Behavioral Drivers of ChatGPT-assisted TOEIC Reading: Evidence from an Extended UTAUT Model

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***Abstract*—This study examined the effectiveness of Artificial Intelligence (AI)-powered Teaching Assistants (AITAs), developed through ChatGPT fine-tuning to support underperforming technical university students in Taiwan, in improving their Test of English for International Communication (TOEIC) reading comprehension. These students are required to meet the English proficiency graduation requirement of a minimum TOEIC score of 550. However, many struggle to attain even 200 out of 495 points in the reading section. Employing a quasi-experimental design, this study involved 226 undergraduate students from non-English major departments over a 12-week period. The experimental group utilized AITAs-driven materials, whereas the control group relied on conventional resources. Learning outcomes were evaluated through pre- and post-tests, and the extended Unified Theory of Acceptance and Use of Technology (UTAUT) was applied to identify the factors influencing students' acceptance of AITAs-driven materials. An analysis of covariance revealed that students in the experimental group achieved significantly higher TOEIC reading scores than those in the control group. The extended UTAUT analysis highlighted that social influence, AI self-efficacy, performance and effort expectancy, and facilitating conditions significantly influenced behavioral intention. Task-technology fit moderated the relationship between behavioral intention and usage behavior. These findings provide robust empirical evidence for the efficacy of AI-driven personalized learning in enhancing TOEIC reading comprehension for university students. Furthermore, the research offers a comprehensive framework for integrating AI tools into language education practices. It addresses the specific challenges and unique educational needs of learners and leverages AI technologies to help language learners meet standardized testing requirements.**

***Keywords*—ChatGPT, Artificial Intelligence (AI)-powered Teaching Assistants (AITAs), Test of English for International Communication (TOEIC) reading, extended Unified Theory of Acceptance and Use of Technology (UTAUT), English as a Foreign Language (EFL), vocational education**

I. Introduction

The rapid advancement of Artificial Intelligence (AI) and digital teaching tools has created new opportunities for improving English as a Foreign Language (EFL) learning [1, 2]. This is particularly crucial in the context of Taiwan's Bilingual Country Policy, which aims to cultivate a globally competitive workforce by emphasizing English proficiency. Thus, most higher education institutions in Taiwan now require standardized English test scores, such as the Test of English for International Communication (TOEIC), as a graduation threshold, reflecting the importance of language skills in the global job market.

In Taiwan's higher education system, TOEIC scores play a crucial role in determining students' academic progression, as most technical universities require a minimum TOEIC score of 550 to meet graduation standards. However, this requirement poses a substantial challenge for students in technical and vocational universities.

Compared with learning contexts in general universities, students in technical and vocational education exhibit different learning backgrounds and educational needs. Their curricula are predominantly oriented toward professional skills and practice-based training, resulting in relatively limited learning time devoted to English-related courses and a general lack of systematically structured, long-term language learning programs. Furthermore, many TVE students must simultaneously manage intensive discipline-specific coursework and part-time employment, which imposes additional constraints on their opportunities for sustained English learning. Consequently, when confronted with high-threshold English proficiency graduation requirements such as the TOEIC, these students are more likely to experience elevated levels of anxiety, diminished language self-efficacy, and maladaptive behavioral responses, including learning withdrawal or avoidance, which may undermine their continuous engagement in English learning.

The TOEIC reading section, which accounts for 495 of the 990 total points, is particularly difficult for these students. It demands advanced comprehension skills and familiarity with business-oriented vocabulary, areas in which technical students typically lack experience. For example, participants in this study had TOEIC reading scores significantly below 200 points, underscoring the gap between their current abilities and graduation requirements. A failure to meet the TOEIC threshold prevents students from graduating despite their technical proficiency in their major subjects.

The challenges these students encounter are multifaceted. Many focus on technical training during their studies and receive limited English instruction. Additionally, demanding course loads and part-time employment leave little time for supplementary language learning. Moreover, low confidence in their English proficiency often leads to disengagement, perpetuating a cycle of low achievement [3]. These behavioral patterns highlight the need for innovative approaches to EFL instruction. Generative AI technologies, such as ChatGPT, offer a feasible way to provide

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personalized, adaptable, and engaging learning resources for TOEIC preparation [4]. Beyond education, AI has already proven effective in professional domains such as healthcare, where tailored AI interactions improve user satisfaction and meet specialized needs [5]. Similarly, Artificial Intelligence (AI)-powered Teaching Assistants (AITAs), such as ChatGPT, can analyze learners' responses, generate customized texts and practice questions, and adapt dynamically to individual needs, thereby enhancing engagement and learning effectiveness [6]. Studies on AITAs learning environments further highlighted their capacity to foster flow experiences, which improve logical reasoning and learning outcomes in language education [7]. These attributes underscore the potential of generative AI in addressing the unique challenges of TOEIC preparation for underperforming learners, offering innovative solutions to bridge the existing gaps in language proficiency. Moreover, the integration of generative AI tools such as ChatGPT is theoretically grounded in the principles of personalized and self-directed learning. According to Knowles [8] and Keller [9], personalized learning involves tailoring educational experiences to meet the unique needs of each learner, while self-directed learning empowers students to actively manage their learning processes. By automatically generating customized instructional materials that adapt to individual proficiency levels and learning paces, ChatGPT not only addresses the shortcomings of traditional, one-size-fits-all approaches but also enhances learner autonomy. This alignment with established pedagogical frameworks reinforces the theoretical justification for employing AI-driven tools to improve TOEIC reading comprehension among underperforming EFL students.

Despite the potential of generative AI in EFL education, a notable gap exists in understanding its specific impact on TOEIC reading comprehension, particularly among underperforming students in technical and vocational education settings. Most existing research has focused on the general benefits of AI in education without addressing the unique needs of this subgroup, including behavioral challenges and high-stakes testing requirements. Furthermore, empirical evidence comparing the effectiveness of AITAs-driven materials with traditional approaches for TOEIC preparation remains limited. Thus, addressing these gaps requires targeted research exploring how generative AI can support personalized learning while strengthening students' motivation and engagement in TOEIC-oriented EFL instruction.

This study aimed to comprehensively assess the value of incorporating generative AI-driven personalized learning into EFL reading instruction. This involved training an AITAs for TOEIC reading and evaluating the quality of EFL learning materials generated by the AITAs to support the reading comprehension skills required for TOEIC success. The study also compared the TOEIC reading performances of students using AITAs-driven materials with those relying on traditional classroom resources. Additionally, it utilized the extended Unified Theory of Acceptance and Use of Technology (UTAUT) to examine the behavioral factors influencing students' acceptance and use of AITAs-driven materials.

By addressing these objectives, this study advances the understanding of how generative AI can be integrated into TOEIC-oriented EFL instruction to support underperforming learners and to enhance learning engagement and outcomes.

Specifically, this study investigated the following research questions:

RQ1: Does the EFL learning material generated by the AITAs exhibit high quality and satisfy the standards required for the TOEIC reading test?

RQ2: Does the use of AITAs-driven materials to assist EFL learning significantly improve participants' TOEIC reading test scores compared with traditional EFL learning materials?

RQ3: Which factors influence learners' behavioral intentions and usage behavior toward AITAs-driven EFL materials?

II. LITERATURE REVIEW

A. Technical and Vocational Universities as a Distinct Context for EFL and AI Adoption

Technical and vocationally oriented universities constitute a distinct segment of higher education in which curricular priorities are closely aligned with applied professional competencies and labor market readiness. In Taiwan, English certification policies have been widely institutionalized as graduation thresholds, with standardized proficiency tests—including TOEIC—frequently positioned as mechanisms to enhance graduates' employability and international competitiveness. This policy orientation has been documented in Taiwanese tertiary EFL research that describes how universities and universities of science and technology have adopted exit requirements and recommended external proficiency tests as formal benchmarks for degree completion [10, 11].

