

# Artificial Intelligence Literacy and Student Learning Engagement: The Mediating Role of Self-Regulated Learning

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DOI: 10.64649/yh.eg.issn3078-4794.20260408

**Abstract:** This research explored the relationships among Chinese university students' artificial intelligence literacy, self-regulated learning, and learning engagement. A cross-sectional questionnaire method was adopted, and 273 valid responses were collected (response rate 47.07%, 156 male and 117 female, age from 18 to 29 with  $SD = 1.34$ ). The results showed that self-regulated learning plays a complete mediating role between artificial intelligence literacy and learning engagement, supporting the initial hypothesis of this research ( $IE = 0.23$  , 95% CI [0.17,0.29]). Notably, different from previous studies, the data from this study indicated that the direct effect between artificial intelligence literacy and learning engagement was not significant, which highlights that in the process of supporting student learning engagement, in addition to enhancing teaching support related to artificial intelligence tools, attention should also be paid to students' self-regulated learning.

**Keywords:** Artificial Intelligence Literacy; Student Learning Engagement; Self-Regulated Learning; Mediating Effect

## 1. Background

Artificial intelligence (AI) is rapidly reshaping how people live, work, and learn. In education, Artificial intelligence literacy (AIL) has become an essential competency for contemporary students. Long and Magerko<sup>[7]</sup> defined AIL as a set of abilities that enable effective interaction with AI and critical evaluation of its outputs, outlining 17 core competencies (e.g., understanding intelligence, AI strengths/weaknesses, machine learning steps). Subsequently, Jones<sup>[5]</sup>, in a scoping review, systematically searched five databases including Scopus and Web of Science, screened 190 records, and included 39 empirical studies. The outcomes show that the field has arrived at a basic consensus to view AIL as a multidimensional construct concept involving knowledge, application, evaluation and ethics.

Large-scale surveys<sup>[4]</sup> ( $n = 15,631$  students in grades 6 to 12) show that most of the students have already been help with learning tasks (74.20% for students in lower secondary school, and 90.20% for those in upper secondary school), practice predates formal teaching and presents challenges for teachers. In this context of the use of AI support, investigating the problem from the perspective of student learning engagement (LE) is of great importance. Fredricks et al.<sup>[3]</sup> defined student learning engagement as a threedimensional construct: behavioral, emotional, and cognitive, and this definition continues to be predominant<sup>[16]</sup>. When students experience being able to control the pace, method, and content of their learning, their learning engagement across these three dimensions improves greatly<sup>[16]</sup>. With the rapid popularization of AI in education, flexibly matching the different degrees of control according to student needs and the characteristics of the activities is an important issue.

However, students who use AI to aid their study, but do not have selfregulation, may incur cognitive overload or superficial learning. For these students, selfregulated learning (SRL) also is important. SRL was first defined by Zimmerman<sup>[20]</sup> as a selfinitiated process by which learners direct their efforts toward acquiring knowledge and skills, which consists of three individual stages: forethought, performance, and selfreflection, and stresses selfadaptation. A study for the year 2025 done by the University of Hong Kong<sup>[19]</sup> found that the interaction between SRL and

AIL in human-AI combined learning environments was synergistic and confirmed SRL as a core capability of balancing use of AI (the ability to judge when to extend use of AI or reduce use of AI). Using a sample of 1,704 Chinese undergraduates, the study found a statistically significant correlation between SRL and AIL ( $r = 0.188$ ,  $p < 0.01$ ) in one learner cluster<sup>[19]</sup>. In the same year, a cross-sectional survey<sup>[17]</sup> also showed that SRL strategies mediated the relationship between the psychological needs satisfaction and AIL, corroborating the applicability of self-determination theory (SDT) in AI education.

In summary, the available research has made clear the significance of AIL, LE, and SRL, and researched relationships between SRL and each of the other two concepts. It is still worth doing systematic evaluation with evidence on the interrelations among all three. On the basis of Zimmerman's SRL model<sup>[20]</sup>, during SRL process, students with more AIL would devise the better goals in the forethought phase, use the more effective learning strategies in the performance phase, modify their actions in the reflection phase, and act more engagingly. Thus, in order to investigate further the mediation effect of SRL between AIL and student LE, to provide insights into how to enhance AIL and enhance engagement in education, we adopt a cross-sectional questionnaire survey to develop this model here.

### 1.1 Artificial Intelligence Literacy and Learning Engagement

AIL is a fundamental ability for students to use AI technology well in the digital age<sup>[7]</sup>. LE is a critical measurement for the quality of student learning. Therefore, LE occupies a core position in educational research<sup>[16]</sup>. LE is a multidimensional construct of behavioral dimension, emotional dimension and cognitive dimension<sup>[3]</sup>, which is an indicator of learning quality and academic success<sup>[16]</sup>.

