

Modeling and profiling AI-mediated informal digital learning of English, achievement emotions, and strategic competence for cross-cultural communication

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Abstract

Artificial intelligence-mediated informal digital learning of English (AI-IDLE) has received increasing attention in foreign language learning. However, few studies have integrated variable-centered and person-centered approaches to investigate how AI-IDLE relates to achievement emotions and strategic competence for cross-cultural communication (SCCC). The present study therefore examined the associations between AI-IDLE and SCCC through two achievement emotions, specifically enjoyment and boredom, using both analytical approaches. Participants were 435 Chinese university EFL undergraduate

students. In Stage 1, a variable-centered analysis was conducted to explore the connections among AI-IDLE, foreign language enjoyment (FLE), foreign language boredom (FLB), and SCCC. The results showed that AI-IDLE directly and positively predicted both FLE and SCCC, while negatively predicting FLB. FLE partially mediated the relationship between AI-IDLE and SCCC. By contrast, FLB did not significantly predict SCCC. In Stage 2, a person-centered analysis was undertaken to identify distinct profiles of students' AI-IDLE. Results demonstrated that three profiles were identified: passive AI-IDLE users, balanced AI-IDLE learners, and proactive AI-IDLE strategists. Specifically, the profile of balanced AI-IDLE learners accounted for the largest proportion ($N = 206$, 47.3%). Theoretical and pedagogical implications were discussed.

Keywords: informal digital learning of English; artificial intelligence; foreign language enjoyment; foreign language boredom; strategic competence for cross-cultural communication

1. Introduction

Informal digital learning of English (IDLE) has developed into a rapidly expanding area within computer-assisted language learning. It enriches traditional, formal instruction by giving learners expanded avenues to encounter a wide range of authentic language input beyond structured educational settings (Liu et al., 2023; Zou et al., 2025a, 2026c). In IDLE contexts, second and foreign language (L2) learners typically exercise considerable autonomy and self-direction, choosing to engage with digital resources and to communicate beyond the classroom with interlocutors from diverse linguistic and cultural backgrounds (Benson, 2011; Lee & Dressman, 2018). In an increasingly artificial intelligence (AI)-mediated educational landscape, technologies (e.g., ChatGPT and Kimi) facilitate more personalized and productive language learning experiences by enabling authentic target-language interaction and providing immediate, adaptive feedback tailored to learners' individual needs (Liu et al., 2024b, 2025). Given the limited amount of foreign language instructional time and challenges associated with large-class language teaching, personalized and interactive out-of-class language learning has become increasingly important and valuable (Sundqvist & Uztosun, 2024).

Existing research has addressed both the antecedents and outcomes of IDLE, showing that motivation (e.g., Liu et al., 2024c; Zou et al., 2025b), emotions (e.g., Liu et al., 2024c; Zou et al., 2025a), and growth mindset (Zou et al., 2026c) could predict learners' participation in IDLE activities, while such engagement was also found to influence learners' cognition (Rezai & Goodarzi, 2025), willingness to communicate (Zou et al., 2026b), and intercultural communication

competence (Lee & Xie, 2023). Drawing on earlier work on IDLE (e.g., Lee, 2020; Zou et al., 2025a, 2025c), AI-mediated informal digital learning of English (AI-IDLE) refers to language learners' self-initiated use of and navigation through AI tools for English acquisition beyond formal instructional settings (Liu et al., 2025). While the extant literature has only explored simple bivariate links between (AI-)IDLE participation and emotions (e.g., Zou et al., 2026b), (AI-)IDLE and motivation (Cui et al., 2025; Liu et al., 2024d; Zou et al., 2025c, 2026a), or IDLE and intercultural communication competence (e.g., Lee, 2020), there is a lack of studies investigating how AI-IDLE interacts with achievement emotions (e.g., enjoyment and boredom) to foster strategic competence for cross-cultural communication (SCCC). We focus on these two emotions for several reasons. Conceptually, foreign language enjoyment (FLE) and foreign language boredom (FLB) form a positive-negative pair that, respectively, fosters engagement and precipitates disengagement, thereby offering a balanced view of learners' affective experiences. Contextually, these two emotions are especially salient in informal and self-directed learning contexts. Without external monitoring, enjoyment serves as a key driver of learners' autonomous and sustained participation, whereas boredom is a primary reason for withdrawal. Both emotions are arguably more pertinent to autonomous digital learning than anxiety, which is more characteristic of evaluative, classroom-based contexts. Empirically, FLE and FLB have emerged as two of the most prominent emotional constructs in current second language acquisition (SLA) research, making their joint examination both timely and theoretically grounded. Therefore, examining the relationships among AI-IDLE, FLE, FLB, and SCCC in an AI-mediated English learning setting is of considerable theoretical and practical importance.

Furthermore, although the existing literature has utilized a variable-centered approach (e.g., structural equation modeling [SEM] or regression analysis) to examine how learners' IDLE shapes their emotions (Liu et al., 2024c; Zou et al., 2025a, 2025c) or their intercultural communication competence (Liu et al., 2023), relying solely on variable-centered methods assumes population homogeneity (Bergman & Andersson, 2015; Yang & Du, 2025). However, the relationships among AI-IDLE, achievement emotions, and SCCC are unlikely to be uniform; rather, they may operate differently across subgroups and take non-linear forms, calling for an approach that can capture such within-sample variation (Bergman & Andersson, 2015). Latent profile analysis (LPA), a prominent person-centered method, addresses this call by partitioning learners into qualitatively distinct profiles according to their characteristic response patterns based on several indicators (Marsh et al., 2009).

Accordingly, integrating variable- and person-centered approaches may yield a more holistic and detailed insight into the associations among AI-IDLE, achievement

emotions, and SCCC. While the variable-centered approach identifies general patterns of associations among variables, the person-centered one can identify the latent profiles underlying L2 learners' AI-IDLE participation and examine how these profiles differ in their achievement emotions and SCCC. Our study is the first attempt to combine the two approaches to explore how students' AI-IDLE participation and their achievement emotions influence their SCCC and how students' AI-IDLE profile memberships are associated with achievement emotions and SCCC.

2. Literature review

This section outlines the theoretical framework of the present study. We first introduce AI-IDLE, followed by control-value theory of achievement emotions and SCCC. Then relevant empirical studies are reviewed to illuminate how these variables interrelate and demonstrate why combining variable- and person-centered approaches offers a deeper insight into learners' AI-IDLE participation.

2.1. AI-IDLE

IDLE has attracted growing scholarly attention in recent years. IDLE characterizes a mode of autonomous language learning whereby L2 learners leverage digital devices and online platforms to facilitate English learning beyond the boundaries of formal education (Lee & Dressman, 2018). Recent research underscores that L2 learners are increasingly adopting GenAI tools (e.g., ChatGPT, DeepSeek, and Doubao) in AI-mediated IDLE to obtain personalized feedback, receive scaffolding for academic writing, and engage in simulated oral interactions beyond formal classrooms (Guan et al., 2024; Liao et al., 2025; Zou et al., 2026a). Participating in IDLE activities can bring L2 learners an array of linguistic, motivational, affective, cognitive, behavioral, and cultural benefits encompassing but not limited to improving their vocabulary knowledge (Lai & Wang, 2025), enhancing their speaking proficiency (Guan et al., 2024; Sundqvist & Uztosun, 2024), strengthening their motivation (Liu, et al., 2025), increasing their FLE (Zou et al., 2025c), mitigating FLB (Zou et al., 2025c), or cultivating self-regulated learning (Rezai & Goodarzi, 2025).

