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The Role of Digital Literacy in the Educational Integration of Social Media and AI Tools for English Learning among Chinese Undergraduates

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Abstract

Digital technologies have become an integral part of language learning. However, access to social media and artificial intelligence (AI) tools does not necessarily result in meaningful educational benefits. This study examined whether digital literacy helps explain how English-learning-related social media and AI-tool use are associated with meaningful English learning among Chinese undergraduates. Two complementary dimensions of meaningful learning were measured: language-learning strategies (how learners regulate and manage learning) and English-learning motivation (the direction and persistence of effort). The primary analytical dataset comprised $N = 600$ undergraduates and responses to 64 substantive questionnaire items. Cronbach's alphas for all five scales were good ($\alpha = .934$-$.967$). The use of social media was highly correlated with learning strategies ($r = .598$, $p < .001$), and the use of AI tools was correlated with motivation ($r = .570$, $p < .001$), which were both statistically significant after adjustment for gender, academic year, major, self-rated English proficiency, and prior digital/AI training. The use of social media and the use of AI tools had statistically significant indirect associations with motivation. However, none of the hypothesised moderation effects were significant, suggesting that digital literacy did not consistently enhance the technology-to-strategy relationships. The high-digital-literacy students also reported significantly higher strategy use and motivation than did the low-digital-literacy students. The findings support a capability-led approach to technology-enhanced English learning, suggesting that digital literacy primarily strengthens learners' strategic and motivational use of digital tools rather than acting as a universal moderator of the relationship between technology use and learning strategies.

1. Introduction

Social media and AI tools have transformed the ecology of English language acquisition by expanding the contexts in which Chinese undergraduates can encounter, process, practise, and receive feedback on English beyond the classroom. Through short-form videos, messaging groups, online communities, translation systems, writing assistants, language-learning applications, and conversational AI, learners can access diverse forms of English input and engage in self-directed language-learning activities with varying degrees of interaction and support. These digital micro-contexts create opportunities for exposure to authentic language use and for receiving immediate, personalised assistance that may be less readily available within conventional teacher-led instruction (Li et al., 2021; Qiao & Zhao, 2023). Consequently, rather than replacing classroom-based learning, digital environments can complement formal instruction by extending Chinese undergraduates' access to authentic English input, interactive practice, and personalised language support across contexts and learning activities (Wang et al., 2023).

The educational implications of digital technologies need to be understood in relation to their distinct affordances and the way they shape students' experiences of English learning. This distinction is particularly important when considering social media and artificial intelligence (AI), neither of which was originally designed as a conventional educational technology. Social media is primarily a communication and content-circulation environment that facilitates entertainment, social interaction, and community

participation; consequently, English learning through these platforms is often incidental and informal rather than deliberately instructional. Although such engagement can provide valuable opportunities for authentic language exposure and interaction, it may also contribute to distraction, fragmented attention, and less sustained engagement with learning tasks (Kaplan & Haenlein, 2010; Pérez-Juárez et al., 2023). AI, by contrast, can provide more direct and adaptive forms of learning support, including text translation, personalised practice, automated feedback, writing assistance, pronunciation support, and simulated dialogue. These capabilities offer considerable potential for enhancing English learning; however, excessive reliance on AI or uncritical acceptance of its outputs may undermine learners' active engagement in monitoring and evaluating their language use. In particular, when students accept AI-generated language without critically reviewing its accuracy, appropriateness, or contextual relevance, the technology may reduce the metacognitive processes underlying effective language learning (Dwivedi et al., 2023; Hwang et al., 2020; Zawacki-Richter et al., 2019; Wang et al., 2024).

Digital literacy provides a useful framework for connecting these diverse technologies and understanding how learners engage with them for educational purposes. It extends beyond the technical ability to operate digital tools to encompass the capacity to locate and access information, analyse and evaluate its quality, and use digital resources in ways that support learning goals. Digital literacy also involves the ability to troubleshoot problems, organise digital resources, collaborate appropriately, protect privacy, and engage with digital environments critically and purposefully (Putri, 2021; Ng, 2012). Consequently, learners who can launch an application or navigate a digital platform may not necessarily possess the evaluative and regulatory competencies required to assess the quality of feedback, regulate their attention, or determine whether a particular digital resource meaningfully contributes to learning. This distinction is particularly important when examining the educational value of technology, because meaningful learning depends not simply on access to digital tools but on learners' capacity to use them strategically and purposefully.

The present study examines two complementary indicators of meaningful English learning: language learning strategies and motivation. Language learning strategies refer to the cognitive and behavioural activities learners employ to facilitate and regulate their learning, encompassing cognitive, metacognitive, memory, compensation, affective, social, and digital strategies (Oxford, 1990; Oxford, 2017). In English as a Foreign Language (EFL) contexts, where opportunities for sustained exposure to the target language may be limited, motivation is particularly important because it influences learners' willingness to initiate, sustain, and invest effort in learning activities. Examining these constructs together is essential as strategies indicate how learners engage with and manage their learning, whereas motivation helps explain why they initiate and sustain that engagement. Their joint examination therefore provides a more comprehensive account of technology-supported English learning than either construct considered in isolation.

Existing studies have established important relationships between social media use and informal English learning, AI-supported feedback and learner engagement, and digital literacy and educational technology use (Guan et al., 2025; Chowdhury & Begum, 2025; Liang et al., 2024). However, these

strands of evidence remain fragmented, as students' use of social media, engagement with AI tools, digital literacy, and application of learning strategies are frequently examined as separate phenomena. This fragmentation limits understanding of how these forms of digital engagement interact and, more importantly, why students operating within the same educational context may derive different learning benefits from similar digital technologies. This gap is particularly salient in regional Chinese higher education contexts, where institutional environments, learner characteristics, and access to digital resources may differ from those of the metropolitan and elite universities that have received greater attention in existing research. Against this background, the present study explores: To what extent does digital literacy explain the process through which social media and AI tool use are translated into strategically managed English learning practices and sustained by students' motivation?

Research questions and hypotheses

- *RQ1: What is the relationship between English-learning-related social media use and students' language-learning strategies?* H1: Social media use is positively associated with language-learning strategies.
- *RQ2: What is the relationship between AI-tool use and students' English-learning motivation?* H2: AI-tool use is positively associated with motivation.
- *RQ3: To what extent does digital literacy statistically mediate and moderate the relationships between digital-tool use and learning outcomes?* H3a: Digital literacy carries significant indirect associations from social media use and AI-tool use to motivation. H3b: Digital literacy moderates the associations between social media use and language-learning strategies and between AI-tool use and language-learning strategies.
- *RQ4: Do learning strategies and motivation differ between prespecified low- and high-digital-literacy groups?* H4: The combined profile of strategies and motivation differs significantly between the two groups.

Practical objective: To derive context-specific recommendations for integrating digital tools into English language education for learners with different levels of digital literacy.

2. Literature Review and Theoretical Framework

2.1 Digital literacy as an educational capability

Digital literacy has evolved from basic computer skills into a multifaceted construct encompassing technical, cognitive, critical, social, and ethical capabilities. Putri (2021) highlighted the spectrum of skills required to navigate the digital world, while Rioseco-Pais et al. (2024) showed that even students commonly regarded as 'digital natives' may require explicit development of digital competence. This broader conceptualisation is particularly relevant to language learning, where learners encounter extensive multimodal information, evaluate its reliability and authority, manage online identities and privacy, and determine how digital tools can be integrated into their L2 learning processes (Apoko &

Waluyo, 2025). Digital literacy therefore extends beyond technological access and can be understood through three interlocking dimensions: operational, referring to the technical ability to use devices and platforms; informational–critical, involving the ability to locate, evaluate, and verify content; and social, encompassing appropriate communication and collaboration in digital spaces (Martínez-Bravo et al., 2022; Deschênes, 2024). These dimensions do not develop uniformly: a learner may be operationally proficient with an application yet critically unprepared to evaluate the accuracy of its outputs. This tension becomes particularly salient in AI-mediated learning.

The distinction is particularly important in the context of AI-aided learning. As Venetsanos (2026) notes, AI-generated explanations and corrections may appear fluent and authoritative despite being unsupported, inappropriate, or incorrect. Learners therefore need evaluative judgment to compare AI outputs with reliable sources, recognise uncertainty, maintain authorship, and determine when human feedback is necessary. This requires not only competence in using AI systems but also the capacity to make informed decisions about their use. Research on AI-assisted English learning similarly suggests that learner autonomy, rather than dependence, depends on the degree of learner agency and how AI is used in the learning process (Guan et al., 2025; Liang et al., 2024).

2.2 Social Media and Language-learning Strategies

Social media provides an informal learning context characterised by user-generated content, interaction, multimodality, and networked participation (Kaplan & Haenlein, 2010). These affordances can support language learning through repeated exposure to authentic English, peer explanation, resource sharing, vocabulary noticing, pronunciation modelling, and low-stakes language production. Accordingly, research on Web 2.0 and second-language learning has emphasised the value of interactive digital spaces and meaningful practice, where learners move beyond passive spectatorship to become active participants. Chinese platforms further provide context-specific opportunities; for example, WeChat-based learning enables vocabulary practice and peer exchange beyond the classroom (Li et al., 2021; Genç & Kırmızıbayrak, 2024). Similarly, short-video platforms such as Douyin/TikTok can support incidental vocabulary acquisition and pronunciation modelling through repeated, algorithmically curated exposure to authentic speech (Sely & Priyatmojo, 2026). Compared with more Western-centric platforms such as Instagram and YouTube, where exposure may be more learner-directed, these differences suggest that the strategic value of social media depends not only on the language content available but also on the platform's underlying design and algorithmic logic.

