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Improving learning performance through AI-enabled task completing and network building: integrating task-technology fit and social-technology fit perspectives

Bo Yang and Yongqiang Sun

School of Information Management, Wuhan University, Wuhan, People's Republic of China

ABSTRACT

Artificial intelligence-enabled learning applications (AILAs) are increasingly used to support personalized learning and peer interactions. However, research often overlooks how technological (i.e., task-technology fit, TTF) and social factors (i.e., social-technology fit, STF) jointly influence student performance. Drawing upon the extension of TTF model, we developed a nomological network model to explore how TTF and STF affect learning performance. A survey was conducted among 278 university students using AILAs. The data analysis indicated that both TTF and STF have significant positive main effects and interaction effects on learning performance. Further, AI-enabled pattern recognition, feedback generation, and content personalization positively influence TTF, while network size and network homophily positively influence STF. Unlike existing research that focuses solely on the technological aspects of AI technologies in education while neglecting their social aspects, our study expands the TTF model by incorporating the STF. Moreover, our study offers a contextualized typology of AI-enabled task completing and AI-enabled network building, providing valuable empirical evidence in the domain of AILAs for higher education. Practically, higher education institutions can acknowledge the technological and social advantages of AILAs, and AILA practitioners can enhance product design based on our findings.

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E-learning; artificial intelligence; task-technology fit; social-technology fit; higher education

1. Introduction

Artificial intelligence (AI) is profoundly reshaping higher education, where AI-enabled learning applications (AILAs) are prominent tools for transforming student learning experiences (Crompton & Burke, 2023; Díaz & Nussbaum, 2024; Zawacki-Richter et al., 2019). These applications are typically characterized as software systems that leverage diverse AI technologies, with the deep analysis of individual student historical interaction data, to personalize and support learning processes (Zhang et al., 2023). This data-driven approach to learning is not only gaining traction but also spearheading growth in the educational technology market. According to a report by The Business Research Company, the global market share of AI in the education sector reached nearly 4 billion USD by 2023 and is expected to grow to 15 billion USD by 2027.

The proliferation of AILAs is largely driven by their potential to offer individually tailored educational pathways (Palahan, 2025). By processing a student's ongoing performance data and past learning history, they aim to enhance learning by adaptively adjusting content, offering personalized feedback in real-time, and providing cognitive scaffolding to deepen engagement (Kasakowskij & Haake, 2025; Uzun et al., 2025). Beyond these personalized functionalities, many AILAs are evolving to incorporate social features that facilitate peer interaction, knowledge sharing, and collaborative learning activities, thereby acknowledging the social factor of learning (Chang et al., 2022; Shea & Bidjerano, 2010; Zhang et al., 2023). These integrated platforms often strive to create user-friendly, immersive ecosystems that effectively integrate personalized learning support with community engagement (Zhang et al., 2023).

Despite these technological advancements and the optimistic discourse surrounding AILAs, critical questions regarding their actual impact on student learning performance persist (Bearman & Ajjawi, 2023). While

proponents highlight enhanced autonomy (Lim et al., 2023), concerns have been raised about issues such as potentially higher dropout rates compared to traditional environments (Fu et al., 2020). Given that learning performance remains an important indicator of educational effectiveness (Isaac et al., 2019), it is crucial to study how AILAs influence students' learning processes and outcomes. Such understanding is significant for educators to discern how AI can genuinely contribute to teaching and learning in higher education (Zawacki-Richter et al., 2019).

Previous research has explored determinants of e-learning performance, including task-technology fit (McGill & Klobas, 2009), user satisfaction (Isaac et al., 2019), and various quality aspects (Cidral et al., 2018). With AI's increasing integration, studies have focused on factors influencing AI adoption and its impact on performance in contexts like AILAs (Fu et al., 2020), AI instructors (Xing et al., 2025; Zhang et al., 2025), and AI chatbots (Budhathoki et al., 2024), often using models like UTAUT or TAM (An et al., 2025; Yin & Goh, 2025; Zou et al., 2023). However, there are still several research gaps to be addressed. To clearly summarize these identified research gaps and contextualize the contribution of this study, a comparative overview of related works is provided in Appendix A.

Previous research often lacks a holistic perspective that considers both the technological and social dimensions of AILAs in supporting student learning and performance. Specifically, the first gap lies in the predominant focus on AILAs as mere technical tools, often overlooking the social support they can offer. While studies have examined technology acceptance variables (An et al., 2025; Dahri et al., 2024; Krouska et al., 2023), AILAs also form adaptive groups of students with similar learning interests and goals (Zawacki-Richter et al., 2019). Learning inherently is a social activity (Brummernhenrich et al., 2025; Shea & Bidjerano, 2010), with interaction and collaboration being key elements of the learning process (Wu et al., 2022). Therefore, investigating AILAs solely from a functional perspective may fail to fully capture the key characteristics of their online interactive learning environment and the theoretical contextualization of their social support mechanisms remain underexplored.

Secondly, the mechanisms through which AILAs enhance learning performance are not fully understood, particularly concerning the fit between AI technology and learning tasks (Lin & Huang, 2008). While some studies explore the impact of perceived technology beliefs on behavioral intention and learning performance, with potential mechanisms including user experience (Zhang et al., 2023), attitude (Chang et al., 2022), and engagement (Fu et al., 2020), task-technology fit (TTF) is a critical lens for e-learning performance (McGill & Klobas, 2009; Wang et al., 2014; Wang & Kartika Sari, 2024). AILAs' adaptive features mean performance largely depends on how well technological supports align with task requirements (Lin & Huang, 2008). Furthermore, unlike individual-use AI tools, such as educational chatbots (Budhathoki et al., 2024) or intelligent tutors (S. Wang et al., 2020), AILAs' rich social features suggest the traditional TTF model may be insufficient, necessitating the integration of social-technology fit (STF) to capture this social dimension (Lu & Yang, 2014; B. Wang et al., 2020).

Thirdly, while technological and social factors in e-learning are acknowledged (Cidral et al., 2018; Kim et al., 2023; Wu & Chen, 2017), their potential synergistic interaction has been largely overlooked. The interaction effect may better reflect the argument that learning performance is the result of the synergistic influence of technological and social factors in the e-learning environment (Shea & Bidjerano, 2010).

To address these gaps, this study aims to investigate the interplay of technological and social factors in AILAs and their impact on student learning performance. Guided by an extension of the TTF model, this study proposes the following research questions:

Research Question 1: What are the dimensions through which AILAs support students' learning from both technological and social perspectives?

Research Question 2: Do TTF and STF mediate the relationship between the identified AI-enabled learning support dimensions and student learning performance in the context of AILAs?

Research Question 3: Is there an interaction effect between TTF and STF in influencing student learning performance when using AILAs?

Based on the TTF model, this study addresses these research questions by introducing the social network constructs from network externality theory. This study contributes by: (1) differentiating and conceptualizing

AI-enabled task completion and AI-enabled network building processes based on the framework of AI roles in learning and network externality theory; (2) extending the TTF model by incorporating STF to better explain performance in socially interactive AILA environments; and (3) examining the interaction effect between TTF and STF, offering a more nuanced understanding of their combined impact on learning outcomes.

The remaining structure of this paper is as follows. In the next section, we review the literature and theoretical foundations, and propose our research model and hypotheses. Section 3 and 4 report our research methods and the results of data analysis, respectively. Finally, section 5 discusses our findings, contributions, and limitations.

2. Theoretical development

Learning applications refer to software that facilitates the learning process by providing educational content and are characterized by ease of use and user-friendliness (Fan & Wang, 2025). These applications can be conveniently accessed via computers, smartphones, and tablets. Initially, these applications merely digitized learning materials, with relatively monotonous and procedural instructional modules (Xu et al., 2014). However, with recent advancements in educational technology, learning applications have increasingly been empowered by AI, leading to the development of AILAs that integrate more adaptive and interactive functionalities (Chang et al., 2022; Zhang et al., 2023). This evolution marks a significant shift from static content delivery rooted in pre-trained knowledge systems to dynamic, personalized learning experiences.

