Ecological Predictors of AI Literacy in Chinese K-12 Teachers: A Structural Equation Modeling Study

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Abstract: Although AI is being rapidly developed and applied in education, gaps remain in factors affect teachers' AI literacy. A cross-sectional survey of 1,680 teachers was conducted to explore relationships between school environment, social environment, teacher self-efficacy, and AI literacy via structural equation modeling (CFI = 0.986; RMSEA = 0.03). The results showed that teachers' AI literacy was 3.89 ± 1 (out of 5) in total, and the theory-practice gap was significant: stronger performance in awareness (β = 0.75) and ethics (β = 0.76), but weaker performance in application literacy (β = 0.72) and evaluation literacy (β = 0.81). School environment had the strongest direct effect on AI literacy (β = 0.270, p < 0.001), followed by teacher self-efficacy, which served as an important mediator (β = 0.259, p < 0.001). Social environment had no direct effect on teachers' AI literacy (β = 0.060, p = 0.362), implying that distal effects need to be mediated by school. Demographic analysis showed urban–rural differences, decline after age 40, and subject differences (science > liberal arts). Therefore, we suggest that policymakers should transfer to supporting school-level interventions with targeted resources allocation. School leaders should create supportive technological environments and self-efficacy programs. In addition, teachers should participate in hands-on training with a focus on practical skills. This study provides useful references for integrating AI into K-12 education in China.

Keywords: AI literacy, AI for teacher education, Teacher self-efficacy, Ecological systems theory

Highlights

1. Social environment influences teachers' AI literacy indirectly through self-efficacy's mediating role, demonstrating interplay between contextual factors and personal beliefs.
2. Teacher's self-efficacy significantly mediates between social environment and AI literacy, indicating how confidence in capabilities facilitates technology adoption.
3. K-12 teachers exhibit notable deficiencies in AI application and evaluation competencies, revealing challenges in practical implementation and critical assessment.
4. School teaching environment directly impacts teachers' AI literacy, highlighting the importance of institutional support, resources, and professional development opportunities.

1. Introduction

Artificial intelligence (AI) is revolutionizing education worldwide by providing tools to personalize learning and enhance teacher efficiency (Su & Ng, 2022). UNESCO has called AI literacy essential for sustainable educational ecosystems and recommended that countries prepare educators for AI teaching (Pedro et al., 2019).

However, teacher AI preparedness is remarkably different across systems. For instance, while in Nordic countries such as Finland, an integrated AI education framework has been developed (and in Singapore a nationwide teacher AI literacy has been put into practice) (Chai et al., 2021), other systems are far behind. For example, only 23% of teachers in the US felt prepared to teach with AI even though 60% indicated interest (Education Week Research Center, 2023). For European systems, research indicated great variation in digital competency framework development, with Estonia and Netherlands leading the field, and others lagging behind in even basic infrastructure (Redecker & Punie, 2017).

Despite China's prominent position in AI worldwide and its ambitious policies in educational technology, there is a paucity of research on the factors of teacher AI literacy in schools, especially at the K-12 level (Hu et al., 2021). We hypothesize that there are substantial gaps between technological availability and classroom use (Li, Chen & Liu, 2023). By utilizing Bronfenbrenner's ecological systems theory as a theoretical lens, this study

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explores how social environment and school factors interact with teacher self-efficacy to influence the development of AI literacy among Chinese teachers.

Research Objectives:

- To test the mediating effect of teacher self-efficacy in the relationship between school/social environment and AI literacy through SEM..
- To quantitatively describe current levels of AI literacy among Chinese K-12 teachers through different demographic characteristics.
- To identify and measure the relative impact of ecological factors (social support, school climate, self-efficacy) on AI literacy through validated instruments.

2. Literature Review

2.1 Definition of Key Concepts

2.1.1 AI literacy: A multidimensional construct

Artificial intelligence literacy is a new requirement for teachers with a background in intelligent education and critical literacy for teachers' competent education and teaching practice in the context of intelligent education (Sperling, et al., 2024). Compared with the traditional requirements of teachers' educational technology ability, the connotation of artificial intelligence literacy is more prosperous, and its requirements and challenges for teachers are also higher. According to related researches, AI literacy usually encompasses four dimensions:

- Awareness: Understanding AI concepts and societal implications (Long & Magerko, 2020).
- Application: Using AI tools for lesson design and student engagement (Guo & Wang, 2025).
- Evaluation: Critically assessing AI outputs for accuracy and bias (Hanna et al., 2024).
- Ethics: Navigating privacy, equity, and transparency challenges (Touretzky et al., 2019). For teachers, AI literacy transcends technical proficiency; it requires integrating tools like adaptive learning platforms while fostering ethical reasoning among students (Velander et al., 2023).

