education sciences

MDPI

Article

Beyond the Books: Exploring Factors Shaping Chinese English Learners' Engagement with Large Language Models for Vocabulary Learning

Xiaochen Wang [1] and Barry Lee Reynolds [2,3,*]

[1] School of Foreign Studies, Xi'an Jiaotong University, Xi'an 710049, China; wangxiaochen666666@outlook.com
[2] Faculty of Education, University of Macau, Room 1014, E33, Av. da Universidade, Taipa, Macau SAR, China
[3] Centre for Cognitive and Brain Sciences, University of Macau, Taipa, Macau SAR, China
* Correspondence: barryreynolds@um.edu.mo

Abstract: Informal English learning plays a crucial role in vocabulary learning, yet few scholars have explored the use of large language models for this purpose. In light of this, our study, integrating Self-Determination Theory (SDT) and the Unified Theory of Acceptance and Use of Technology (UTAUT), employed Structural Equation Modeling (SEM) to investigate factors influencing 568 Chinese English learners' use of large language models for vocabulary learning. Our findings identified six significant factors from those models—perceived autonomy, perceived competence, perceived relatedness, performance expectancy, effort expectancy, and social influence—that significantly shape learners' intentions and behaviors towards utilizing large language models for vocabulary learning. Notably, effort expectancy emerged as the most influential factor, while facilitating conditions did not significantly impact usage intentions. This research offers insights for future curriculum design and policy formulation, highlighting the importance of understanding learners' perspectives on technology use in education.

Keywords: SDT; UTAUT; vocabulary learning; large language models; Chinese context

check for updates

Citation: Wang, X.; Reynolds, B.L. Beyond the Books: Exploring Factors Shaping Chinese English Learners' Engagement with Large Language Models for Vocabulary Learning. *Educ. Sci.* **2024**, *14*, 496. https://doi.org/10.3390/educsci14050496

Academic Editor: Martin Howard

Received: 7 March 2024
Revised: 29 April 2024
Accepted: 2 May 2024
Published: 6 May 2024

1. Introduction

The advent of technology has revolutionized the way learners acquire new vocabulary, shifting from traditional classroom settings to more dynamic, informal digital platforms [1,2]. This transition emphasizes personalized learning experiences, enabling learners to engage with new words in contexts that resonate with their interests and daily lives [3]. Amidst this evolution, the role of informal digital platforms becomes increasingly pivotal, serving as a bridge between the learner's current linguistic capabilities and their potential for expansion [4]. Firstly, informal digital platforms offer unparalleled accessibility to diverse linguistic resources, allowing learners to encounter vocabulary in authentic contexts beyond the confines of structured curriculum [5]. Secondly, these platforms facilitate a learner-centered approach, where individuals can control their pace and exposure to new words, enhancing retention and application [6]. Thirdly, the integration of multimedia resources on these platforms caters to various learning performances, increasing the efficacy of vocabulary acquisition [7]. Lastly, understanding the impact and mechanisms of vocabulary learning through informal digital platforms is crucial for curriculum designers and policy makers to refine educational tools, making language learning more effective and engaging for a global audience [8].

Given the significant shift in vocabulary learning from traditional classrooms to informal platforms, this paper integrates SDT and the UTAUT to examine the factors influencing Chinese English learners' use of large language models for vocabulary learning. Large language models, such as ChatGPT, are artificial intelligence systems trained on extensive text datasets, enabling them to generate human-like text and engage in natural language interactions [9]. They are capable of understanding context and producing responses that closely resemble human conversation. The novelty of this study lies in two main aspects. First, it explores the realm of vocabulary learning facilitated by large language models, an area yet to be thoroughly explored. Second, it combines SDT and UTAUT models to construct a novel framework for analyzing learners' engagement with technology in English vocabulary acquisition. This innovative approach not only broadens the theoretical understanding of technology-enhanced language learning but also offers practical insights into how large language models can be effectively harnessed to enhance vocabulary learning among Chinese EFL learners. By bridging these two theories, the study aims to provide a comprehensive analysis of the motivational and acceptance factors that drive learners' interaction with advanced language learning technologies.

2. Literature Review

2.1. Self-Determination Theory

In the context of technology-enhanced language learning, SDT has been applied as a macro-theory to discuss students' learning motivation [10,11]. It is an organismic meta-theory of human motivation and well-being, which begins with the assumption that people are, by nature, active, engaged, and orientated towards growth and development [12]. Basic psychological needs theory is one of the six mini theories that make up SDT and maintains that the need for support through environmental and social scaffolding enables our inherent human capacity for healthy development, self-regulation, and social integrity to flourish and thrive. It mainly includes three elements: the needs for autonomy, relatedness, and competence [13]. To be exact, autonomy refers to the need for freedom or perceived choice over one's actions [10]. It refers to the learners' freedom to choose and navigate their learning path. In the context of the present study, this entails selecting vocabulary and contexts that align with their interests and learning goals while using large language models for vocabulary learning. Competence refers to the need to master one's pursuits or learning. In this context, it reflects the students' ability to effectively learn and master new vocabulary through interactions with the language model, thereby enhancing their language proficiency. Relatedness refers to the sense or feeling of being connected to other people. In this setting, it pertains to the learners' sense of connection with a broader community of language learners, facilitated through shared experiences and exchanges enabled by the language model's interactive platform.