AILAs possess the capability to enhance students' learning outcomes through both technological and social aspects. From a technological standpoint, AILAs can analyze vast quantities of data pertaining to student behavior, preferences, and performance (Ilić et al., 2023). This data-driven approach enables the provision of highly personalized learning content and adaptive learning pathways. Socially, AILAs can foster connections among students who share similar learning goals and interests, thereby facilitating collaborative learning environments (Hwang et al., 2021). Recognizing these dual capabilities, this study differentiates and conceptualizes two core processes of AI-enabled learning: AI-enabled task completion and AI-enabled network building.

Learning performance, as a critical indicator of educational technology effectiveness, has been a focal point in numerous studies (Cidral et al., 2018; Wu et al., 2022). Students can leverage the rich functional modules within AILAs to support their learning activities and improve overall learning efficiency (Chang et al., 2022). Additionally, AILAs can provide personalized learning materials that foster reflective thinking, aiding students in generating new ideas and creatively completing tasks (Urban et al., 2024).

A central theoretical lens for understanding the impact of educational technology on student learning outcomes is TTF (Goodhue & Thompson, 1995). TTF suggests that if an educational technology is well-suited to the learning tasks students need to perform, it will lead to enhanced learning performance (McGill & Klobas, 2009). While extensively applied in e-learning research, its application to the context of AILAs (Isaac et al., 2019; Lin & Huang, 2008; McGill & Klobas, 2009), which are characterized by adaptive and often social features, warrants further exploration. However, the traditional TTF model, with its primary focus on the fit between task requirements and technological characteristics, may not fully capture the nuances of current AILAs, many of which incorporate significant social features. Learning is a social process (Shea & Bidjerano, 2010), and the capacity of AILAs to facilitate interaction and collaboration suggests the need to consider an additional dimension of fit (i.e. STF). Therefore, this study proposes an extension to the TTF model by incorporating STF, considering both as mediating mechanisms through which the socio-technical characteristics of AILAs influence student learning performance. Furthermore, recognizing that technological and social factors in learning environments to operate in an interactive manner (Shea & Bidjerano, 2010), this study also aims to explore the potential interaction effect between TTF and STF on learning performance. Accordingly, this study presents a research model (as shown in Figure 1).

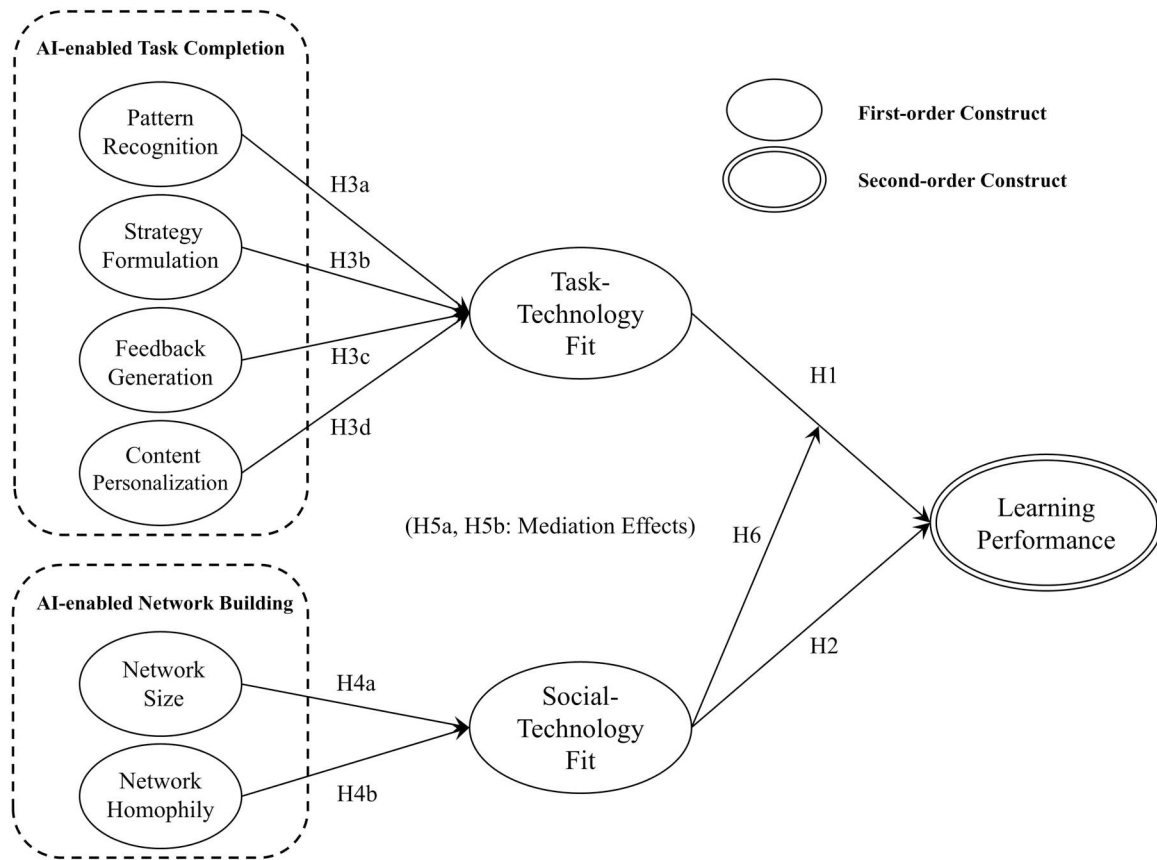


Figure 1. Research model.

2.1. TTF, STF, and learning performance

The TTF model was initially used to understand how organizations and individuals can more effectively utilize information technology (IT) (Goodhue & Thompson, 1995), and has been widely used to assess the impact of task and technology characteristics on individual IT performance (Howard & Rose, 2019).

Although TTF has not yet been investigated in the context of AILAs, its significance for student learning outcomes has been comprehensively examined within the broader e-learning literature (Isaac et al., 2019; McGill & Klobas, 2009; Wang & Kartika Sari, 2024). These studies indicate a fundamental principle: the integration of educational technology with the demands of learning tasks, when utilized effectively by students, results in a favorable impact on their performance (McGill & Klobas, 2009). In the context of AILAs, TTF refers to the alignment between the functionalities of the AI technology and the requirements of student learning tasks (Goodhue & Thompson, 1995). It represents a student's subjective judgment of how well the AILA serves as a pathway or method to meet the needs of their academic work (Isaac et al., 2019; Zhang et al., 2017). For instance, AILAs can simplify daily processes through automation, thereby improving efficiency and reducing cognitive load (Sharma et al., 2024). Consequently, students can allocate more cognitive resources to higher-order thinking processes, such as creativity. The consistent finding across various e-learning studies is that a high degree of TTF leads to improved student learning outcomes. Therefore, we propose:

H1. TTF positively influences learning performance.

As IT increasingly integrate social functionalities, their influence extends beyond individual task completion to affect social interactions and connections (Wu et al., 2022; Wu & Chen, 2017). This necessitates a theoretical expansion of the traditional TTF model. STF has emerged as a relevant construct, defined as the degree to which a technology aligns with and supports users' social needs (Lu & Yang, 2014). Research on socially rich IT platforms, such as social media and social e-commerce (Chakraborty et al., 2025; Lu & Yang, 2014), has highlighted the utility of incorporating STF to complement the TTF model. This extension is particularly

significant as it addresses the limitations of the TTF model, which often inadequately accounts for social factors, thereby enhancing its explanatory power in the context of technologies designed with social networking capabilities (B. Wang et al., 2020). In this study, STF is conceptualized as the extent to which an AILA effectively meets the social and collaborative requirements of students within their learning environment. AILAs create a more interactive platform that can enhance student interaction. For example, students can learn about the progress of other students with similar learning goals and interests and interact with others through modules such as circles, discussion groups, and study networks (Dang et al., 2019). This aligns with social learning theory, which posits that collaborative learning environments, where students can observe and learn from high-performing peers' strategies, contribute to enhanced individual learning performance (Badghish et al., 2024). Moreover, constructivist learning theory suggests that active peer interaction facilitates the co-construction of knowledge, making learning more effective (Wu et al., 2022). Previous research has demonstrated a positive impact of technology-facilitated social interaction on key outcomes such as learning performance (Hook et al., 2020). Therefore, we propose:

H2. STF positively influences learning performance.

