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Towards a Unified Model of Generative Intelligence Acceptance (UMGA) in Second Language Learning: A Review and Integration

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ABSTRACT

Given the potential benefits of generative artificial intelligence (GenAI) for second language (L2) learning, numerous studies have explored the factors influencing learners' adoption of GenAI in this context. However, these studies are often constrained by the theoretical models they rely on, with no single model fully capturing the social, cognitive and motivational factors that shape L2 learners' GenAI adoption. To address this gap, this study aims to develop a comprehensive model that integrates these various factors to more accurately predict this behavioral intention of L2 learners. To this end, we first reviewed five existing models that have been applied to explain L2 learners' GenAI adoption: Technology Acceptance Model, Hedonic Motivation System Adoption Model, Control-Value Theory, Unified Theory of Acceptance and Use of Technology and the L2 Motivational Self System. We then synthesized and refined relevant components from these models to create a Unified Model of Generative Intelligence Acceptance (UMGA). This new model, which incorporates seven core components, provides a more holistic and less biased framework for understanding the determinants of L2 learners' GenAI adoption.

Keywords: GenAI adoption, determinants, second language learners, Unified Model of Generative Intelligence Acceptance

Introduction

In recent years, the field of generative artificial intelligence (GenAI) has been dominated by the advent of transformers, a deep learning architecture introduced in the 2017 paper Attention Is All You Need Transformers dramatically improved the ability of AI systems to process and generate sequences of data, making them particularly well-suited for natural language processing[1]. OpenAI's Generative Pretrained Transformers (GPT) models, starting with GPT-2 (2019) and progressing to GPT-3 (2020) and beyond, represent some of the most advanced generative language models. These models, trained on massive corpora of text data, are capable of generating coherent, contextually appropriate text based on a given prompt. GPT models have become widely known for their ability to write essays, stories, code and engage in conversations with humans. In 2023, OpenAI launched GPT-4, which improved the model's reasoning capabilities and multimodal functionality (the ability to process both text and images)[2].

GenAI tools like ChatGPT are powerful and flexible resources for second language (L2) learners. In theory, by offering personalized, real-time feedback, a vast range of interactive content and the ability to engage with the language at any time and place, they significantly enhance the language learning process[3]. The combination of conversational practice, contextual learning and the ability to receive instant corrections and explanations makes GenAI a particularly valuable resource for SLA, especially when used alongside more traditional methods of language instruction. Recent empirical studies have demonstrated that GenAI could benefit the improvement of L2 skills such as writing, speaking, reading, listening, vocabulary and pragmatics[4-8]. Besides, it also helps improve psychological experience of SLA such as emotions, engagement and self-efficacy[9-11].

As highlighted[12], the full realization of the benefits of GenAI necessitates the active engagement of L2 learners. In response to this imperative, a growing body of research has investigated the factors that influence the adoption of GenAI among these learners[13-15]. These studies, based on different theories, help researchers understand the factors influencing second language learners' acceptance of GenAI from multiple perspectives. However, each theory has its scope of applicability and limitations. A single theory may not be able to fully explain the complexity of technology acceptance. By integrating multiple theories, researchers can address the shortcomings of individual theories and develop a more comprehensive analytical framework. Therefore, this study aims to review the existing models of GenAI acceptance applied to second language acquisition and ultimately integrate a new, comprehensive theoretical model, namely, a Unified Model of Generative Intelligence Acceptance (UMGA) Specifically, this study addresses the following two research questions:

RQ1. What models have been used for GenAI acceptance in the existing literature on SLA?

RQ2. What is the UMGA like?

Data Resource and Collection

To explore the GenAI acceptance models in SLA, we curated the dataset for our study exclusively from the Web of Science as of 10 November 2024, based on a set of well-defined criteria. Web of Science is among the most widely recognized and utilized academic databases worldwide, trusted by researchers and institutions for their comprehensive literature coverage. This database indexes high-quality scholarly works across a broad range of disciplines, including journal articles, conference proceedings, books, patents and other influential publications. Additionally, it maintains rigorous selection standards to ensure the quality and academic significance of the indexed materials. With its extensive global reach, reliable data update mechanisms and robust cross-language support, Web of Science plays a pivotal role in scientific evaluation and academic exchange. Thus, choosing this database for our literature analysis ensures a comprehensive, timely and precise foundation for our research.

Our data collection process was structured around four key criteria: (1) Topic: keywords such as "second language ChatGPT acceptance," "foreign language generative artificial intelligence acceptance," "second language ChatGPT intention," "foreign language generative artificial intelligence intention," "English generative artificial intelligence intention," and "English ChatGPT intention"; (2) Document Type: research articles; (3) Language: English; (4) Publication Year: 2022–2024, reflecting the period since the launch of ChatGPT in 2022. The initial search yielded 264 articles published between 2023 and 2024 from Web of Science, we then applied the following exclusion criteria to refine our selection: (1) articles not directly related to GenAI acceptance models in SLA, which may have resulted from search algorithm limitations; (2) duplicate articles. After applying these filters, we were left with 12 relevant articles published between 2023 and 2024 **(Table 1)**.

Table 1: The included studies on GenAI acceptance in SLA.

