# The Promotive Effect of Student AI Literacy on English Autonomous Learning Ability

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***Abstract:*** *With the deep integration of artificial intelligence technology into the education field, the relationship between students' AI literacy and their English autonomous learning ability has become an emerging topic in language education research. This study elucidates the promotive effect of AI literacy on English autonomous learning ability and its underlying mechanisms, and it defines the multidimensional competence structures of the two literacies as well as their shared theoretical starting point of self-regulation. Furthermore, this study proposes three driving pathways, namely intelligent information processing, human-computer collaboration strategies, and adaptive feedback mechanisms, and it analyzes three types of moderating factors, including algorithmic cognitive beliefs, learning task types, and interaction density. This study constructs an integrated theoretical framework that explains how AI literacy promotes English autonomous learning ability.*

***Keywords:*** *Student AI Literacy; English Autonomous Learning Ability; Intelligent Information Processing; Human-Computer Collaboration Strategies; Adaptive Feedback Mechanisms; Moderating Factors*

## Introduction

Against the backdrop of the evolving digital learning ecosystem, artificial intelligence tools have become normalized components of the English learning environment, and thus AI literacy has emerged as a core variable affecting the language learning process. The formation of English autonomous learning ability is also reshaped by the intelligent technology environment. Existing research mostly focuses on the functional description of AI tools, and it has not yet systematically addressed the mechanism through which AI literacy promotes English autonomous learning ability. The lack of understanding of the pathways, mechanisms, and boundary conditions tends to lead to ambiguous goals and misaligned strategies in educational applications. This study constructs a theoretically coherent framework that progresses layer by layer from the connotation of abilities, to the driving pathways, and then to the moderating factors, thereby revealing the conditions and patterns underlying the promotive effect.

## 1. Theoretical Connotations of Student AI Literacy and English Autonomous Learning Ability and Their Relational Basis

### *1.1 Definition of the Multidimensional Competence Structure of Student AI Literacy*

Student AI literacy is not a single set of technical operation skills; rather, it is a composite competence structure that encompasses cognitive, metacognitive, and socio-emotional dimensions. Its core components include the formation of algorithmic awareness, the establishment of data interpretation ability, and the application of human-computer interaction strategies. Algorithmic awareness refers to the learner's ability to recognize the underlying logic of intelligent systems in information recommendation and learning path planning, thereby moving beyond passive acceptance toward critical understanding. Data interpretation ability is manifested as the accurate reading and meaningful extraction of data visualization results generated by learning analytics tools, which provides a basis for subsequent learning decisions. Human-computer interaction strategies involve the learner's systematic skills in actively setting interaction goals, adjusting interaction frequency, and evaluating interaction benefits, and they constitute the behavioral manifestation layer of AI literacy.

From the perspective of competency levels, student AI literacy can be further distinguished into foundational literacy and generative literacy. Foundational literacy encompasses the recognition of basic functions of AI tools and the proficiency in operating them, which ensures that learners can access the intelligent learning environment without barriers. Generative literacy, on the other hand, is manifested as a higher-order ability to use AI for problem restructuring, task decomposition, and strategy optimization, and it emphasizes that learners view AI as a cognitive partner rather than a mere tool. The two types of literacy form a progressive relationship, with the former providing the operational basis for the latter, and the latter in turn promoting the former toward flexible adaptation. This multidimensional competence structure establishes a clear theoretical premise for the subsequent exploration of its relationship with English autonomous learning ability[1].

### *1.2 Cognitive and Metacognitive Dimensions of English Autonomous Learning Ability*

The cognitive dimension of English autonomous learning ability is mainly manifested in the learner's ability to construct the language knowledge system and in the learner's strategic processing level of learning tasks. In the learning context of English as a foreign language, the cognitive dimension covers the self-discovery of vocabulary and grammatical rules, the inferential monitoring during discourse comprehension, and the error correction mechanism during language output production. The learner needs to actively set the type and difficulty of language input, select appropriate learning materials according to the learner's own language level, and use memory strategies and inductive strategies to strengthen the language internalization process. A high level of performance in the cognitive dimension is reflected in the learner's ability to independently identify cognitive conflicts in language learning and to mobilize existing knowledge resources to resolve them without relying on external instructions.

The metacognitive dimension focuses on the learner's ability to plan, monitor, and regulate the learner's own English learning process. Specifically, it includes the stage-based setting of learning goals, the continuous evaluation of the effectiveness of learning strategies, and the self-feedback attribution of learning outcomes. Metacognitive ability enables the learner to step beyond the execution level of specific language tasks and to form an overall grasp of learning efficiency, difficulty distribution, and progress trajectory. In the process of English autonomous learning, metacognitive monitoring is particularly manifested as active intervention in attention allocation, time management, and emotional fluctuations. The cognitive dimension and the metacognitive dimension are nested within each other, with the former providing the operational framework for learning actions and the latter endowing the actions with mechanisms for direction adjustment and quality control, thereby jointly constituting the complete psychological structure of English autonomous learning ability.