However, prior evidence from Taiwanese tertiary EFL contexts indicates that certification-based exit policies do not necessarily generate sustained learning engagement or broadly positive washback. Pan and Newfields reported that the overall washback associated with proficiency graduation requirements was limited, with only partial motivational effects and indications that lower-proficiency learners may be less likely to be meaningfully encouraged under such regimes, particularly when competing academic demands constrain time and effort devoted to English learning [10]. Complementarily, Pan and In'nami [11] questioned whether TOEIC-based exit testing can be assumed to produce the intended downstream outcomes (e.g., employability gains) and highlighted that cutoff-driven testing policies may not translate into learning experiences aligned with workplace-relevant communicative competence. Together, these studies suggest that in vocationally oriented settings, English learning may be framed as instrumental test preparation rather than sustained competence development, thereby raising concerns about both the effectiveness and equity of certification-driven approaches.

Within this policy environment, TOEIC reading development becomes both practically consequential and pedagogically challenging, particularly for learners whose foundational linguistic resources require reinforcement. Empirical findings from a Taiwanese technical-college sample show that TOEIC listening and reading performance is strongly associated with vocabulary size, underscoring the centrality of foundational language knowledge for success on workplace-oriented assessments [12]. This relationship implies that scalable supports emphasizing individualized scaffolding and repeated, targeted practice may be especially relevant in technical and vocational universities. Generative AI–supported learning materials are a plausible candidate for providing such personalization at scale; nevertheless, adoption and sustained use should not be presumed to mirror patterns observed in more research-intensive university contexts. Accordingly, technical and vocational universities warrant focused investigation as a high-stakes setting where policy pressures and learner needs intersect, and where the potential benefits—and constraints—of AI-assisted EFL learning must be empirically established.

B. Use of Large Language Models in Education

Large Language Models (LLMs) have emerged as transformative tools in language education given their sophistication in natural language processing and generation. OpenAI's GPT series (including GPT-4), Anthropic's Claude, and Google's Gemini represent distinct implementations of LLMs, each demonstrating the capability to understand contexts and generate contextually appropriate responses. These advanced language models, built on different architectures and training approaches, share core capabilities that make them valuable for language teaching and learning applications [13]. Although the broad architectural foundation of LLMs lies in transformer models trained on vast text corpora, their specific value in language education stems from their ability to process and generate linguistically accurate and contextually appropriate content.

Recent studies have demonstrated the significant impact of LLMs on various aspects of language instruction. Bonner *et al.* [14] found that LLMs can effectively support vocabulary acquisition and grammar instruction by generating examples and explanations tailored to learners' proficiency levels. In writing instruction, LLMs have demonstrated promise in providing detailed feedback on grammatical accuracy, style, and coherence [1]. Mohamed [15] highlighted the capability of LLMs to create level-appropriate reading materials that maintain pedagogical progression while incorporating target vocabulary and grammatical structures. This adaptability in generating instructional content allows for more personalized language learning experiences that are particularly beneficial for learners at different proficiency levels.

The interactive capabilities of LLMs have revolutionized language practice opportunities. Studies indicate that LLMs can create authentic language practice environments where learners can engage in meaningful conversations while being able to make mistakes [4]. This setting is particularly valuable for EFL contexts, in which opportunities for authentic language practice may be limited. Labadze *et al.* [16] found that LLMs can maintain contextually appropriate conversations across various topics, helping learners develop fluency and confidence. The immediate personalized feedback provided by LLMs during these interactions helps learners identify and correct errors in real time, supporting their language development [17].

However, research has also emphasized the importance of implementing LLMs in language education. Jia and Tu [18] highlighted the need for the careful integration of LLMs into traditional language teaching methods, noting that although LLMs provide immediate feedback and practice opportunities, they should complement rather than replace human instruction. Tirumala *et al.* [19] addressed the importance of ensuring linguistic accuracy in LLM-generated content, particularly in language learning applications. Mohamed [15] highlighted the need to consider cultural and linguistic nuances when using LLMs for language instruction, especially in EFL contexts, where cultural understanding is vital for language acquisition. These considerations underscore the importance of thoughtful implementation strategies that maximize the benefits of LLMs while addressing their limitations in language education settings.

C. Integrating Generative AI in EFL Instruction: Theoretical Foundations and Pedagogical Implications

Reading comprehension remains a critical challenge for EFL students, particularly in technical and vocational contexts where specialized vocabulary and complex texts are prevalent [20]. Early studies investigating the role of information technology in language education demonstrated that multimedia environments, interactive tools, and digital resources can enhance vocabulary development and reading fluency [21, 22]. However, these IT-based approaches often fall short in systematically incorporating business-specific vocabulary and managing the complex syntactic and semantic features that characterize TOEIC reading passages. Subsequent research employing mobile devices showed positive outcomes in reading instruction and learner engagement [23], yet such studies primarily focused on general language acquisition rather than the specific demands of standardized testing. More recently, advancements in AI technologies have introduced innovative possibilities for personalized reading comprehension support. For instance, AI-powered reading assistants have been shown to analyze learners' vocabulary knowledge and reading patterns to provide adaptive scaffolding [24], while AI-based annotation systems generate contextual explanations and vocabulary support that significantly improve comprehension [25]. Additionally, AI-driven systems have demonstrated the capacity to generate practice materials that mirror standardized test formats while adapting to individual proficiency levels and dynamically modulating text complexity to suit learner needs, a feature particularly beneficial for addressing the layered and business-oriented nature of TOEIC passages [4]. While AI has been proven effective in reading instruction [15], limited research exists on how such advanced AI technologies can be specifically leveraged to support underperforming technical university students in meeting standardized test requirements such as the TOEIC. This research gap is particularly significant, considering the unique challenges faced by technical university students who must balance demanding technical coursework with the need to achieve language proficiency.

In recent years, the academic community has increasingly focused on the application of generative artificial intelligence—particularly ChatGPT—in the context of EFL instruction. A systematic review by Lo *et al.* [26] of seventy empirical studies conducted within the first eighteen months following the advent of ChatGPT revealed that the tool offers several advantages, including enhanced learning opportunities, the provision of personalized learning experiences, and robust support for teacher instruction. Nevertheless, concerns remain regarding potential inaccuracies, privacy issues, and the misuse of ChatGPT for academic misconduct. Specific investigations into the role of ChatGPT in teaching English writing have shown that students perceive the AI-generated feedback as practical, interactive, and adaptive, effectively addressing both superficial grammatical errors and deeper structural issues in compositions [27, 28]. Similarly, emerging research on speaking practice indicates that ChatGPT can serve as an effective conversational partner, significantly improving learners' speaking self-efficacy, reducing anxiety, and enhancing overall enjoyment during language practice [29]. Moreover, studies exploring autonomous learning have demonstrated that ChatGPT's flexibility and personalized features empower language learners to access materials tailored to their individual knowledge levels and interests, thereby facilitating greater self-monitoring and control over their learning progress [30]. Generative AI has also been integrated into practical EFL teaching models where, for instance, educators employ ChatGPT as an instructional assistant to generate customized reading passages, dialogue examples, and practice exercises that align with learners' proficiency levels, while also providing immediate feedback during classroom interactions. In writing instruction, ChatGPT functions as an intelligent tutor by offering corrective feedback and suggestions for improving essay structure and coherence, thus alleviating some of the workload on instructor. Additionally, by serving as a simulated conversation partner, ChatGPT enables learners to engage in interactive dialogue practice that adapts to their language proficiency and supports comprehensive skill development. Although the existing literature demonstrates that generative AI plays a multifaceted role in EFL education—from providing writing guidance and facilitating speaking practice to supporting self-directed learning—the potential of these tools to specifically enhance standardized test preparation for underperforming technical university students remains underexplored.

