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*Article*

# Research Trends in Mapping Engagement in AI-Supported Multimodal Language Learning: A Network Analysis of Psychological Factors

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**Abstract**
As artificial intelligence (AI) increasingly reshapes language learning through multimodal environments involving text, audio, and images, recent research has called for more dynamic and system-oriented approaches to understanding learner engagement. Against this background, the present study examined the relationships among AI literacy, growth mindset, self-efficacy, flow, and engagement in AI-supported multimodal language learning. Guided by Sociocultural theory (SCT), data were collected from a sample of 776 participants and analyzed using network analysis. The results revealed a fully connected and entirely positive network structure, suggesting that these variables function as closely related components of a broader learner-related psychological system. Among the five nodes, engagement emerged as the most central position, as indicated by the highest values of strength, closeness, betweenness, and expected influence. In addition, growth mindset, self-efficacy, and AI literacy showed comparatively stronger connections with engagement, whereas flow was positively associated with engagement but to a lesser extent. These findings suggest that engagement in AI-supported multimodal language learning is structurally associated not only with positive learning experiences but also with learners' adaptive beliefs, perceived capability, and technological competence. The study contributes to the research trends in understanding AI engagement by offering a novel network-based perspective on engagement in contemporary AI-mediated language learning.

**Keywords**
AI-supported multimodal language learning, engagement, language learner, network analysis, Sociocultural theory

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## 1 Introduction

With the rapid development of artificial intelligence (AI), language learning is increasingly taking place in environments characterized by the integration of multiple modes of communication and representation (Derakhshan, 2025; Liu & Fan, 2026; Roy et al., 2026; Yang, 2026). Learners no longer rely exclusively on written explanations; instead, they interact with AI-supported systems through a range of modalities, including text, voice, images, and other forms of input and output (Ren et al., 2026). This shift toward AI-supported multimodal language learning has substantially expanded opportunities for adaptive feedback, interaction, and personalized support (Derakhshan & Park, 2026a; Fu et al., 2026), thereby reshaping how learners participate in learning activities (Cohn et al., 2025). In these environments, learning is not simply a matter of receiving information, but entails actively navigating diverse semiotic resources, responding to AI-generated guidance, and sustaining involvement across dynamically evolving tasks (Derakhshan et al., 2026). Against this background, engagement has become a particularly important issue, as it reflects the extent to which learners cognitively, behaviorally, and affectively invest effort, attention, and persistence in the learning process (Wang & Guo, 2026). Understanding engagement in AI-supported multimodal language learning is therefore essential for explaining why some learners participate actively and productively, whereas others struggle to maintain meaningful involvement over time (Derakhshan & Li, 2026; Wang, 2026). This issue has become especially timely as recent AI-assisted language learning research has increasingly shifted toward dynamic and system-oriented understandings of learner engagement.

In contemporary second language acquisition, generative AI and multimodal platforms are increasingly transforming learners from passive recipients of instructional content into active co-constructors of knowledge (Teng & Huang, 2026; Wang & Gao, 2025). Whereas earlier AI-assisted language learning research focused mainly on technology acceptance, general attitudes, and isolated learning outcomes, recent inquiry has increasingly emphasized the complex psychological mechanisms that sustain learner participation across dynamic AI-mediated interactions (Liu et al., 2025; Wang & Wang, 2026). A growing body of research has examined learner-related factors in AI-supported learning, with particular attention to constructs such as AI literacy, growth mindset, self-efficacy, flow, and engagement (Wang et al., 2025; Zhang & Jing, 2026). Existing studies have generally shown that these variables are positively associated with adaptive learning behaviors, sustained motivation, and improved learning outcomes (Wang et al., 2026; Wang & Xue, 2024). At the same time, scholarship on multimodal learning has emphasized that learners' experiences are shaped by the orchestration and integration of multiple semiotic resources, especially in digitally mediated environments (Dong & Gan, 2026; Roy et al., 2026). However, current research has largely treated these factors as independent predictors or discrete outcome variables and has most often relied on linear, variable-centered approaches to explain their relationships. Although such approaches are valuable for testing directional hypotheses, they may overlook the possibility that learner attributes operate as interconnected and self-organizing psychological systems. Given the cognitive and emotional demands of navigating AI feedback and multimodal input, a system-oriented approach is needed to map how these psychological resources dynamically coalesce within AI-supported multimodal language learning.

To address this gap, our study investigates the networked relationships among AI literacy, growth mindset, self-efficacy, flow, and engagement in AI-supported multimodal language learning. Guided by Sociocultural Theory, this study views such learning as a tool-mediated activity in which learners interact with AI-generated texts, audio, images, feedback, and task prompts to construct meaning and sustain participation. Within this framework, AI literacy, growth mindset, self-efficacy, and flow are conceptualized as learner-related psychological resources that may support mediated participation, while engagement is understood as the quality and intensity of learners' cognitive, behavioral, and emotional involvement in AI-mediated meaning-making practices. Rather than treating these variables as isolated predictors in a linear model, the study adopts network analysis to examine how they are structurally interconnected within a shared psychological system. Specifically, the study addresses two research questions:

RQ1: How are these learner-related resources connected in AI-supported multimodal language learning?

RQ2: Which factor occupies the most central position in this SCT-informed network of learner participation?

## 2 Literature Review

### 2.1 AI-supported Multimodal Learning

AI-supported multimodal learning refers to a learning process in which learners engage with AI tools through multiple semiotic modes, such as text, voice, image, and, in some cases, video, to construct meaning, complete tasks, and develop knowledge (Dong & Gan, 2026). More specifically, it involves the coordinated use of multiple representational channels through AI-mediated systems, enabling learners to process and produce meaning across modalities within integrated learning activities. Unlike traditional digital learning, which often relies primarily on written input and output, AI-supported multimodal learning enables learners to simultaneously navigate, select, and integrate diverse representational resources within a single learning episode (Sun et al., 2025). In language education, such learning may involve engaging with AI-generated explanations, listening to synthesized speech, interpreting visual prompts, producing multimodal responses (spoken and written), and receiving immediate, adaptive feedback across modalities (Li & Wang, 2025). From this perspective, multimodality is not merely a technical feature of digital tools, but a fundamental meaning-making condition that shapes how learners interpret information, express understanding, and negotiate learning goals (Dong & Gan, 2026). Accordingly, AI-supported multimodal learning can be understood as a technology-mediated, interaction-rich, and cognitively demanding environment in which learners actively coordinate multiple modes to support comprehension, interaction, and participation (Roy et al., 2026).