Previous studies have leveraged SDT to explore how learners utilize technology for English language acquisition. For instance, Jeon [14] investigated the use of a self-directed interactive app for informal EFL learning from an SDT perspective. Fathali and Okada [15] used SDT to probe into Japanese EFL learners' intentions towards adopting learning technologies for language study outside the classroom. Similarly, Chen and Zhao [16] applied SDT to explore students' motivation and acceptance of gamified English vocabulary learning apps. He and Li [17] investigated the predictors of Chinese students' sustained engagement with mobile learning for second language acquisition from SDT. Their findings suggest that SDT provides a robust framework for examining learners' technology adoption patterns, helping educators and researchers identify key factors that influence engagement in technology-enhanced language learning contexts. Building on these foundations, we posit that SDT is suited for investigating how Chinese English learners use large language models for vocabulary learning. This theoretical framework, with its emphasis on autonomy, competence, and relatedness, provides a comprehensive lens through which to understand the motivational dynamics at play when learners interact with large language models for vocabulary. The key finding from these collective studies is that SDT effectively elucidates the multifaceted motivational processes that improve engagement in technology-enhanced language learning environments. Hence, we propose the following three hypotheses:

H1. *Perceived autonomy has a significant influence on learners' intention to use large language models for vocabulary learning.*

H2. *Perceived competence has a significant influence on learners' intention to use large language models for vocabulary learning.*

H3. *Perceived relatedness has a significant influence on learners' intention to use large language models for vocabulary learning.*

2.2. UTAUT

Although many computer-assisted language learning frameworks cater to EFL learners, the UTAUT stands out as the predominant one for examining the acceptance of technological tools [18,19]. This comprehensive model underpins the rationale for technology adoption, which incorporates eight critical elements derived from various theories. To be exact, it includes the theory of reasoned action, the technology acceptance model (TAM), the motivational model, the theory of planned behavior (TPB), a synthesis of TAM and TPB, the model of personal computer utilization, the innovation diffusion theory, and the social cognitive theory [20]. Within the UTAUT framework, four key factors—performance expectancy, effort expectancy, social influence, and facilitating conditions—play a significant role in shaping an individual's behavioral intention towards technology use [21]. Performance expectancy is the user's belief in the technology's potential to improve their performance, while effort expectancy relates to ease of use. Social influence reflects the perceived importance of others' views on their technology usage, and facilitating conditions are the degree to which an individual believes that an organizational and technological infrastructure supports their system use.

In recent years, scholars have employed the UTAUT to investigate language learning across various contexts. For instance, Hsu [19] applied the UTAUT framework to examine the motivations behind EFL learners' acceptance and use of Language Massive Open Online Courses for language acquisition. Similarly, Tan [22] utilized the UTAUT model to assess the needs of Taiwanese college students for English e-learning websites as tools for learning English. Furthermore, Zhang and Yu [23] examined the factors influencing users' intentions to engage with English vocabulary applications, as well as their actual usage patterns, through the lens of the UTAUT model. These studies underscore the UTAUT model's robust applicability in understanding the dynamics of technology adoption within the realm of language learning, signifying its potential to unravel the complexities of vocabulary acquisition through large language model platforms. Therefore, this study proposes four hypotheses to explore the adoption of large language model platforms for vocabulary learning.

H4. *Performance expectancy has a significant influence on learners' intention to use large language models for vocabulary learning.*

H5. *Effort expectancy has a significant influence on learners' intention to use large language models for vocabulary learning.*

H6. *Social influence has a significant influence on learners' intention to use large language models for vocabulary learning.*

H7. *Facilitating conditions have a significant influence on learners' intention to use large language models for vocabulary learning.*

3. Methodology

3.1. Research Design

In this study, a quantitative research design utilizing SEM was employed to explore the factors influencing Chinese English learners' adoption of large language models for vocabulary learning. This approach was chosen for its ability to test complex relationships between observed and latent variables, allowing for a comprehensive analysis of how various factors, as informed by SDT and UTAUT, impact learners' behavioral intentions. It is most appropriate for this research as it facilitates the examination of multiple dependent relationships simultaneously, offering insights into the effects of psychological and technological determinants on learners' engagement with large language models for vocabulary learning, thus providing a robust framework for addressing the proposed research question. Against this backdrop, the following research question was proposed:

RQ: What factors may influence Chinese English learners' use of large language models for vocabulary learning?

3.2. Participants

The study involved 568 participants who were all recruited online. The recruitment criteria were twofold: first, they were willing to actively participate in the study after being informed of its specific objectives and procedures. Second, all participants had prior experience using large language models for vocabulary learning. The participants in the study were predominantly female, comprising 72.36% of the total with 411 individuals, while males accounted for 27.64% with 157 individuals. In terms of age distribution, the majority fell within the 20–22 age range, representing 49.65% with 282 participants. Those aged 19 and below made up 14.61% with 83 participants, and the 23 and above age group constituted 35.74% with 203 participants. A significant portion of the participants held a Bachelor's degree, accounting for 62.85% or 357 individuals. Master's degree holders were 33.8% with 192 participants, and PhD holders were the smallest group at 3.35% with 19 participants. Regarding university level, 12.85% of participants came from Tier A (985 universities, which are part of a Chinese government project to develop world-class universities), 9.15% from Tier B (211 universities, recognized by the Chinese Ministry of Education for prioritizing high-quality education and research), and a large majority of 78% from Tier C (other universities). The participants' fields of study varied, with the largest group being from Arts and Humanities at 32.39% or 184 individuals, followed by Social Sciences at 26.76% with 152 participants. Natural Sciences and Engineering were represented by 13.56% and 17.96% of the participants, respectively, with 77 and 102 individuals. The category labeled "Others" comprised 9.33% or 53 participants.

