ISSN 2522-6398 Vol. 8, Issue 12: 64-71, DOI: 10.25236/FER.2025.081210

Beyond Usability: The Role of Interest and Attitude in Sustaining AI Translation Tool Use among MTI Students

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Abstract: *This study investigates the psychological mechanisms driving the sustained intention to use AI tools in translation learning, moving beyond the established roles of perceived usefulness and ease of use. Drawing on an integrated framework combining the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT), we propose that these technological perceptions foster long-term engagement by shaping learners' attitudes and intrinsic interest. Data from 311 Master of Translation and Interpreting (MTI) students were analyzed using structural equation modeling (SEM). The results confirm that while perceived usefulness and ease of use directly influence sustained intention, their impact is predominantly mediated through a sequential psychological process: they first cultivate a positive AI learning attitude, which in turn sparks a genuine AI learning interest, with interest emerging as the strongest direct predictor of sustained use. This research underscores that the key to lasting AI integration in education lies not merely in creating useful tools, but in designing experiences that are intrinsically interesting and psychologically rewarding for learners.*

Keywords: *Artificial Intelligence; Translation Learning; Sustained Intention; Technology Acceptance Model; Self-Determination Theory; Structural Equation Modelling*

1. Introduction

The integration of Artificial Intelligence (AI) into the landscape of foreign language education, particularly in the domain of translation training, represents a paradigm shift from traditional pedagogical approaches [1]. AI-powered tools, ranging from neural machine translation and computer-assisted translation (CAT) systems to intelligent terminology management and conversational AI agents, are increasingly being embedded into the curriculum of programs such as the Master of Translation and Interpreting (MTI). This trend, often termed as “AI-empowered learning,” promises to enhance translation efficiency, provide immediate feedback, and grant access to vast linguistic resources, thereby fundamentally altering the learning process [2].

As these technologies transition from novel supplements to core pedagogical components, the key question for educators and researchers shifts from initial adoption to long-term continuance. While the usefulness and ease of use of a technology—core constructs of the seminal Technology Acceptance Model (TAM)—are well-established predictors of its initial acceptance, they provide an incomplete picture for explaining sustained intention to use [3]. The mere presence of a useful and easy-to-use tool does not automatically guarantee that learners will remain engaged with it over time, especially in a complex, skill-based domain like translation.

This gap underscores a critical research need: to move beyond a purely utilitarian perspective and delve into the psychological and affective mechanisms that bridge the gap between external technological perceptions and internal, long-term behavioral intentions. Current understanding of how learners' cognitive assessments (e.g., perceived usefulness) are transformed into durable motivation through the development of positive attitudes and intrinsic interest remains limited. It is precisely within this conceptual space that the present study positions itself.

By developing and testing a comprehensive model that integrates the utilitarian framework of TAM with the motivational lens of Self-Determination Theory (SDT), this research seeks to illuminate the “black box” of the learner's mind. It aims to investigate not only if perceived usefulness and ease of use influence sustained intention but, more importantly, how—by examining the critical mediating roles of

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AI learning attitude and AI learning interest. The findings are expected to offer nuanced insights for optimizing AI-integrated pedagogical strategies, ensuring that these powerful tools are not only adopted but also embraced as engaging partners in the lifelong journey of translation learning.

2. Literature Review

2.1 Theoretical Foundation

The present study is grounded in an integrated theoretical framework combining the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT). This integration provides a robust lens for examining both the utilitarian and motivational drivers of sustained intention to use AI in learning.

The Technology Acceptance Model posits that an individual's behavioral intention to use a technology is primarily determined by two core beliefs: Perceived Usefulness (PU), defined as the degree to which a person believes that using a system would enhance his or her job performance, and Perceived Ease of Use (PEU), the degree to which a person believes that using a system would be free from effort [4]. While TAM powerfully predicts initial adoption, it has been critiqued for its limited emphasis on intrinsic motivational factors in sustained usage contexts.

Self-Determination Theory addresses this gap by distinguishing between extrinsic and intrinsic motivation [5]. It argues that sustained, high-quality engagement is fueled by the satisfaction of three basic psychological needs: autonomy (feeling of volition), competence (feeling effective), and relatedness (feeling connected to others). In educational technology contexts, tools that are easy to use can satisfy the need for competence, while those that are useful can support feelings of autonomy by enabling more effective goal achievement. Crucially, when these needs are supported, they can catalyze the development of intrinsic motivation—engaging in an activity for its inherent interest and enjoyment.

