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Article

Impact of AI-assisted Learning on EFL Vocabulary Acquisition: A Study Based on Technology Acceptance Model

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Abstract: Vocabulary acquisition plays a pivotal role in English as a Foreign Language (EFL) learning. Despite the growing application of artificial intelligence (AI) in this field, empirical research evaluating learners' attitudes and acceptance of using AI-assisted technology in vocabulary acquisition is limited. This paper aims to contribute to bridging the gap by examining the impact of AI on vocabulary acquisition and assessing EFL learners' attitudes towards its use. Employing a quantitative research approach, this empirical study adapts a modified questionnaire from the theory of Technology Acceptance Model (TAM) and utilizing structural equation modeling (SEM) for data analysis. The questionnaire assessed those learners' perceptions regarding perceived ease of use (PEU), perceived usefulness (PU), intention to use (IU), and actual use (AU), with data collected from 395 EFL learners. The findings reveal generally positive attitudes towards the use of AI tools and reflect high expectations for its potential benefits in enhancing vocabulary learning experience. The Structural Equation Model (SEM) analysis confirmed the positive relationships, advocating for AI integration into EFL education to enhance vocabulary learning outcomes.

Keywords: AI-assisted technology; EFL education; vocabulary learning; technology acceptance model

1. Introduction

The contemporary domain of language learning has witnessed a transformative shift driven by advancements in artificial intelligence (AI) technology. As technology permeates every aspect of society, it extends into education (Son et al., 2023; Woo & Choi, 2021; Wen, 2022), presenting new possibilities for enhancing learning experiences. Within English as a Foreign Language (EFL) learning, AI-assisted tools have emerged as potent catalysts, revolutionizing traditional pedagogical approaches. Numerous scholars have focused on the advantageous effects of AI-assisted learning technologies on English language acquisition (Pokrivcakova, 2019; Semerikov et al., 2021; Hong, 2023; Liu et al., 2024; Liang & Zhang, 2024; Zhao et al., 2025). Vocabulary learning, a dynamic and crucial aspect of EFL learning, plays a significant role in overall language proficiency (Zimmerman, 1996; Nation, 2001; Schmitt, 2008; Milton & Fitzpatrick, 2014; Clenton & Booth, 2020; Nation, 2022; Teng & Zhang, 2024). AI tools are increasingly recognized as valuable resources for enhancing vocabulary acquisition (Nation, 2022; Betal, 2023). One major obstacle students encounter is acquiring vocabulary, due to limited classroom time and insufficient exposure to the second language outside of the classroom (Hao et al., 2021). Consequently, vocabulary learning often falls short of expectations for EFL learners (Du, 2004; Gibson, 2016). Traditional methods, such as rote memorization, often lack engagement and fail to provide effective learning experiences (Mediha & Mede, 2014; Zai, 2023).

Recent research has concentrated on various aspects of vocabulary learning, including the impact of multimedia input (Mohsen & Balakumar, 2011; Türk & Erçetin, 2012; Kennedy et al., 2013; Teng, 2022), the use of mobile devices (Stockwell, 2007, 2010; Lu, 2008; Basoglu & Akdemir, 2010; Mahdi, 2017), and the effectiveness of learning through games (Abrams & Walsh, 2014; Behl et al., 2022; Waluyo & Bucol, 2021; Panmei & Waluyo, 2022). While these strands of research collectively suggest that technology can enrich vocabulary learning, they mainly focus on earlier forms of digital support and provide limited insight into how recent AI systems, especially generative AI, may reshape vocabulary development through adaptive, dialogic, and personalized interaction. According to De Freitas et al. (2022), deep learning and machine learning are subfields of AI. Kim and Gofman (2018) noted that deep learning includes understanding of vision and human language, along with large datasets analysis. Recent advancements in Large Language Models (LLMs) have shown their proficiency in natural language processing (Naveed et al., 2025). LLMs have revolutionized language interpretation and generation within digital language processing (Bharathi Mohan et al., 2024). Since their emergence at the end of 2022, generative AI like ChatGPT have become increasingly visible in second language learning, facilitating language acquisition through non-traditional means (Liu et al., 2024). These models leverage deep learning and natural language processing to provide contextually relevant and pedagogically sound interactions. For EFL learners, large language models (LLMs) like ChatGPT offer language practice and feedback, as well as adaptive learning environments that personalize vocabulary instruction (Son et al., 2023). LLMs use natural language processing to understand and generate languages, providing student-centered learning experiences (Alsadoon, 2021; Belda-Medina & Calvo-Ferrer, 2022). The definition of LLMs is advanced AI systems, such as chatbots like ChatGPT and DeepSeek, which are transformer-based with billions of parameters, pre-trained on vast text data, enabling them to understand and generate human-like language for tasks like vocabulary learning, with capabilities including in-context learning and instruction following (Das et al., 2025; Naveed et al., 2025).

Meanwhile, the current literature remains uneven. Recent reviews show that research on ChatGPT and LLMs in language learning has expanded rapidly, yet much of it still concentrates on writing, general learner perceptions, and broad pedagogical affordances, whereas vocabulary-focused investigations and rigorous quantitative evaluations remain comparatively limited (Lo et al., 2024; Yang & Li, 2024). In addition, although emerging studies suggest that LLM-based chatbots can significantly improve both receptive and productive vocabulary knowledge and even support delayed retention, such evidence is still relatively scarce in EFL-specific vocabulary contexts and has not been sufficiently connected to learners' acceptance of these tools (Zhang & Huang, 2024). This is an important omission because the educational value of AI does not depend only on technical affordances, but also on whether learners perceive such tools as useful, manageable, and worth integrating into their actual study routines. Recent studies grounded in technology acceptance perspectives further suggest that learners' sustained use of ChatGPT is shaped by factors such as perceived usefulness, perceived ease of use, trust, enjoyment, and anxiety (Tram et al., 2024; Liu et al., 2024). However, existing research has rarely brought these two lines of inquiry, namely the effectiveness of AI-assisted vocabulary learning and learners' acceptance of these tools, together within a single coherent analytical framework. AI-based learning methods support digital competencies and independent learning, allowing access to educational content anytime and anywhere (Arini et al., 2022; Manurung & Supiatman, 2020). Although AI-powered language learning tools have emerged to aid efficient language acquisition, there are still limitations and challenges (Woo & Choi, 2021; Betal, 2023; Zhang & Huang, 2024). In this paper, AI-assisted technology is defined as the broad category of AI-leveraging applications for language learning and our primary focus under AI tools is on LLMs.