Author(s)	Title	Model
1. Dehghani and Mashhadi[16]	Exploring Iranian English as a foreign language teachers' acceptance of ChatGPT in English language teaching: Extending the technology acceptance model.	TAM
2. Liu and Ma[17]	Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model	TAM
3. Liu, et al.[18]	Exploring AI-mediated informal digital learning of English (AI-IDLE): A mixed-method investigation of Chinese EFL learners' AI adoption and experience	TAM
4. Liu[19]	Second language writing anxiety and ChatGPT adoption as an automated writing evaluation tool	TAM
5. Ma[20]	Exploring the acceptance of generative artificial intelligence for language learning among EFL postgraduate students: An extended TAM approach	TAM
6. Mutammimah, et al.[21]	Understanding teachers' perspective toward ChatGPT acceptance in English language teaching	TAM
7. Qu and Wu[22]	ChatGPT as a CALL tool in language education: A study of hedonic motivation adoption models in English learning environments	HMSAM
8. Shen and Guo[23]	"I feel AI is neither too good nor too bad": Unveiling Chinese EFL teachers' perceived emotions in generative AI-mediated L2 classes	TAM, CVT
9. Tram, et al.[24]	ChatGPT as a tool for self-learning English among EFL learners: A multi-methods study	TAM
10. Xu and Thien[25]	Unleashing the power of perceived enjoyment: exploring Chinese undergraduate EFL learners' intention to use ChatGPT for English learning	UTAUT
11. Ziqi, et al.[26]	L2 students' barriers in engaging with form and content-focused AI-generated feedback in revising their compositions	TAM
12. Zou, et al.[27]	Exploring English as a foreign language learners' adoption and utilisation of ChatGPT for speaking practice through an extended technology acceptance model	TAM
13. Huang and Mizumoto[28]	Examining the relationship between the L2 motivational self system and technology acceptance model post ChatGPT introduction and utilization	TAM, L2MSS

Note: TAM = Technology Acceptance Model; HMSAM = Hedonic Motivation System Adoption Model; CVT = Control-Value Theory; UTAUT = Unified Theory of Acceptance and Use of Technology; L2MSS = L2 Motivational Self System.

Models For Gen AI Acceptance In SLA

Technology acceptance model

Based on our review on the models for GenAI acceptance in SLA, the Technology Acceptance Model (TAM) is the most widely adopted theoretical framework for understanding and predicting how L2 learners come to accept and use GenAI[29-31]. Developed by[32], TAM aims to explain the factors influencing individuals' decisions to accept or reject new technologies, particularly in the context of information systems. TAM posits that individual behavior is shaped by attitudes, which are, in turn, influenced by underlying beliefs. Specifically, TAM emphasizes how the perceived ease of use and perceived usefulness of a technology impact its acceptance by users[33].

TAM identifies several key factors that explain how individuals adopt and interact with technology. These components are crucial for understanding the drivers of technology acceptance. The primary elements of TAM include Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Using (ATU) and Behavioral Intention to Use (BI) [34].

PU refers to the extent to which an individual believes that using a technology will enhance their performance or productivity in a given context. When users perceive a technology as beneficial, they are more likely to adopt it. For example, a software tool that improves task efficiency is seen as useful, thereby increasing its acceptance.

PEOU reflects how effortless an individual believes it will be to use a technology. The more intuitive and user-friendly the technology, the more likely users are to embrace it. A system that is easy to navigate encourages comfort and willingness to adopt it.

ATU captures users' positive or negative feelings toward a technology, influenced by both its perceived usefulness and ease of use. If a technology is viewed as both helpful and easy to use, users are likely to develop a favorable attitude toward it, which reflects their overall emotional response.

BI represents the user's intention or willingness to engage with the technology, which is a strong predictor of actual usage behavior. A positive attitude toward a technology typically leads to a stronger intention to use it, thus linking perceptions and attitudes to actual behavior.

The relationships between these components unfold as follows **(Figure 1)**: PU and PEOU influence ATU, which in turn affects BI-the most reliable predictor of actual usage. According to TAM, if users perceive a technology as both useful and easy to use, they are more likely to have a positive attitude toward it and, consequently, are more likely to adopt and continue using it.

TAM has played a pivotal role in understanding how users perceive and adopt new technologies. It provides a robust foundation for researchers and practitioners to explore the psychological and social factors influencing technology usage, while offering valuable insights into designing user-friendly and effective technologies. Despite its limitations, TAM remains a core framework in the study of technology adoption and acceptance.

Hedonic motivation system adoption model

The Hedonic Motivation System Adoption Model (HMSAM), introduced[35], expands upon the TAM to address its limitations in explaining the adoption of entertainment technologies like video games and social media. Unlike traditional models that focus primarily on utility and efficiency, the HMSAM recognizes that these technologies also fulfill users' emotional needs. Hedonic Motivation is central to this model, which includes variables such as PEOU, PU and BI from TAM, along with Curiosity, Joy, Control and Focused Immersion (FI)[36]. These variables interact to influence users' acceptance of technology.