Theoretically, Regarding Zimmerman's SRL perspective<sup>[20]</sup>: SRL framework of AIL can impact/enhance LE in the following: First, students with more AIL can better choose the right AI tools to complete specific tasks, such as using AI to practice in a personalized way. This behaviour avoids the trial-and-error costs and enhances learning efficiency. Second, students with higher AIL can better understand the feedback provided by AI tools and, therefore, regulate their own learning structure more effectively by monitoring it. This fosters students' autonomy and improves students' engagement with learning cognition.

Empirically: Drawing on social cognitive theory, in a survey of 431 learners through a structural equation model, they found that<sup>[9]</sup>, AIL has a significant positive direct effect on LE. The author characterizes AIL as learners' ability to choose, apply and criticize AI products, and regards it as the primary antecedent of achieving deeper LE<sup>[9]</sup>.

Based on the above theoretical inference and empirical evidence, we should assume that AIL will positively promote students' LE by enhancing their abilities to obtain resources, choose strategies, self-regulate, and so on. In such a sense, this study sets up the following hypothesis:

H1: Artificial intelligence literacy is positively associated with learning engagement.

### 1.2 The Mediating Role of Self-Regulated Learning

SRL. This relates to learners' capability of setting learning goals, monitoring their learning, reflecting on, and modifying their strategies and actions in the learning process so as to meet the learning goal<sup>[20]</sup>. Shen and Teng<sup>[11]</sup>, in a recent empirical study, measurement structure of SRL strategies (six factors) and LE (three factors: behavioral, emotional, and cognitive) was validated in the context of online English learning. Their research finding corroborates the emphasis of the SRL plays an critical role on learners' learning process (being able to exert active control over their own cognition and behavior), which is precisely the core essence of the three phases: forethought, performance and self-reflection in Zimmerman<sup>[20]</sup> SRL cyclic model.

### 1.2.1 Relation between Artificial Intelligence Literacy and Self-Regulated Learning:

Theoretically: According to SRL theory, students with higher AIL are more likely to be more reasonably utilize AI tools to assist their learning. First, enhancing AIL can help students more effectively filter learning resources and identify the reliability of AI-generated content, thereby supporting them in making more precise goal setting during the forethought phase. Second, students can adjust their learning strategies in real time with the aid of AI tool feedback, thereby strengthening self-regulation during the performance phase and the self-reflection phase. Thus, AIL may positively promote students' SRL.

Empirically: Shafiee Rad's <sup>[10]</sup> study, an analysis with a sample size of 60, summarized that 77% of participants acknowledged that the AI platform enhanced engagement and SRL abilities, while 23% reported technical usability issues (e.g., system response, interface design), this further indicates that AI intervention can effectively improve reading ability and promote the process of self-regulated learning. Xi et al <sup>[18]</sup> structured a structural equation modeling analysis of 520 college students, this research found that AIL has a significant positive effect on online SRL, with a standardized coefficient of 0.227 ( $p < 0.001$ ), thus verifying the predictive role of AIL in enhancing students' SRL.

H2: Artificial intelligence literacy is positively associated with self-regulated learning.

### 1.2.2 Relation between Self-Regulated Learning and Learning Engagement:

Theoretically, Zimmerman's SRL framework <sup>[20]</sup>: Students with higher levels of SRL, due to their stronger ability to independently solve difficult problems, are often more willing to actively participate in classroom interactions and sustain engagement in learning activities. This self-management ability is precisely an important foundation for maintaining high levels of LE. Therefore, the improvement of SRL levels may promote students' LE.

Empirically: Shen and Teng <sup>[11]</sup>, in a qualitative study of 328 EFL undergraduates, found that among various SRL strategies, help seeking ability is the most powerful factor in enhancing LE, providing direct empirical support for the positive predictive relationship between SRL and LE. In the next year, a study <sup>[12]</sup> on university students' academic engagement reported that SRL significantly and positively predicted academic LE, in addition, the direct SRL → LE path remained significant ( $\beta = 0.332$ ) even after accounting for mediating achievement.

H3: Self-regulated learning is positively associated with learning engagement.

In summary, learners with higher AIL tend to select AI tools more purposefully and leverage feedback from AI tools to improve the three stages of SRL (goal setting, strategy adjustment, and outcome evaluation) when using them. This enhanced SRL sustains learners' behavioral, emotional, and cognitive engagement during the learning process.