Although research on L2 learners' IDLE has expanded considerably in recent years (Lai & Wang, 2025; Lee, 2020; Liu et al., 2023, 2024c; Zou et al., 2025c, 2026a), the mechanisms through which learners integrate AI technologies into their IDLE practices remain underexplored. Given the inherently self-directed and autonomous nature of AI-IDLE contexts (Reinders et al., 2022), learners are likely to experience a range of affective responses while engaging in informal digital

learning. For example, Zou et al. (2025a) characterized FLE as a salient positive emotion and FLB as a common negative one among Chinese and Iranian EFL learners, demonstrating how two emotions played mediating roles in learners' IDLE engagement and their willingness to communicate (WTC) in digital environments. Although research on IDLE and emotions has expanded in recent years, little is known about how AI-IDLE participation, FLE, FLB, and SCCC are interconnected.

2.2. Control-value theory of achievement emotions

In the field of educational psychology, control-value theory (CVT; Pekrun, 2006) has become one of the most influential theoretical frameworks for explaining factors that give rise to achievement emotions and the ways in which these emotions influence learning outcomes. According to CVT, these emotions arise from learners' perceived sense of control over a learning task, combined with the personal valuation they attach to it (Pekrun, 2006; Pekrun & Perry, 2014). They are categorized into valence, activation, and objective focus (Pekrun, 2006). In our study, CVT is not adopted as a fully operationalized model. Rather, it serves as an interpretive theoretical lens that helps contextualize the links between AI-IDLE, achievement emotions, and SCCC. This study examines two achievement emotions that have received growing attention in recent scholarship: FLE, a positive activating emotion arising from language learning tasks (Dewaele & MacIntyre, 2014, 2016), and FLB, a negative deactivating emotion linked to disengagement and diminished effort (Pawlak et al., 2022, 2026). Unpacking how these emotions relate to AI-IDLE and SCCC, the present study turns to CVT to make sense of the ways in which learners' AI-IDLE may influence their emotions and their SCCC in AI-enhanced language learning contexts.

FLE denotes a positive emotional experience arising from the fulfillment of learners' psychological needs in L2 learning (Dewaele & MacIntyre, 2014, 2016). According to the three-dimensional taxonomy proposed by CVT, FLE is conceptualized as a positive activating achievement emotion that facilitates learners' active involvement in language learning (Dewaele & MacIntyre, 2014, 2016; Derakhshan & Fathi, 2024). Empirical research further suggests that FLE is a multi-dimensional construct encompassing three interrelated dimensions: private enjoyment, teacher-related enjoyment, and classroom atmosphere enjoyment (Li et al., 2018). Apart from personal and private enjoyment, this emotion also stems from peer interactions and a supportive classroom climate created by the teacher (Elahi Shirvan et al., 2025; Kruk et al., 2025; Li et al., 2018; Solhi et al., 2024). The present study, however, specifically concentrates on the private dimension of FLE as it captures learners' internally experienced positive emotions, including feelings of personal satisfaction derived from the language learning

process. Notably, this study focuses on self-directed informal English learning, which occurs largely outside formal instruction and is characterized by individual interactions with AI tools in the absence of direct peer or teacher support. Under this condition, private or personal involvement is particularly relevant because learners' emotional responses are primarily shaped by their personal participation in AI-mediated learning activities.

An expanding body of scholarship has shown that FLE promotes successful language learning. Higher FLE, in particular, has been linked to increased learner engagement (Derakhshan & Fathi, 2024; Zou et al., 2025b), enhanced linguistic competence (Li et al., 2023), and greater WTC (Lee et al., 2024; Zou et al., 2025c). Empirical findings also consistently indicate that FLE positively predicts learners' IDLE engagement (Liu et al., 2024a, 2024b). Given its significant contribution to SLA, it is important to further investigate the precursors and consequences of FLE beyond the structured classroom context, particularly in the AI-mediated digital era. Concerning FLB, it is categorized as a negative, deactivating, and activity-oriented achievement emotion (Pekrun & Perry, 2014). Empirical evidence indicates that frequent experiences of boredom among L2 learners are associated with diminished attention, lower academic engagement, and a greater tendency to withdraw from learning tasks (Kruk, 2022; Kruk et al., 2021, 2025; Pawlak et al., 2022, 2025, 2026). Nevertheless, despite growing scholarly attention to boredom in SLA (Kruk, 2022; Kruk et al., 2022; Pawlak et al., 2022, 2024; Solhi et al., 2024), research into the antecedents and potential consequences of FLB in AI-mediated language learning environments remains relatively scarce.

Despite the growing interest in AI-assisted language learning, empirical investigations regarding the relationship between AI-IDLE and achievement emotions remain limited. Nevertheless, the existing studies suggest that AI-IDLE may create favorable conditions for the development of positive emotional experiences in L2 learning. For example, Liu et al. (2025) found that learners who engaged more actively in AI-IDLE not only reported a more vividly developed ideal L2 self but also experienced higher levels of FLE. Similarly, Zou et al. (2025a) investigated the interplay between IDLE engagement, FLE, FLB, and WTC using a cross-cultural sample of 626 Chinese and Iranian EFL learners. Their findings indicated that more frequent participation in IDLE was associated with lower levels of FLB across both groups, possibly because of the multimodal affordances embedded in IDLE practices.

2.3. SCCC

In today's increasingly multicultural societies, SCCC has attracted considerable attention in both academic and professional spheres (Lee, 2020; Spitzberg, 2000).

Li-sheng (2000) conceptualizes SCCC as a strategic component of communicative competence that enables learners to employ both verbal and non-verbal communication strategies to compensate for communication difficulties arising from contextual constraints or limitations in other areas of communicative competence, thereby enhancing the overall effectiveness of communication.

Such competence has gained particular significance in the context of English as an international language (EIL), where English functions as a global lingua franca connecting speakers from diverse linguistic and cultural backgrounds. In this context, effective communication is increasingly situated among multilingual users rather than framed primarily as exchanges between native and non-native English speakers. In such settings, effective communication does not necessarily rely on conforming to native-speaker norms; instead, it depends on the competence to negotiate meaning, employ communication strategies, and handle potential cross-cultural misunderstandings (Byram, 1997). Thus, SCCC constitutes a key competence that enables learners to strategically deploy linguistic and pragmatic resources to sustain shared understanding and communicative effectiveness. In other words, SCCC aligns closely with the communicative demands of EIL contexts.

Moreover, digital environments provide technologically mediated spaces in which learners can develop intercultural connections, negotiate cultural meanings, and exchange information with individuals from diverse linguistic and cultural backgrounds (Chun, 2011). In out-of-class informal digital language learning contexts, Liu et al. (2023) conceptualized intercultural communication competence (ICC) as learners' accumulated and negotiated repertoires developed through both formal instruction and informal learning experiences, which enable them to participate in intercultural communication effectively and appropriately. Drawing on quantitative data from 1,490 Chinese college students, they identified knowledge of self, knowledge of others, attitudes, awareness, and intercultural communication skills as the key dimensions for assessing ICC. These elements demonstrate that ICC encompasses not only communicative performance but also foundational cultural knowledge, attitudes toward cultural diversity, and a reflective awareness of cultural differences. While SCCC and ICC constructs are related, they remain conceptually different. ICC mainly refers to learners' overall ability to comprehend, interpret, and respond effectively to cultural variation, integrating cultural knowledge, attitudes, and awareness with communicative abilities (Spitzberg & Changnon, 2009). In contrast, SCCC places greater emphasis on the strategic and pragmatic management of communication in order to negotiate meaning and maintain interaction (Lee, 2020; Li-sheng, 2000). In this sense, SCCC can be understood as a more strategy-oriented construct within intercultural communication processes, particularly significant in dynamic multilingual and digitally mediated communication environments.