3.3. Instruments

3.3.1. Basic Psychological Needs Scale

In this study, the assessment of basic psychological needs was conducted using a modified version of the questionnaire originally developed by Ryan et al. [11]. This adaptation was influenced by Jeon [14], who tailored the questionnaire to explore a self-directed interactive app for informal EFL learning within an SDT framework. Following a similar modification approach as Jeon [14], we adapted the wording of the questionnaire to specifically address the use of large language models for vocabulary learning. This involved changing references from "interactive app" to "large language models" to better reflect the technology being studied. Additionally, we adjusted some of the contextual descriptions within the questions to align with the digital nature of large language models and their application in vocabulary learning, ensuring the questionnaire was relevant to our specific research context. The questionnaire employs a five-point Likert scale, providing options ranging from "strongly disagree" to "strongly agree", to collect the participants' agreement with various statements. This scale comprises three key dimensions: perceived autonomy, perceived competence, and perceived relatedness. The questionnaire includes three items per dimension, culminating in a total of nine questions (see Appendix A).

3.3.2. UTAUT Scale

In terms of UTAUT, items were meticulously developed in accordance with the UTAUT framework as delineated by Venkatesh et al. [21]. To ensure alignment with the specific context of our investigation, certain modifications were made to the original items, tailoring them to more accurately probe the nuances of using large language models for vocabulary learning among Chinese English learners. The questionnaire employs a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), allowing participants to express the degree of their agreement with each statement. The scale encompasses five dimensions, namely, performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention. Each of these dimensions is represented by three items, culminating in a total of fifteen questions (see Appendix B).

3.4. Data Collection

Data for this research were gathered through the Chinese online survey platform, Wenjuanxing. To recruit participants for our study, we employed a two-pronged approach that leveraged both academic networks and social media platforms, catering to a diverse and comprehensive sample pool reflective of our research objectives. Initially, we collaborated with professors from various universities across China, who assisted in distributing our survey to potential participants within the academic community. This method ensured that our study reached individuals with a vested interest in the adoption of large language models for vocabulary learning. Simultaneously, we expanded our recruitment efforts to include social media channels, recognizing the platforms' vast reach and the potential to engage a broader demographic. Through targeted posts and advertisements on popular social media sites, we were able to attract participants beyond the academic sphere, including individuals from different professional backgrounds, age groups, and geographic locations. This dual approach ensured a broad reach among potential participants.

3.5. Data Analysis

The data analysis for this study was rigorously conducted using SPSS 26 and AMOS 26 software, structured into four steps to ensure a comprehensive examination of the collected data. In the first step, we initiated the process by meticulously screening out invalid questionnaires. This included responses where participants had uniformly selected the same option across the survey and those where the completion time suggested insufficient engagement with the questions. The second step involved conducting descriptive analyses to present an overview of the distribution and variability associated with the SDT and UTAUT items. Moving on to the third step, we assessed the reliability and validity of the data. This was achieved by calculating the Cronbach's alpha (α) values for each variable to gauge internal consistency, followed by a confirmatory factor analysis to ensure the validity of the constructs. The final step entailed a path analysis, which was executed to examine the hypothesized relationships between the factors, thereby providing a robust understanding of the interplay among the variables under study.

4. Results

4.1. Descriptive Statistics

Table 1 provides the Means (M) and Standard Deviations (SD) for the items. The *M* values for all items went beyond 3, indicating Chinese EFL learners' generally positive attitudes towards integrating large language models into vocabulary learning. The SD values ranged from 0.74 to 1.16, which displayed moderate variability among the responses. A close examination of the high values for social influence suggest that the opinions and behaviors of others are potentially strong factors in influencing learners' acceptance and utilization of this technology. The univariate skewness and kurtosis values of all scale items were also computed. The absolute values of skewness and kurtosis for all items were below 2 and 10, respectively, which indicated the normality of the dataset [24].

Table 1. Descriptive statistics.

Constructs	Items	M	SD	Kurtosis	Skewness	α (>0.7)
Perceived Autonomy	PA1	3.42	1.16	−0.20	−0.59	0.78
	PA2	3.43	0.95	−0.10	−0.50	
	PA3	3.13	1.08	0.03	−0.61	
Perceived Competence	PC1	3.57	1.07	−0.43	−0.28	0.84
	PC2	3.44	1.01	−0.30	−0.35	
	PC3	3.58	0.91	−0.29	−0.33	
Perceived Relatedness	PR1	3.45	0.97	−0.14	−0.45	0.82
	PR2	3.39	1.04	−0.26	−0.47	
	PR3	3.48	0.95	−0.32	−0.26	
Performance Expectancy	PE1	3.52	1.07	−0.26	−0.50	0.78
	PE2	3.60	0.84	−0.18	−0.60	
	PE3	3.36	0.97	−0.11	−0.46	
Effort Expectancy	EE1	3.32	1.13	−0.16	−0.54	0.79
	EE2	3.26	1.00	−0.03	−0.47	
	EE3	2.95	0.97	−0.05	−0.42	
Social Influence	SI1	3.90	0.86	−0.51	−0.28	0.78
	SI2	3.82	0.74	−0.35	−0.34	
	SI3	3.82	0.88	−0.44	−0.26	
Facilitating Conditions	FC1	3.57	0.96	−0.27	−0.43	0.78
	FC2	3.52	0.95	−0.12	−0.68	
	FC3	3.34	1.04	−0.20	−0.43	
Behavioral Intention	BI1	3.48	0.96	−0.24	−0.38	0.87
	BI2	3.42	1.12	−0.35	−0.39	
	BI3	3.12	1.10	−0.04	−0.52	

Note: PA = Perceived Autonomy; PC = Perceived Competence; PR = Perceived Relatedness; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention.