2.2. AI-enabled task completion and TTF

The TTF model provides a comprehensive theoretical explanation of how the technical and task characteristics of AILAs influence TTF (Lin & Huang, 2008). However, merely considering generic technical and task characteristics as antecedents of TTF does not adequately contextualize which specific features of AILAs can enhance student learning performance. Similarly, the antecedents of STF also require contextualization. Therefore, following the contextualization approach proposed in the TTF model by previous research (Chung et al., 2015; Wang et al., 2021), we consider AI-enabled task completion and AI-enabled network building as antecedents to TTF and STF. This contextual approach helps researchers construct a conceptual framework specific to a particular technological context (Liang et al., 2021) and is widely adopted in research on TTF (Liang et al., 2021; Lin & Huang, 2008; Shahzad et al., 2023). To structure this contextualization, we first conceptualize the core functionalities of AILAs as supporting two distinct processes, derived from their socio-technical characteristics: AI-enabled task completion and AI-enabled network building. We define AI-enabled task completion as the set of instrumental AI functionalities that personalize and optimize a student's learning process, thereby supporting the direct execution of educational tasks. In contrast, we define AI-enabled network building as the set of relational AI functionalities that structure the social environment of learning by leveraging network characteristics. This process focuses on facilitating social interaction among users through mechanisms that shape the network's size and composition. Specifically, in line with Ilić et al. (2023) and considering the practical functional characteristics of AILAs, we propose four dimensions of AI-enabled task completion: pattern recognition, strategy formulation, feedback generation, and content personalization. Moreover, drawing from the literature on network externalities (Kang et al., 2024; Yong Chun & Hahn, 2007), we propose network size and network homophily as two key dimensions of AI-enabled network building.

Ilić et al. (2023) conducted a systematic review of recent AI for education research and proposed a framework of roles of AI in learning. This framework allows us to integrate four dimensions: pattern recognition, strategy formulation, feedback generation, and content personalization to explore the impact of AI-enabled task completion on TTF. **First**, AI-enabled pattern recognition refers to the ability of AILAs to recognize individual learning styles, assess current learning states, and understand their learning capabilities (Montebello, 2018). AILAs can identify students' learning states, preferences, and styles by analyzing historical learning data, thereby helping students understand their own learning situations. Previous research indicates that students believe intelligent learning systems' recognition of their learning states positively promotes learning activities (Chen, 2009). **Second**, AI-enabled strategy formulation refers to the extent to which AILAs support students in systematically planning methods to enhance their learning. AILAs can help students formulate targeted learning strategies, such as content selection and time allocation, which aid in self-regulation of their learning processes (Lim et al., 2023). **Third**, AI-enabled feedback generation refers to the quality and effectiveness of feedback provided by AILAs. Educational research indicates that feedback from learning mentors is one of the most effective ways to support student learning (Hattie & Timperley, 2007). This post-performance information on learners can promote self-monitoring and intrinsic motivation

(Brummernhenrich et al., 2025; Wong et al., 2019). **Fourth**, AI-enabled content personalization refers to the extent to which AILAs provide personalized learning content based on students' preferences and needs. By customizing content to suit learners' individual characteristics, AILAs facilitate meaningful connections between new and existing knowledge frameworks, a fundamental aspect of effective pedagogy (Rodríguez-Ardura & Meseguer-Artola, 2021). Existing research provides extensive empirical evidence that personalized learning materials aligned with learners' goals can effectively promote learning activities (Esteban-Millat et al., 2014; Leung et al., 2023; Xu et al., 2014).

Collectively, these four dimensions of AI-enabled task completion represent key functionalities that determine the extent to which AILAs fit students' learning activities. When these AI capabilities effectively support the diverse tasks involved in learning, they should directly cause students to perceive a higher degree of fit between the technology and their learning requirements. Therefore, based on the TTF model, we propose the following hypotheses:

- H3a. AI-enabled pattern recognition has a positive effect on TTF.
- H3b. AI-enabled strategy formulation has a positive effect on TTF.
- H3c. AI-enabled feedback generation has a positive effect on TTF.
- H3d. AI-enabled content personalization has a positive effect on TTF.

2.3. AI-enabled network building and STF

To conceptualize the antecedents of STF in the AILA context, this study draws upon the theory of network externalities. This theory helps to explain how the value of a network-based technology increases with the number of users and the intensity of their interactions (Yong Chun & Hahn, 2007). From this perspective, we identify two key dimensions of AI-enabled network building: network size and network homophily. Network size represents the breadth of the network, while network homophily pertains to the degree of similarity among its members (Sun et al., 2022).

Network size, in this study, refers to students' perception about the size of their current learning network membership (Chiu et al., 2013). According to network effect theory, the degree of social interaction increases with the number of users within the network (Ma, 2021). Perceived network size can enhance social presence, thereby establishing social connections and promoting social interaction (Tseng et al., 2018). The larger the student size in the network of AILAs, the more active the community atmosphere and the more frequent the discussions. Prior studies have examined the positive impact of network size on the connections established by users with others in the network (Sun et al., 2022). Therefore, this study posits that a larger network size, by enabling more opportunities for interaction and discussion, will positively influence students' perception that the AILA fits their social needs.

- H4a. Network size has a positive effect on STF.

Network homophily refers to the closeness of students' connections with peers in the network who have similar learning goals and interests (Sun et al., 2022). The similarity-attraction hypothesis states that people are more inclined to establish social connections with those who have similar characteristics (Osei-Frimpong et al., 2022). In the context of AILAs, this similarity plays an important role in fostering meaningful community interactions, communication, and collaborative learning (Xu et al., 2021). Existing studies have examined the positive impact of network homophily on community participation, suggesting that similarity-based connections are a key driver of social engagement (Hook et al., 2020). In the AILA context, AI-enabled homophily should therefore directly enhance the perceived fit with students' social needs. Therefore, we propose:

- H4b. Network homophily has a positive effect on STF.

2.4. The mediating roles of TTF and STF

In hypotheses 1–4, we discussed how AI-enabled task completing and network building respectively affect TTF and STF, and how TTF and STF affect learning performance. Prior studies on the mediating effect of TTF

and STF on the positive relationship between AI-enabled task completing and network building and learning performance are limited. As fit encompasses two dimensions of TTF and STF, it is meaningful to capture the psychological process through which students use AILAs to improve their learning performance through the mediation of TTF and STF. Previous educational research has identified TTF as a key mediating variable in how the function of educational technology contributes to student performance (McGill & Klobas, 2009; Wang & Kartika Sari, 2024). Similarly, it is plausible that the social characteristics of an AILA (e.g. AI-enabled network building) influence performance by affecting how well the technology is perceived to meet social needs (STF). This study extends this logic by proposing that both TTF and STF act as mediators. Hence, we hypothesize:

H5a. TTF plays a mediating role between AI-enabled task completing (i.e. pattern recognition, strategy formulation, feedback generation, and content personalization) and learning performance.

H5b. STF plays a mediating role between AI-enabled network building (i.e. network size and network homophily) and learning performance.