Existing research has increasingly documented the expanding role of AI in language learning, particularly in relation to automated writing support, conversational practice, personalized feedback, and adaptive content delivery (Sun et al., 2026; Wang & Guo, 2026). More recently, the development of generative AI has further extended these affordances by enabling learners to interact with multimodal outputs, including text, audio, and visual content, in more flexible, responsive, and context-sensitive ways (Zhou & Wang, 2026). Studies have shown that such environments may enhance learners' access to input, opportunities for output, and the timeliness and specificity of feedback (Zhou & Ma, 2025). At the same time, research on multimodal learning has highlighted that learners' understanding is often strengthened when verbal, auditory, and visual resources are meaningfully integrated rather than presented in isolation (Zhou, 2025). However, much of the existing literature has tended to focus on learning outcomes, technology acceptance, or general attitudes toward AI, while paying less attention to how learners' underlying psychological resources dynamically interact and co-develop within AI-supported multimodal settings. As a result, the relational structure and systemic organization of learner-related factors in such environments remains insufficiently understood and require more integrative and analytically sophisticated investigation. In alignment with recent research trends in digital SLA, multimodal AI environments require learners to continuously negotiate meaning across verbal, auditory, and visual channels (Prihandoko et al., 2025). Scholars have increasingly recognized that navigating these complex semiotic landscapes depends not merely on the availability of AI tools, but on how technological affordances interact with learners' internal psychological states during real-time learning processes (Tran et al., 2026).

### 2.2 Engagement in AI-Supported Multimodal Learning

Engagement is widely recognized as a multidimensional construct that reflects the quality, depth, and intensity of learners' involvement in educational activities (Hiver et al., 2024). In broad terms, it is commonly understood to include behavioral participation, cognitive investment, and emotional involvement in learning tasks (Oga-Baldwin, 2019). More comprehensively, engagement encompasses the extent to which learners actively direct attention, sustain effort over time, regulate their participation, and maintain meaningful connections with learning processes and goals (Wang & Wang, 2024). Rather than indicating mere attendance or task completion, engagement represents an active, self-regulated state of involvement in which learners continuously allocate cognitive, behavioral, and affective resources to task performance (Wang et al., 2022). In language education, engagement is particularly important because successful learning often depends on sustained interaction, iterative practice, and the active deployment of linguistic resources across time and contexts (Wang & Guo, 2026). Within technology-enhanced environments, engagement has also been linked to learners' willingness to explore digital tools, respond to feedback, and remain committed to challenging tasks (Aubrey et al., 2022). Therefore, engagement should not be viewed as a simple outcome of instruction, but as a dynamic, context-sensitive state of participation that reflects how learners position themselves within a given learning environment and how actively they invest in ongoing knowledge construction.

In AI-supported multimodal learning, engagement becomes even more complex because learners are required to simultaneously coordinate multiple semiotic resources, interpret diverse forms of input, and respond to AI-generated support in real time (Dong & Gan, 2026). Their participation is shaped not only by task demands, but also by how they interact with adaptive multimodal feedback, navigate across representational modes, and sustain attention amid dynamically shifting learning cues (Roy et al., 2026). For this reason, engagement in such contexts may function as more than a downstream learning outcome; it may also serve as a central, integrative mechanism that organizes and connects learners' technological, motivational, and experiential resources within the learning system (Hiver et al., 2024). Prior studies have shown that engagement in AI-supported learning can be associated with factors such as perceived usefulness, self-regulation, motivation, and confidence (Wang & Guo, 2026). Nevertheless, these factors have often been examined separately or through linear, variable-centered predictive models, which may not fully capture their reciprocal and interdependent relationships. Consequently, it remains unclear whether engagement occupies a structurally central and influential position within a broader network of learner-related variables in AI-supported multimodal language learning contexts, an issue that warrants systematic investigation.

### 2.3 Psychological Factors Associated with Engagement

Engagement in AI-supported multimodal learning is likely to be shaped by a constellation of interrelated and mutually reinforcing psychological factors rather than by a single individual attribute (Hiver et al., 2024). In such environments, learners are expected to interpret complex multimodal input, interact dynamically with AI-generated feedback, and sustain participation across technology-mediated tasks that demand flexibility, persistence, and self-regulation (Wang & Wang, 2024). As a result, engagement should be understood as embedded within a broader, system-like configuration of learner-related resources, including competence, beliefs, and experience (Aubrey et al., 2022). Among the many factors that may be relevant, AI literacy, growth mindset, self-efficacy, and flow appear particularly important. AI literacy concerns learners' capacity to critically understand, evaluate, and effectively use AI tools. Growth mindset reflects their beliefs about the malleability of ability. Self-efficacy captures their perceived capability to successfully manage learning demands. Flow represents a state of deep absorption and enjoyment during task performance. Collectively, these factors provide a theoretically grounded and empirically relevant framework for explaining individual differences in the quality, intensity, and persistence of engagement in AI-supported multimodal language learning.

AI literacy has emerged as a key construct in recent discussions of AI-supported education because it reflects learners' ability to understand, evaluate, and strategically use AI tools in purposeful, ethical, and context-sensitive ways (Chiu et al., 2024). In language learning contexts, this literacy extends beyond technical familiarity and includes the ability to critically interpret AI-generated content, recognize the affordances and limitations of different systems, and integrate AI support into language practice and task completion (Xie et al., 2025). This competence is especially important in AI-supported multimodal language learning, where learners often work with multiple forms of input and output, such as written explanations, spoken feedback, and visual prompts (Ng et al., 2024). Learners with stronger AI literacy may be better prepared to navigate multimodal resources, make informed strategic decisions, and regulate their interaction with AI systems more effectively (Chiu et al., 2024). Prior studies on digital learning have consistently shown that technology-related competence supports active participation by reducing uncertainty, enhancing perceived control, and facilitating more effective engagement with tasks and feedback (Wang et al., 2025). It is therefore plausible that AI literacy serves as a foundational enabling resource for sustained engagement in AI-supported multimodal language learning.