III. Method

A. Participants

A total of 226 individuals (133 female and 93 male) comprised the study sample for the experiment and analysis. The participants ranged from freshmen to senior-year students at a four-year technical university in central Taiwan and were aged between 18 and 22 years. This institutional setting is primarily oriented toward cultivating application-focused graduates with practical industry competencies. Most students enter the university from technical and vocational high schools, where their prior learning experiences are largely concentrated on specialized fields such as information technology, management, logistics, and design. To ensure the baseline consistency of participants' English reading proficiency, the university conducted a fundamental academic competency assessment at the beginning of the semester. On the basis of the assessment results, students were categorized into three levels: A, B, and C, with each level receiving corresponding English instruction tailored to their proficiency. All study participants were selected from C-level classes, representing a group with relatively lower English reading proficiency. All participants provided informed consent, were advised that participation was voluntary, and retained the right to withdraw at any time. Ethical approval was obtained from the Institutional Review Board in 2025.

B. Instructional Design and Flow

This study employed a quasi-experimental design in which participants were divided into an experimental group (n = 113) and a control group (n = 113). Students were randomly assigned to either group. To control for potential instructional variability, both groups were taught by the same instructor, thereby ensuring consistency in teaching style, instructional pacing, and classroom management across conditions.

In the initial week of the experimental process, the research objectives and procedures were explained to all participants in both groups. A pre-test involving TOEIC simulation questions was administered to establish baseline proficiency levels. The test results indicated that all participants' reading section scores were significantly below 200 (M = 147.11, t = 20.328, p < 0.001). This result highlighted the participants' notable deficiencies in vocabulary comprehension, grammatical usage, and reading proficiency.

From weeks 2 to 11, the experimental and control groups were trained in the same 10-week course. The experimental group received instructions using supplementary learning materials generated by AITAs during regular class hours, whereas the control group was exposed to traditional teaching methods for TOEIC courses. Following the 12-week training period, both groups participated in a post-test TOEIC examination. The experimental group also completed a questionnaire survey. The experimental process is illustrated in Fig. 1.

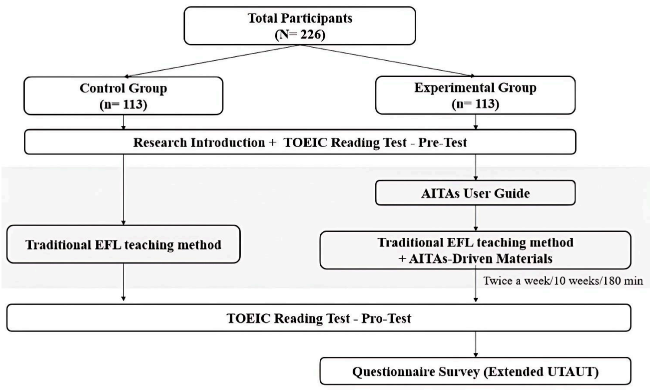

Fig. 1. Experimental process.

The teaching schedule was structured to include two classes per week, each lasting three hours. In the control group, the instruction was entirely teacher led, employing traditional teaching methods, such as TOEIC textbooks, PowerPoint presentations, and other instructional tools to deliver and practice TOEIC-related content. Conversely, the experimental group adhered to the same 3-hour course schedule, with 120 min allocated to traditional instruction. The remaining 60 min were dedicated to "learning scenario topics" activities, which were automatically generated by the AITAs. These learning units encompassed three key topics: vocabulary, grammar, and reading, aiming to further enhance the students' learning outcomes. Participants were permitted to flexibly adjust the sequence and timing of the learning units according to their individual progress, thereby promoting greater autonomy and adaptability in the learning process.

The supplementary learning content generated by the AITAs was verified for quality by two professional English teachers to ensure that the learning materials were of high quality and aligned with the TOEIC exam.

C. Configuring and Training AITAs

In terms of fine-tuning to train AITAs' learning materials, the TOEIC exam primarily tests scenarios and topics pertaining to business and daily life. Therefore, we referred to 13 common scenario topics proposed by the official Taiwanese TOEIC testing website[1] to create vocabulary, grammar, and reading learning materials. These topics encompassed office environments, human resources, manufacturing, dining out, corporate development, entertainment, finance or budgeting, general business, healthcare, housing or corporate real estate, travel, and procurement or technical aspects. All instructional materials used in this study were independently collected, organized, and developed by the course instructor.

The vocabulary training set included 10,000 frequently tested words. The grammar training set encompassed the most commonly tested grammatical structures and examples, covering topics such as tenses, passive voice, conditional sentences, comparisons and superlatives, infinitives and gerunds, relative pronouns, prepositions, modal verbs, and direct and indirect sentences. The reading training set comprised 254 passages (long and short). These passages were primarily collected from publicly available sample materials released on the official TOEIC website and were supplemented with instructional texts originally authored by the course instructor. All materials were either publicly accessible or instructor-developed, and no proprietary, non-public, or restricted TOEIC test content was used.

This study utilized the My GPTs feature within ChatGPT to configure and train AITAs (My GPTs/Create a GPT/Create), naming it "AITAs–TOEIC". Subsequently, within the configuration interface, interactions with the GPT Builder were conducted to progressively configure the attributes of AITAs, including its name, description, instructions, and conversation initiation settings. The configured prompt is illustrated in Fig. 2.

Subsequently, the comprehensively collected TOEIC training set, including vocabulary, grammar, and reading materials, was individually uploaded to serve as the knowledge base for "AITAs–TOEIC", ensuring that it provides accurate and relevant information, as illustrated in Fig. 3. Furthermore, if a new TOEIC training set needs to be added in the future, the same procedure can be followed for expansion, thereby maintaining the completeness and up-to-dateness of the knowledge base and ensuring the continuous optimization of the system's response capability and accuracy. In configuring and training the "AITAs–TOEIC," we have taken stringent measures to ensure ethical compliance. The knowledge base was restricted to publicly available materials published on the official TOEIC website (e.g., topic outlines and freely accessible sample materials) and instructor-authored practice materials developed to align with those public sources; no proprietary, non-public TOEIC test forms or restricted content were uploaded. Moreover, students access the AITAs tool in their own secure online environment, where no personal data is collected or monitored, thereby eliminating risks related to data privacy or confidentiality breaches. Additionally, the system's configuration involves rigorous prompt instructions that restrict responses to the validated domain of TOEIC training, effectively mitigating potential biases inherent in generative AI outputs. These measures collectively ensure that our implementation of AITAs-driven materials adheres to ethical standards and addresses concerns related to data privacy and AI bias. Finally, a link to the "AITAs-TOEIC" was shared with the learners, enabling them to use this tool in their TOEIC studies.

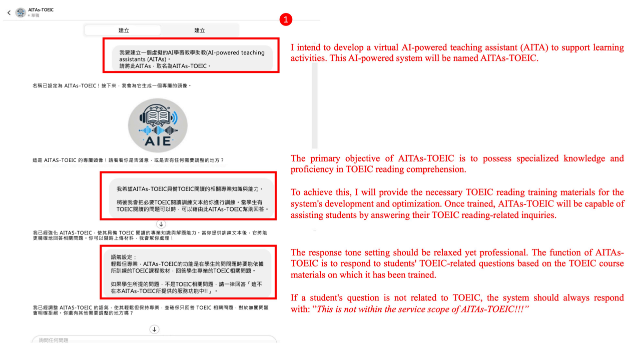

Fig. 2. Configuration step 1 for AITAs.

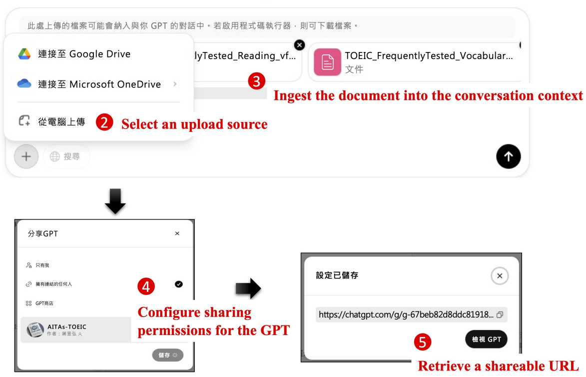

Fig. 3. Configuration steps 2–5 for AITAs.

To control for external factors, all students registered with ChatGPT and logged in successfully before the experiment began. To prevent erroneous content generation, learners were given learning prompts and sequential input instructions. Notion note-taking software was used to document students' weekly learning progress, ensuring consistent schedule completion.