4.2. Reliability Checks and the Measurement Model

This section reports the results of reliability, multivariate normality, convergent validity, discriminant validity, and the measurement model. In the current study, the reliability coefficients for the variables all surpassed the recommended benchmark of 0.7, indicating that the scales possess adequate reliability [25].

Secondly, the assessment of multivariate normality and sampling adequacy was conducted through the Keiser–Meyer–Olkin (KMO) measure and Bartlett's Test of Sphericity. Bartlett's Test yielded a significant value ($p < 0.001$), and the KMO index was 0.73, surpassing the recommended threshold of 0.6 as advised by Tabachnick and Fidell [26], thereby confirming the data's suitability for factor analysis.

Following the confirmatory factor analysis (CFA) guidelines proposed by Collier [24], composite reliability (CR) and average variance extracted (AVE) scores for each factor were calculated to examine convergent validity. The findings revealed that the CR values for all factors exceeded the recommended threshold of 0.7, and all AVE values surpassed the 0.5 benchmark, thereby affirming convergent validity [25]. For the assessment of discriminant validity, both the square roots of the AVEs and the inter-factor correlation coefficients for the eight factors were computed and juxtaposed (see Table 2). This analysis indicated that the square roots of the AVEs for all factors were greater than their respective inter-factor correlation coefficients, thus establishing discriminant validity.

Table 2. Convergent validity and discriminant validity.

CR	AVE	-	PA	PC	PR	PE	EE	SI	FC	BI
0.78	0.54	PA	**0.74**							
0.84	0.63	PC	0.01	**0.79**						
0.82	0.61	PR	0.09	0.22 ***	**0.78**					
0.79	0.55	PE	−0.05	0.13	0.15	**0.74**				
0.79	0.55	EE	−0.01	0.13	0.16	0.07	**0.74**			
0.78	0.54	SI	−0.02	0.15	0.19 ***	−0.11	−0.07	**0.74**		
0.78	0.54	FC	0.37 ***	0.16	0.20 ***	−0.04	0.00	−0.05	**0.74**	
0.87	0.70	BI	0.14	0.38 ***	0.42 ***	0.25 ***	0.37 ***	0.30 ***	0.04	**0.84**

Note: (1) The square root of AVE is demonstrated along the diagonal line in bold; (2) $p < 0.001$ = ***; PA = Perceived Autonomy; PC = Perceived Competence; PR = Perceived Relatedness; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention.

Lastly, to further investigate the construct validity, a measurement model was developed utilizing Amos. The model's fit was evaluated by calculating seven goodness-of-fit indices, including the Comparative Fit Index (CFI), Normed Fit Index (NFI), Incremental Fit Index (IFI), Root Mean Square Error of Approximation (RMSEA), Tucker–Lewis Index (TLI), Parsimony Normed Fit Index (PNFI), and Standardized Root Mean Squared Residual (SRMR). As illustrated in Table 3, the model demonstrated a good fit with the data, as all indices satisfied the recommended benchmark values [24,25,27].

Table 3. Goodness-of-fit indices.

	χ^2/df	CFI	NFI	IFI	RMSEA	TLI	SRMR
Our model	1.52	0.98	0.94	0.98	0.03	0.97	0.03
RV	<5	>0.9	>0.9	>0.9	<0.1	>0.9	<0.05

Note: RV = Recommended Value.

4.3. The Structural Model and Hypotheses Testing

The analysis of the hypothesis test results revealed that six out of seven hypothesized relationships were positively supported, indicating a significant influence on behavioral intention (see Table 4, Figure 1). Perceived autonomy, competence, relatedness, performance expectancy, effort expectancy, and social influence all demonstrated positive path coefficients ranging from 0.17 to 0.31, with all p-values indicating high statistical significance ($p < 0.001$). These findings suggest that these factors are strong predictors of behavioral intention to use large language models for vocabulary learning. Notably, effort expectancy emerged as the strongest predictor, asserting that ease of use is a key determinant in the intention to adopt large language models. However, the relationship between facilitating conditions and behavioral intention deviated from this trend, with a negative path coefficient of −0.09 and a p-value slightly above the conventional threshold for significance ($p = 0.06$), indicating an unsupported hypothesis. This suggests that the presence of facilitating conditions may not be as useful a predictor of behavioral intention as initially expected within this context.

Table 4. Hypothesis test results.

Hypotheses	β	*p*	*t*	S.E.	Results
H1: PA→BI	0.17	***	3.65	0.059	Supported
H2: PC→BI	0.23	***	5.12	0.050	Supported
H3: PR→BI	0.25	***	5.23	0.051	Supported
H4: PE→BI	0.20	***	4.46	0.051	Supported
H5: EE→BI	0.31	***	6.69	0.053	Supported
H6: SI→BI	0.26	***	5.43	0.060	Supported
H7: FC→BI	−0.09	0.06	−1.86	0.058	Unsupported

Note: (1) PA = Perceived Autonomy; PC = Perceived Competence; PR = Perceived Relatedness; PE = Performance Expectancy; EE = Effort Expectancy; SI = Social Influence; FC = Facilitating Conditions; BI = Behavioral Intention. (2) $p < 0.001$ = ***;