Growth mindset may also play an important role in shaping engagement in AI-supported multimodal language learning (Zarrinabadi & Mantou Lou, 2022). Defined as the belief that abilities can be developed through effort, learning, and appropriate strategies, growth mindset has been widely associated with adaptive motivational orientations and constructive responses to challenge and failure (Elahi Shirvan et al., 2024). Learners who endorse this belief are generally more likely to persist in the face of difficulty, interpret errors as opportunities for improvement, and remain open to iterative feedback and revision (Teng et al., 2024). These qualities are particularly relevant in AI-supported learning environments, where learners often face novel tools, recursive feedback loops, and tasks requiring continuous adjustment and refinement (Elahi Shirvan et al., 2024). In multimodal learning situations, the complexity of processing information across different modes may further heighten the need for an adaptive and resilient learning orientation (Zarrinabadi & Mantou Lou, 2022). Previous studies have linked growth mindset to stronger academic involvement, persistence, and motivation, suggesting that it may help learners maintain constructive and sustained engagement even under cognitively demanding conditions (Teng, 2026). In this sense, growth mindset may provide an important motivational and regulatory foundation for active and sustained engagement in AI-supported multimodal language learning.

Self-efficacy is another factor closely associated with engagement because it reflects learners' judgments about their capability to successfully perform specific tasks (Graham, 2022). A substantial body of educational research has shown that learners with stronger self-efficacy tend to exert greater effort, demonstrate higher persistence, and engage more actively in learning activities (Sun et al., 2025). In AI-supported learning, self-efficacy may become particularly salient because learners must not only deal with academic content but also manage their interaction with AI systems, evaluate the reliability of AI-generated outputs, and regulate their responses to technologically mediated feedback (Sari & Han, 2024). This challenge can be even more pronounced in multimodal environments, where learners need to coordinate multiple streams of information, sustain attention across varied representations, and make informed decisions about task responses (Sun et al., 2026). Learners who believe they can effectively handle such demands are more likely to remain actively involved and translate technological affordances into meaningful learning behaviors (Graham, 2022). Accordingly, self-efficacy can be viewed as a critical agentic resource that enables learners to engage productively and confidently in AI-supported multimodal language learning tasks.

Flow represents an experiential state characterized by deep concentration, strong involvement, and intrinsic enjoyment during task engagement, and it has often been regarded as an important condition for optimal learning and high-quality participation (Aubrey et al., 2025). When learners experience flow, they tend to become fully absorbed in the activity, minimize awareness of external distractions, and sustain focused effort over extended periods (Dai & Wang, 2025). Such a state may be especially relevant in AI-supported multimodal language learning because AI tools often provide immediate, adaptive feedback, interactive scaffolding, and flexible access to multimodal resources, all of which may enhance the sense of immersion during task performance (Bodea & Trofimovich, 2024). Previous research has suggested that flow is positively associated with enjoyment, persistence, and sustained engagement in technology-enhanced learning contexts (Gao et al., 2025). At the same time, flow is unlikely to emerge independently from other learner-related factors (Dai & Wang, 2025). Learners' AI literacy, self-efficacy, and growth-oriented beliefs may jointly influence the extent to which they enter, maintain, and benefit from flow states during AI-supported multimodal learning (Aubrey et al., 2025).

Taken together, the foregoing review suggests that AI literacy, growth mindset, self-efficacy, flow, and engagement should not be treated as isolated constructs in AI-supported multimodal language learning. From a Sociocultural Theory perspective, these constructs can be understood as interconnected learner-related resources involved in mediated participation. AI literacy reflects learners' capacity to understand, evaluate, and appropriate AI tools as mediational means. Growth mindset shapes how learners interpret difficulty, feedback, and revision as opportunities for development. Self-efficacy represents learners' agentic belief in managing tool-mediated multimodal tasks, while flow captures the experiential quality of absorption and enjoyment during mediated activity. Engagement, in turn, reflects learners' cognitive, behavioral, and emotional investment in AI-supported meaning-making practices. Although previous studies have documented associations among some of these variables, less attention has been paid to how they are structurally organized within a unified system. Accordingly, a network-based perspective is useful for clarifying how these psychological resources are interconnected and how they collectively support learner participation in AI-supported multimodal language learning.

### 2.4 Theoretical Framework: Sociocultural Theory

Sociocultural theory (SCT) views learning as a socially situated, interaction-driven, and tool-mediated process, rather than a purely internal and individual activity (Vygotsky & Cole, 1978). From this perspective, learners develop knowledge, skills, and ways of thinking through interaction with others and through social interaction and the mediation of cultural tools, signs, and symbolic resources (Lantolf & Pavlenko, 1995). Language itself is regarded as a central mediational means, while technological tools function as semiotic artifacts that actively shape learners' cognition, perception, and action within learning activities (Lantolf, 2006). In contemporary digital environments, AI tools have increasingly become such mediational resources, especially when they provide learners with access to integrated multimodal representations, including text, audio, and visual input (Lantolf & Xi, 2023). Accordingly, AI-supported multimodal language learning can be understood as a dynamic meaning-making process in which learners engage with AI-mediated resources to interpret input, express understanding, receive feedback, and co-construct knowledge across multiple representational modes.

In the present study, SCT serves as the overarching conceptual lens for understanding how engagement and related psychological factors are situated within AI-supported multimodal language learning. From this perspective, AI literacy is understood as learners' capacity to recognize, appropriate, and strategically use AI tools as mediational means, while engagement reflects their active participation in tool-mediated meaning-making practices. Growth mindset, self-efficacy, and flow are likewise interpreted as learner-related resources that shape how students respond to AI-generated feedback, multimodal representations, and task demands. These resources may support learners' regulation of participation and gradual internalization of productive ways of using AI-mediated support. Rather than treating the variables as isolated personal traits, this study conceptualizes them as relational elements within a broader system of mediated activity. It should be noted that network edges represent statistical associations rather than direct evidence of SCT processes. Nevertheless, interpreted through SCT, these associations can illuminate how psychological resources are structurally connected within AI-supported multimodal language learning.

# 3 Method

## 3.1 Participants

A total of 776 undergraduate students participated in the present study. To be eligible, students had to be enrolled in an undergraduate program, have previous experience using AI tools for multimodal English learning, and provide informed consent to participate. In this study, AI-supported multimodal English learning referred to students' use of AI tools to access, process, or produce English learning content through multiple semiotic modes, including written text, spoken input or output, synthesized speech, visual prompts, and AI-generated feedback. Typical activities included conversational AI-based English dialogue practice, AI-assisted writing or pronunciation feedback, image-prompted speaking or writing tasks, and AI-generated explanations combining textual and auditory resources. The final sample consisted of 312 male students (40.21%) and 464 female students (59.79%). In terms of age, 268 students (34.54%) were between 18 and 19 years old, 321 (41.37%) were aged 20 to 21, and the remaining 187 (24.10%) were 22 years old or above. Regarding academic background, 362 participants (46.65%) came from the humanities and social sciences, 320 (41.24%) were from science and engineering, and 94 (12.11%) represented other disciplines.