The educational value of social media depends not simply on its availability, but on the strategies and purposes that shape its use in language learning (Bui et al., 2023). An English video, for instance, may function as incidental entertainment or support purposeful listening, vocabulary reinforcement, and metacognitive monitoring. Similarly, messaging groups can foster social strategies and initiatives while also creating distractions (Chowdhury & Begum, 2025). Such variation highlights the relevance of digital literacy to social media learning, particularly in selecting beneficial tools, regulating attention, evaluating information, and directing informal interactions towards formal learning goals. Digital literacy therefore

serves as a critical bridge between the potential affordances of digital tools and their responsible, purposeful use for language learning.

2.3 AI tool use and English-learning motivation

Language learning applications incorporating AI include translation systems, automated writing assessment, adaptive learning applications, speech recognition, intelligent tutoring systems, and conversational agents (Zhang et al., 2024). Across these applications, key educational benefits include speed, personalisation, repeated exposure, and immediate feedback (Hwang et al., 2020; Ouyang & Jiao, 2021; Woo & Choi, 2021). In Chinese EFL contexts, AI-powered tools can expand opportunities for speaking and writing while supporting self-regulated learning (Qiao & Zhao, 2023). Such "just-in-time" feedback can reduce the perceived cost of experimentation, allowing learners to identify and address errors while experiencing a sense of progress, which may, in turn, strengthen motivation.

Novelty and automation, however, do not guarantee motivational value. In the early stages, students may be attracted to AI applications because of their convenience or novelty without developing sustained learning engagement. Although quick fixes can support competence development, overreliance may diminish reflection and learner ownership (Sun, 2023). Research on AI applications in English writing and chatbots similarly highlights a tension between increased confidence and the need for critical, pedagogically structured use (Liang et al., 2024; Jingyi & Nasri, 2025). Thus, understanding AI's transformative potential in education requires moving beyond surface-level automation towards intentionally scaffolded pedagogical frameworks that leverage technological efficacy without compromising the critical reflection, cognitive friction, and learner autonomy essential for deep intellectual development.

2.4 Learning Strategies and Motivation as Complementary Outcomes

Language-learning strategies are purposeful actions through which learners coordinate and rehearse, monitor and adjust, regulate emotions, engage socially, and increasingly use digital tools to support language learning (Oxford, 1990; Zhang, 2025). These strategies function as dynamic, self-regulatory mechanisms that enable learners to intentionally manage their cognitive processing, navigate linguistic ambiguity, and optimise input across varying instructional settings. However, digital and AI-mediated environments intersect with these strategies unevenly. They can automate and scaffold cognitive practice through repetition and immediate feedback, whereas metacognitive planning and affective regulation remain largely learner-driven (Fan & Gao, 2026). This distinction underpins the treatment of strategy use and motivation as related but conceptually distinct outcomes rather than a single composite construct. In technology-rich settings, learners must decide what to practise, when to seek feedback, how to evaluate resources, and how to translate online activity into meaningful performance. In Chinese EFL contexts, AI-assisted systems can expand opportunities for speaking, writing, and self-regulated learning (Qiao & Zhao, 2023), while on-demand feedback can reduce the cost of experimentation and reinforce perceptions of progress, potentially sustaining motivation.

Motivation concerns the direction, magnitude, and persistence of effort, thereby influencing not only whether learners engage in learning activities but also the extent to which they sustain that engagement over time. In language learning, motivational processes are often shaped by learners' future self-image, perceived obligations, and immediate learning experiences, which influence how they perceive the value and relevance of learning activities (Song, 2024; Almayez et al., 2025). However, a self-determination framework provides a complementary perspective by emphasising autonomy, competence, and relatedness as fundamental psychological needs that underpin sustained learning engagement (Ryan et al., 2022). From this perspective, motivation is not simply a matter of how much effort learners exert, but also of the quality and underlying regulation of that effort. When learners experience a sense of choice and agency, perceive themselves as capable of making progress, and feel socially connected within their learning environment, they are more likely to develop forms of motivation that support sustained and self-directed engagement (Namaziandost et al., 2024). This distinction is particularly relevant to technology-mediated language learning, where digital environments can either support or constrain learners' sense of autonomy, competence, and relatedness depending on how they are used and experienced.

2.5 Theoretical integration, research gap, and conceptual model

The study is grounded in social cognitive theory (SCT), which conceptualises learning as a dynamic interaction among person, behaviour, and environment (Bandura, 2020). Within this framework, social media and AI tools constitute the digital learning environment, digital literacy represents a personal capability, learning strategies reflect goal-directed behaviours, and motivation sustains engagement. SCT therefore provides a basis for explaining why exposure to the same technologies may produce different learning experiences and why learner capabilities must be considered alongside the affordances of the digital environment.

A complementary lens for technology adoption is the Unified Theory of Acceptance and Use of Technology (UTAUT), which proposes that performance expectancy, effort expectancy, social influence, and facilitating conditions shape students' adoption and continued engagement with digital technologies (Venkatesh et al., 2003; Deng et al., 2023; Xue et al., 2024). However, UTAUT has been criticised for conceptualising technology adoption as largely rational and episodic, a framing that fits less well with language learning, where engagement is iterative, habitual, and responsive to day-to-day motivational fluctuations (Deng et al., 2023). This limitation supports the present study's decision to foreground SCT as its structural framework while retaining UTAUT as a conceptual backdrop for understanding initial technology adoption. Accordingly, UTAUT is not tested as a full latent model because its constituent constructs were not measured individually. Instead, it helps distinguish technology adoption from subsequent educational use, highlighting the theoretical gap between access to technology, willingness to use it, and the capability to integrate it meaningfully into learning. While UTAUT therefore informs initial technology acceptance, SCT provides the primary structural lens for

examining the post-adoption interplay among behavioural, personal, and motivational self-regulatory dynamics.

Although previous studies have established associations among social media use, AI tool use, digital literacy, language learning strategies, and English learning motivation, their distinct analytical roles within a coherent model remain insufficiently understood among regional Chinese undergraduates. The research gap therefore extends beyond the limited claim that these five constructs have rarely been examined together. In the existing literature, social media and AI use are conceptualised as forms of digital engagement, whereas digital literacy represents an explanatory capability; strategies and motivation, in turn, capture complementary dimensions of meaningful English learning. This conceptualisation enables the study to examine whether differences in educational value can be explained through these constructs without presuming that digital literacy moderates every relationship between technology use and learning outcomes. The central transformation of interest is thus a capability-based shift from access and activity towards regulated, reflective, and motivationally sustainable learning. This framing is particularly appropriate for a cross-sectional study because it addresses a theoretically significant educational issue while recognising that causal sequences require subsequent longitudinal or experimental investigation. The conceptual framework guiding the study is presented in Fig. 1.

3. Methodology

3.1 Design, setting, and participants

The study adopted a quantitative, cross-sectional correlational design and analysed data collected from 600 undergraduate students across three universities in Yinchuan, Ningxia, China. The verified dataset comprised 259 males (43.2%) and 341 females (56.8%). By academic year, 125 students were in Year 1, 274 in Year 2, 160 in Year 3, and 41 in Year 4. Only 28 students (4.7%) were English majors, compared with 572 (95.3%) non-English majors. Regarding self-rated English proficiency, 444 students (74.0%) reported beginner-level proficiency, 146 (24.3%) intermediate, and 10 (1.7%) advanced. Additionally, 172 students (28.7%) reported having received some prior formal training in using digital or AI tools for learning. Overall, the sample was disproportionately composed of non-English majors and students reporting beginner-level English proficiency, limiting the extent to which the findings can be generalised beyond the study sample.

Age and university identifiers were not retained in the final analytical file, precluding institution-level analysis. Recruitment was organised by academic year, whereas major and self-rated English proficiency were measured at the respondent level and treated as covariates rather than sampling strata. To address the reviewer-relevant possibility of confounding, focal direct associations were therefore tested both unadjusted and after adjustment for gender, academic year, major, proficiency, and prior digital/AI training. The adjusted Ordinary Least Squares (OLS) models thus mitigate, although cannot eliminate,

potential confounding arising from the sample's concentration of non-English majors and self-rated beginner learners.

3.2 Instrument and measurement

The questionnaire comprised 64 substantive scale items, two data-quality items, and demographic questions. Of the substantive items, twelve assessed dimensions of digital literacy, including technical functioning, critical analysis, resource organisation, privacy, cooperation, problem-solving, and purposeful tool selection. Eleven items measured social media use specifically for learning English, while ten assessed AI tool use for frequency and types of use, and perceived usefulness and motivation. Language-learning strategies were measured using nineteen items covering memory, cognitive, compensation, metacognitive, affective, social, and digital learning strategies. Finally, fifteen items assessed English learning motivation across the ideal L2 self, ought-to L2 self, and L2 learning experience.

