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AI-powered personalized learning: Enhancing self-efficacy, motivation, and digital literacy in adult education through expectancy-value theory

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ABSTRACT

Although the implementation of artificial intelligence (AI) in educational contexts has gained increasing prominence, empirical research specifically examining its influence on crucial learner-related variables (e.g., self-efficacy, motivation, and digital literacy) among adult male learners of English as a Foreign Language (EFL) in China remains limited. The present study addresses this gap by investigating the effects of AI-powered personalized learning interventions on these key constructs. A total of 183 intermediate-level Chinese male EFL learners were randomly assigned either to an experimental group (EG), which received AI-personalized instruction, or to a control group (CG), which engaged in traditional instruction methods. Data were gathered through pre- and post-intervention surveys and analyzed using independent t-tests. Results indicated that compared to participants in the CG, learners in the EG exhibited statistically significant improvements in self-efficacy, motivation, and digital literacy. These findings offer robust empirical evidence supporting the effectiveness of AI-personalized instructional strategies in enhancing essential learner attributes within the adult male EFL context in China. Thus, the study advocates for the strategic integration of AI-powered personalized learning, highlighting its considerable potential to optimize language learning outcomes within adult EFL education.

1. Research background

Expectancy-Value Theory (EVT) posits that individuals' motivation to engage in a task depends on two key dimensions: *expectancy* (their belief in successfully performing the task) and *value* (their perception of the task's importance, interest, or utility) (Eccles & Wigfield, 2002; Rosenzweig et al., 2022). These dimensions are further nuanced into *attainment value* (personal significance), *intrinsic value* (enjoyment), *utility value* (practical benefits), and *cost* (perceived barriers) (Lazowski & Hulleman, 2016). In EFL contexts, EVT provides a critical lens to examine how AI tools influence learners' motivation by shaping their confidence in language tasks (*expectancy*) and their perceived relevance of Artificial Intelligence (AI)-mediated learning (*value*) (Hiver et al., 2020). This theoretical framework is particularly salient in China's higher education landscape, where rapid technological adoption intersects with cultural values of academic achievement (Li, 2024).

AI, encompassing a broad spectrum of computational methodologies designed to replicate human cognitive functions, has emerged

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as a transformative force across various sectors, most notably in education (Bhutoria, 2022; Crompton & Burke, 2023). Defined as the simulation of human intellectual processes by machines, particularly by computer systems (Labadze et al., 2023), AI now occupies an increasingly prominent role in English as a Foreign Language (EFL) education (Lihang et al., 2025; Rezai, Soyoof, et al., 2024). Its integration into educational practices presents considerable potential benefits, such as providing individualized instruction and immediate formative feedback; nevertheless, it simultaneously introduces significant challenges, including issues related to data privacy and the risk of excessive reliance on technological support (Dasam et al., 2024; Zhou & Hou, 2024). Although AI-driven platforms can adapt instruction to learners' individual preferences and thereby enhance engagement, concerns persist regarding their potential impact on the development of critical interpersonal abilities and the indispensable role of human interaction within language acquisition processes (Dai & Liu, 2024; Ding et al., 2024).

Building upon these advancements, AI-personalized learning specifically denotes the utilization of AI algorithms to individualize educational content and instructional methods according to the distinct needs of each learner (Montag et al., 2023; Vijayakumar & Panwale, 2025). This approach offers considerable advantages for EFL learners, particularly by adapting materials and resources to their unique proficiency levels and individual learning styles. According to Binhammad et al. (2024), personalized learning can significantly promote learner engagement through the provision of instructional content that is appropriately challenging yet attainable, thereby fostering learners' sense of progress and achievement. Furthermore, AI-driven personalization facilitates targeted feedback that addresses specific learner weaknesses while reinforcing existing strengths, a feature essential for effective language acquisition (Rezai, Namaziandost, et al., 2024; Xiong, 2024). Consequently, this customized instructional approach seeks to optimize the overall learning experience, thus ensuring that learners receive the individualized support and guidance necessary for their academic success.

To better elucidate the underlying mechanisms contributing to the efficacy of AI-personalized learning, EVT provides a valuable theoretical framework. This theory, as noted above, proposes that an individual's motivation and achievement outcomes are influenced by both their expectation of success in performing a task and the perceived value attributed to that task (Wang & Xue, 2022; Wigfield & Eccles, 2000). More precisely, according to Loh (2019), expectancy refers to an individual's beliefs regarding their capability to successfully execute a task, whereas value encompasses perceptions surrounding a task's importance, intrinsic interest, and practical utility. AI-personalized learning has the potential to enhance learners' expectancy for success by presenting appropriately challenging tasks coupled with immediate feedback, thereby fostering a greater sense of competence (Bhutoria, 2022; Hardaker & Glenn, 2025). Additionally, the perceived value of learning experiences may be augmented by delivering relevant and engaging content tailored to the learners' distinct interests and educational goals. Hence, from the perspective of EVT, AI-driven personalization can substantially enhance EFL learners' self-efficacy and motivation by aligning instructional experiences closely with their individually defined needs and aspirations.

As a foundational element of Bandura's Social Cognitive Theory, self-efficacy is defined as an individual's belief in their capability to systematically organize and execute the actions necessary to manage future situations successfully (Bandura, 1997). Within the context of EFL instruction, self-efficacy specifically pertains to learners' confidence in their ability to effectively acquire and utilize the English language (Genc et al., 2016). This psychological construct holds considerable significance, as it markedly influences learners' academic performance, motivation, and perseverance (Pawlak & Kruk, 2022; Schunk & DiBenedetto, 2020). High levels of self-efficacy enable individuals to engage proactively in learning activities, establish ambitious objectives, and effectively navigate arising challenges (Wang & Bai, 2017; Urhahne & Wijnia, 2023). Furthermore, learners who believe themselves capable of successfully performing necessary tasks are more inclined to actively pursue these tasks, thus leading to improvements in learning outcomes (Lee & Jang, 2024). In the contemporary digital era, comprehending and cultivating self-efficacy among EFL learners is increasingly imperative, particularly as technology continues to significantly reshape educational environments (Moos & Azevedo, 2009; Wang et al., 2013). Indeed, academic self-efficacy—a domain-specific self-belief regarding one's ability to succeed academically—serves as a crucial predictor of learners' educational achievement and success (Alqurashi, 2016; Wang et al., 2022).