For vocabulary learning, students utilized "AITAs–TOEIC" to randomly generate the 100 most frequently tested words for each scenario. The prompts and

[1] https://www.toeic.com.tw/toeic/listening-reading/about/content/

outputs generated by the "AITAs–TOEIC" are shown in Fig. 4. The scenario topic was updated weekly, and vocabulary learning was structured around the newly generated thematic vocabulary.

Fig. 4. Example of vocabulary related to the office scenario generated by the AITAs.

For grammar learning, segregating content on the basis of specific scenarios or topics was difficult. Therefore, students used the "AITAs–TOEIC" to generate the most commonly tested grammatical sentence structures for TOEIC. The prompt was as follows: "Please refer to the grammar training dataset and generate the definition of "passive voice" along with the most frequently tested sentence structures". Thereafter, "AITAs–TOEIC" generated the corresponding explanations and examples for each commonly tested grammatical sentence structure, as shown in Fig. 5.

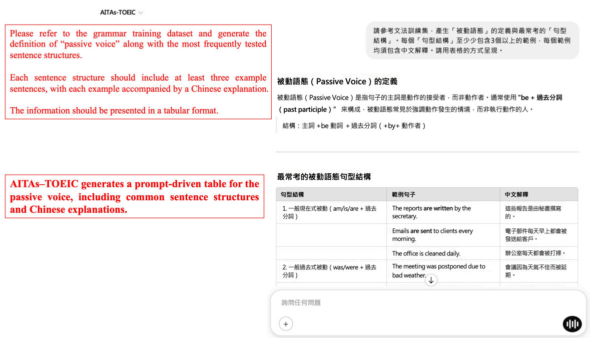

Fig. 5. Example of grammar regarding the passive voice generated by AITAs.

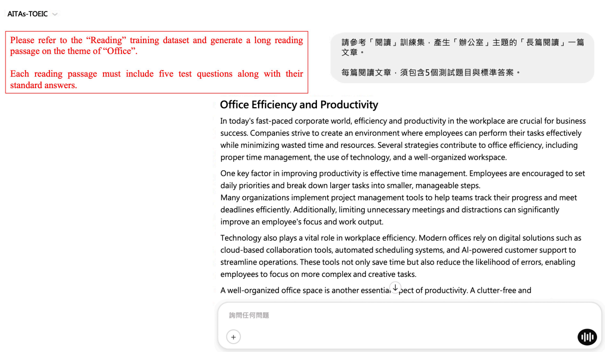

Fig. 6. Example of long reading passage related to the office scenario generated by AITAs.

For the reading learning, we referred to the commonly tested scenario topics outlined in the official TOEIC test in Taiwan. Each week, four reading articles (two long and two short) were generated for each scenario, with each article containing five test questions and their corresponding standard answers. The generated long and short reading learning content is respectively presented in Figs. 6 and 7. The scenario topic was updated weekly, and new articles consistent with the new scenario were generated for further study.

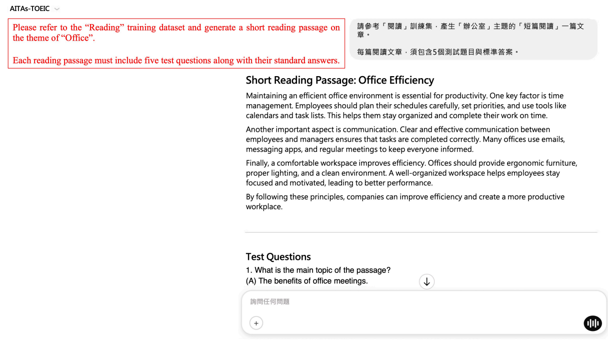

Fig. 7. Example of short reading passage related to the office scenario generated by AITAs.

The actual learning scenarios of students utilizing the "AITAs–TOEIC" are presented in Fig. 8.

Fig. 8. Actual learning scenarios of students utilizing the AITAs.

D. *Research Frameworks*

To determine whether AITAs-driven materials can enhance students' learning outcomes, all participants completed TOEIC simulation pre- and post-tests. The difficulty level of the TOEIC simulation test was defined as easy by the instructing teacher. The simulation focused on the reading section of the TOEIC examination, covering question types such as sentence completion, paragraph completion, and single- and multiple-passage reading. The experimental and control groups had identical content in the pre- and post-tests. Subsequently, the average scores of all tests and a one-way Analysis of Covariance (ANCOVA) were used to examine students' TOEIC learning outcomes in the two different forms of instruction.

We employed the extended Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh *et al.* [31] to further understand the attitudes and behavioral intentions of students toward using AITAs-driven materials. This model was selected given its effectiveness in predicting and explaining technology adoption behaviors in educational contexts. The UTAUT offers a structured framework that evaluates key factors such as Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), all of which are relevant to understanding how students interact with the AITAs [32]. These constructs provide insights into the perceived usefulness and ease of integrating the AITAs into EFL instruction. Furthermore, the model's flexibility allowed for the inclusion of context-specific variables, such as AI Self-Efficacy (AISE) and Task–Technology Fit (TTF), which addressed the unique challenges faced by underperforming EFL learners in technical and vocational education. Agyei and Razi [33] and Zou *et al.* [34] demonstrated the model's robustness in similar settings, confirming its relevance in evaluating students' acceptance of innovative learning technologies. Similarly, Muhamed and Kamsin [35] highlighted that teachers' acceptance and intention to use AI technologies in instruction may differ from students due to role-specific expectations and contextual factors, reinforcing the importance of considering user roles in UTAUT-based analyses. Therefore, applying the extended UTAUT in this study facilitated an in-depth understanding of the behavioral and contextual factors that influence the adoption of AI-driven tools, bridging theoretical rigor and practical relevance.

The operational definitions of all variables are described as follows:

- Performance Expectancy (PE) refers to the extent to which learners expect that utilizing AITAs-driven materials will enhance their learning outcomes. This includes the perceived impact on learning efficiency, productivity, and academic performance. The questionnaire items were developed based on Venkatesh *et al.* [36] and Agyei and Razi [33].
- Effort Expectancy (EE) refers to learners' perceptions of the ease of use and convenience associated with AITAs-driven materials. This includes the clarity of operation, ease of learning, and the extent to which the materials enable learners to achieve their learning objectives with reduced effort. The items were designed based on the frameworks proposed by Venkatesh *et al.* [36] and Agyei and Razi [33].
- Social Influence (SI) refers to the impact of teachers, peers, or the learning environment in encouraging learners to use AITAs-driven materials, shaped by external expectations or support. The questionnaire items were developed based on Venkatesh *et al.* [36] and Agyei and Razi [33].
- Facilitating Conditions (FC) refer to the resources, knowledge, and technological compatibility that support learners in using AITAs-driven materials, including access to assistance when needed. The questionnaire items were based on Venkatesh *et al.* [36] and Agyei and Razi [33].
- AI Self-Efficacy (AISE) refers to learners' confidence in their ability to effectively use AITA, including their knowledge of the AITAs' applications, understanding of its underlying logic, and capacity to generate learning materials. The questionnaire items were developed based on Cancino and Towle [3].
- Task－Technology Fit (TTF) refers to the extent to which AITAs-driven materials align with students' learning needs, including the accuracy, relevance, and clarity of information, as well as well-defined classifications that enhance learnability. The questionnaire items were developed based on Lo Presti *et al.* [37].
- Behavioral Intention (BI) refers to students' willingness to use AITAs-driven materials in the future, encompassing their plans, predictions, and likelihood of recommending them to others. The questionnaire items were developed based on Venkatesh *et al.* [36] and Agyei and Razi [33].
- Usage behavior (UB) refers to students' self-reported usage patterns of AITAs-driven materials, including frequency, preferences, and the extent to which they adopt them as primary learning tools. UB was measured via the post-intervention questionnaire; no system-level usage logs or learning analytics were collected. The questionnaire items were developed based on Wang *et al.* [38].