2.1.2 Ecological systems theory

Research on the influencing factors of AI literacy among K-12 teachers is relatively scarce. Among the existing research on the influencing factors of teachers' data and information literacy, mostly employing qualitative researches focus on the single prospective including the importance of information, the importance of learning digital skills and the importance of technology (Audrin, C., & Audrin, B, 2022). Bronfenbrenner's framework posits that teacher growth is shaped by nested systems:

- Macro: National policies, cultural attitudes, and technological infrastructure.
- Meso: School resources, leadership, and peer collaboration.
- Micro: Individual traits like self-efficacy and openness to innovation.
- Prior studies highlight school environments as catalysts for digital literacy (Powell & Bodur, 2019), while societal support (e.g., funding, public trust) sets the stage for scalable change (Yeager et al., 2022).

2.1.3 Teacher self-efficacy

Self-efficacy is a person's belief in their ability to perform a task, developed under social cognitive theory. Bandura's self-efficacy theory posits that teachers' confidence in using AI predicts adoption behaviors (An et al., 2023). High self-efficacy correlates with persistence in overcoming technical barriers and experimenting with AI tools. Despite having a low degree of self-efficacy, a teacher may do well on a given assignment (Compeau & Higgins, 1995). The same is true of teacher self-efficacy beliefs. A teacher may perform well on a specific task but may need a higher level of self-efficacy.

2.2 Relationships among the Key Concepts

2.2.1 Relationship between the competencies of teaching environments

Ecological teaching theory emphasizes that the learning environment profoundly shapes cognitive, emotional, and behavioral development by mediating the interactions between learners and their surrounding systems (Leijen, Pedaste & Lepp, 2020). This environment encompasses both the broader social context—such as societal norms, family dynamics, and cultural values—and the immediate school setting, including classrooms, pedagogical resources, and institutional structures. Within schools, elements like collaborative learning spaces and technology integration cultivate learners' social adaptability, ethical values, and interpersonal skills, thereby extending ripple effects beyond the classroom (Leijen, Pedaste & Lepp, 2020). In the era of artificial intelligence (AI), these dynamics evolve further: AI-enriched school environments—characterized by adaptive tools, ethical AI curricula, and interdisciplinary projects—can proactively reshape the social environment by equipping students with AI literacy that informs societal discourses on technology, equity, and innovation (Hartinah et al., 2020). Empirical evidence underscores this causal pathway, as AI-enhanced assessments and tutoring systems in schools promote social competencies such as teamwork, communication, and help-seeking behaviors, which in turn reduce inequities and normalize inclusive norms across communities (Bigman, 2025). By integrating AI to support culturally responsive pedagogies and human-centered designs, school environments thus serve as catalysts for broader social transformation. Based on this, the following hypothesis is proposed:

H1. School Teaching Environment has a positive effect on Social Environment.

2.2.2 Relationship between the competencies of teaching environment and perceived self-environment

In its realization, man's essence is the sum of all social relations. Marxist philosophy holds that sociality is the essential attribute of human beings. Human growth and development are bound to be restricted by the social environment. The formation of various qualities of K-12 teachers cannot exist independently from society, and the social environment significantly impacts teachers' cognition and behavior. As the cradle of young people's growth, primary and secondary schools are the main places to train successors for society. As one of the subjects of primary and secondary education activities, teachers' cognition and behavior are closely related to regional economic development and educational policies and regulations (Hanushek, Piopiunik & Wiederhold, 2019). Based on the above analysis, the following hypotheses are proposed in this study:

H2. School Teaching Environment has a positive effect on Teacher self-efficacy.

H3. Social Teaching Environment has a positive effect on Teacher self-efficacy.

2.2.3 Relationship between the competencies of teaching environment and AI literacy

According to ecosystem theory, the teaching environment can be divided into a macroscopic social teaching environment and a middle school teaching environment. In the existing studies on the impact of teaching on teacher literacy, social and cultural environment has a potential impact on teachers' academic literacy and information literacy, etc (Bury, 2016). The school environment positively impacts teachers' individual and professional development, among which campus cultural atmosphere, teacher relationship, teacher-student relationship, and training opportunities are essential factors affecting teachers' professional literacy (Powell & Bodur, 2019). Social environment (modified nature, interpersonal relationship, and social consciousness form), including the exceptional environment of the school, is an objective factor affecting the growth of teachers and plays a vital role in the cultivation and development of teachers' self-quality (Yeager, et al., 2022). Based on the above analysis, the following hypotheses are proposed in this study:

H4. School Teaching Environment has a positive effect on Teacher AI Literacy.

H5. Social Teaching Environment has a positive effect on Teacher AI Literacy.

2.2.4 Relationship between the competencies of perceived self-environment and AI literacy

K-12 teachers are the main objects of AI literacy development, and their self-efficacy in AI literacy awareness, technology application knowledge, intelligent evaluation ability, ethical cognition, and other aspects have an essential impact on the development of AI literacy (Lim, 2023). Teacher self-efficacy, as a subjective factor of teachers, determines the different levels and directions of teachers' individual growth in the same environment (Saglam, et al., 2023). Yang et al. pointed out that teachers' practical knowledge and perception of the ease of use of artificial intelligence affect teachers' judgment on the application value of artificial intelligence in education (Yang, Luo & Dong, 2020). In summary, teacher self-efficacy is believed to have a specific impact on teachers' artificial intelligence literacy. Based on this, the following hypothesis is proposed:

H6. Teacher self-efficacy has a positive effect on Teacher AI Literacy.