The integration of AI into personalized learning platforms presents a promising avenue for enhancing adult EFL learners' self-efficacy, particularly when examined through the lens of EVT (Chan & Zhou, 2023; Wigfield & Eccles, 2000). According to this theoretical framework, learners' motivation is shaped by their expectations of success and by the perceived value attributed to learning tasks. AI-powered personalization can effectively influence both of these dimensions. For instance, AI algorithms can deliver immediate, customized feedback, reinforcing learners' progress and highlighting specific areas requiring improvement (Wei, 2023). This continuous feedback loop fosters a sense of competence, which Bandura and Locke (2003) identify as a crucial determinant of self-efficacy. In the context of adult education, where learners frequently navigate academic responsibilities alongside professional and personal obligations, personalized AI-powered learning facilitates goal-setting tailored to individual needs and enables real-time progress monitoring. Such customization cultivates learners' sense of control and enhances their capacity for self-regulation (Bhutoria, 2022; Deng & Yu, 2023). Furthermore, AI-driven technologies can provide targeted prompts and encouragement, thus reinforcing learner confidence and alleviating anxiety, especially in confronting complex tasks (Ismail & Alharkan, 2024; Namaziandost & Rezai, 2024). The implementation of adaptive learning pathways, carefully aligned with learners' unique styles and learning paces, promotes frequent opportunities for successful completions, thereby nurturing learners' self-efficacy (Chang et al., 2022; Gyonyoru & Katona, 2025). Additionally, through AI-generated analytics, learners can visualize their progress concretely—a factor well-established in the literature as instrumental in enhancing self-efficacy (Chen et al., 2020; Wu & Yu, 2024). As AI integration continues to expand within educational environments, investigating its impact on EFL learners' self-efficacy becomes increasingly crucial.

Motivation occupies a central position within the domain of second language acquisition, particularly in the context of EFL instruction. Broadly conceptualized, motivation refers to the psychological processes that activate, steer, and sustain behavior toward the achievement of language-learning objectives (Dörnyei & Ushioda, 2021; Lamb, 2017). In the EFL context, motivation encompasses far more than transient enthusiasm; rather, it is a sustained driving force that significantly influences learners' engagement, perseverance, and, ultimately, language proficiency development. Consistent with Deci and Ryan's Self-Determination Theory (SDT), intrinsic motivation—which arises from inherent interest and personal enjoyment—holds particular potency in fostering deep learning processes and long-term learner engagement (Hennebry-Leung & Lamb, 2024; Ryan & Deci, 2020). Nonetheless, extrinsic motivation, anchored in external rewards and pressures, likewise serves a critical function within EFL learning, especially in structured educational settings (Dörnyei, 2020; Noels et al., 2020). In the era of globalization, where proficiency in English increasingly conveys significant value, learners' motivational drives may originate from various sources, including instrumental objectives (e.g., professional and career advancement), integrative goals (e.g., cultural engagement and integration), and aspirations for personal growth (Gregersen & Mercer, 2022; Martin, 2020). As a consequence, fostering and sustaining learner motivation constitutes an essential task for EFL practitioners, as motivation directly shapes and determines learners' subsequent academic success.

Through the application of EVT, AI-personalized learning has the potential to influence motivation significantly (Wigfield & Eccles, 2000). This theoretical framework suggests that a learner's motivation is determined by their expectations of success and the subjective value they assign to a learning task. AI-driven personalization can effectively address both components. Primarily, AI algorithms are capable of analyzing learners' performance data to offer adaptive feedback and content recommendations, thus enhancing both perceived competence and expectations of success (Luckin et al., 2016; Xiong, 2024). As noted by Roll and Wylie (2016), AI's ability to provide detailed and timely feedback is crucial for fostering a sense of progress and accomplishment. Additionally, personalized learning platforms can customize educational activities to fit individual learners' interests, goals, and learning styles, thereby increasing the perceived value of the learning task (Hardaker & Glenn, 2025; Vijayakumar & Panwale, 2025). For adult learners, who often encounter time constraints and possess diverse learning needs, AI-driven personalization enables flexible and autonomous learning experiences, fostering a sense of control and self-efficacy (Binhammad et al., 2024). Furthermore, AI can incorporate elements of gamification, such as progress tracking, badges, and personalized challenges, to boost intrinsic motivation and make the learning process more engaging (Justin & Joy, 2024; Landers & Landers, 2014). The "flow" state, as described by Csikszentmihalyi and Larson (2014), in which learners are challenged but not overwhelmed, is also supported by AI's adaptive capabilities. AI can dynamically adjust the difficulty level to keep learners within their zone of proximal development. Consequently, AI-personalized learning has the potential to cultivate a more dynamic, engaging, and motivating learning environment, thereby improving outcomes for adult EFL learners.

The final variable examined in this investigation was digital literacy. For adult EFL learners, digital literacy transcends a mere collection of technical skills; it encompasses a range of competencies essential for effective interaction with digital resources aimed at language development (Eshet, 2004; Tinmaz et al., 2022). As Van Laar et al. (2017) indicate, these competencies include the ability to critically assess online information, employ digital tools for communicative practices, and navigate the sociocultural dimensions of digital environments. From a pedagogical standpoint, strong digital literacy skills enable learners to access authentic language corpora, engage in distributed learning communities, and tailor their learning trajectories (Audrin & Audrin, 2022; Jiang, 2025). Moreover, in professional settings, digital literacy is crucial for EFL learners to effectively engage in globalized communication networks, where digital mediation plays a significant role (Barkati et al., 2024; Dashtestani & Hojatpanah, 2022; Oberländer et al., 2020). Consequently, the development of digital literacy is not merely an auxiliary educational goal but a fundamental prerequisite for successful language acquisition and professional integration within the modern digital landscape.

From the standpoint of EVT, AI-personalized learning can significantly impact EFL learners' digital literacy. AI-personalized systems, which are designed to adapt to individual learning profiles, have the potential to enhance learners' expectations of success by offering tailored feedback and adaptive learning pathways (Binhammad et al., 2024; Hardaker & Glenn, 2025; Tabora et al., 2024). Personalized vocabulary acquisition modules and grammar explanation interfaces can boost learners' confidence in their ability to utilize digital tools for language development (Bhutoria, 2022; Namaziandost & Rezai, 2024; Shafiee Rad et al., 2024). Furthermore, the incorporation of interactive simulations and virtual language exchange environments can emphasize the utility value of digital literacy by underscoring its relevance to real-world communicative contexts. However, as noted by Dasam et al. (2024), it is crucial to recognize that usability challenges or perceptions of AI-generated feedback as irrelevant or unclear may diminish learners' expectancy of success, thereby impeding digital literacy development. Therefore, the design and implementation of AI-personalized learning systems must prioritize user-centered design principles and ensure the delivery of transparent, actionable feedback to optimize the enhancement of adult EFL learners' digital literacy.

The existing literature on AI-driven personalized learning underscores its positive impact on various educational outcomes. Shete et al. (2024) established a favorable relationship between AI-based adaptive learning and enhanced academic achievement, engagement, and satisfaction. Lim and Zhang (2022) corroborated the positive effects of AI-driven personalization in language learning, highlighting improvements in learner outcomes such as motivation and engagement. Du and Daniel (2024) demonstrated that AI-powered chatbots can enhance learners' speaking skills, while Huang et al. (2022) found that AI-enabled personalized recommendations significantly boost learning engagement and motivation in flipped classroom environments. Yang and Wen (2023) posited that AI personalization promotes students' academic development by enhancing motivation and self-efficacy. Rahimi et al. (2024) further supported the role of AI-assisted learning in cultivating personalized motivation and engagement. Additional studies, including those by Guo and Li (2024), Wang and Xue (2024), and Yuan and Liu (2024), collectively highlighted the positive effects of AI tools on EFL learners' engagement, enjoyment, and motivation. Furthermore, Pokrivcakova (2023), Zhi and Wang (2024), and Zou et al. (2023) reported favorable attitudes toward AI integration in educational contexts.