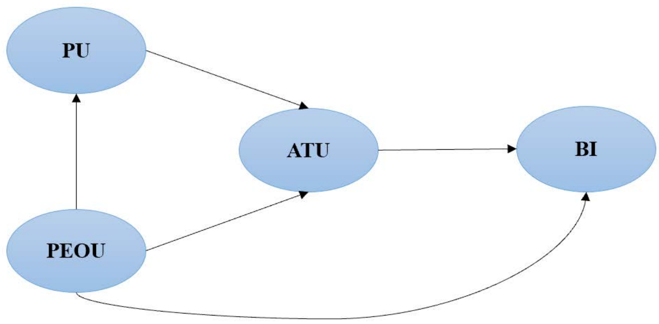

Figure 1: Theoretical framework of TAM.
Note: PU = Perceived Usefulness, PEOU = Perceived Ease of Use, ATU = Attitude Toward Using, BI = Behavioral Intention to Use

Curiosity represents a user's desire to explore new technologies, particularly in entertainment applications. It is the intrinsic drive that encourages initial use and deeper engagement. Joy refers to the pleasure users derive from technology, which, unlike perceived usefulness, focuses on hedonic motivation. Control is the sense of autonomy users feel while interacting with a system, while Focused Immersion (FI) describes the deep concentration users experience when immersed in a system.

PEOU influences PU, curiosity, joy and control as it affects how users engage with the system. When a technology is easy to use, it not only increases users' perceptions of its usefulness (PU) but also encourages them to explore its features (curiosity), generates positive emotional experiences (joy) and promotes a sense of autonomy and mastery (control). Together, these factors enhance user immersion and play a crucial role in driving long-term adoption behavior **(Figure 2)**.

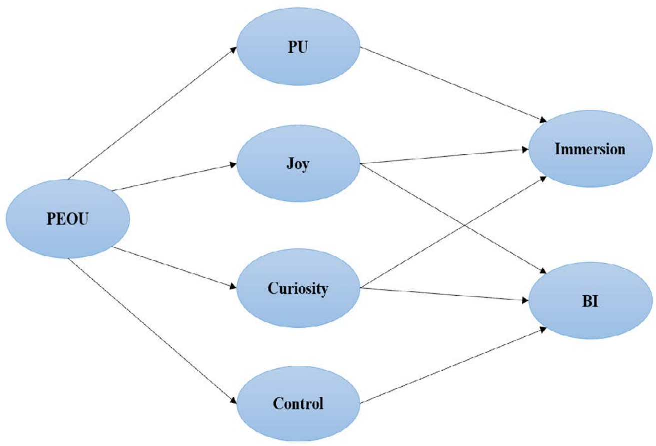

Figure 2: Theoretical framework of HMSAM.
Note: PU = Perceived Usefulness, PEOU = Perceived Ease of Use; BI = Behavioral Intention to Use

Control-value theory

Control-Value Theory (CVT), developed[37], provides a comprehensive framework for understanding the antecedents of emotions in academic settings. The theory highlights the roles of control-value appraisals as the proximal antecedents of emotions: control-the student's perception of their ability to influence outcomes-and value-the importance or personal relevance a student places on a task-in shaping their emotional experiences in learning environments.

Control refers to how much influence students believe they have over the outcomes of their learning efforts. When students feel that they have control over their learning, they tend to feel more competent and motivated. Conversely, if they perceive little control, they may experience negative emotions such as frustration or helplessness. Value, on the other hand, pertains to the importance a student assigns to a particular task. This can be intrinsic (e.g., enjoyment of the task) and extrinsic (e.g., its usefulness for future goals). Tasks that are highly valued are more likely to engage students and boosting effort.

Emotions play a central role in CVT. Positive emotions, such as joy, pride and interest, are associated with increased motivation and improved academic performance. These emotions are more likely to arise when students feel both a sense of control over their learning and a high value for the task at hand. On the other hand, negative emotions such as anxiety, boredom and frustration can diminish motivation and hinder academic achievement. These negative emotional responses often occur when students feel they lack control or do not find the task to be personally meaningful.

In addition to control and value, CVT also recognizes the role of distal antecedents in shaping students' emotions, which refer to broader, long-term influences (e.g., early experiences, personality traits or societal factors) that shape how individuals perceive control and value in achievement contexts, which in turn influence their emotional experiences and reactions. These distal factors help explain why some people might respond more positively or negatively to achievement situations based on their previous experiences and general beliefs.

In summary, CVT emphasizes the dynamic relationship between control and value in determining the emotional responses that influence learning outcomes **(Figure 3)**. By addressing these factors, educators can better support students, fostering positive emotional experiences and enhancing motivation, which ultimately contributes to improved academic performance[38].