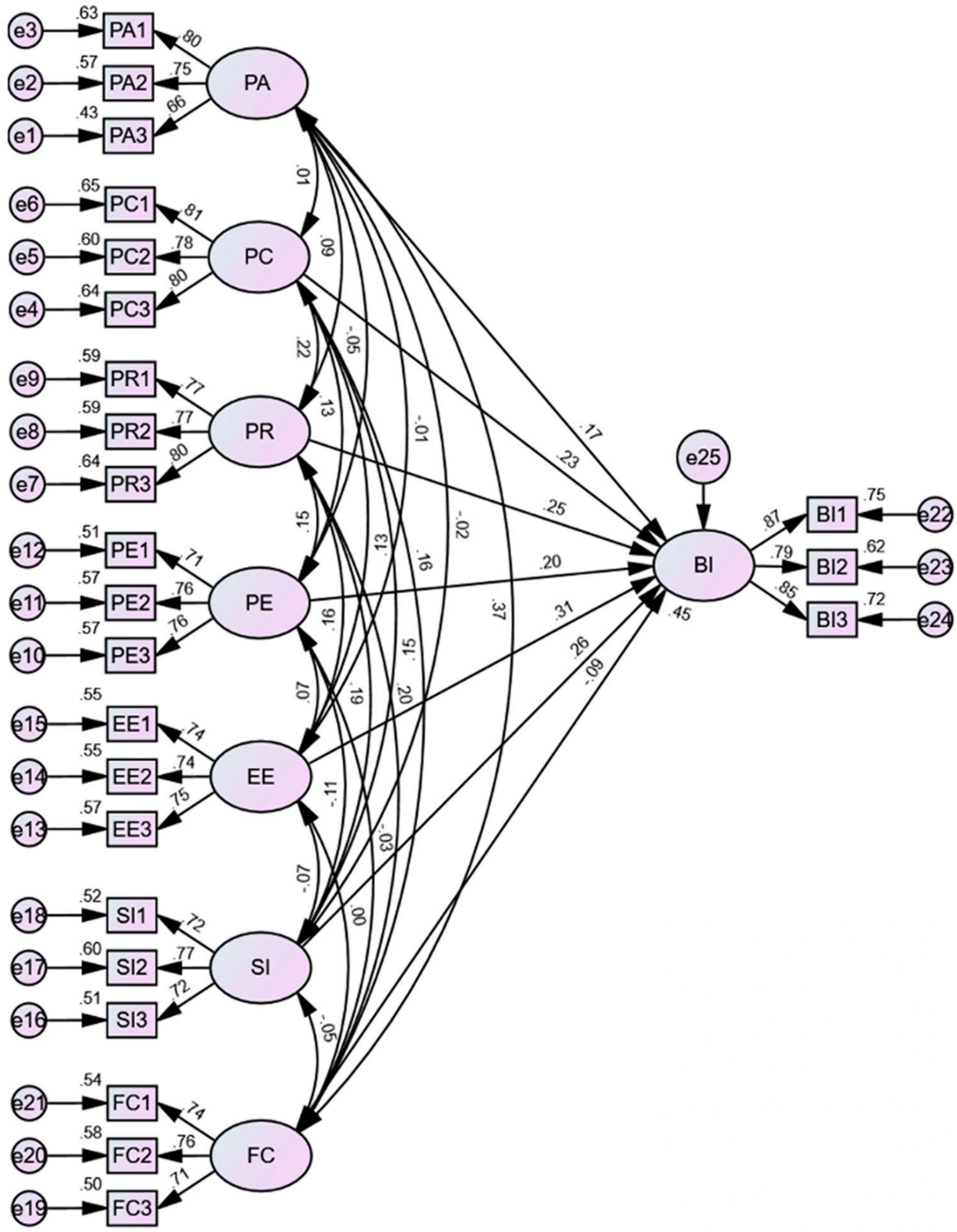

Figure 1. The final structural model.

5. Discussion

This research combined SDT and the UTAUT to explore the dynamics behind English learners' adoption of large language models for enhancing their vocabulary acquisition. By employing SEM, it meticulously explored the multitude of factors that affect learners' behavioral intentions. This exploration not only broadens the empirical base of SDT and UTAUT within the novel realm of large language models but also innovatively merges these theories to refine and extend the technological acceptance model framework. Consequently, this study offers a nuanced theoretical perspective on the integration of large language models in language learning, particularly focusing on vocabulary development among Chinese English learners.

Firstly, perceived autonomy (H1), perceived competence (H2), and perceived relatedness (H3) are positively linked to behavioral intention to use technology, with respective beta values of 0.17, 0.23, and 0.25, all significant at $p < 0.001$. The validation of the first three hypotheses aligns with and enhances the existing literature on SDT, particularly in the technology adoption context. Traditional SDT research has emphasized the importance of fulfilling autonomy, competence, and relatedness needs in educational settings [10,12]. Our findings contribute to this body of work by demonstrating that these needs are equally crucial in shaping intentions to adopt large language models for vocabulary learning. This is significant because it demonstrates that SDT's principles apply not only to traditional learning environments but also to new technological contexts, highlighting the versatility of SDT. In addition, our research adds value to the existing corpus by bridging the gap between SDT and large language models, illustrating how a theoretical framework traditionally associated with education can be effectively applied to the rapidly evolving landscape of AI technologies. Notably, they echo past research suggesting that when technology users' psychological needs are met, their engagement with technology is not only more likely but also more sustainable [15–17]. This expands upon the understanding of user motivation in technology acceptance models, providing empirical support for a more nuanced approach that incorporates SDT's psychological needs alongside traditional predictors of technology use.