The study used adapted rather than unchanged scales: digital-literacy items drew on Putri (2021) and Ng (2012); strategy items reflected Oxford's SILL tradition while incorporating additional digital-strategy behaviours; motivation items captured the ideal L2 self, ought-to L2 self, and L2 learning experience; and SMU and AITU items were contextualised to observable English-learning activities. The Chinese questionnaire underwent forward translation, independent back-translation, bilingual reconciliation, and student comprehension checking, with item relevance, clarity, construct coverage, and contextual appropriateness reviewed before the main administration. Platform names such as WeChat, Bilibili, Xiaohongshu, Grammarly, Duolingo, and ChatGPT were illustrative of relevant functions rather than representative of all platforms. The study did not, for example, provide ChatGPT access, assume its legal authorisation in mainland China, or estimate brand-level adoption rates from the AI scale.

Table 1
Construct measurement and analytical roles

Construct	Items	Analytical role	Core content
Social Media Use (SMU)	8	Predictor	English-learning-specific browsing, groups, resource search, posting, sharing, interaction
AI Tool Use (AITU)	10	Predictor	Translation, writing support, AI practice, conversation, feedback, confidence, self-paced learning
Digital Literacy (DL)	12	Indirect pathway, moderator, grouping variable	Technical, cognitive, critical, ethical, collaborative, goal-aligned digital capability
Language-Learning Strategies (LLS)	19	Outcome	Memory, cognitive, compensation, metacognitive, affective, social, and digital strategies
Motivation (MOT)	15	Outcome	Ideal L2 self, ought-to L2 self, learning experience

3.3 Data Cleaning and Attention Checking

There were no missing data on the 64 substantive items in the verified data set. The survey also included an instructed-response item requesting selection of response category 4. From the 600 retained records, 416 individuals marked the requested category and 184 individuals marked another category. The primary analysis was performed using all 600 records in the archived analytical file, and the conclusions drawn were repeated in the 416-person subset of the quality-check sample as a sensitivity analysis, not by redefining the sample.

3.4 Statistical analysis

Data analyses included descriptive statistics, Cronbach's alpha, Pearson correlations, ordinary least-squares regression, bootstrapping with the statistical indirect-effect model, centred interaction regressions, and a prespecified comparison of the digital-literacy group. H1 and H2 were initially modelled unadjusted for gender, academic year, major, self-rated proficiency, or previous digital/AI training and later adjusted for these factors. H3a checked two cross-sectional statistical indirect pathways: SMU → DL → MOT and AITU → DL → MOT. H3b tested the interactions between SMU and DL and between AITU and DL for predicting LLS and MOT, respectively. In H4, low DL was set as the lowest 3rd of the distribution, and high DL was set as the highest 3rd of the distribution, with the middle 3rd of the distribution omitted for this extreme-group comparison. Both multivariate group tests and univariate group tests were used. The indirect coefficients reported below are unstandardised and were estimated using 5,000 bootstrap resamples.

4. Results

4.1 Descriptive statistics, reliability, and correlations

The five composite scores were calculated as item means. DL had the highest mean (M = 3.663, SD = 0.717), followed by AITU (M = 3.565, SD = 0.687), MOT (M = 3.328, SD = 0.636), LLS (M = 3.285, SD = 0.701), and SMU (M = 2.814, SD = 0.763). Internal consistency was excellent across all scales, ranging from α = .934 for SMU to α = .967 for LLS. The very high coefficients indicate reliable item covariance but should not be treated as proof of construct validity by themselves.

Table 2
Descriptive statistics and internal consistency (N = 600)

Construct	*M*	*SD*	Observed range	Cronbach's α
SMU	2.814	0.763	1.00–5.00	.934
AITU	3.565	0.687	1.00–5.00	.945
DL	3.663	0.717	1.00–5.00	.948
LLS	3.285	0.701	1.00–5.00	.967
MOT	3.328	0.636	1.00–5.00	.955

As Fig. 2 below shows, the five constructs vary in their mean positions on the common 1–5 response scale. Social-media use has the lowest mean, whereas digital literacy and AI-tool use have comparatively higher average scores. Because all constructs use the observed 1–5 metric in the dataset, the bar heights can be compared directly as descriptive positions. However, this comparison does not imply that the constructs are substantively equivalent.

All five constructs were positively correlated at $p < .001$. The focal H1 correlation between SMU and LLS was $r = .598$, and the focal H2 correlation between AITU and MOT was $r = .570$. DL correlated with SMU ($r = .401$), AITU ($r = .549$), LLS ($r = .442$), and MOT ($r = .399$). The strongest overall relationship was between LLS and MOT ($r = .751$), confirming that the two outcomes are closely connected while remaining separately measured dimensions of meaningful learning.

Table 3
Pearson correlations among the principal constructs

Variable	SMU	AITU	DL	LLS	MOT
SMU	1.000				
AITU	.437	1.000			
DL	.401	.549	1.000		
LLS	.598	.594	.442	1.000	
MOT	.510	.570	.399	.751	1.000

4.2 Direct associations: H1 and H2

H1 was supported. In the unadjusted regression, SMU positively predicted LLS, $B = .550$, $SE = .030$, 95% CI [.490, .609], standardised $\beta = .598$, $p < .001$, with $R^2 = .358$, F (1, 598) = 333.46. After adjustment for gender, academic year, major, prior digital/AI training, and self-rated English proficiency, the SMU–LLS association remained significant, $B = .523$, $SE = .031$, standardised $\beta = .569$, $p < .001$, with $R^2 = .388$, F (6, 593) = 62.66. H2 was also supported. AITU positively predicted MOT, $B = .528$, $SE = .031$, 95% CI [.467, .589], standardised $\beta = .570$, $p < .001$, with $R^2 = .325$, F (1, 598) = 287.93. The adjusted association

remained significant, B = .510, SE = .031, standardised β = .551, p < .001, with R^2 = .356, F (6, 593) = 54.63. These models show that the focal relationships remain substantial after statistical adjustment, while the cross-sectional design prevents causal interpretation.

The two adjusted standardised coefficients are similar in magnitude, as shown in Fig. 3. This comparison is descriptive rather than a formal test of coefficient equality. Still, it indicates that social media use is strongly associated with strategy use and that AI tool use is similarly strongly associated with motivation in this sample.

4.3 Digital literacy as a statistical indirect pathway: H3a

Both prespecified motivation pathways supported H3a. For SMU → DL → MOT, the unstandardised indirect effect was .077 with a 95% bootstrap CI [.039, .123]. For AITU → DL → MOT, the unstandardised indirect effect was .062 with a 95% bootstrap CI [.008, .127]. Both intervals excluded zero. Covariate-adjusted sensitivity models yielded the same conclusion, with unstandardised indirect effects of .081 and .064. The indirect effects were estimated using 5,000 bootstrap resamples. These are statistical indirect associations and should not be interpreted as evidence that technology use caused digital literacy or that digital literacy caused motivation because all variables were measured at one time point.

As Fig. 4 shows, both indirect-effect estimates are positive, and their bootstrap confidence intervals exclude zero. The intervals are wider than the point estimates, especially for the AITU pathway, which warns against introducing digital literacy as a determinative process. The evidence is consistent with digital literacy helping explain part of the relationship between digital engagement and motivation, while reciprocal or omitted-variable explanations remain possible.

4.4 Digital literacy as a moderator: H3b

The data did not support H3b. The SMU × DL interaction predicting LLS was not significant: B = − .011, SE = .030, t = − .358, p = .720. The AITU × DL interaction was positive but also failed to reach the .05 threshold: B = .056, SE = .030, t = 1.855, and p = .064. The substantive conclusion obtained from covariate-adjusted models was the same. An interaction plot is thus not given as evidence of moderation. This null result restricts the interpretation of digital literacy: DL is correlated with the level of technology engagement and with the learning outcomes and has significant indirect associations, but evidence so far does not indicate a consistent tendency of strengthening relationships between technology and strategy. Although neither interaction was statistically significant, DL retained positive main associations with both outcomes (LLS: r = .442, p < .001; MOT: r = .399, p < .001).

4.5 Digital-literacy group differences: H4

H4 was supported. Low DL was defined as a composite score at or below 3.417 (n = 208) and high DL as a score at or above 4.000 (n = 213); 179 middle-third respondents were omitted only from this comparison. The multivariate difference across LLS and MOT was significant: Wilks' λ = .697, F (2, 418) = 90.99, p < .001. High-DL students reported higher LLS (M = 3.706, SD = 0.640) than low-DL students (M = 2.882, SD = 0.638), F (1, 419) = 175.17, p < .001, partial η^2 = .295. Motivation was also higher in the high-

DL group (M = 3.663, SD = 0.627) than in the low-DL group (M = 3.020, SD = 0.595), F (1, 419) = 116.46, p < .001, partial η^2 = .217.

As Fig. 5 shows, the high-digital-literacy group reports higher mean scores than the low-digital-literacy group on both language-learning strategies and motivation, with the difference being more pronounced for language-learning strategies. These groups are not latent learner profiles or diagnostic categories; rather, they are analytical groups derived from the observed distribution of digital-literacy scores. This pattern supports differentiated support while avoiding the claim that high- and low-digital-literacy students constitute fixed learner types.

