Exploring the Impact of K-12 Teachers' AI Literacy on Student Learning Motivation in STEM Classrooms

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Abstract: *More recently, AI has evolved to support complex teaching and learning activities. AI is now reshaping core aspects of education, including curriculum content, instructional methods, and learning assessment. Nevertheless, due to teachers' different levels of AI literacy, the pedagogical effects in STEM education are distinct. Meanwhile, students have anxiety and weak motivation for learning language. Limited attention of study on AI literacy and AI integration into education has been given to K-12, especially middle schools. In Chinese secondary school contexts, there is a lack of validated instruments and longitudinal studies on K-12 teachers' AI literacy. Significant empirical gaps on enhancing teachers' AI literacy remain, particularly studies that directly link specific dimensions of teachers' AI literacy with students' learning motivation. To address these limitations, this project proposes a mixed-methods study that examines how a targeted teacher-education programme can develop K-12 STEM teachers' AI literacy and, in turn, enhance students' learning motivation.*

Keywords: teachers' AI literacy, students learning motivation, K-12 STEM education, teacher education

1. Introduction

At present, the world is at a turning point and education must be fundamentally reimagined and practiced. UNESCO's recent anthology on artificial intelligence (AI) and the future of education highlights that the rise of AI has triggered a multidimensional dialogue that cuts across disciplines, regions, languages, and worldviews (UNESCO, 2025). While some commentators portray AI as a panacea for educational reform, others caution that it may exacerbate social inequalities and erode the humanistic core of education.

Early applications of AI in education mainly targeted administrative automation and the delivery of standardized content. More recently, AI has evolved to support complex teaching and learning activities. AI is now reshaping core aspects of education, including curriculum content, instructional methods, and learning assessment.

Nevertheless, due to teachers' different levels of AI literacy, the pedagogical effects in STEM education are distinct. Meanwhile, students have anxiety and weak motivation for learning STEM, which requires teachers to address misconceptions and create more engaging learning environments. A systematic review investigating AI literacy and AI integration into education identified that most studies focused on university teachers or students, while limited attention has been given to K-12, especially middle schools. In Chinese secondary school contexts, there is a lack of validated instruments and longitudinal studies on K-12 teachers' AI literacy. Although scholars and policymakers increasingly acknowledge the importance of enhancing teachers' AI literacy, significant empirical gaps remain, particularly studies that directly link specific dimensions of teachers' AI literacy with students' learning motivation.

To address these limitations, this project proposes a mixed-methods study that examines how a targeted teacher-education programme can develop K-12 STEM teachers' AI literacy and, in turn, enhance students' learning motivation.

The contribution of this research is to identify key dimensions of AI literacy and reveal the shortcomings of current teachers' AI literacy (for example, ethical awareness is generally lower than technical operation ability). Findings from the intervention will inform teachers' instructional design for integrating AI into K-12 classrooms in pedagogically meaningful and responsible ways. The outcomes of this research not only provide solid empirical evidence for educational theories but also offer specific and operational guidance and suggestions for the design of teachers' professional development plans, the allocation of educational resources, and the formulation of related educational policies, promoting the implementation of the digitalization strategy in education.

2. Literature Review

2.1. AI Literacy in K-12 Education

AI literacy refers to the knowledge, skills, and attitudes that enable individuals to understand AI technologies, use AI tools effectively, and critically evaluate AI outputs (Lintner, 2024). In essence, AI literacy builds on digital literacy, requiring not only technical know-how but also the ability to interpret AI system behaviors and their societal implications. For K-12 teachers in STEM, AI literacy encompasses understanding fundamental AI concepts (e.g., machine learning, algorithms), knowing how to integrate AI-driven tools into teaching, and being aware of ethical issues such as bias and data privacy. This competence is increasingly crucial in the digital age: as AI reshapes industries and everyday life, teachers need AI literacy to prepare students for the future and to harness AI for personalized, engaging learning (Yang et al., 2025).

Recent research has emphasized the importance of multi-dimensional frameworks for conceptualizing AI literacy in education. One framework is the Affective, Behavioral, Cognitive, Ethical (ABCE) model proposed by Celik (2023), which captures four integral dimensions: affective, behavioral, cognitive, and ethical. To operationalize this framework, Ng et al. (2024) developed a 32-item AI Literacy Questionnaire (AILQ), which was validated successfully among secondary school educators, providing strong empirical support for these interconnected dimensions.