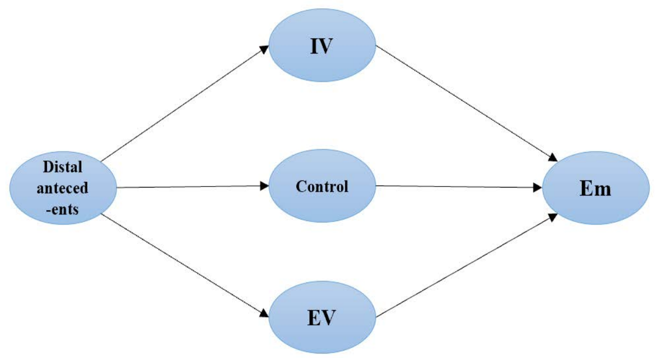

Figure 3: Theoretical framework of CVT.
Note: IV = intrinsic value, EV = extrinsic value, Em = emotions

Unified theory of acceptance and use of technology

The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by[39], offers a comprehensive framework designed to explain and predict user acceptance of new technologies. This model integrates elements from several previous theories of technology adoption and use (e.g., TAM), aiming to provide a unified approach that highlights the key factors influencing technology adoption.

The UTAUT model identifies four main constructs that directly impact users' intentions and behaviors toward adopting new technology. Performance Expectancy (PE) refers to the extent to which an individual believes that using a particular technology will improve their job performance or productivity. This concept is similar to PU in TAM, emphasizing the anticipated benefits in terms of task efficiency. Effort Expectancy (EE) reflects the perceived ease of using the technology, essentially measuring how much effort an individual thinks are required for adoption. This construct parallels PEOU in TAM, highlighting the importance of the technology being user-friendly. Social Influence (SI) represents the degree to which an individual perceives that significant other, such as peers, colleagues or family members, believe they should use the technology. This construct underscores the role of social norms and peer pressure in shaping technology adoption decisions. Finally, Facilitating Conditions (FC) refer to the perceived availability of necessary resources, infrastructure or support (such as hardware, software or training) that enable the effective use of the technology. This includes access to technical support and any other required resources that facilitate successful adoption.

Together, these four constructs influence the key outcome: BI **(Figure 4)**. The UTAUT model provides valuable insights for both researchers and practitioners by identifying the factors that drive technology adoption across different contexts and user groups. The model has been widely applied in various fields, including e-commerce, healthcare, education and mobile technology adoption, making it a robust tool for understanding the factors that determine technology acceptance and use in modern settings[40-43].

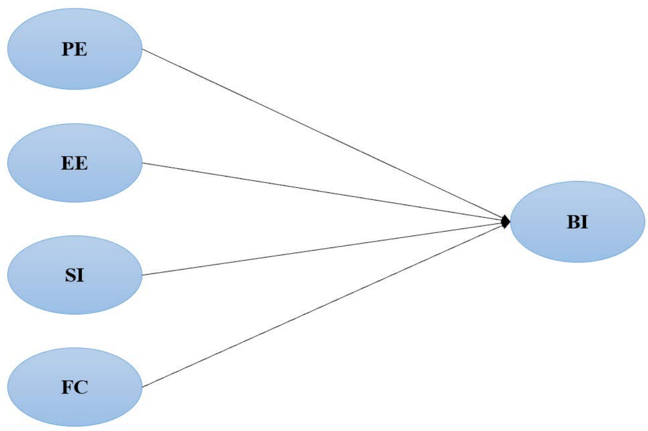

Figure 4: Theoretical framework of UTAUT.
Note: PE = Performance Expectancy, Effort Expectancy (EE); BI = Behavioral Intention to Use

L2 Motivational self-system

Unlike models such as TAM, HMSAM and UTAUT, which are rooted in management theory, the L2 Motivational Self System (L2MSS) is a psycholinguistic framework. Proposed[44], L2MSS offers a theoretical approach to understanding motivation in SLA. It is built on the notion that L2 learning motivation can be explained through three key components: the ideal L2 self, the ought-to L2 self and the L2 learning experience.

However, most research tends to focus on the ideal L2 self and the ought-to L2 self, while giving relatively little attention to the L2 learning experience[45-47]. This imbalance arises because the first two components are rooted in the Self-Discrepancy Theory from psychology, which is closely tied to motivation and easier to measure. In contrast, the L2 learning experience is a more complex concept that includes factors such as the learner's specific learning process, context, strategies and emotional responses. These aspects are difficult to standardize or quantify into a universally applicable measurement tool. Although the learning experience does influence motivation and learning outcomes, its complexity often results in it being oversimplified or overlooked in theoretical research.

The ideal L2 self refers to the learner's vision of themselves as a proficient second language speaker. It encompasses their aspirations and personal goals for mastering the language. Motivation is driven by the desire to become this ideal version of oneself, often fueled by intrinsic factors such as personal values, cultural interests or career objectives. On the other hand, the ought-to L2 self reflects the learner's perception of external pressures or expectations related to language learning. This includes the demands of others-such as parents, teachers, employers or society-who may expect the learner to acquire certain language skills. Motivation in this case stems from the desire to meet these external expectations and avoid negative consequences, such as social or professional failure.

L2MSS highlights the role of identity and self-concept in motivating language learners. It suggests that learners are more likely to be motivated to study a second language when they have a clear vision of their future self as a competent speaker (the ideal L2 self) or when they feel a sense of obligation to meet external expectations (the ought-to L2 self). L2MSS has gained significant influence in SLA research, as it expands the understanding of motivation beyond traditional models. It integrates both intrinsic (self-driven) and extrinsic (externally-driven) factors into a comprehensive framework **(Figure 5)**.