Despite the extensive research in this field, a gap persists in understanding the specific effects of AI-powered personalized learning on self-efficacy and digital literacy among adult learners in the context of language learning. Most studies predominantly concentrate on younger learners or broader academic outcomes, underscoring the need for research that directly addresses adult learners. This study seeks to bridge this gap by investigating the impact of AI personalization on Chinese adult learners, providing valuable insights into tailoring AI to the unique needs and challenges of this demographic. By focusing on self-efficacy and digital literacy, this research enhances the understanding of AI's role in optimizing adult learners' educational experiences. This study aligns with the broader literature by illustrating AI's potential to adapt to individual learning styles and needs, offering personalized learning experiences that support academic growth and engagement. Accordingly, the study addressed the following research questions:

1. Does AI-powered personalized learning significantly improve Chinese adult learners' self-efficacy?
2. Does AI-powered personalized learning significantly enhance Chinese adult learners' motivation?
3. Does AI-based personalized learning significantly promote Chinese adult learners' digital literacy?

2. Method of the research

2.1. Research design

The study utilized a true experimental design to explore the impact of AI-personalized learning on the self-efficacy, motivation, and digital literacy of Chinese adult learners. In this methodological framework, participants were randomly assigned to one of two groups: the experimental group (EG), which received AI-powered personalized learning interventions, and the control group (CG), which engaged in a traditional learning approach. The use of random assignment, a defining characteristic of true experimental design, ensured that both groups were comparable at the outset of the study. Pre-tests and post-tests were conducted for both groups to evaluate changes in the dependent variables throughout the intervention. The deliberate and well-reasoned choice of a true experimental design was aimed at maximizing control over extraneous variables, thereby enhancing the study's capacity to establish causal relationships between the intervention and its outcomes (Creswell & Creswell, 2017). Given the study's objective to assess whether AI-personalized learning markedly enhanced the specified variables, this design provided the necessary rigor to draw valid and reliable conclusions.

2.2. Research participants

This study was conducted within the EFL context, specifically targeting adult learners in China who were striving to enhance their English proficiency. The EFL setting holds particular significance in China, where English functions as a vital instrument for academic progression, professional advancement, and global communication. Unlike English as a Second Language (ESL) environments, where learners are immersed in the target language, the EFL context examined in this study represents a non-immersive setting. Here, learners primarily encounter English through formal instruction rather than daily interactions. This backdrop accentuates the importance of innovative methodologies, such as AI-personalized learning, to effectively address challenges related to motivation, self-efficacy, and digital literacy among Chinese EFL learners.

The study comprised 271 male Chinese adult learners, whose ages ranged from 31 to 37 years, with an average age of 34.2 years ($SD = 2.4$). All participants were native Mandarin Chinese speakers, ensuring linguistic homogeneity. A purposive sampling method was utilized to select participants, chosen for its effectiveness in targeting individuals who met specific study criteria—namely, intermediate English proficiency and familiarity with digital tools. Eligibility required participants to demonstrate intermediate English proficiency, as evidenced by Oxford Quick Placement Test (OQPT) scores ranging from 30 to 47 out of 60, in addition to a minimum of six months of experience with basic AI-powered tools. To form the EG and CG, the authors initially administered the OQPT to the entire pool of 271 learners. Participants were then ranked according to their scores and assigned to either the EG or CG using stratified randomization. Instructors for both groups were selected based on their qualifications and experience in EFL teaching. Specifically, four instructors were recruited, each holding a master's degree in TESOL and possessing a minimum of five years of teaching experience. To ensure consistency, all instructors underwent a two-hour training session prior to the commencement of the study, during which they were briefed on the research objectives and provided with standardized lesson plans.

The authors engaged with potential participants through the administrative offices of three language institutes. An initial recruitment email was disseminated, outlining the study's purpose, procedures, and expected time commitment. Interested learners attended an orientation session during which they received comprehensive verbal and written explanations of the study. Informed consent was obtained at this stage, with participants signing consent forms that highlighted their right to withdraw at any time without repercussions. Confidentiality and anonymity were assured by assigning each participant a unique identifier, and all data were stored securely on a password-protected server, accessible exclusively to the research team. It is worth noting that the study received formal approval from the Ethics Committee for Research at the first author's institution.

2.3. Research instruments

The first instrument employed in this study was the Oxford Quick Placement Test (OQPT), a globally recognized and standardized assessment of English language proficiency developed by Oxford University Press in collaboration with the University of Cambridge Local Examinations Syndicate (UCLES). The OQPT is designed to categorize learners based on their English proficiency levels and comprises three primary sections: grammar, vocabulary, and reading comprehension. The grammar section evaluates learners' knowledge of grammatical structures, the vocabulary section measures their understanding and application of English lexical items, and the reading comprehension section assesses their ability to interpret and analyze written texts. Each section consists of multiple-choice questions, exemplified by the following grammar item: "She ___ to the store every Saturday." (a) go, (b) goes, (c) going, (d) gone. Scoring is based on awarding one point for each correct response, with the cumulative score determining the learner's proficiency level according to a predefined rubric aligned with the Common European Framework of Reference for Languages (CEFR). In the present study, the OQPT was administered to all participants prior to the experiment to ensure the inclusion of only intermediate-level learners. From an initial pool of 271 EFL learners, 183 participants scored within the intermediate range and were subsequently selected for the study. This selection process ensured comparability between the EG and CG in terms of English language proficiency.

To measure self-efficacy, the Generalized Self-Efficacy Scale (GSES), developed by Schwarzer and Jerusalem (1995), was utilized. The GSES was chosen for its well-established reputation as a reliable and widely validated instrument for assessing general self-efficacy across diverse populations and contexts, including educational settings. The scale consists of 10 items, each designed to evaluate an individual's confidence in their ability to manage various situations. These situations encompass, but are not limited to, overcoming obstacles, handling demanding tasks, and coping with stress. Although the original authors did not explicitly delineate distinct subscales, the GSES can be conceptually interpreted as comprising two key dimensions: (1) problem-solving efficacy, which pertains to an individual's belief in their capacity to resolve challenging problems; and (2) resilience efficacy, which reflects confidence in managing stressful and adverse circumstances. For example, one item from the GSES states: "I can always manage to solve difficult problems if I try hard enough." Participants responded to each item using a 4-point Likert scale, ranging from "not at all true" to "exactly true." While the GSES is widely recognized for its high reliability and validity across various cultural and contextual settings, the current study necessitated a contextual adaptation to align with the specific focus on AI-personalized learning. Consequently, the instrument was modified to assess learners' self-efficacy within the context of AI-driven educational experiences. This adaptation preserved the core constructs of the original scale while ensuring its relevance to the study's objectives. A pilot study was conducted to evaluate the reliability and validity of the modified instrument, and expert judgment was sought to confirm its content validity. The pilot study yielded a Cronbach's alpha coefficient of 0.80, indicating high internal consistency. This result suggests that the items within the adapted scale are strongly interrelated and consistently measure the same underlying construct.