Integrating these theories, we propose that TAM's PU and PEU act as foundational antecedents that support learners' psychological needs, which in turn foster positive attitudes and intrinsic interest—key affective-cognitive states leading to sustained intention. This fusion allows for a more holistic analysis that moves beyond initial acceptance to explain the psychological mechanisms underlying long-term engagement with AI translation tools.

2.2 Variable Definitions and Hypotheses Development

2.2.1 Core Constructs and Relationships

Based on the integrated framework, this study focuses on the following five constructs:

Perceived Usefulness (PU) and Perceived Ease of Use (PE) are positioned as exogenous variables representing learners' cognitive appraisal of the AI tool. AI Learning Attitude reflects a relatively enduring positive or negative evaluation of using AI for translation learning [6]. According to TAM, PU and PE are key antecedents of attitude. From an SDT perspective, a tool that is useful and easy to use can support feelings of competence and autonomy, thereby fostering a positive attitude. AI Learning Interest (IN): This construct signifies a state of intrinsic motivation and genuine cognitive engagement with the AI-assisted learning process [7]. SDT positions interest as a potent form of intrinsic motivation, which can be triggered when external factors (like a useful and easy-to-use tool) satisfy basic psychological needs. Sustained Intention to Use AI (SI): This is the dependent variable, denoting the learner's conscious plan and motivation to continue using AI tools for their translation studies in the long run.

2.2.2 Research Model and Hypotheses

Based on the above explorations, this study proposes the following hypotheses:

H1: Learners’ Perceived Ease of Use (PE) positively influences (a) their AI Learning Attitude (AT), (b) their AI Learning Interest (IN), and (c) their Sustained Intention to use AI assist EFL translation study (SI).

H2: Learners’ Perceived Usefulness (PU) positively influences (a) their AI Learning Attitude (AT), (b) their AI Learning Interest (IN), and (c) their Sustained Intention to use AI assist EFL translation study (SI).

H3: Learners’ AI Learning Attitude (AT) positively influences their AI Learning Interest (IN).

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H4: Learners' AI Learning Attitude (AT) positively influences their Sustained Intention to use AI assist EFL translation study (SI).

H5: Learners' AI Learning Interest (IN) positively influences their Sustained Intention to use AI assist EFL translation study (SI).

H6: Learners' AI Learning Attitude (AT) mediates the relationship between their Perceived Ease of Use (PE) and their Sustained Intention to use AI assist EFL translation study (SI).

H7: Learners' AI Learning Attitude (AT) mediates the relationship between their Perceived Usefulness (PU) and their Sustained Intention to use AI assist EFL translation study (SI).

H7: Learners' AI Learning Interest (IN) mediates the relationship between their Perceived Ease of Use (PE) and their Sustained Intention to use AI assist EFL translation study (SI).

H8: Learners' AI Learning Interest (IN) mediates the relationship between their Perceived Usefulness (PU) and their Sustained Intention to use AI assist EFL translation study (SI).

H9: Learners' AI Learning Attitude (AT) and their AI Learning Interest (IN) sequentially mediates the relationship between their Perceived Ease of Use (PE) and their Sustained Intention to use AI assist EFL translation study (SI).

H10: Learners' AI Learning Attitude (AT) and their AI Learning Interest (IN) sequentially mediates the relationship between their Perceived Usefulness (PU) and their Sustained Intention to use AI assist EFL translation study (SI).

3. Method

3.1 Sampling and Data collection procedures

The present study draws on a sample of 311 Master of Translation and Interpreting (MTI) candidates enrolled at six comprehensive universities situated in central and eastern China. All respondents were actively integrating institutionally sanctioned AI-powered translation tools—accessible via smartphone or desktop—into their pedagogical workflow, including but not limited to computer-assisted translation (CAT) suites, neural machine-translation interfaces, intelligent terminology-management systems, speech-to-text transcription services, and conversational AI agents for target-language revision. Following a compulsory briefing session delivered by programme instructors, 311 valid questionnaires were retained from 320 submitted returns (350 instruments originally distributed), yielding an effective response rate of 88.8 %.

3.2 Instruments

This research draws on five psychometrically robust scales. To capture perceived usefulness (PE), we adopted Huang & Zou's four-item index[8] ($\alpha = 0.883$); perceived ease of use (PU) was assessed via Teo et al.'s five-item instrument[9] ($\alpha = 0.934$); attitudes toward AI-based learning (AT) were measured with Hwang & Chang's five-item scale[10] ($\alpha = 0.920$); interest in AI-supported learning (IN) employed the same authors' six-item instrument ($\alpha = 0.926$); and participants' sustained intention to keep using AI for translation tasks (SI) was gauged through Maqableh et al.'s four-item adaptation[11] ($\alpha = 0.925$). Every scale retained its original 5-point Likert format (1 = strongly disagree, 5 = strongly agree) and comfortably exceeds the $\alpha \geq .80$ threshold recommended for applied-linguistics work.