Collectively, these frameworks underscore that AI literacy is a complex construct extending well beyond mere technical or programming skills. For K–12 STEM educators, achieving AI literacy means confidently integrating AI tools and illustrative examples into everyday lessons, facilitating critical discussions with students about the broader social implications of AI, and cultivating classroom environments that embrace ethical standards in the use of AI technologies (Yang et al., 2025; Celik, 2023). Given the pervasive role of AI in modern education, such competencies are not just beneficial but essential. As AI reshapes the traditional classroom dynamic into a collaborative interaction between teachers, AI systems, and students, exemplified by intelligent tutoring systems or automated assessment tools, teachers who possess robust AI literacy will be better equipped to navigate this evolving educational landscape. They can demystify AI for students, nurture critical thinking skills, and prepare the next generation to thrive responsibly and effectively in an increasingly AI-saturated world (Cukurova & Miao, 2024).

2.2. AI Literacy Assessment Tools for Teachers

Over the past few years, the assessment of AI literacy has moved from conceptual groundwork to the development and validation of psychometric instruments. To empirically evaluate teachers' AI literacy, researchers have proposed a range of scales. Lintner (2024) reviewed 16 AI-literacy instruments across 22 studies, most of which target general adult populations rather than teachers specifically, for example, the AI Literacy Scale (Wang et al., 2023), the AI Literacy Questionnaire (Ng et al., 2024) and SNAIL (Laupichler, 2023).

A series of works adapts the TPACK framework by explicitly embedding AI, often termed Intelligent-TPACK (I-TPACK). Building on teachers' technological (TK), pedagogical (PK), and content knowledge (CK), as well as their intersections (TPK, TCK, and TPACK) (Mishra & Koehler, 2006), Celik (2023) introduces an ethics component and emphasizes the importance of professional knowledge for ethically integrating AI into instruction. In this model, Intelligent-TK, Intelligent-TPK, Intelligent-TCK, Intelligent-TPACK, and Ethics jointly describe teachers' perceived readiness to apply AI in pedagogical practice (see Fig. 1).

Subsequent studies have applied or extended I-TPACK in empirical contexts. For higher education, Al-Abdullatif (2024) examined factors affecting faculty adoption of generative AI, finding that I-TPACK and perceived trust mediate the link between AI literacy and GenAI acceptance. At a theoretical level, Chiu (2025) systematizes five I-TPACK knowledge domains and proposes implementation strategies (teacher capacity building, curriculum integration, collaboration networks, and assessment reform), while calling for cross-cultural adaptation and indicator-system development.

In Chinese secondary school contexts, empirical validations for K–12 teachers appear limited in the archival literature. Existing studies (e.g., Delphi and SEM-based validations in selected higher-vocational settings) suggest feasibility but fall short of establishing a widely adopted, K–12-specific Chinese I-TPACK instrument (Zhuang, 2024).

In this study, I-TPACK is not merely background knowledge but the core analytical framework of teachers' AI literacy. Moreover, the dimensions (e.g., PK and TPK) related to teaching integration within it will serve as important antecedent variables to explain the differences in students' motivation.

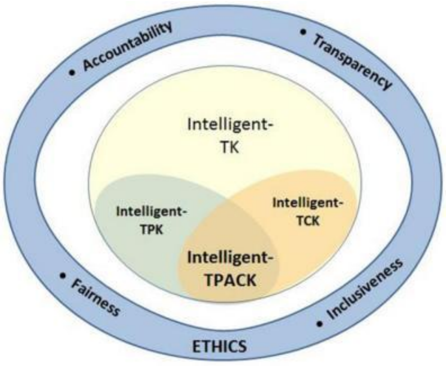

Fig.1. Intelligent-TPACK framework and its components (Celik, 2023)

2.3. Linking AI Literacy to Student Learning Motivation

This study will not focus on students' general technology acceptance, but on how teachers' AI literacy influences students' learning motivation through classroom practice. The classroom practices can be about how teachers integrate AI into the classroom, how they design tasks, and how they provide support to influence students' autonomy, competence, and relatedness.

Self-determination theory (SDT) proposed by Ryan and Deci (2020) provides a useful lens to understand how teachers' AI literacy impacts student learning motivation. SDT proposes that people have three psychological needs: autonomy, competence, and relatedness because it believes these basic psychological needs are the fundamental sources of human motivation. This theory posits that satisfying basic psychological needs fosters intrinsic motivation, thereby supporting sustained and meaningful learning behaviors (Ryan & Deci, 2020).

A lot of studies adopt SDT to analyze student learning motivation with AI tools considering satisfaction of three needs. Firstly, with targeted training and policy support for teachers, AI has the potential to enhance the autonomy of students in schools of the Global South in English as a Foreign Language (EFL) learning (Kundu & Bej, 2025). Teachers are likely to design learning activities with room for choice while students have opportunities for self-study with intelligent tutoring systems (autonomy). Secondly, Chiu et al. (2024) conducted a study on how teacher support moderates the effects of student expertise on needs satisfaction and intrinsic motivation to learn with AI technologies (i.e. chatbot) at the secondary level. It reveals that students' competence on study with the chatbot relied on teacher support and the need for relatedness could be satisfied better by teacher support (competence). Thirdly, Im et al. (2025) reported that integration of AI in learning can increase student motivation through an interactive and adaptive approach (relatedness).