## 3.2 Instruments

Data were gathered using a self-report questionnaire administered in Chinese. The questionnaire was composed of two parts. The first part collected demographic information, whereas the second part assessed five major variables related to AI-assisted multimodal English learning, namely AI literacy, growth mindset, flow, self-efficacy, and engagement. All items were rated on a five-point Likert scale, with response options ranging from 1 (strongly disagree) to 5 (strongly agree).

### *3.2.1. AI Literacy*

AI literacy was measured using an adapted version of the scale developed by Lu et al. (2025). The scale comprises four dimensions: awareness, usage, evaluation, and ethics, with three items for each dimension. A sample item is: "*I can skillfully use AI tools to support my multimodal English learning*." The internal consistency of the scale was satisfactory. Cronbach's alpha coefficients were 0.841 for awareness, 0.857 for usage, 0.849 for evaluation, and 0.838 for ethics, while the overall scale reliability was 0.892. Confirmatory factor analysis (CFA) also indicated a good fit to the data: Chi-square/ degrees of freedom ratio ($\chi^2/df$) = 1.199, Root Mean Square Error of Approximation (*RMSEA*) = 0.016, Normed Fit Index (*NFI*) = 0.988, Relative Fit Index (*RFI*) = 0.983, Incremental Fit Index (*IFI*) = 0.998, Tucker-Lewis Index (*TLI*) = 0.997, and Comparative Fit Index (*CFI*) = 0.998.

### *3.2.2. Growth Mindset*

Growth mindset was measured using a four-item scale adapted from Papi et al. (2019) to fit the context of AI-assisted multimodal English learning. A sample item is: "*No matter how much intelligence you have for learning languages, you can always improve it substantially in AI-assisted multimodal English learning*." The scale demonstrated satisfactory internal consistency, with a Cronbach's alpha of .844. CFA also supported the adequacy of the measurement model: $\chi^2/df$ = 1.935, *RMSEA* = 0.035, *NFI* = 0.997, *RFI* = 0.991, *IFI* = 0.998, *TLI* = 0.995, and *CFI* = 0.998.

#### *3.2.3. Flow*

Flow was measured using a five-item scale adapted from Hong et al. (2017) and revised to suit the context of AI-assisted multimodal English learning. A sample item is: "*Time seemed to pass very quickly when I used AI tools for multimodal English learning*." The scale demonstrated good internal consistency, with a Cronbach's alpha of 0.855. CFA indicated a good fit to the data: $\chi^2/df = 2.209$, $RMSEA = 0.039$, $NFI = 0.993$, $RFI = 0.986$, $IFI = 0.996$, $TLI = 0.992$, and $CFI = 0.996$.

#### *3.2.4. Self-efficacy*

Self-efficacy was assessed using an adapted version of the questionnaire developed by Kutuk et al. (2023), revised to reflect the context of AI-assisted multimodal English learning. The scale comprised two dimensions: L2 reception self-efficacy (five items) and L2 production self-efficacy (six items). A sample item is: "*I am confident that I can understand most English learning materials in AI-assisted multimodal English learning without relying heavily on dictionaries or translation tools*." The scale showed good internal consistency, with Cronbach's alpha coefficients of 0.865 for receptive self-efficacy and 0.889 for productive self-efficacy. The overall reliability of the scale was 0.893. CFA further demonstrated a good fit to the data: $\chi^2/df = 2.900$, $RMSEA = 0.050$, $NFI = 0.971$, $RFI = 0.963$, $IFI = 0.981$, $TLI = 0.975$, and $CFI = 0.981$.

#### *3.2.5. Engagement*

Engagement was measured using an adapted version of the scale developed by Eerdemutu et al. (2024), revised for the context of AI-assisted multimodal English learning. The scale consists of three dimensions: behavioral engagement, cognitive engagement, and emotional engagement. A sample item is: "*I try to connect what I am learning through AI-assisted multimodal English learning with what I have learned before*." The scale demonstrated satisfactory internal consistency, with Cronbach's alpha coefficients of 0.828 for behavioral engagement, 0.859 for cognitive engagement, and 0.845 for emotional engagement. The overall reliability of the scale was .868. CFA indicated a good fit to the data: $\chi^2/df = 1.513$, $RMSEA = 0.026$, $NFI = 0.989$, $RFI = 0.984$, $IFI = 0.996$, $TLI = 0.995$, and $CFI = 0.996$.

### 3.3 Data collection procedure

Data collection took place in March 2026. With the support of instructors from several universities in China, the online questionnaire was distributed via the Wenjuanxing platform. Throughout the process, ethical standards were strictly followed. Before responding to the survey, participants were informed of the purpose of the study, the voluntary nature of participation, the confidentiality of their responses, and their right to withdraw at any point without penalty. Online informed consent was obtained from all participants prior to participation. A total of 815 questionnaires were initially collected. After excluding 39 invalid responses due to poor response quality, 776 valid questionnaires were retained for the final analysis, accounting for 95.21% of the total responses.

### 3.4 Data analysis

Data were analysed using SPSS 27.0, AMOS 26.0, and R 4.2.0. To begin with, common method bias was tested, and the dataset was subsequently checked for normality through skewness and kurtosis values. Descriptive statistics and Pearson correlations were then generated to provide an initial overview of the relationships among the variables. In the second step, the psychometric properties of the measurement model were examined, with particular attention to scale reliability and validity. The third step involved network analysis, which was conducted to uncover structural pattern of associations among the study variables. For this purpose, the qgraph and networktools packages were used to estimate and visualise the network, and node centrality was further assessed using the centrality Plot function. The network structure was estimated using LASSO regularization with EBIC model selection implemented in graphs (Epskamp et al., 2012). This approach is widely used in contemporary psychological network modelling because it estimates a sparse and stable network structure by retaining the most meaningful associations while reducing the risk of false-positive connections. To evaluate how well the model fitted the data, several fit indices were examined, including $\chi^2$/df, NFI, RFI, IFI, TLI, CFI, and RMSEA. According to the criteria proposed by Kline (2023), an acceptable model fit is indicated by a $\chi^2/df$ value below 5, NFI, RFI, IFI, TLI, and CFI values above .90, and an RMSEA value below 0.10. These indices were used to ensure the adequacy of the measurement model prior to network estimation.