3.3 Data Analysis

Analytical procedures were executed with SPSS 26.0 and AMOS 24.0. Initial screening comprised descriptive statistics and bivariate correlations to characterise the data set. Measurement properties were then scrutinised through confirmatory factor analysis before estimating the structural model via structural equation modelling, enabling simultaneous examination of direct, indirect and mediating effects. Model adequacy was assessed against the following thresholds: $\chi^2/df \leq 3$, CFI, GFI, AGFI and TLI $\geq .90$, RMSEA $\leq .08$, and SRMR $\leq .10$[12].

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4. Results

4.1 Correlation Analysis, Reliability and Validity Test

The data satisfy univariate normality criteria (skewness ≤ |2|, kurtosis ≤ |7|)[13], and bivariate correlations range from 0.276 to 0.419, remaining comfortably below the 0.85 multicollinearity ceiling (Table 1). Harman's single-factor test extracted 38.57 % of total variance from the first unrotated component, falling short of the 40 % threshold and implying that common-method bias is trivial. Measurement properties are robust: all standardized loadings exceed 0.50, Cronbach's α and composite reliability are above 0.80 for every construct, average variance extracted (AVE) surpasses 0.50, and each AVE is greater than the largest squared correlation with another factor, thereby affirming both convergent and discriminant validity (Table 2).

Table 1 Descriptive Statistics, Correlation, and AVE square roots.

Factors	PU	PE	AT	IN	SI
PU	0.809				
PE	0.339	0.860			
AT	0.357	0.276	0.801		
IN	0.403	0.419	0.343	0.822	
SI	0.332	0.256	0.333	0.325	0.871
Mean	3.479	3.330	3.596	3.429	3.377
SD	1.100	0.840	1.129	1.036	1.028
Skewness	-0.702	-0.675	-0.492	-0.893	-0.067
Kurtosis	-0.650	0.131	-0.763	-0.162	-1.089

Note. SD: standard deviation.

Table 2 Factor analysis, construct reliability and convergent validity.

Factors	Items	Estimate	S.E.	Z-value	P	Factor Loading	α	C.R.	AVE
PU	PU1	1				0.785	0.883	0.883	0.654
	PU2	0.862	0.044	19.591	***	0.823			
	PU3	0.898	0.039	23.026	***	0.792			
	PU4	0.927	0.045	20.600	***	0.834			
PE	PE1	1				0.837	0.934	0.934	0.74
	PE2	1.125	0.043	26.163	***	0.902			
	PE3	1.133	0.039	29.051	***	0.865			
	PE4	0.928	0.038	24.421	***	0.833			
	PE5	1.019	0.041	24.854	***	0.862			
AT	AT1	1				0.882	0.920	0.92	0.697

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	AT2	1.125	0.043	26.163	***	0.873			
	AT3	0.908	0.038	23.895	***	0.807			
	AT4	0.933	0.039	23.923	***	0.796			
	AT5	1.007	0.043	23.419	***	0.812			
	IN1	1				0.835			
	IN2	1.111	0.042	26.452	***	0.847			
IN	IN3	0.973	0.038	25.605	***	0.795	0.926	0.926	0.676
	IN4	0.988	0.041	24.098	***	0.815			
	IN5	0.929	0.039	23.821	***	0.809			
	IN6	0.989	0.047	21.043	***	0.832			
	SI1	1				0.859			
SI	SI2	0.956	0.041	23.317	***	0.863	0.925	0.926	0.758
	SI3	1.001	0.037	27.054	***	0.871			
	SI4	0.983	0.043	22.860	***	0.889			

Note. ***p<0.001; SD=Standard Deviation

4.2 Regression Analysis

The hypothesized structural model demonstrated an acceptable fit to the data (χ^2/df = 1.97; GFI = .96; AGFI = .93; CFI = .96; TLI = .95; IFI = .96; RMSEA = .039; SRMR = .027). Path coefficient estimates, detailed in Table 4, provided support for all proposed hypotheses. Perceived ease of use (PE) was a significant antecedent, positively influencing AI learning attitude (β = .167, p < .001), AI learning interest (β = .284, p < .001), and sustained intention (β = .119, p < .05), thus confirming H1a, H1b, and H1c. Similarly, perceived usefulness (PU) significantly predicted attitude (β = .297, p < .001), interest (β = .303, p < .001), and intention (β = .059, p < .05), supporting H2a, H2b, and H2c. Furthermore, AI learning attitude positively affected both interest (β = .128, p = .001) and sustained intention (β = .173, p < .001), validating H3 and H4. Finally, AI learning interest emerged as the strongest direct predictor of sustained intention (β = .231, p < .001), supporting H5(see Table 3).