While there are some empirical studies related to intercultural communication competence in SLA (Peng & Wu, 2016), research investigating the link between IDLE and SCCC is very limited. Reviewing the extant IDLE literature, we found that only two empirical studies have explored how L2 learners' IDLE practices made an impact on SCCC (i.e., Lee, 2020; Liu et al., 2023). Specifically, Lee (2020) found that students' IDLE engagement influenced their SCCC, mediated by their perceptions of varieties of English. Similarly, Liu et al. (2023) demonstrated that participation in IDLE activities enabled Chinese EFL learners to acquire English linguistic and cultural knowledge, develop curious and open attitudes, gain greater insight into diverse cultures, and strengthen their ability to engage in intercultural communication. However, the relationship between AI-IDLE and SCCC has not yet been investigated. Building upon the above-mentioned empirical studies, it is, therefore, likely that AI-mediated IDLE will also exert a positive influence on SCCC.

When it comes to the link between achievement emotions (i.e., FLE and FLB) and SCCC, some empirical studies have already corroborated that FLE plays a positive role in SCCC, while FLB negatively predicts SCCC in L2 learning contexts. More specifically, Fathi et al. (2023) indicated that FLE had a significantly direct and positive effect on ICC. Consistent with this finding, Tang et al. (2024) reported that FLE significantly and positively predicted ICC, whereas FLB exerted negative effects on ICC.

2.4. Combining variable- and person-centered approaches in AI-IDLE

The study of (AI-)IDLE has been dominated by variable-centered methods, particularly structural equation modeling and regression analysis, which focus on overall relationships among focal constructs, their antecedents, and associated outcomes. A variable-centered approach, for instance, was used to investigate how Chinese students' AI-IDLE participation interacts with FLE and ideal L2 self (e.g., Liu, et al., 2025). In our study, we first employed the variable-centered approach to examine how AI-IDLE participation contributes to learners' achievement emotions (i.e., FLE and FLB) and SCCC. This approach alone, however, may be insufficient to reveal how learners' FLE, FLB, and SCCC vary across distinct profiles with respect to AI-IDLE participation. We therefore complemented it with a person-centered approach.

From a person-centered perspective, LPA is used to uncover variation among individuals by grouping those with comparable characteristic patterns. Guo et al. (2025) used LPA to identify distinct profiles of IDLE participation among Chinese L2 learners. They examined how these profiles functioned both as outcomes of emotion regulation strategies and as antecedents of WTC. In our study, the person-centered approach was adopted to investigate profiles of Chinese EFL learners' AI-IDLE participation, and to examine how achievement emotions

and SCCC differ across these profiles. Put differently, the person-centered analysis can complement and extend findings generated through the variable-centered approach (Feng et al., 2023). Integrating these two approaches may therefore offer a more comprehensive and fine-grained account of the interplay among AI-IDLE, achievement emotions, and SCCC.

Moreover, while a wealth of IDLE research has adopted the variable-centered approach (Lee, 2020; Lee et al., 2024; Liu et al., 2023; Zou et al., 2025c), relatively few studies have employed the person-centered approach to examine distinct learner profiles (Lai & Wang, 2025; Peng et al., 2022). Using cluster analysis, Lee and Xie (2023) identified distinct IDLE profiles among Korean EFL learners. The results revealed that highly engaged IDLE learners tended to exhibit more vivid ideal L2 selves, stronger enjoyment, and greater grit compared with their less engaged counterparts. Similarly, in a recent study, Guo et al. (2025) utilized LPA to identify distinct profiles of learners' IDLE practices. They uncovered three profiles labeled moderate, active, and passive IDLE learners. The active IDLE learners, who exhibited the highest levels of both productive and receptive IDLE engagement, also reported the greatest WTC in digital and non-digital contexts. Similarly, another study conducted by Smith et al. (2025) identified student profiles through LPA based on individual characteristics. The study uncovered five learner groups distinguished by their patterns of motivation, effort, and engagement in out-of-class activities. As the variable-centered approach (e.g., SEM) may not be the most appropriate means of capturing how L2 learners cluster into distinct profiles, the person-centered approach offers a valuable complement. However, research employing the person-centered approach to identify L2 learners' AI-IDLE profiles remains limited. Although research on AI-IDLE has expanded substantially, learners' AI-IDLE profiles have rarely been examined from the person-centered perspective. Integrating variable- and person-centered approaches may provide greater insight into the associations among AI-IDLE, achievement emotions, and SCCC.

2.5. The current study

This study advances AI-IDLE research by combining variable-centered (SEM) and person-centered (LPA) approaches, thereby providing more nuanced insights into the associations between AI-IDLE and FLE, FLB, and SCCC. This investigation was guided by the following research questions:

RQ1: To what extent does Chinese EFL learners' AI-IDLE participation influence their SCCC through their achievement emotions?

- RQ2: What latent profiles emerge among Chinese EFL learners based on their AI-IDLE participation?
- RQ3: How do these AI-IDLE profiles differ in learners’ achievement emotions and SCCC?

3. Stage 1: Variable-centered approach

In Stage 1, we tested a structural equation model examining how Chinese EFL learners’ AI-IDLE participation predicted their achievement emotions (FLE and FLB), and SCCC.

3.1. Method

3.1.1. Research context and participants

The research was carried out in two phases. Participants in both stages were recruited through convenience sampling from three universities (Creswell & Creswell, 2018). Between January and April 2025, three instructors helped distribute an online survey by sharing a digital poster with a QR code through Tencent QQ and WeChat. To be eligible, participants had to be enrolled at a Chinese university and self-identify as EFL learners.

Table 1 Demographics

Variable	Category	N	%
gender	male	86	19.7
	female	349	80.3
age	< 18	4	0.9
	18-22	430	98.8
	> 22	1	0.2
study program	arts and humanities	216	49.7
	social sciences	6	1.3
	science, technology, engineering, and mathematics (STEM)	12	2.8
	health sciences	31	7.1
	other	170	39.1
ownership of types of digital devices (e.g., smartphone, laptop, etc.)	1	17	3.9
	2	269	61.8
	3	128	29.4
	more than 3	21	4.9
stable wi-fi	yes	414	95.2
	no	21	4.8
sufficient mobile data monthly	yes	414	95.2
	no	21	4.8

A total of 435 Chinese university undergraduates completed the online questionnaire. Table 1 presents the demographic information of the participants, including their gender, age, study program, device ownership, wi-fi access, and monthly mobile data allowance. These statistics can provide insights into foundational technological conditions that support informal digital language learning among Chinese university EFL learners.

3.1.2. Data collection and analysis

Data were gathered using Wenjuanxing, one of the commonly used digital survey platforms in China (see supplementary material). The bilingual questionnaire (English and Chinese) began with informed consent, allowing only those who selected “Yes” to proceed. It comprised two sections: demographics and 30 items measuring AI-IDLE, FLE, FLB, and SCCC on a six-point Likert scale (1 = *strongly disagree* to 6 = *strongly agree*).

- 1) *AI-IDLE Scale* (8 items): Learners’ engagement in AI-IDLE was measured using the eight-item scale developed by Liu et al. (2024a, 2025). The instrument assesses how extensively learners draw on GenAI tools to facilitate English learning outside formal classroom settings. In the current study, the scale demonstrated excellent internal consistency, yielding a Cronbach’s alpha of .92. An example item is the following: “I use AI-powered speech recognition tools to practice speaking English and receive immediate feedback on my fluency and intonation beyond the classroom.”
- 2) *Foreign Language Enjoyment Scale* (7 items): We used Liu et al.’s (2025) FLE scale, which was developed for informal digital learning of English contexts and subsequently validated in an AI-IDLE setting by Zou et al. (2026b). Its content validity was then reviewed by three experienced scholars in CALL. It should be noted that this FLE scale exclusively captures the private dimension of enjoyment as self-directed and autonomous English learning activities primarily emphasize learners’ internal, individual experiences of enjoyment. The value of Cronbach’s alpha of the overall FLE scale was .91, demonstrating excellent internal consistency. An example item is: “I am not tired of learning English.”
- 3) *Foreign Language Boredom Scale* (11 items): Respondents’ FLB was assessed with the scale developed and psychometrically validated by Li et al. (2023). In the current sample, the instrument showed excellent internal consistency, as indicated by a Cronbach’s alpha of .94. An example item is “So much practice on the same (English-related) subject matter makes me restless.”