In the network analysis, node importance was quantified using expected influence, strength, closeness, and betweenness (Bringmann et al., 2019). As strength is generally considered the most robust centrality indicator in psychological network research, it was adopted as the primary basis for identifying the most central nodes, while the other indices were reported as supplementary evidence (Bringmann et al., 2019). Network accuracy and stability were examined using the bootnet package. Accuracy was assessed through bootstrapped 95% confidence intervals for edge weights, with narrower intervals indicating greater estimation precision. Stability was evaluated using the correlation stability (CS) coefficient, for which values above .25 are considered acceptable and values above 0.50 preferable (Epskamp et al., 2018).

## 4 Results

### 4.1 Preliminary analysis

To examine the possible influence of common method bias, Harman's single-factor test was conducted (Harman, 1976). The results yielded multiple factors with eigenvalues greater than 1, and the first unrotated factor accounted for 24.425% of the total variance, which did not exceed the recommended 50% cutoff. This suggests that common method bias was not a serious concern in the present study. Table 1 presents the descriptive statistics and bivariate correlations for the five core variables. Overall, the mean values were above the scale midpoint, indicating that participants generally reported relatively positive levels on these constructs in the context of AI-assisted multimodal English learning. In addition, the skewness and kurtosis values fell within the acceptable ranges for univariate normality, that is, below 2 and 7, respectively (Kline, 2023). Pearson correlation analysis further showed that all variables were positively and significantly related to one another.

Table 1

*Descriptive Statistics and Pearson Correlations*

| **Variable** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| 1 AI literacy | 1 | | | | |
| 2 Growth mindset | .277** | 1 | | | |
| 3 Flow | .335** | .233** | 1 | | |
| 4 Self-efficacy | .266** | .232** | .268** | 1 | |
| 5 Engagement | .407** | .425** | .336** | .402** | 1 |
| M | 3.528 | 3.467 | 3.622 | 3.538 | 3.655 |
| SD | .558 | .900 | .822 | .599 | .618 |
| Skewness | -.399 | -.820 | -.645 | -.172 | -.507 |
| Kurtosis | .807 | .329 | .400 | .953 | .889 |

Note**.** $^{**}p < .01$

### 4.2. Measurement model

Table 2 summarises the CFA results for the measurement model. The findings showed that all study constructs demonstrated adequate reliability and validity. Specifically, the composite reliability (CR) values for all constructs were above 0.70, and the average variance extracted (AVE) values all exceeded 0.50, indicating satisfactory internal consistency and convergent validity (Hair et al., 2021). Furthermore, discriminant validity was supported, as the square root of the AVE for each construct was higher than its correlations with the other constructs (Fornell & Larcker, 1981).

Table 2

*Results of CFA*

| **Variable** | **CR** | **AVE** | **The Square root of AVE and correlation coefficient matrix** | | | | |
|---|---|---|---|---|---|---|---|
| | | | **1** | **2** | **3** | **4** | **5** |
| AI literacy | .828 | .546 | **.739** | | | | |
| G. mindset | .845 | .576 | .342 | **.759** | | | |
| Flow | .855 | .542 | .412 | .270 | **.736** | | |
| Self-efficacy | .713 | .554 | .368 | .315 | .364 | **.744** | |
| Engagement | .781 | .544 | .545 | .539 | .427 | .590 | **.737** |

Note. The values on the diagonal represent the square roots of the AVE

### 4.3. Network analysis outcomes

Theoretically, a network with five nodes can contain 10 edges [$n(n-1)/2=5\times4/2$]. As shown in Figure 1, all 10 possible edges were present in the estimated network, and the nodes were closely interconnected. As reported in Table 3, the strongest edge weight was observed between growth mindset and engagement, followed by the connections between self-efficacy and engagement, AI literacy and engagement, and AI literacy and flow. The remaining edge weights ranged from 0.049 for the link between growth mindset and self-efficacy to 0.149 for the link between flow and engagement.

Figure 1

*Network Structure of the Study Variables*

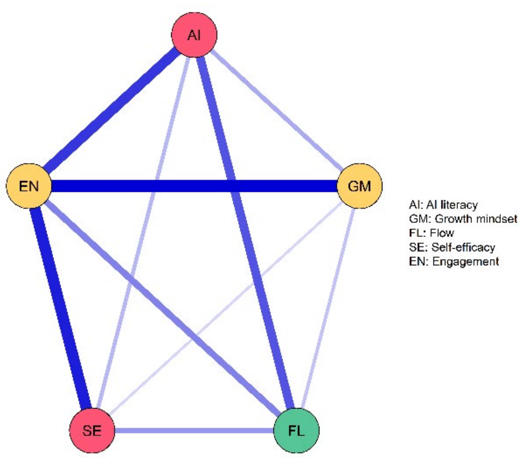


Table 3

*Weighted Adjacency Matrix*

| | AI Literacy | Growth Mindset | Flow | Self-efficacy | Engagement |
|---|---|---|---|---|---|
| AI Literacy | - | | | | |
| Growth Mindset | .100 | - | | | |
| Flow | .205 | .072 | - | | |
| Self-efficacy | .085 | .049 | .125 | - | |
| Engagement | .240 | .304 | .149 | .270 | - |

The standardized centrality indices for all nodes, including betweenness, closeness, strength, and expected influence, are presented in Table 4 and Figure 2. The results showed that Engagement scored higher than all other nodes across all four centrality indicators. By contrast, the standardized centrality values of the remaining four nodes were mostly negative or close to zero, and the differences among them were relatively small. These findings suggest that engagement occupied the most central position in the network and played a prominent role in connecting and transmitting associations among the nodes. More importantly, the high centrality of engagement can be understood as a structural phenomenon, providing empirical evidence for theoretical models that position engagement at the core of technology-mediated SLA.