After clarifying the working definition and scope of AI, this research aims to advance English vocabulary learning by exploring innovative AI-assisted methods and their efficacy in enhancing vocabulary acquisition among EFL learners. It also examines the acceptance of these tools based on the Technology Acceptance Model, offering insights for educators, learners, and other stakeholders on integrating AI in EFL settings effectively.

2. Literature Review

As AI-supported vocabulary learning is still developing, this section reviews research on technology-supported and AI-assisted EFL learning with a focus on vocabulary acquisition. It first outlines key views of vocabulary knowledge and then examines how AI-related tools have been used to support vocabulary learning. The review does not simply list previous studies. Instead, it considers where findings converge, where they differ, and what these differences imply for the present study. The final part discusses the use of the TAM in AI-assisted

EFL learning and explains why TAM remains useful, while also noting that AI-based learning contexts may involve factors that go beyond the original model.

2.1. Background Knowledge of Vocabulary Learning

Vocabulary acquisition is a central part of foreign language learning and supports learners' listening, speaking, reading, and writing development (Nation, 2001; Gorjian et al., 2011). Nation (2010) points out that knowing a word involves a wide range of features. In vocabulary research, word knowledge is often discussed in terms of receptive and productive dimensions (Webb, 2005; Nation, 2010). Receptive knowledge helps learners understand words in reading and listening, while productive knowledge enables them to use words in speaking and writing (Crow, 1986; Nation, 2010; Lei & Reynolds, 2022). Nation (2010) further explains that word knowledge includes form, meaning, and use. Table 1 presents this framework and shows that vocabulary learning involves more than the ability to match words with meanings.

Table 1. Nation's (2010) Vocabulary Knowledge Framework.

Knowledge Domain	Core Component	Receptive Knowledge (Listening/Reading)	Productive Knowledge (Speaking/Writing)
Form	Speaking	What does the word sound like?	How is the word pronounced?
	Writing	What does the word look like?	How is the word written and spelled?
	Word Parts	What parts are recognizable in this word?	What word parts are needed to express the meaning?
Meaning	Referents	What does the word refer to?	What word can refer to this?
	Fundamental Concept	What does the word mean?	What word can express this meaning?
	Associations	What other words do this make us think of?	What other words could we use instead of this one?
Use	Functions of Grammar	In what pattern does the word occur?	In what pattern must we use this word?
	Collocations	What words or types of words occur with this one?	What words or types of words must we use with this one?
	Constraints on Use	Where, when, and how often would we expect to meet this word?	Where and when can we use this word?

This broad view of vocabulary learning is important because effective vocabulary development requires more than memorization. Learners need to know pronunciation, spelling, usage, and the ways words function in different contexts (Schmitt, 2008; Nation, 2022; Gibson, 2016). For this reason, vocabulary learning has long been seen as one of the most difficult parts of EFL learning. Traditional methods often rely on word lists, repetition, and isolated practice. Such methods can help short-term recall, but they do not always support deeper word knowledge or sustained engagement. By contrast, technology-supported learning has been found to offer richer input, more flexible access, and more opportunities for repeated exposure and practice (Abraham, 2008; Chen et al., 2016; Mahdi, 2017; Hao et al., 2021). This shift in focus has opened the way for recent work on AI-assisted vocabulary learning.

2.2. The Application of AI in EFL Vocabulary Learning

AI has received growing attention in language learning research in recent years (Lin & Lin, 2019; Hao et al., 2021; Jeon, 2021; Liu & Chen, 2023; Alsadoon, 2021; Yunjiu et al., 2022; Liang & Zhang, 2024; Wen et al., 2024; Yang, 2025). In broad terms, this development is tied to the wider expansion of interactive digital technologies in language education (Eslami & Ahmadi, 2019; Burston, 2014). It has also strengthened related areas such as CALL and TELL, which provide much of the pedagogical background for current AI-supported learning research (Liu & Chen, 2023). Existing studies have examined a wide range of tools, including generative AI in vocabulary assessment and testing (Jeon, 2021; Yunjiu et al., 2022), AI-powered applications and digital games for vocabulary practice (Abraham, 2008; Chen et al., 2016; Panmei & Waluyo, 2022; Polyzi & Moussiades, 2023; Liang & Zhang, 2024), and chatbots or related systems that support vocabulary learning through interaction and feedback (Alsadoon, 2021; Behl et al., 2022; Dağdeler, 2023; Wei, 2023; Khalil et al., 2025). Other work has shown that intelligent tutoring systems and virtual language assistants may also support vocabulary development by providing adaptive feedback, personalized pacing, and multimedia input (VanLehn, 2011; Slavuj et al., 2015; Baker et al., 2020; Şahin Kızıl et al., 2025).

A broad point of agreement in this literature is that technology-supported learning often benefits vocabulary development. Meta-analytic and review studies have reported positive effects for technology-assisted vocabulary learning, especially in retention and learning efficiency (Hao et al., 2021; Lin & Lin, 2019; Bahari et al., 2022). Hao et al. (2021), drawing on 45 studies with 2,374 EFL learners, found that technology-supported approaches tended to outperform traditional methods and that mobile learning environments were especially promising. Lin and Lin (2019) likewise reported a strong positive effect of mobile-assisted interventions on vocabulary learning. Similar findings appear in studies on CALL tools, mobile learning, text messaging, and game-based learning, all of which suggest that technology can support vocabulary comprehension, retention, and engagement (Ma & Kelly, 2006; Lu, 2008; Abrams & Walsh, 2014; Kingsley & Grabner-Hagen, 2017).

These positive findings are not as uniform as they first appear. The studies often group together very different tools and learning conditions. Some focus on drill-based software, some on mobile practice, some on games, and others on chatbot-based interaction. These tools do not work in the same way. In some cases, the likely source of improvement is repeated exposure. In others, it may be motivation, task design, or immediate feedback. As a result, it is difficult to treat technology as a single type of intervention. Even when overall findings are positive, the reported gains may depend on how the tool is designed, how long the treatment lasts, and what kind of learners are involved. Recent review work on AI-supported L2 vocabulary acquisition also notes that the field is growing quickly but remains fragmented and lacks a unified theoretical framework, which makes it harder to compare results across studies or explain why some tools appear more effective than others (Yang, 2025). This challenge becomes clearer in recent work on generative AI and large language model tools. While AI is often discussed as a broad category, the evidence base is uneven. Recent reviews of ChatGPT in second language learning show that the field has expanded rapidly, but much of the literature has focused on writing tasks, general attitudes, and learners' perceptions rather than vocabulary-specific outcomes (Lo et al., 2024; Yang & Li, 2024). These reviews also point out that the methodological patterns of current studies are not yet balanced, with many studies emphasizing short-term classroom use or self-reported benefits rather than more focused evidence on vocabulary learning. By contrast, vocabulary-focused studies remain fewer in number. Some recent work suggests that LLM-based chatbots can improve receptive and productive vocabulary knowledge and may also support delayed retention (Zhang & Huang, 2024). Even so, this line of research is still developing, and it remains unclear whether these gains come from the AI system itself or from the increased interaction, feedback, and attention built into the learning tasks. This means that the research does not simply show that AI works. Rather, it suggests that the effect of AI depends on what kind of tool is used, how it is integrated into learning, and what kind of vocabulary knowledge is being measured.