- 4) *Strategic Competence for Cross-cultural Communication Scale* (4 items): Respondents' SCCC was measured with Lee's (2020) scale, which was developed and validated for informal digital language learning contexts. In the current study, the overall scale produced a Cronbach's alpha of .77, suggesting acceptable internal consistency. An example item is: "I can explain my own culture and customs clearly in English to people from other cultures."

As the original scales were in English, a back-translation procedure combined with collaborative reconciliation was employed to produce the Chinese version. The forward translation was independently completed by two bilingual (Chinese and English) researchers with expertise in language education. The back-translated version was prepared by another member of the research team who specialized in translation studies. Discrepancies across versions were discussed and resolved in an online meeting with all parties involved. After the bilingual questionnaire had been finalized and data collection completed, the following analytical procedures were undertaken.

Statistical analyses were conducted in SPSS 29.0 and AMOS 29.0, adopting a five-step SEM procedure (Collier, 2020; Kline, 2023). After screening the dataset and removing responses completed in less than 60 seconds, the distributional properties of the data were examined using skewness, kurtosis, means, and standard deviations. Internal consistency was subsequently assessed using Cronbach's alpha, and construct validity was verified through confirmatory factor analysis (CFA). The structural model was subsequently tested to examine the associations among AI-IDLE, FLE, FLB, and SCCC. It should be noted that the specific thresholds applied at each step are detailed in the following section.

3.2. Findings

The findings are presented through descriptive statistics of AI-IDLE, FLE, FLB, and SCCC, followed by reliability and validity tests, and structural and mediation analyses addressing RQ1.

3.2.1. Descriptive statistics

Table 2 shows descriptive statistics of each variable. It indicates frequent AI-IDLE participation, high FLE and SCCC, and moderate FLB ($M = 3.28-4.26$). Standard deviations ($SD = 1.05-1.16$) reflect acceptable variability, and skewness/kurtosis values fell within Kline's (2023) thresholds ($|3|$, $|8|$), confirming normality.

Table 2 Descriptive statistics of each construct

Constructs	<i>M</i>	<i>SD</i>	skewness (< 3)	kurtosis (< 8)	Cronbach's α (> .7)
AI-IDLE	4.26	1.07	-0.55	0.09	.92
FLE	3.67	1.12	-0.29	0.10	.91
FLB	3.28	1.16	0.10	-0.20	.94
SCCC	3.97	1.05	-0.36	0.18	.77

Note. AI-IDLE = AI-mediated informal digital learning of English, FLE = foreign language enjoyment, FLB = foreign language boredom, SCCC = strategic competence for cross-cultural communication

3.2.2. Assessment of reliability and validity

The Cronbach's α values of four variables were .92 (AI-IDLE), .91 (FLE), .94 (FLB), and .77 (SCCC) (see Table 3). Following Kline's (2023) guidelines, .70 was adopted as the threshold for acceptable reliability; all Cronbach's α values surpassed this benchmark, indicating adequate internal consistency. Additionally, based on the recommended threshold for factor loadings, two items (F2 and AI5) were removed from subsequent analyses due to their relatively low standardized loadings (.54 for F2 and .50 for AI5) within the FLE and AI-IDLE constructs.

Table 3 Reliability and convergent validity of the constructs

Constructs	Items	factor loading (in CFA)	AVE	CR
AI-IDLE	AI1	.78	.64	.92
	AI2	.79		
	AI3	.78		
	AI4	.85		
	AI6	.79		
	AI7	.76		
	AI8	.82		
	AI5	.50		
FLE	F1	.85	.64	.91
	F3	.68		
	F4	.91		
	F5	.70		
	F6	.74		
	F7	.89		
	F2	.54		
	F8	.82		
FLB	B1	.80	.58	.94
	B2	.84		
	B3	.69		
	B4	.73		
	B5	.80		
	B6	.76		
	B7	.78		
	B8	.77		
	B9	.78		
	B10	.77		
	B11	.66		
SCCC	SC1	.62	.5	.78
	SC2	.64		
	SC3	.60		
	SC4	.85		

Note. AVE = average variance extracted, CR = composite reliability

Construct validity was assessed by examining both convergent and discriminant validity. The results demonstrated satisfactory evidence of convergent validity for all latent constructs, with composite reliability (CR) values exceeding the recommended threshold of .70 and average variance extracted (AVE) values surpassing the criterion of .50 (Collier, 2020; Hair et al., 2009) (see Table 3). The results presented in Table 4 provided evidence of discriminant validity as the AVE square root for every construct was higher than its correlations with all remaining constructs.

The measurement model, comprising four constructs and their observed variables, was tested in AMOS 29. All six fit indices (the chi-square to degrees of freedom ratio [χ^2/df], incremental fit index [IFI > .9], Tucker-Lewis index [TLI > .9], comparative fit index [CFI > .9], parsimony goodness-of-fit index [PGFI > .5], and root mean square error of approximation [RMSEA < .08]) met recommended thresholds (Collier, 2020), indicating satisfactory model fit and strong construct validity (see Table 5).

Table 4 The discriminant validity of AI-IDLE, FLE, FLB, and SCCC

Constructs	Square root of AVE and squared correlation coefficient matrix			
	AI-IDLE	FLE	FLB	SCCC
AI-IDLE	.80			
FLE	.33	.80		
FLB	-.19	-.47	.76	
SCCC	.34	.32	-.13	.69

Table 5 Model fit indices of AI-IDLE, FLE, FLB, and SCCC

	χ^2/df	IFI	TLI	CFI	PGFI	RMSEA
Measurement model	3.29	.906	.90	.905	.70	.08
Initial structural model	3.97	.88	.86	.88	.68	.08
Finalized structural model	2.94	.91	.902	.91	.71	.07
Benchmark values (Kline, 2023)	< 3	> .9	> .9	> .9	> .5	< .08
Evaluation	Good	Good	Good	Good	Good	Good

Note. χ^2/df = chi-square/degrees of freedom, IFI = incremental fit index, TLI = tucker-lewis index, CFI = comparative fit index, PGFI = parsimony goodness-of-fit index, RMSEA = root mean square error of approximation

3.2.3. Results of the structural model

SEM was conducted in AMOS 29 to investigate the pathways linking AI-IDLE participation with learners' FLE, FLB, and SCCC. The initial estimation of structural model indicated an unsatisfactory model fit, with five of the six fit indices (i.e., χ^2/df , IFI, TLI, CFI, and RMSEA) falling outside the recommended ranges. Therefore, the model was subsequently refined based on modification indices (MI) following Collier's (2020) guidance. Following the MI results, six pairs of error terms (eA1-eA2, eF5-eF6, eB6-eB7, eB7-eB8, eB9-eB11, and eB10-eB11) within

the AI-IDLE, FLE, and FLB constructs were permitted to covary to minimize item redundancy and enhance model fit (see Figure 1). For instance, the residual correlation between AI1 and AI2 is theoretically justifiable because both items measure learners' interactive use of AI tools for spoken English practice out of class. AI1 refers to engaging in conversations with AI-powered chatbots, whereas AI2 focuses on practicing speaking through AI-powered speech recognition with immediate feedback. Because both items capture closely related behaviors involving AI-mediated speaking interaction and feedback, their residuals were allowed to co-vary. This correlated error term was therefore theoretically justified, and the remaining error pairs were specified following the same rationale.