The instrument utilized in this study is an adapted version of the 18-item motivation questionnaire originally developed by Noels et al. (2000) to assess motivation among individuals learning a second language. This widely recognized tool was selected for its demonstrated efficacy in capturing motivational constructs relevant to language acquisition. The questionnaire comprises three primary sub-components: intrinsic motivation, which pertains to an internal drive to learn for personal satisfaction or enjoyment; extrinsic motivation, which is driven by external rewards or recognition; and amotivation, which reflects a lack of interest or engagement in the learning process. An example item, "I study Chinese because I enjoy the process of learning it," exemplifies intrinsic motivation and requires respondents to evaluate their personal connection to the learning experience using a 5-point Likert scale, ranging from "Strongly agree" (5) to "Strongly disagree" (1). To ensure the instrument's relevance to the context of AI-personalized learning, the questionnaire was meticulously adapted, with its phrasing refined to align with the unique features of the technological intervention. A pilot study involving a small cohort of Chinese adult learners was conducted to assess the clarity and appropriateness of the revised items, while input from language education specialists confirmed the instrument's content validity. Reliability analysis produced a Cronbach's alpha coefficient of 0.92, indicating excellent internal consistency.

The final instrument employed in this study was a questionnaire originally developed by Muawanah et al. (2024). Its selection was guided by its comprehensive coverage of digital literacy, a central construct in investigating the effects of AI-personalized learning on Chinese adult EFL learners, as well as its established application in peer-reviewed research related to technology-mediated education. The original instrument consisted of 28 items divided into four sub-components—Digital Literacy, AI, Sustainability of Regional Language (SRL), and E-learning Application—each comprising seven items. An example item, "I can confidently use digital tools to improve my English learning," highlights the instrument's focus on practical digital skills. Responses were recorded on a 5-point Likert scale ranging from 1 (Strongly disagree) to 5 (Strongly agree), chosen for its simplicity and analytical clarity. To ensure alignment with the context of AI-personalized learning, the authors adapted the Digital Literacy sub-component by rephrasing items to emphasize AI-driven tools. For instance, "digital tools" was modified to "AI-based learning tools" where appropriate. This adaptation was validated through a pilot study involving 30 Chinese adult EFL learners with similar characteristics, as well as expert judgment from three specialists in EFL and psychometrics. The validation process ensured face and content validity by confirming the relevance of the items to the study's specific context. The pilot test also refined item clarity, and the adapted scale demonstrated high reliability, achieving a Cronbach's alpha coefficient of 0.85, which indicates strong internal consistency.

2.4. Research data collection procedures

The data collection procedures for this study were conducted in several distinct phases, each of which was critical to ensuring the reliability and validity of the findings. First, the instruments designed to measure self-efficacy, motivation, and digital literacy were translated into the participants' native language, Mandarin Chinese. This step was imperative to mitigate linguistic barriers and ensure that participants could fully comprehend the assessment items. Second, following the translation process, the reliability and validity of the translated instruments were rigorously assessed. This involved conducting pilot studies and applying appropriate statistical analyses to verify the consistency and accuracy of the measures. Third, prior to the implementation of the interventions, pre-tests were administered to both the EG and CG. These pre-tests, which utilized the translated and validated instruments, established baseline levels of self-efficacy, motivation, and digital literacy for all participants. This baseline data was essential for evaluating the changes attributable to the interventions.

The EG participated in a highly innovative and personalized learning experience powered by AI technology, specifically utilizing

ChatGPT-based systems. Over the six-week intervention period, participants in the EG engaged in a series of structured yet adaptive learning activities designed to enhance their self-efficacy, motivation, and digital literacy. Each session was meticulously planned to incorporate interactive and dynamic tasks tailored to individual learning needs. For example, grammar exercises were customized to align with each learner's proficiency level, with the AI system dynamically adjusting the complexity of sentences and grammatical rules based on real-time performance. Similarly, vocabulary quizzes were personalized to focus on words and phrases relevant to the learner's current knowledge while introducing new terms at an appropriate pace. These activities were integrated into the AI platform, which provided immediate feedback, detailed explanations, and targeted suggestions for improvement, enabling learners to address gaps in their understanding promptly.

In addition to grammar and vocabulary tasks, the EG engaged in reading comprehension activities that were dynamically adapted to their skill level. The AI system selected texts from the Top-Notch Book 1 curriculum and modified them to match each learner's reading ability, progressively increasing the text complexity as their comprehension improved. Following each reading, learners answered comprehension questions, with the AI offering detailed feedback on their responses. This approach not only reinforced reading skills but also fostered critical thinking and analytical abilities. Furthermore, the EG participated in virtual conversation simulations, a distinctive feature of the AI-powered intervention. These simulations allowed learners to practice speaking in realistic scenarios, such as ordering food at a restaurant or asking for directions. The AI functioned as a conversational partner, providing real-time corrections and suggestions to enhance pronunciation, fluency, and grammatical accuracy. This immersive experience played a pivotal role in building learners' confidence in their speaking abilities, a critical factor in strengthening self-efficacy and motivation.

The AI system also played a pivotal role in monitoring and analyzing each learner's progress throughout the intervention. Following each session, the system generated detailed, personalized reports that highlighted strengths, identified areas for improvement, and provided tailored recommendations for future activities. These reports were accessible to both learners and instructors, fostering a collaborative approach to the learning process. For instance, if a learner encountered difficulties with a specific grammar concept, the system would recommend supplementary exercises or resources to address the challenge. Conversely, if a learner demonstrated proficiency in a particular area, the system would introduce more advanced tasks to sustain engagement and promote further development. This continuous feedback mechanism ensured that learners remained motivated and actively invested in their progress. By the conclusion of the six-week period, participants in the EG had not only completed the five units of the Top-Notch Book 1 curriculum but had also cultivated a stronger sense of autonomy and confidence in their language learning abilities, attributable to the personalized and adaptive nature of the AI-powered intervention.

In contrast, the CG received instruction through a conventional, teacher-centered approach. Although the same five units from Top Notch Book 1 were covered, the instructional methodology adhered to traditional practices, with the teacher delivering explanations, guiding practice, and providing feedback in a whole-class setting. Activities included textbook exercises, worksheets, and group discussions, such as vocabulary drills, grammar exercises, reading comprehension tasks, and peer speaking practice. Notably, the CG did not have access to the individualized, adaptive feedback or personalized learning pathways offered by the AI system. Both groups were allocated equal instructional time and resources, with 65-minute sessions conducted twice weekly over the six-week period. The primary distinction between the groups lay in the AI-powered personalization and real-time feedback provided to the EG, as opposed to the non-adaptive, traditional instruction delivered to the CG.