Based on the theoretical and conceptual review, a conceptual framework has been developed showing the relationship between the variables of the study as well as the interconnectedness of the hypotheses guiding the study (See Fig. 1).

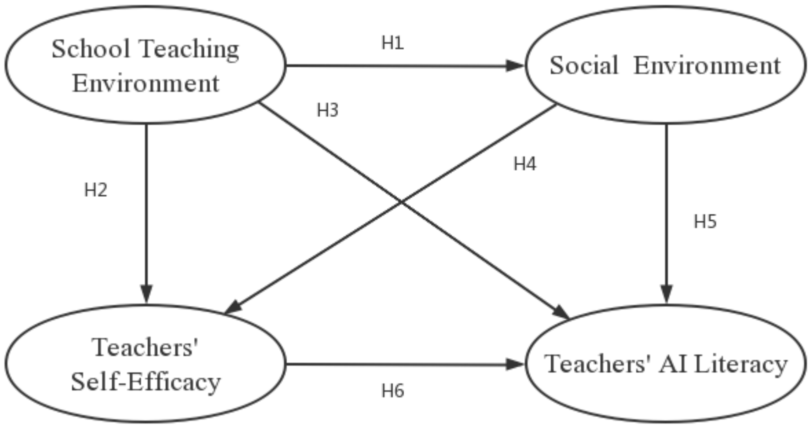

Figure 1: The hypothesized research model

3. Method

3.1 Sample

A four-month survey conducted from October 2022 to February 2023 is used for the study. A total of 1,970 questioners were collected randomly from formal K-12 schools in central China. The data was carefully screened through two quality control criteria: (1) Time validation of completion. Completion time should not be less than 120 seconds for participants to give adequate responses; (2) Completeness of responses. Questioners with over 50% of the values missing in the key sections of educational background and AI literacy items were eliminated as invalid. After careful screening, 1,680 valid samples were retained for structural equation modeling analysis (representing an 85.3% response rate).

Sampling was conducted in central China, which includes a large proportion of rural and suburban schools representative of Chinese educational settings. It is well known that central China has 60% of China's basic education schools. Sampling in urban China would result in a more biased sample of Chinese teachers and would inflate technological capabilities of teachers when compared to those from central China. Geographic distribution (47.3% rural, 19.6% suburban, 33.1% urban) reflects the geographic distribution of educational institutions in central China and is more generalizable to the broader Chinese population.

3.2 Participants

This study used a survey to explore the current state of AI literacy among Chinese K-12 teachers and identify related influencing factors. Teachers with at least one year of working experience in formal Chinese schools (grades 1-12) were eligible to participate. To reduce possible bias in sampling from different subject areas, we used systematic random sampling and proportionally allocated the sample according to the actual proportion of teachers from different subjects in the target areas.

All participants who agreed to participate in the survey provided informed consent, and the study was conducted in an ethical research according to the institutional review board. Demographic information listed in Table 1 indicates that although the proportion of females (52.8%) is slightly different from the reported proportion of Chinese K-12 teachers who are approximately 53% women (Hu, 2024), it is reasonable to assume that females are overrepresented in this sample. The elementary and secondary education level distribution is expected because China as an educational system has the majority of teachers at these levels. The hierarchical distribution of titles (34.6% beginner, 44.5% intermediate, 20.1% deputy senior, 0.8% senior) is reasonable because most schools in China have a pyramid structure in terms of professional title levels.

Table 1: Demographic information of the selected participants

Demographic	Level	Sample Size	Percentage	Total
Gender	Male	793	47.2%	1680
	Female	887	52.8%	
Location	Rural	794	47.3%	1680
	Suburban	330	19.6%	
	Urban	556	33.1%	
Educational Background	Below Bachelor	37	2.2%	1680
	Bachelor	1500	89.3%	
	Postgraduate	143	8.5%	
Age	≤31	302	33.1%	1680
	31-40	513	30.5%	
	41-50	591	35.2%	
	≥51	274	16.3%	
Title	Beginner	581	34.6%	1680
	Intermediate	747	44.5%	
	Deputy Senior	338	20.1%	
	Senior	14	0.8%	
Teaching Subject	Liberal Art	876	52.1%	1680
	Science	526	31.4%	
	Others	278	16.5%	

3.3 Instrument

This study adopted a culturally adapted questionnaire based on two published frameworks of AI literacy (Ng et al., 2021; Zhao, Wu & Luo, 2022). The adaptation was conducted in three systematic steps (Liu et al., 2022): (1) Translation and back-translation by bilingual education experts; (2) Content validation by expert panel (n=5 specialists in AI education); (3) Pilot testing with 150 teachers to validate construct validity in the Chinese cultural context. The final version of the questionnaire contained three parts: "Basic Information of K-12 teachers", "Current Status of AIL among K-12 Teachers", and "Influencing Factors of AIL among K-12 Teachers". The AIL scale consisted of 20 items measuring four constructs: AI awareness literacy (KUAI), AI application literacy (AAI), AI evaluation literacy (EAIA), and AI ethics literacy (AIE). The influencing factors part was based on UNESCO's Framework for Teachers' ICT Competence (2018) and relevant literature and contained three parts: school teaching environment (STE, 4 items), social environment (SE, 5 items), and teachers' self-efficacy (TSE, 5 items) (Hu, Zhang & Wang, 2021; Sanchez, 2013).