Table 6 Standardized hypotheses testing results of paths

Paths	β	p	BCCI 95%		Results
			Lower bound	Upper bound	
AI-IDLE $\rightarrow$ FLE	.356***	$p < .001$	.246	.456	Supported
AI-IDLE $\rightarrow$ FLB	-.217***	$p < .001$	-.328	-.100	Supported
AI-IDLE $\rightarrow$ SCCC	.293***	$p < .001$	.168	.420	Supported
FLE $\rightarrow$ SCCC	.255***	$p < .001$	.099	.407	Supported
FLB $\rightarrow$ SCCC	.036 ^{n.s.}	$p = .577$	-.096	.163	Unsupported
indirect effects					
AI-IDLE $\rightarrow$ FLE $\rightarrow$ SCCC	.07	$p < .001$	.02	.12	Partial mediation
AI-IDLE $\rightarrow$ FLB $\rightarrow$ SCCC	-.01	$p = .577$	-.03	.02	No mediation

Note. BCCI = bias-corrected bootstrap 95% confidence intervals, *** $p < .001$, n.s. = non-significant, AI-IDLE = AI-mediated informal digital learning of English, FLE = foreign language enjoyment, FLB = foreign language boredom, SCCC = strategic competence for cross-cultural communication

After model refinement, the revised structural model achieved acceptable fit, with all evaluated fit indices meeting the recommended cutoff criteria. Path analysis based on the final model supported four paths. Specifically, AI-IDLE directly and positively predicted SCCC ($\beta = .293$, $p < .001$, BCCI 95% [.168, .420]). AI-IDLE positively predicted FLE ($\beta = .356$, $p < .001$, BCCI 95% [.246, .456]), while negatively predicted FLB ($\beta = -.217$, $p < .001$, BCCI 95% [-.328, -.100]). FLE significantly predicted SCCC ($\beta = .255$, $p < .001$, BCCI 95% [.099, .407]), while FLB failed to predict SCCC ($\beta = .036$, $p = .577$, BCCI 95% [-.096, .163]). The R^2 values (see Figure 1) suggested that AI-IDLE explained 13% of the variance in FLE and 5% of the variance in FLB. The three variables (i.e., AI-IDLE, FLE, FLB) explained 20% of the variance in SCCC. The mediating effects of FLE and FLB in the relationship between AI-IDLE and SCCC were assessed using AMOS 29 with a bias-corrected bootstrap approach based on 2,000 bootstrap samples and 95% confidence intervals. As reported in Table 6, the indirect pathway via FLE was statistically significant, indicating partial mediation between AI-IDLE and SCCC (BCCI 95% [.02, .12], $p < .001$), because the bootstrap confidence interval excluded zero (Collier, 2020). However, the indirect pathway through FLB was insignificant,

with the confidence interval containing zero (BCCI 95% [-.03, .02], $p = .577$) (Collier, 2020). Thus, no significant mediating effect of FLB was identified in the relationship between AI-IDLE and SCCC (Collier, 2020).

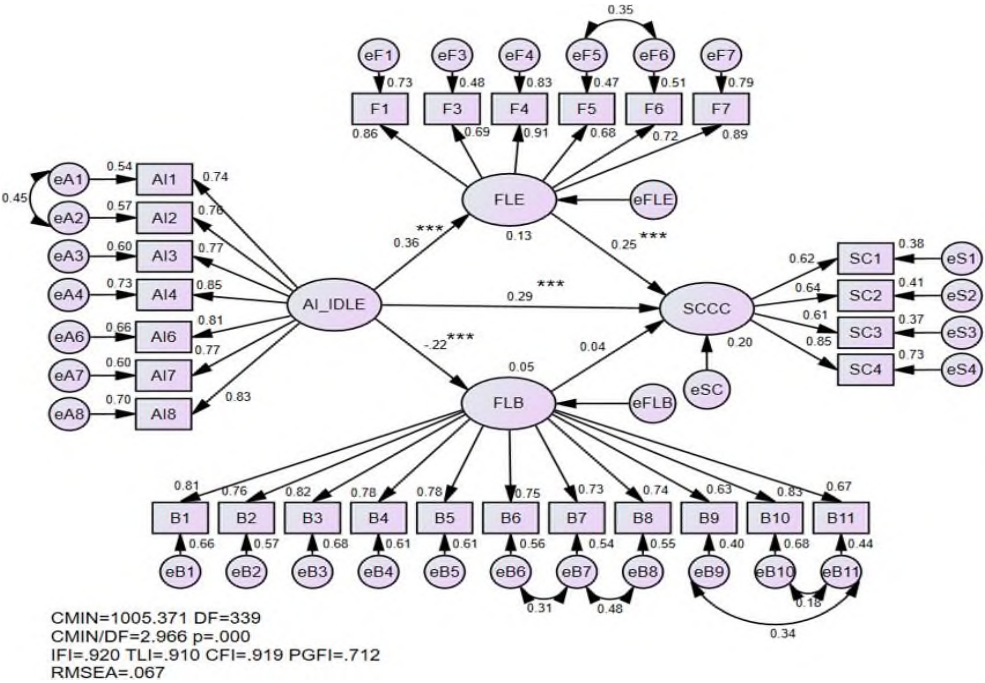


Figure 1 The structural equation model of AI-IDLE, FLE, FLB, and SCCC (AI-IDLE = AI-mediated informal digital learning of English, FLE = foreign language enjoyment, FLB = foreign language boredom, SCCC = strategic competence for cross-cultural communication)

4. Stage 2: Person-centered approach

4.1. Method

4.1.1. Participants

In Stage 2, the person-centered approach was employed to identify latent profiles based on learners' AI-IDLE characteristics. The analysis drew on the same instruments and dataset as Stage 1 ($N = 435$). Learners' AI-IDLE participation profiles served as an independent variable, while achievement emotions and SCCC were regarded as outcome variables.

4.1.2. Data analysis

LPA was performed in Mplus 8.3 to identify the optimal profile solution (Muthén & Muthén, 2017). Model fit was assessed using the Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size adjusted BIC (aBIC), Lo-Mendell-Rubin likelihood ratio test (L-M-R LRT), and bootstrap likelihood ratio test (BLRT), and entropy, with lower information criteria and significant LRT/BLRT p -values ($p < .05$) indicating better fit and entropy $> .80$ reflecting strong classification accuracy. The smallest cluster frequency was higher than 5%, indicating highly satisfactory classification. Following the identification of the latent profiles, a series of one-way analyses of variance (ANOVAs) was computed to determine whether FLE, FLB, and SCCC differed significantly across the identified profiles. Profile membership was specified as the independent variable, and the three constructs as the dependent variables. When significant differences were detected, Games-Howell post-hoc tests were conducted to identify which specific profiles differed from one another, and effect size (η^2) was reported as a measure of effect size.

4.2. Findings

4.2.1. Profiles of AI-IDLE

As shown in Table 7, the fit indices supported a three-profile solution as the optimal model, comprising proactive AI-IDLE strategists, balanced AI-IDLE learners, and passive AI-IDLE users. Model fit was assessed using several information criteria, including AIC, BIC, and aBIC, for which smaller values indicated a better fit. Table 7 shows that all three indices decreased progressively across profiles ranging from one to five profiles. The Lo-Mendell-Rubin likelihood ratio test (L-M-R LRT) and the bootstrap likelihood ratio test (BLRT) were used to compare the k -profile model with the $k-1$ profile model. The non-significant result of the L-M-R LRT for the four-profile model ($.06 > .05$) suggested that the three-profile model was sufficient. Entropy was also considered to evaluate the accuracy of classification, with higher values (approaching 1) indicating clearer classification. The results showed that the entropy values for all models exceeded the recommended benchmark of .80 (Lubke & Muthén, 2007), with the three-profile and four-profile models demonstrating the highest entropy. Finally, the smallest class proportion in the three-profile model (15.9%) was well above the recommended minimum threshold of 5% for latent profiles (Masyn, 2017). Overall, the 3-profile model was selected as the optimal model solution (see Table 7), which aligned with the theoretical foundation. Table 8 presents the classification probabilities which confirmed distinct profile membership.