In terms of the UTAUT, performance expectancy, effort expectancy, and social influence were all found to positively influence behavioral intention to use technology, as evidenced by their respective support of H4 ($\beta = 0.20$), H5 ($\beta = 0.31$), and H6 ($\beta = 0.26$), with p-values indicating statistical significance ($p < 0.001$). These findings are consistent with the core factors of the UTAUT model, confirming that users' intentions to adopt technology are strongly influenced by their expectations of the technology's performance, the ease of its use, and the extent to which they perceive that they should use the technology [18–21]. Notably, effort expectancy emerged as the strongest predictor among them, which aligns with the current emphasis on user-friendly design as a critical factor in technology adoption [22,23]. However, the relationship between facilitating conditions and behavioral intention was not supported (H7: $\beta = -0.09$, $p = 0.063$), suggesting an unexpected negative influence or potentially a non-significant role of facilitating conditions in this context, which is different from the findings of Hsu [19]. The negligible impact of facilitating conditions on the motivation to use large language models for vocabulary learning may stem from the inherent accessibility and ease of use of the platform. Users expect such technologies to be readily available without additional support or infrastructure. Furthermore, the direct and immediate engagement with large language models, which offer personalized and instant feedback, likely surpasses the influence of external facilitating conditions on a learner's motivation to use the platform for educational purposes.

The findings from our study have several important implications for the teaching of vocabulary in China. Firstly, the significance of perceived autonomy, competence, and relatedness underscores the need for educational approaches that empower learners [28,29]. Teachers and curriculum designers should integrate large language models into vocabulary teaching in ways that foster learners' sense of control, challenge, and connection to the learning content [30,31]. By creating learning environments that leverage these models for personalized vocabulary exercises, real-world application tasks, and interactive learning experiences, teachers can significantly enhance motivation and engagement among Chinese English learners [32,33]. Additionally, the recognition of effort expectancy as a critical factor suggests that language teachers should serve as strategic planners, crafting activities or providing guidance on how to effectively use these models for vocabulary learning as a way to alleviate potential barriers to adoption [34].

For Chinese learners, the study's findings highlight the importance of leveraging large language models as a strategic tool for enhancing their vocabulary learning. Given the impact of effort expectancy, learners are encouraged to familiarize themselves with the functionalities of these models, exploring various features that can aid in their vocabulary acquisition. This exploration should be guided by an active approach to learning, where learners seek out or create opportunities to use these models in contextually meaningful ways, such as writing practice, reading comprehension, and conversational simulations [1]. Moreover, the social influence factor suggests the benefit of forming study groups or online communities where learners can share tips, resources, and experiences related to using large language models for vocabulary learning [35]. Such collective efforts can not only improve individual learning outcomes but also contribute to a more collaborative and supportive learning environment [36]. Lastly, learners should be mindful of their autonomy, competence, and relatedness needs, actively engaging with learning activities that satisfy these psychological drivers to maintain motivation and persistence in learning English vocabulary [37]. In this sense, learners could select personalized vocabulary exercises (autonomy), take on level-appropriate challenges through adaptive quizzes (competence), and connect with a learning community to share insights (relatedness), thus bolstering their motivation and enduring engagement with English vocabulary learning [38–40].

6. Conclusions

Utilizing SEM and integrating SDT with the UTAUT framework, this study examined factors influencing Chinese English learners' use of large language models for vocabulary learning. Our findings revealed that six factors—perceived autonomy, perceived competence, perceived relatedness, performance expectancy, effort expectancy, and social influence—significantly shape learners' intentions and behaviors towards using these advanced technological tools. Notably, effort expectancy emerged as the most influential factor, underscoring the critical role of user-friendly interfaces in facilitating the adoption of technological aids in language learning. Surprisingly, facilitating conditions did not significantly affect usage intentions, suggesting that the intrinsic features of the technology itself, rather than external support conditions, are the key drivers of its use in educational contexts.

This study has certain limitations that warrant mention. Firstly, data collection relied primarily on online surveys, which may not capture a fully representative sample of the population, potentially limiting the generalizability of the findings. Secondly, the research lacked a longitudinal approach, meaning it did not track the long-term behavior and attitudes of participants towards using large language models for vocabulary learning. Consequently, the study might not account for changes over time in user perceptions or the sustained impact of the identified factors on technology adoption.

In this sense, future research could address these limitations by employing diverse data collection methods, including interviews or observations, to ensure a more comprehensive understanding of users' experiences and perceptions. Additionally, longitudinal studies could be conducted to track the evolving usage patterns and attitudes towards large language models over an extended period. This would enable researchers to explore how user engagement and motivation fluctuate over time, providing insights into the long-term effectiveness and sustainability of incorporating such technologies into language learning practices. Moreover, investigating the interplay between individual characteristics and contextual factors could offer deeper insights into the complexities of technology adoption in educational settings. Such endeavors would contribute to the development of more robust theoretical frameworks and practical guidelines for effectively integrating large language models into language education programs.

