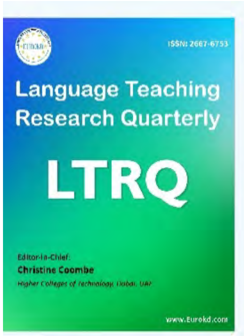

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Thematic Collection[1]

The Role of ChatGPT in English Language Learning: A Hedonic Motivation Perspective on Student Adoption in Chinese Universities

Yizhuo Zhou[1], Xuande Wu[2]*, Kunyang Qu[3]

[1]Xi'an International Studies University, China
[2]The University of Edinburgh, The United Kingdom
[3]The University of Reading, The United Kingdom

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Abstract

Recent advancements in artificial intelligence, particularly OpenAI's ChatGPT, have transformed English language learning through Computer-Assisted Language Learning (CALL) tools. This study examined the adoption of ChatGPT among university-level English learners employing the Hedonic Motivation System Adoption Model (HMSAM). An online survey was conducted with 266 valid responses, analyzed using Structural Equation Modelling (SEM) to assess the key factors influencing ChatGPT adoption. According to the findings, the main factors influencing students' inclination to utilize ChatGPT are perceived usefulness, boredom, and a sense of control. These findings highlight important considerations for integrating AI in English education, suggesting that practical AI tools must address both functional and motivational aspects of learning. The study offers insights for educators and developers in designing AI-driven language learning tools that align with students' needs and motivations, potentially shaping the future of English education.

Keywords: *ChatGPT, Artificial Intelligence, AI Adoption, Hedonic Motivation System Adoption Model (HMSAM)*

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* Corresponding author.
E-mail address: Xuande.Wu@ed.ac.uk

Introduction
As technology integrates more deeply with education, particularly within the specialised field of English language teaching, incorporating digital tools has become an essential complement to traditional teaching methods. CALL has emerged as a fundamental component in enhancing linguistic capabilities and changing the educational landscape.

In China's higher education, English teaching is increasingly adopting technological interventions. For instance, Grammarly, a widely popular grammar correction tool, utilises generative technology to assist learners in identifying and rectifying grammatical errors in English sentences. ELSA, a speech recognition system, employs similar technology to convert learners' spoken inputs into text, providing pronunciation assessments and corrections to enhance pronunciation accuracy. WriteLab and Rosetta Stone, through offering writing suggestions and simulated conversational practices, respectively, aid learners in improving their English writing and spoken communication skills.

Moreover, WordUp, a vocabulary expansion tool, recommends appropriate words and phrases based on the learner's level and needs, effectively aiding in expanding their vocabulary. These innovative approaches apply to learners of various ages and foster a culture of autonomous learning. Despite existing research demonstrating multiple benefits of CALL, domestic literature on its impact on college students' intrinsic motivation remains relatively scarce. Intrinsic motivation, the drive to engage in activities for satisfaction and interest, is particularly significant for technological models as it directly relates to voluntary participation and creativity (Ryan & Deci, 2000).

This study employs the Hedonic Motivation System Adoption Model (HMSAM) to explore ChatGPT's applicability in the English learning context. The HMSAM model emphasises the critical role of intrinsic motivation and immersive experiences in shaping user attitudes and engagement, including enjoyment, entertainment, emotional satisfaction, and cognitive absorption (Lowry et al., 2013; Sidek et al., 2020). By applying HMSAM to English learning, this research aims to provide a comprehensive understanding of students' acceptance of AI in English learning and investigate how intrinsic motivation and immersive experiences influence their attitudes and participation levels. Specifically, this study will delve into the intrinsic motivations of Chinese university students using ChatGPT as an English learning resource and analyse how these motivations affect their acceptance and usage of this learning tool.

In today's era of advancing technology, understanding the efficacy and mechanisms behind these tools is crucial for optimising their potential and aiding learners in achieving their language learning goals. Through the HMSAM framework, this research will provide in-depth insights into Chinese university students' perceptions of ChatGPT and the interplay between their intrinsic motivations.

CALL and ChatGPT concerning Undergraduate and Postgraduate Students
Recent AI tech has deeply impacted education. GPTs, especially well-known versions, have drawn much attention. These advancements have spawned many CALL tools, enhancing English learning at all levels. CALL is a well-established term that plays a pivotal role in English education. It refers to using computer technology to assist in language instruction, encompassing a range of computer-based activities such as interactive exercises, multimedia materials, and online communication tools. Through CALL tools, students can engage in

activities like grammar correction, vocabulary expansion, and pronunciation assessment, enhancing their linguistic capabilities. Empirical evidence suggests integrating CALL into language curricula can elevate students' language competencies, learning motivation, and engagement (Levy, 2006). The ability of CALL to give students immediate, personalised feedback is one of its main benefits. CALL systems can analyse learners' responses and provide focused feedback on their grammar, vocabulary, pronunciation, and general language performance using automated assessment tools (Chapelle, 2001). This personalised feedback not only aids students in identifying and correcting errors but also fosters metacognitive awareness, enabling them to reflect on and refine their learning strategies (Chun & Plass, 1996).

Despite its numerous benefits, CALL has limitations. Primarily, CALL systems often lack the capacity for understanding and cannot respond to learners' inquiries naturally and appropriately. This is because most CALL systems are rule-based, relying on pre-programmed response patterns, and thus are less adept at handling the intricacy and variability of human language (Warschauer & Healey, 1998). Consequently, when students interact with CALL agents, they may experience frustration or disinterest if the agent fails to meet their communicative needs.

Advancements in language modelling have facilitated the development of conversational agents like ChatGPT. Powered by large-scale language models and employing deep learning algorithms, ChatGPT generates human-like responses in conversational contexts. This technology offers students more interactive and engaging interactions, thus enhancing the language learning experience. A significant advantage of ChatGPT is its ability to produce contextually appropriate responses, aiding students in practising language skills more authentically and communicatively by simulating real-life conversations. ChatGPT allows learners to engage in meaningful interactions, develop their speaking and listening skills, and be exposed to authentic language use (Brown et al., 2020). Additionally, ChatGPT's continual learning ability enables it to adjust and improve its responses over time, enhancing the quality of the learning experience.

However, despite ChatGPT's vast potential, it is crucial to acknowledge its limitations. Due to biases in its training data, ChatGPT may generate inaccurate or biased information like other language models (Bender et al., 2021). This prompts questions about ChatGPT's reliability and credibility, especially in academics, where accuracy and objectivity are crucial. Moreover, the lack of human intervention in ChatGPT's response generation process may limit its ability to offer nuanced feedback and guidance tailored to individual learners' needs.