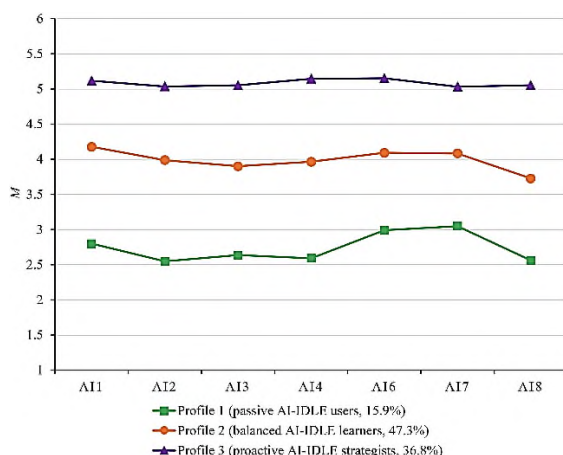
Table 7 Model fit indices for different profile models

Number of classes	AIC	BIC	aBIC	L-M-R LRT (<i>p</i>)	BLRT (<i>p</i>)	Entropy	Smallest cluster frequency
1	9162.79	9219.85	9175.42	/	/	/	435 (100%)
2	8007.11	8096.77	8026.96	.009	< .001	.845	197 (45.3%)
3*	7472.44	7594.70	7499.49	< .001	< .001	.897	69 (15.9%)
4	7317.55	7472.41	7351.816	.06	< .001	.897	30(6.9%)
5	7188.48	7375.95	7229.97	.35	< .001	.893	28 (6.4%)

Note. *The selected optimal model profile is demonstrated

Table 8 Average latent profile probabilities for most likely latent profile membership

profiles	1	2	3
1. Passive AI-IDLE users	.96	.04	.00
2. Balanced AI-IDLE learners	.03	.95	.03
3. Proactive AI-IDLE strategists	.00	.04	.96

**Figure 2** Latent profiles of students' AI-IDLE participation (AI-IDLE = AI-mediated informal digital learning of English)

4.2.2. Description of the identified profiles

The overall configuration of the AI-IDLE profiles was depicted by comparing the three profiles' scores across the seven AI-IDLE items. As presented in Figure 2, the three latent profiles showed clearly distinguishable levels of AI-IDLE engagement. Profile 1 comprised learners with relatively low AI-IDLE scores and was thus labeled "passive AI-IDLE users." This profile was the smallest group, representing 15.9% of the total sample ($N = 69$). The second profile consisted of learners demonstrating moderate to relatively high levels of AI-IDLE and was thus termed "balanced AI-IDLE learners." This group represented the highest percentage of participants,

comprising 47.3% of the sample ($N = 206$). The third profile, labeled “proactive AI-IDLE strategists,” included learners who showed high levels of AI-IDLE participation. This group accounted for 36.8% of the total sample ($N = 160$).

4.2.3. Differences between achievement emotions and SCCC across the profiles

Following the profile classification, group comparisons were conducted using one-way ANOVA to determine whether the three AI-IDLE groups exhibited differences in FLE, FLB, and SCCC constructs. As can be seen from Table 9, the three identified profiles of AI-IDLE differed significantly regarding FLE ($F = 12.87$, $p < .001$), FLB ($F = 5.649$, $p = .004$), and SCCC ($F = 18.629$, $p < .001$). In the case of FLE, the proactive AI-IDLE strategists profile scored highest ($M = 3.87$, $SD = 1.02$), followed by the balanced AI-IDLE learners ($M = 3.60$, $SD = 0.83$) and the passive AI-IDLE users ($M = 3.20$, $SD = 0.89$). For FLB, the passive AI-IDLE users reported the highest level of boredom ($M = 3.45$, $SD = 0.88$), followed by the balanced AI-IDLE learners ($M = 3.36$, $SD = 0.79$), whereas the proactive AI-IDLE strategists exhibited the lowest level of this emotion ($M = 3.09$, $SD = 1.03$). In terms of SCCC, the proactive AI-IDLE strategists again attained the highest score ($M = 4.23$, $SD = 0.83$), followed by the balanced AI-IDLE learners ($M = 3.88$, $SD = 0.73$) and the passive AI-IDLE users ($M = 3.59$, $SD = 0.80$).

Table 9 Mean scores of outcomes variables and ANOVA across profiles of AI-IDLE

Profiles	Profile 1: passive AI-IDLE users	Profile 2: balanced AI-IDLE learners	Profile 3: pro- active AI-IDLE strategists	ANOVA results		
Sample size and proportion	$N = 69$ (15.9%)	$N = 206$ (47.3%)	$N = 160$ (36.8%)	post hoc (Games-Howell)		
	$M (SD)$	$M (SD)$	$M (SD)$	F	p	η^2
FLE	3.20 (.89)	3.6 (.83)	3.87 (1.02)	12.87***	< .001	.056 $P1 < P2 < P3$
FLB	3.45 (.88)	3.36 (.79)	3.09 (1.03)	5.649**	.004	.025 $P3 < P1$; $P3 < P2$
SCCC	3.59 (.80)	3.88 (.73)	4.23 (.83)	18.629***	< .001	.079 $P1 < P2 < P3$

Note. *** $p < .001$, ** $p < .005$, M = mean, SD = standard deviation, ANOVA = analyses of variance, P = profile, FLE = foreign language enjoyment; FLB = foreign language boredom; SCCC = strategic competence for cross-cultural communication

5. Discussion

Drawing on both SEM and LPA approaches, the present study examined the relationships among AI-IDLE, FLE, FLB, and SCCC, and identified three profiles of AI-IDLE participation. The variable-centered analysis revealed that AI-IDLE positively predicted learners’ FLE and SCCC while negatively predicting FLB, thereby capturing the overall structural associations among these constructs. Complementing

these findings, the person-centered analysis uncovered three different profiles: proactive AI-IDLE strategists, balanced AI-IDLE learners, and passive AI-IDLE users, which differed significantly in their achievement emotions and SCCC, thus illuminating the heterogeneity. While the SEM path model suggested that FLB did not directly impact SCCC at the aggregate level, the LPA profile comparison nuanced this finding by showing that proactive AI strategists experienced significantly lower FLB than passive users, underscoring the necessity of capturing individual heterogeneity. Thus, the two approaches offered a more comprehensive account of how AI-IDLE related to learners' emotions and SCCC.

5.1. The role of AI-IDLE in achievement emotions and SCCC

When it comes to RQ1, the findings indicated that learners with more active AI-IDLE engagement reported greater enjoyment and less boredom in their language learning. This finding echoes the study conducted by Liu et al. (2025), which identified AI-IDLE as a positive predictor of learner enjoyment. It also resonates with Zou et al.'s (2025b) findings concerning the negative effect of AI-IDLE on language boredom. Rather than merely reflecting a technological novelty effect, this relationship can be interpreted in light of the affordances of AI-mediated learning environments (Yang & Du, 2025). AI-powered chatbots typically provide adaptive and tailored feedback, interactive interaction, and immediate and flexible learning opportunities, allowing learners to personalize their learning experiences and engage with authentic materials (Kohnke et al., 2023). Such affordances can maximize learners' autonomy and agency, which in turn may foster their positive emotions and alleviate their negative feelings (Zou et al., 2025b). In this sense, AI-IDLE may create emotionally supportive learning conditions that promote enjoyment and reduce the sense of monotony often associated with boredom.