Another issue concerns the learners who have been studied. Many earlier studies focused on adolescents or university students in structured classroom settings (Ma & Kelly, 2006; Lu, 2008; Abrams & Walsh, 2014; Kingsley & Grabner-Hagen, 2017). This has produced useful findings, but it also narrows the picture. The role of AI-assisted vocabulary learning may be different for learners with different educational backgrounds, different levels of self-regulation, or more self-directed learning habits. Recent work on AI-mediated informal digital learning of English suggests that learners are using AI not only inside formal courses but also in out-of-class settings, where autonomy and personal learning goals play a larger role (Liu et al., 2024). This shift creates a further discrepancy in the literature. On the one hand, AI tools are often presented as effective learning support. On the other hand, the context in which learners use these tools is becoming more varied, which means that findings from teacher-guided classroom studies may not transfer directly to more independent learning settings.

2.3. Integrating TAM with AI-assisted EFL Learning

Since it was proposed, TAM has become one of the most widely used models for explaining technology acceptance in educational settings (Fathema et al., 2015; Chintalapati & Daruri, 2017; Scherer et al., 2019; Liu et al., 2024). In language learning research, it has been used to examine learners' intention to adopt online platforms and digital tools. For example, Alfadda and Mahdi (2021) applied TAM to the use of Zoom in language courses and found that perceived usefulness and perceived ease of use significantly influenced students' intention to use the platform. Chen et al. (2024) extended TAM in the context of AI-assisted L2 learning and showed that AI self-efficacy, anxiety, and attitude also played important roles in actual use. These studies support the view that TAM is still a useful starting point for examining how learners respond to new technologies. According to Davis (1989), TAM explains technology acceptance mainly through perceived usefulness, perceived ease of use, intention to use, and actual use. In simple terms, learners are more likely to adopt a tool when they believe it is helpful and not difficult to use (Davis, 1989; Al-Emran et al., 2018). Schepers and Wetzels (2007) likewise argue that perceived usefulness and perceived ease of use are central in shaping attitude and behavioral intention. This logic is relevant to EFL vocabulary learning. If learners see AI-assisted tools as useful for vocabulary study and easy to operate, they are more likely to accept them and include them in their learning routines (Liu et al., 2024). The main definitions used in the present study are summarized in Table 2.

Table 2. TAM components.

Construct	Definition
Perceived Ease of Use (PEU)	The degree to which a person believes that using a particular system would enhance his or her job performance.
Perceived Usefulness (PU)	People tend to use or not use an application to the extent they believe will help them perform their job better.
Intention to Use (IU)	The degree to which learners are ready to use applications in their vocabulary learning.
Actual Use (AU)	The extent to which learners actually use applications in their L2 vocabulary learning.

However, the use of TAM in AI-assisted learning also reveals a theoretical tension. The original TAM focuses mainly on cognitive judgments about usefulness and ease of use. Yet recent AI-related studies suggest that learners' responses to AI tools may involve a wider set of factors. Chen et al. (2024) found that self-efficacy and anxiety matter in learners' actual use of AI for L2 learning. Liu et al. (2024) also show that AI adoption in informal English learning is connected to learners' attitudes, experiences, and practices beyond the classroom. In other words, TAM remains helpful, but AI-based language learning may be more complex than earlier forms of educational technology. This is especially true when the tools are conversational, open-ended, and used in flexible learning contexts rather than within fixed classroom platforms.

A second limitation in the current literature is that studies of TAM and AI-assisted language learning have rarely focused on vocabulary learning. Existing research has examined general English learning, online course platforms, or broad AI tool use, but there is still limited work that connects learner acceptance with vocabulary-specific learning experience and outcomes. The vocabulary literature has tended to emphasize whether technology improves performance, while acceptance studies have focused more on intention and attitude. As a result, the relationship between these two dimensions remains underexplored. This gap provides the rationale for the present study.

To fill this niche, the present study adopts TAM as its theoretical basis to examine EFL learners' perceptions and acceptance of AI-assisted vocabulary learning. It also investigates whether learners see AI-assisted tools as helpful for vocabulary learning and whether such tools have a positive influence on vocabulary use. Specifically, this study is guided by the following two research questions:

(1) Do EFL learners perceive AI-assisted technologies as helpful in their vocabulary learning process?
(2) Does the use of AI-assisted technologies have a positive impact on L2 learners' productivity in vocabulary use?

3. Methods

3.1. Research Context

Situated in the Chinese EFL context, this study employed a quantitative approach to examine the relationships among key variables related to AI-assisted vocabulary learning. Recent research shows that Chinese EFL learners have started to use AI tools and large language model platforms in both classroom-related and self-directed English learning contexts (Liu et al., 2024; Chen et al., 2024). The study is grounded in the Technology Acceptance Model developed by Davis (1989), which provides the theoretical basis for explaining learners' acceptance and use of AI-assisted technology. Data was gathered through an online survey adapted from a TAM-based questionnaire.

According to Davis (1989), PU and PEU enhance attitudes toward technology, determining the IU and AU of technology. Figure 1 presents the structural diagram based on TAM and our research inquiry.

The diagram encompasses the subsequent hypotheses:

H1: *PEU positively predicts PU.*

H2: *PU positively predicts IU.*

H3: *PEU positively predicts IU.*

H4: *IU positively predicts* AU.

According to Davis (1989), the TAM model can be drawn in Figure 1 as follows:

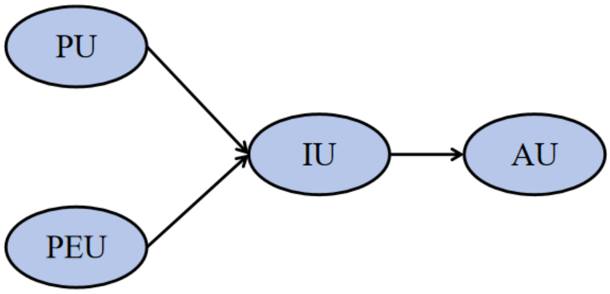

Figure 1. TAM Model.