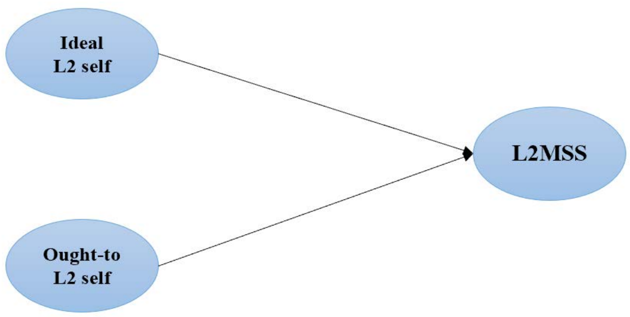

Figure 5: Key components of L2MSS.

Establishing Unified Model of Genai Acceptance (UMGA) In Sla

PEOU, control and EE

The concepts of PEOU in TAM, control in CVT and HMSAM and EE in UTAUT indeed overlap to some extent. In TAM, PEOU reflects an individual's perception of how easy a task or technology is to operate. In CVT, the sense of control of the task significantly influences emotions and motivation. If a task is perceived as easy, students are more likely to experience a sense of control, thus promoting positive emotions and motivation.

In HMSAM, control emphasizes an individual's sense of mastery over their learning process and outcomes. When individuals perceive control, they typically exhibit higher motivation and better learning outcomes. This is similar to the perceived control in CVT, both focusing on how one's perception of controlling their behavior outcomes influences emotions and motivation.

In UTAUT, EE is the expectation of how easy it will be to complete a task or use a technology. This concept overlaps with perceived control in CVT. If an individual expects a task or technology to be easy, they are more likely to feel a sense of control in the task, thus enhancing motivation.

In summary, the concepts of control in CVT are more encompassing. Perceived control can include PEOU in TAM, control in HMSAM and EE in UTAUT.

PU, PE, intrinsic value, extrinsic value, ideal L2 self and ought-to L2 self

The concepts of PU in TAM, value in CVT, PE in UTAUT and ideal L2 self and ought-to L2 self in L2MSS indeed overlap to some extent. PU refers to the perception of the task or technology's utility in achieving personal goals. In CVT, the extrinsic value of the task significantly influences emotions and motivation. If a task is perceived as useful, students are more likely to experience a sense of task value, thus promoting positive emotions and motivation.

In UTAUT, PE refers to the belief that using a technology or completing a task will help individuals achieve their goals. This concept also overlaps with extrinsic value in CVT. If an individual expects a task or technology to be beneficial, they are more likely to feel a sense of value in the task, thus enhancing motivation.

In L2MSS, ideal L2 self represents an individual's ideal vision of their SLA, while ought-to L2 self refers to the perception of external expectations (e.g., from teachers, parents) regarding language learning. These concepts overlap with intrinsic value and extrinsic value in CVT, as both involve how individuals connect language learning to their long-term goals or external expectations, influencing their motivation.

In summary, Extrinsic value can encompass PU in TAM, PE in UTAUT and ought-to L2 self in L2MSS. Lastly, intrinsic value can cover the ideal L2 self in L2MSS.

SI, FC and distal antecedents

In the context of CVT, distal antecedents refer to the long-term, background or contextual factors that shape individuals' emotional experiences in achievement-related contexts, though they are not immediate triggers of specific emotional reactions. These distal antecedents set the stage for more immediate emotional responses and can include factors such as early life experiences, cultural or societal influences and personality traits. They influence how individuals perceive their control over outcomes and the value they place on tasks, which in turn affects their emotional responses, such as enjoyment, anxiety or pride. Distal antecedents thus provide the broader context that shapes individuals' motivation and emotional reactions to achievement tasks over time.

Interestingly, there are conceptual overlaps between facilitating conditions in UTAUT, social influences in UTAUT and distal antecedents in CVT. All these factors influence an individual's behavior indirectly, through contextual or external influences. Facilitating conditions in UTAUT are external factors that make a task easier to complete, thus impacting an individual's sense of control. Similarly, distal antecedents in CVT shape perceptions of control by providing a broader context, such as early experiences or societal expectations, that influences emotional responses and motivation in achievement settings.

In addition, social influences in UTAUT overlap with distal antecedents in CVT, particularly with respect to how social and cultural factors indirectly shape an individual's perception of control and value. Social expectations, cultural norms and support systems can all influence how much an individual values a particular task and how much control they believe they have over its outcome. These influences, whether intrinsic or extrinsic, can significantly affect an individual's motivation to engage in a task, reflecting the broader role of distal antecedents in shaping emotional responses and achievement-related behaviors.

Unified Model of GenAI Acceptance

Building on the previous analysis, we have developed the Unified Model of GenAI Acceptance (UMGA) by integrating components from TAM, HMSAM, UTAUT and L2MSS. The UMGA consists of 7 key components: FC, SI, ideal L2 self, PU, PEOU, Joy and BI. The relationships among these components are illustrated in **(Figure 6)**.