Table A1 in Appendix presents the final items of the questionnaire. A 5-point Likert scale was used to gauge the degree of agreement between statements. To ensure that the participants understood the subtle nuances of semantics to the greatest extent possible, a questionnaire was administered in the students' native language Chinese.

E. Research Hypotheses and Model

The research hypotheses and model are shown in Fig. 9. The following are the inferences for each hypothesis.

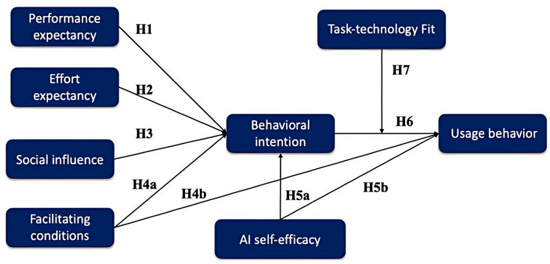

Fig. 9. Research hypotheses and model.

Performance expectancy, defined as the degree to which individuals believe a technology will enhance their performance, is a critical determinant of behavioral intention [31]. Alhadiah [39] reported that students' perceptions of technology's usefulness positively influence their intent to use mobile-assisted language learning Agyei and Razi [33] found performance expectancy to be a key predictor of behavioral intention in adopting AI-enhanced flipped classrooms. Zou *et al.* [34] emphasized its role in fostering satisfaction and sustained use of educational technologies. Thus, we hypothesize the following:

H1: Performance expectancy is positively related to behavioral intention.

When learners find a technology intuitive and simple to use, their likelihood of adopting it increases significantly. Alhadiah [39] found that ease of use directly enhanced learners' acceptance of mobile-assisted language tools. Agyei and Razi [33] similarly emphasized that effort expectancy is a critical factor in predicting students' intention to utilize AI-driven flipped classrooms. Zou *et al.* [34] also identified effort expectancy as central to improving user satisfaction and engagement with educational technologies. Based on these findings, we hypothesize the following:

H2: Effort expectancy is positively related to behavioral intention.

Social influence refers to the extent to which individuals perceive that important others, such as peers, instructors, or colleagues, expect them to use a particular technology [31]. Alhadiah [39] demonstrated that peer and instructor recommendations were pivotal in promoting students' acceptance of mobile-assisted language learning tools. Agyei and Razi [33] observed that collaborative learning environments, supported by mentors, facilitated the adoption of AI-driven flipped classrooms. Zou *et al.* [34] underscored that social influence boosts learner motivation and engagement in technology use. Thus, we propose the following hypothesis:

H3: Social influence is positively related to behavioral intention.

Facilitating conditions, which encompass the resources and support available to users, play a critical role in the adoption of technology. In the realm of language learning, access to appropriate infrastructure and technical support has been shown to significantly affect learners' intentions to adopt new tools. Alhadiah [39] highlighted that the provision of essential resources and assistance positively influences learners' acceptance of mobile-assisted language learning. Moreover, Agyei and Razi [33] and Zou *et al.* [34] demonstrated that institutional support and an enabling learning environment are vital in fostering technology-related behaviors among learners. Based on these findings, we propose the following hypotheses:

H4a: Facilitating conditions are positively related to behavioral intention.

H4b: Facilitating conditions are positively related to usage behavior.

AI self-efficacy refers to an individual's belief in their ability to effectively utilize AI tools. Bessadok and Hersi [40] demonstrated that higher levels of AI self-efficacy significantly enhance students' behavioral intentions to adopt AI-driven learning platforms. Similarly, Agyei and Razi [33] found that individuals with greater confidence in their AI-related skills were more likely to adopt AI-powered flipped classrooms. Furthermore, AI self-efficacy plays a crucial role in determining actual usage behavior [39]. Jia and Tu [18] highlighted that learners with higher confidence in their AI capabilities are more likely to actively engage with AI tools. Alhadiah [39] also revealed that increased AI self-efficacy led to greater engagement with AI-based learning environments. Based on these findings, we propose the following hypothesis:

H5a: AI self-efficacy is positively related to behavioral intention.

H5b: AI self-efficacy is positively related to usage behavior.

When learners demonstrate high intention to use a technology, they tend to engage with it in practice. Zhang *et al.* [7] showed that students' intention to use AI-powered learning tools strongly influenced their actual usage in language learning environments. Similarly, Humida *et al.* [41] emphasized that students who indicated greater behavioral intention to use e-learning platforms were more involved in their actual usage. Based on these findings, we propose the following hypothesis:

H6: Behavioral intention is positively related to usage behavior.

A well-aligned TTF strengthens the link between users' behavioral intention and their actual behavior by ensuring the technology meets specific needs [42]. Presti *et al.* [37] demonstrated that TTF enhanced the transition from intention to action in educational technology use. Al-Mamary *et al.* [43] noted that AI learning tools designed to align with specific tasks enhanced both students' behavioral intention and their actual usage behavior. Based on these findings, we propose the following hypothesis:

H7: Task-technology fit moderates the positive relationship between behavioral intention and usage behavior.

IV. Data Analysis and Results

A. Analysis of Learning Achievement

RQ1: Does the EFL learning material generated by the AITAs exhibit high quality and satisfy the standards required for the TOEIC reading test?

We employed Krippendorff's alpha as an indicator of interrater reliability, which determines the similarity of data collected by different raters to ensure the reliability of the assessment results. This approach is advantageous because it supports categorical, ordinal, interval, and ratio types of data and accounts for missing data [44]. The informative, useful, and answerable assessment metrics were manually labeled on a scale of 1–5 by two domain experts (English teachers). Table 1 shows the results of interrater reliability, indicating that AITAs-driven materials had good reliability (Krippendorff's $\alpha = 0.906$).

Table 1. Performance of interrater reliability

	Krippendorff's α	LL 95%	UL 95%
Ordinal	0.906	0.872	0.924

Note: Lower Limit (LL); Upper Limit (UL)

RQ2: Does the use of AITAs-driven materials to assist EFL learning significantly improve participants' TOEIC reading test scores compared with traditional EFL learning materials?

The ANCOVA was used to evaluate students' learning achievement in the experimental and control groups.

Table 2. One-way ANCOVA result of the post-test scores of the two groups

Group	n	Mean	SD	Adjusted Mean	Adjusted SE	F	Cohen's d
Experimental group	113	305.11	25.055	305.219	2.667	182.260^{***}	0.449
Control group	113	262.84	22.130	262.728	2.704		

Note: $^*p < .05$; $^{**}p < .01$; and $^{***}p < .001$

The test of homogeneity of within-group regression coefficient was first preceded before one-way ANCOVA. The regression coefficient homogeneity test result shown that it does not violate the hypothesis of regression coefficient homogeneity ($F = 0.084$, $p = 0.772 > 0.05$), indicating that the assumption was tenable and that the ANCOVA could be used to interpret the relationships between students' prior knowledge and their learning achievement in the post-test. Table 2 presents the results of learning achievement as indicated by the post-test scores of both groups. For the experimental group, the adjusted means and standard errors were 305.219 and 2.667, respectively, whereas those for the control group were 262.728 and 2.704, respectively. These findings revealed a statistically significant difference between the post-test scores of the two groups (F (1, 223) = 182.260, $p < 0.001$). Furthermore, Cohen's $d = 0.449$ indicates a moderate effect size between the two groups [45], suggesting that, compared to the control group, the experimental group demonstrated improved performance after the use of AITAs-driven materials, highlighting the effectiveness of the experimental approach in enhancing learning outcomes.

B. Statistical Methodology

RQ3: Which factors influence learners' behavioral intention and usage behavior toward AITAs-driven EFL materials?

The demographic characteristics of the sample indicated that the experimental group consisted of 113 participants. In terms of gender distribution, 63% were female ($n = 71$), while 37% were male ($n = 42$). Regarding grade level, 23% were first-year students ($n = 26$), 18% were second-year students ($n = 20$), 32% were third-year students ($n = 36$), and 27% were fourth-year students ($n = 31$). The participants were enrolled in various academic disciplines, with 48% from the School of Business ($n = 54$), 33% from the School of Languages and Literature ($n = 37$), 21% from the School of Information and Logistics ($n = 24$), and 12% from the School of Design ($n = 14$).