3.2. Participants

The research with 395 participants, detailed in Table 3, encompasses a broad range of ages, educational backgrounds, and English proficiency levels, etc. This sample allows for a robust analysis of how different groups perceive and benefit from AI-assisted vocabulary learning tools. The participant data underscores the study's relevance across varying educational contexts. One demographic item in the questionnaire combined current occupation and highest level of education into a single categorical response. This design limited the interpretability of the variable as a standard demographic indicator. Accordingly, the item was retained only for descriptive purposes and was not treated as a substantive explanatory variable in the main analyses.

Table 3. Basic Information of Participants.

Basic Information	Choices	Frequency	Proportion (%)
Gender	Male	108	27.3
	Female	287	72.7
Age	<18	18	4.6
	18–30	326	82.5
	30–40	42	10.6
	>40	9	2.3
Self-reported current status	High school	19	4.8
	Bachelor's degree	198	50.1
	Master's degree	46	11.6
	Doctoral degree	13	3.3
	Employed	75	19.0
	Others	44	11.1
English proficiency	Beginning	72	18.2
	Intermediate	193	48.9
	Advanced	75	19.0
	Fluent	51	12.9
	Native	4	1.0
Learning duration	<6 years	38	9.6
	7–9 years	143	36.2
	>10 years	214	54.2
Total		395	100

3.3. Data Collection

To ensure the reliability and validity of the numerical results, this study developed a survey questionnaire based on Davis's Technology Acceptance Model (TAM) as shown in Figure 1. We further revised the questionnaire by incorporating changes based on the survey metrics from Liu et al.'s (2024) article. Finally, the survey was modified and supplemented based on the fundamental aspects of EFL English vocabulary learning. The questionnaire was designed by using a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). After the initial version was designed, a pilot test was conducted and approximately 35 participants were recruited via an online platform, which led to further revisions based on their feedback. The aim of this process is to assess the feasibility and effectiveness of the questionnaire for subsequent implementation. The final version of the questionnaire comprised two parts. The first section gathered demographic data, including gender, age, educational background, employment status, self-assessment of English proficiency, and duration of English study. The second one was four TAM sub-scales from Davis (1989), consisting of PEU, PU, IU, and AU. Ultimately, 18 items were generated for the TAM scale (see Appendix A). Data collection was conducted utilizing both online and offline methods. Online data were gathered through Wenjuanxing, a professional online survey platform based in China, while offline data collection involved the random selection from university students, facilitated by the scanning of QR codes and direct recruitment on university campuses. Online participants were randomly chosen from various Chinese social media platforms and forums, such as Douban, Xiaohongshu, Weibo, QQ groups, and Baidu post bars. Both online and offline participants received an informed consent form before starting the survey to ensure they understood the investigation's purpose, procedures and confidentiality. Ethical considerations were rigorously maintained to ensure the anonymity and privacy of the participants throughout the survey process.

3.4. Data Analysis

The Structural Equation Modeling (SEM) approach was employed for quantitative analysis to achieve our research objectives, conducted by SPSS 29 and AMOS 29. SEM was chosen for its ability to investigate complex relationships between variables and reveal the direct and indirect effects of AI on English vocabulary acquisition, based on the TAM. This approach provides substantial insights into learners' attitudes toward AI-assisted vocabulary learning.

Before the main analysis, the raw questionnaire data were screened to improve data quality. A total of 631 responses were initially collected. Responses with an excessively short completion time were removed, as such cases may indicate insufficient engagement with the questionnaire (DeSimone & Harms, 2017). In addition, responses showing the same option across all items were excluded because they suggested non-differentiated answering patterns (Chauliac et al., 2023). After this screening process, 395 valid responses were retained for the final analysis. This screening procedure was intended to reduce the influence of careless or low-quality responses in the dataset. Reporting these pre-processing steps is also consistent with current expectations for transparency in quantitative research reporting. After data screening, descriptive statistics were calculated for the main variables, including means and standard deviations. The measurement model was then evaluated by examining standardized factor loadings, Cronbach's alpha, composite reliability, and average variance extracted. Finally, the structural model was tested in AMOS 29 to examine the hypothesized relationships among the TAM constructs and to assess the role of AI-assisted learning in EFL vocabulary acquisition.

4. Results

4.1. Descriptive Analysis

Table 4 provides descriptive statistical analyses for four constructs: PU, PEU, IU, and AU. The analysis presents the mean (M) score of the 18 items, ranging from 3.66 to 3.99, with standard deviations (SD) ranging from 0.94 to 1.18. The *M* value of all items exceeded 3.50, indicating that participants held highly positive attitudes towards the ease of use and usefulness of AI technologies in their daily English vocabulary learning.

Table 4. Descriptive analysis.

Constructs	Items	M	SD	Std. Estimate
PU	Q7	3.77	0.981	0.962
	Q8	3.76	1.026	1.052
	Q9	3.86	1.063	1.129
	Q10	3.83	0.968	0.937
	Q11	3.78	0.983	0.966
PEU	Q12	3.72	0.985	0.969
	Q13	3.66	0.958	0.919
	Q14	3.90	1.08	1.166
	Q15	3.85	0.951	0.905
	Q16	3.82	0.977	0.954
	Q17	3.83	0.94	0.883
IU	Q18	3.89	1.021	1.043
	Q19	3.99	0.998	0.996
	Q20	3.99	0.959	0.92
	Q21	3.83	0.975	0.952
AU	Q22	3.81	0.997	0.994
	Q23	3.80	0.987	0.973
	Q24	3.81	1.18	1.393

PU (Q7–Q11) shows mean satisfaction scores (M) between 3.76 and 3.86, with low dispersion (SDs 0.968–1.063) and high consistency (Std. Estimate 0.937–1.129). PEU (Q12–Q17) reports mean ease-of-use scores from 3.66 to 3.90, with minimal variability (SDs 0.94–1.08) and moderate consistency (Std. Estimate 0.883–1.166). IU (Q18–Q21) suggests strong usage intention, with means from 3.83 to 3.99, low variability (SDs 0.959–1.021), and high agreement (Std. Estimate 0.92–1.043). AU (Q22–Q24) indicates frequent use with means of 3.80 to 3.81, higher dispersion (SDs 0.987–1.18), and lower consistency (Std. Estimate 0.973–1.393).

4.2. Reliability and Validity checks

The predominant aspects were measured in scale forms throughout this research, testing the data quality of the measurements is an important prerequisite to ensure that the subsequent analyses are meaningful. The internal consistency of these constructs was first examined through Cronbach's Alpha reliability test. If the value of Cronbach's Alpha is 0.70–0.79, then it is acceptable. If the value is between 0.80–0.89, it is good. If the value is above 0.90–1.0, it means excellent. In this study, according to Table 5, the Cronbach's ɑ values of the four TAM latent variables were 0.869 (PU), 0.883 (PEU), 0.889 (IU), 0.775 (AU), and 0.952 (Total) respectively, varying from 0.7 to 1.0, which reflects that all the constructs in the research maintain valid internal consistency.

