1582	.254	.000
BI1	177	4.2260	.91998	3.2260		-3.2260	.263	.000
BI2	177	4.2260	.91998	3.2260		-3.2260	.263	.000
BI3	177	4.0339	.94085	3.0339		-3.0339	.271	.000
ITE	181	3.3370	.76899	2.3370		-2.3370	.308	.000
AU	181	2.8287	.72146				.310	.000

B. Descriptive Analysis for Respondent Profile

Table 3 displays the profiles of all the respondents, including their age distributions. The largest number of respondents (n = 176) belonged to the 17–24 age group. Table 3 also provides information on the respondents' nationality, experience, and occupation, which vary across various levels. Saudi Arabia had the largest number of respondents (n = 175). The most common occupation was translation (n = 172). Finally, most respondents had 1–5 years of experience (n = 142).

TABLE 3
RESPONDENT PROFILE

Category	Values	Frequency	Percent
Age	under 17	0	0
	17–24	176	97.2
	25–29	4	2.2
	30–39	1	0.6
	40–49	0	0
	50–59	0	0
	Over 59	0	0
	Total	181	100
Nationality	Saudi	175	96.7
	Non-Saudi	6	3.3
	Total	181	100
Occupation	Translator	9	5.0
	Translation student	172	95.0
	Translation instructor	0	0
	Other	0	0
	Total	181	100
Experience	Less than 1 year	28	15.5
	1–5 years	142	78.5
	6–10 years	10	5.5
	More than 10 years	1	.6
	Total	181	100

A. Descriptive Analysis for Variables

Table 4 presents the descriptive statistics for each item in the constructs. According to the results, the most highly rated attribute among the variables was BI, with an average mean of 4.19 (standard deviation [SD] = .87633; variance = .768). SN was the next most highly rated, with an average mean of 4.13 (SD = .70004; variance = .856). PU received a slightly lower rating with a mean of 3.9 (SD = 1.379; variance = .490), followed by PEU with a mean of 3.75 (SD = .85085; variance = .724. IT experience came next, with a mean of 3.34 (SD = .76899; variance = .591). AU was the lowest, with a mean of 2.83 (SD = .72146; variance = .521).

TABLE 4
DESCRIPTIVE STATISTICS

Items	N	Mean	SD	Variance
	Statistic	Statistic	Statistic	Statistic
PUS1	177	4.1299	.93545	.875
PUS2	177	3.9209	.96793	.937
PUS3	177	4.1638	.97190	.945
PUS4	177	4.0000	.80482	.648
PUS5	177	3.7006	.89547	.802
PUS6	177	3.4859	.88618	.785
PUS7	177	3.7571	.86127	.742
Average PUS	181	3.9006	.70004	.490
PEU1	177	3.6441	1.00729	1.015
PEU2	177	3.3898	1.02830	1.057
PEU3	177	3.8136	.97947	.959
PEU4	177	3.6271	.90889	.826
Average PEU	181	3.7459	.85085	.724
SN1	177	4.1073	.96224	.926
SN2	177	4.1017	1.01738	1.035
SN3	177	4.1582	.95813	.918
Average SN	181	4.1271	.92519	.856
BI1	177	4.2260	.91998	.846
BI2	177	4.2260	.91998	.846
BI3	177	4.0339	.94085	.885
Average BI	181	4.1934	.87633	.768
ITE	181	3.3370	.76899	.591
AU	181	2.8287	.72146	.521

B. Reliability Test

To assess the consistency of the attributes comprising the proposed model, Cronbach's α was measured as a reliability test for the survey instrument. The model consisted of four constructs. The results of the reliability test, as shown in Table 5, revealed that all four attributes in the model exhibited high reliability, ranging between 0.85 and 0.95. After establishing the reliability of the model, we investigate the impact of PU, PEU, and social approval on BI using SEM.

TABLE 5
RELIABILITY TEST

Constructs	Sample	Items	Cronbach's α	Reliability
Perceived usefulness	181	7	.862	High
Perceived ease of use	181	4	.859	High
Subjective norm	181	3	.937	High
Behavioral intention	181	3	.908	High

C. Validity and Reliability Analysis for Variables

The open data measurement model's overall construct validity was confirmed by calculating the average variance estimates (AVE) and composite reliability (CR) values for all latent variables, which were above 0.7 (see Table 6). The diagonal of the matrix in Table 6 shows that all AVE values were satisfactory, above 0.5. The squared correlations below this diagonal represent the paired correlations for the corresponding latent variable pairs. The paired correlations were lower than the corresponding AVE values, which is a positive indicator of the model, except for SN and BI. Therefore, the conditions for confirming discriminant and convergent validity were met with PU and PEU, validating the open-data measurement model's overall construct validity.