In addition to the original adaptation, CFs analysis were also conducted to verify the validity of construct characteristics in the Chinese context. The four-factor model of AI literacy presented a satisfactory fit (χ^2/df = 2.84, CFI = 0.934, TLI = 0.921, RMSEA = 0.052, SRMR = 0.048), indicating that the adapted instrument was suitable for use on AI literacy of Chinese K-12 teachers. All items used a 5-point Likert scale (1 = "strongly disagree" to 5 = "strongly agree"), and a higher score indicated stronger agreement or competency.

Internal consistency was assessed using Cronbach's α coefficients, and excellent reliability were obtained for AI literacy scale (α = 0.937) and good reliability were obtained for influencing factors scale (α = 0.875). Composite reliability for each constructed was calculated and ranged from 0.841 to 0.923, all larger than the recommended level of 0.7. Construct validity of the measurement was assessed through exploratory (EFA) and confirmatory factor analysis (CFA). EFA results showed that KMO was 0.937 (>0.7) and the Bartlett's sphericity test was highly significant ($p < 0.001$), indicating good sampling adequacy. CFA results confirmed the expected factor structure. All factor loadings were larger than 0.6 and average variance extracted (AVE) values ranged from 0.578 to 0.694, which all met the convergent validity criteria.

3.4 Data Analysis

Two analytical strategies were employed. Descriptive and correlation analyses were used to describe the levels of AI literacy and explore associations between measurement variables and demographic variables (gender, age, educational background, teaching level, location). Structural equation modeling (SEM) is particularly good at maximizing predictive power (Hair et al., 2019), thus it could help this research optimal for exploring factors of teachers' AIL. SPSS 22.0 was used for descriptive statistics and AMOS 24.0 for SEM analysis.

4. Results

4.1 Descriptive and Correlational Statistics

Table 2 presents the means and standard deviations for teachers' AI literacy (AIL), school teaching environment (STE), social teaching environment (SE), and teachers' self-efficacy (TSE). Following recommendations for structural equation modeling (Hu & Bentler, 1999), we analyze the basic statistical assumptions of structures for such data sets. The mean scores for AIL (M = 4.029), STE (M = 4.281), SE (M = 4.744), and TSE (M = 4.245) all exceeded the midpoint of 3 on a 5-point Likert scale, indicating generally positive perceptions among teachers. These above-average scores suggest teachers possess relatively high views of their AI literacy, perceive supportive teaching environments, and exhibit strong self-efficacy, which may facilitate the adoption of AI in educational settings.

Table 2: Mean and Standard deviation of the key constructs

	Items	Mean(SD)
AIL	20	4.029 (0.862)
STE	5	4.281(0.828)
SE	5	4.744 (0.763)
TSE	5	4.245(0.798)

Table 3 displays correlations among key constructs and demographics. Notably, AIL showed strong positive correlations with STE (r = 0.609, p < 0.01, 95% CI [0.57, 0.65]), SE (r = 0.355, p < 0.01, 95% CI [0.31, 0.41]), and TSE (r = 0.637, p < 0.01, 95% CI [0.60, 0.68]), suggesting that teachers' AI literacy is closely tied to their teaching environments and self-efficacy (Cohen's d ≈ 0.5–0.8 for practical significance). These correlations between AIL, STE, SE, and TSE highlight their interconnectedness, where gains in one (e.g., school environment) may enhance others, though effect sizes imply context-specific influences rather than universal drivers.

Table 3: Correlations of the key constructs

	D1	D2	D3	D4	D5	D6	AIL	STE	SE	TSE
D1	1									
D2	-0.311**	1								
D3	-0.198**	0.053*	1							
D4	0.002	0.000	-0.005	1						
D5	-0.135**	0.290**	0.052*	0.064**	1					
D6	-0.297**	0.711**	-0.017	-0.061*	0.193**	1				
AIL	0.036	-0.055*	0.007	-0.010	-0.030	-0.020	1			
STE	0.022	0.015	0.003	0.549**	-0.004	0.006	0.609**	1		
SE	0.016	-0.008	-0.002	0.019	0.007	-0.032	0.355**	0.497**	1	
TSE	0.035	0.446*	0.012*	0.528**	0.134**	-0.012	0.637**	0.557**	0.552**	1

Note: ** p < 0.01; * p < 0.05. D1, Gender; D2, Age; D3, Teaching Subject; D4, Location; D5, Educational Background; D6, Ttitle; SD, standard deviation; AIL, AI Literacy; STE，School Teaching Environment; SE, Social Environment; TSE, Teachers' Self-Efficacy.