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Table 5. Reliability.

Constructs	Cronbach's Alpha	Item Number
PU	0.869	5
PEU	0.883	6
IU	0.889	4
AU	0.775	3
Total	0.952	18

Regarding the validity test, we first computed the standardized factor loading of each item, the values of CR and the average variance extracted (AVE) in each variable to check convergent validity. The CFA measurement model was estimated to examine the relationships between the observed questionnaire items and their corresponding latent constructs. Figure 2 illustrates the final CFA measurement model after item evaluation and deletion. According to Table 6, the CFA model showed good fit, with χ^2/df = 2.218 (<3, good), RMSEA = 0.056 (<0.06, good; Hu & Bentler, 1999), GFI = 0.942 (>0.90, good), CFI = 0.975 (>0.95, excellent), TLI = 0.968 (>0.95, excellent), indicating good to excellent fit. During CFA, both items by factor loadings and model fit are evaluated. Q7, an instructional statement, was excluded because it served as a guide for participants and did not measure any construct. This aligns with CFA practice because the measurement model specifies the relationships between latent constructs and their observed indicators; therefore, only measurement items were included in the CFA model (Rosseel, 2012). Items with loadings below 0.4, like Q12 and Q13 (loadings around 0.126 and 0.30), were considered for removal. High modification indices (Q12 with Q6, MI = 29.433; Q13 with another, MI = 75.998) suggested shared variance, so Q12 and Q13 were deleted to avoid unsupported error correlations. Removing Q12 and Q 13 improved model fit, as evidenced by the final fit indices (CMIN/DF = 2.177, etc.), consistent with CFA practices where items with low loadings and high MIs are removed to enhance parsimony (Prudon, 2015). Thus, synthesizing the outcomes from this analysis can indicate that there is substantial fitting accuracy in CFA model of this scale.

Table 6. CFA Goodness Fit Indices.

Indices	Model Fit Value	Reference Guideline	Interpretation
CMIN/DF	2.218	<3.00 indicates acceptable fit	Acceptable
GFI	0.942	≥0.90 indicates acceptable fit	Acceptable
AGFI	0.915	≥0.90 indicates acceptable fit	Acceptable
CFI	0.975	≥0.95 indicates good fit	Good
TLI(NMFI)	0.968	≥0.95 indicates good fit	Good
RMSEA	0.056	≤0.06 indicates good fit	Good

Notes: Fit thresholds are reported as commonly used reference guidelines rather than absolute decision rules.

Convergent validity (AVE) and composite reliability (CR) of each dimension will be further examined under the premise that the CFA model of this scale has a good fit. The test procedure calculates the standardized factor loading of each measurement question item on the corresponding dimensions through the established CFA model. Then, the AVE and CR of each dimension were calculated by the formula of AVE and CR. According to the threshold of the value, the minimum AVE value is required to be above 0.5, and the minimum CR value is required to reach 0.7 in order to indicate a good convergent validity and composite reliability.

The analysis results (shown in Table 7) apparently offer that in this validity test of AI assisted questionnaire, the AVE value of each dimension reached more than 0.5 and the CR value reached above 0.7, which can indicate comprehensively that each dimension has good convergent validity and composite reliability.

Table 7. Convergent Validity (AVE) and Composite Reliability (CR).

Factor loading	Estimate	AVE	CR
Q11 ← PU	0.81	0.584	0.849
Q10 ← PU	0.81		
Q9 ← PU	0.70		
Q8 ← PU	0.72		
Q17 ← PEU	0.76	0.601	0.857
Q16 ← PEU	0.79		
Q15 ← PEU	0.83		
Q14 ← PEU	0.72		
Q21 ← IU	0.75	0.668	0.889
Q20 ← IU	0.83		
Q19 ← IU	0.83		
Q18 ← IU	0.86		
Q24 ← AU	0.59	0.574	0.798
Q23 ← AU	0.82		
Q22 ← AU	0.84		

4.3. Discriminant Validity

Fornell and Larcker (1981) mentioned, if the results of the majority of factors are lower than the standards, a slightly higher individual factors can be accepted. The figures in Table 8 clearly illustrate that within this text concerning discriminant validity, the square roots of the AVE values for the dimensions are usually higher than most of the standardized correlation coefficients between them, thus indicating that there is a good discriminant validity between all the dimensions.

Table 8. Discriminant Validity.

	PU	PEU	IU	AU
PU	0.76			
PEU	0.786 **	0.78		
IU	0.729 **	0.800 **	0.82	
AU	0.643 **	0.700 **	0.771 **	0.76

** Correlation is significant at the 0.01 level (2-tailed).

4.4. SEM Model

Having established convergent validity and discriminant validity, as reported in Tables 7 and 8, the structural equation model was further evaluated. According to the results of model fit test in Table 9, CMIN/DF = 2.177 is under the range of 3 to 5; RMSEA = 0.055, which is in the excellent range of below 0.08. In addition, the results of the tests of IFI, CFI, and TLI have reached an excellent level of 0.9 or more. Therefore, synthesizing the results of this analysis can indicate that the SEM model of this scale has good fit.

Table 9. SEM Model Fit.

	Model Fit Value	Reference Guideline	Interpretation
CMIN/DF	2.177	<3.00 indicates acceptable fit	Acceptable
IFI	0.975	≥0.95 indicates good fit	Good
CFI	0.975	≥0.95 indicates good fit	Good
TLI(NMFI)	0.969	≥0.95 indicates good fit	Good
RMSEA	0.055	≤0.06 indicates good fit	Good

4.5. Hypothesis Test Results

Table 10 shows four supported hypotheses. β represents the strength of the relationship, S.E. measures the precision of the estimate, t-value assesses significance, $p < 0.05$ indicates significance (with *** for $p < 0.001$), and R^2 shows the proportion of variance explained by the model. PEU positively influences PU and vice versa (β = 0.886, $p < 0.001$, *t*-value = 10.165), and significantly predicts IU (β = 0.843, $p < 0.001$, *t*-value = 7.641). PU does not predict IU (β = 0.088, $p = 0.368$, *t*-value = 0.9). IU significantly affects AU (β = 0.906, $p < 0.001$, *t*-value = 10.946). R^2 scores indicate PEU and PU explain 85% of IU's variance, and 82% of the change in AU.