TABLE 6
AVE AND CR VALUES

Latent variables	CR values	PUS	PEU	SN	BI
Perceived usefulness	0.841	**0.742**			
Perceived ease of use	0.864	.310**	**0.841**		
Subjective norm	0.937	.254**	.240**	**0.942**	
Behavioral Intention	0.909	.513**	.324**	.180*	**0.920**

D. Statistical Estimates for the Structural Model

Next, the hypothesized relationships between the latent variables in the measurement model are introduced, and the fit statistics for the structural model are presented in Table 8. This study established hypotheses to examine the acceptance of cloud-based CAT tools among translation students, supported by collected data. The Chi-square value for the model was significant at 276.680 ($p = 0.000$) with 139 degrees of freedom. However, other fit indices, such as the comparative fit index (CFI), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), and root mean square error of approximation (RMSEA) were well aligned with their recommended values, and the normed fit index (NFI) value was equal to 0.877. The measurement and structural models both demonstrated a good model fit, and the large sample size (n = 181) used for the SEM made the significant Chi-square value acceptable for this model.

Table 8 indicates that the model has two endogenous and three exogenous latent variables. BI explained 53.7% of the variance (squared multiple correlations (SMC) = 0.537), PU explained 28.6% (SMC = 0.286), PEU explained 12.8% (SMC = 0.128), and AU explained 2.2% (SMC = 0.22)). The SMC values reported in this study contributed to an acceptable level of predictability for the structural model used with an adjusted R2 value of 0.40 or was considered acceptable. The only exception was AU, for which the R2 value was < 0.40. The results of the SEM indicate that PU (β = 0.767, p = 0.00) has a significant effect on BI; in contrast, PEU (β = 0.017, p = .832) and SN (β = 0.052, p = .323) are not predictors of BI to use cloud-based CAT tools. PEU is affected by IT experience (β = 0.387, p = 0.00). IT experience does not affect perceived usefulness (β= -.066, p=.396). There is a significant relationship between PEU and PU (β = 0.518, p = 0.00). Finally, there is a significant relationship between BI and AU (β = 0.131, p = .05).

TABLE 7
STATISTICAL ESTIMATES FOR THE STRUCTURAL MODEL

Independent and dependent variable relationships		Estimates		
Independent variables	Dependent variables	B	CR.	P
Perceived ease of use	IT experience	.387	4.702	***
Perceived usefulness	IT experience	-.066	-.849	.396
Perceived usefulness	Perceived ease of use	.518	6.174	***
Behavioral Intention	Subjective norm	.052	.988	.323
Behavioral intention	Perceived usefulness	.767	7.508	***
Behavioral intention	Perceived ease of use	.017	.213	.832
Actual use	Behavioral intention	.131	1.951	.051
R2 for Perceived usefulness		.286		
R2 for Perceived ease of use		.128		
R2 for Behavioral intention		.537		
R2 for Actual use		.022		
Chi-square (χ2)		276.680		
Probability level		.000		
Degrees of freedom		139		
CMIN/df (χ2/pdf)		1.991		
Comparative fit index, CFI		.934		
Goodness of fit, GFI		.859		
Adjusted goodness of fit, AG FI		.808		
Normed fit index, NFI		.877		
Root mean square error of approximation, RMSEA		.074		
Sample size		181		

The SEM model is shown in Figure 2 showing the analysis results.