Based on theoretical reasoning and empirical evidence above, AIL may promote LE by enhancing SRL, and SRL may play a key mediating bridging role between the two. Accordingly, this study proposes the following hypothesis:

H4: Self-regulated learning mediates the relationship between artificial intelligence literacy and learning engagement.

## 1.3 The Present Study

Drawing on Zimmerman's <sup>[20]</sup> SRL framework, the present study targets Chinese undergraduate students to examine a mediation model in which SRL serves as the key mechanism linking AIL to LE.

From the theoretical perspective, this study is expected to expand the understanding of the internal mechanisms among the three fields of AIL, LE, and SRL.

From the practical perspective, the present research may provide empirical insights for Chinese university educators in designing learning environments involving artificial intelligence tools and guiding students towards learning engagement.

## 2. Method

### 2.1 Research Design

This research employed a cross-sectional questionnaire design to examine the relationships among AIL, SRL, and LE.

### 2.2 Participants and Procedure

The researchers used an online questionnaire platform (Questionnaire Star) to create and distribute electronic questionnaires. On the first page of the questionnaire, the researchers clearly explained the research purpose, the principle of anonymous data processing, the right to voluntary participation, and the freedom to withdraw from the study at any time to all potential participants.

To ensure the semantic accuracy of the translation, we invited one bilingual professional to independently perform translation and back-translation. The consistency rate between the back-translation and the original translation was 94.4% (5 out of 54 items had sentence structure discrepancies that did not affect the meaning).

To reduce possible effects from psychological defense and social approval, the questionnaire was filled out completely anonymously, and all items had no right or wrong answers<sup>[14]</sup>. The researchers informed participants that they should respond based on their personal true feelings. The entire questionnaire included three core scales and demographic variables, with the average completion time for valid questionnaires being approximately 4.3 minutes. All collected data were used solely for this academic research and will not be disclosed to the public or used for other commercial purposes.

The researchers' online questionnaires received 580 returned questionnaires/responses. After excluding invalid responses with completion times that were too short (<100 seconds), those with consecutive identical answers to multiple items, or those with obvious logical contradictions, a total of 273 valid questionnaires were obtained, yielding an effective response rate of 47.07% ("effective response rate" =  $273/580 \times 100\%$ ). Among the valid sample, there were 156 male participants (57.14%) and 117 female participants (42.86%); the participants' average age was 20.4 years (SD=1.34), with an age range of 18 to 29 years; and the average years of education was 13.9 years (SD=1.02).

### 2.3 Measures

#### 2.3.1 Artificial Intelligence Literacy

This research used the Chinese translation version of Artificial Intelligence Literacy survey from Wang et.al<sup>[15]</sup>. The scale contains 12 items (e.g. "I can skillfully use AI applications or products to help me with my daily work."). The items are rated on a 7-point Likert scale (1 = very disagree to 7 = very agree with 3 items being reverse scored.). The higher the total score for the 12 items, the higher level of AIL. In this research Cronbach's alpha was 0.887, and KMO was 0.908.

#### 2.3.2 Self-Regulated Learning

This research used the Chinese translation version of Self-Regulated Learning survey from Barnard et al.<sup>[1]</sup>. The scale contains 24 items (e.g. "I ask myself a lot of questions about the course material when studying for an online course."). The items are rated on a 5-point Likert scale (1 = very disagree to 5 = very agree). The higher the total score for the 24 items, the higher level of SRL. In this research Cronbach's alpha was 0.967, and KMO was 0.952.

### 2.3.3 Learning Engagement

This research used the Chinese translation version of Learning Engagement survey from Maroco<sup>[8]</sup>. The scale contains 15 items (e.g. “I feel excited about the schoolwork.”). The items are rated on a 5-point Likert scale (0 = never to 4 = always with 1 item being reverse scored.). The higher the total score for the 15 items, the higher level of LE. In this research Cronbach’s alpha was 0.933, and KMO was 0.923.

### 2.4 Data Analysis

In this research, data processing was performed using SPSS 32.0 and PROCESS v4.2 Model 4 (Hayes, 2022). After screening, valid questionnaires were scored according to the questionnaire design to calculate dimension scores, and the final scores for each participant on the three questionnaires were computed as experimental data. The following analyses were then conducted:

In terms of descriptive statistics, the mean and standard deviation were calculated for AIL, SRL, LE, respectively. Cronbach’s  $\alpha$  was also calculated to examine the internal consistency of the data obtained from the three scales.

In terms of correlation analysis, the correlation coefficient matrix for the three variables (AIL, SRL, and LE) was computed.