According to CVT, FC and SI are distal antecedents that shape emotions, such as joy in HMSAM. These antecedents influence emotional responses by affecting an individual's PEOU, which relates to their sense of control over GenAI and the intrinsic (ideal L2 self) and extrinsic values (PU) they assign to it. Specifically, SI affect how users perceive their ability to use GenAI (PEOU), while SI affects ideal L2 self (intrinsic value) and PU (extrinsic value) of GenAI. Furthermore, based on UTAUT, both FC and SI can directly impact BI, which represents the user's intention to adopt or use GenAI. In terms of PU, which is associated with the ought-to L2 self (extrinsic motivation), the HMSAM model suggests that PU not only influences joy but also has a direct impact on BI. In TAM, PEOU (which is closely linked to the user's sense of control) also has a direct effect on both PU and BI[48].

It should be noted that in developing HMSAM, key modifications were made to align the model with long-term goal achievement, particularly in mastering GenAI and improving L2 skills. Curiosity was removed from the model, as it is seen as a secondary factor supporting exploration rather than a central driver. The focus shifted to the "ideal L2 self," a motivational construct reflecting an individual's future vision, which plays a more central role in sustained motivation for long-term goals. Similarly, attitude was also removed, since it was found less predictive of technology usage compared to PE and EE. These changes align the model with UTAUT, which excludes attitude for a more direct, actionable framework on technology adoption. Additionally, immersion was removed from HMSAM. While it can enhance learning, it is not a central factor influencing BI in our model.

To sum up, UMGA synthesizes these models to show that FC and SI play key roles in shaping emotions (like joy) and BI, with PEOU and value (both intrinsic and extrinsic, namely ideal L2 self and PU) acting as mediators.

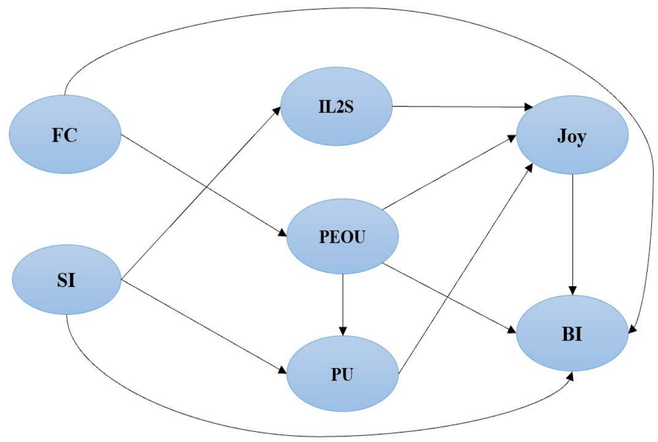

Figure 6: Theoretical framework of UMGA.
Note: FC = facilitating conditions; SI = social influence; IL2S =ideal L2 self; PEOU = perceived ease of use; PU = perceived usefulness; BI = behavioral intention.

Discussion

UMGA developed in this study is a comprehensive and innovative framework that integrates multiple established models to understand the adoption of GenAI, particularly in the context of SLA. By focusing on cognitive and emotional and social factors and considering long-term motivation, the model offers a nuanced view of GenAI adoption (the items for assessing the components of UMGA is presented in Appendix). Below are key observations and insights regarding the strengths and further considerations of UMGA.

Strengths of UMGA

Comprehensive integration of theoretical models

The UMGA draws on the strengths of multiple existing models, including TAM, HMSAM, UTAUT and L2MSS. This integration allows the model to encompass a wide range of factors that influence GenAI adoption, such as FC, SI, PEOU, PU, Joy and Ideal L2 Self. This holistic approach makes the model highly applicable to GenAI adoption in SLA, where technology use is often driven by multiple factors.

Emphasis on emotional and motivational factors

One of the key strengths of the UMGA is its focus on emotional responses, particularly Joy and intrinsic motivation through ideal L2 self. The inclusion of these factors acknowledges that GenAI engagement is not solely driven by cognitive perceptions of utility and ease of use but also by emotional satisfaction and long-term personal goals. In SLA, where motivation can be highly variable, this focus on emotional and identity-driven factors can help explain sustained engagement and long-term use of technology like GenAI.

Role of social factors in UMGA

By incorporating social factors like FC and SI, UMGA becomes a more robust and dynamic model that captures the full range of influences on GenAI adoption. These social dimensions highlight the importance of not just individual motivations or perceived utility but also the social context in which technology is used. This makes the UMGA particularly well-suited for understanding technology adoption in environments like L2 education, where social dynamics and institutional support often play a decisive role in shaping users' behavior and attitudes toward new technologies.

Clear pathways and mediating effects

The model clearly outlines how various factors influence BI. Social factors like FC and SI influence emotional responses (e.g., Joy) and cognitive factors (e.g., PEOU, PU and ideal L2 self), which then mediate BI. The mediation of PEOU and PU and ideal L2 self between social factors and BI provides a clear, structured pathway for understanding technology adoption. This pathway helps explain why certain users may be more likely to adopt and continue using GenAI tools for SLA.

Streamlined framework

By removing constructs like Curiosity, the UMGA becomes more streamlined and focused on the core factors that directly influence technology acceptance and sustained use. The simplification of the model makes it more applicable and easier to test empirically, which is essential for its practical application.