In terms of technology usage habits, 94% of participants ($n = 106$) regularly incorporated technology into their learning, while 6% ($n = 7$) used it only occasionally or not at all. The most commonly used technological devices included computers (95%, $n = 107$), tablets (81%, $n = 92$), and interactive whiteboards (64%, $n = 72$). Furthermore, this study examined participants' engagement with AI-related technologies. The findings revealed that the most frequently used AI tools were generative chatbots (98%, $n = 111$), AI-generated graphics (76%, $n = 86$), and AI-generated music (36%, $n = 41$), indicating that participants possessed relatively extensive experience in using these AI tools.

To ensure the validity of the measurement model, this study assessed the convergent validity of the variables. All item loadings exceeded the recommended threshold of 0.7 [46]. As presented in Table 3, both Cronbach's α and composite reliability for the latent variables surpassed the 0.7 benchmark. Additionally, the Average Variance Extracted (AVE) for each variable exceeded the recommended minimum of 0.5, confirming adequate convergent validity [47].

Moreover, to evaluate discriminant validity (see Table 4), this study verified that the square root of the AVE for each variable was greater than the inter-construct correlations [48]. Furthermore, the Heterotrait-Monotrait Ratio (HTMT), which assesses the average of HTMT correlations, remained below the 0.85 threshold in all cases [46], providing additional support for discriminant validity.

Table 3. Convergent validity of the variables

Variables	Cronbach's α	CR	AVE
PE	0.895	0.922	0.772
EE	0.888	0.917	0.759
SI	0.824	0.841	0.586
FC	0.757	0.797	0.582
AISE	0.899	0.931	0.837
TTF	0.934	0.952	0.892
BI	0.942	0.954	0.869
UB	0.952	0.961	0.893

Note: performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), AI Self-Efficacy (AISE), Task–Technology Fit (TTF), Behavioral Intention (BI), and Usage Behavior (UB)

Table 4. Discriminant validity

Variables	Latent variable correlations								
	No.	1	2	3	4	5	6	7	8
PE	1	**0.882**							
EE	2	0.513	**0.834**						
SI	3	0.363	0.562	**0.831**					
FC	4	0.680	0.322	0.448	**0.901**				
AISE	5	0.492	0.533	0.386	0.522	**0.822**			
TTF	6	0.440	0.528	0.602	0.598	0.546	**0.774**		
BI	7	0.374	0.465	0.455	0.564	0.446	0.573	**0.918**	
UB	8	0.342	0.632	0.457	0.352	0.485	0.389	0.633	**0.893**

Note: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Condition (FC), AI Self-Efficacy (AISE), Task–Technology Fit (TTF), Behavioral Intention (BI), and Usage Behavior (UB).

C. Statistical Methodology

This study employed the PLS-SEM algorithm using the weighting path scheme in SmartPLS 4 (Version 4.0.9.6), with a maximum of 3000 iterations and default initial weights. Additionally, following the recommendations of Sarstedt *et al.* [49], a nonparametric bootstrapping procedure was conducted with 5000 resamples to assess the statistical significance of the PLS-SEM results.

The assessment of the structural model involved estimating the model fit, path loadings, and R2 values. The standardized Root Mean Square Residual (SRMR) is an approximate measure of overall model fit. In this study, the SRMR composite factor model was 0.056, indicating good overall model fit [46].

The structural model was estimated using path coefficients and R2 values, with the former being used to assess the statistical significance of the hypotheses and the latter to assess the model's ability to explain the variance in the dependent variables. The results of the path analysis are shown in Fig. 10.

The BI of AITA-assisted EFL learning was mainly explained by PE ($\beta = 0.244$, $p < 0.001$), EE ($\beta = 0.219$, $p < 0.001$), SI ($\beta = 0.412$, $p < 0.001$), FC ($\beta = 0.154$, $p < 0.05$), and AISE ($\beta = 0.359$, $p < 0.001$). The factors affecting BI, ranked from the highest to lowest, were SI, AISE, PE, EE, and FC. Moreover, the results indicated that the UB of AITA-assisted EFL learning was primarily explained by BI ($\beta = 0.383$, $p < 0.001$) and AISE ($\beta = 0.238$, $p < 0.01$). The TTF positively moderated the effect of BI on UB ($\beta = 0.182$, $p < 0.05$).

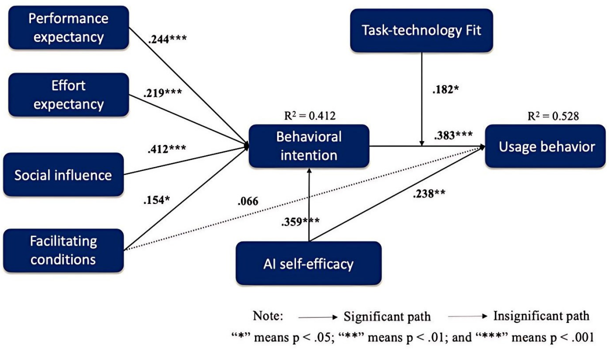

Fig. 10. Structural model analysis results.

V. Discussion and Implications

A. Examining the Quality of AITAs-Driven Materials and Differences in Learning Strategies for Enhanced Learning Performance

Krippendorff's alpha was used to assess the quality and TOEIC reading test standard adherence of the EFL materials generated by the AITAs, as evaluated by two proficient English teachers. The materials demonstrated good reliability and quality, with a Krippendorff's alpha of 0.906. Previous research has highlighted the advantages of LLMs such as ChatGPT–AITAs in language learning owing to their ability to produce unlimited, customized reading and writing practices tailored to learners' needs [17, 19]. This personalization benefits students who struggle with generic materials and lack tailored support in traditional classrooms. As LLMs memorize more data before overfitting and forget less, they are effective for educational purposes [19]. They can adjust text complexity, topics, and genres on the basis of learners' background knowledge and interests, offering more meaningful practices than static textbooks [50]. By capturing important aspects of meaning through conceptual roles, LLMs suggest ways to make them more human-like [50]. By leveraging LLMs, educators can provide personalized and adaptive EFL materials to enhance students' comprehension and literacy skills [39]. In addition, TOEIC reading passages specifically assess skills such as scanning for key information, making inferences, understanding complex syntactic structures, and interpreting business-oriented vocabulary. These skills often present challenges for technical university students who, despite their strong analytical and problem-solving abilities, may have limited exposure to the nuanced language and business contexts required for success in TOEIC reading. The high quality of AITAs-driven materials underscores their potential for use in EFL reading instruction.

An ANCOVA was conducted to compare the efficacy of AITAs-driven materials and conventional EFL resources by evaluating the post-test TOEIC reading scores of the experimental and control groups. The results showed that the experimental group, aided by the AITAs, achieved significantly higher post-test scores than the control group, indicating improved learning outcomes. This finding is consistent with Huamani-Anco and Maraza-Quispe (2025), who reported that ChatGPT enhances the coherence and creativity of students' written works [51]. This improvement may be attributed to the increased motivation and self-directed learning fostered by AITAs-driven materials, aligning with the findings of Labadze *et al.* [16] on the role of AI chatbots in personalized education. According to Keller's [9] ARCS model, generating personalized materials using an AITAs enhances motivation by providing autonomy, relevance, confidence, and satisfaction. Learners become more engaged and take ownership of their learning by critiquing and refining materials to foster self-directed learning [8]. Thus, learners' autonomy and self-direction are key factors driving improved outcomes [52].

B. Factors Positively Associated with Behavioral Intention

We used the extended UTAUT model to investigate the factors influencing learners' Behavioral Intention and the subsequent usage behavior of EFL learning facilitated by AITAs. Our findings indicate that the key antecedents of BI are Social Influence, AI Self-Efficacy, Performance Expectancy, Effort Expectancy, and Facilitating Conditions. Consistent with previous research in technology acceptance for language learning [53, 54], our results underscore the importance of peer and mentor support in reducing learners' doubts and fears about new technologies. This support not only enhances collaborative learning environments but also bolsters AI self-efficacy, as noted by Escalante *et al.* [55] and further echoed in studies [56].