Nevertheless, within the context of English education for undergraduate and graduate students in Chinese universities, the understanding of the application of AI still needs to be improved. Thus, integrating CALL and conversational agents like ChatGPT into language education holds significant promise in supporting the language learning journey of undergraduates and graduates. By delving deeper into the application of AI in education, we can better understand learners' motivations and cognition, providing insightful implications for educational practices. Through continuous efforts and innovation, we can better harness AI technology to improve the English learning experience for university undergraduates and postgraduate students.

Theoretical Frameworks

The Hedonic-Motivation System (HMS) is critical to understanding user engagement with information systems that tap into intrinsic motivations. HMS highlights the enjoyment and emotional aspects of tech use. The study explores this by introducing the HMS Adoption Model (HMSAM) to understand HMS-driven adoption better.

The HMSAM model offers a fresh approach to understanding HMS adoption, focusing on cognitive absorption (CA) as a key to system acceptance. It builds on van der Heijden's (2004) work, which identified hedonic motivation as a primary adoption factor. CA is seen as a mediator that boosts engagement and satisfaction, leading to more profound system use. This is backed by studies highlighting CA's role in IT acceptance and usage. The model also integrates concepts from Fishbein and Ajzen on behavioural strategies to shape user responses to technology.

There is a research gap in the use of HMSAM among ESL students at Chinese universities with CALL tools. This study targets this by exploring the intrinsic motivation of these students using ChatGPT, assessing how cognitive absorption mediates their acceptance and ongoing use of CALL tools, and aiming to uncover drivers of sustained tool usage.

Understanding these motivational drivers provides key insights that aid in designing and implementing more effective educational technologies. This study recommends creating visually appealing, user-friendly learning environments that achieve educational objectives and align with learners' psychological needs by emphasising the importance of hedonic motivation in technology adoption. In summary, HMSAM provides a robust framework for analysing the adoption of educational technology, especially in environments where user engagement and intrinsic motivation are crucial. By clarifying the mechanisms through which hedonic and cognitive factors influence technology acceptance and use, the study's findings are anticipated to substantially contribute to information systems and educational technology, giving these fields more theoretical depth and real-world application.

For designers of language learning software, understanding the dimensions of cognitive absorption can guide them in developing products that better meet user expectations and psychological needs. For instance, enhancing the sense of control can be achieved through customisable learning paths and adjustable difficulty settings, while stimulating curiosity requires diversity in content and increased interactivity. Moreover, for educators and policymakers, applying the cognitive absorption model extends beyond enhancing learners' language capabilities to broadly involve technology to enhance participation and efficiency throughout the educational process. Implementing strategies based on HMSAM can better design course structures and optimise teaching methods, thereby improving the quality of educational outcomes and learner satisfaction.

This research underscores the potential of HMSAM in educational technology, such as ChatGPT, and suggests its broader application. Future studies could delve into the cultural and educational variations of cognitive absorption and refine technological interventions for global educational innovation, sparking new avenues of research and development.

Moreover, as artificial intelligence and machine learning technologies advance, integrating these cutting-edge technologies into HMSAM could open up new research and large language model (LLM) areas. For instance, predicting users' cognitive absorption states through data analytics or automatically adjusting learning content and difficulty to maximise user engagement and learning efficiency. By thoroughly exploring the application of HMSAM in Open AI ChatGPT, this paper closes a gap in existing research and validates the model's effectiveness and applicability through empirical research. This further development and application of the theory are expected to advance significantly theoretical innovation and practical improvements in educational technology, especially in enhancing user experience and educational interactivity. By scientifically analysing and applying the mechanisms of cognitive absorption, future educational technologies can be more humane and effectively serve the needs of global learners.

Research Model and Hypotheses

Perceived Ease of Use (PEOU) is vital in technology adoption studies, gauging how effortlessly individuals can adopt and master new tech. OpenAI's ChatGPT has fuelled interest in GPT models that use extensive data for natural language tasks, offering human-like text generation and creative writing. These models, including ChatGPT, serve as advanced chatbots and may replace human operators. Their role in education sparks debate, with some educators optimistic about AI's future in learning, noting that contextualised learning, which AI can enhance, leads to better long-term knowledge retention.

Personal Innovativeness in IT (PIIT), coined by Agarwal and Prasad in 1998, describes the propensity to engage with new IT. Their work suggests that PIIT could influence how individuals react to new IT, proposing that those seeing a tool as user-friendly may be more open to innovation. This is relevant to ChatGPT's ease of use, which could affect learners' willingness to adopt new tools. Incorporating PIIT helps explain perception formation and its effect on usage intentions. Davis's Technology Acceptance Model (TAM) (1989) and its extensions by Venkatesh and Davis (2000) recognise ease of use and individual differences, like PIIT, as crucial in tech adoption, affirming the need to factor in personal traits when examining technology acceptance.

Qu and Wu's (2024) study examined the link between ease of use and personal innovativeness in AI adoption, revealing that those with higher innovativeness find AI systems more user-friendly, boosting their readiness to embrace new tech. This underscores the interaction between individual traits like innovativeness and perceived usability in adopting IT. Studying this interaction in ChatGPT can show how user perceptions of ease influence their innovative IT use. From this basis, a hypothesis is formulated:

RH_1: Perceived ease of use of ChatGPT may influence students' innovativeness.

Perceived Usefulness (PU) and Ease of Use (PEOU) are key in technology adoption, with PU assessing how technology aids tasks and PEOU gauging its simplicity. Studies confirm PU and PEOU improve attitudes and intentions to use tech (Venkatesh et al., 2003). Enhanced PU and PEOU can increase acceptance of AI tools like ChatGPT, aiding language education.

When learners perceive a large language model to be highly useful, they believe using the AI model can enhance their language learning outcomes and improve their learning effectiveness (Venkatesh et al., 2003). For example, learners may perceive the tool as providing rich and diverse learning resources to help them expand their vocabulary, improve their grammar skills, or enhance their oral expression abilities. This perception of usefulness triggers learners' interest and motivation, making them more willing to use the AI system for learning.

Ease of Use (PEOU) is pivotal for learners' acceptance and continued use of ChatGPT (Venkatesh et al., 2003). Learners are likelier to adopt and persist with a straightforward and user-friendly system. GPT's ability to generate human-like, creative text from vast digital data enhances this ease. Yet, just enhancing PU and PEOU might not fully drive motivation and engagement. Curiosity (CU), an intrinsic motivator, is crucial in language learning (Silvia, 2012). Innovatively inclined learners are often more curious (Agarwal & Karahanna, 2000), making curiosity a key psychological element that can boost positive attitudes and interaction with AI in language learning tools.