Further considerations

As with any new theoretical model, empirical testing is crucial to validate the relationships proposed in UMGA. While the model's components make theoretical sense, testing with real-world data from GenAI users will be essential to determine the strength of the proposed links between social factors, emotional responses, cognitive perceptions and behavioral intention. This data could help refine the model and identify areas for improvement.

Conclusion

UMGA is an advanced and well-rounded framework that offers valuable insights into the factors influencing GenAI adoption, especially in the context of SLA. By integrating social, cognitive, emotional and motivational components, the model provides a holistic understanding of GenAI acceptance. The decision to streamline the model by removing less predictive constructs, like Curiosity, improves its focus and clarity, making it a more effective tool for understanding user behavior. With further empirical validation in future studies, UMGA has the potential to become a powerful tool for predicting and enhancing GenAI adoption in SLA.

References

1. Patil S, Shrikhande P. Improving Conversational AI using Transformer and Reinforcement Learning from Human Feedback (RLHF). Int J Research in Applied Sci and Eng Techno 2024;12:1366-1375.
2. Mallikarjuna B, Chittemsetty P. Generative Artificial Intelligence: Fundamentals and Evolution. In Raza K, Ahmad N, Singh D. Generative AI: Current Trends and Applications. Springer Nature Singapore 2024:3-17.
3. Kristiawan D, Bashar K, Pradana D. Artificial Intelligence in English Language Learning: A Systematic Review of AI Tools, Applications and Pedagogical Outcomes. The Art of Teaching English as a Foreign Language (TATEFL) 2024;5:207-218.
4. Guo K, Pan M, Li Y, Lai C. Effects of an AI-supported approach to peer feedback on university EFL students' feedback quality and writing ability. The Internet and Higher Education 2024;63.
5. Hameed D, Haq D. Teaching Listening Skills to EFL Students Using AI-Driven Technology-Based Media. Evolutionary Studies In Imaginative Culture 2024:1989-1999.
6. Qassrawi R, ElMashharawi A, Itmeizeh M, Tami M. AI-Powered Applications for Improving EFL Students' Speaking Proficiency in Higher Education. Forum for Linguistic Studies 2024;06:535-549.
7. Wang Y, Wu J, Chen F, Wang Z, Li J, Wang L. Empirical Assessment of AI-Powered Tools for Vocabulary Acquisition in EFL Instruction. IEEE Access PP 2024:1-1.
8. Zheng S. The effects of chatbot use on foreign language reading anxiety and reading performance among Chinese secondary school students. Computers and Education: Artificial Intelligence 2024;7:100271.
9. Wang Q, Gao Y, Wang X. Exploring engagement, self-efficacy and anxiety in large language model EFL learning: A latent profile analysis of Chinese university students. International Journal of Human–Computer Interaction 2024:1-10.
10. Wang Y, Xue L. Using AI-driven chatbots to foster Chinese EFL students' academic engagement: An intervention study. Computers in Human Behavior 2024;108353.
11. Yang L, Zhao S. AI-induced emotions in L2 education: Exploring EFL students' perceived emotions and regulation strategies. Computers in Human Behavior 2024;159:108337.
12. Wu H, Wang Y, Wang Y. "To use or not to use?": A mixed-methods study on the determinants of EFL college learners' behavioral intention to use AI in the distributed learning context. International Review of Research in Open and Distributed Learning 2024;25(3):158-178.
13. Alasmari T. Acceptance Factors of Generative AI in EFL Teaching: A Pedagogical Perspective. JETL 2024;9:196.
14. Kong SC, Yang Y, Hou C. Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model. Computers and Education: Artificial Intelligence 2024;7:100328.
15. Zeng J, Li X. Modeling the Continuous Intention to Use Generative AI as an Educational Tool for EFL Learners among Vocational College Students in Guangzhou, China. J Innovation and Development 2024;8:18-27.
16. Dehghani H, Mashhadi A. Exploring Iranian english as a foreign language teachers' acceptance of ChatGPT in english language teaching: Extending the technology acceptance model. Education and Information Technologies 2024.
17. Liu G, Ma C. Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. Innovation in Language Learning and Teaching 2023;18(2):125-138.
18. Liu Z. Second language writing anxiety and ChatGPT adoption as an automated writing evaluation tool. J Applied Research in Higher Education, ahead-of-print(ahead-of-print) 2024.
19. Liu GL, Darvin R, Ma C. Exploring AI-mediated informal digital learning of English (AI-IDLE): A mixed-method investigation of Chinese EFL learners' AI adoption and experiences. Computer Assisted Language Learning 2024:1-29.
20. Ma M. Exploring the acceptance of generative artificial intelligence for language learning among EFL postgraduate students: An extended TAM approach. Int J Applied Linguistics 2024.
21. Mutammimah H, Rejeki S, Kustini S, Amelia R. Understanding Teachers' Perspective toward ChatGPT Acceptance in English Language Teaching. Int J Techno in Education 2024;7:290-307.
22. Qu K, Wu X. ChatGPT as a CALL tool in language education: A study of hedonic motivation adoption models in English learning environments. Education and Information Technologies2024; 29(15):19471-19503.
23. Shen Y, Guo H. "I feel AI is neither too good nor too bad": Unveiling Chinese EFL teachers' perceived emotions in generative AI-Mediated L2 classes. Computers in Human Behavior 2024;161:108429.