4.2 Measurement Model

Reliability and validity of the questionnaire were assessed to ensure the consistency and accuracy of the measurement tools. Reliability, reflecting the stability of test results, was evaluated using Cronbach's α via SPSS.

According to Nunnally (1978), α values above 0.7 indicate high reliability. Validity, which measures the accuracy of the instrument, was assessed using factor loadings and the Kaiser-Meyer-Olkin (KMO) test, with KMO values above 0.7 considered acceptable (Sanchez, 2013). Table 4 summarizes metrics: Cronbach's α (0.84–0.87), composite reliability (CR; 0.93–0.96), and average variance extracted (AVE; 0.64–0.76), all meeting thresholds. Fornell-Larcker criteria confirmed discriminant validity (square root of AVE > inter-construct correlations). These results indicate that the questionnaire reliably and accurately measures AIL, STE, SE, and TSE, providing a solid foundation for the structural model analysis.

Table 4: Statistical summary of reliability and validity of the questionnaire

	Items	Cronbach's α	Factor Loading	CR	AVE
AIL	20	0.843	0.807–0.867	0.927	0.724
STE	5	0.871	0.737-0.851	0.938	0.643
SE	5	0.836	0.835–0.924	0.942	0.756
TSE	5	0.859	0.825–0.905	0.961	0.693

4.3 Structural Model

Figure 2 shows the interaction between demographic variables, teacher AI literacy (AIL), school teaching environment (STE), social teaching environment (SE), and teacher self-efficacy (TSE) and their mutual influence, with significant SEM results inserted. Model fit was assessed using multiple indices, all indicating a good fit: CFI = 0.986 (>0.900), RMSEA = 0.030 (<0.080), SRMR = 0.062 (<0.080), and Chi-square test ($p < 0.001$), as shown in Table 5, aligning with Hair et al. (2017).

Table 5: Results of the fitness in the hypothesis model

	P	CFI	RMSEA	SRMR
Structural Model	0.000	0.986	0.030	0.062
Fit Criteria	＜0.001	＞0.900	＜0.080	＜0.080

Non-significant pathways were removed, and significant path coefficients were retained in Table 6. Significant paths included STE to SE (β = 0.245, $p < 0.001$), STE to TSE (β = 0.295, $p < 0.001$), SE to TSE (β = 0.221, $p < 0.001$), STE to AIL (β = 0.270, $p < 0.001$), and TSE to AIL (β = 0.259, $p < 0.001$). The path from SE to AIL (β = 0.060, p = 0.362) was non-significant, rejecting hypothesis H5. Paths suggest STE and TSE as primary AIL drivers (total R^2 = 0.45, moderate effect), with SE indirectly influencing via TSE (indirect β = 0.05, 95% CI [0.01, 0.10]). This aligns with reciprocal ecological influences, where school-level factors mutually shape social contexts without strict causality..

Table 6: Path coefficient estimates in the hypothesized model

	Path Coefficient (β)	Direct Effects	P
STE--->SE	0.245	0.065	0.000
STE--->TSE	0.295	0.061	0.000
SE--->TSE	0.221	0.063	0.000
STE--->AIL	0.270	0.081	0.000
SE--->AIL	0.060	0.066	0.362
TSE--->AIL	0.259	0.079	0.000

Note: *** $p < 0.001$. AIL, AI Literacy; STE, School Teaching Environment; SE, Social Environment; TSE, Teachers' Self-Efficacy.