Our study further revealed that AISE is a significant predictor of BI, aligning with earlier findings [33, 40], suggesting that learners with higher technological self-efficacy are more inclined to adopt AI applications in language learning. Similarly, both PE and EE positively impact BI, indicating that learners who perceive AI-driven tools as useful and easy to use—findings also reported in mobile-assisted language learning research [16, 57]—are more likely to form positive behavioral intentions. Additionally, FC plays a crucial role, as robust organizational and technical support facilitates the effective adoption of new learning methods [34, 39].

Moreover, the Task-Technology Fit in our model was found to positively moderate the relationship between BI and UB. When learners perceive a strong alignment between the AI technology and the specific learning tasks, their intentions are more likely to translate into effective usage, thereby enhancing learning outcomes [37]. This observation is consistent with integrative models that merge UTAUT with TTF perspectives [58].

Despite the overall explanatory power of the extended UTAUT model, several limitations warrant discussion. Given that the UTAUT was established and validated nearly 20 years ago, its constructs may not fully capture the evolving dynamics of technology adoption in today's rapidly changing educational contexts. For instance, our study noted potential misalignments between self-reported BI and self-reported Usage Behavior (UB), as well as overlapping influences among variables such as AISE and FC. In addition, because BI and UB were measured using the same post-intervention self-report instrument (without system-level usage logs), common-method variance and social-desirability bias may have inflated some observed associations; future studies should triangulate survey data with objective usage traces (e.g., prompt counts and time-on-task) where feasible. These unexpected findings suggest that while the extended UTAUT provides a useful framework, it may require further refinement or the inclusion of additional variables—such as learning willingness or perceived value—to better account for the nuances of generative AI applications in EFL settings. Higher education institutions should thus consider these limitations when integrating generative AI technologies, ensuring that resources and training are aligned with the diverse needs of students and that the human element in teaching remains paramount.

To deepen our discussion further, we integrated insights from prior research in language learning technologies. Lin *et al.* [59] have extended UTAUT by incorporating factors such as perceived risk and hedonic motivation, while Tian *et al.* [60] have combined UTAUT with the Expectation-Confirmation Model to explore post-adoption behaviors. These extensions highlight UTAUT's adaptability, although our study detected potential overlaps—particularly between AISE and FC—that underscore the need for additional constructs to capture the full spectrum of learners' motivations. Incorporating variables like learning willingness or perceived value [61, 62] may help explain the intention–behavior gap more comprehensively.

Overall, our empirical findings largely corroborate the established literature on technology acceptance in language learning, while also indicating that further refinement of the UTAUT framework is necessary to fully understand the complexities of integrating generative AI tools into EFL instruction. This deeper theoretical integration not only reinforces the validity of our results but also contributes novel insights into the evolving landscape of AI-driven language learning.

C. Contextualizing Findings across Institutional Settings and Cultural-Linguistic Contexts

From a cross-setting perspective, the learning gains observed in this study are broadly consistent with emerging experimental evidence from mainstream university contexts showing that ChatGPT-supported reading environments can reduce cognitive load and reading anxiety while improving foreign-language reading achievement [63]. Our intervention differs in two ways that matter for interpretation. First, it targeted TOEIC reading, a workplace-oriented standardized assessment that is frequently used as an institutional benchmark in Taiwanese higher education [10, 11], rather than academic paper reading. Second, the participants were low-proficiency learners in a technical university. The significant post-test advantage of the experimental group therefore suggests that generative AI-supported materials can be pedagogically meaningful even when learners begin with limited linguistic resources and when instruction must be scaled to large, heterogeneous cohorts.

With respect to adoption mechanisms, UTAUT2-based research in general higher education contexts has tended to highlight habit, performance expectancy, and hedonic motivation as prominent predictors of students' intention to use ChatGPT, with behavioral intention remaining a key proximal driver of actual use [64]. In contrast, our extended UTAUT results in a technical university indicated that social influence and AI self-efficacy were among the strongest predictors of behavioral intention, while task-technology fit amplified the translation of intention into usage behavior. One plausible interpretation is that, in vocationally oriented settings where learners may have less prior experience using generative AI for academic purposes and may be more dependent on structured instructional guidance, normative cues and scaffolded confidence building become comparatively more salient. This interpretation is also consistent with early-adoption evidence from a U.S. public research university showing that instructor encouragement and perceived instructional support vary substantially across courses and are consequential for whether and how students use ChatGPT for academic work [65].

These contextual differences are theoretically and practically consequential for the research gap in technical and vocational higher education. Technical universities are often characterized by application-focused curricula, intensive major requirements, and comparatively constrained opportunities for extensive English reading practice, which may magnify the perceived utility of on-demand, personalized materials while simultaneously increasing the need for facilitating conditions and task-aligned design [10, 12]. The moderating role of task–technology fit in our model underscores that the benefits of generative AI are not automatic; rather, they depend on purposeful alignment between the AI's affordances (e.g., adaptive text generation and immediate feedback) and the specific subskills demanded by TOEIC reading (e.g., vocabulary-in-context, grammar-in-use, and passage-level inference). Accordingly, evidence from research universities—where students often engage in self-directed academic reading and may already possess higher baseline proficiency—should not be assumed to transfer directly to technical university cohorts without testing and adaptation.

Finally, the shared linguistic and cultural background of participants warrants explicit consideration when interpreting both adoption and performance. Technology acceptance research has shown that culturally patterned values can shape the strength of social norms and other belief–intention pathways, such that normative influence may be more pronounced in contexts where interdependent orientations are salient [66, 67]. In an EFL classroom where learners share the same first language (Mandarin Chinese), interaction with AI tools may also involve strategic code-switching or L1-mediated scaffolding (e.g., requesting explanations or paraphrases in the L1 while practicing English input), which can lower cognitive load during comprehension but may also alter the balance between meaning negotiation and target-language exposure. Future multi-site and cross-cultural replications should therefore examine whether the relative importance of social influence and AI self-efficacy, as well as the magnitude of reading gains, remains stable across languages, cultural settings, and institutional missions.

D. Recommendations for Practice

1) AITAs-driven materials as effective instructional designs

AITAs-driven materials are innovative and effective tools that enhance learner motivation and engagement. Leveraging ongoing formative evaluation and, where available in future implementations, learning analytics, educators can continuously refine these materials to ensure contextual relevance and alignment with learner needs, thereby maximizing their impact on learning outcomes. For example, educators should adopt a cyclical process of evaluation and revision—using regular assessments and feedback sessions—to update content with current TOEIC business vocabulary and adjust text complexity to meet learners' needs.

2) Promoting positive perceptions of technology

As SI, AISE, PE, EE, and FC directly influence BI and UB, efforts should be directed toward fostering supportive environments that build trust and confidence among learners. Strengthening social and cognitive support systems can mitigate apprehension and improve learners' acceptance of technology. Enhancing TTF further ensures that the technology meets the specific demands of educational tasks, facilitating both intention formation and sustained use. Institutions are encouraged to organize professional development workshops and peer-led training sessions for educators, focusing on effective integration strategies for AITAs-driven materials. Moreover, educators should design scenario-based modules that specifically target the business-oriented language and complex structures found in TOEIC reading passages.

3) Ensuring robust facilitating conditions

Before implementing emerging technologies, educators must prioritize the development of robust facilitating conditions, such as clear instructional prompts and dependable infrastructure. These measures are essential to preventing the generation of unsuitable materials and fostering trust in the system. In technology-enhanced learning implementations, these conditions play a crucial role in enabling learners to view technology as a reliable and valuable educational tool. To this end, schools should invest in high-speed internet, up-to-date hardware, and user-friendly platforms, as well as provide comprehensive manuals and technical support to ensure seamless integration of AITAs-driven resources.