4.6 Platform context and sensitivity analysis

Multiple response platform indicators demonstrate the context of social-media learning. 75.5% of the respondents chose Douyin/TikTok, followed by Bilibili (52.8%), Xiaohongshu (44.7%), and WeChat (41.0%). Weibo (12.3%), QQ (11.2%), other platforms (5.7%), YouTube (5.2%), Instagram (4.7%), and Twitter/X (2.8%) were less frequently selected. Percentages relate to platform selection in English learning, rather than platform-specific causal effects. AI items were recorded by functional activity rather than brand-level selection, so no defensible ChatGPT, Grammarly, or Duolingo adoption percentage is reported.

Note

Percentages do not sum to 100% because respondents could select multiple social-media platforms used for English learning.

Short-video and curation environments are particularly prominent in students' social media use for English learning, as shown in Fig. 6, while messaging and community platforms also play important roles. This pattern supports defining social media functionally rather than through a limited set of named platforms. The educational implication is therefore to design tasks around functions such as multimodal input, interaction, resource curation, and peer feedback, rather than assuming that any single platform inherently produces a particular learning outcome.

A further robustness check was conducted through a data-quality sensitivity analysis. Among the 416 respondents who provided the instructed answer, the same general conclusions emerged: SMU-LLS and AITU-MOT remained positive and significant, as did the two indirect pathways through DL, while both moderation interactions remained nonsignificant. This convergence indicates that the central hypothesis decisions are not driven solely by respondents who missed the attention item. Nevertheless, the proportion of non-passers remains an important limitation of the retained dataset.

5. Discussion

5.1 Social media as a strategic learning environment

The close association between social media use (SMU) and language-learning strategies (LLS) suggests that when directed towards English learning, social media can function as a strategic learning environment. This finding aligns with research showing that participatory digital platforms facilitate language exposure, peer interaction, resource sharing, and informal L2 practice beyond the classroom (Apoko & Waluyo, 2025; Genç & Kırmızıbayrak, 2024; Li et al., 2021). From an SCT perspective, these environments expand opportunities for observation, interaction, feedback, and self-directed practice, with strategy use representing learners' behavioural responses to such opportunities. The strong association (r = .598) remained robust after controlling for proficiency and major, indicating that this relationship extends beyond disciplinary or proficiency differences. The substantial use of Douyin/TikTok for English learning (75.5%) further supports evidence that short-video platforms can facilitate vocabulary acquisition and pronunciation exposure (Sely & Priyatmojo, 2026).

However, the lower mean for social media use (SMU) (M = 2.814) relative to the other constructs suggests that general platform engagement should not be equated with educational use. Students may be highly active on social media while using it only infrequently or incidentally for English learning (Bui et al., 2023; Chowdhury & Begum, 2025). The prominence of short-video platforms further highlights this distinction: although they can support listening, vocabulary development, and multimodal comprehension, they may also promote rapid switching, passive viewing, and fragmented attention (Pérez-Juárez et al., 2023). Thus, digital-literacy instruction should emphasise purposeful, self-regulated engagement, including attention regulation and transforming content into active learning through note-taking, retrieval, summarisation, comparison, and follow-up production.

5.2 AI support and motivational quality

The significant relationship between AI tool use and learning motivation (r = .570) is consistent with research identifying personalisation, timely feedback, speed, and low-pressure practice as key motivational affordances of AI-supported learning (Hwang et al., 2020; Ouyang & Jiao, 2021; Qiao & Zhao, 2023; Jingyi & Nasri, 2025; Zhang et al., 2024). AI tools enable learners to receive immediate feedback without teacher marking, practise repeatedly at their own pace, and make errors without the embarrassment associated with public performance. These affordances may strengthen perceived competence and autonomy, thereby supporting sustained motivation, consistent with Self-Determination Theory (Ryan et al., 2022; Namaziandost et al., 2024). The finding also accords with UTAUT's post-adoption logic, whereby tools perceived as useful and manageable are more readily incorporated into learners' study routines.

However, the study does not establish which specific aspects of AI use drive motivation. Some AITU items assess perceived usefulness, confidence, and motivational value, while motivation measures also reference technology-supported learning, creating conceptual proximity that may inflate the observed association. Accordingly, the findings should be interpreted cautiously as indicating that students reporting more frequent and positive AI-supported learning also tend to report higher motivation (Fan & Gao, 2026; Liang et al., 2024; Sun, 2023). Future research should distinguish behavioural usage logs from perceived usefulness, confidence, and motivational perceptions to reduce conceptual overlap and

common-method variance. This caution is consistent with concerns that passive acceptance of AI outputs, without metacognitive evaluation, may undermine learner autonomy, critical reflection, and ownership of learning (Dwivedi et al., 2023; Liang et al., 2024; Sun, 2023).

5.3 What digital literacy does and does not do

The indirect-effect results provide strong evidence for the central capability argument. Digital literacy partially accounted for the relationships between both forms of digital engagement and motivation, suggesting that technology becomes educationally valuable when learners can critically evaluate, regulate, organise, and integrate digital activities with learning goals. This finding aligns with Martinez-Bravo et al. (2022), Putri (2021), Ng (2012), and Rioseco-Pais et al. (2024). Specifically, learners who can verify AI-generated outputs, assess social-media information, select appropriate tools, and manage distractions are better positioned to engage productively with digital environments. The significantly higher strategy usage and motivation among high-digital-literacy learners further indicates that technical familiarity alone does not ensure critical or regulatory competence.

The null moderation findings are theoretically significant because they suggest that digital literacy is not a universal capability that strengthens every technology–learning relationship. Instead, digital literacy appears to function as a general capability associated with learning outcomes and as an indirect explanatory pathway, while its effects may depend on task-specific dimensions. Consistent with Deschênes (2024) and Martínez-Bravo et al. (2022), digital literacy is better understood as a multidimensional construct encompassing operational, critical, and social competencies. For instance, critical-evaluation literacy may shape learners' reliance on AI-generated outputs, whereas technical and collaborative competencies may be more relevant to social-media engagement (Deschênes, 2024; Venetsanos, 2026). Thus, the null moderation results (p = .720 for SMU; p = .064 for AITU) establish an important boundary to claims that digital literacy universally amplifies technology–strategy relationships.

The distinction between significant indirect effects and nonsignificant interactions is therefore theoretically important because they address different questions. The mediation models examine whether part of the relationship between technology engagement and motivation operates statistically through differences in digital literacy. In contrast, the moderation models examine whether the strength of the technology–strategy relationship varies according to levels of digital literacy. The findings support the first proposition but not the second. Digital literacy may therefore represent one pathway through which digitally engaged learners develop stronger motivation, without functioning as an omnibus factor that amplifies all technology–learning relationships. This distinction sharpens the paper's conceptual contribution. It suggests a more focused research agenda in which future studies examine whether specific digital-literacy dimensions, rather than a global composite, moderate relationships under particular tasks, platforms, proficiency levels, or forms of AI assistance (Guan et al., 2025; Liang et al., 2024; Putri, 2021).

5.4 Theoretical contribution

The findings support a differentiated but complementary application of SCT and UTAUT. SCT provides the stronger explanatory foundation because its triadic reciprocal framework connects digital environments, learner capabilities, strategic behaviours, and motivation (Bandura, 2020). In this model, social media and AI tools constitute environmental opportunities, digital literacy represents personal capability, language learning strategies reflect self-regulatory behaviour, and motivation sustains engagement. UTAUT is narrower, but its emphasis on performance and effort expectancy helps explain initial technology acceptance (Deng et al., 2023; Venkatesh et al., 2003; Xue et al., 2024). However, its adoption-oriented assumptions are less suited to continuous educational learning. The findings therefore suggest a progression from technology acceptance to educational value: adoption provides access to technological affordances, while capability enables learners to convert these affordances into meaningful learning strategically. This distinction positions SCT and UTAUT as complementary rather than interchangeable theoretical perspectives.

The framework also justifies examining learning strategies and motivation as complementary outcomes. Although strongly correlated (r = .751), they represent distinct dimensions of meaningful learning: strategies concern how learners regulate and implement learning, whereas motivation concerns the direction and persistence of engagement (Oxford, 2017; Song, 2024). Digital engagement that generates short-term interest without strengthening strategic regulation may be unsustainable, while strategic knowledge without sufficient motivation may not be consistently enacted. Thus, their joint consideration captures complementary dimensions of meaningful English learning without treating them as a single or newly defined construct.

5.5 Comparison with prior research and contextual contribution

The findings demonstrate a particularly strong association between general language-learning strategies and social media use, suggesting that informal, socially mediated learning may extend beyond specific linguistic skills. This supports the view that digital environments can facilitate cognitive, social, and metacognitive engagement when used purposefully, while evidence of digital distraction (Pérez-Juárez et al., 2023) warrants caution in generalising beyond English-learning activities. Similarly, the AI findings align with evidence that feedback-rich and conversational systems can enhance motivation and self-regulation (Qiao & Zhao, 2023; Guan et al., 2025), while reinforcing the importance of pedagogy, learner judgement, and human oversight (Zawacki-Richter et al., 2019; Wang et al., 2024). The findings further extend this literature by highlighting the accessibility of self-directed digital tools for regional Chinese undergraduates, 74.0% of whom were non-English majors who identified as beginners and may particularly benefit from targeted feedback and scaffolding.