In terms of mediation effect testing, a mediation model was established using the aforementioned PROCESS plugin, with AIL as the independent variable X, LE as the dependent variable Y, and SRL as the mediator variable M. The significance of the mediation effect was tested using the Bootstrap method, with 5,000 resampling iterations and a 95% confidence interval (Bias-Corrected Bootstrap Confidence Interval).

## 3. Results

### 3.1 Descriptive Statistics and Correlation

**Table 1. Descriptive Statistics and Correlation Matrix for Study Variables**

| Variable                           | M     | SD   | 1      | 2      | 3      | 4      | 5     | 6 |
|------------------------------------|-------|------|--------|--------|--------|--------|-------|---|
| 1.Artificial Intelligence Literacy | 5.45  | 1.01 | 1      |        |        |        |       |   |
| 2.Self-Regulated Learning          | 3.69  | 0.77 | 0.54** | 1      |        |        |       |   |
| 3.Learning Engagement              | 3.97  | 0.70 | 0.34** | 0.61** | 1      |        |       |   |
| 4.Age                              | 20.37 | 1.34 | -0.06  | -0.10  | -0.03  | 1      |       |   |
| 5.Gender                           | -     | 0.50 | 0.00   | 0.00   | 0.00   | -0.06  | 1     |   |
| 6.Years of education               | 13.93 | 1.02 | -0.05  | -0.13* | -0.15* | 0.60** | -0.10 | 1 |

Note: N=273.

In gender, male was computed as 1 and female was computed as 2.

\*\*. Correlation is significant at the 0.01 level (2-tailed).

\*. Correlation is significant at the 0.05 level (2-tailed).

### 3.2 Mediating Effect

**Table 2. Bootstrap Mediating Effect test results**

| Effect type | Path       | Effect | BootSE | p       | BootLLCI | BootULCI |
|-------------|------------|--------|--------|---------|----------|----------|
| DE          | AIL→LE     | 0.00   | 0.04   | 0.84    | -0.07    | 0.09     |
| DE          | AIL→SRL    | 0.41   | 0.04   | < 0.001 | 0.34     | 0.49     |
| DE          | SRL→LE     | 0.55   | 0.05   | < 0.001 | 0.44     | 0.65     |
| IE          | AIL→SRL→LE | 0.23   | 0.03   | -       | 0.17     | 0.29     |

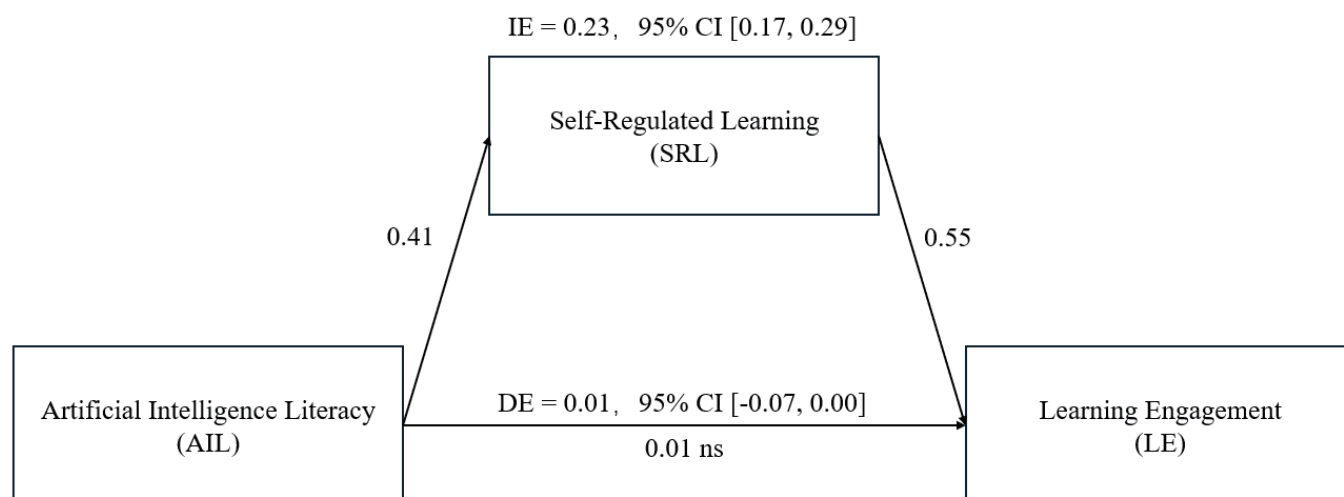


**Figure 1. Mediating Effect of SRL in the relation between AIL and LE, ( $p < 0.001$ , ns = not significant)**

## 4. Discussion

### 4.1 Theoretical Implications

The core finding of this study is that SRL completely mediates the relationship between AIL and LE. According to the data, the direct effect of AIL on LE was not significant after including the mediator ( $\beta = 0.01$ ,  $p > 0.05$ ), while the indirect effect was significant ( $\beta = 0.23$ , BootLLCI = 0.17, BootULCI = 0.29). This result indicates that although AIL itself is not directly associated with higher learning engagement, it can be related to learning engagement through activating and optimizing students' SRL processes.