Following the six-week intervention period, post-tests were administered to both groups. These post-tests were identical to the pre-tests, utilizing the same translated instruments to measure changes in self-efficacy, motivation, and digital literacy. The data collected from the post-tests, when compared with the pre-test data, enabled a rigorous evaluation of the impact of AI-personalized learning on the targeted variables. This comparative analysis provided critical insights into the effectiveness of the AI-driven intervention relative to traditional instructional methods.

2.5. Research data analysis procedures

The data analysis for this study was conducted using SPSS version 28.0, employing both descriptive and inferential statistical methods. Descriptive statistics were used to summarize the key characteristics of the dataset, including means, standard deviations, and frequencies. Inferential statistics, specifically independent samples t-tests, were applied to determine whether statistically significant differences existed between the means of the two independent groups. This test was selected for its appropriateness in comparing the means of distinct groups. Prior to conducting the t-tests, the assumptions required for parametric testing were rigorously examined, and the results of these checks confirmed their satisfaction. Specifically, the assumptions of independence of observations, normality of data distribution within each group, and homogeneity of variances were systematically evaluated. Independence of observations was ensured by the study design, as participants in each group were unrelated and did not influence one another. Normality was assessed through both visual methods and statistical tests. Visual inspection of histograms and Q-Q plots revealed distributions consistent with normality, while the Shapiro-Wilk test provided statistical confirmation of approximate normality ($p > 0.05$ for all groups). Furthermore, Levene's test for equality of variances demonstrated no significant differences in variances between the groups ($p = 0.12$), thereby satisfying the assumption of homogeneity. The fulfillment of these assumptions ensures the validity and reliability of the *t*-test results.

3. Results and discussion

3.1. Results and discussion of the first research question

The first research question focused on whether AI-mediated personalized instruction could produce a statistically significant improvement in the self-efficacy of Chinese adult learners. To address this question, independent samples t-tests were utilized. The initial phase of analysis involved comparing pre-intervention self-efficacy scores between the EG and CG to establish baseline equivalence. Descriptive statistics indicated mean self-efficacy scores of 17.36 (SD = 4.59) for the EG and 18.71 (SD = 5.68) for the CG (see Appendix, Table A). Following this, an independent samples *t*-test was conducted to determine the statistical significance of the observed difference between the groups. The results of this analysis are presented in Table 1.

As shown in Table 1, the results indicated that Levene's test for homogeneity of variances (F = 3.65, p = .058) did not reveal a statistically significant violation of the assumption of equal variances. The subsequent independent samples *t*-test (t = -1.78, df = 181, p = .077) demonstrated that there was no statistically significant difference between the EG and CG in terms of self-efficacy scores at the pre-intervention phase ($p > .05$), thereby confirming baseline equivalence. Following the intervention, self-efficacy was reassessed. Descriptive statistics revealed an increase in the mean self-efficacy score for the EG to 27.47 (SD = 7.94), compared to a mean of 22.45 (SD = 8.06) for the CG (see Appendix, Table B). An independent samples *t*-test was then conducted to examine the post-intervention differences between the groups, with the results presented in Table 2.

As illustrated in Table 2, Levene's test for homogeneity of variances (F = 0.059, p = .808) confirmed that the assumption of equal variances was met. The subsequent independent samples *t*-test (t = 4.24, df = 181, $p < .001$) revealed a statistically significant difference between the EG and CG, with the EG demonstrating significantly higher self-efficacy scores. The observed mean difference of 5.02 (95 % CI [2.68, 7.35]) indicates a substantial improvement in self-efficacy among participants who engaged in AI-mediated personalized instruction. These findings suggest that AI-driven personalized learning had a significant positive impact on the self-efficacy of Chinese adult learners. Although the two groups exhibited comparable self-efficacy levels at the pre-intervention stage, a marked improvement was observed in the EG following the intervention, as evidenced by the statistically significant difference in post-test scores. This notable enhancement in self-efficacy within the EG can be attributed to the adaptive nature of AI-powered learning, which tailors content and feedback to meet individual learner needs. These results align with the findings of Lim and Zhang (2022), who demonstrated that AI-driven personalization positively influences learner outcomes, including self-efficacy. Similarly, Yang and Wen (2023) argued that AI-powered personalized learning fosters academic development, further supporting the observed improvements in self-efficacy in the current study. Additionally, these findings are consistent with Rahimi et al. (2024), who emphasized the role of ChatGPT-assisted learning in promoting self-regulation and motivation, both of which are closely associated with self-efficacy.

These findings can be meaningfully interpreted through the lens of EVT, which posits that individuals' motivation and performance are influenced by their expectations of success and the perceived value of the task (Wigfield & Eccles, 2000). It is plausible to argue that AI-powered personalized learning environments inherently address both dimensions of this theory. First, the personalized nature of AI-driven learning is likely to bolster learners' expectations for success (Vijayakumar & Panwale, 2025). By utilizing advanced algorithms, AI systems can adapt to individual learning styles, paces, and prior knowledge, providing tailored challenges that balance difficulty with achievability. This adaptive approach fosters a sense of progress and accomplishment, as learners experience incremental successes (Rezai, Namaziandost, et al., 2024; Xiong, 2024). Furthermore, as highlighted by Binhammad et al. (2024), AI systems often deliver immediate and constructive feedback, which can further reinforce learners' self-efficacy. For example, if an AI system provides specific and actionable feedback on a learner's pronunciation, the learner is more likely to develop confidence in their ability to improve (Fariani et al., 2023). This sense of competence, cultivated through personalized challenges and timely feedback, aligns with the expectancy component of the theory, as it strengthens learners' belief in their capacity to succeed (Bandura, 1997; Zimmerman, 2000).

Second, the value component of EVT is also likely addressed by AI-personalized learning. AI systems can curate learning content that is both relevant and engaging, tailored to the individual interests and goals of learners. For instance, if a student demonstrates a particular interest in business English, the AI system can provide authentic materials and tasks related to that domain, thereby

Table 1
Results of independent samples test for self-efficacy pre-test scores.

		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 % Confidence Interval of the Difference	
									Lower	Upper
Self-efficacy Pre-test	Equal variances assumed	3.650	.058	− 1.778	181	.077	− 1.35559	.76245	− 2.86003	.14885
	Equal variances not assumed			− 1.776	172.620	.078	− 1.35559	.76333	− 2.86225	.15107

Table 2
Results of independent samples test for self-efficacy post-test scores.