The educational role of digital platforms should be interpreted within the specific technological and sociocultural context in which they are used. Platform interpretation is context-dependent. In China, Douyin/TikTok, Bilibili, Xiaohongshu, and WeChat support distinctive forms of vocabulary practice, short-form speech exposure, curation, and peer interaction (Li et al., 2021; Sely & Priyatmojo, 2026), differing

from platform configurations centred on YouTube, Instagram, or X. However, these differences suggest that platform functions may be more analytically stable than platform brands, with educational affordances encompassing multimodal input, content curation, messaging, community engagement, and sharing. This function-oriented perspective is consistent with Genç and Kırmızıbayrak (2024) and provides a useful basis for comparative research across digital ecosystems. Nevertheless, digital access alone does not ensure strategic learning. As Zawacki-Richter et al. (2019) and Wang et al. (2024) emphasise, effective technology-enhanced learning requires pedagogical scaffolding, human oversight, and deliberate learner agency.

6. Practical Implications

Digital literacy should be understood as a component of language-learning capacity rather than generic computer literacy. Support should therefore focus on evaluating sources, verifying AI-generated content, understanding privacy and data use, managing attention, effective prompting, interpreting automated feedback, organising resources, and reflecting on whether digital tools support defined English-learning objectives. Since H3b was not supported, such training should not be justified on the assumption that higher digital literacy will amplify all technology effects. Rather, its value lies in promoting the quality and accountability of digital engagement while reducing disparities in digital learning capabilities among learners.

Teachers should integrate social media and AI activities around language-learning goals rather than enthusiasm for the platforms themselves. Short-video activities, for instance, can be paired with transcription, vocabulary identification, pronunciation comparison, or critical summarisation. Messaging groups can support collaborative editing, peer explanation, and responsible interaction. AI tasks can require students to compare AI-generated feedback with reference materials, explain which suggestions they accepted or rejected and why, revise without AI assistance, and identify areas of uncertainty. These practices remain learner-centred while making the learning process visible. A simple AI-verification checklist could require students to submit prompt histories, identify potential hallucinations or grammatical errors in AI-generated output, and justify their acceptance or rejection of each suggestion.

At the programme level, the findings support a phased and differentiated support model that responds to substantial differences in learners' digital literacy (DL). Rather than adopting uniform workshops, diagnostic assessment at programme entry could identify learners requiring systematic support without treating low DL as an inherent learner characteristic. Lower-DL learners could receive guided tool-selection templates, worked examples, verification checklists, and stepwise reflection, while higher-DL learners could undertake more challenging activities involving critical evaluation, multimodal synthesis, authorship, and cross-platform transfer. Routines for evaluating information, managing privacy, and selecting appropriate tools could be introduced through workshops, embedded in course activities and authentic English-learning tasks, and progressively foregrounded in later modules to strengthen independent judgement and responsible technology use. Progress could be assessed through both learning products, demonstrating what learners can do, and reflective explanations, indicating how and

why they make particular technological and learning choices, rather than through standalone digital-skills sessions. In mainland China, institutions should also avoid assuming ubiquitous access to particular generative-AI products; recommendations should instead emphasise accessible and permitted tools based on pedagogical functions rather than brand names. Collectively, these measures could gradually reduce scaffolding while strengthening learners' independence, critical judgement, authorship, and capacity to transfer responsible digital practices across technologies and learning contexts.

7. Limitations and Future Research

- Cross-Sectional Design: The cross-sectional design precludes strict causal inference, temporal ordering, and causal mediation among SMU, AITU, DL, LLS, and MOT.
- Self-Report Measures and Method Variance: All key constructs are based on participant self-reports rather than objective task performance, direct proficiency assessments, or digital trace data, creating potential for common-method variance.
- Sample Composition: The sample is predominantly non-English majors (95.3%) and self-rated beginners (74.0%) from three universities in Ningxia, including only 10 self-rated advanced learners. This limits direct generalisability to elite urban universities and more advanced EFL populations.
- Attention Check Rate: Of the 600 respondents, 184 (30.7%) failed the instructed-response attention check. Although sensitivity analysis produced the same hypothesis decisions in the pass-only subsample (n = 416), the relatively high failure rate warrants caution in interpreting the findings.
- Measurement should be further strengthened. Future research should move beyond separating AI-use frequency from perceived usefulness and motivational responses by treating AI literacy as a distinct construct where theoretically warranted, alongside objective proficiency, task performance, teacher ratings, or digital-trace measures. Longitudinal and experimental designs could then assess whether targeted digital-literacy interventions produce sustained changes in educational outcomes across specific social media or AI functions.

8. Conclusion

This study demonstrates that social media and AI tools play distinct yet complementary roles in Chinese undergraduates' English learning. Using digital literacy as an explanatory variable and a statistical indirect pathway, the study examined how students' use of these technologies relates to language-learning strategies and motivation. Social media use was strongly associated with strategic language management, whereas AI-tool use was more strongly associated with learning motivation. Digital literacy also showed significant indirect associations through these technology-use pathways, while students with higher digital literacy reported significantly stronger strategy use and motivation. However, digital literacy did not significantly moderate the focal technology-to-strategy relationships. Thus, the findings suggest that digital literacy should not be interpreted as a universal multiplier that consistently amplifies technology effects, but rather as a core learner capability that facilitates the conversion of digital

engagement into strategically and motivationally meaningful learning. This distinction highlights the importance of moving beyond technology access toward responsible, differentiated, and purpose-driven integration of social media and AI. Educators should therefore develop learners' capacity to critically, purposefully, and autonomously select and use digital tools, recognising that technology access and acceptance do not automatically translate into meaningful learning outcomes.

Declarations

Funding statement

This research did not receive any specific funding from public, commercial, or not-for-profit organizations. The study was conducted without external financial support.

Ethics statement: Approval Statement

The protocol was approved by University Research Ethics Committee (UREC) Kuala Lumpur University of Science and Technology in accordance with the Research Ethics and University Research Ethics Procedure provided by KLUST Research Management Centre.

Ethics statement: Accordance Statement

The research was conducted in accordance with the Research Ethics and University Research Ethics Procedure provided by the KLUST Research Management Centre. A copy of the relevant research ethics policy has been attached in the related file section for reference.

Ethics Approval and Consent to Participate Statement

This study involved human participants who provided informed consent before participation. All human-related procedures were performed in accordance with the Research Ethics and University Research Ethics Procedure provided by KLUST Research Management Centre. Participation was voluntary, and confidentiality and anonymity were maintained throughout the research process.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon request.

Clinical trial Number

Not Applicable

Authors Contribution Statement

All authors contributed to the development and refinement of the study, reviewed the manuscript critically for important intellectual content, approved the final version, and agreed to be accountable for all aspects of the work.

Guo Rongrong: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Visualization, Writing – original draft, and Project administration.

Charanjit Kaur Swaran Singh: Supervision, Methodology, Validation, Writing – review and editing, and Resources.

Wong Siew Ping: Data curation, Visualization, Writing- review and editing

Li Gang: Investigation, Data curation, Validation, Writing – review and editing, and Resources.

References

1. Almayez MA, Al-Khresheh MH, Al-Qadri AH, Alkhateeb IA, Alomaim TIM. Motivation and English self-efficacy in online learning applications among Saudi EFL learners: Exploring the mediating role of self-regulated learning strategies. Acta Psychol. 2025;254:104796. https://doi.org/10.1016/j.actpsy.2025.104796.
2. Apoko TW, Waluyo B. Social media for English language acquisition in Indonesian higher education: Constructivism and connectivism frameworks. Social Sci Humanit Open. 2025;11., Article 101382. https://doi.org/10.1016/j.ssaho.2025.101382.
3. Bandura A. Social Cognitive Theory: An Agentic Perspective. Psychology: J Hellenic Psychol Soc. 2020;12(3):313–33. https://doi.org/10.12681/psy_hps.23964.
4. Bui HP, Ulla MB, Tarrayo VN, Pham CT. The roles of social media in education: affective, behavioral, and cognitive dimensions. Front Psychol. 2023;14., Article 1287728. https://doi.org/10.3389/fpsyg.2023.1287728.
5. Chowdhury EK, Begum R. The academic implications of social media use and multitasking: Evidence from university students in a developing nation. Social Sci Humanit Open. 2025;11:Article101623. https://doi.org/10.1016/j.ssaho.2025.101623.
6. Deng P, Chen B, Wang L. Predicting students' continued intention to use an e-learning platform for college English study: The mediating effect of e-satisfaction and habit. Front Psychol. 2023;14:1182980. https://doi.org/10.3389/fpsyg.2023.1182980.
7. Deschênes AA. Digital literacy, the use of collaborative technologies, and perceived social proximity in a hybrid work environment: Technology as a social binder. Computers Hum Behav Rep. 2024;13., Article 100351. https://doi.org/10.1016/j.chbr.2023.100351.
8. Dwivedi YK, Kshetri N, Hughes L, Slade EL, Jeyaraj A, Kar AK, Baabdullah AM, Koohang A, Raghavan V, Ahuja M, Albanna H, Albashrawi MA, Al-Busaidi KA, Balakrishnan J, Barlette Y, Basu S, Bose I, Brooks L, Buhalis D, Wright R. (2023). Opinion paper: So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