While most existing studies focus on students' own AI literacy or their direct interaction with AI tools, SDT also implies a crucial contextual pathway: teachers' AI literacy shapes how AI is integrated into classroom activities, which in turn affects students' perceived autonomy, competence, and relatedness. For example, teachers who can design AI-enhanced tasks that support choice, provide optimally challenging feedback, and foster supportive peer interaction are more likely to sustain students' motivation in STEM learning.

There is still insufficient evidence on whether and how K-12 teachers' AI literacy affects student learning motivation in STEM classrooms, particularly through these SDT-based pathways.

3. Research Questions

Based on the above review, three gaps can be identified. First, although research on AI literacy and AI integration into education is growing, most empirical studies focus on university teachers or students rather than on K-12, especially secondary-level, classrooms. Consequently, little is known about the relationship between teachers' AI literacy and students' learning motivation in STEM lessons. Second, in Chinese secondary school contexts, there is a lack of validated instruments and longitudinal studies on K-12 teachers' AI literacy. Third, existing work typically relies on self-reported measures of teachers' AI integration, with few performance-based tasks (e.g., lesson design, micro-teaching, classroom situational judgement test) and limited evidence for the predictive validity of these measures over time.

To fill the above-mentioned gaps, the present project design and evaluate a teacher education programme aimed at enhancing K–12 STEM teachers' AI literacy, and will examine how teachers' AI literacy levels and their development over time relate to students' learning motivation. Specifically, this research aims to answer the following questions:

1. To what extent do K-12 STEM teachers' AI literacy levels, assessed through both self-reported and performance-based tasks, improve after participating in the teacher education programme?

2. To what extent are teachers' AI literacy levels and their changes over time associated with changes in students' learning motivation in STEM classrooms?

3. What is the mechanism for developing teachers' AI literacy to enhance students' learning motivation?

4. Methodology

This project will employ a mixed-methods, two-phase design in four Chinese middle schools. It will evaluate a teacher education programme aimed at enhancing science teachers' AI literacy and examine how teachers' AI literacy relates to students' learning motivation in STEM classes. There will be two parts of this research, including a formative study and the experimental study. The formative phase will include pre-interviews with participating teachers to refine the instruments and the design of the teacher education programme. The main phase will implement the programme and systematically observe and examine middle-school science teachers' classroom practices and their students' learning motivation.

The proposed research will be conducted in middle schools in a major city in mainland China (e.g., Shenzhen). These schools have actively promoted the smart classroom or educational technology pilot projects, and are willing to open the classroom for research with a foundation in AI application, which is suitable for this pedagogical intervention research.

4.1. Participants

In-service science teachers will be recruited on a voluntary basis. All students in their classes (aged 13–14, Grades 8–9) will be invited to participate. In addition, IT specialists and general studies teachers will be invited as key informants to provide complementary perspectives on AI integration.

4.2. Study 1: Formative Study

The researcher will conduct a semi-structured interview with each participant teacher to investigate their demographic and professional background, their teaching needs and students' learning needs, and to identify the barriers and enablers that affect the AI education in K-12 STEM classrooms. For example, the information of background could be gender, years of teaching, student expertise, prior experience with the specific AI (e.g., ChatGPT, Doubao) integration, previous experience with other AI tools, how they use AI in class and some other open-ended questions.

Based on the needs of teachers and students, a series of workshop related to AI will be designed and organized. The training content includes:

Workshop 1: introduction of AI and generative AI (concepts, problem, application);

Workshop 2: using Gen-AI(e.g., ChatGPT, Doubao) for instructional design;

Workshop 3: AI-generated content (AIGC) to develop teaching materials and test papers;

Workshop 4: Optimizing the classroom with AI, e.g. experiencing virtual scenarios, digital teachers, interdisciplinary learning, homework design and correction.

In the next stage (Study 2), teachers from the treatment group will participate in the workshops.

The interviews will be conducted in Chinese, the first language of the participants to reduce barrier. Each interview will last around 40 minutes. The researcher will record the entire interview and take notes.

The interview transcripts will be in both Mandarin Chinese and English and analyzed with a thematic analysis approach. By identifying repetitive patterns in the text to distill the core theme (Braun & Clarke, 2006), it can reveal teachers' cognition and attitude towards AI. Then, a qualitative code and a clear codebook are compiled. After reading the interview scripts, the potentially useful information is marked to form open coding, and at the same time, the segments that conform to the codes in the decoding set are extracted, which are called closed coding. Encode the open-ended answers by theme and eliminate invalid data.