Moreover, students' AI-IDLE participation had a positive and significant influence on their SCCC. This finding aligns with Lee (2020), who found that Korean EFL learners' IDLE engagement was positively related to their intercultural communication competence. It is also in line with Liu et al. (2023), who revealed that digital language learning contributed to learners' capacity for effective and contextually appropriate intercultural interactions while expanding their cultural knowledge. Through AI-powered platforms, learners are exposed to diverse linguistic input and intercultural communication scenarios, which may encourage them to employ strategies for negotiating meaning, managing misunderstandings, and sustaining intercultural communication (Xia et al., 2024).

Furthermore, the study demonstrated that a stronger sense of FLE enables higher SCCC, an insight that is corroborated by the significant predictive role

of FLE in SCCC. This result echoes Fathi et al. (2023), who found that Iranian university EFL learners reporting higher enjoyment tended to demonstrate stronger intercultural communication competence and greater WTC. However, in this research, learners' FLB failed to predict their SCCC, which diverges from the findings reported by Tang et al. (2024). This unexpected finding warrants careful interpretation and may be explained by two contextual factors: the examination-oriented culture of Chinese higher education and the self-directed structure of AI-IDLE environments. First, learning in Chinese higher education is strongly exam-oriented. In such contexts, students may continue to invest effort in developing their SCCC even when they feel bored, because English proficiency is closely tied to their long-term academic and career aspirations (Feng et al., 2023; Li et al., 2024). As a result, boredom may not necessarily translate into a decline in SCCC. Second, the self-directed structure of AI-IDLE environments may partially buffer the negative effects of boredom (Zou et al., 2025b, 2026b). Because informal digital learning is flexible and learner-controlled, students who become bored can readily switch to a different task, explore alternative resources, or interact with AI tools in more engaging ways (Liu et al., 2024b, 2025). Conceptually, this lack of predictive significance highlights the functional divergence between affective states and strategic competence. FLB represents a temporary affective experience associated with low arousal and behavioral withdrawal (Pawlak et al., 2026), whereas SCCC reflects a domain-specific cognitive and pragmatic capability used to negotiate meaning and resolve communicative friction (Lee, 2020). In AI-IDLE settings, occasional episodes of boredom may alter immediate task engagement without directly dampening or compromising learners' strategic repertoire for cross-cultural communication.

Finally, this study underscored that FLE played a dual role in influencing learners' SCCC: it directly contributed to higher levels of SCCC and indirectly connected EFL learners' AI-IDLE participation with their SCCC through a mediating pathway. Consistent with prior work showing the salient role of enjoyment in technology-mediated learning (Zou et al., 2026b), our findings foreground that enjoyment served as a mediator between AI-IDLE participation and SCCC.

5.2. The AI-IDLE profiles

Regarding RQ2, three profiles of learners' AI-IDLE participation were identified in the present study: passive AI-IDLE users, balanced AI-IDLE learners, and proactive AI-IDLE strategists. The results are consistent with Guo et al. (2025), who similarly reported three IDLE profiles: moderate, active, and passive IDLE learners. It suggests that three profiles can be identified across both AI-mediated and non-AI-mediated learning environments. However, the three-profile solution diverges from

Smith et al. (2025), who identified five distinct profiles. One possible reason for this discrepancy lies in the different constructs used to derive the profiles. The present study identified profiles based solely on items measuring AI-IDLE, whereas Smith et al. (2025) drew on five constructs (i.e., out-of-class behavior, digital behavior, effort, current L2 self, and ideal L2 self) to identify profiles through LPA. It therefore appears that the choice of indicators can substantially shape the resulting profile solutions.

The passive AI-IDLE users' profile, which accounted for 15.9% of participants, represented the smallest group. There are two factors that may have contributed to the low participation of AI-IDLE in this group. First, students representing this profile may manifest skeptical attitudes toward the effectiveness of AI-powered tools for language learning (Kohnke et al., 2023). As AI technologies become more widely integrated into language learning, some learners remain unsure about how effectively these tools can support the development of their English proficiency. As a result, they may perceive limited pedagogical value in using AI for language practice and engage less frequently in AI-IDLE activities. In addition, these learners may assign relatively low personal value to English learning in relation to their future academic or career trajectories (Zou et al., 2025c). Learners who perceive English as less valuable for achieving their future goals are less inclined to devote sustained effort to autonomous and self-directed language learning (Lai & Wang, 2025). Thus, their AI-IDLE participation remains passive.

The balanced AI-IDLE learners' profile, comprising 47.3% of the respondents, represented the most prevalent group in the sample. Students assigned to this profile demonstrated moderate to relatively high levels of AI-IDLE participation. Such an AI-IDLE pattern may be impacted by the broader educational and cultural context in China, particularly the test-oriented academic environment and the impact of Confucian heritage culture, which promotes a balanced learning approach and emphasizes sustained effort as a pathway to achievement (Yang & Du, 2025; Yang, & Liu, 2025). The exam-oriented nature of Chinese education system, particularly including English course examinations, English proficiency certification tests, and English-related competitions or debates, may encourage students to extend their AI-IDLE participation (Zou et al., 2025c). Driven by these academic and career considerations, learners appear to engage in AI-IDLE at a moderate level.

The second most common profile, proactive AI-IDLE strategists, accounted for 36.8% of the participants. Learners representing this profile demonstrated active and self-initiated participation in AI-IDLE. Several factors may help explain the emergence of this group. First, these learners tend to cultivate a clear awareness of the learning affordances provided by AI-powered tools. As they increasingly recognized that such tools could support language practice, provide feedback and explanations, and simulate authentic interaction, they perceived AI as an efficient resource for improving their English proficiency (Kohnke et al., 2023; Zou et al.,

2026b). This self-initiated and proactive engagement resonates with recent qualitative evidence (e.g., Liao et al., 2025), which revealed that EFL learners perceive GenAI tools as customized virtual tutors (“having my own teacher beside me”) that reduce search time and provide instant scaffolded feedback, thereby encouraging sustained AI-IDLE participation. This perceived usefulness likely motivated them to embed AI-based tools into their regular language learning practices (Zou et al., 2026b). Second, AI systems, particularly large language models, are trained on extensive linguistic datasets, enabling them to offer learners timely, diverse, and context-sensitive language input (Lu & Zeng, 2025). Such systems allow learners to quickly evaluate their current language proficiency through interactive exchanges and receive personalized feedback. In addition, the availability of timely and informative feedback from AI-powered chatbots may enhance learners’ sense of progress and learning efficiency, thereby encouraging more frequent and proactive engagement with AI-mediated learning activities (Guan et al., 2024). Moreover, learners may encounter social comparison and competitive pressures from their peers, for English proficiency is often regarded as an important asset for academic advancement and future career opportunities. Although such pressure is initially external in nature, it may become internalized over time: As learners come to personally realize the value of English proficiency for their academic and career goals, this externally originating impetus can be gradually integrated into intrinsic motivation (Zou et al., 2026b). Through this process of internalization, the pressure to succeed may cultivate a stronger sense of agency and responsibility for their own language development (Liu et al., 2024b), which in turn encourages them to actively seek out learning opportunities, including strategic use of AI tools to support their autonomous language learning (Lai & Wang, 2025). On the whole, these results suggest that such learners do not view AI simply as an external support resource; rather, they incorporate it into their autonomous language learning activities. The consistent patterns observed across three profiles further indicate a strong correlation between EFL learners’ achievement emotions and their SCCC.