9. Fan K, Gao T. The role of AI-mediated metacognitive interventions in EFL writing development: A cross-sectional study of textual accuracy, lexical sophistication, and cohesion. Acta Psychol. 2026;267., Article 107069. https://doi.org/10.1016/j.actpsy.2026.107069.
10. Genç G, Kırmızıbayrak Ö. The use of Web 2.0 tools in English language learning: A systematic review. Multidisciplinary Reviews. 2024;7(5):2024102. https://doi.org/10.31893/multirev.2024102.
11. Guan L, Zhang EY, Gu MM. Examining generative AI-mediated informal digital learning of English practices with social cognitive theory: A mixed-methods study. ReCALL. 2025;37(3):315–31. https://doi.org/10.1017/S0958344024000259.
12. Hwang GJ, Xie H, Wah BW, Gašević D. Vision, challenges, roles and research issues of artificial intelligence in education. Computers Education: Artif Intell. 2020;1:100001. https://doi.org/10.1016/j.caeai.2020.100001.
13. Jingyi S, Nasri NM. Enhancing English speaking motivation among Chinese university students: The role of immediate feedback in AI-driven chatbots. Int J Acad Res Progressive Educ Dev. 2025;14(2):710–26. http://dx.doi.org/10.6007/IJARPED/v14-i2/25239.
14. Kaplan AM, Haenlein M. Users of the world, unite! The challenges and opportunities of social media. Bus Horiz. 2010;53(1):59–68. https://doi.org/10.1016/j.bushor.2009.09.003.
15. Li F, Fan S, Wang Y, Lu J. Chinese university students' experience of WeChat-based English-language vocabulary learning. Educ Sci. 2021;11(9):554. https://doi.org/10.3390/educsci11090554.
16. Liang J, Huang F, Teo T. Understanding Chinese university EFL learners' perceptions of AI in English writing. Int J Computer-Assisted Lang Learn Teach. 2024;14(1):1–16. https://doi.org/10.4018/IJCALLT.358918.
17. Martínez-Bravo MC, Chalezquer CS, Serrano-Puche J. Dimensions of digital literacy in the 21st century competency frameworks. Sustainability. 2022;14(3):1867. https://doi.org/10.3390/su14031867.
18. Namaziandost E, Çakmak F, Heydarnejad T, Rezai A. The predictive effects of learner autonomy and academic engagement on willingness to communicate, foreign language learning self-esteem, and L2 grit in an EFL context. Acta Psychol. 2024;250., Article 104528. https://doi.org/10.1016/j.actpsy.2024.104528.
19. Ng W. Can we teach digital natives digital literacy? Comput Educ. 2012;59(3):1065–78. https://doi.org/10.1016/j.compedu.2012.04.016.
20. Ouyang F, Jiao P. Artificial intelligence in education: The three paradigms. Computers Education: Artif Intell. 2021;2:100020. https://doi.org/10.1016/j.caeai.2021.100020.
21. Oxford RL. Language learning strategies: What every teacher should know. Newbury House; 1990.
22. Oxford RL. Teaching and researching language learning strategies: Self-regulation in context. Routledge; 2017.
23. Pérez-Juárez MÁ, González-Ortega D, Aguiar-Pérez JM. Digital distractions from the point of view of higher education students. Sustainability. 2023;15(7):6044. https://doi.org/10.3390/su15076044.

24. Putri G. Digital literacy: A conceptual framework for survival skills in the digital era. J Educational Multimedia Hypermedia. 2021;13(1):93–106.
25. Qiao H, Zhao A. Artificial intelligence-based language learning: Illuminating the impact on speaking skills and self-regulation in Chinese EFL context. Front Psychol. 2023;14:1255594. https://doi.org/10.3389/fpsyg.2023.1255594.
26. Rioseco-Pais M, Silva-Quiroz J, Vargas-Vitoria R. Digital competences and years of access to technologies among Chilean university students: An analysis based on the DIGCOMP framework. Sustainability. 2024;16(22):9876. https://doi.org/10.3390/su16229876.
27. Ryan RM, Duineveld JJ, Domenico D, Ryan SI, Steward WS, B. A., Bradshaw EL. We know this much is (meta-analytically) true: A meta-review of meta-analytic findings evaluating self-determination theory. Psychol Bull. 2022;148(11–12):813–42. https://psycnet.apa.org/doi/10.1037/bul0000385.
28. Sely GRA, Priyatmojo AS. Incidental English vocabulary learning through TikTok: A conceptual analysis. J Engl Lang Educ. 2026;11(1):661–9. https://doi.org/10.31004/jele.v11i1.2064.
29. Song Y. Assessing the interactions between learning enjoyment, motivation, burnout, and grit in EFL students: a mixed-methods approach. BMC Psychol. 2024;12(1):796. https://doi.org/10.1186/s40359-024-02303-6.
30. Sun M. (2023). Exploring the opportunities and challenges of AI technology in college English teaching. In *Proceedings of the 7th International Seminar on Education, Management and Social Sciences* (pp. 1532–1541). Atlantis Press. https://doi.org/10.2991/978-2-38476-126-5_171
31. Venetsanos DT. A tripartite feedback framework for AI-assisted assessment of complex reports in higher education. AI Educ. 2026;2(3):26. https://doi.org/10.3390/aieduc2030026.
32. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Q. 2003;27(3):425–78. https://doi.org/10.2307/30036540.
33. Wang S, Wang F, Zhu Z, Wang J, Tran T, Du Z. Artificial intelligence in education: A systematic literature review. Expert Syst Appl. 2024;252:124167. https://doi.org/10.1016/j.eswa.2024.124167.
34. Wang Y, Yasmin F, Akbar A. Impact of the internet on English language learning among university students: Mediating role of academic self-efficacy. Front Psychol. 2023;14:1184185. https://doi.org/10.3389/fpsyg.2023.1184185.
35. Woo JH, Choi H. Systematic review for AI-based language learning tools. J Digit Contents Soc. 2021;22(11):1783–92. https://doi.org/10.9728/dcs.2021.22.11.1783.
36. Xue L, Rashid AM, Ouyang S. The unified theory of acceptance and use of technology (UTAUT) in higher education: A systematic review. Sage Open. 2024;14(1):21582440241229570. https://doi.org/10.1177/21582440241229570.
37. Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education: Where are the educators? Int J Educational Technol High Educ. 2019;16(39):1–27. https://doi.org/10.1186/s41239-019-0171-0.
38. Zhang J, Zhu C, Zhang Z. AI-powered language learning: The role of NLP in grammar, spelling, and pronunciation feedback. Appl Comput Eng. 2024;102(1):18–23. https://doi.org/10.54254/2755-

2721/102/20240962.
39. Zhang Q. Active language learning strategies in Chinese university English education: Effects on proficiency, motivation, and teacher engagement. Acta Psychol. 2025;261., Article 105914. https://doi.org/10.1016/j.actpsy.2025.105914.