Gamified tools have shown that usefulness, ease, and curiosity are positively linked (Palos-Sanchez et al., 2022). These tools boost curiosity and engagement by offering rewarding challenges (Sidek et al., 2020), thus improving the perceived value of the learning system and deepening learner interest, aiding effective language acquisition. Hence, boosting a system's perceived value, simplicity, and curiosity is essential for learner adoption and use, as supported by gamification studies (Palos-Sanchez et al., 2022).

RH$_2$: Perceived ease of use of ChatGPT may influence students' perceived usefulness and curiosity.
RH$_3$: Users' innovativeness may influence students' perceived usefulness and curiosity.

Boredom (BO), characterised by low engagement and activation, can negatively impact student engagement and outcomes (Xie, 2021). Research suggests that those with higher Personal Innovativeness in IT (PIIT) are less prone to boredom (López-Bonilla & López-Bonilla, 2012), and incorporating boredom into HMSAM has shed light on how negative emotions affect system adoption (Deng & Yu, 2023).

The study of the relationship between computer-assisted tools like ChatGPT and boredom is still a relatively emerging field. However, there is a potential that these technologies could be a solution to language learning boredom (Zhou et al., 2023). This study is unique in its aim to bridge this gap and enhance our understanding of the potential of AI in language training by investigating the association between the perceived ease of use of ChatGPT and boredom.

Based on these theoretical foundations, the following hypotheses are proposed:

RH$_4$: Students' innovativeness in information technology may influence their experience of boredom.
RH$_5$: Students' perceived ease of use of ChatGPT may influence the sensation of boredom.

Control (CO) is the user's perceived mastery over AI system interactions, and it is essential in software use. Studies have shown that perceived ineffectiveness and lack of confidence can diminish this sense of control in educational software usage (Venkatesh et al., 2003). Conversely, High Perceived Usefulness (PU) can boost the feeling of control in tech use. Thus, the user-friendliness of ChatGPT could grant students enhanced control. Yet, the link between Personal Innovativeness in IT (PIIT) and internal motivators like control remains under-examined.

Studies indicate that students who are skeptical of new technology may feel less control when using language learning aids (Agarwal & Karahanna, 2000), linking innovativeness and tech acceptance to perceived control. Thus, it’s logical to propose that PIIT could influence control perceptions.

In this context, the current study seeks to explore the effect of PIIT on intrinsic motivation. A detailed analysis of the PIIT-motivation link will deepen our understanding of learner motivation and behaviour with language aids. The insights gained could contribute to the development of more engaging and effective language learning tools, ultimately enhancing learner engagement and outcomes.

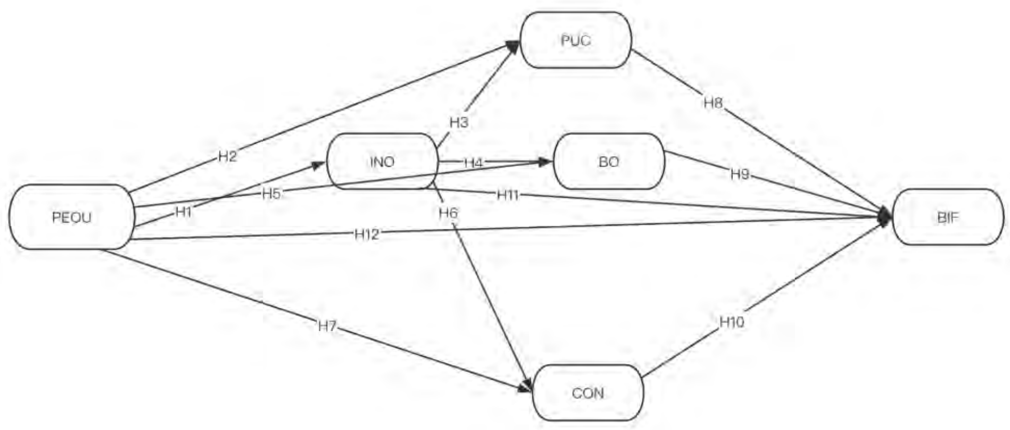
RH$_6$: Students’ innovativeness may impact their sense of control with ChatGPT.
RH$_7$: Students’ perceived ease of use of ChatGPT may influence their sense of control.

Focus Immersion (FI) measures deep engagement in activities and tuning out distractions (Agarwal & Karahanna, 2000). Prolonged ChatGPT uses signals for deep content engagement, and FI is a gauge for system engagement. In blended learning, control and curiosity impact immersion within HMSAM (Sidek et al., 2020). Boredom also influences FI (Oluwajana et al., 2019), while PU boosts FI in gamified settings (Palos-Sanchez et al., 2022). Innovativeness is linked to cognitive immersion and FI (Agarwal & Karahanna, 2000), and VR studies show a positive innovativeness-immersion correlation (Kari & Kosa, 2023).

Behavioural Intention to Use (BIU) is the predicted user behaviour (Davis, 1989) and a TAM2 prerequisite for actual use (Venkatesh et al., 2003). Control can diminish cognitive obstacles, increasing system use willingness, while boredom can lower BIU (Oluwajana et al., 2019). Curiosity within HMSAM bolsters system engagement, fostering repeated satisfying interactions (Sidek et al., 2020). PU is a strong BIU predictor (Venkatesh et al., 2003), with empirical data supporting PU’s influence among e-commerce users (Oematan et al., 2024). Additionally, FI is tied to satisfaction and loyalty in tech experiences (Sidek et al., 2020), with VR immersion predicting usage intentions (Kari & Kosa, 2023). Based on these previous findings, the following research hypotheses are proposed:

RH$_8$: Students’ perceived usefulness and curiosity about ChatGPT may impact their behavioural intention to use ChatGPT and focus immersion with ChatGPT.
RH$_9$: Students’ boredom experienced while using ChatGPT may impact their behavioural intention to use it significantly and focus immersion with ChatGPT.
RH$_{10}$: Students’ sense of control over ChatGPT may impact their behavioural intention to use and focus immersion.
RH$_{11}$: Students’ innovativeness in information technology may impact their behavioural intention to use it significantly and focus on immersion with ChatGPT.
RH$_{12}$: Students’ perceived usefulness of ChatGPT may impact their behavioural intention to use and focus immersion.