5.3. Differences between achievement emotions and SCCC across three AI-IDLE profiles

With respect to RQ3, the study demonstrated that EFL learners’ FLE, FLB, and SCCC differed significantly across three profiles of AI-IDLE. As learners’ participation in AI-IDLE increased, their FLE and SCCC were enhanced, while their FLB diminished accordingly. Our finding lends further support to existing evidence that autonomous AI-IDLE participation is associated with greater enjoyment in the language learning process (Zou et al., 2026b). Regarding FLB, the passive AI-IDLE users exhibited the highest level of boredom, followed by the balanced AI-

IDLE learners, with the proactive AI-IDLE strategists reporting the lowest level of boredom. These novel results extend prior work by demonstrating that engaging in digital learning activities may diminish learners' feelings of boredom (Zou et al., 2026b). One possible interpretation of this interesting insight may lie in emotion regulation (Guo et al., 2025). As self-directed language learning beyond the classroom often involves complex emotional experiences, it requires learners to regulate their emotions without their teachers' support, thereby helping balance their motivational, behavioral, emotional, cognitive, and cultural dimensions (Lee & Xie, 2023; Smith et al., 2025; Zou et al., 2026b).

The results also demonstrated that learners who engaged more frequently in AI-IDLE activities tended to demonstrate stronger SCCC. The three identified AI-IDLE profiles demonstrated significantly different levels of SCCC, indicating that the degree of AI-IDLE participation could substantially influence learners' strategic communication abilities. To be specific, learners characterized by higher levels of AI-IDLE participation tended to report stronger SCCC, whereas those with limited participation exhibited comparatively lower levels. This pattern echoes the findings reported by Guo et al. (2025), who found that active IDLE learners exhibited a significantly greater WTC in digital settings compared with moderate and passive IDLE learners. This finding may be attributable to the experiential and interactive nature of AI-IDLE participation. By regularly interacting with AI-powered platforms, learners are exposed to diverse communicative scenarios, obtain prompt feedback, and are encouraged to experiment with different linguistic and pragmatic strategies (Xia et al., 2024). Such frequent AI-IDLE participation may gradually strengthen learners' ability to manage communication misunderstandings, negotiate meaning, and adjust their language use (Liu et al., 2023). To sum up, the heterogeneity demonstrated by profile analysis underscores distinct patterns of AI-IDLE practices that would be overlooked in the aggregated results typically produced by the variable-centered approach (Lai & Wang, 2025; Marsh et al., 2009).

6. Pedagogical implications

In light of the SEM and LPA results, some implications can be put forward. In view of the positive predictive role of AI-IDLE in FLE and SCCC, teachers could integrate AI-mediated IDLE activities into their instructional practices, designing interactive and enjoyable tasks or seminars. For example, teachers can invite some foreigners to join AI-assisted virtual chatrooms, and motivate students to share their opinions in English. This approach could facilitate learners' autonomous engagement with multiple AI-supported learning affordances outside the

classroom, sustaining their positive emotions and enhancing their intercultural communication competence (Lee, 2020). Beyond fostering positive emotions, AI-IDLE participation may also help alleviate negative ones. Given the negative predictive role of AI-IDLE in FLB, educators could implement targeted interventions to help learners regulate negative emotions. For example, teachers may design AI-supported intercultural communication simulations, where students interact with AI-generated interlocutors representing different cultural backgrounds. This approach can help mitigate boredom while enhancing SCCC. Finally, based on three profiles of AI-IDLE, it is possible to implement specific interventions that can be designed for each AI-IDLE profile. For passive AI-IDLE users' group, who display relatively limited AI-IDLE participation, teachers are encouraged to provide structured guidance and scaffolded entry points to AI-IDLE (e.g., guided AI-assisted discussion tasks). Such scaffolding may help reduce boredom and gradually foster enjoyment in AI-mediated language learning. With respect to the balanced AI-IDLE learners group, who show moderate-to-high levels of AI-IDLE participation, teachers may design interactive AI-mediated collaborative tasks (e.g., role-play simulations) to help learners actively immerse in AI-mediated language learning activities. This approach could further enhance learners' enjoyment and promote their SCCC. With regard to proactive AI-IDLE strategists group, who exhibited the highest levels of autonomous AI-IDLE participation, educators may benefit from encouraging more advanced and complex AI-assisted learning practices (e.g., reflective tasks that deepen learners' intercultural awareness) (Yang & Du, 2025).

7. Limitations and future directions

Although the present study provides fresh perspectives on AI-IDLE research, several limitations should be acknowledged. First, the use of self-reported data may have introduced potential biases (e.g., social desirability bias and inaccurate subjective evaluations of one's own abilities). Therefore, future research should employ supplementary data collection approaches (e.g., semi-structured interviews and reflective journals) to attain a more comprehensively validated understanding of L2 learners' AI-IDLE, achievement emotions, and SCCC across other contexts. Second, this study did not explore Chinese EFL learners' AI-IDLE participation changes in the long run, thus failing to reveal the longitudinal AI-IDLE participation changes of language learners. As such, longitudinal research capturing the dynamic interplay among AI-IDLE, emotional variables, and cultural factors is needed. Third, learners' AI-IDLE participation may not only function as a precursor to emotional and cultural factors but also be shaped by, and entangled with, contextual influences, including teacher support and parental attitudes. Accordingly, we advocate

that future investigations incorporate these considerations to yield a more in-depth understanding of the ways in which L2 learners draw on to support their IDLE. Further, while the current study focused exclusively on the FLE-private dimension within a self-directed informal learning context, future research should seek to consider all three dimensions of FLE in AI-mediated language learning contexts to obtain a more holistic insight into learners' emotional experiences. Lastly, because the study drew exclusively on Chinese university students, caution is warranted in extending the findings to learners in other cultural settings and educational institutions. Therefore, future research may recruit participants from other countries to examine the mechanisms underlying AI-IDLE participation.

8. Conclusion

By integrating variable- and person-centered perspectives, this study investigates how AI-IDLE participation relates to achievement emotions (FLE and FLB) and SCCC. The results contribute to research on AI-mediated informal language learning and individual differences in SLA by showing that greater engagement with AI-IDLE was associated with higher FLE and SCCC, as well as lower FLB. The study also highlights the mediating role of FLE, which serves as an affective pathway linking AI-IDLE participation with SCCC. Furthermore, the three profiles of AI-IDLE were identified (including passive AI-IDLE users, balanced AI-IDLE learners, and proactive AI-IDLE strategists). Learners' enjoyment, boredom, and SCCC differed significantly across the three profiles of AI-IDLE. On the whole, the study reveals significant theoretical contributions. From a theoretical perspective, the findings extend CVT (Pekrun, 2006; Pekrun & Perry, 2014) by providing empirical evidence of how AI-IDLE participation is associated with learners' achievement emotions as proximal affective outcomes and SCCC as a distal learning outcome. In addition, by integrating variable- and person-centered approaches, the study extends prior research on AI-IDLE in Chinese EFL contexts, thereby enabling a more differentiated perspective on the structural relationships among the variables while capturing population heterogeneity (Yang & Du, 2025).

Acknowledgments

We sincerely thank the editors and the anonymous reviewers for their constructive feedback and insightful suggestions. Our gratitude also extends to all the participants who kindly volunteered to take part in this study.

Funding

This study was supported by Macao Polytechnic University research grant: *Understanding Metacognition in GenAI Use for Language Teaching and Research* (Grant No. RP/FLT-05/2026) awarded to the second author: Mark Feng Teng. This study is also supported by the Hunan Province Key Teaching Reform Project for Regular Undergraduate Universities, *Research on Innovative Approaches and Models of College Foreign Language Education and Instruction in the Context of Generative Artificial Intelligence* (Project No. 202502002177), awarded to the third author, Xueyun He.

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