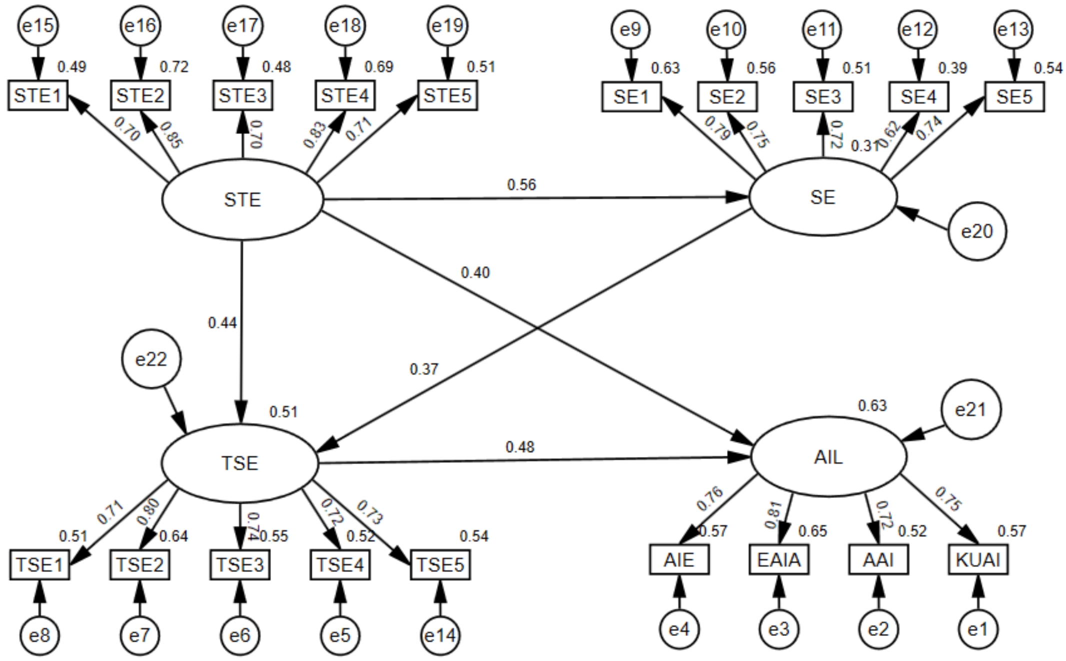

Figure 2: Structural model of the relationships among School Teaching Environment, Social Environment, Teachers' Self-Efficacy and AI Literacy

5. Discussion

5.1 Bridging the AI Application-Evaluation Gap

The results indicate that Chinese K-12 teachers have moderate levels of AI literacy (M = 3.89 out of 5), and almost half of the teachers scored below the mean. More worryingly, the theory-practice gap was significant: stronger performance in the theoretical dimension—awareness (KUAI, β = 0.75) and ethics (AIE, β = 0.76), but weaker performance in practical competencies—application literacy (AAI, β = 0.72) and evaluation literacy (EAIA, β = 0.81). Teachers grasp AI concepts but show modest operational skills (effect size d ≈ 0.3–0.5), limiting classroom integration.

This finding contrasts markedly with international research. Systematic government-led AI integration initiatives, along with strong technical infrastructure, result in higher application competencies among teachers in Nordic countries (Saheb & Saheb, 2022). Likewise, comprehensive professional development programs focusing on hands-on practice at institutional and systemic levels result in higher application competencies among Singaporean educators (Chai et al., 2023). The substantial gap between low AI literacy and fast technological development offers increasingly great challenges for educational digitalization in China and might widen existing digital divides in Chinese education.

5.2 School Environments as Catalysts

School teaching environment (STE) was found to be the strongest predictor of AI literacy (β = 0.270, $p < 0.001$) and Hypothesis 1 was supported. In agreement with Bronfenbrenner's ecological systems theory, microsystem environments, which are the immediate settings where individuals are embedded and involved in direct interactions, have the primary influence on developmental processes (Krebs, 2009). As a proximal environment, schools have the most immediate and longest influence on teachers' technological competency development.

Demographic analyses provide insights into the ecological nature of teachers' AI literacy development. Gender differences show female teachers exhibiting higher AI literacy than their male counterparts, contrasting with Western research indicating male advantage in technology use (Steinberg & Hohenberger, 2023). This may reflect the feminized nature of China's teaching profession and women's enhanced collaborative learning orientations. Age-related patterns demonstrate that younger teachers (under 30) exhibit the highest AI literacy levels, with sharp declines observed after age 40. This supports ecological systems theory's emphasis on environmental resource availability and suggests generational digital divide effects (Lim, 2023).

Geographic disparities reveal significant urban-rural differences in AI literacy, reflecting what we term "digital ecosystem disparities." Urban schools typically possess richer technological microsystems and superior access to macrosystem policies. Subject-based variations (science teachers outperforming liberal arts teachers) indicate that disciplinary cultures influence technology adoption, with STEM fields potentially establishing more favorable mesosystem connections to AI technologies.

5.3 Self-efficacy: The Linchpin

Teacher self-efficacy (TSE) shows partial mediating effects ($\beta = 0.259$, $p < 0.001$), which confirm Hypothesis 3. Social cognitive theory holds self-efficacy is an important factor in behavioral change (Bandura, 1986). Teachers with high self-efficacy tend to see AI as an opportunity rather than a threat and display exploratory behaviors to improve their competencies (Hartinah et al., 2020). School exerts influence on AI literacy directly ($\beta = 0.270$) and indirectly through self-efficacy ($\beta = 0.295 \times 0.259 = 0.076$), indicating partial mediation in which schools affect teachers' AI literacy through two pathways: resource provision and confidence building.

Schools can improve teacher self-efficacy by implementing interventions reflecting Bandura's four sources of self-efficacy: (1) hierarchical teacher training programs providing mastery experiences (Martins & Von Wangenheim, 2022); (2) peer mentoring systems offering teachers modeling and vicarious experiences along with emotional support (Alam, 2021); (3) administrative recognition and social persuasion towards teachers' AI integration practices; and (4) comprehensive technical support systems reducing implementation and facilitate emotional regulation (Street, 2013).