Figure 1
The Proposed Research Model



Methodology

Employing a structural equation modelling (SEM) paradigm, this investigation gathered data from a cohort of 266 ESL students enrolled at Chinese universities, utilising a meticulously designed random online survey. The principal aim of this study was to construct an exhaustive model that would elucidate the intricate interplay between various learner characteristics and their engagement with Open AI ChatGPT, as well as the subsequent impact on their English language learning motivation. To achieve this goal, the research was based on a quantitative paradigm, emphasizing the collection and thorough statistical analysis of empirical numerical data, which resulted in insightful and substantial findings (Creswell, 2014).

This study's methodological precision facilitated a detailed analysis of the link between students' views on the CALL software, ChatGPT, and their internal and external English language learning motivations. Rigorous factor analysis confirmed the research's robustness and relevance using established analytical methods. Furthermore, the study's dependability and accuracy were meticulously assessed to maintain exemplary scholarly standards.

The research framework presented herein profoundly explores and dissects the determinants influencing ESL learners' motivation within the Chinese academic milieu. It unveils the multifaceted interactions and potential ramifications of successfully incorporating CALLs into the language learning ecosystem. This study contributes to the academic discourse and is a pivotal reference for educators and LLM developers aiming to enhance the efficacy of language acquisition technologies.

Participants and Recruitment

The participants in this study are English learners in China, specifically undergraduate and postgraduate students from Chinese universities who had previously used ChatGPT to learn English. Participants were recruited using an online random sampling method through WeChat and Xiaohongshu. All participants provided informed consent, ensuring adherence to ethical standards and protocols.

Data was collected using the Questionnaire Star platform between March 17th and April 27th, 2024. Coupons were provided to encourage participation. Of the 283 initial responses, 21 were excluded due to quality issues, leaving a final sample of 266 valid responses, resulting in a 93.9% response rate. Participant information is detailed in Table 1. Due to time and contextual constraints, non-random sampling was utilised, in line with recommendations by Etikan et al. (2016). In sum, this study investigates six key dimensions and their mediating relationships, exploring the connection between the intrinsic motivation of ESL learners and their use of large language models like ChatGPT.

Table 1

Participant Information

Background	Category	Percentage (%)	Frequency
Educational level	Bachelor's degree	66.2	176
	Master's degree	30.1	80
	PhD degree	3.8	10
Total		100	266

Research Instrument

Informed by previous research, adjustments were made before data collection to improve the clarity and structure of the questions. The scale used in this study comprised two sections, with participant anonymity safeguarded throughout the process. The first section gathered demographic information, while the second included 29 items covering six constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Behavioural Intention to Use, Focused Immersion (BIUFI), Curiosity (CU), Sense of Control (CO), Personal Innovativeness in IT (PIIT), and Boredom (BO). Responses were collected on a six-point Likert scale, grounded in well-established methodological frameworks.

Data Analysis

To ensure the reliability and validity of its instruments, this study employed confirmatory factor analysis (CFA) using SEM, along with mediation analysis for data evaluation. This approach aligns with established quantitative research standards in education (Hair et al., 2012; Byrne, 2013) and previous language learning studies (e.g., Qu & Wu, 2024; Zhou et al., 2023).

The investigation focused on seven constructs to decode the link between Chinese university students' intrinsic English learning motivation and their use of ChatGPT, informed by evidence of intrinsic motivation's role in learning (Deci & Ryan, 1985; Vallerand, 1997). SEM analysis, executed with SPSS and Amos, followed Hair et al.'s (2013) two-step approach, first verifying measurement model reliability and validity (Fornell & Larcker, 1981; Hair et al., 2014), then appraising structural model paths, predictive relevance, and mediating/moderating effects (Chin et al., 2003; Hayes, 2022). This approach enabled a nuanced examination of the intrinsic motivation-technology use relationship and its underlying dynamics. It enhanced our grasp of how learners' motivation intersects with tech adoption, with implications for educational strategies and policymaking.

Results

Measurement Validation

The author carefully assessed the accuracy and robustness of the model. Factor loadings were analysed and confirmed to surpass the 0.70 threshold using Partial Least Squares Structural

Equation Modeling (PLS-SEM). This means that more than half of the variance in the indicators was explained, as advised by Sarstedt et al. (2014) and Hair et al. (2019).

Reliability checks using Cronbach's alpha and composite reliability (CR) demonstrated strong internal consistency, with values exceeding the 0.70 threshold (Chin, 1998; Hair et al., 2019). Additionally, convergent and discriminant validity were demonstrated, and separate and correct construct representation was ensured by Average Variance Extracted (AVE) values exceeding the 0.50 threshold (Fornell & Larcker, 1981; Hair et al., 2019). The thorough validation of the measurement model confirmed its appropriateness and dependability, meeting specified standards for validity, consistency, and factor loadings, thus ensuring the integrity of the ensuing analyses (Hair et al., 2019).

Table 2

Reliability and Validity Test of the Measurement

Components	Items	Factor loading	Cronbach's alpha	AVE	CR
Perceived ease of use (PEOU)	PEOU1	0.750**	0.853	0.695	0.823
	PEOU2	0.759**			
	PEOU3	0.679**			
	PEOU4	0.683**			
	PEOU5	0.592*			
Personal Innovativeness in Information Technology (PIIT)	INO1	0.750**	0.822	0.731	0.821
	INO2	0.749**			
	INO3	0.671**			
	INO4	0.750**			
Perceived usefulness (PU)Curiosity (CU)	CU1	0.626**	0.880	0.652	0.838
	CU2	0.593**			
	CU3	0.632**			
	CU4	0.717**			
	CU5	0.666**			
	CU6	0.669**			
	CU7	0.656**			
Control (CO)	CO1	0.675**	0.775	0.701	0.743
	CO2	0.719**			
	CO3	0.707**			
Boredom (BO)	BO1	0.887**	0.927	0.895	0.942
	BO2	0.923**			
	BO3	0.890**			
	BO4	0.881**			
Behavioural intention to use (BIU)Focused immersion (FI)	BIF1	0.545**	0.883	0.657	0.819
	BIF2	0.627**			
	BIF3	0.700**			
	BIF4	0.736**			
	BIF5	0.683**			
	BIF6	0.634**			

** $p<0.01$

Structural Equation Model (SEM) Results

The fit metrics for the structural equation model evaluation are shown in Table 3. The CMIN/DF ratio of 1.806 shows a good model fit within the permissible range of less than 3 (Tabachnick & Fidell, 2007). Strong alignment between the model and the actual data is suggested by the IFI Delta2 score of 0.933, TLI rho2 of 0.923, and CFI of 0.913, all of which are higher than the proposed criterion of 0.90 (Bollen, 1989; Tucker & Lewis, 1973; Bentler, 1990). Furthermore, a satisfactory match between the hypothesised model and empirical data is indicated by the RMSEA value of 0.055, which is well within the permissible range of 0.08 (Steiger, 1990, 2007). Overall, these fit indices confirm the model's appropriateness for the data, indicating that the relationships between the variables are accurately represented.