		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 % Confidence Interval of the Difference	
									Lower	Upper
Self-efficacy Post-test	Equal variances assumed	.059	.808	4.244	181	.000	5.01684	1.18223	2.68411	7.34957
	Equal variances not assumed			4.243	180.876	.000	5.01684	1.18233	2.68391	7.34978

increasing the perceived value of the learning experience (Rezai, Soyoof, et al., 2024; Shafiee Rad et al., 2024). This alignment with personal interests and professional aspirations can significantly enhance learners' intrinsic motivation, fostering deeper engagement and persistence (Deci & Ryan, 2000). Moreover, as highlighted by Namaziandost and Rezai (2024), the flexibility and convenience offered by AI-powered learning platforms may further amplify the perceived utility value of language learning, particularly for adult learners who often balance multiple responsibilities. The ability to learn at one's own pace and on one's own schedule renders language acquisition more accessible and appealing, addressing the practical constraints faced by many learners.

3.2. Results and discussion of the second research question

The second research question aimed to determine the impact of AI-driven personalized learning on the motivational levels of adult Chinese learners. To address this question, a comparative analysis was conducted using independent samples t-tests. Initially, pre-intervention motivational scores were examined across the EG and CG to establish baseline equivalence. Descriptive statistics indicated a mean motivation score of 49.09 ($SD = 12.00$) for the EG and 48.54 ($SD = 12.04$) for the CG (See Appendix, Table C). Following this, an independent samples *t*-test was performed to assess the statistical significance of the observed differences between the groups. The results of this analysis are presented in Table 3.

As shown in Table 3, Levene's test for homogeneity of variances ($F = 0.201$, $p = .654$) confirmed that the assumption of equal variances was met. Concurrently, the *t*-test results ($t = 0.309$, $df = 181$, $p = .758$) indicated no statistically significant difference between the EG and CG in motivational levels at the pre-intervention phase ($p > .05$), thereby establishing baseline equivalence. Following the intervention, motivational levels were reassessed for both groups. Post-intervention descriptive statistics (See Appendix, Table D) revealed an increase in mean motivation scores to 60.17 ($SD = 10.88$) for the EG and 52.38 ($SD = 13.37$) for the CG. To determine the statistical significance of the post-intervention differences between the groups, an independent samples *t*-test was conducted, with the results detailed in Table 4.

An analysis of Table 4 revealed that Levene's test for homogeneity of variances ($F = 6.704$, $p = .010$) indicated a violation of the equal variances assumption, necessitating the use of results from the unequal variances condition. Subsequent *t*-test analysis ($t = 4.320$, $df = 173.07$, $p < .001$) confirmed a statistically significant difference between the EG and CG, with the EG demonstrating significantly higher motivational scores. The observed mean difference of 7.79 (95 % CI [4.23, 11.35]) reflects a substantial improvement in motivation among learners exposed to AI-driven personalized learning. These findings provide evidence that the intervention had a significant positive impact on the motivational levels of Chinese adult learners. Although the two groups exhibited comparable motivation levels at the pre-intervention phase, the EG showed a marked increase following the intervention, as evidenced by the statistically significant post-intervention difference. The mean difference of 7.79 points (95 % CI [4.23, 11.35]) suggests that AI-

Table 3
Results of the independent samples test for motivation pre-test scores.

		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 % Confidence Interval of the Difference	
									Lower	Upper
Motivation Pre-test	Equal variances assumed	.201	.654	.309	181	.758	.54849	1.77715	− 2.95810	4.05509
	Equal variances not assumed			.309	180.960	.758	.54849	1.77719	− 2.95818	4.05517

Table 4
Results of independent samples test for motivation post-test scores.

		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 % Confidence Interval of the Difference	
									Lower	Upper
Motivation Posttest	Equal variances assumed	6.704	.010	4.325	181	.000	7.78930	1.80114	4.23537	11.34323
	Equal variances not assumed			4.320	173.065	.000	7.78930	1.80315	4.23030	11.34830

driven personalized learning not only enhanced motivation but also produced a practically meaningful effect size. The significant motivational gains observed in the EG can be attributed to the adaptive and interactive features of AI-driven learning, which enable individualized content delivery, immediate feedback, and the promotion of learner autonomy.

These findings align with studies by Huang et al. (2022) and Yuan and Liu (2024). Huang et al. (2022) found that AI-enabled personalized recommendations significantly increased learning engagement and motivation in a flipped classroom setting, while Yuan and Liu (2024) highlighted the role of AI tools in enhancing EFL learners' engagement and enjoyment. These results resonate with the current study's findings, where AI personalization led to significant improvements in motivation. Furthermore, Wang and Xue (2024) provided additional support by demonstrating that AI-driven chatbots and tools enhance academic engagement and willingness to communicate, respectively, which is consistent with the motivational gains observed in the EG.

From the perspective of EVT, the observed increase in motivation among adult EFL learners can be attributed to the personalized features of AI-based learning systems. These systems significantly influence learners' expectations of success and their perception of the value of learning (Chan & Zhou, 2023; Nagle, 2021; Wigfield & Eccles, 2000). AI technologies adapt to individual learning styles and paces, creating an environment where tasks are calibrated to be neither overly simplistic nor excessively challenging, thereby fostering a sense of achievable success. This sense of accomplishment, coupled with immediate and tailored feedback, reinforces learners' belief in their ability to improve (Bandura, 1997; Dasam et al., 2024). Furthermore, AI systems can curate content that aligns with learners' personal interests and goals, enhancing the relevance and value of the learning materials. As noted by Namaziandost and Rezai (2024), if a learner expresses an interest in travel, the AI can provide authentic language materials, such as dialogues for airport interactions or hotel reservations, making the learning process more engaging and practical. The flexibility and convenience offered by AI, enabling learners to study at their own pace and schedule, further amplify the perceived utility of the learning experience, particularly for adult learners managing multiple responsibilities (Loh, 2019; Zimmerman, 2002).

Furthermore, the motivational benefits of AI-personalized learning can also be interpreted through the lens of Self-Determination Theory (SDT), which emphasizes the significance of three psychological needs (i.e., autonomy, competence, and relatedness) in fostering intrinsic motivation (Deci & Ryan, 2015). AI-powered learning environments are particularly effective in addressing these needs. For example, the adaptive nature of AI fosters a sense of autonomy by enabling learners to select their learning paths and regulate their progress. This is especially critical for adult learners, who often favor self-directed learning approaches (Darden, 2014). Additionally, as highlighted by Rezai, Soyoof, et al. (2024), AI systems that deliver personalized feedback and track progress in real-time can enhance learners' sense of competence by providing tangible evidence of improvement. For instance, AI-powered tools that visualize progress in specific areas, such as vocabulary acquisition or grammatical accuracy, can significantly bolster learners' confidence. Moreover, AI platforms incorporating interactive features, such as virtual language exchange partners or collaborative group activities, can cultivate a sense of relatedness by facilitating social interaction and cooperation, even in virtual environments (Dornyei, 2013; Wang et al., 2023). AI-driven chatbots that respond to queries or offer explanations can also mitigate frustration and uncertainty, helping learners feel more supported and assured. By addressing these psychological needs, AI-personalized learning environments not only enhance intrinsic motivation but also promote sustained engagement and success in language learning (Ryan &

Table 5
Independent samples test for pre-test digital literacy scores.