### *1.3 Theoretical Logical Starting Point of the Interaction Between the Two Types of Literacy*

The interaction between AI literacy and English autonomous learning ability can be explained from two theoretical perspectives: information processing efficiency and cognitive load redistribution. AI tools can pre-filter, annotate difficulty levels, and restructure a large amount of input materials in English learning, which reduces the filtering cost for learners during the information acquisition stage. This process allows learners to redirect the cognitive resources originally used for retrieval and filtering toward deeper language processing and strategic reflection, thereby enhancing the per-unit-time benefit of autonomous learning. At the same time, the instant feedback and personalized path suggestions provided by AI objectively simulate the scaffolding function of teachers or peers, and they offer a low-risk trial-and-error space for learners' autonomous decision-making, thus increasing the feasibility of metacognitive monitoring.

From the dynamic perspective of ability development, AI literacy acts as a catalytic medium rather than a mere auxiliary tool for English autonomous learning ability. When learners possess a high level of AI literacy, they can actively transform the analytical results generated by AI (such as vocabulary mastery probabilities and grammatical error distributions) into the basis for adjusting their own learning plans, thereby achieving an ability transition from "being guided by AI" to "collaborating with AI." Conversely, learners with a stronger English autonomous learning ability tend to proactively invoke AI tools for problem localization and strategy search when encountering language learning obstacles, thus forming a positive cycle between the two types of literacy. The logical starting point of this interaction lies in the fact that the two share a core mechanism, namely the self-regulation ability of the learning process: AI literacy expands the information sources and operational means for regulation, while English autonomous learning ability provides the intentional framework and executive drive for regulation[2].

## 2. Pathways and Mechanisms of AI Literacy Driving the Enhancement of English Autonomous Learning Ability

### *2.1 The Gain Effect of Intelligent Information Processing on the Autonomous Filtering of Learning Resources*

Intelligent information processing ability, as the core technical dimension of student AI literacy, significantly improves the efficiency of autonomous filtering among massive digital resources for English learners. In traditional English autonomous learning contexts, learners face the dilemma of information overload and varying quality of resources, and the filtering process consumes substantial cognitive resources while being prone to decision-making biases. Learners with intelligent information processing ability can actively set filtering parameters such as language difficulty thresholds, topic relevance, and corpus timeliness by leveraging the underlying logic of natural language processing and recommendation algorithms, thereby enabling AI tools to pre-classify and rank the relevance of raw corpora. This process frees learners from inefficient item-by-item comparisons and reallocates cognitive resources to resource value judgment and learning sequence decision-making, thus enhancing the accuracy and economy of autonomous filtering.

From the perspective of the gain effect's mechanism, intelligent information processing not only reduces the external cost of resource acquisition but also reshapes the learner's internal evaluation framework for the value of learning resources. In the process of repeatedly using AI for information filtering, learners gradually internalize the linguistic feature dimensions underlying algorithmic classification (such as word frequency levels, syntactic complexity, and discourse coherence), and they develop a clearer understanding of the match between their own language proficiency and task demands. This internalization enables learners to maintain a high level of resource judgment even when AI assistance is unavailable, thus achieving a shift from tool dependence to ability transfer. The gain effect of intelligent information processing on the autonomous filtering of learning resources therefore has a dual nature: it manifests as both an immediate efficiency improvement and a long-term structural refinement of filtering strategies.

### *2.2 The Catalytic Role of Human-Computer Collaboration Strategies in the Adaptation of English Learning Goals*

Human-computer collaboration strategies are manifested as the learner's conscious integration of AI tools into the dynamic process of setting and adjusting English learning goals, and their catalytic role focuses on the refinement of goal granularity and the enhancement of goal flexibility. In traditional autonomous learning models, the English learning goals set by learners often remain at the macro level (such as improving reading comprehension ability or expanding vocabulary size), and they lack operability and stage-based assessment criteria. Learners with human-computer collaboration strategy abilities can use the language proficiency diagnostic function of AI to break down macro goals into multiple sub-goals with clear levels and explicit time frames. For example, they can locate weak vocabulary areas based on a vocabulary mastery heatmap generated by AI, and then set targeted review goals accordingly. In this process, AI serves as a cognitive partner for goal decomposition rather than a mere task executor[3].