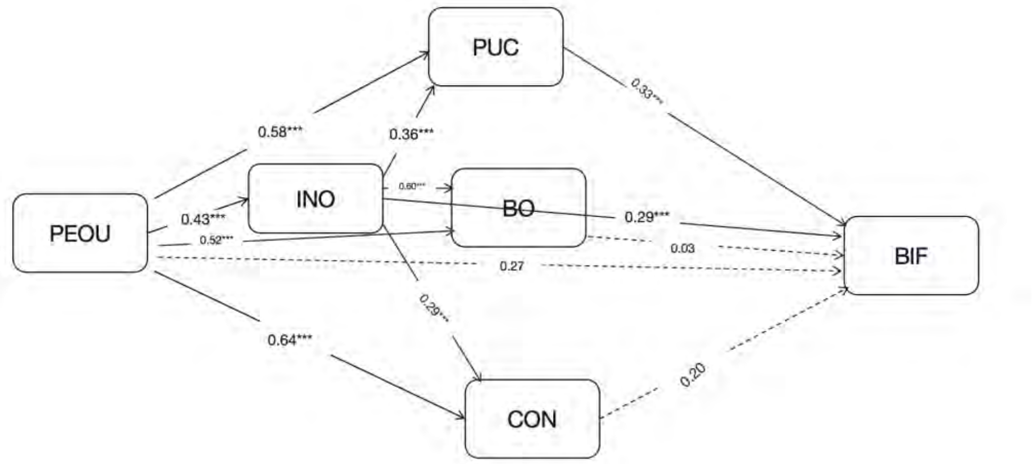
Table 3

Model Fit Results

Indices	Values
PCMIN/DF	1.806
IFI Delta2	0.933
TLI rho2	0.923
CFI	0.933
RMSEA	0.055

Figure 2

The Model with Path Coefficients



****p <0.001, **p <0.01, *p <0.0*

Table 4 delineates the outcomes for the proposed relational paths, with nine demonstrating statistical significance. The data notably corroborate hypotheses H1, H2, and H3. It is evident that learners' perceived ChatGPT's ease of use markedly propels users' information technology innovation (β=0.375, p<0.001) and substantially influences their perceived usefulness and curiosity (β=0.555, p<0.001). Furthermore, users' innovation in information technology significantly affects their perceived usefulness and curiosity. These pronounced linkages highlight the pivotal role of intuitive interfaces in educational technologies, as they are directly linked to enhancing the perceived benefits of language learning applications.

The findings supporting the validity of hypotheses H4, H5, H6, and H7 highlight the vital function that perceived ease of use plays in improving users' sense of control (β=0.398, p<0.001), curiosity (β=0.317, p<0.001), and level of boredom (β=-0.301, p<0.001), while also lowering boredom (β=-0.301, p<0.001). However, personal ennui (β=-0.04, p>0.05), sensation of control (β=0.189, p>0.05), and perceived ease of use (β=0.247, p>0.05) did not significantly affect sustained attention or the intention to continue using the technology, supporting neither of the H9, H10, or H12 hypotheses. This implies that the likelihood of embracing new technologies might not markedly affect users' sense of control, boredom, or curiosity when engaging with language learning through ChatGPT. The results suggest that individual innovative abilities are not pivotal in shaping interactions with ChatGPT regarding tool management, maintaining engagement, or cultivating curiosity. The study model with path coefficients and each path's significance is shown in Figure 2.

Table 4

The Results of Hypothesis Testing

Hypothesis	Path	Regression Weight	Std Regression Weight	SE	CR	p	Results
H1	PEOU→INO	0.431	0.375	0.088	4.89	***	Accepted
H2	PEOU→PUC	0.581	0.555	0.082	7.099	***	Accepted
H3	INO→PUC	0.358	0.394	0.06	5.949	***	Accepted
H4	INO→BO	0.598	0.398	0.117	5.122	***	Accepted
H5	PEOU→BO	-0.52	-0.301	0.131	-3.977	***	Accepted
H6	INO→CON	0.311	0.317	0.066	4.674	***	Accepted
H7	PEOU→CON	0.691	0.611	0.093	7.441	***	Accepted
H8	PUC→BIF	0.33	0.317	0.089	3.714	***	Accepted
H9	BO→BIF	-0.025	-0.04	0.029	-0.872	0.383	Rejected
H10	CON→BIF	0.183	0.189	0.087	2.105	0.035	Rejected
H11	INO→BIF	0.289	0.305	0.071	4.06	***	Accepted
H12	PEOU→BIF	0.269	0.247	0.105	2.566	0.01	Rejected

*** $p<0.001$

Mediating Analysis

In this investigation, SPSS and Amos were utilised for mediation analysis, applying models designed for both simple and parallel mediation. The analysis identified seven significant mediating pathways ($p<0.05$), underscoring the mediators' critical role in the nexus between independent and dependent variables. The LLCI and ULCI denote the probable range for the population parameters, quantifying the uncertainty in the mediation effect estimates. The LLCI sets the lower limit, while the ULCI defines the upper limit. The p-value quantifies the odds of observing the data given no actual association in the population, with lower values indicating more substantial evidence against the null hypothesis, hence a more substantial relationship. The "C./P." column classifies the mediation as either complete ("C"), representing the lack of direct effect and the sole indirect effect, or partial ("P") mediation effect, reflecting the presence of both direct and indirect effects. Confidence intervals and the kind of mediation are included in the tables that display the overall, direct, and indirect impacts of Perceived Ease of Use (PEOU) on Behavioral Intention to Use (BIU) and Behavioral Involvement Focus (BIF). The overall effect of PEOU on BIF is discovered to be 0.461 ($p<0.001$), signifying a robust and statistically noteworthy correlation. Similarly, there is a substantial direct effect of PEOU on BIF at 0.269 ($p<0.001$). The indirect effects of PEOU on BIF through several mediating pathways are further demonstrated in the tables, where the overall indirect effects are computed at 0.192, 0.125, and 0.051. Confidence intervals that do not include 0 show that all these effects were significant. This suggests comprehension of the interaction and influence of mediators between PEOU and BIF by highlighting their considerable involvement in the connection.