4) Balancing guidance and autonomy

While concerns about overreliance on generative technologies in education are valid [68], this study demonstrates how these tools can be effectively integrated to enrich the learning process without compromising learner autonomy. With appropriate teacher guidance, students can utilize AITAs-driven materials as a means to unlock their potential rather than as a crutch. Specifically, educators should implement a structured Guidance–Practice–Transformation (G–P–T) model [69]. In the Guidance phase, teachers introduce AITA-generated materials alongside clear instructions and targeted prompts. In the Practice phase, students engage with these materials in small groups or individual tasks that require them to apply and analyze the content. Finally, in the Transformation phase, learners critically reflect on their outputs—through written assignments or group discussions—to compare AI-generated content with traditional resources and solidify their understanding. This balanced approach promotes self-direction, critical thinking, and reflective practices, ensuring that generative AI complements rather than supplants traditional pedagogical methods.

E. Future Research Directions

This study sheds light on how AI-driven Teaching Assistants (AITAs) can boost TOEIC reading comprehension for low-proficiency EFL learners in a technical university, and how learners' acceptance can be explained through an extended UTAUT model. Nevertheless, it is important to acknowledge that all extended UTAUT constructs—including usage behavior—were measured via self-report because system logs or usage analytics were not available [28]. This single-source, self-reported measurement design may introduce common-method variance. Self-reported usage may be affected by recall or social-desirability bias and may not fully represent learners' actual interaction patterns with the AITAs. Accordingly, the reported relationships involving usage behavior should be interpreted as perceptions of use rather than verified behavioral traces. Future research could triangulate survey responses with objective usage traces (e.g., number of prompts, time-on-task, and types of AI-supported activities) to provide a more behaviorally grounded account of adoption and learning mechanisms. In addition, because the sample was drawn from a single technical university and a single proficiency band (C-level), the generalizability of the findings to other institutional types (e.g., research universities), disciplines, or proficiency levels is necessarily limited. Replication across multiple technical/vocational institutions, as well as comparative designs spanning universities with different missions and student profiles, would help determine which adoption drivers and learning gains are robust and which are context-contingent.

Moreover, while the instructor was instructed not to provide additional individualized guidance during the AITA-supported learning sessions, informal interactions or variations in instructional facilitation could not be entirely eliminated. Consequently, although the findings suggest that the observed differences in learning outcomes were primarily attributable to the use of AITAs-driven materials, the potential influence of unmeasured interactional factors cannot be fully ruled out. Future research is encouraged to employ more fine-grained observational methods, classroom interaction coding, or system log data to more precisely capture and control for instructional interaction dynamics.

Nevertheless, although the statistical analyses provide robust evidence of learning outcomes and behavioral relationships, the absence of qualitative data (e.g., interviews or open-ended responses) limits a deeper understanding of learners' experiences and interaction processes with the AITAs. Future research is therefore encouraged to incorporate qualitative methods to capture learners' perceptions, strategies, and contextual factors underlying their use of AI-powered learning tools.

Looking ahead, it would be fascinating to investigate the long-term effects of AITAs on broader language skills and career outcomes, extending beyond the immediate gains in TOEIC reading comprehension observed in our study [68]. Comparative studies across diverse educational environments—with varying levels of technological access and differing cultural attitudes toward technology—could further reveal the scalability of AI-driven tools. In terms of scalability, our findings suggest that AITAs have the potential to offer affordable, tailored learning solutions in resource-constrained settings. However, scaling these applications requires overcoming practical hurdles such as ensuring robust technological infrastructure, providing adequate teacher training, and integrating AI tools seamlessly into existing curricula [16].

On the ethical front, as AI applications become more widespread in education, issues related to data privacy and security become increasingly important. Future research should address ethical implications by developing clear guidelines and frameworks—such as compliance with GDPR and other relevant policies—to protect student data and ensure fairness. Moreover, while AITAs offer significant support, they cannot replace the nuanced role of human teachers in fostering critical thinking and social interaction [4]. Ensuring equitable access to these technologies is also crucial; smart policies will be necessary to bridge the digital divide and guarantee that underserved populations benefit from AI-enhanced Learning environments [68].

VI. Conclusion

This study evaluated ChatGPT-configured AI-powered Teaching Assistants (AITAs) as supplemental TOEIC reading support for low-proficiency EFL learners at a technical university. First, expert validation indicated that the AITAs-generated materials aligned with core TOEIC reading requirements and achieved high interrater reliability. Second, after controlling for baseline performance, students using AITAs-driven materials attained significantly higher TOEIC reading post-test scores than peers using conventional resources. Third, the extended adoption model showed that social influence, AI self-efficacy, performance expectancy, effort expectancy, and facilitating conditions predicted behavioral intention, and task-technology fit strengthened the intention-to-usage link. Overall, the findings support task-aligned, instructor-curated generative-AI materials as an effective and scalable approach to enhance TOEIC reading preparation in similar EFL contexts.

Appendix

Table A1. Scale items

Variables	Description of items	Sources
Performance Expectancy	PE1: I find AITAs-driven materials useful in my learning. PE2: Using AITAs-driven materials enables me to accomplish learning activities more quickly. PE3: Using AITAs-driven materials increases my learning productivity. PE4: Using AITAs-driven materials will boost my course marks.	[33, 36]
Effort Expectancy	EE1: My interaction with AITAs-driven materials is clear and understandable. EE2: I am skillful at using AITAs-driven materials. EE3: Learning to use AITAs-driven materials is easy for me. EE4: I find it easy to use AITAs-driven materials to do what I want it to do.	[33, 36]
Social Influence	SI1: The ELT teachers encourage me to use helpful AITAs-driven materials. SI2: The study partners encourage me to use helpful AITAs-driven materials. SI3: People who influence my behavior think I should use AITAs-driven materials. SI4: In general, the ELT course encourages us to use AITAs-driven materials for learning.	[33, 36]
Facilitating Conditions	FC1: I have the resources necessary to use AITAs-driven materials. FC2: I have the knowledge necessary to use AITAs-driven materials. FC3: The AITAs-driven materials are compatible with the other technologies I use. FC4: I can get help from others when I have difficulties with AITAs-driven materials.	[33, 36]
Artificial Intelligence Self-Efficacy	AISE1: I believe I possess the ability to use AITAs. AISE 2: I believe I have the relevant application knowledge for using AITAs. AISE 3: I think I can understand the logic of using AITAs. AISE 4: I believe I can easily use AITAs to generate the learning materials I need.	[3]
Task–Technology Fit	TTF1: The AITAs-driven materials can meet my learning needs. TTF2: The AITAs-driven materials can provide the necessary information for my academic studies. TTF3: The AITAs-driven materials are accurate and appropriate. TTF4: The AITAs-driven materials have clear definitions and classifications, making them easy to learn.	[37]
Behavioral Intention	BI1: I intend to use AITAs-driven materials to help in learning EFL in the future. BI2: I predict that I will use AITAs-driven materials to help in learning EFL in the future. BI3: I plan to use AITAs-driven materials to help in learning EFL in the future. BI4: I would recommend AITAs-driven materials to my colleagues for their EFL learning.	[33, 36]
Usage Behavior	UB1: I tend to use AITAs-driven materials for learning EFL. UB2: I would like to use AITAs-driven materials for learning EFL. UB3: I prefer to use AITAs-driven materials for learning EFL when available. UB4: I do most learning tasks by using AITAs-driven materials.	[4]

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, T.-C. Huang and Y.-H. Chiang; methodology, T.-C. Huang, H.-P. Tseng and Y.-H. Chiang; software, H.-P. Tseng and C.-H. Lu; formal analysis, T.-C. Huang and C.-Y. Chang; investigation, H.-P. Tseng and C.-Y. Chang; resources, T.-C. Huang and C.-H. Lu; data curation, H.-P. Tseng and C.-H. Lu; writing—original draft preparation, Y.-H. Chiang and T.-C. Huang; writing—review and editing, Y.-H. Chiang, H.-P. Tseng and T.-C. Huang; visualization, C.-Y. Chang and H.-P. Tseng. All authors have read and approved the final version of the manuscript.

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