2.5. The interaction effect between TTF and STF

Constructivist learning theory posits that learning is a multifaceted process that combines individual cognitive engagement with social interaction; effective learning, therefore, necessitates the integration of both cognitive and social approaches (Wu et al., 2022). The cognitive approach involves students' personal interpretation and construction of knowledge, a process that can be supported by the rich functional modules of AILAs. In contrast, the social approach emphasizes peer interaction and collaborative knowledge construction, which has the potential to enhance the internalization of individual knowledge (Wu et al., 2022). Moreover, the Communities of Inquiry framework posits that learning performance is the outcome of the interplay between social and technological factors in online collaborative learning environments (Shea & Bidjerano, 2010). Therefore, TTF and STF may jointly, rather than independently, impact learning performance. When STF is relatively high, students can receive diverse forms of informational support from others, such as learning resources and strategies, and emotional support like encouragement (Dang et al., 2019). This may enhance students' personal learning in the functional modules of AILAs. Hence, we propose:

H6. STF reinforces the positive effect of TTF on learning performance.

3. Research methodology

3.1. Research setting

This study takes AILAs as the research context to verify and analyze the research model. We did not specify AILAs; instead, we asked the students participating in the survey to report their most frequently used AILA. This approach allows us to obtain their perceptions on the various constructs involved in using AILAs, thereby effectively capturing the impacts of these constructs. We selected Chinese university students who use AILAs for learning purposes as the research subjects. Taking China's leading online English learning application, Liulishuo, as an example, as of June 2022, the AILA had about 30 million college student users, indicating a high popularity of AILAs among Chinese university students. Liulishuo supports students' English-speaking learning through various AI technologies, including natural language processing, recommendation algorithms, and knowledge graphs (Chang et al., 2022). The AILA contains extensive learning materials and customizes personalized learning plans based on students' proficiency levels, also providing automatic pronunciation evaluation and correction through AI technology. Two years after its launch, Liulishuo added a learning community function to strengthen the connections between students with similar learning interests through circles. This indicates that Liulishuo, in addition to its adaptive learning system, can also establish connections between users. The other AILAs reported by respondents in this study also possess similar features to Liulishuo, combining technology-driven support and community-building aspects to enhance student learning.

3.2. Measurement

All measurements in this study are sourced from prior research and have been contextually adjusted. We employed a two-step process for instrument development, a common practice when investigating emerging technological phenomena. First, we ensured conceptual relevance by defining our constructs based on recent AI in education literature. Second, we operationalized these constructs by adapting items from well-validated instruments in the broader e-learning and technology use domains. All first-order constructs were measured using a 7-point Likert scale for reflective measurement, ranging from 1 (strongly disagree) to 7 (strongly agree). Learning performance is considered a second-order structure, consisting of two dimensions: learning creativity and learning productivity. Learning productivity and creativity were adapted items from Shirish et al. (2021). To measure TTF and STF, we adapted scales from Zhang et al. (2017) and Cidral et al. (2018), respectively. Measurement items for AI-enabled pattern recognition, strategy formulation, feedback generation, and content personalization were adapted from Montebello (2018), Subramanian and Nosek (2001), Xu et al. (2014) and Esteban-Millat et al. (2014), respectively. Measurement items for network size and network homophily were adapted from Chiu et al. (2013) and Cheng et al. (2011), respectively. Appendix B presents all constructs and their measurement items used in this study.

3.3. Data collection

To ensure the ecological validity of our study and capture authentic user experiences, we aimed to recruit university students who had prior experience with AILAs. The data collection was facilitated by wxj.cn, a reputable online survey platform in China, analogous to MTurk, which maintains a large and diverse pool of university student participants. We utilized the platform's targeted recruitment services, for which an information service fee was paid, to reach students who had previously used AILAs. During the survey collection phase, at the beginning of the questionnaire, participants were provided with a concise overview of AILAs to ensure their comprehension of the research context. To deepen participants' recollections of their AILA usage experiences, we requested them to report on their most frequently used application. Subsequently, they were asked to respond to follow-up questions based on their practical experiences with this application. Responses from participants who indicated an application that did not meet the criteria of an AILA were identified and excluded from the final dataset. Attention screening techniques were also employed to filter out invalid responses. In the end, we received 278 valid responses. Notably, the AILAs widely used by participants included apps such as Liulishuo, Xuexitong, and Fenbi, covering various domains of university student learning, including language acquisition, academic coursework, and career guidance. Appendix C presents the demographic characteristics of the participants and the distribution of most frequently used AILAs by participants. While diverse in target user base, the AILAs frequently used by our participants share core AI-enabled functionalities aimed at enhancing learning. These commonalities typically include personalized learning support (e.g. tailored content, adaptive pacing, or individualized feedback) and, in many cases, features facilitating social interaction or collaborative learning (e.g. discussion forums, peer ranking, or group study features). This underlying commonality in core AI functionalities supports the applicability of our research model across the various AILAs reported by the participants, allowing for an examination of general perceptions and experiences with AI in learning environments rather than the efficacy of a single application.

4. Data analysis and results

For data analysis, this study utilized partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4 software. The selection of PLS-SEM was based on several key considerations (Hair et al., 2011). Firstly, the primary goal of this research is prediction-oriented, aiming to identify key driver constructs that explain variance in learning performance, a strength of the PLS-SEM approach. Secondly, PLS-SEM is well-suited for examining complex structural models involving multiple constructs and relationships, as presented in our research framework. Thirdly, PLS-SEM demonstrates robustness with what might be considered moderate sample sizes ($N=278$ in this study) and does not require stringent assumptions

regarding data normality, making it particularly appropriate given our sample characteristics and the nature of self-reported survey data.

4.1. Measurement model

We use reliability, convergent validity, and discriminant validity to assess the measurement models of all first-order constructs. We assess the reliability of the constructs by examining composite reliability (CR) and average variance extracted (AVE). As shown in Appendix D, all constructs have CRs greater than 0.75 and AVEs greater than 0.5, which exceed the recommended thresholds of 0.7 and 0.5, respectively. Therefore, we can consider all constructs to have adequate reliability. As shown in Appendix E, most loadings of the constructs are greater than 0.7, with a few greater than 0.65, suggesting that all constructs have good convergent validity. As shown in Appendix D, the square roots of the AVEs of all constructs are greater than their correlations with other constructs. As shown in Appendix E, the loadings on each construct are greater than the cross-loadings. These results indicate that all constructs have good discriminant validity.

4.2. Structural model

The results of PLS are shown in Figure 2. The results indicate that TTF and STF significantly influence learning performance ($\beta = 0.591$, $t = 11.909$; $\beta = 0.176$, $t = 3.359$, respectively; two-tailed test, the same below), supporting hypotheses H1 and H2. The results also indicate that, except for AI-enabled strategy formulation ($\beta = 0.097$, $t = 1.324$), pattern recognition, feedback generation, and content personalization significantly influence TTF ($\beta = 0.194$, $t = 2.710$; $\beta = 0.195$, $t = 2.996$, $\beta = 0.137$, $t = 2.197$, respectively), supporting hypotheses H3a, H3c, H3d, but not supporting hypothesis H3b. The results also show that network size and network homophily significantly influence STF ($\beta = 0.186$, $t = 3.319$; $\beta = 0.434$, $t = 7.709$, respectively), supporting hypotheses H4a and H4b.