Table 10. Hypothesis Test Results.

Path	β	S.E.	*t*-Value	P	R^2
IU ← PEU	0.843	0.112	7.641	***	0.85
IU ← PU	0.088	0.091	0.9	0.368	
AU ← IU	0.906	0.079	10.946	***	0.82
PEU ↔ PU	0.886	0.049	10.165	***	

Note: β = standardized path coefficient; S.E. = standard error of β; t-value = β/S.E.; P = *p*-value, with *** indicating $p < 0.001$; R^2 = coefficient of determination for the endogenous variable.

In the classic TAM, three key factors, PU, PEU, and IU, shape users' intentions to use AI technology. PU involves beliefs about the technology's performance enhancement, while PEU relates to the effortlessness of its use, and attitudes reflect overall evaluations of the technology. According to TAM, PU and PEU influence attitudes, which in turn shape usage intentions and lead to actual use (Davis, 1989; Schepers & Wetzels, 2007). In this study, PEU and PU are interrelated (as shown in Figure 3). Significant correlations are found between PEU and IU, and between IU and AU, supporting the model's assumptions. However, PU does not significantly influence IU, indicating that convenience, rather than usefulness, drives willingness to use the technology.

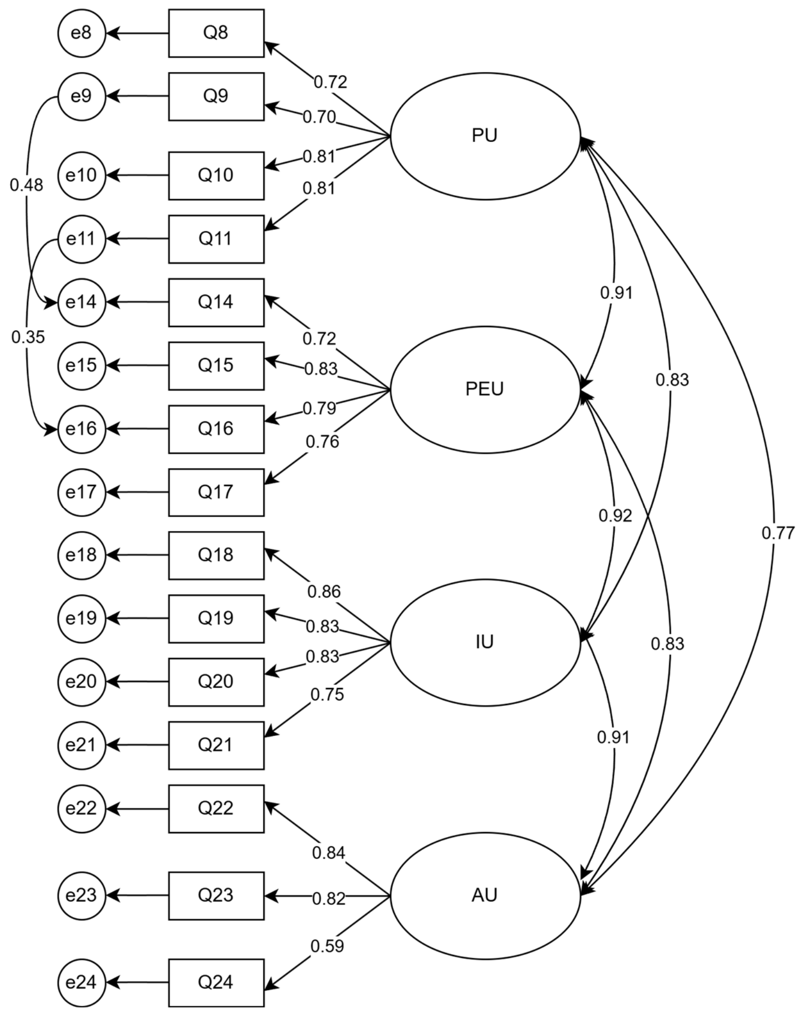

Figure 2. CFA Model.

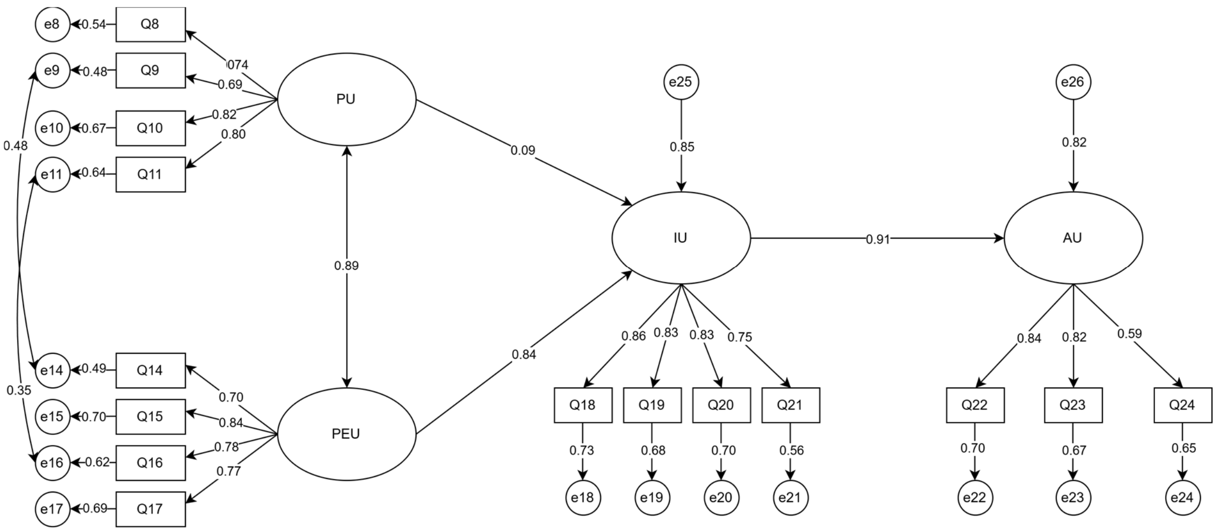

Figure 3. SEM with Path Coefficients.

5. Discussion

In this study, by confirming four hypotheses, a conceptual model that can explain significant changes in the actual usage (R^2 = 82%) of AI technologies is statistically constructed and validated. According to prior TAM literature (Davis, 1989; Liu et al., 2024), PEU has been identified as significant predictor of PU in quantitative analysis and PEU does not directly predict IU. However, in this study, the quantitative results demonstrated that PU and PEU correlated with each other, and PU does not directly predict IU; PEU does have significant effects on IU. Moreover, the strong and positive impact of IU on AU (β = 0.906 ***, R^2 = 0.82) confirms that the utilization of AI technologies in English vocabulary learning is contingent on L2 learners' willingness and intention to employ the technologies for vocabulary learning. The semi-open question demonstrated in complementary ways that L2 learners in this study prefer to use those AI technologies which are easy to use. Most of the respondents chose to use vocabulary APPs to learn English vocabulary instead of choosing large language models (such as ChatGPT or NewBing, etc.), which may be due to the fact that most of the students in mainland China would believe vocabulary APPs would be simpler to use, and think that LLMs would be more difficult to use or harder to reach.