By distilling the key themes and narrative patterns that teachers encounter during the integration of AI, we can understand the real teaching and learning situations, e.g. teacher learning experiences and usage intention on AI, students' feedback on teacher integrating AI into classroom, guidance resource of AI and so on. This could help us reconsider and refine the process of teacher training on AI and the design of the following study. It may indicate a hint that what kind of AI tool and AIGC are suitable to be used in classroom teaching. In this way, it could form a related report of all participating teachers.

4.3. Study 2: Main Study

In this experimental study, the treatment will be that teacher joins the workshops mentioned in 4.2 sections (T0 period) and uses AI tools (e.g. ChatGPT, Doubao) in the class. Two experimental groups of teachers are: teachers who are willing to use AI tools in the class (AT) and those without AI assistance (NAT). Teachers will be included in each condition. The classes taught by treatment-group teachers will constitute the student treatment group (STG), and the classes taught by comparison-group teachers will constitute the student comparison group (SCG). Where feasible, classes (rather than individual students) will be randomly assigned to conditions to reduce selection bias.

There will be two cycles over two semesters. The main study will consist of a naturalistic lesson observation, which will last around ten months with participant teachers working with the researcher each semester.

Cycle 1 (C1): Pilot the workshops and the teachers' classes in one school to examine whether the current research is reliable and valid, and develop suitable observation and interview instruments. This period will last for two months.

Cycle 2 (C2): Modify and conduct the study based on the results of cycle 1. Later, accumulate curricular materials and broaden to all schools. This period will be two semesters (around eight months).

For the cooperation mechanism, establish a communication mechanism with the school's academic affairs office and teaching and research groups to promptly address technical or classroom issues. For risk control, anticipate risks such as malfunctions of AI tools and teacher resistance, and prepare alternative activities or interview arrangements. If we are unable to enter a certain class, activate a backup class or adjust the sample size.

Multiple methods will provide a holistic understanding of the mechanism between teacher AI literacy and student learning motivation. The researchers will employ methodological and data source for triangulation cross-validation, including self-report scales, performance-based evidence (rubric scores of teaching design, situational judgement test scores), behavioral evidence (lesson observations, log data), and outcome evidence (student learning motivation surveys). The different data streams will draw conclusions and robust mechanism. In this way, it can offer deep insights and shed light to the research questions. The data collection methods are as follows.

Teachers' AI literacy will be assessed using the Intelligent-TPACK (I-TPACK) scale (Celik, 2023) with 5 dimensions (Intelligent TK, Intelligent TPK, Intelligent TCK, Intelligent TPACK, and Ethics) and 29 items as the primary instrument and the AI-TPACK scale (Ning, 2024) with a set of 39 items and 7 dimensions (CK, PK, AI-TK, PCK, AI-TCK, AI-TPK and AI-TPACK) as a supplementary measure. The items for AI literacy could be "I know how to interact with AI-based tools in daily life", "I have knowledge to select AI-based tools to sustain students' motivation ", "I can teach lessons that combine my teaching content, AI-based tools, and teaching strategies" (Celik, 2023), "I can use AI to broaden the knowledge horizons of students", and "I am able to use a variety of diverse teaching methods in the classroom" (Ning, 2024). Both scales will be administered to all participating teachers before and after the intervention. The questionnaires will measure all participating students' intrinsic motivation to learn STEM and three needs satisfactions before and after the intervention. All items in the questionnaires would be rated on a 5-point scale. Students' learning motivation will be measured by the interest or enjoyment scale of the Intrinsic Motivation Inventory (IMI) (McAuley et al., 1989). For each administration, scale responses will be entered into SPSS (or R) for data cleaning (e.g., checking missing values, out-of-range responses, and response patterns).

Descriptive statistics (means, standard deviations) will first be computed for each subscale and for the total scores, separately for the treatment and comparison groups at pre-test and post-test. Internal consistency will be examined using Cronbach's alpha for each subscale.

To assess changes over time and differences between groups, pre–post differences in teachers' AI literacy will be analysed using paired-samples tests within groups and independent-samples tests or ANCOVA / multilevel models between groups, controlling for baseline scores where appropriate. Effect sizes (e.g., Cohen's d) will be reported alongside p-values given the relatively small teacher sample.

Since these scales are self-reported, they may be affected by biases such as social desirability and common-method variance. Procedurally, anonymity and confidentiality will be emphasised, and items from different constructs will be interleaved to reduce response patterns. Statistically, Harman's single-factor test and, where feasible, marker-variable approaches will be used to check for common-method bias. The self-report data will also be triangulated with performance-based tasks (e.g., lesson plans, classroom observations) to mitigate overreliance on a single method.

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