		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 % Confidence Interval of the Difference	
									Lower	Upper
DLPre	Equal variances assumed	2.050	.154	1.022	181	.308	.72850	.71262	− .67761	2.13461
	Equal variances not assumed			1.023	180.470	.308	.72850	.71236	− .67713	2.13413

Deci, 2020).

3.3. Results and discussion of the third research question

The third research question sought to determine whether AI-mediated personalized learning had a statistically significant impact on the digital literacy proficiencies of Chinese adult learners. To address this question, independent samples *t*-tests were employed. Prior to the intervention, digital literacy levels were assessed across both groups to establish baseline equivalence. As outlined in Table 1, the EG demonstrated a mean score of 15.71 (SD = 4.97), while the CG exhibited a mean score of 14.98 (SD = 4.66) (See Appendix, Table E). Following this, an independent samples *t*-test was conducted to compare the pre-intervention scores between the two groups. The results of this analysis are presented in Table 5.

A review of Table 5 revealed that Levene's test for homogeneity of variances confirmed the tenability of the equal variance assumption ($F = 2.05$, $p = .154$). The *t*-test results indicated no statistically significant difference between the EG and CG at the pre-intervention phase ($t(181) = 1.02$, $p = .308$, 95 % CI [-0.68, 2.13]). This finding establishes baseline equivalence between the two groups in terms of digital literacy. Following the intervention, digital literacy scores were reassessed for both groups. As outlined in Table 2, the EG demonstrated a significantly higher mean score ($M = 25.16$, $SD = 6.74$) compared to the CG ($M = 17.29$, $SD = 6.23$) (See Appendix, Table F). An independent samples *t*-test was then conducted to compare the post-intervention scores, with the results detailed in Table 6.

An examination of Table 6 revealed that Levene's test for homogeneity of variances confirmed the tenability of the equal variance assumption ($F = 0.56$, $p = .455$). Subsequent *t*-test analysis demonstrated a statistically significant difference between the EG and CG ($t(181) = 8.21$, $p < .001$, 95 % CI [5.98, 9.77]). The observed mean difference of 7.88 points (SE = 0.96) indicates a substantial positive impact of the AI-mediated personalized learning intervention on the digital literacy proficiencies of the EG. These findings provide evidence that AI-mediated personalized learning significantly enhanced the digital literacy of Chinese adult learners in the EG compared to the CG. The lack of statistically significant differences at the pre-intervention phase supports the conclusion that the observed post-intervention disparities are likely attributable to the intervention. The notable improvement in the EG's digital literacy scores highlights the potential of AI-driven personalized learning as an effective tool for developing digital competencies among adult learners.

These results align with the findings of Du and Daniel (2024), who demonstrated the efficacy of AI-powered chatbots in facilitating speaking practice and enhancing learners' digital skills. Similarly, Guo and Li (2024) corroborated these findings by illustrating that AI chatbots can function as personalized writing assistance tools, improving learners' digital literacy and autonomy. The results of this study also resonate with prior research (e.g., Blake, 2024; Liu et al., 2024; Tseng & Warschauer, 2023), which highlighted the positive impact of personalized learning experiences on language learning outcomes. Furthermore, the findings are consistent with earlier studies (e.g., Pokrivcakova, 2023; Zhi & Wang, 2024; Zou et al., 2023), which reported that both teachers and students hold favorable perceptions of interactive AI-driven learning models.

Similar to previous findings, these results can be effectively interpreted through the framework of EVT. It is plausible that the personalized nature of AI systems increased learners' perceived expectancy of success and the value they attributed to the learning activity. According to EVT, individuals' motivation and achievement-related behaviors are influenced by their beliefs about their likelihood of success (expectancy) and the importance they assign to the task (value) (Eccles & Wigfield, 2002). Recent research has emphasized the role of personalized feedback and adaptive learning pathways in enhancing learner motivation and engagement (Lazowski & Hulleman, 2016). AI-personalized learning, by tailoring content, pacing, and feedback to individual learners' needs, likely bolstered their confidence in their ability to improve their digital literacy. As highlighted by Liu and Fan (2025), the adaptive features of AI systems may have provided learners with tasks that were appropriately challenging, thereby increasing their perceived expectancy of success. Additionally, the relevance and personalized feedback offered by AI could have heightened the perceived value of the learning experience, as learners observed tangible improvements in their digital skills. According to Darvin (2025), AI algorithms, by identifying specific weaknesses in digital literacy, might have delivered targeted exercises and resources, making the learning process more efficient and effective. This tailored approach likely fostered a sense of accomplishment and relevance, motivating learners to engage more deeply with the material and improve their digital literacy. The ability of AI to provide immediate, actionable feedback

Table 6
Results of independent samples test for post-test digital literacy scores.

		Levene's Test for Equality of Variances		*t*-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95 % Confidence Interval of the Difference	
									Lower	Upper
DLPost	Equal variances assumed	.561	.455	8.205	181	.000	7.87733	.96011	5.98287	9.77179
	Equal variances not assumed			8.208	180.194	.000	7.87733	.95970	5.98363	9.77103

has been identified as a critical factor in enhancing learning outcomes and motivation (Wang et al., 2025; Seo et al., 2021).

Furthermore, the observed improvement in digital literacy can be further elucidated through the Technology Acceptance Model (TAM). TAM posits that perceived usefulness and perceived ease of use are critical factors influencing technology adoption and usage (Davis, 1989). It is plausible that the user-friendly interface and adaptive features of AI-personalized learning platforms contributed to a high perceived ease of use. AI systems often feature intuitive interfaces and seamless integration of digital tools, which may have reduced the cognitive load associated with acquiring new digital skills (Kumar & Anu, 2024; Saif et al., 2024). Additionally, the perceived usefulness of AI-personalized learning in enhancing digital literacy is likely linked to its ability to provide immediate and relevant feedback, track progress, and offer customized learning pathways. As emphasized by Venkatesh et al. (2016), facilitating conditions and social influence play significant roles in technology adoption. More recent studies have also highlighted the importance of perceived enjoyment and hedonic motivation in technology acceptance, particularly in educational contexts (Teo et al., 2018). AI-personalized learning platforms may have offered robust technical support and a supportive learning environment, further enhancing learners' acceptance and engagement. The adaptability of AI to individual learning styles and preferences, combined with real-time feedback, likely made the learning process more efficient and engaging, thereby increasing its perceived usefulness. As argued by Yilmaz et al. (2023), learners may have perceived the AI-enhanced learning environment as a valuable tool for acquiring and practicing digital literacy skills, contributing to the observed significant improvements. Moreover, factors such as algorithmic transparency and trust in AI systems could influence perceived usefulness, as learners are more likely to engage with systems they understand and trust (Goldenthal et al., 2021).