24. Tram NHM, Nguyen TT, Tran CD. ChatGPT as a tool for self-learning English among EFL learners: A multi-methods study. System 2024;127:103528.

25. Xu X, Thien LM. Unleashing the power of perceived enjoyment: exploring Chinese undergraduate EFL learners' intention to use ChatGPT for English learning. J Applied Research in Higher Education, ahead-of-print(ahead-of-print), 2024.

26. Ziqi C, Xinhua Z, Qi L, Wei W. L2 students' barriers in engaging with form and content-focused AI-generated feedback in revising their compositions. Computer Assisted Language Learning 2024:1-21.

27. Zou B, Wang C, Yan Y, Du X, Ji Y. Exploring English as a Foreign Language Learners' Adoption and Utilisation of ChatGPT for Speaking Practice Through an Extended Technology Acceptance Model. Int J Applied Linguistics 2024.

28. Huang J, Mizumoto A. Examining the relationship between the L2 motivational self system and technology acceptance model post ChatGPT introduction and utilization. Computers and Education: Artificial Intelligence 2024;7:100302.

29. Wang J, Luo R. Measuring Students' Acceptance of Using Tencent Conference Application in EFL Learning Based on the Technology Acceptance Model 2022:75-84.

30. Wang Y, Yu L, Yu Z. An extended CCtalk technology acceptance model in EFL education. Education and Information Technologies 2022;27:1-20.

31. Xu J, Deng Q. Exploring Chinese Secondary School Students' Acceptance of Live Video-Streamed Teaching Platforms in EFL Class: An Application of the Technology Acceptance Model. Behavioral Sciences 2024;14:593.

32. Davis F. Perceived usefulness, perceived ease of use and user acceptance of information technology. MIS Quarterly 1989;13:319.

33. Davis FD, Granić A. Revolution of TAM. In The Technology Acceptance Model: 30 Years of TAM. Springer Int Publishing 2024:59-101.

34. Marangunić N, Granić A. Technology acceptance model: a literature review from 1986 to 2013. Universal Access in the Information Society 2015;14(1):81-95.

35. Lowry P, Gaskin J, Twyman N, Hammer B, Roberts T. Taking "Fun and Games" Seriously: Proposing the Hedonic-Motivation System Adoption Model (HMSAM). J Association for Information Systems 2013;14:617-671.

36. Palos-Sanchez P, Saura J, Martín-Velicia F. A Case Study on a Hedonic-Motivation System Adoption Model in a Game-Based Student Response System. Int J Human-Computer Interaction 2022;40.

37. Pekrun R. The control-value theory of achievement emotions: assumptions, corollaries and implications for educational research and practice. Educational Psychology Review 2006;18:315-341.

38. Shao K, Pekrun R, Marsh HW, Loderer K. Control-value appraisals, achievement emotions and foreign language performance: A latent interaction analysis. Learning and Instruction 2020;69:101356.

39. Venkatesh V, Thong J, Xu X. Unified Theory of Acceptance and Use of Technology: A synthesis and the road ahead. J Association for Information Systems 2016;17:328-376.

40. Alsahli S, Hor SY, Lam M. Physicians' acceptance and adoption of mobile health applications during the COVID-19 pandemic in Saudi Arabia: Extending the unified theory of acceptance and use of technology model. Health information management : J Health Information Management Association of Australia 2024.

41. Farhi F. Examining the factors fostering metaverse experience browser acceptance under unified theory of acceptance and use of technology (UTAUT). Journal of Infrastructure, Policy and Development 2024;8:2594.

42. Geiger S, Aufderlandwehr J, Esser A, Schadendorf T, Muehlbauer T, Skoda EM, Teufel M, Bäuerle A. Determining the acceptance of e-mental health interventions in elite athletes using the unified theory of acceptance and use of technology. Frontiers in Sports and Active Living 2024;6.

43. Liangyong X, Rashid A, Ouyang S. The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. SAGE Open 2024;14.

44. Dörnyei Z. The psychology of the language learner: Individual differences in second language acquisition. Lawrence Erlbaum 2005.

45. Ali I, Anwar F, Roohi S, Nasir Y, Dang Q. A Qualitative Study of the Ideal L2 Self and the Ought to L2 Self: A Case of the Pakistani Students Studying Chinese in Shanghai, PR China. Linguistica Antverpiensia 19:2097-2115.

46. Bagheri Nevisi R, Afsooshin M. Ideal L2 Self, Ought-to L2 Self and EFL Learners' L2 Functional Use 2019.

47. Hui Wen C, Lin C, Azlan A. The Influence of Task-based Language Teaching on Ideal L2 Self and Ought-to L2 Self among Mandarin Learners (Pengaruh Pengajaran Bahasa berasaskan Tugas kepada Ideal L2 Self dan Ought-to L2 Self dalam kalangan Pelajar Bahasa Mandarin). Jurnal Pendidikan Malaysia 2020;45:21-29.

48. Vaswani A, Shazeer N, Parmar N, et al. Attention Is All You Need. Computation and Language 2017.