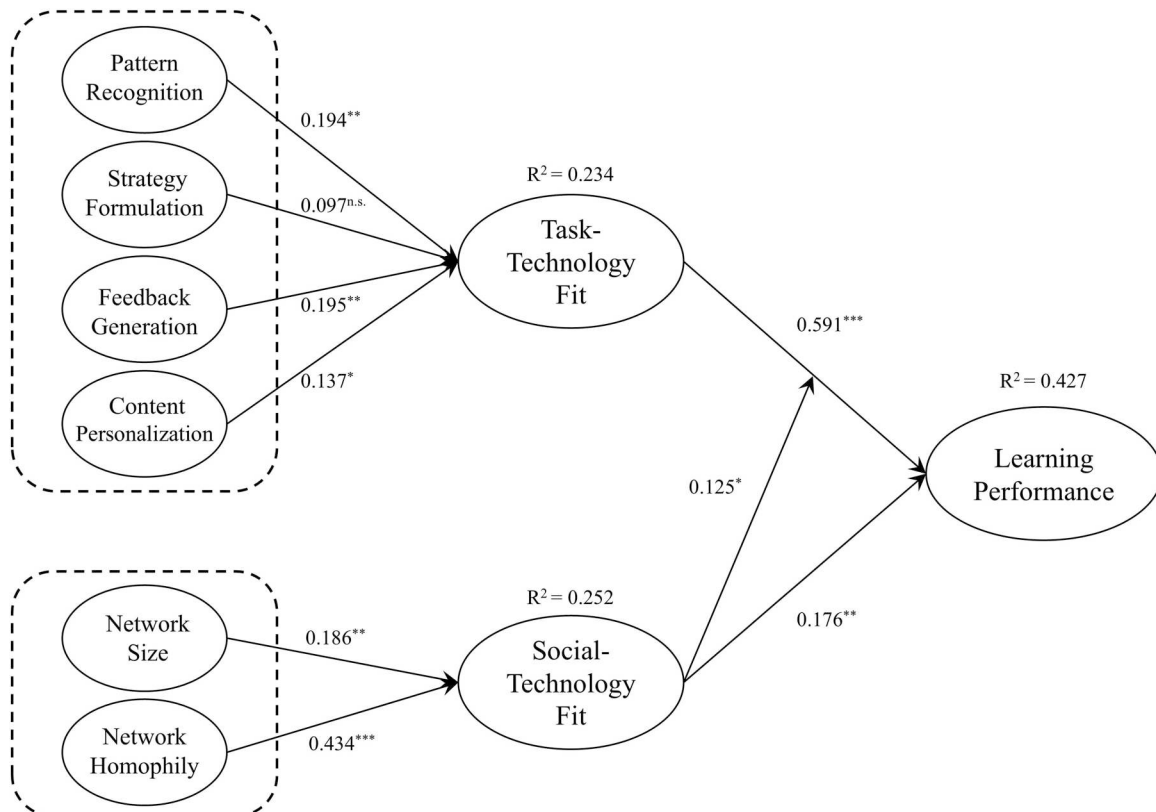


Figure 2. PLS results.

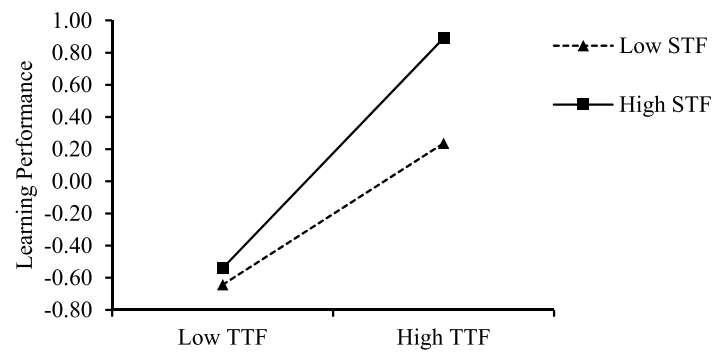


Figure 3. Interaction effect between TTF and STF. Note: TTF = Task-technology fit, STF = Social-technology fit.

In addition, we used the approach proposed by Zhao et al. (2010) to examine the mediating roles of TTF and STF. As shown in Appendix F, TTF and STF partially mediate the influence of AI-enabled task completion and network building on learning performance, respectively, supporting hypotheses H5a and H5b. The simple slope analysis results indicate that the effect of the interaction component on learning performance was positively significant ($\beta = 0.125$, $t = 2.540$), supporting hypothesis H6. The interaction effect is shown in Figure 3. Regarding the explained variance, TTF and STF explained 42.7% of the variance in learning performance. AI-enabled pattern recognition, strategy formulation, feedback generation, and content personalization explained 23.4% of the variance in TTF. Network size and network homophily explained 25.2% of the variance in STF.

5. Discussion and conclusion

This study investigated how TTF and STF influence students' learning performance within AILAs, and conceptualized their antecedents. Our findings offer several key insights.

5.1. Key findings

First, consistent with our hypotheses (H1 and H2) and prior e-learning research, both TTF and STF were found to positively impact learning performance. This indicates that for AILAs to be effective, they must not only align well with students' learning tasks (TTF) but also satisfy their social and collaborative learning needs (STF) (Tang & Hew, 2017). The mediating roles of TTF and STF in the relationships between these AI-enabled support dimensions and learning performance were also confirmed (H5a and H5b). These findings directly address RQ2 by confirming the importance of these fit constructs as mediators. It is important to note, however, that the impact of TTF on learning performance ($\beta = 0.591$) was significantly larger than that of STF ($\beta = 0.176$). Given that participants in our study predominantly use AILAs as instrumental tools for learning (see Appendix C), the direct fit with the primary task (i.e. TTF) is logically the dominant driver of performance. This finding powerfully reinforces the central proposition of the TTF model: a technology's impact on performance is primarily a function of its utility for the task at hand (Goodhue & Thompson, 1995). Moreover, this finding is corroborated by recent e-learning studies, which similarly found that task-oriented factors like e-content interaction and system quality have a more significant impact on use and performance than social factors (Cidral et al., 2018; Wu et al., 2022).

Second, concerning the antecedents of these fit constructs (addressing RQ1 and partially RQ2), AI-enabled pattern recognition, feedback generation, and content personalization significantly and positively influenced TTF (supporting H3a, H3c, H3d). This highlights that AILAs providing adaptive recognition of learning states, timely and helpful feedback, and tailored content are perceived by students as fitting their task requirements, which in turn boosts performance (Ilić et al., 2023). Notably, the effect of content personalization on TTF was comparatively weaker. This may be because students now perceive personalization as a foundational feature (Esteban-Millat et al., 2014), attributing a higher task fit to more novel and diagnostic AI capabilities like pattern recognition and feedback generation. Furthermore, as self-regulated learners, university students likely value these diagnostic tools more, as they directly support active self-

monitoring and evaluation rather than the relatively passive function of content delivery (Lim et al., 2023). Similarly, network size and network homophily positively affected STF (supporting H4a and H4b), suggesting that AILAs with larger, more active communities and the ability to connect students with similar interests are perceived as fitting their social needs. These findings clearly describe the technological features (pattern recognition, feedback, personalization) and social characteristics (network size, homophily) that drive the perceived fit and subsequent performance benefits of AILAs. Furthermore, the study yielded an unanticipated outcome. The mediation analysis demonstrated an indirect effect of AI-enabled strategy formulation on learning performance, but its direct effect on TTF was not significant. One possible explanation is that, drawing from constructivist theories (Piaget, 1971), learning strategies are personalized and autonomously constructed. In contrast to the direct task-relatedness of other dimensions in AI-enabled task completion, learning strategies originate from students' cognitive structures and experiences. They are formed through repeated self-regulation as students encounter different situations. On the other hand, the strategies provided by AILAs are external strategies. If these strategies are not highly aligned with task requirements or effectively integrated into learners' existing strategies, learners may not directly benefit from these strategies, resulting in a non-significant effect. Additionally, the strategies provided by AILAs may also be incompatible with students' own learning plans, hence limiting the impact of this dimension on TTF.

Third, and crucially for RQ3, this study reveals a significant positive interaction effect, where STF reinforces the positive influence of TTF on learning performance (supporting H6). This finding is novel and particularly important, highlighting that the value of AILAs is maximized when their technological and social affordances are synergistically realized. This rationale is grounded in established educational theories. From a constructivist learning perspective, effective learning necessitates the integration of both cognitive (task-oriented) and social approaches (Tang & Hew, 2017; Wu et al., 2022). Our results empirically demonstrate this principle: a supportive social environment allows students to more effectively leverage an AILA's task-oriented features for cognitive gains. This synergy is further explained by the Community of Inquiry framework, which posits that a successful educational experience emerges from the interplay of cognitive and social presences (Shea & Bidjerano, 2010). According to the framework, learning performance – a key aspect of cognitive presence – is not achieved in isolation but is critically supported by social presence (Shea et al., 2022). A high STF fosters this necessary social presence, creating a supportive climate for the inquiry and collaborative validation of knowledge essential for deep learning. Thus, a well-developed social environment provides the foundation upon which the cognitive benefits of a well-fitting technological tool can be fully realized.