According to Zimmerman's <sup>[20]</sup> SRL framework, the explanation of the finding is that during the forethought phase, students with higher AIL are likely better able to use AI tools to screen reliable resources and clarify learning goals <sup>[15]</sup>, so that lays a directional foundation for engagement behaviors. During the performance phase, they can use AI feedback to adjust learning strategies in real time <sup>[10]</sup>, sustaining continuous engagement at both cognitive and behavioral levels. During the self-reflection phase, they are more likely to evaluate their own learning outcomes based on AI-generated results and accordingly optimize subsequent actions <sup>[18]</sup>. This series of SRL processes collectively constitutes the key steps in the transformation from AIL to LE. Without this process, AIL may remain at the level of tool use, making it difficult to translate into stable affective engagement, cognitive strategies, or persistent behavioral participation.

However, it is worth noting that the complete mediation model revealed in this study differs from the direct effect reported in some previous literature <sup>[9]</sup>, which holds that AIL can not only positively influence LE through SRL but also have a direct positive effect on LE. This difference may stem from sample characteristics (e.g., Chinese undergraduate students).

Furthermore, SRL and LE were both significantly negatively correlated with years of education ( $r = -0.13$ ,  $p < 0.05$ ;  $r = -0.15$ ,  $p < 0.05$ , respectively) is differentiation suggests that even though upper-year students do not differ from lower-year students in terms of AIL, they face more challenges in both SRL and LE.

### 4.2 Practical Implications

The findings of this study have certain reference value for higher education practice. First, when cultivating students' AIL, universities should simultaneously embed SRL training alongside the teaching of AI tool operation skills, helping students transform AIL into actionable self-regulated behaviors, as Barnard et al. <sup>[1]</sup> emphasized the critical importance of SRL in technology-assisted

learning environments.

Finally, for students, this study suggests that they should actively integrate AIL with self-management abilities, rather than merely pursuing the frequency of tool use or technical proficiency. Granstrom & Oppi<sup>[4]</sup> have pointed out that current students generally exhibit insufficient metacognitive engagement and a lack of critical thinking when using AI tools. Therefore, in light of the data from this research, this study argues that students need to embed AIL into the closed loop of goal planning, strategy execution, and outcome reflection in order to break through superficial application and achieve truly high-quality LE.

## 5. Limitations and Future Research

In terms of research design, this study employed a cross-sectional survey design, with data collected within a fixed period. Although a mediation model was established and results consistent with the initial hypotheses were obtained, the findings still carry uncertainty<sup>[13]</sup>. Future research could adopt longitudinal tracking designs or conduct interventions to further ascertain the causal pathways and temporal sequences among the variables.

In terms of the sample, the survey questionnaires of this study were mainly concentrated in specific Chinese universities. Although the sample size met the basic requirements, differences in geographical distribution and student levels have not been fully substantiated. Students from different regions and different types of universities may differ in AIL, SRL, and LE<sup>[6]</sup>. In a 2025 survey based on 941 Chinese college students<sup>[6]</sup>, it was found that students from "Double First-Class" universities scored significantly higher than those from non-"Double First-Class" universities in terms of proficiency in AI technology, communication skills, critical evaluation, creative application, and ethical competency development. Therefore, future research could expand the sample collection scope to cover student populations from more institutions and increase the sample size.

In terms of the construction of the theoretical model, this study mainly focuses on three aspects: AIL, SRL, and LE. However, the mechanisms underlying AIL and student LE may involve more complex factors/variables, encompassing more than just the dimension of SRL. In future research, other variables could be further incorporated into the existing model to consider their mediating or moderating roles between AIL and LE, thereby providing a more comprehensive simulation of the theoretical process through which AIL empowers student LE.

## 6. Conclusion

This research confirms that self-regulated learning (SRL) serves as a complete mediator between artificial intelligence literacy (AIL) and student learning engagement (LE) among Chinese undergraduates. Although AIL does not directly affect LE, it significantly facilitates LE through the enhancement of SRL processes (specifically, goal setting, strategy adjustment, and self-reflection within Zimmerman's cyclical framework). For educators, integrating SRL training under AI-integrated learning environments is essential to translate technical competence into sustained behavioral, emotional, and cognitive engagement of students.

## Author Biography

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