Author Contributions: Conceptualization, X.W. and B.L.R.; methodology, X.W. and B.L.R.; software, X.W.; validation, X.W.; formal analysis, X.W.; investigation, X.W.; resources, X.W.; data curation, X.W.; writing—original draft preparation, X.W.; writing—review and editing, B.L.R.; visualization, X.W.; supervision, B.L.R.; project administration, B.L.R.; funding acquisition, B.L.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: While the first author's institution could not provide an ethics review due to the research topic not being related to the Medical School, our research meticulously adhered to the international standards for conducting research as outlined by the International TESOL Association to ensure ethical compliance. Specifically, in the recruitment of participants, we implemented a thorough process that included informing potential participants about the research and their role in it, providing a clear statement of the research's purpose, and detailing the research procedures and the types of information to be collected. We emphasized the voluntary nature of participation, ensuring that individuals were aware that there was no penalty for refusal and that they could withdraw at any time without consequence. The protection of participant confidentiality was clearly communicated, along with adequate contact information for any inquiries regarding the research. We also informed participants about any foreseeable risks and discomforts associated with their cooperation. Importantly, we secured signed consent forms from each participant, detailing the terms of our agreement and maintaining these documents on file, thus upholding the ethical standards required for responsible and respectful research practice.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study can be made available upon reasonable request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Basic Psychological Needs Scale

Perceived Autonomy

1. I experience a lot of freedom when learning vocabulary through large language models.
2. I can find something interesting to learn vocabulary through large language models.
3. Learning vocabulary through large language models provides me with interesting options and choices.

Perceived Competence

1. My ability to understand and use new words is well-matched with the activities provided by the large language models.
2. I feel competent at learning vocabulary through large language models.
3. I feel capable and effective in learning vocabulary through large language models.

Perceived Relatedness

1. I receive support from large language models when learning vocabulary.
2. Large language models provide me with meaningful information that I can rely on when learning vocabulary.
3. I feel comfortable when learning vocabulary through large language models.

Appendix B. UTAUT Scale

Performance Expectancy

1. Using large language models is helpful for learning vocabulary.
2. Using large language models can improve my vocabulary skills.
3. Using large language models allows me to learn vocabulary quickly.

Effort Expectancy

1. Using large language models is easy.
2. The user interface and functionality of large language models are easy to navigate for vocabulary learning.
3. Learning vocabulary through large language models is straightforward.

Social Influence

1. My teacher encourages me to use large language models for vocabulary learning.
2. My classmates use large language models for vocabulary learning.
3. Many people use large language models for vocabulary learning.

Facilitating Conditions

1. I have the requisite learning knowledge to use large language models for vocabulary learning.
2. I have access to the necessary auxiliary resources to learn vocabulary through large language models.

3. I have knowledgeable individuals to consult regarding the use of large language models for vocabulary learning.

Behavioral Intention

1. I am willing to continue using large language models for vocabulary learning.
2. I am willing to recommend large language models to my friends for vocabulary learning.
3. I am willing to share my experiences and achievements regarding vocabulary learning through large language models.

References

1. Reynolds, B.L. Introduction: A Scoping Review of Second Language Vocabulary Learning in the Wild. In *Vocabulary Learning in the Wild*; Reynolds, B.L., Ed.; Springer: Singapore, 2023.
2. Soyoof, A.; Reynolds, B.L.; Vazquez-Calvo, B.; McLay, K. Informal digital learning of English (IDLE): A scoping review of what has been done and a look towards what is to come. *Comput. Assist. Lang. Learn.* **2023**, *36*, 608–640. [CrossRef]
3. Lee, J.S. Quantity and Diversity of Informal Digital Learning of English. *Lang. Learn. Technol.* **2019**, *23*, 114–126.
4. Zhang, Y.; Liu, G. Revisiting informal digital learning of English (IDLE): A structural equation modeling approach in a university EFL context. *Comput. Assist. Lang. Learn.* **2022**, 1–33. [CrossRef]
5. Liu, G.; Ma, C. Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. *Innov. Lang. Learn. Teach.* **2023**, *18*, 125–138. [CrossRef]
6. Liu, G.L.; Wang, Y. Modeling EFL teachers' intention to integrate informal digital learning of English (IDLE) into the classroom using the theory of planned behavior. *System* **2024**, *120*, 103193. [CrossRef]
7. Lee, J.S.; Sylvén, L.K. The role of Informal Digital Learning of English in Korean and Swedish EFL learners' communication behaviour. *Br. J. Educ. Technol.* **2021**, *52*, 1279–1296. [CrossRef]
8. Lee, J.S. The role of informal digital learning of English and a high-stakes English test on perceptions of English as an international language. *Australas. J. Educ. Technol.* **2020**, *36*, 155–168. [CrossRef]
9. Kasneci, E.; Seßler, K.; Küchemann, S.; Bannert, M.; Dementieva, D.; Fischer, F.; Kasneci, G. ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.* **2023**, *103*, 102274. [CrossRef]
10. Ryan, R.M.; Deci, E.L. *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*; Guilford Publications: New York, NY, USA, 2017.
11. Ryan, R.M.; Rigby, C.S.; Przybylski, A. The motivational pull of video games: A self-determination theory approach. *Motiv. Emot.* **2006**, *30*, 344–360. [CrossRef]
12. Deci, E.L.; Ryan, R.M. Optimizing students' motivation in the era of testing and pressure: A self-determination theory perspective. In *Building Autonomous Learners: Perspectives from Research and Practice Using Self-Determination Theory*; Wang, J., Liu, C.W., Ryan, R.M., Eds.; Springer: Singapore, 2016; pp. 9–29.
13. Deci, E.L.; Ryan, R.M. *Intrinsic Motivation and Self-Determination in Human Behaviour*; Plenum: New York, NY, USA, 1985.
14. Jeon, J. Exploring a self-directed interactive app for informal EFL learning: A self-determination theory perspective. *Educ. Inf. Technol.* **2022**, *27*, 5767–5787. [CrossRef]
15. Fathali, S.; Okada, T. Technology acceptance model in technology-enhanced OCLL contexts: A self-determination theory approach. *Australas. J. Educ. Technol.* **2018**, *34*, 138–154. [CrossRef]
16. Chen, Y.; Zhao, S. Understanding Chinese EFL Learners' Acceptance of Gamified Vocabulary Learning Apps: An Integration of Self-Determination Theory and Technology Acceptance Model. *Sustainability* **2022**, *14*, 11288. [CrossRef]
17. He, L.; Li, C. Continuance intention to use mobile learning for second language acquisition based on the technology acceptance model and self-determination theory. *Front. Psychol.* **2023**, *14*, 1185851. [CrossRef] [PubMed]
18. Hoi, V.N. Understanding higher education learners' acceptance and use of mobile devices for language learning: A Rasch-based path modeling approach. *Comput. Educ.* **2020**, *146*, 103761. [CrossRef]
19. Hsu, L. EFL learners' self-determination and acceptance of LMOOCs: The UTAUT model. *Comput. Assist. Lang. Learn.* **2023**, *36*, 1177–1205. [CrossRef]
20. Abd Rahman, S.F.; Md Yunus, M.; Hashim, H. Applying UTAUT in predicting ESL lecturers intention to use flipped learning. *Sustainability* **2021**, *13*, 8571. [CrossRef]
21. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User acceptance of information technology: Toward a unified view. *MIS Quart.* **2003**, *27*, 425–478. [CrossRef]
22. Tan, P.J.B. Applying the UTAUT to understand factors affecting the use of English e-learning websites in Taiwan. *Sage Open* **2013**, *3*, 2158244013503837. [CrossRef]
23. Zhang, K.; Yu, Z. Extending the UTAUT model of gamified English vocabulary applications by adding new personality constructs. *Sustainability* **2022**, *14*, 6259. [CrossRef]
24. Collier, J.E. *Applied Structural Equation Modeling Using AMOS: Basic to Advanced Techniques*; Routledge: London, UK, 2020.
25. Kline, R.B. *Principles and Practice of Structural Equation Modeling*; Guilford Publications: New York, NY, USA, 2023.
26. Tabachnick, B.G.; Fidell, L.S. *Using Multivariate Statistics*; Pearson: Harlow, UK, 2019.