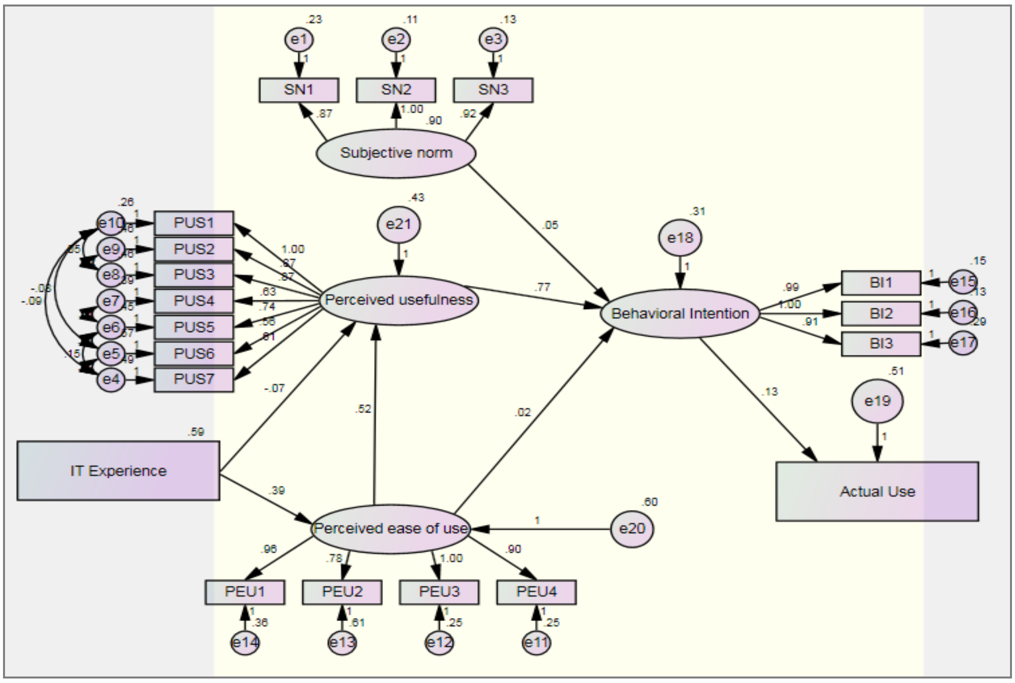

Figure 2. SEM Model

Finally, the hypothesis test results are shown in Table 8.

TABLE 8
HYPOTHESES TEST RESULTS

Research Hypothesis	Results
H1: IT experience has a positive effect and substantial impact on the PU of cloud-based CAT tools.	Rejected
H2: IT experience has a positive effect and substantial impact on the PEU of cloud-based CAT tools.	Supported
H3: PEU has a positive effect and substantial impact on the PU of cloud-based CAT tools.	Supported
H4: PEU has a positive effect and great impact on the BI to use cloud-based CAT tools.	Rejected
H5: PU has a positive effect and great impact on the BI to use cloud-based CAT tools.	Supported
H6: SN has a positive effect and great impact on the BI to use cloud-based CAT tools.	Rejected

V. DISCUSSION

This study investigated factors affecting the use of cloud-based CAT tools among translation students. SEM was used to analyze the data and examine the relationships between different variables.

The findings described in the previous section indicate that the BI variable, which refers to an individual's willingness to use cloud-based CAT tools, explains the highest amount of variance (53.7%). This finding suggests that the intention to use cloud-based CAT tools is a crucial factor in determining whether a translation student will adopt the technology. This construct is important because it reflects an individual's motivation and commitment to using technology, which can highly impact actual user behavior. In other words, if students have a positive AT toward using cloud-based CAT tools and are motivated to use them, they are more likely to adopt them. These findings are broadly consistent with those of previous studies that examined the factors that influence technology adoption. Pedagogically, these findings have important implications for translation instructors attempting to promote the adoption of cloud-based CAT tools by translation students. To increase BI, they should focus on demonstrating the benefits of the tools to students and highlight their usefulness in improving translation quality and efficiency. They should also work on creating a positive AT toward the use of these tools among their students through training and education programs that emphasize the value of cloud-based CAT tools in the translation process.

PU, which refers to the extent to which a tool is perceived as beneficial, explained 28.6% of the variance, making it the second-most important factor. Translation students are more likely to use a tool if they believe that it will be useful in their work. This confirms other findings on translation technology adoption (e.g., Al-Maroof et al., 2020; Sam et al., 2015). These findings have important implications not only for tool developers but also for translation instructors who are attempting to promote the adoption of cloud-based CAT tools among translation students. To increase PU, researchers should focus on demonstrating how these tools can improve translation quality and efficiency. This could involve providing training and education programs that show students how to use the tools effectively and highlight the benefits of using these tools in terms of saving time, increased accuracy, and improved translation quality.

PEU, the degree to which a tool is perceived as easy to use, explained 12.8% of the variance. This suggests that the ease of use of cloud-based CAT tools is an important consideration for translation students, although it is less important than the PU or BI. The impact of PEU on translation technologies has also been confirmed in other studies (Yang et al., 2019; Al-Maroof et al., 2020). These findings highlight the importance of user experience and usability in technology adoption and encourage tool developers and providers to prioritize usability and user experience when designing cloud-based CAT tools. By making these tools as intuitive and as easy to use as possible, developers can reduce barriers to adoption and increase the likelihood of translation students using them. However, PEU is less significant than PU and BI in influencing translation students' adoption of cloud-based CAT tools. This suggests that although ease of use is an important consideration, it should not be the only focus of tool development efforts. Rather, developers should focus on demonstrating the benefits of these tools and fostering positive AT toward their use among potential users.