5.4 The Non-significant Social Pathway

The non-significant direct effect of social environment on AI literacy ($\beta = 0.066$, $p = 0.362$) carries theoretical significance as it challenges assumptions regarding policy effectiveness, failing to support Hypothesis 5. This finding suggests that distal policy interventions may prove ineffective without translation through school-level mediations, aligning with Bronfenbrenner's mesosystem emphasis. It implies that macrosystem variables—including national AI policies, media discourse, and public attitudes—may insufficient to influence teacher competencies without proximal mediation mechanisms.

This pattern may reflect implementation gaps in China's AI education policies. While the State Council's "AI Development Plan" (2017) established clear objectives for teacher training in AI education, resource allocation and support mechanisms vary considerably across regions. Additionally, social environment effects may operate on longer time scales than captured in this cross-sectional study, as policies possess inherent lifecycles requiring years to reach educational practice. Within Chinese educational contexts, social influences may traverse multiple administrative hierarchies, diminishing direct effects while strengthening indirect pathways through school leadership (Sui et al., 2020; Vestrucci, Lumbreras & Oviedo, 2021).

The findings strongly support Bronfenbrenner's (2000) ecological systems theory, suggesting that connections between microsystems (school-community linkages) may be more meaningful than isolated macrosystem effects. The indirect effect of social environment through school environment ($\beta = 0.245 \times 0.270 = 0.066$) indicates that when social policies fail to reach schools effectively, their intended impacts may never materialize. This contrasts with studies in federalized systems such as Germany or Australia, where direct effects were observed (Niemann, Eickelmann & Drossel, 2025), or Finland, where indirect effects successfully bridged macro and micro levels through robust school-community partnerships (Malone, 2020).

5.5 Theoretical Integration Within Ecological Systems Framework

Ecological systems theory posits that microsystem environments are primary environments for development. Schools are immediate and prolonged interaction environments where teachers obtain resources, training, and peer support for development of AI literacy. Significant positive correlations between school and social environments ($\beta = 0.245$) show that effective AI literacy development requires connection at the meso level of ecological systems, including school-based initiatives that connect with broader social support systems such as policy contexts, community resources, and peer networks.

Schools have the indirect effect of social environment on teacher development through school environment ($\beta = 0.066$) shows that macrosystem variables such as culture and values, policy, and technology do influence conditions at the school level where teachers are developed indirectly. Findings on demographic patterns show that historical timing of technology use leads to current competencies. Cohort effects (age $r = -0.06$) urge stage-tailored support, integrating ecological layers for holistic AI literacy growth.

6. Conclusion and Implications

In this study, structural equation modeling was used to explore ecological predictors of AI literacy among Chinese K-12 teachers. Findings show moderate levels of AI literacy (M = 3.89 out of 5), with a theory-practice gap: teachers display stronger performance in AI awareness ($\beta = 0.75$) and ethics ($\beta = 0.76$) but significant weaknesses in practical application ($\beta = 0.72$) and evaluation skills ($\beta = 0.81$). The ecological analysis shows that school teaching environment exerts the strongest direct effects on AI literacy ($\beta = 0.270$, $p < 0.01$), while teacher self-efficacy is a significant mediator ($\beta = 0.259$, $p < 0.01$). Notably, social environment shows no significant direct effects ($\beta = 0.066$, $p = 0.362$), suggesting that distal policy influences require proximal school-level mediation to impact teacher competencies.

6.1 Implications for Government and Policy Makers

Given the non-significant direct effect of social environment, policy makers should focus less on developing macro-level policies and more on providing concrete school-level support by providing funding for school infrastructure and training programmes. Considering the steep decline in AI literacy after the age of 40, cohort-specific interventions should be provided for different age groups, including mentorship systems and age-appropriate professional development programmes.

Policy recommendations are as follows: (1) build regional AI education resource centres to assist schools in implementing programmes; (2) design differentiated funding policies to address urban-rural divides; (3) construct cohort and career-stage-specific professional development frameworks; and (4) build policy monitoring systems that focus on school-level outcomes instead of system-level inputs.

6.2 Implications for School Leaders

Given that school is one of the significant predictors of AI literacy ($\beta = 0.270$), school leaders play a critical role in shaping enabling environments for AI integration. However, considering that not all schools have the infrastructure, funding, or policy support to implement AI technologies immediately. Therefore, school leaders should adopt a phased and context-sensitive approach when promoting AI literacy. Schools with greater resources may gradually introduce designated AI learning spaces, structured collaboration opportunities, and technical support systems. School leaders should implement programmes that address the four sources of Bandura's model of self-efficacy, including scaffolded mastery experiences, peer modelling opportunities, administrative encouragement and stress-reduction activities: (1) developing school-based AI integration strategic plans; (2) peer modelling through classroom observations and lesson planning; (3) establishing technical support protocols for AI tool implementation; (4) developing stress-reduction activities to mitigate technology-related anxiety.