Table 5

Mediating Effects of the Path: PEOU→PUC→BIF

Total effect of PEOU→PUC→BIF				
Estimate	LLCI	ULCI	p	c./p.
.461	.188	.740	.003	c.
Direct effect of PEOU→PUC→BIF				
Estimate	LLCI	ULCI	p	
.269	.007	.575	.042	
Indirect effect(s) of PEOU→PUC→BIF				
Estimate	LLCI	ULCI	p	
.192	.080	.332	.002	

Table 6

Mediating Effects of the Path: PEOU→INO→BIF

Total effect of PEOU→INO→BIF				
Estimate	LLCI	ULCI	p	c./p.
.394	.123	.725	.007	c.
Direct effect of PEOU→INO→BIF				
Estimate	LLCI	ULCI	p	
.269	.007	.575	.042	
Indirect effect(s) of PEOU→INO→BIF				
Estimate	LLCI	ULCI	p	
.125	.056	.251	.002	

Table 5-11 also lists three specific indirect pathways: PEOU→PUC→BIF, PEOU→INO→BIF, for two simple mediation models, and “PEOU→INO→PUC→BIF” for a serial mediation model. These pathways represent the indirect influence of PEOU on BIF through different mechanisms. The confidence intervals for all three pathways do not cross zero. In the “C./P.” column, the paths “PEOU→PUC→BIF” and “PEOU→INO→BIF” are classified as complete mediation, meaning only indirect effects exist between PEOU and BIF. The path “PEOU→INO→PUC→BIF” is also classified as a complete mediating effect.

Table 7

Mediating Effects of the Research Model: PEOU→INO→PUC→BIF

Total effect of PEOU→INO→PUC→BIF				
Estimate	LLCI	ULCI	p	c./p.
.320	.072	.628	.020	c.
Direct effect of PEOU→INO→PUC→BIF				
Estimate	LLCI	ULCI	p	
.269	.007	.575	.042	
Indirect effect(s) of PEOU→INO→PUC→BIF				
Estimate	LLCI	ULCI	p	
.051	.023	.105	.001	

Table 8 details the mediating influence of the "INO→PUC→BIF" trajectory, exhibiting a notable positive mediation with a total effect size of 0.387 ($p<0.05$). This suggests that individual innovation capacity impacts continued usage intention and Behavioral Involvement Focus (BIF) via the Perceived Usefulness and Curiosity (PUC) intermediary. Within the " C./P." column, this pathway is characterised as exhibiting partial mediation, indicating the presence of both direct and indirect pathways linking innovation capacity to behavioural outcomes.

Table 8

Mediating Effects of the Research Model: INO→PUC→BIF

Total effect of INO→PUC→BIF				
Estimate	LLCI	ULCI	p	c./p.
.387	.129	.671	.009	p.
Direct effect of INO→PUC→BIF				
Estimate	LLCI	ULCI	p	
.269	.007	.575	.042	
Indirect effect(s) of INO→PUC→BIF				
Estimate	LLCI	ULCI	p	
.269	.007	.575	.042	

A substantial and statistically significant association ($p<0.001$) is indicated by the total effect of perceived ease of use (PEOU) on perceived usefulness and curiosity (PUC), which is measured at 0.735 in Table 9, which depicts the mediating role of the "PEOU→INO→PUC" pathway. Significantly, PEOU directly influences PUC of 0.581 ($p<0.001$), indicating a strong direct relationship between perceived utility and ease of use unaffected by mediators. The analysis also reveals Significant indirect effects, emphasising the function of intermediary variables in the PEOU-PUC link. Statistically significant, the total indirect effect of PEOU on PUC is 0.154. The partial mediation indicated by the "C./P." column shows that both direct and indirect effects significantly contribute to the overall influence of PEOU on PUC.

Table 9

Mediating Effects of the Path: PEOU→INO→PUC

The total effect of PEOU→INO→PUC				
Estimate	LLCI	ULCI	p	c./p.
.735	.584	.905	.001	p.
Direct effect of PEOU→INO→PUC				
Estimate	LLCI	ULCI	p	
.581	.426	.745	.002	
Indirect effect(s) of PEOU→INO→PUC				
Estimate	LLCI	ULCI	p	
.154	.088	.260	.001	

Table 10 illustrates the impact of the "PEOU→INO→CON" sequence, where the total effect of Perceived Ease of Use (PEOU) on control (CON) is recorded at 0.768, which is statistically significant ($p<0.001$). The direct effect of PEOU on CON is also substantial, at 0.643 ($p<0.001$), confirming a strong relationship between ease of use and perceived control, independent of mediators. Additionally, the analysis identifies significant indirect effects, highlighting the role of mediating variables in the PEOU-CON relationship. The total indirect effect size of PEOU on CON is 0.125, with statistical significance. The “C./P.” column indicates partial mediation, demonstrating that both the direct effects of PEOU on CON and the indirect effects through mediators are meaningful.

Table10

Mediating Effects of the Path: PEOU→INO→CON

Total effect of PEOU→INO→CON				
Estimate	LLCI	ULCI	p	c./p.
.768	.604	.999	.001	p.
Direct effect of PEOU→INO→CON				
Estimate	LLCI	ULCI	p	
.643	.477	.846	.001	
Indirect effect(s) of PEOU→INO→CON				
Estimate	LLCI	ULCI	p	
.125	.066	.239	.000	

Table 11 illustrates the mediating effect in the "PEOU→INO→BO" pathway. The results show a significant total effect of Perceived Ease of Use (PEOU) on boredom (BO), with statistical significance ($p<0.001$), underscoring a strong and meaningful relationship. Additionally, PEOU’s direct effect on BO remains significant, suggesting a notable association between perceived ease of use and boredom, independent of mediating variables. The analysis also identifies significant indirect effects, indicating that PEOU influences boredom through intervening factors. The total indirect effect size calculated from the PEOU on BO was 0.258, which is sizable and statistically significant, with confidence interval limits (BootLLCI and BootULCI) not including zero. The notation "P" in the "P./C." column denotes partial mediation, implying that PEOU’s effects on BO—both direct and indirect—are noteworthy.

Table11

Mediating Effects of the Path: PEOU→INO→BO

Total effect of PEOU→INO→BO				
Estimate	LLCI	ULCI	p	c./p.
-.263	-.509	-.005	.044	p.
Direct effect of PEOU→INO→BO				
Estimate	LLCI	ULCI	p	
-.520	-.766	-.260	.003	
Indirect effect(s) of PEOU→INO→BO				
Estimate	LLCI	ULCI	p	
.258	.127	.456	.001	

In conclusion, the SEM and mediation analysis underscores the crucial role of mediating variables in the relationship between Perceived Ease of Use (PEOU) and key dependent variables, including Behavioural Involvement Focus (BIF), Perceived Usefulness and Curiosity (PUC), and boredom (BO). The analysis, conducted using SPSS with Amos, reveals multiple statistically significant pathways through which PEOU exerts influence, offering more profound insight into the underlying mechanisms. These findings highlight the importance of accounting for both direct and indirect effects when exploring the impact of PEOU on user behaviour and attitudes.