The AU, which refers to the extent to which a tool is used, explained only 2.2% of the variance. This suggests that AU is not a major factor in determining whether translation students will adopt cloud-based CAT tools. In other words, making a tool available to users is insufficient to ensure its adoption, suggesting that translation instructors should not focus solely on increasing the AU of these tools but should rather focus on promoting their PU, BI, and ease of use among potential users. These findings highlight the importance of addressing attitudinal and motivational factors such as PU, BI, and ease of use in promoting technology adoption.

The analysis showed that PU has a significant effect on BI, indicating that translators are more likely to use a tool if they believe it will be useful, which is generally consistent with the findings of other TAM studies. However, these findings also show that PEU and SN were not significant predictors of BI when a specific cloud-based CAT tool was used. These findings are unexpected, as these factors are important predictors of translation technology adoption in previous TAM research (e.g., Rossi & Chevrot, 2019; Estelles & Monzó, 2015). Thus, these findings may be specific to the context of cloud-based CAT tools and may not be generalizable to other types of translation technologies. This finding implies that demonstrating the usefulness of cloud-based CAT tools to potential users should be prioritized over focusing on ease of use or social norms.

The findings revealed that IT experience affects PEU, suggesting that students with more experience in using technology may find cloud-based CAT tools easier to use because they may be more familiar with the technology and the process of using it. Consequently, translation instructors and curriculum designers must consider providing training and education programs tailored to the level of IT experience of their target audience to ensure that these programs are effective and accessible to all students. Another implication can be linked to Alotaibi's (2020) and Sil-Hee's (2019) recommendations for CAT tool developers to further improve the helpfulness and learnability attributes of these tools and enhance translators' experience and satisfaction levels.

However, the results indicate that IT experience does not affect PU, suggesting that simply having experience with technology may not be sufficient to convince translation students of the value of these tools. Rather, the benefits of cloud-based CAT tools and how they can improve the quality and efficiency of translation work should be emphasized to increase the perceptions of usefulness among translation students.

The results revealed a significant link between PEU and PU, suggesting that if translation students perceived cloud-based CAT tools as easy to use, they were more likely to perceive them as useful for achieving their goals. The finding resonates with findings from previous studies (e.g., Estelles & Monzó, 2015; Sam et al., 2015). This finding has important implications for tool developers and providers, as they should focus on improving the usability and user experience of these tools, reducing barriers to adoption, and increasing the likelihood that translation students will perceive them as easy to use (Alotaibi, 2020).

Finally, the findings indicated a significant relationship between BI and AU, highlighting the importance of understanding the factors influencing the adoption of cloud-based CAT tools among translation students. Adoption rates can be increased by focusing on fostering a positive AT toward these tools and increasing BI among potential users, which can enhance the quality and efficiency of translation work among students.

VI. Conclusion

In this study, we explored the factors that influence the acceptance and use of cloud-based CAT tools among translation students, using the TAM as a theoretical framework. This study aimed to identify the factors that affect the adoption of these tools.

The study was conducted using a survey of 181 translation students, and the data were analyzed using SEM. The results showed that the intention to use cloud-based CAT tools and their PU were the most important factors in determining whether translation students would adopt these tools. Ease of use of cloud-based CAT tools is also an important consideration, particularly for translation students with limited IT experience.

The findings of this study have important implications for tool developers and providers attempting to promote the adoption of cloud-based CAT tools among translation students. This study suggests that translation instructors should focus on demonstrating the usefulness of these tools and the manner in which they can improve the quality and efficiency of translation. However, tool developers should focus on improving the usability and user experience of these tools to reduce barriers to adoption and increase the likelihood that translation students will perceive them as easy to use.

Although this study provides valuable insights into the factors that influence the adoption of cloud-based CAT tools among translation students, it has several limitations. First, the sample of 181 participants may not be representative of the entire population of translation students. Larger sample sizes may have provided more robust and generalizable results. Furthermore, this study was conducted in Saudi Arabia, which limits the generalizability of the findings to other countries and regions. Cultural and contextual differences may affect the acceptance and adoption of cloud-based CAT tools differently. Future studies could address these limitations using larger sample sizes, incorporating qualitative data, and longitudinal designs to examine changes in attitudes and behaviors over time.

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