Table 4

*Centrality Indices of All Nodes*

| | Betweenness | Closeness | Strength | Expected Influence |
|---|---|---|---|---|
| AI Literacy | -.447 | .020 | -.050 | -.050 |
| Engagement | 1.789 | 1.706 | 1.741 | 1.741 |
| Flow | -.447 | -.809 | -.479 | -.479 |
| Growth Mindset | -.447 | -.548 | -.615 | -.615 |
| Self-efficacy | -.447 | -.369 | -.597 | -.597 |

Figure 2

*Centrality Plot*

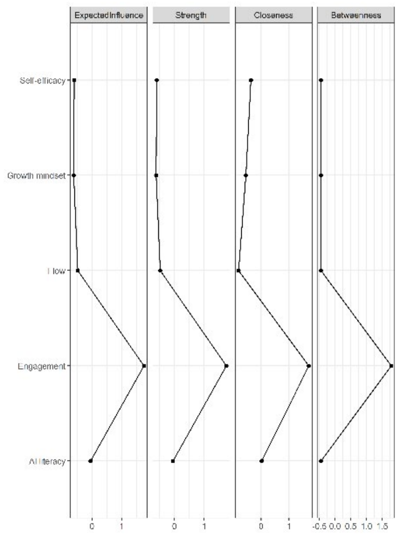
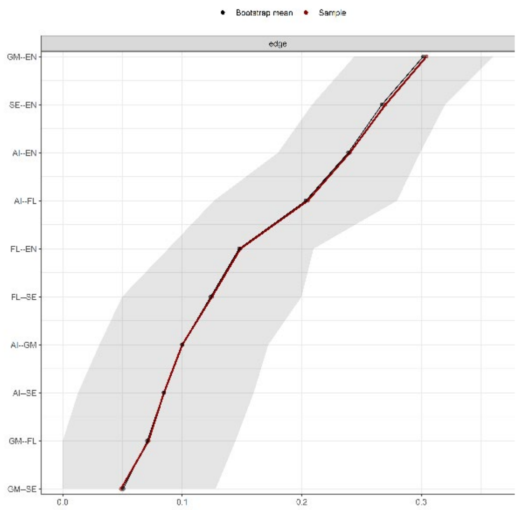


Figure 3 presents the accuracy of the edge-weight estimates in the network model. The grey areas indicate the 95% confidence intervals obtained through non-parametric bootstrapping, with narrower intervals reflecting greater precision and wider intervals indicating lower precision. The red dots represent the sample estimates, whereas the black dots represent the bootstrapped mean estimates, with edge weights ordered from highest to lowest. As shown in Figure 3, the sample estimates were highly similar to the bootstrapped mean estimates and generally fell within the bootstrapped 95% confidence intervals, suggesting acceptable accuracy of the edge-weight estimates, although the precision varied across edges. Figure 4 further presents the bootstrapped difference tests for edge weights. In this figure, grey indicates that the difference between two edges is not statistically significant, whereas black indicates a statistically significant difference.

Figure 3

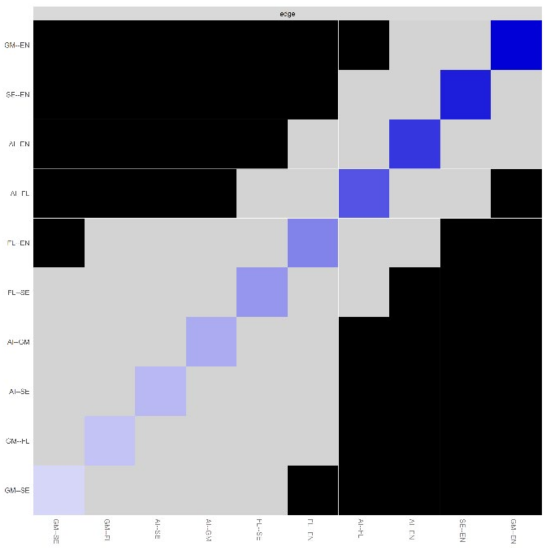
*Accuracy of Edge-weight Estimation*




Note. AI: AI literacy, EE: engagement, FL: flow, SE: self-efficacy, GM: growth mindset

Figure 4

*Bootstrapped Difference Test for Edge Weights*




Note. AI: AI literacy, EE: engagement, FL: flow, SE: self-efficacy, GM: growth mindset

The stability of the centrality indices is presented in Figure 5. The correlation stability coefficients for expected influence, strength, closeness, and betweenness were 0.75, 0.75, 0.75, and 0.59, respectively. All of these values exceeded the recommended threshold of 0.50 (Epskamp et al., 2018), indicating satisfactory stability of the centrality indices. Overall, the network estimates in the present study showed acceptable stability. The results of the bootstrapped difference tests for node centrality indices are presented in Figure 6.

Figure 5

*Stability of Centrality Indices*

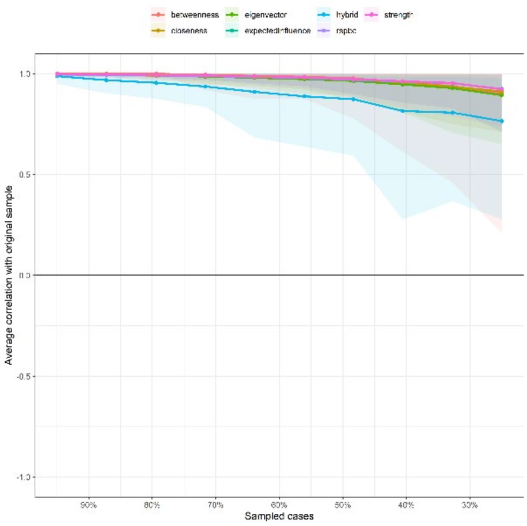
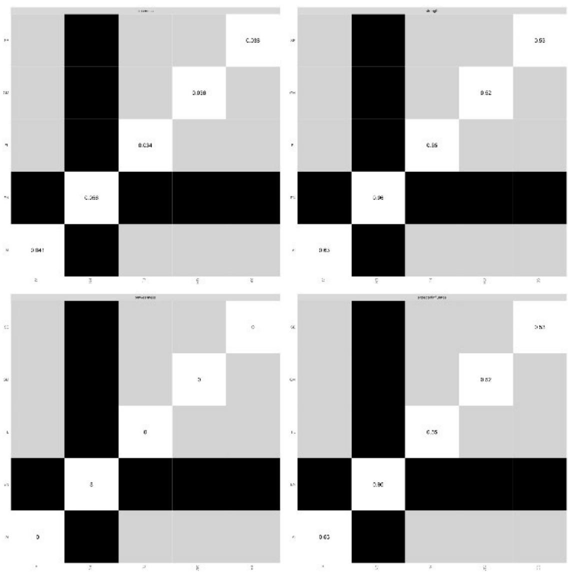



Figure 6

*Bootstrapped Difference Test for Node Centrality*



Note. AI: AI literacy, EE: engagement, FL: flow, SE: self-efficacy, GM: growth mindset