Discussion

The development of CALL tools has significantly transformed pedagogical approaches, leading to substantial advancements in language training technology. This study explored the adoption of ChatGPT in English language learning among Chinese university students, framed within the Hedonic Motivation System Adoption Model (HMSAM). The results provide nuanced insights into how various factors, such as perceived ease of use (PEOU), personal innovativeness, curiosity, and control—interact to influence learners' engagement and intention to continue using ChatGPT. These findings contribute to the broader discourse on the role of artificial intelligence (AI) in education, especially in contexts where intrinsic motivation plays a pivotal role in technology adoption.

In line with previous research (Davis, 1989), this study reconfirms that perceived ease of use (PEOU) plays a crucial role in determining how students perceive the usefulness of ChatGPT. When a tool is easy to use, students are more likely to see its benefits in aiding their language learning. This finding also consists with numerous studies that have expanded on HMSAM over the years, further solidifying the importance of PEOU in technology adoption across various fields (Francke & Alexander, 2018; Palos-Sanchez et al., 2022; Florensia & Suryadibrata, 2023). In the context of language learning, a user-friendly interface allows students to take full advantage of ChatGPT's functions without technological distractions. Similar results were also found in the research by Belda-Medina & Calvo-Ferrer (2022), which emphasized that the accessibility of chatbots can significantly affect students' motivation and interaction with the software. By making the interface simple and intuitive, students are better able to focus on the cognitive demands of language acquisition, rather than being overwhelmed by complex technological processes.

Furthermore, the results of this study emphasize the important role of personal innovativeness in enhancing intrinsic motivators, such as the sense of control and curiosity. Specifically, students with high innovativeness are more likely to feel confident in navigating the tool, which increases their sense of control over the learning process. This contrasts with the findings drawn by Qu and Wu (2024), which indicated that the tendency to embrace new technologies may not substantially influence users' sense of control when interacting with ChatGPT. This difference may be attributed to the distinct demographics of the studies; while Qu and Wu focused on international students in the UK, this study surveyed Chinese students. Cultural differences, educational expectations, and familiarity with emerging technologies in each context could potentially explain this divergence in findings. Consistent with Agarwal and Karahanna's (2000) study, this research shows that students who are open to exploring new technologies tend to be more curious about ChatGPT's capabilities and its potential to enhance their learning. This heightened curiosity drives them to explore the tool's features more thoroughly, which aligns with Silvia and Kashdan's (2021) findings, identifying curiosity as a key factor in fostering deeper interaction and exploration of new technologies.

In contrast to early predictions (Van Tilburg & Igou, 2017; Watson et al., 2013), the results imply that perceived ease of use, boredom, and sense of control have no discernible effects on sustained attention or the intention to use the platform going forward. While ease of use and curiosity help reduce boredom, the result shows that these factors alone do not guarantee long-term engagement with ChatGPT. Although boredom was reduced initially, it did not have a significant long-term impact on students' intention to keep using the tool. This suggests that although these elements might be involved in the tool's initial acceptability, their impact on long-term involvement is less. These findings point to the need to reconsider these aspects' relative importance when it comes to extended utilisation of technology and to look into other factors that can encourage continued use of these platforms.

The mediation analysis reveals several critical pathways in which Perceived Ease of Use (PEOU) influences key behavioural outcomes, both directly and indirectly. Specifically, PEOU impacts Behavioural Intention to Use and Focused Immersion (BIF), Perceived Usefulness and Curiosity (PUC), Boredom (BO), and Control (CON), mediated by other important variables. These findings highlight the intricate mechanisms through which user perceptions of ease of use shape their behavioural intentions and engagement.

The analysis reveals several instances of complete mediation, where Perceived Ease of Use (PEOU) affects Behavioural Intention to Use and Focused Immersion (BIF) entirely through Perceived Usefulness and Curiosity (PUC) and Personal Innovativeness in Information Technology (INO). In these cases, PEOU does not exert a direct effect on BIF; rather, its influence is fully mediated by PUC and INO. In other words, students who perceive a system as easy to use are more likely to develop a stronger intention to use it and experience deeper immersion if they also find the system useful and engaging, or if they exhibit a natural inclination towards innovation in technology. Without the presence of these factors—perceived usefulness and curiosity, or personal innovativeness in information technology—the perceived ease of use alone is insufficient to directly enhance their behavioural intention to use or their level of focused immersion. This finding is in line with Venkatesh and Davis's (2000) research, which highlighted the critical role of mediating factors such as perceived usefulness in shaping the relationship between perceived ease of use and behavioural intention to use.

Additionally, partial mediation was observed in this research. For example, while perceived ease of use has a direct effect on boredom, it also has an indirect effect through personal innovativeness in information technology. This suggests that both the direct and indirect effects of perceived ease of use play a significant role in influencing boredom. In other words, students who are naturally more innovative or curious about new technologies are less likely to feel bored with a system. This finding is in line with Agarwal and Prasad's (2007) research, which pointed out that personal innovativeness in technology plays a key role in moderating user experiences, especially in terms of engagement and boredom with technology. Similarly, the relationship between perceived ease of use and control is partially mediated by personal innovativeness in information technology, indicating that while perceived ease of use directly affects users' perceptions of control, personal innovativeness also acts as a mediator in this relationship. In simple terms, students who are more willing to explore new technology not only feel more control because of the system's ease of use but also because of their personal comfort and curiosity with new tools. This finding aligns with previous research (Kim & Kim, 2022; Qu & Wu, 2024), which highlighted that individuals with higher levels of personal innovativeness are more likely to feel confident and in control when interacting with new technologies.

The study also draws on the HMSAM, which identifies enjoyment and engagement as pivotal motivators for language learning applications (Lowry et al., 2013; van der Heijden, 2004). This highlights the importance of hedonic, or pleasure-driven, aspects in enhancing the learning experience within large language models (LLMs) like ChatGPT. In language learning, where intrinsic motivation plays a central role, fostering an enjoyable experience can significantly boost learners' willingness to explore and use new tools like ChatGPT. This aligns with findings from prior studies (Bruner & Kumar, 2005; Deng & Yu, 2023), which suggest that users are more likely to adopt technology when they derive emotional satisfaction from its use. Moreover, structural Equation Modeling (SEM) analysis confirms the validity of the proposed research model, with fit indices indicating an alignment between the theoretical framework and the empirical data. This strengthens the hypothesised relationships among the variables and validates the model's capacity to explain user behaviour in the context of CALL.