The previous data indicate that respondents generally hold positive attitudes towards the usefulness, ease of use, and intention to use AI in English vocabulary learning, with a high frequency of actual use. Although some items show variation in standard deviation and standard estimates, overall, the data is relatively consistent, indicating a unified perception among respondents regarding these technologies. These results strongly support the application of AI in English vocabulary acquisition. In the descriptive analysis, Q14 and Q24 are particularly noteworthy due to their large standard deviations, indicating significant divergence in respondents' views on these items. Q14 has a high mean, suggesting that respondents generally find using AI tools for learning word formation easy. However, the high standard deviation indicates substantial variation, possibly due to differences in technological proficiency, prior experience with AI tools, or individual learning preferences (Fitas, 2025). Q24 shows the largest standard deviation, indicating considerable variation in the frequency of using AI to look up words. While the high mean suggests frequent use by many, the variation implies some use it infrequently or not at all, potentially due to varying needs for word lookup, preferences for traditional methods, or limited access to technology. To gain the deeper understanding of these factors, future studies could integrate qualitative methods, such as interviews or focus groups, to explore the underlying reasons for these differences.

This research puts forward various implications for language educators and other individuals involved. Firstly, it highlights the educational potential of AI and encourages curriculum designers and policymakers to recognize their value in promoting creative engagement with these technologies for EFL learners. The learners who lack of the ability or access to these large language model will use those vocabulary APPs because they are easy to use. Through envisioning new approaches to language teaching that incorporate these AI technologies, teachers can empower students to cultivate independent methods of learning. Furthermore, the powerful link between intention and actual use highlights the importance of fostering that initial willingness. Since PEU is the primary driver of IU in our study, pedagogical strategies should concentrate on creating positive initial experiences with AI tools. This could involve selecting a few user-friendly tools rather than overwhelming students with many options, ensuring adequate technical support, and integrating tools into activities that are perceived as low-stakes and enjoyable. By focusing on maximizing PEU to build IU, educators can significantly increase the likelihood of sustained actual use of these technologies for vocabulary learning.

In terms of the last semi-open question in the survey, the majority of participants reported using vocabulary apps when they learn new vocabulary, as shown in Figure 4. Actually in some regions where access to international AI-chatbot tools is restricted (such as China), vocabulary apps can utilize domestic technologies to ensure accessibility (Jiang, 2024). Besides, vocabulary apps are designed with user-friendly interfaces that require minimal digital literacy, making them suitable and convenient for a broader range of learners, including those who may not be as tech-savvy. In contrast, using general LLM tools often necessitates a higher level of digital literacy, such as the ability to craft effective prompts and interpret complex responses, which can be challenging for some learners (Yuen & Schlote, 2024). Most vocabulary apps are engaging and convenient, supporting their suitability for EFL learners (Divekar et al., 2021; Pikhart, 2021).

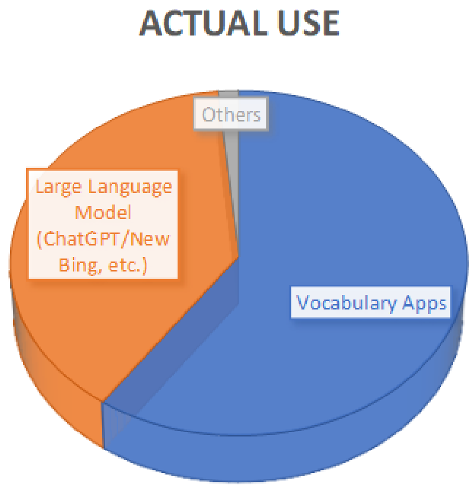

Figure 4. Actual Use of Participants.

Therefore, while TAM provides a robust framework, our findings emphasize the pronounced importance of PEU in the context of AI-assisted vocabulary learning for EFL students. It appears that for these learners, the immediate convenience and navigability of a technology can be more decisive in shaping their intention to use it than its perceived utility alone, a factor that has significant repercussions for both the design of educational AI tools and their pedagogical implementation in language classrooms. For more targeted educational recommendations, educators could leverage AI to design engaging vocabulary games, such as personalized quizzes or interactive story-based scenarios. Another impactful approach is guiding learners to use or even co-develop customized vocabulary chatbots offering features like spaced repetition and contextual examples for effective word memorization and application. These specific integrations can translate AI's potential into tangible pedagogical strategies.

6. Conclusions

In conclusion, these results contribute to the existing literature by applying TAM to the relatively under-explored domain of AI-assisted language learning. Our findings indicate that PEU significantly influences learners' intention to use these tools, whereas PU does not have a direct significant effect. Specifically, this research extends TAM by demonstrating that in the context of educational technology for vocabulary learning, perceived ease of use may be a more critical determinant of technology adoption than perceived usefulness. Consequently, developers should prioritize creating intuitive and accessible interfaces that cater to users with varying levels of technological expertise. For educators, the results underscore the importance of selecting and recommending AI tools that are not only feature-rich but also user-friendly, thereby facilitating greater student engagement and learning outcomes.

Several limitations should be acknowledged in this study. First, the study relies on self-reported data, which may be subject to response bias. Second, the sample is limited to EFL learners in China, which may affect the generalizability of the findings. Third, the study design is cross-sectional, which limits our ability to draw causal inferences, meaning it is not concluded that the use of AI assisted technology directly causes improved vocabulary retention or efficiency. While the study identifies associations, such as higher perceived efficiency among frequent AI users, these are correlational and may be influenced by other factors, for example learning motivation or prior proficiency, not captured in this design. This limitation suggests that future research should employ longitudinal or experimental designs to explore the causal impact of AI chatbots on actual vocabulary retention and learning outcomes, incorporating objective assessments to validate learners' perceptions and enhance the robustness of findings. Future research directions can focus more on the learning outcomes of students using AI technology in long-term language acquisition. Finally, the use of a survey questionnaire may not capture the full complexity of participants' experiences with AI-assisted learning tools. Despite these limitations, it is hoped that this research will provide valuable insights into the impact of AI-assisted learning on EFL vocabulary acquisition and contribute to the existing literature in the field of language education.