5.2. Theoretical implications

This study offers several theoretical contributions to higher education research, particularly by addressing underexplored facets of the socio-technical influence of AILAs on student learning performance. First, this study advances the conceptualization of how AILAs support university students' learning by differentiating and empirically investigating two key processes: AI-enabled task completion and AI-enabled network building. While existing research has acknowledged the potential of AILAs in higher education (Chen et al., 2021; Crompton & Burke, 2023; Salas-Pilco & Yang, 2022), research investigating how these applications, characterized by analyzing individual historical interaction data, enhance student learning performance remains limited. This study offers a more nuanced typology of the distinct technological and social aspects of AILAs. Specifically, prior literature on AILAs tends to focus on the technological antecedents aimed at individual learning support, such as technology use (Chen & Wei, 2024) or UTAUT constructs (An et al., 2025; Dahri et al., 2024; Liu et al., 2025), often without contextualizing these features within a task-oriented framework. Some review studies have attempted to outline key features of AILAs but have not empirically tested their effects and linked them to TTF (Ilić et al., 2023; Jeon et al., 2023; Sikström et al., 2024; Sun et al., 2025). Our conceptualization of AI-enabled task completion, including pattern recognition, strategy formulation, feedback generation, and content personalization, provides a structured understanding of how specific AI capabilities align with learning tasks (Isaac et al., 2019; McGill & Klobas, 2009; Wang & Kartika Sari, 2024). Furthermore, while the social dimension of e-learning is recognized, the unique ways AILAs leverage AI to foster network building (i.e. network size and particularly network homophily driven by AI algorithms) have been less explored. Previous studies on social features in AI-enabled learning often examined broader social presence or general collaborative tools without identifying AI's role in structuring these interactions based on

similarity (Chang et al., 2022; Chen & Wei, 2024; Zhang et al., 2023). By conceptualizing network homophily as a key AI-enabled networking characteristic, alongside network size, this study offers a novel perspective on the social aspects of AILAs, distinguishing them from systems that merely offer a space for interaction without actively building connections (Krouska et al., 2023; Zou et al., 2023).

Second, this study extends the TTF model in the AILA context by integrating STF, thereby providing a more holistic framework to understand learning performance. The TTF model has been a significant theory in explaining technology impact in various e-learning settings (e.g. McGill & Klobas, 2009; Rai & Selnes, 2019; Wang et al., 2014; Wang & Kartika Sari, 2024). However, its application to AILAs, which are inherently socio-technical systems, has been rare. Importantly, traditional TTF model often neglects the increasing social interaction embedded within modern learning technologies. While some research acknowledges social factors in AI-enabled learning (Chen & Wei, 2024; Fu et al., 2020; Zhang et al., 2023), they typically do not integrate the “fit” perspective for social aspects as a direct mediator alongside TTF for learning performance in AILAs. Our study proposes this integration, arguing that the effectiveness of AILAs stems not only from how well their technological features support learning tasks (TTF) but also from how well their social features meet students’ collaborative and interactive needs (STF) (Chakraborty et al., 2025; Lu & Yang, 2014; Wu & Chen, 2017). This approach offers a more robust explanatory mechanism than models focusing solely on technology acceptance (An et al., 2025; Zou et al., 2023) or singular aspects of fit (Wang & Kartika Sari, 2024). This extension is crucial as AILAs increasingly blend individualized learning paths with community-based knowledge sharing (Hayashi et al., 2025; Shi et al., 2025; Tsai et al., 2025), a duality that demands a theoretical lens capable of capturing both TTF and STF (Chakraborty et al., 2025; Lu & Yang, 2014). Our findings empirically validate TTF and STF as critical mediators, clarifying the pathways through which AI-enabled task completion and network building translate into enhanced learning performance.

Third, this study deepens our understanding of how AILAs influence student learning outcomes by exploring the interaction effect between TTF and STF. While prior research has increasingly recognized the need to consider both technological and social aspects of e-learning environments, often through the lens of affordances (Tang & Hew, 2017) or the impact of socially-oriented regulatory processes (Hwang et al., 2021), the interaction effect between how well the technology fits the task and how well it fits social learning needs has been largely overlooked. Previous studies have focused on the independent direct effects of technological and social factors (Chang et al., 2022; Cidral et al., 2018; Kim et al., 2023; Wu et al., 2022) or the combined effects of distinct pedagogical factors rather than the interaction of fit perceptions derived from a single e-learning system (Tsai et al., 2025). This study moves beyond viewing technological and social aspects in isolation, demonstrating that their combined perceived fit can yield a significant positive interaction effect on learning outcomes, a mechanism not empirically tested within the TTF/STF framework in current socio-technical studies (Chakraborty et al., 2025; Díaz & Nussbaum, 2024; Lu & Yang, 2014).

5.3. Practical implications

The research also holds some practical implications for key stakeholders. First, higher education institutions and educators should recognize that, in the era when AI chatbots based on large language models are popular, AILAs still have unique advantages in supporting personalized learning based on existing interaction data with students and promoting social interaction. Therefore, institutions should critically evaluate and strategically integrate AILAs that demonstrate strong capabilities in both personalized task support and community building into their digital learning ecosystems. Educators, in turn, can be guided by our findings to select AILAs that best match their pedagogical goals, considering not only how an AILA supports learning tasks but also how it facilitates peer learning. For instance, educators could design learning activities that leverage AILAs for individualized practice on core concepts (enhancing TTF) and then use the AILA’s social features for collaborative problem-solving or peer review (enhancing STF).

Second, this study provides AILA practitioners (developers and designers) with a framework to assess and enhance the impact of AILAs on student learning performance. Practitioners should recognize that TTF remains a more important factor in promoting student learning performance, while STF can be considered a significant secondary promoting factor and a key enhancer of TTF’s impact. Therefore, they should prioritize investment in technological functions that directly support learning tasks. This means focusing on the

core utility of the AILA for achieving learning objectives, ensuring that AI features are helpful and aligned with pedagogical goals.

Third, AILAs practitioners can optimize the technical function design of AILAs from several aspects: pattern recognition, feedback generation, and content personalization. Specifically, for pattern recognition, developers should focus on refining AI algorithms to accurately diagnose individual student learning states, styles, and knowledge gaps, leading to more precise adaptive support. For feedback generation, the aim should be to provide not just immediate and accurate feedback, but also constructive and actionable feedback that guides students' learning processes. Regarding content personalization, AILAs should offer truly individualized learning pathways that adapt in real-time to student progress and preferences. Moreover, regarding its social function module, although increasing the user base and network homophily is beneficial, they should realize that compared to investing in advertising to increase the user scale, it may be more important and cost-effective to invest in AI algorithms and interface designs that effectively identify and connect students with similar learning goals and interests, thereby fostering genuine network homophily. For example, AILAs could implement features that suggest relevant study partners or groups based on learning progress, interests, or even complementary skill sets, thereby making the social aspect more meaningful.