Tools like ChatGPT are poised to transform language acquisition. For educators, it is crucial to focus on creating user-friendly, engaging language learning applications that foster intrinsic motivation. These resources ought to be manufactured with learners' changing requirements for dynamic learning environments. Subsequent studies are required to examine the enduring impacts of the recognised parameters on user involvement and uncover other variables that could potentially impact the consistent uptake of language education platforms. Studies spanning cultural boundaries also shed light on how cultural variations impact the implementation and application of CALL technologies in language learning. Examining the elements that contribute to the successful adoption and ongoing usage of these advances is crucial as the landscape of educational technology changes. This study lays the groundwork for the creation of more valuable and captivating educational technologies by shedding light on the relative importance of perceived ease of use and intrinsic motivation in the context of English language acquisition in Chinese higher education.

Conclusion

This investigation delineates the association between the viewpoints of Chinese university students concerning the implementation of ChatGPT in students' English learning and their intrinsic motivation, as conceptualised within the Hedonic Motivation System Adoption Model (HMSAM) framework. The study concludes that using ChatGPT as an additional language learning aid significantly increases Chinese students' inherent desire to become fluent English speakers. This discovery offers a crucial perspective on the implementation and uptake of ChatGPT in CALL, highlighting the importance of elements like control, weariness, and usability in combining learners' motivational dynamics and engagement.

The findings reveal a significant influence of ChatGPT's usability on the innovation consciousness of users; the system's ease of use correlates with a higher propensity to embrace and adopt new technological advancements in information technology. Moreover, usability impacts users' perceived usefulness and curiosity; they recognise the tool's potential to enhance their learning outcomes and pique their intellectual interest. These findings support the idea that broad language models add to the perceived worth of language learning resources. Additionally, the study identifies that usability affects users' sense of control, curiosity, and fatigue. Engaging with OpenAI provides learners with greater control over their learning process, fosters curiosity, and reduces fatigue throughout the educational experience. These outcomes underscore the vital contribution of tool utility in crafting appealing and constructive learning experiences.

Contrary to expectations, the findings do not corroborate a direct effect of individual innovative capacity on users' sustained attention and willingness to continue using the tool.

This suggests that within the realm of language learning via ChatGPT, individual innovative capacity may not directly affect users' sense of control, fatigue levels, and curiosity. Consequently, designing and promoting analogous language learning systems should focus on enhancing usability and practicality to augment user engagement and motivational impetus.

This study's salient findings offer pivotal guidance for developing and deploying English learning tools. Comprehending students' perceptions and motivations towards Open AI ChatGPT is vital in fostering learners' enthusiasm and participation. These contributions are of significant value to scholarly research and provide indispensable insights for the innovation and evolution of English language instruction and education.

Despite several significant findings, this research has a number of limitations that should be taken into account. First, because of regional and cultural disparities, the sample was limited to undergraduate and graduate students in China, which may have limited the application of the data. To improve the generalizability of the results, subsequent investigations could include students from a wider range of ethnic backgrounds and geographic origins in the sample. Second, self-report bias may have crept into the data-gathering process, which was an online survey. Although measures were taken to ensure data accuracy and reliability, the possibility of subjective biases or memory distortions from participants cannot be completely ruled out. Future studies may consider integrating other data collection methods, such as observation or experimental designs, to provide more comprehensive and objective data. Furthermore, the study utilised a cross-sectional design, which can only establish correlations rather than determine causal relationships. While the study constructed a logical research model and analysed it using structural equation modelling, further longitudinal studies are needed to validate our findings and establish causality.

Another limitation is that this study focused exclusively on the impact of ChatGPT as an auxiliary language-learning tool without considering other possible factors. Future research could explore the effects of other generative AI models and compare their effectiveness in enhancing students' intrinsic motivation. Lastly, this study only examined students' perceptions and intrinsic motivation regarding the ChatGPT without investigating other potential influencing factors, such as the role of teachers and the teaching environment. Future studies could include these factors for a more thorough examination and comprehension.

In summary, despite yielding important findings, this research requires further exploration to address its limitations and provide a more comprehensive and in-depth understanding. This will help advance the field of computer-assisted language learning and provide more accurate guidance for educational practices and policymaking.

The findings of this study offer significant insights for future research, contributing to the advancement of the field of computer-assisted language learning tools (CALLs). Below are potential directions and implications for future research. Firstly, future studies can further explore the differences in perceptions and intrinsic motivation among various learner groups regarding ChatGPT. This study focused solely on the perspectives of Chinese university students. Future research could consider learners of different ages, genders, educational backgrounds, and English proficiency levels to obtain a more comprehensive understanding and cater to diverse learner needs.

Secondly, longitudinal research designs may be used in further investigations to confirm the connections found in this study and prove causation. Monitoring students' learning processes and motivational shifts over time can provide more trustworthy information regarding the long-term effects of Open AI ChatGPT on learners' intrinsic motivation.

Further investigations may also examine the effects of additional data-driven language learning resources on students' intrinsic motivation. By comparing the efficacy of various resources, researchers and educators can make better decisions about the language learning tools students use.

Investigating how teachers' roles and the classroom environment impact students' intrinsic motivation is a critical area of research. Teachers play a vital role in facilitating language acquisition, and their guidance and encouragement significantly shape students' motivation. To gain deeper insights into their influence on learners' intrinsic motivation, future studies should explore the specific roles teachers play, their instructional methods, and key aspects of the learning environment, such as the accessibility and interactivity of learning resources.

Finally, future studies could explore integrating with other teaching methods and resources to enhance language learning outcomes. For example, research could examine how combining ChatGPT with face-to-face classroom instruction can create a richer and more diverse learning experience. This would help to promote the development of blended teaching models and provide more effective language learning solutions.

In conclusion, future research can further expand and deepen the understanding of computer-assisted language learning by exploring different learner groups, employing longitudinal research designs, comparing the effects of various tools, considering the roles of teachers and teaching environments, and integrating different teaching methods and resources. This will provide more specific and effective guidance for educational practice and policy-making, fostering innovation and progress in language learning.

ORCID

https://orcid.org/0009-0000-3502-7498

https://orcid.org/0000-0002-0417-8848

https://orcid.org/0009-0002-6863-8935

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