Table 3 Research Model Regression Weight and Hypotheses

DV	IV	B	S.E.	C.R.	P	β	R^2	Hypotheses	Result
AT	PE	0.232	0.043	5.395	***	0.167	0.158	H1a	Supported
	PU	0.287	0.056	5.125	***	0.297		H2a	Supported
IN	PE	0.326	0.061	5.344	***	0.284	0.263	H1b	Supported
	PU	0.357	0.059	6.051	***	0.303		H2b	Supported
	AT	0.167	0.052	3.212	**	0.128		H3	Supported
SI	PU	0.087	0.038	2.289	**	0.059	0.162	H2c	Supported
	PE	0.145	0.057	2.544	**	0.119		H1c	Supported
	AT	0.179	0.053	3.377	***	0.173		H4	Supported
	IN	0.216	0.073	2.959	***	0.231		H5	Supported

Note. ****p*<0.001; ***p*<0.01; **p*<0.05.

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4.3 Mediation Analysis

Bootstrapping analysis with 5,000 resamples revealed multiple significant mediation pathways in the model (see Table 4). For perceived ease of use (PE), three indirect paths to sustained intention (SI) were identified: through AI learning attitude (AT) alone (β = 0.041, 95% CI [0.012, 0.065]), through the sequential mediation of AT and AI learning interest (IN) (β = 0.013, 95% CI [0.005, 0.011]), and through IN alone (β = 0.079, 95% CI [0.037, 0.115]). The direct effect of PE on SI remained significant (β = 0.059, 95% CI [0.003, 0.101]), indicating partial mediation, with the total effect reaching β = 0.192.

Similarly, for perceived usefulness (PU), significant indirect paths to SI were found through AT alone (β = 0.060, 95% CI [0.045, 0.088]), through the AT→IN chain (β = 0.009, 95% CI [0.002, 0.013]), and through IN alone (β = 0.073, 95% CI [0.036, 0.102]). The direct effect of PU on SI was also significant (β = 0.136, 95% CI [0.027, 0.139]), suggesting partial mediation, with a substantial total effect of β = 0.278.

The overall model demonstrated strong predictive power for sustained intention, with a total effect of β = 0.455 across all pathways. These findings confirm the complex mediating mechanisms through which both perceived ease of use and perceived usefulness influence students' sustained intention to use AI for translation learning, with multiple parallel and sequential mediation paths operating simultaneously.

Table 4 Mediation Analysis

Mediation Path	Point Estimate	Product of Coefficient		Bootstrapping		
				Bias-corrected 95% CI		
		SE	Z-value	Lower	Upper	*P-value*
PE→AT→SI	0.041	0.012	3.417	0.012	0.065	0.000
PE→AT→IN→SI	0.013	0.005	2.600	0.005	0.011	0.001
PE→IN→SI	0.079	0.016	4.938	0.037	0.115	0.000
Direct Effect (PE→SI)	0.059	0.028	2.107	0.003	0.101	0.002
Total Effect (PE→SI)	0.192	0.049	3.918	0.074	0.278	0.000
PU→AT→SI	0.06	0.014	4.286	0.045	0.088	0.000
PU→AT→IN→SI	0.009	0.003	3.000	0.002	0.013	0.000
PU→IN→SI	0.073	0.017	4.294	0.036	0.102	0.000
Direct Effect (PU→SI)	0.136	0.036	3.778	0.027	0.139	0.002
Total Effect (PU→SI)	0.278	0.041	6.780	0.167	0.351	0.000
Total Effect	0.455	0.102	4.461	0.297	0.483	0.000

5. Discussion

The present study developed and empirically tested a comprehensive model to elucidate the psychological mechanisms underlying sustained intention to use AI for translation learning. The findings not only confirm the significant direct drivers of intention but, more importantly, unravel the complex parallel and sequential mediating processes involved. The discussion will interpret these key findings in relation to the existing literature.