Figures

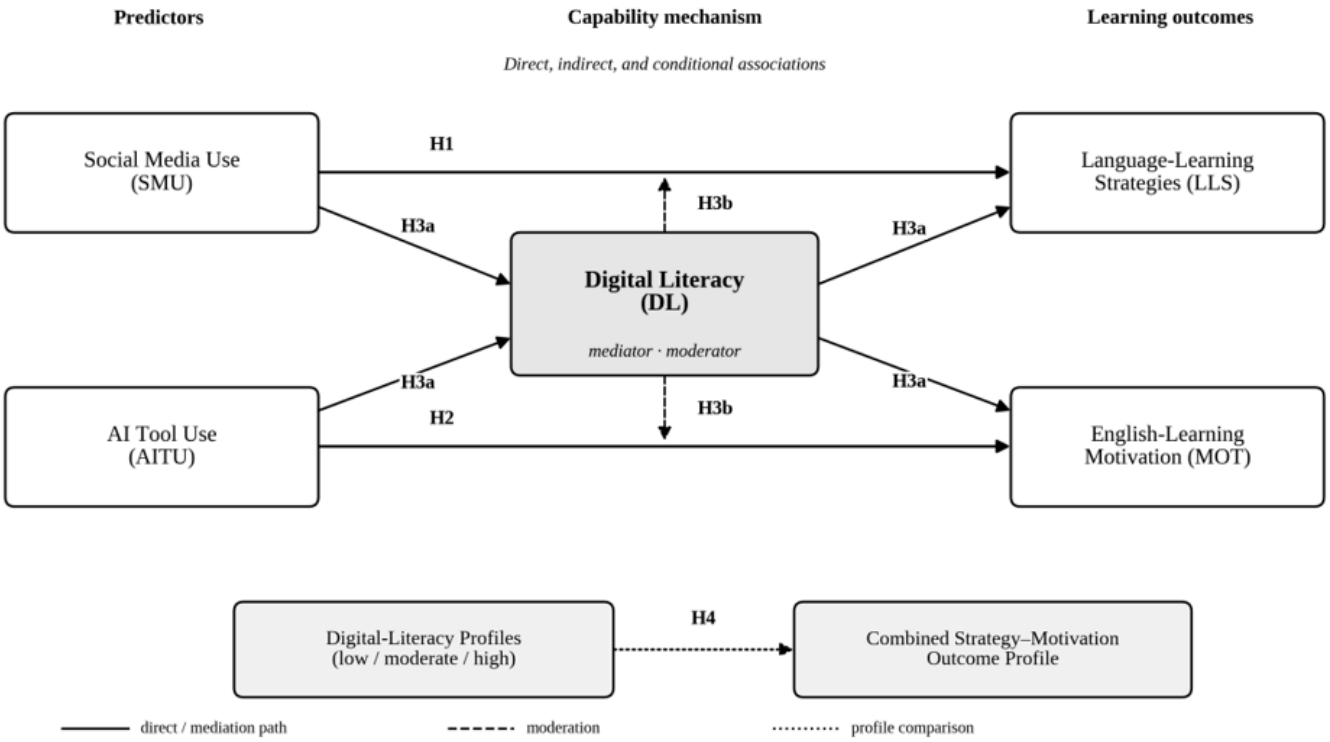


Figure 1

Conceptual model of the study

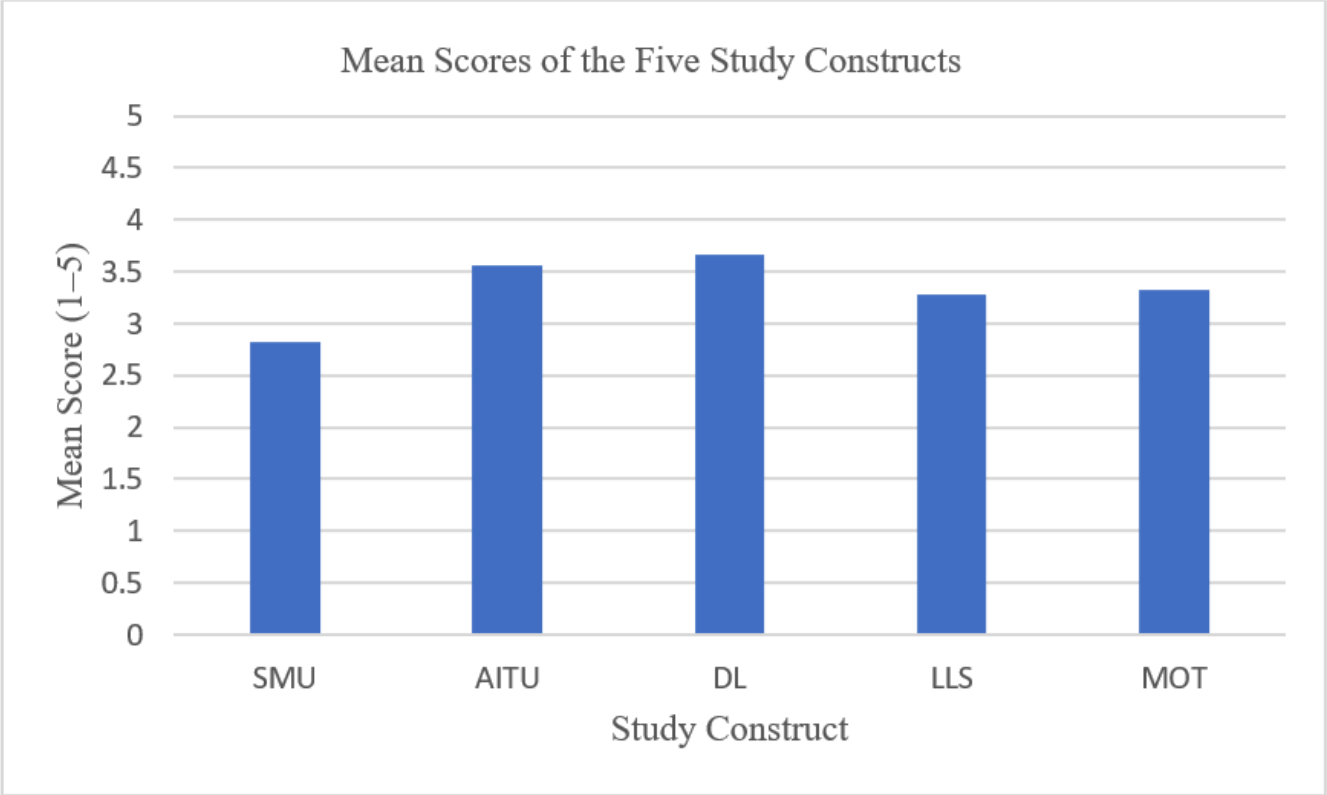


Figure 2

Mean scores of the five study constructs

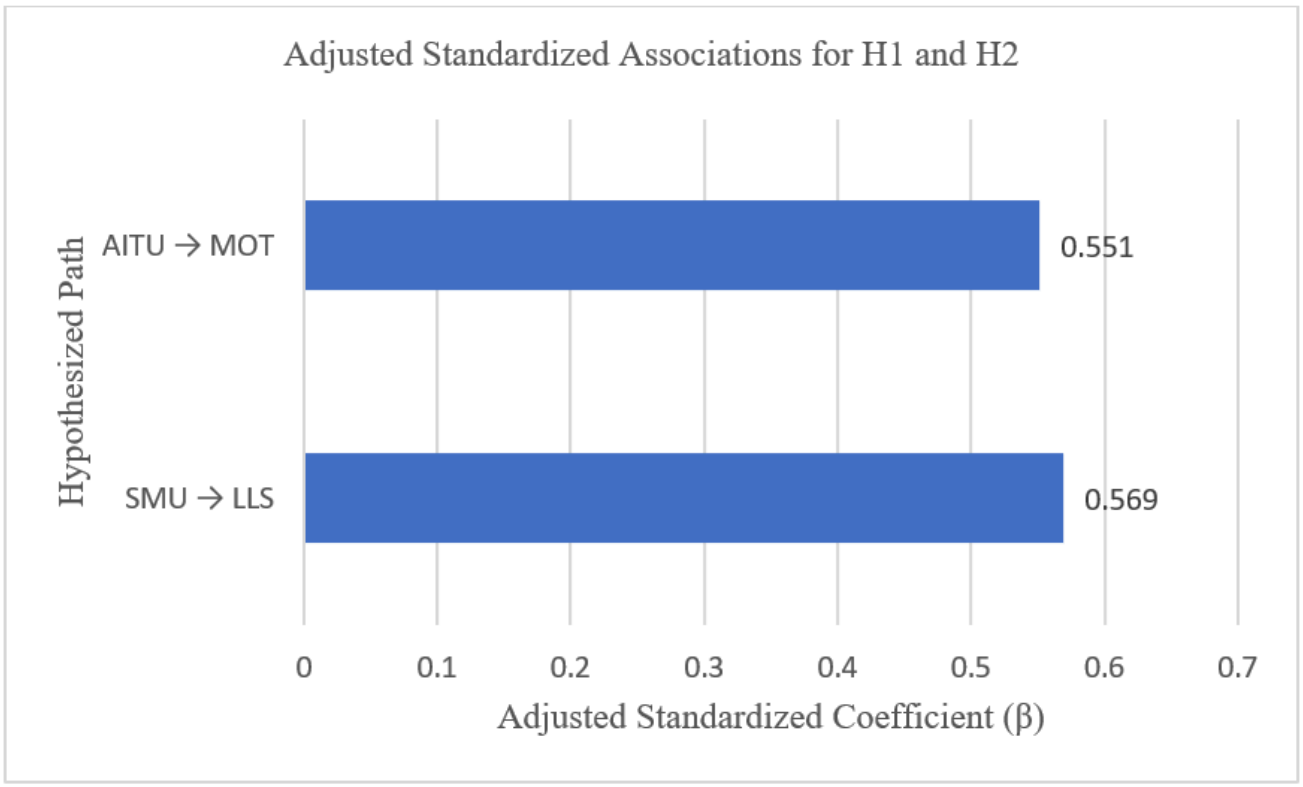


Figure 3

Adjusted standardised associations for H1 and H2

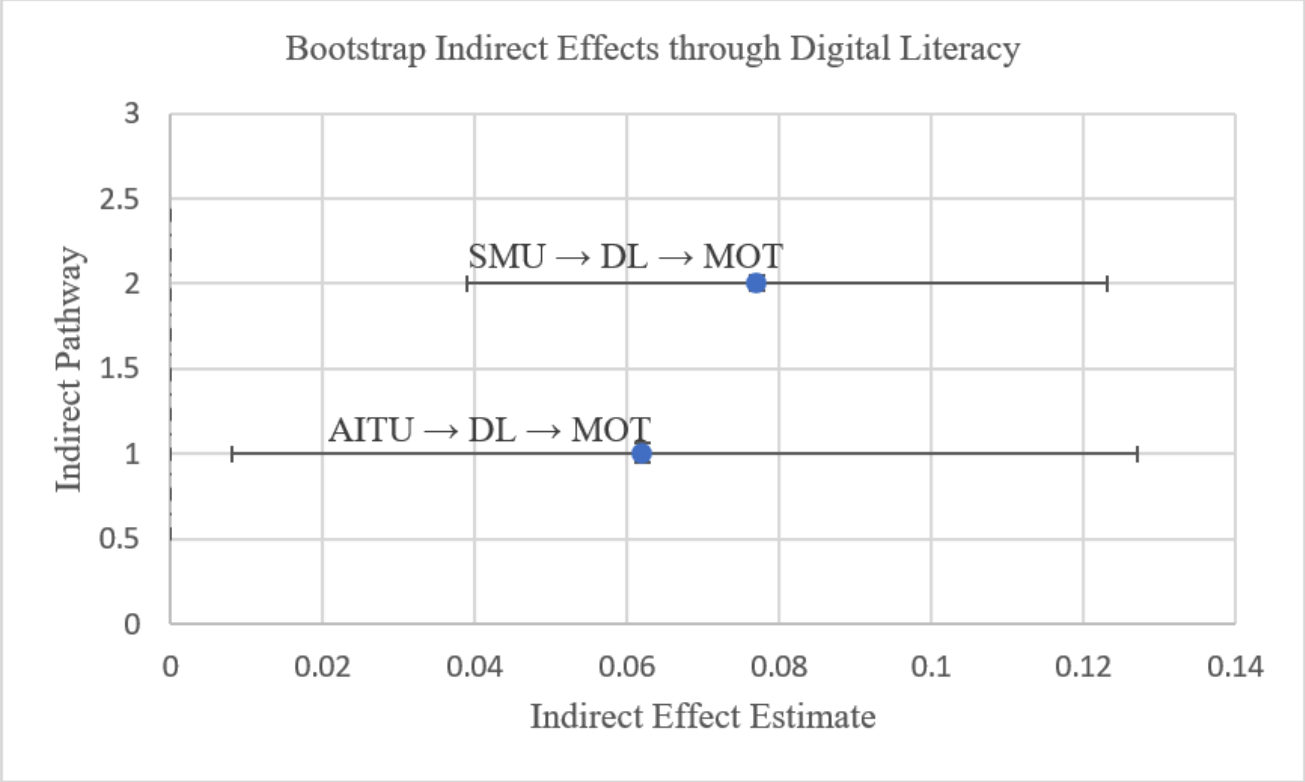