27. Wheaton, B.; Muthen, B.; Alwin, D.F.; Summers, G.F. Assessing reliability and stability in panel models. *Sociol. Methodol.* **1977**, *8*, 84–136. [CrossRef]
28. Wang, Y.; Derakhshan, A. Enhancing Chinese and Iranian EFL students' willingness to attend classes: The role of teacher confirmation and caring. *Porta Linguarum* **2023**, *39*, 165–192.
29. Wang, Y.; Wang, Y.; Pan, Z.; Ortega-Martín, J.L. The predicting role of EFL students' achievement emotions and technological self-efficacy in their technology acceptance. *Asia Pac. Educ. Res.* **2023**, 1–12. [CrossRef]
30. Gao, Y.; Wang, Q.; Wang, X. Exploring EFL University Teachers' Beliefs in Integrating ChatGPT and other Large Language Models in Language Education: A Study in China. *Asia Pac. J. Educ.* **2024**, *44*, 29–44. [CrossRef]
31. Wang, X.; Gao, Y.; Sun, F.; Wang, Q. Unveiling the tapestry of teacher belief research: Tracing the present and forging the future through bibliometric analysis. *Curr. Psychol.* **2023**, 1–14. [CrossRef]
32. Wang, X.; Sun, F.; Wang, Q.; Li, X. Motivation and affordance: A study of graduate students majoring in translation in China. *Front. Educ.* **2022**, *7*, 1010889. [CrossRef]
33. Wang, Y.; Kruk, M. Modeling the interaction between teacher credibility, teacher confirmation, and English major students' academic engagement: A sequential mixed-methods approach. *Stud. Second Lang. Learn. Teach.* **2024**. [CrossRef]
34. Pan, Z.; Wang, Y.; Derakhshan, A. Unpacking Chinese EFL students' academic engagement and psychological well-being: The roles of language teachers' affective scaffolding. *J. Psycholinguist. Res.* **2023**, *52*, 1799–1819. [CrossRef] [PubMed]
35. Gao, Y.; Wang, X. Towards Understanding Teacher Mentoring, Learner WCF Beliefs, and Learner Revision Practices through Peer Review Feedback: A Sociocultural Perspective. *J. Lang. Educ.* **2022**, *8*, 58–72. [CrossRef]
36. Teng, F.; Reynolds, B.L. Effects of individual and group metacognitive prompts on EFL reading comprehension and incidental vocabulary learning. *PLoS ONE* **2019**, *14*, e0215902. [CrossRef]
37. Gao, Y.; Wang, X.; Fan, P. Exploring male English major's motivation trajectory through complex dynamic systems theory. *Curr. Psychol.* **2023**, *43*, 9089–9100. [CrossRef]
38. Wang, Q.; Sun, F.; Wang, X.; Gao, Y. Exploring Undergraduate Students' Digital Multitasking in Class: An Empirical Study in China. *Sustainability* **2023**, *15*, 10184. [CrossRef]
39. Wu, H.; Wang, Y.; Wang, Y. How burnout, resilience, and engagement interplay among EFL learners: A mixed-methods investigation in the Chinese senior high school context. *Porta Linguarum.* **2024**, 193–213. [CrossRef]
40. Wu, H.; Zeng, Y.; Fan, Z. Unveiling Chinese senior high school EFL students' burnout and engagement: Profiles and antecedents. *Acta Psychologica* **2024**, *243*, 104153. [CrossRef] [PubMed]