5.4. Limitations

This study also has some limitations. First, this study did not specify the types of AILAs used by the students, instead proposing a relatively broad research model. Therefore, the applicability of the model across different types of AILAs may need further investigation by considering contextual variables. Future research could address this by conducting comparative studies across distinct AILA categories (e.g. language learning AILAs vs. STEM-focused AILAs). Such studies might investigate whether the relative importance of TTF, STF, or their antecedents varies depending on the learning domain. Case studies of specific AILAs could also provide deeper insights into how context shapes the proposed relationships. Second, while our sample size of 278 meets established guidelines for PLS-SEM and demonstrates sufficient statistical power, it is primarily composed of university students from a single country. Although this provides valuable insights, future research could benefit from larger and more diverse samples across different cultural contexts. For instance, cultural dimensions such as individualism-collectivism or power distance might influence the perceived importance of STF. Cross-cultural validation would strengthen the generalizability of the findings of this study. Third, our study captures students' perceptions of learning performance rather than objective performance metrics. While valuable for understanding user evaluations, we acknowledge this as a limitation of our survey-based approach. Future research should seek to validate our model by incorporating actual performance data. For instance, subsequent studies could augment a survey methodology with objective outcomes like student grades (e.g. McGill & Klobas, 2009) or employ an experimental design to capture objective behavioral data, learning efficiency metrics, and performance on standardized tests (e.g. Leung et al., 2023). Finally, embedding generative AI technology into AILAs is a technological trend. As AILAs designed for educational purposes based on large language models emerge, future studies should aim to further supplement and expand our research model. Specifically, future research could investigate how interactions with AILAs powered by generative AI influence the existing constructs. It would also be valuable to explore whether new antecedents, related to the capabilities of generative AI (e.g. quality of AI-generated explanations, perceived anthropomorphism of AI agents), become salient antecedents of TTF and STF.

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Notes on Contributors

Bo Yang is a PhD candidate of School of Information Management, Wuhan University. His research focuses on AI technology in education, AI chatbots, and human-AI interactions. His work has appeared in *Information Processing & Management*, *International Journal of Contemporary Hospitality Management*, *Information Technology & People*, *Aslib Journal of Information Management*, and the conferences on information systems including Hawaii International Conference on System Sciences (HICSS) and Pacific Asia Conference on Information Systems (PACIS).

Yongqiang Sun is a Professor of the School of Information Management, Wuhan University, and Associate Head of the Center for Studies of Information Resources. His current research interests include knowledge management, virtual community, and human-AI interactions. His research has appeared in leading educational journals such as *Studies in Higher Education*, *Computers & Education*, and *British Journal of Educational Technology* and leading information systems journals such as *Information Systems Research*, *Journal of the Association for Information Systems*, *Information Systems Journal*, *Decision Support Systems*, and *Information & Management*.

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Appendices

Appendix A. Selected studies on the adoption of AILAs and the impact of using AILAs on learning performance

Studies	Technology factors (Identifies the technological dimensions of AI-enabled learning?)	Social factors (Identifies the social dimensions of AI-enabled learning?)	Mechanism	DV	Interaction effect of social and technological factors	Theory
(An et al., 2025)	Yes (No)	No	L2 motivation	Behavioral intention	No	UTAUT
(Chang et al., 2022)	Yes (No)	Yes (No)	Attitude	Learning performance, continuous intention	No	Uses and gratifications theory
(Chen & Wei, 2024)	Yes (No)	Yes (No)	Learning adaptability	Intercultural communication competence	No	/
(Chou et al., 2022)	Yes (No)	No	Interaction experience	Learning effectiveness	No	/
(Dahri et al., 2024)	Yes (No)	No	Satisfaction, use, Behavioral intention	Academic performance	No	UTAUT
(Fu et al., 2020)	Yes (Yes)	No	Engagement	Continuous learning intention	No	Affordance theory
(Gao, 2023)	Yes (No)	No	Gratifications	Continuous intention	No	Uses and gratifications theory
(Huang & Zou, 2024)	Yes (No)	No	ECM constructs	Continuance intention	No	Expectation confirmation model
(Krouska et al., 2023)	Yes (No)	No	Behavioral intention	Use behavior	No	UTAUT
(Liu et al., 2025)	Yes (No)	Yes (No)	Adoption intention	Usage behavior	No	UTAUT
(Yuan & Liu, 2025)	Yes (No)	No	/	Engagement, enjoyment	No	Self-determination theory
(Zhang et al., 2023)	Yes (Yes)	Yes (No)	Flow, self-expansion	Continuous intention	No	Affordance theory
(Zou et al., 2023)	Yes (No)	No	Extrinsic motivation, PEOU	Behavioral intention	No	TAM
Research Gap 1: Limited contextualization of AILA-specific technological (task completion) and social (network building) features. Research Gap 2: Insufficient exploration of integrated socio-technical mechanisms explaining AILA impact on learning performance Research Gap 3: Lack of investigation into the interaction effects between social and technological factors.						
This study	Yes (Yes: pattern recognition, strategy formulation, feedback generation, content personalization)	Yes (Yes: network size, network homophily)	TTF and STF	Learning performance	Yes	Task-technology fit model; Network externality theory

Note: The focus of this research is AI-enabled Learning Applications (AILAs). Therefore, a key characteristic of the AI systems in the studies included in this table is the use of individual student historical interaction data to provide personalized learning support.

Appendix B. Measures.

Constructs	Items	Source
Learning productivity (LP)	The AILA I use for learning help me to ... LP1: improve the quality of my learning. LP2: improve my productivity. LP3: accomplish more learning task than would otherwise be possible. LP4: to perform my learning better.	(Shirish et al., 2021)
Learning creativity (LC)	The AILA I use for learning help me to ... LC1: identify innovative ways of learning. LC2: come up with new ideas relating to my learning. LC3: try out innovative ideas.	
Task-technology fit (TTF)	TTF1: I think that using AILA is well suited for the way I like to improve my learning performance. TTF2: AILA is a good medium to provide the way I like to improve my learning performance. TTF3: I think that using AILA is a good way to improve my learning performance.	(Zhang et al., 2017)
Social-technology fit (STF)	STF1: I learned more from others in this AILA than conventional learning methods. STF2: The AILA frequently attempted to elicit student interaction STF3: In this AILA, it was easy for me to follow interaction among other students.	(Cidral et al., 2018)
AI-enabled pattern recognition (APR)	APR1: The AILA can recognize my learning style. APR2: The AILA can judge my learning state. APR3: The AILA can evaluate my learning ability.	(Montebello, 2018)
AI-enabled strategy formulation (ASM)	ASF1: The AILA can support my learning strategic decisions ASF2: The AILA can help make key learning decisions for me. ASF3: The AILA can support me in developing learning strategies during the learning process.	(Subramanian & Nosek, 2001)
AI-enabled feedback generation (AFG)	AFG1: The AILA's feedback to my learning is prompt. AFG2: The AILA's feedback to my learning is accurate. AFG3: The AILA's feedback to my learning is helpful. AFG4: The AILA's feedback makes my learning easy.	(Xu et al., 2014)
AI-enabled content personalization (ACP)	ACP1: Using the AILA enables me to learn the content I need. ACP2: Using the AILA enables me to choose what I want to learn. ACP3: Using the AILA enables me to control my learning progress.	(Esteban-Millat et al., 2014)
Network size (NS)	NS1: I think that many students use this AILA. NS2: I think that most students use this AILA. NS3: The AILA has an extremely large user base. NS4: I think many schoolmates or friends around me use this AILA.	(Chiu et al., 2013)
Network homophily (NH)	NH1: This AILA is helpful for formation of connections between me and learners with similar learning interests. NH2: This AILA is helpful for formation of a climate for knowledge exchange between me and learners with similar learning interests. NH3: This AILA is helpful for formation of collaborative learning among learners with similar learning interests.	(Cheng et al., 2011)

Appendix C. Participant Characteristics (N = 278)

Table C1. Demographic characteristics of participants

Variables	Levels	Frequency	Percentage (%)
Gender	Male	85	30.6
	Female	193	69.4
Age	18–25	260	93.5
	>25	18	6.5
Education	Associate college	9	3.2
	Undergraduate	213	76.6
	Master or above	56	20.1
Usage frequency	At least once daily	107	38.5
	At least once per week	150	50.4
	At least once per 2 weeks	13	4.7
	At least once per month	6	2.2
	Less than once a month	2	0.7
Usage experience	Less than 3 months	11	4.0
	Less than 6 months	37	13.3
	Less than 1 year	57	20.5
	Less than 2 years	81	29.1
	Less than 3 years	51	18.3
	More than 3 years	41	14.7

Note: A post-hoc power analysis was conducted using G*Power 3.1.9.7 to assess the achieved statistical power with our sample size. For detecting a medium effect size ($f^2 = 0.15$) at a significance level of $\alpha = 0.05$, our sample size of 278 achieves a statistical power of greater than 0.99.