The catalytic role of human-computer collaboration strategies in the adaptation of learning goals is also reflected in the dynamic goal adjustment mechanism. In the process of English learning, learners' actual progress often deviates from initial expectations, and they need to recalibrate their goals based on feedback information. Students with high AI literacy can proactively invoke AI tools to conduct multidimensional assessments of periodic learning outputs (such as writing samples or oral recordings), and they obtain data-driven feedback on grammatical accuracy, lexical richness, or fluency indicators. Based on these data, learners can identify the gap between original goals and current abilities, and then either lower overly high goal thresholds or add transitional intermediate goals. This human-computer collaborative goal adjustment process avoids the frustration or complacency caused by rigid goals, and it forms a closed loop of goal setting, execution monitoring, and feedback revision, thereby significantly enhancing the direction-maintaining ability of English autonomous learning.

### *2.3 The Reinforcement Link of Adaptive Feedback Mechanisms for Self-Monitoring of the Learning Process*

Adaptive feedback mechanisms refer to the technical characteristic of AI systems that dynamically adjust the content and presentation mode of feedback based on the learner's real-time performance, and their reinforcement for self-monitoring of the learning process manifests as a progressive link from external information input to the internalization of internal monitoring standards. In the process of English autonomous learning, learners' self-monitoring often falls into subjective bias due to a lack of objective reference, which is manifested as misjudgment of the quality of their own language output or delayed detection of learning bottlenecks. Adaptive feedback mechanisms establish external calibration points for self-monitoring by providing immediate, specific, and diagnostic information that matches the learner's current proficiency level (such as grammatical error categorization, pronunciation deviation annotation, and logical cohesion absence alerts). Learners compare this feedback information with their own expectations, which enables them to more accurately locate execution deviations, thereby triggering targeted strategy adjustments.

The higher-order stage of this reinforcement link is manifested as the internalization of feedback and the autonomous transfer of monitoring standards. When learners remain in an adaptive feedback environment for an extended period, they gradually master the evaluation dimensions and judgment rules that the AI system relies on, such as recognizing the system's logic for determining discourse coherence or its scoring basis for lexical collocation appropriateness. This internalization of rules enables learners to actively invoke similar evaluation criteria to monitor their own learning process even in the absence of feedback, thereby achieving a transition from external reinforcement to internal generation. The adaptive feedback mechanism thus not only enhances the immediate precision of self-monitoring but also improves the sustainability of monitoring ability, constituting a key neurocognitive pathway through which AI literacy drives the enhancement of English autonomous learning ability.

## 3. Individual and Environmental Moderating Factors for the Exertion of the Promotive Effect

### *3.1 Threshold Moderation of Learners' Algorithmic Cognitive Beliefs on the Effect Intensity*

Learners' algorithmic cognitive beliefs refer to individuals' subjective understanding of and trust in the operating logic, output reliability, and potential limitations of AI systems, and this belief dimension plays a threshold moderating role in the effect of AI literacy on promoting English autonomous learning ability. When learners hold a high level of algorithmic cognitive beliefs, they can accurately distinguish between different output types of AI tools (such as deterministic feedback versus probabilistic suggestions), and they can choose to adopt or question the information provided by AI according to the task context. This selective adoption mechanism avoids the two extreme behaviors of blind reliance or complete rejection, thereby enabling the gain effects of AI assistance on various dimensions of autonomous learning ability to cross the minimum effective threshold. Conversely, learners with low algorithmic cognitive beliefs tend to view AI as a black-box system: they either over-trust all its outputs, leading to the atrophy of metacognitive monitoring, or completely ignore its analytical value, losing opportunities for efficiency improvement. Both scenarios keep the promotive effect at a relatively low level[4].

From the perspective of the nonlinear characteristics of the moderating effect, the influence of algorithmic cognitive beliefs on effect intensity presents a marginally diminishing threshold curve. Within a certain range, an increase in the belief level significantly enhances the conversion rate from AI literacy to autonomous learning ability, because learners can more effectively extract diagnostic information from AI feedback and integrate it into their own learning strategy systems. When the belief level exceeds a certain critical point, further increase in trust in algorithms no longer brings a proportional gain in the effect; instead, it may induce a tendency toward cognitive offloading, namely learners transferring too much decision-making responsibility to the AI system, thereby weakening the depth of autonomous planning and reflection. This threshold moderation mechanism indicates that the condition for maximizing the promotive effect is not an unlimited increase in algorithmic cognitive beliefs, but rather maintaining them within an appropriate range, so that learners maintain a critical trust in AI tools and an active interactive stance.