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5.1 Key Findings and Interpretation

Our results robustly support the core propositions of the research model. First, the significant direct effects of Perceived Ease of Use (PE) and Perceived Usefulness (PU) on Sustained Intention (SI) reaffirm the enduring relevance of TAM's core constructs in the context of AI-assisted learning. However, the relatively smaller direct effect of PU ($\beta = .059$) compared to its substantial total effect ($\beta = .278$) signals that its influence is predominantly channeled through internal psychological states, a point elaborated below.

Second, the central role of affective-cognitive states is strongly validated. The finding that AI Learning Interest (IN) is the strongest direct predictor of intention ($\beta = .231$) underscores a pivotal shift from purely utilitarian adoption to a more holistic, engagement-driven continuance model. This suggests that when learners find AI tools interesting and intellectually stimulating, their motivation to persist evolves from a sense of obligation to a genuine desire to engage. Similarly, AI Learning Attitude (AT) serves as a critical linchpin, directly influencing intention and also acting as a vital precursor to interest.

5.2 The Interplay of Direct and Mediating Effects

The mediation analysis provides a nuanced understanding of how external perceptions translate into behavioral intentions. For Perceived Ease of Use, we identified a multifaceted impact. The significant indirect paths via AT alone and via IN alone indicate that ease of use fosters intention by both shaping a positive general disposition and by making the learning process itself more intriguing. Notably, the path through IN alone was the strongest indirect pathway for PE ($\beta = 0.079$), implying that reducing usability barriers is a powerful lever for sparking the interest that ultimately sustains use. The significant direct effect confirms that effortless interaction with the AI tool remains a non-negotiable baseline requirement for learners.

For Perceived Usefulness, the mediation pattern is even more pronounced. While a direct effect persists, the majority of its impact is indirect. The significant mediation through AT→IN→SI reveals a sequential cognitive-affective sequence: the recognition of the tool's utility first cultivates a positive attitude, which then deepens into a genuine interest, finally culminating in sustained intention. This chain elucidates the process through which an instrumental belief is transformed into an intrinsic motivational force. The presence of multiple significant pathways confirms that PU operates through a network of psychological mechanisms rather than a single route.

6. Conclusion

This study set out to investigate the determinants of sustained intention to use AI for translation learning, moving beyond a simplistic direct-effect model to unravel the underlying psychological mechanisms. The findings conclusively demonstrate that learners' continuance intention is not merely a function of their initial perceptions of the technology's usefulness and ease of use. Instead, it is profoundly shaped by a more complex internal process where these perceptions are transformed into a positive attitude and, ultimately, a genuine interest in the AI-augmented learning activity itself.

Theoretical contributions of this work lie in its successful integration of affective constructs into a technology acceptance framework, thereby providing a more holistic explanation of user behavior in educational contexts. By empirically validating a model with multiple parallel and sequential mediation paths, we offer a refined understanding of how cognitive evaluations (perceived usefulness) and usability perceptions (perceived ease of use) operate through distinct yet interconnected channels to foster long-term engagement.

From a practical standpoint, the results offer clear guidance. To ensure the sustained adoption of AI in translation education, instructors and developers should focus not only on proving the tool's utility and ensuring its usability but, critically, on designing experiences that are intrinsically interesting. Fostering a positive attitude is a crucial first step, but the ultimate key to persistence is sparking the learner's curiosity and intellectual engagement. In essence, the most effective AI translation tools are those that are not just seen as useful assistants but are experienced as fascinating partners in the learning journey.

While this study provides valuable insights, it also opens avenues for future research. Longitudinal studies could track how these relationships evolve as learners progress from novices to proficient users. Furthermore, incorporating other variables, such as learning styles or specific AI functionalities, could further enrich our understanding and help tailor even more effective and engaging AI-powered

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educational environments.

Acknowledgement

Funded by: 2025 Anhui Provincial Translators Association Research Project on Translation in Anhui(FYAH20250301), Huainan Normal University Scientific Research Project (2024XJZD023), Huainan Normal University Educational Reform Research Projects (2022hsjyxm20, 2024hsjyxm06), Special Research Project on Digital Transformation of Higher Education, Graduate Employment Association of China (GJX25Z2110), Anhui Provincial Educational Research Project (2024jyxm0460) and Anhui Provincial Outstanding Research and Innovation Team in Philosophy and Social Sciences for Higher Education Institutions: "Translation, Dissemination, and Sino-Western Cultural Exchange Research Innovation Team on *Huainanzi*" (Project No. 2023AH010052).

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