4. Conclusions and implication

The primary objective of this study was to investigate the impact of AI-personalized learning on Chinese adult learners' self-efficacy, motivation, and digital literacy. The findings demonstrated that AI-powered personalized learning significantly enhanced all three targeted constructs. Specifically, independent samples t-tests revealed statistically significant improvements in self-efficacy, motivation, and digital literacy among learners who engaged with AI-personalized learning compared to those in the CG. These improvements are particularly significant in the context of adult education, where learners often face diverse needs and time constraints. The ability of AI to deliver customized learning pathways and provide immediate, adaptive feedback appears to align well with the preferences and requirements of adult learners. Moreover, the notable increase in digital literacy scores suggests that AI-powered learning not only facilitates effective content delivery but also equips learners with essential skills for navigating the digital world. These outcomes highlight the potential of AI to create more engaging and effective learning environments for adult populations.

From a theoretical perspective, this study offers valuable contributions to EVT. The findings extend this theory by demonstrating that AI-personalized learning can significantly enhance both the expectancy and value components. First, the personalized nature of AI systems, which provide tailored content and immediate feedback, likely increases learners' perceived competence, thereby strengthening their expectations of success. Second, the adaptive and engaging learning experiences facilitated by AI may elevate the perceived value of learning, making it more relevant and enjoyable. As a result, learners are more likely to invest effort and persist in their learning endeavors. In essence, the AI system functions as a dynamic scaffold, adapting to learners' abilities and aspirations, thereby validating and expanding the application of EVT within a technologically mediated educational context.

The findings of this study carry specific and actionable implications for key stakeholders within the educational landscape, particularly in the context of EFL learning. For EFL learners, the integration of AI-driven personalized learning represents a transformative shift in language acquisition. A concrete example is the use of AI-powered platforms to provide real-time pronunciation feedback tailored to individual phonetic challenges. For instance, an adult Chinese learner struggling with English vowel sounds such as /ɪ/ and /iː/ could benefit from an AI system that identifies specific pronunciation errors and delivers targeted interactive drills focused on those areas. Furthermore, by automating routine tasks like vocabulary quizzes and grammar exercises, AI tools enable learners to dedicate more time to communicative activities and authentic language use. This not only enhances learner autonomy but also creates a more engaging and flexible learning experience, which is especially critical for adult learners juggling professional and personal responsibilities. For university administrators, the study's findings highlight the need for strategic investment in AI-driven educational technologies. Universities can leverage these insights to design blended learning programs that combine the strengths of AI with traditional teaching methods. For example, institutions could establish AI-powered language labs where students receive personalized practice and feedback, complementing classroom instruction. However, successful implementation requires faculty training on how to integrate AI tools into their teaching practices and interpret the data generated by these systems. Such training ensures that educators can effectively harness AI technologies to enhance student outcomes while maintaining pedagogical rigor.

Material developers are another group directly impacted by these findings. They should prioritize the creation of adaptive learning platforms capable of delivering dynamic, personalized feedback and content. For instance, developing AI-driven writing tools that offer nuanced feedback on grammar, style, and coherence could significantly improve learners' writing proficiency. These tools should be designed to adapt to individual learners' progress, offering increasingly complex exercises as proficiency grows. Additionally, material developers must ensure that AI systems incorporate accessibility features and cultural sensitivity to cater to diverse learner populations. Policymakers also stand to benefit from the insights generated by this study. Recognizing the potential of AI to address educational disparities and promote lifelong learning, policymakers could implement pilot programs in adult education centers. These programs could focus on integrating AI tools for digital literacy and language acquisition, providing valuable data on effective implementation strategies. Such initiatives would not only enhance individual learning outcomes but also contribute to building a digitally competent workforce. Moreover, policies should emphasize equitable access to AI-powered learning tools, ensuring that underserved communities are not left behind. By fostering collaboration among researchers, educators, and technology developers, policymakers can help create inclusive and effective learning environments.

5. Limitations and directions for further research

Despite the significant findings regarding the positive impact of AI-personalized learning on Chinese adult learners' self-efficacy, motivation, and digital literacy, several limitations must be acknowledged, offering avenues for future research. First, the study's sample, consisting exclusively of 183 male Chinese adults aged 31–37 at an intermediate English proficiency level, limits the generalizability of the results. To address this, future studies should expand the participant pool to include diverse age groups, proficiency levels, and cultural backgrounds, thereby enhancing the external validity of the findings. Second, the geographical restriction to three language institutes in Beijing raises concerns about the potential influence of regional and cultural factors on the observed outcomes. Consequently, subsequent research should replicate the study in varied geographical and cultural contexts to determine the consistency of the findings across different settings. Additionally, the exclusive reliance on ChatGPT as the AI-powered personalized learning tool restricts the scope of conclusions regarding the broader efficacy of AI technologies. Future studies should, therefore, compare and contrast various AI platforms, learning systems, and methodologies to identify the specific features that most effectively enhance learning outcomes. Furthermore, while the six-week intervention period provided valuable initial insights, it may not fully capture the long-term effects of AI-personalized learning. Longitudinal studies are needed to assess the sustained impact of these tools over extended periods. Finally, the study's focus on students' perspectives overlooks the critical role of teachers. To provide a more comprehensive understanding of AI integration in education, future research should investigate teachers' perceptions, experiences, and challenges, thereby informing the development of strategies that optimize benefits for both learners and educators.

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CRediT authorship contribution statement

Abdul Salam Zarina: Writing – review & editing, Methodology, Investigation, Formal analysis. **Lyu Wenwen:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization.

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Appendix

Table A Results of the descriptive statistics for the self-efficacy pre-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Self-efficacy Pre-test	EG	92	17.3587	4.58756	.47829
	CG	91	18.7143	5.67506	.59491

Table B Results of the descriptive statistics for the self-efficacy post-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Self-efficacy Pre-test	EG	92	27.4674	7.93580	.82736
	CG	91	22.4505	8.05711	.84461

Table C Results of the descriptive statistics for the motivation pre-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Motivation Pretest	EG	92	49.0870	11.99693	1.25077
	CG	91	48.5385	12.04372	1.26253

Table D Results of the descriptive statistics for the motivation post-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Motivation Posttest	EG	92	60.1739	10.87957	1.13427
	CG	91	52.3846	13.37142	1.40171

Table E Results of the descriptive statistics for the digital literacy pre-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Digital Literacy Pre-test	EG	92	15.7065	4.97364	.51854
	CG	91	14.9780	4.65947	.48844

Table F Results of the descriptive statistics for the digital literacy post-test.

	Groups	N	Mean	Std. Deviation	Std. Error Mean
Digital Literacy Post-test	EG	92	25.1630	6.74052	.70275
	CG	91	17.2857	6.23482	.65359

Data availability

Data will be made available on request.

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