Author Contributions

Y.S.: conceptualization, methodology, writing—original draft preparation; J.L.: formal analysis, writing—review and editing; N.S.: data curation, investigation, supervision. All authors have read and agreed to the published version of the manuscript. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Faculty of Humanities and Social Sciences of City University of Macau (protocol code FHSS250228).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study. Online informed consent has been obtained from the participants to publish this paper and by proceeding to complete the survey, participants indicate their informed consent to take part in this study.

Data Availability Statement

Raw data is available from the authors upon reasonable request.

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Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT-4 to assist with the Chinese-to-English translation of questionnaire items Q7–Q24. After using this tool, the authors reviewed and edited the translated content as needed, checked the semantic equivalence and appropriateness of the translated questionnaire items, and take full responsibility for the content of the published article.

Appendix A

AI-Assisted Learning Questionnaire (Bilingual)

Survey Consent Statement:

We are doctoral students in Applied Linguistics conducting research on AI-assisted technology and English vocabulary learning. We sincerely invite you to participate in our survey on AI-assisted technologies. AI-assisted technology refers to the use of artificial intelligence algorithms and technologies in online learning platforms and applications to provide users with personalized, intelligent learning support and services, such as ChatGPT, Newbing, online dictionary apps, and photo translation services. Your participation is very important to our research. We solemnly promise that your responses will be kept strictly confidential, used only for this study, and not disclosed to any third parties. If you have any questions about AI-assisted technology or this survey, please contact and confirm with us before proceeding with the questionnaire. Please feel free to fill out the survey, and thank you for your cooperation!

调查问卷声明:

我们是应用语言学的博士生，正在进行一项关于 AI 辅助技术和英语词汇学习的研究。我们诚挚地邀请您参加我们关于 AI 辅助技术的调查问卷。AI 辅助技术是指利用人工智能算法和技术，在线学习平台和应用程序中为用户提供个性化、智能化的学习支持和服务的技术，如: Chatgpt, Newbing, 在线词典 app, 拍照翻译等。您的参与对于我们的研究十分重要。我们郑重承诺，您的回答将被严格保密，仅用于本研究，并不会泄露给任何第三方。如果您对 AI-assisted technology 以及本问卷的项目仍有疑问，请在继续填写问卷之前先与我们联系和确认。请您放心填写，谢谢您的配合!

Q1. Are you willing to give informed consent and attend this online questionnaire? (If you select “No”, you will not need to access the items below.)

- ○ Yes
- ○ No

Q2. Gender

- ○ Male
- ○ Female

Q3. Your age

- ○ <18
- ○ 18–30
- ○ 30–40
- ○ > 40

Q4. Please select your current educational or occupational status.

- ○ High school or equivalent
- ○ Undergraduate student
- ○ Master’s student
- ○ Doctoral student
- ○ Employed
- ○ Other

Q5. How would you rate your English proficiency?

- ○ 1 (Beginner)
- ○ 2 (Intermediate)
- ○ 3 (Advanced)
- ○ 4 (Fluent)
- ○ 5 (Native)

Q6. How long have you been studying English?

- ○ Less than 6 years
- ○ 7–9 years
- ○ More than 10 years

Q7. Please choose the appropriate option based on the statements below. Use the following scale to select your response: 5—Strongly Agree, 4—Agree, 3—Neither Agree nor Disagree, 2—Disagree, 1—Strongly Disagree.

Chinese Version	**English Versions**
AI辅助技术能够帮助我更快地记忆单词的词义和拼写 (Q7)	AI-assisted technology can help me memorize word meanings and spellings more quickly.
我认为使用AI辅助技术可以有效提升我的词汇构词 (如前缀、后缀、派生等) 能力 (Q8)	I believe that using AI-assisted technology can effectively enhance my ability to understand word formation, such as prefixes, suffixes, and derivations.
AI辅助技术对提高我的单词发音非常有帮助 (Q9)	AI-assisted technology is very helpful in improving my word pronunciation.

AI辅助技术能够更有效地提高我的词汇搭配和造句能力（Q10）	AI-assisted technology can more effectively enhance my vocabulary collocations and sentence construction skills.
使用AI辅助技术能够更有效地帮助我识记近义词和反义词（Q11）	Using AI-assisted technology can help me more effectively remember synonyms and antonyms.
使用AI辅助技术来学习词汇的拼写和意义非常容易（Q12）	Using AI-assisted technology to learn the spelling and meaning of vocabulary is very easy.
用AI辅助技术来学习词汇构词的过程对我来说很简单（Q13）	Using AI-assisted technology to learn word formation is very simple for me.
我觉得用AI辅助技术来练习单词发音很方便（Q14）	I find it very convenient to practice word pronunciation using AI-assisted technology.
我觉得使用AI辅助技术来学习词汇的用法（搭配和造句）非常方便（Q15）	I find it very convenient to learn vocabulary usage (collocations and sentence construction) using AI-assisted technology.
用AI辅助技术学习近义词和反义词对我来说很方便（Q16）	Learning synonyms and antonyms with AI-assisted technology is very convenient for me.
我觉得AI辅助技术提供的内容很容易理解（Q17）	I find the content provided by AI-assisted technology easy to understand.
我有意愿在将来继续使用AI辅助技术来学习词汇（Q18）	I am willing to continue using AI-assisted technology to learn vocabulary in the future.
如果有机会，我愿意尝试更多的AI辅助技术来扩展我的词汇量（Q19）	Given the opportunity, I would like to explore more AI-assisted technologies to expand my vocabulary.
我对在未来的词汇学习中使用AI辅助技术持积极态度（Q20）	I have a positive attitude towards using AI-assisted technology for vocabulary learning in the future.
我愿意花时间和精力来更好地学习使用AI辅助技术（Q21）	I am willing to invest time and effort to better learn how to use AI-assisted technology.
AI辅助技术对我在词汇学习中的自信心有所提升（Q22）	AI-assisted technology has boosted my confidence in vocabulary learning.
AI辅助技术对我在词汇学习中的学习兴趣有所增加（Q23）	AI-assisted technology has increased my interest in vocabulary learning.
我经常使用AI辅助技术来查单词（Q24）	I frequently use AI-assisted technology to look up words.

Note: Q1–Q6 and Q25 were originally developed and administered in English. Q7 includes an English response instruction and a bilingual item statement. The item statements from Q7 to Q24 were translated from Chinese into English and are therefore presented in both Chinese and English.

Q25 Which AI-assisted technologies have you used? Please select the types of tools you have used (multiple choices are allowed):
- ○ Vocabulary learning apps
- ○ Large language models (e.g., ChatGPT/New Bing)
- ○ Others (please specify)

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