6.3 Implications for Teachers

As teachers are the strongest predictors of AI literacy ($\beta = 0.72$ and $\beta = 0.81$), they should actively engage in AI literacy enhancement and maximise self-efficacy development. Recognizing barriers to advanced AI tool access, emphasis should be placed on foundational AI knowledge, pedagogical adaptations using accessible open-source resources, and self-directed growth. To bridge competency gaps, teachers can prioritize: (1) engaging in experiential AI training via open-access tools or platforms; (2) constructing practical and context-appropriate criteria to evaluate AI-generated content; (3) joining peer collaboration networks to share insights and teaching practices; (4) exploring subject-specific integration strategies that align with available resources; (5) cultivating a growth mindset to stay informed about evolving AI developments.

7. Limitations and Future Research

This study is subject to two principal limitations. First, the sample was predominantly drawn from a central Chinese province—strategically selected as a "middle" region to approximate national averages in socioeconomic development and educational infrastructure, thereby capturing a representative midpoint in AI literacy distribution. While this purposive choice mitigated extremes associated with coastal metropolises or remote western areas, the geographic concentration nonetheless constrains generalizability to China's heterogeneous regional contexts, including more affluent eastern provinces (e.g., Guangdong) or agrarian western ones (e.g., Gansu). Compounding this, the non-random sampling further tempers extrapolative claims. Future research should prioritize probability-based sampling across multifaceted strata, encompassing diverse provinces, urban-rural locales, and institutional archetypes, to bolster external validity. Second, the reliance on cross-sectional quantitative data precludes causal inferences or temporal dynamics. Subsequent studies should integrate mixed-methods approaches, including qualitative explorations of lived experiences and longitudinal tracking of AI literacy evolution, to illuminate developmental pathways. Notwithstanding these constraints, the substantive findings retain robustness within the sampled context.

AI Statement: No AI tools were used in the preparation of this manuscript. All aspects of the work were completed solely by the authors, who take full responsibility for the originality, accuracy, and integrity of the content.

Ethics Statement: All subjects gave their informed consent for inclusion before they participated in the study. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethics Committee of Ajman University (Reference number: H-F-H-3—A) on 31 August 2023.

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Appendix 1: Questionnaire

Basic information

1. Your gender is

□Male □Female

2. Your school location is

□rural

□suburban

□urban

3.Your educational background is

□Below Bachelor

□Bachelor

□Postgraduate

4. Your age is

□≤30 years old

□31–40 years old

□41–50 years old

□≥51 years old

5.Your title is

□Beginner

□Intermediate

□Deputy Senior

□Senior

6.Your teaching subject is

□Liberal Art

□Science

□Others

Knowing and Understanding AI

1. I am able to discern between smart and non-smart instructional equipment.

2. I am aware of how AI in education may benefit me.

3. I can recognise AI technology in goods or services that are intended for use in education.

4. When utilising educational AI goods, I feel at ease.

5. In Smart era, I believe that educators should actively learn how to employ sophisticated technology to support learning and teaching.

Applying AI

1. I am competent in using educational AI tools to assist me in my day-to-day teaching activities.

2. I can pick up new educational AI products rather quickly.

3. I can increase the effectiveness of my instruction by using educational AI solutions.

4. I may assist and direct pupils as they use instructional AI products.

5. I can use curriculum teaching and educational AI technologies.

Evaluating AI Application

1. I am proficient in utilising educational AI technologies to help me with my daily teaching tasks.

2. I am quite fast to take up new educational AI goods.

3. By using educational AI technologies, I can improve the efficacy of my lesson.

4. I may guide and help students while they utilise educational AI goods.

5. I am capable of using curriculum teaching and AI technology in education.

AI Ethics

1. When using educational AI products, I always abide by ethical standards.

2. I pay close attention to privacy, information security, and other problems while utilising educational AI products.

3. I'm concerned about the abuse of educational AI.

4. When implementing instructional AI technology, I constantly take safety and ethical concerns into account.

5. I have the ability to quickly spot ethical lapses in the use of artificial intelligence in the classroom.

School Teaching Environment

1. The school can meet the requirements of intelligent teaching hardware facilities (such as touch screen electronic whiteboard, interactive all-in-one computer, etc.).

2. The school can meet the requirements of intelligent teaching related software.

3. The school attaches great importance to the application of intelligent technology in teachers' teaching.

4. The school provides teachers with training opportunities to improve their intelligent educational literacy.

Social Environment

1. My province has clearly proposed policies or action plans related to teachers' intelligent educational literacy.

2. The district where I teach gives full financial support to the application of intelligent technology in teaching.

3. The region where I teach gives full publicity and support to the application of intelligent technology in teaching.

4. My district often holds events (such as smart technology teaching competitions, etc.) to encourage teachers to use smart technology in teaching.

5. My region often invites AI experts to conduct training activities.

Teacher Self-Efficacy

1. The application of intelligent technology in daily teaching will make the teaching effect double with half the effort.

2. Applying smart technology to everyday teaching will lead to better career development for me.

3. I am confident to choose the appropriate intelligent technology for course teaching according to the new curriculum standards.

4. By choosing the right smart technology, I can effectively promote student learning and improve the effectiveness of classroom teaching.

5. I think my own intelligent education quality can be effectively improved through teacher training and other ways.