## 5 Discussion

### 5.1 Trend 1: From linear dependencies to networked psychological systems

The present study revealed a fully connected and positive network, which aligns with the broader trend in SLA research toward understanding learner psychology as an interconnected and dynamic system rather than a set of linear dependencies. More specifically, AI literacy, growth mindset, self-efficacy, flow, and engagement were all linked through non-zero edges, indicating that learners' technological competence, adaptive beliefs, perceived capability, and positive experiential state may function together in coordinated and interdependent ways. This pattern is understandable in multimodal AI-supported contexts, where learners are required to interpret diverse forms of input, respond to AI-generated feedback, and sustain participation across dynamic learning activities (Roy et al., 2026). In such settings, learning is unlikely to depend on a single personal attribute. Instead, it appears to reflect the simultaneous activation and interaction of multiple learner-related resources (Dong & Gan, 2026). The overall network structure identified in this study therefore highlights the systemic nature of engagement and suggests that participation in AI-supported multimodal language learning should be understood as a relational, dynamic, and contextually embedded phenomenon rather than a discrete outcome.

This finding also extends previous research in meaningful ways. Existing studies on AI-supported learning have generally shown that AI literacy, self-efficacy, growth mindset, and flow are positively associated with adaptive learning processes and outcomes (Wang et al., 2025; Wang & Guo, 2026), yet these variables have often been examined as separate predictors or outcomes within linear models. By contrast, the present network structure indicates that these factors may be better understood as co-constitutive elements within a shared psychological system. In this sense, the current findings are broadly consistent with earlier work emphasizing the importance of multiple psychological resources in technology-enhanced learning, while at the same time moving beyond such work by demonstrating how these resources are structurally organized and mutually embedded within a single learning context. This more integrated picture is particularly valuable in AI-supported multimodal language learning, where learners continuously coordinate multiple semiotic resources and tool-mediated supports. Accordingly, the present study contributes to the literature by demonstrating that engagement is not merely associated with several individual factors, but situated within a dense network of reciprocal psychological connections.

### 5.2 Trend 2: Engagement as a central system engine, not a downstream outcome

A particularly noteworthy finding of this study is that engagement emerged as the most central node in the network, supporting the emerging view that engagement functions as a central system engine rather than merely a downstream outcome. Compared with the other four variables, engagement showed the highest values for betweenness, closeness, strength, and expected influence, indicating that it occupied the most influential and structurally prominent position in the system (Wang et al., 2026). This result suggests that engagement is not simply one psychological factor among others, but rather the primary hub through which multiple learner-related resources are interconnected and coordinated in AI-supported multimodal language learning. Such a finding is broadly in line with previous research that has consistently emphasized the importance of engagement for high-quality participation, persistence, and successful learning in technology-enhanced environments (Lin & Wang, 2025). However, whereas earlier studies have often demonstrated the importance of engagement by treating it as an outcome variable (Ding & Wang, 2025), the present study further shows that its significance is also structural and systemic in nature. In other words, engagement appears to function not only as an indicator of successful learning involvement, but also as a central organizing element within the broader psychological network.

This structurally central role of engagement can be further understood from a sociocultural perspective. In AI-supported multimodal language learning, learners do not merely receive information from technological tools; rather, they actively participate in tool-mediated meaning-making processes through interaction with text, audio, images, feedback, and task demands (Roy et al., 2026). From this perspective, engagement reflects the degree to which learners are genuinely involved in mediated learning practices, making it reasonable that this construct occupies a pivotal position in the network. More importantly, the centrality of engagement enriches its conceptual meaning in this context. Rather than functioning only as the endpoint of motivational or cognitive influences (Liu et al., 2022), engagement may be better understood as a process-oriented system state that reflects how learners coordinate technological competence, adaptive beliefs, perceived capability, and experiential involvement during AI-mediated activity. Its central position therefore suggests that engagement is the site where different learner-related resources are activated, connected, and expressed through interaction with AI tools, multimodal feedback, and task demands. This interpretation offers a more dynamic understanding of engagement and positions it as both an indicator and organizer of mediated learner participation in contemporary AI-mediated language learning contexts.

### 5.3. Trend 3: The primacy of adaptive beliefs and AI literacy over transient flow

The pattern of edge weights further suggests the primacy of adaptive beliefs and AI literacy over transient flow in sustaining learner engagement in AI-supported multimodal language learning. Among the four psychological factors, growth mindset showed the strongest connection with engagement, suggesting that learners' beliefs about the malleability of ability may be especially important in AI-supported multimodal language learning. This finding indicates that learners who view challenges, errors, and revision as part of growth are more likely to remain actively involved in AI-mediated tasks. Such an interpretation is understandable in multimodal environments, where learners often need to process diverse forms of input, respond to iterative feedback, and adjust their performance across repeated interactions. In this sense, engagement appears to be structurally associated not simply with immediate success, but also with a willingness to treat difficulty as constructive and developmental. This result is broadly consistent with previous studies showing that growth mindset supports persistence, adaptive coping, and higher levels of academic involvement (Teng et al., 2024; Teng, 2026). At the same time, the present study extends earlier work by showing that growth mindset is not only positively related to engagement, but is also the factor most closely tied to it within the current network. This highlights the particularly salient role of adaptive beliefs in sustaining participation in AI-supported multimodal language learning.

Self-efficacy also showed a strong association with engagement, underscoring the importance of learners' confidence in managing tasks and using AI-supported resources effectively. In AI-supported multimodal language learning, learners are expected to handle not only academic demands but also interactions with multiple modes of representation and AI-generated feedback. Under such circumstances, learners who believe they can successfully cope with these demands are more likely to invest effort, persist through difficulty, and remain psychologically involved in the learning process. This finding aligns with a large body of previous research suggesting that self-efficacy is a robust predictor of active participation, persistence, and academic effort across technology-enhanced learning settings (Sun et al., 2025; Teng et al., 2025). However, the present study contributes a more nuanced perspective by showing that self-efficacy is not merely a background predictor of engagement, but one of the most structurally integrated components of the network. This suggests that confidence may represent a crucial learner-related resource that is structurally connected with sustained and meaningful participation in multimodal AI environments.