### *3.2 Differential Constraints of English Learning Task Types on the Effectiveness of AI Assistance*

English learning task types can be distinguished into closed-skills training tasks and open-ended communicative expression tasks based on cognitive processing levels and output forms, and the two types of tasks impose significantly different constraints on the effectiveness of AI assistance. Closed tasks (such as grammatical gap-filling, vocabulary matching, and pronunciation correction) have clear correct answers or evaluation criteria, and AI systems can provide highly accurate immediate judgments and targeted practice suggestions. In such tasks, the effectiveness of AI assistance is relatively high, and the promotive effect of student AI literacy on English autonomous learning ability is manifested as an increase in task completion speed and a reduction in error rates, with the effect being stable and measurable. Open-ended tasks (such as free writing, thematic oral expression, and cross-cultural pragmatic inference) involve creative language generation and context-sensitive judgments, and although the outputs of existing AI tools possess surface fluency, they have limitations in deep semantic coherence and cultural appropriateness.

This differential constraint is further manifested as a shift in the functional role of AI literacy across different task types. In closed tasks, AI primarily serves as a tool for precise measurement and repetitive practice, and the value of student AI literacy is reflected in the ability to respond quickly to feedback information and to summarize error patterns. In open-ended tasks, the role of AI needs to shift from an evaluator to a dialogue stimulator or a draft generator, and the higher-order performance of student AI literacy is reflected in the ability to make pragmatic revisions and stylistic adjustments to AI-generated content. Learners who fail to recognize this difference in task types may over-rely on the finished output of AI in open-ended tasks, leading to a decline in the autonomy of creative language expression. English learning task types thus constitute a moderating variable for the effectiveness of AI assistance, determining the specific pathways and upper limits of the effect of AI literacy on promoting autonomous learning ability.

### *3.3 The Modal Influence of Interaction Density in the Digital Learning Space on Conversion Efficiency*

The digital learning space refers to the collection of physical and interface environments in which learners interact with AI systems, and its interaction density (the frequency and depth of information exchange between the learner and AI tools per unit time) exerts a modal influence on the conversion efficiency from AI literacy to English autonomous learning ability. Under low interaction density conditions, learners invoke AI tools only when encountering clear obstacles (such as vocabulary lookup or grammar checking), and the interaction behavior is discretely distributed. In this mode, AI primarily serves as a problem-solving terminal, and its effect on the overall structural transformation of autonomous learning ability is limited, with conversion efficiency constrained by the passive triggering characteristic of interaction. As interaction density increases to a moderate level, learners begin to embed AI into multiple nodes of the learning process (such as difficulty assessment during the preview stage, strategy exploration during practice, and error tracing during the review stage), and the interaction behavior exhibits a chain-like distribution, with conversion efficiency rising significantly accordingly.

When the interaction density exceeds a certain threshold, the conversion efficiency may undergo a modal shift, namely from positive gain to an efficiency plateau or even efficiency decline. Excessively high interaction density means that learners frequently interrupt the language processing flow to obtain AI feedback, and such interruptions disrupt the continuous cognitive processing required for discourse comprehension or production, thereby weakening the natural development of autonomous language ability. Furthermore, high-density interaction is prone to inducing cognitive overload, and under the dual burden of simultaneously handling language tasks and interaction operations, learners have difficulty processing and integrating AI feedback deeply. Therefore, a curvilinear, inverted U-shaped relationship exists between interaction density in the digital learning space and conversion efficiency, with moderate interaction density constituting the modal condition for maximizing the promotive effect. This finding suggests that the improvement of conversion efficiency does not depend on an unlimited increase in the frequency of interaction, but rather on the dynamic match between interaction timing and task-related cognitive load.

## Conclusion

This study systematically examines the promotive effect of student AI literacy on English autonomous learning ability from the perspective of theoretical construction. It clarifies the connotative dimensions of the two core ability structures and the theoretical starting point of their interaction. It reveals three driving pathways, namely intelligent information processing, human-computer collaboration strategies, and adaptive feedback mechanisms. It also identifies three types of moderating factors, including algorithmic cognitive beliefs, learning task types, and digital interaction density. The main contribution of this study lies in integrating scattered phenomena of AI-assisted learning into a hierarchical and mechanistic explanatory framework, and it points out that the promotion of autonomous learning ability by AI literacy is not a linear or unconditional process, but is instead multiply moderated by individual cognitive beliefs, task contexts, and interaction modalities. Future research directions can be developed along three dimensions. First, future research can explore the differential weights of the structural dimensions of AI literacy and their impact on the promotive effect for learner groups at different educational stages or with different language proficiency levels. Second, future research can further refine the classification system of English learning tasks and examine the gradient changes in AI assistance effectiveness under different levels of cognitive demands within the same task type. Third, by employing longitudinal tracking designs, future research can test whether a bidirectional recursive developmental relationship exists between AI literacy and English autonomous learning ability, as well as the changes in the roles of various moderating factors over the temporal dimension. Advancing these directions will help deepen the understanding of language learning mechanisms in the intelligent era.

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