Table C2. Distribution of most frequently used AILAs by participants

AILA reported	Category	Frequency	Percentage (%)
Xuexitong	Comprehensive Course Learning Platforms	75	27.0
China University MOOC		34	12.2
Zhidao		14	5.0
Liulishuo	L2 Language Learning Applications	39	14.0
Fenbi	Career Preparation Platforms	33	11.9
Zuoyebang	Subject Problem-Solving	14	5.0
Other AILAs	/	69	24.8

Note: The specific AILA names reported in this table include all applications with a reported usage frequency greater than 10 participants. AILAs reported by 10 or fewer participants were consolidated into the “Other AILAs” category. The categorization is based on the primary function of the AILA as reported.

Appendix D. Measurement model and correlation matrix

	Mean	SD	AVE	CR	ACP	AFG	APR	ASF	LC	LSE	ML	OT	PF	LP
ACP	5.709	0.779	0.509	0.756	0.713									
AFG	5.350	0.862	0.558	0.834	0.402	0.747								
APR	5.094	0.937	0.545	0.782	0.356	0.534	0.738							
ASF	5.400	0.976	0.675	0.862	0.377	0.511	0.534	0.822						
LC	4.999	1.075	0.731	0.890	0.248	0.367	0.428	0.331	0.855					
LP	5.691	0.739	0.603	0.820	0.388	0.463	0.435	0.390	0.428	0.776				
NH	4.996	1.123	0.707	0.879	0.222	0.180	0.195	0.276	0.317	0.181	0.841			
NS	5.781	0.872	0.576	0.844	0.302	0.090	0.099	−0.009	0.128	0.296	0.179	0.759		
STF	4.807	1.081	0.653	0.849	0.110	0.155	0.168	0.072	0.390	0.224	0.467	0.264	0.808	
TTF	5.496	0.828	0.701	0.875	0.321	0.403	0.398	0.352	0.429	0.626	0.245	0.270	0.337	0.837

Note: ACP = AI-enabled Content Personalization, AFG = AI-enabled Feedback Generation, APR = AI-enabled Pattern Recognition, ASF = AI-enabled Strategy Formulation, NS = Network Size, NH = Network Homophily, TTF = Task-technology Fit, STF = Social-technology Fit, LC = Learning Creativity, LP = learning Productivity, AVEs' square roots are denoted by the boldfaced diagonal elements.

Appendix E. Loadings and cross loadings.

	ACP	AFG	APR	NH	ASF	LC	STF	LP	NS	TTF
ACP1	0.752	0.306	0.239	0.192	0.300	0.150	0.080	0.276	0.223	0.240
ACP2	0.732	0.213	0.212	0.192	0.158	0.190	0.145	0.281	0.267	0.214
ACP3	0.651	0.333	0.306	0.091	0.338	0.192	0.014	0.273	0.159	0.230
AFG1	0.210	0.677	0.300	−0.011	0.381	0.148	0.003	0.307	−0.032	0.233
AFG2	0.309	0.815	0.457	0.102	0.380	0.285	0.146	0.345	0.075	0.347
AFG3	0.358	0.741	0.435	0.131	0.431	0.332	0.090	0.374	0.152	0.289
AFG4	0.311	0.749	0.386	0.282	0.349	0.307	0.192	0.358	0.055	0.320
APR1	0.279	0.508	0.799	0.134	0.504	0.335	0.063	0.387	0.031	0.359
APR2	0.291	0.367	0.702	0.158	0.288	0.256	0.155	0.257	0.105	0.208
APR3	0.229	0.283	0.709	0.152	0.344	0.346	0.181	0.294	0.104	0.284
NH1	0.170	0.167	0.196	0.825	0.292	0.263	0.398	0.156	0.084	0.236
NH2	0.235	0.185	0.173	0.854	0.224	0.234	0.375	0.175	0.183	0.206
NH3	0.157	0.106	0.125	0.844	0.180	0.300	0.403	0.127	0.185	0.176
ASF1	0.273	0.440	0.489	0.246	0.849	0.243	0.036	0.315	−0.023	0.340
ASF2	0.298	0.422	0.363	0.298	0.829	0.261	0.111	0.298	−0.023	0.233
ASF3	0.366	0.396	0.442	0.145	0.785	0.319	0.044	0.348	0.024	0.275
LC1	0.214	0.359	0.439	0.175	0.353	0.833	0.249	0.367	0.096	0.361
LC2	0.183	0.260	0.293	0.291	0.219	0.839	0.350	0.323	0.097	0.330
LC3	0.235	0.320	0.365	0.341	0.277	0.892	0.398	0.404	0.134	0.405
STF1	0.108	0.062	0.165	0.351	0.119	0.256	0.747	0.111	0.173	0.182
STF2	0.145	0.177	0.185	0.323	0.049	0.417	0.817	0.285	0.246	0.368
STF3	0.015	0.124	0.061	0.459	0.018	0.260	0.856	0.131	0.214	0.248
LP1	0.333	0.348	0.403	0.087	0.338	0.348	0.147	0.787	0.249	0.526
LP2	0.220	0.408	0.308	0.137	0.248	0.337	0.196	0.771	0.166	0.469
LP3	0.353	0.322	0.299	0.200	0.323	0.311	0.180	0.771	0.275	0.462
NS1	0.268	0.052	0.031	0.086	0.046	0.020	0.169	0.237	0.684	0.147
NS2	0.211	0.026	−0.007	0.150	−0.106	0.006	0.182	0.175	0.777	0.144
NS3	0.334	0.166	0.155	0.141	0.109	0.120	0.152	0.263	0.756	0.274
NS4	0.163	0.053	0.115	0.158	−0.040	0.198	0.265	0.234	0.813	0.249
TTF1	0.241	0.307	0.349	0.123	0.244	0.330	0.270	0.538	0.235	0.846
TTF2	0.297	0.342	0.284	0.249	0.271	0.340	0.260	0.522	0.211	0.812
TTF3	0.268	0.362	0.365	0.239	0.362	0.403	0.314	0.514	0.232	0.852

Note: ACP = AI-enabled Content Personalization, AFG = AI-enabled Feedback Generation, APR = AI-enabled Pattern Recognition, ASF = AI-enabled Strategy Formulation, NS = Network Size, NH = Network Homophily, TTF = Task-technology Fit, STF = Social-technology Fit, LC = Learning Creativity, LP = learning Productivity.

Appendix F. Results of mediating effect

Paths	Indirect Effect			Direct Effect			Results
	Size	LLCI	ULCI	Size	LLCI	ULCI	
APR→TTF→LP	0.147	0.097	0.203	0.253	0.174	0.332	Partial
ASF→TTF→LP	0.138	0.082	0.200	0.193	0.116	0.270	Partial
AFG→TTF→LP	0.173	0.115	0.237	0.254	0.166	0.342	Partial
ACP→TTF→LP	0.169	0.105	0.244	0.187	0.089	0.284	Partial
NS→STF→LP	0.076	0.036	0.128	0.119	0.019	0.219	Partial
NH→STF→LP	0.093	0.054	0.140	0.121	0.036	0.205	Partial

Note: ACP = AI-enabled Content Personalization, AFG = AI-enabled Feedback Generation, APR = AI-enabled Pattern Recognition, ASF = AI-enabled Strategy Formulation, NS = Network Size, NH = Network Homophily, TTF = Task-technology Fit, STF = Social-technology Fit, LP = learning Performance.