Figure 4

Bootstrap indirect effects through digital literacy

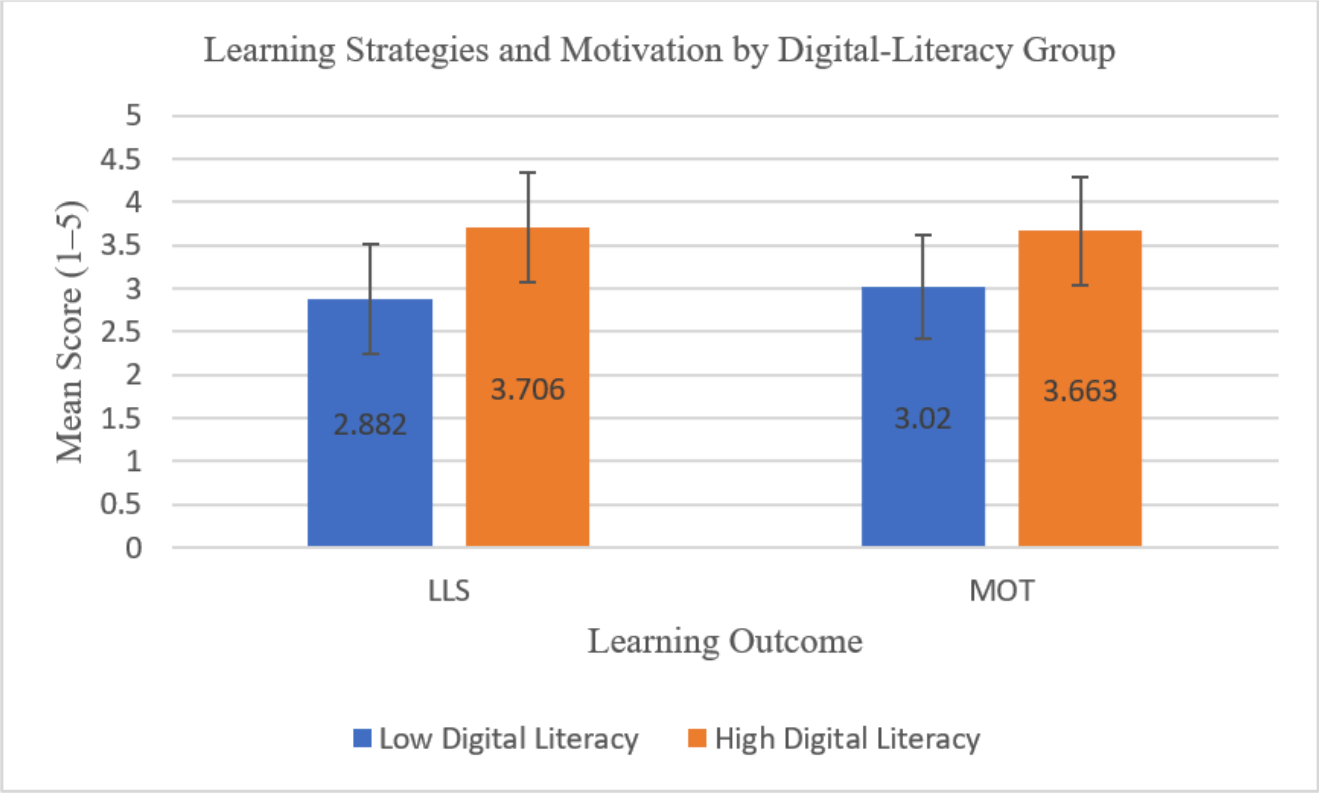


Figure 5

Mean differences in learning strategies and motivation between low- and high-digital-literacy groups

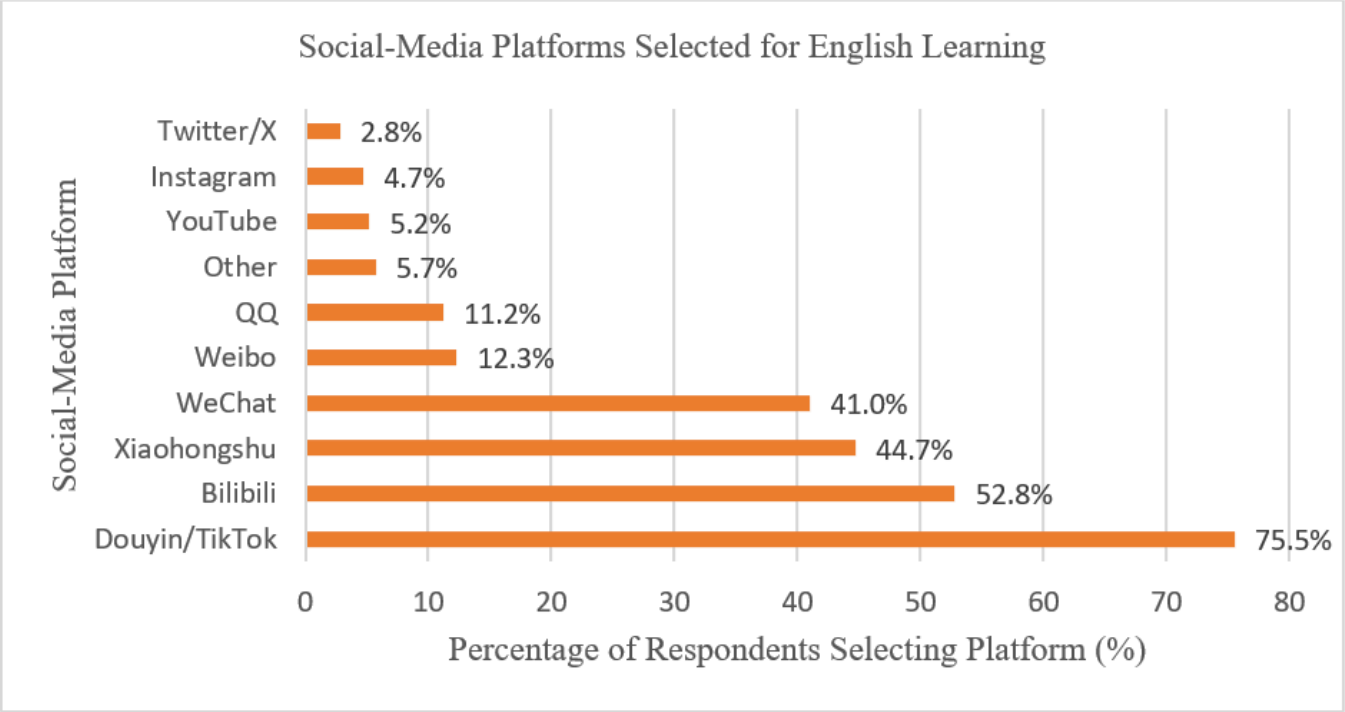


Figure 6

Social-media platforms selected for English learning