AI literacy was likewise closely connected to engagement, indicating that learners' ability to understand, evaluate, and use AI tools meaningfully is highly relevant to their participation in AI-supported multimodal language learning. This result suggests that engagement in such environments is closely associated not only with motivation or confidence, but also with learners' capacity to navigate AI-generated support critically and strategically. Because AI-supported multimodal language learning often involves shifting between written explanations, spoken prompts, visual cues, and automated feedback, learners with stronger AI literacy may be better equipped to interpret available resources and maintain purposeful involvement in tasks. This finding is consistent with previous research emphasizing the value of digital competence and technology-related literacy for promoting active participation in technology-enhanced learning (Xie et al., 2025; Wang et al., 2025). At the same time, the present study adds to the literature by demonstrating that AI literacy is positioned in close structural proximity to engagement within the same psychological system, rather than simply acting as a distal background variable. This underscores that technological competence is an integral component of learner participation in contemporary AI-mediated language learning.

Compared with growth mindset, self-efficacy, and AI literacy, flow showed a weaker but still positive connection with engagement, suggesting that immersive and enjoyable learning experiences remain relevant, even if they are not the strongest correlate in the network. Such a result is in line with prior studies that have linked flow to persistence, enjoyment, and active engagement in digital learning environments (Dai & Wang, 2025; Gao et al., 2025). However, this relatively weaker connection may reflect the specific nature of AI-mediated multimodal learning. Many AI-supported tasks are short, feedback-oriented, and goal-directed, requiring learners to shift among prompts, AI responses, revisions, and multimodal resources rather than remain in a continuous state of absorption. As learners process text, audio, images, and AI-generated feedback, the cognitive effort involved may interrupt time distortion and deep immersion, which are central indicators of flow. Another possible explanation concerns measurement. Although the adapted five-item flow scale was psychometrically acceptable, it may not fully capture interaction-specific flow in human-AI learning, such as conversational continuity, perceived responsiveness, and human-AI co-regulation.

## 6 Limitations and Future Directions

Despite its contributions, the present study has several limitations that should be acknowledged. First, the cross-sectional design limits the ability to draw causal or temporal inferences about the relationships among AI literacy, growth mindset, self-efficacy, flow, and engagement. Although network analysis provides valuable insight into the structural interconnections among variables, it cannot determine the directionality or developmental sequencing of these relationships. Second, the study relied on self-report data, which may be subject to common method bias and may not fully capture learners' actual behavioral engagement in AI-supported multimodal language learning contexts. Third, although the study was situated in AI-supported multimodal language learning, the selected variables primarily reflected learner-related psychological factors rather than direct behavioral or interactional indicators of multimodal AI use. As a result, the study offers a theoretically meaningful but still incomplete and indirectly measured account of learner participation. These limitations suggest that the findings should be interpreted with appropriate caution and viewed as an initial step toward a more comprehensive understanding of engagement in AI-mediated learning.

Future research can build on the present study by adopting more diversified designs and methods to capture the complexity of AI-supported multimodal language learning more fully. Longitudinal research would be particularly valuable for examining how the relationships among engagement and related psychological factors develop and reconfigure over time, and whether changes in one variable lead to shifts in the broader network. In addition, future studies may combine network analysis with qualitative methods, such as interviews, classroom observations, or learning journals, to explore how learners experience AI-supported multimodal language learning in actual practice. Researchers may also incorporate behavioral indicators, including tool use frequency, interaction patterns across text, audio, and visual modes, and task completion traces, in order to bridge the gap between psychological networks and observable learning behaviors. Finally, future work could compare different learner groups, proficiency levels, or educational settings to determine whether the structure of engagement remains stable across contexts. Such efforts would deepen understanding of learner participation in increasingly complex and evolving AI-mediated language learning ecosystems.

## 7 Conclusion and Implications

This study investigated the relationships among AI literacy, growth mindset, self-efficacy, flow, and engagement in AI-supported multimodal language learning through a network analytic approach. The findings revealed a fully connected and entirely positive network, suggesting that these variables functioned as closely related components of a broader interdependent and dynamically organized learner-related psychological system rather than as isolated factors. Among them, engagement emerged as the most central node, indicating that it occupied the most influential structural position in the network. In addition, growth mindset, self-efficacy, and AI literacy showed particularly close connections with engagement, highlighting the importance of adaptive beliefs, perceived capability, and technological competence in sustaining learner participation. These findings contribute to the growing literature on AI-supported multimodal language learning by offering a more systemic and integrative understanding of how psychological resources are interconnected in contemporary AI-mediated learning environments. Overall, the study demonstrates that engagement should be understood not only as a desirable learning outcome but also as a central organizing construct within the broader psychological ecology of AI-supported multimodal language learning.

The present study offers several theoretical contributions to the emerging literature on AI-supported multimodal language learning. First, by adopting a network analytic approach, it moves beyond the dominant linear logic in previous research and provides a more integrated account of how learner-related factors are structurally interconnected within the same context. Rather than treating AI literacy, growth mindset, self-efficacy, flow, and engagement as separate predictors or outcomes, the present study conceptualizes them as mutually constitutive and reciprocally influential elements within a broader psychological system. Second, the findings refine current understandings of engagement by showing that engagement is not merely an endpoint of learning processes, but a central structural hub that organizes and coordinates relationships among other psychological resources. This insight extends prior work that has mainly emphasized the importance of engagement at the outcome level. Third, from a sociocultural perspective, the study highlights that learner participation in AI-supported multimodal language learning is shaped through mediated interaction with technological tools, multimodal feedback, and diverse semiotic resources, thereby offering a more context-sensitive account of engagement in contemporary AI-mediated language learning.

The findings also carry important pedagogical implications for the design and implementation of AI-supported multimodal language learning. Since engagement emerged as the central node in the network, teachers and instructional designers should regard the promotion of engagement as a primary objective rather than a secondary by-product of technology use. More specifically, the close associations of engagement with growth mindset, self-efficacy, and AI literacy suggest that effective pedagogy should not focus exclusively on introducing AI tools, but also on cultivating the psychological conditions that support sustained participation. For example, teachers may encourage students to view errors and revisions as valuable aspects of learning, thereby fostering a stronger growth mindset. They may also strengthen self-efficacy by providing scaffolded tasks, clear guidance, and achievable learning goals in AI-mediated activities. In addition, learners need explicit support in understanding how to evaluate and use multimodal AI resources critically and strategically. In this way, pedagogical practice can better translate technological affordances into meaningful and lasting engagement. Taken together, these pedagogical strategies suggest that effective AI-supported instruction should integrate technological design with psychological scaffolding in order to translate AI affordances into sustained learner engagement.

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