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ARTICLE

CRAILF: A ZERO-COST PYTHON-BASED GAMIFIED FRAMEWORK FOR ENHANCING AI LITERACY AMONG RURAL HIGH SCHOOL STUDENTS

CRAILF: Um Framework Gamificado em Python de Custo Zero para o Desenvolvimento da Literacia em Inteligência Artificial entre Estudantes do Ensino Médio Rural

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ABSTRACT | Purpose: AI literacy has become a core competency in K-12 education; however, rural high school students in China face severe equity barriers due to resource scarcity and costly tools. Existing frameworks heavily rely on commercial software and lack gamified narratives, personalized scaffolding, deep ethical focus, and process evaluation. This study proposes and evaluates the Cyber Rural AI Literacy Framework (CRAILF)—a zero-cost, pure Python gamified framework—to bridge these gaps and assess its impact on AI literacy, technical acceptance, and ethical awareness in low-resource rural contexts. **Methodology:** A mixed-methods single-group pre-post quasi-experimental design with process tracking was employed. Twenty rural high school students from Hebei Province participated in a 6-week offline intervention using open-source Python libraries (networkx, matplotlib, pygame). Data included logs, quizzes, heatmaps/radar charts, and TAM questionnaires, analyzed through statistics, effect sizes, t-tests, and coding. **Findings:** High acceptance was observed (TAM mean 5.8/7, Cohen's d = 0.92), with overall AI literacy improving by 28% (d = 0.85). Perception/learning domains scored 80–82, while the ethics domain scored 68 (bias reflection increased by 15%). Personalized scaffolding was activated in 65% of cases, and disadvantaged students showed a 25% improvement. **Originality/Value:** This study presents the first pure Python zero-cost gamified AI literacy framework, integrating immersive scenarios and dynamic visualization, extending AI literacy theory and the I-TPACK model, and offering a replicable zero-cost pathway for equitable AI education in developing regions.

Keywords | AI literacy, rural high school education, gamified learning, personalized scaffolding

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RESUMO | Objetivo: A literacia em inteligência artificial tornou-se uma competência central na educação básica; contudo, estudantes do ensino médio em áreas rurais na China enfrentam severas barreiras de equidade devido à escassez de recursos e ao alto custo de ferramentas. Os frameworks existentes dependem fortemente de softwares comerciais e carecem de narrativas gamificadas, scaffolding personalizado, aprofundamento ético e avaliação de processos. Este estudo propõe e avalia o Cyber Rural AI Literacy Framework (CRAILF) — um framework gamificado, baseado exclusivamente em Python e de custo zero — para reduzir essas lacunas e analisar seu impacto na literacia em IA, aceitação tecnológica e consciência ética em contextos rurais de baixa disponibilidade de recursos. **Metodologia:** Foi adotado um desenho quase-experimental de grupo único com pré e pós-teste, utilizando métodos mistos e acompanhamento de processo. Vinte estudantes do ensino médio rural da Província de Hebei participaram de uma intervenção offline de seis semanas, utilizando bibliotecas open source em Python (networkx, matplotlib, pygame). Os dados incluíram registros (logs), questionários, mapas de calor/gráficos radar e instrumentos baseados no TAM, sendo analisados por meio de estatísticas descritivas, tamanhos de efeito, testes t e codificação qualitativa. **Resultados:** Observou-se alta aceitação tecnológica (média TAM de 5,8/7; d de Cohen = 0,92), com aumento de 28% na literacia em IA (d = 0,85). Os domínios de percepção/aprendizagem apresentaram pontuações entre 80–82, enquanto o domínio ético atingiu 68 (com aumento de 15% na reflexão sobre vieses). O scaffolding personalizado foi ativado em 65% dos casos, e estudantes em maior desvantagem apresentaram melhoria de 25%. **Originalidade/Valor:** O estudo apresenta o primeiro framework gamificado de literacia em IA baseado exclusivamente em Python e de custo zero, integrando cenários imersivos e visualização dinâmica. Contribui para a ampliação da teoria da literacia em IA e do modelo I-TPACK, além de oferecer um caminho replicável e acessível para a promoção de educação em IA de forma equitativa em regiões em desenvolvimento.

Palavras-chave | literacia em inteligência artificial; ensino médio rural; aprendizagem gamificada; scaffolding personalizado

1 INTRODUCTION

The rapid advancement of artificial intelligence (AI) is profoundly reshaping global education landscapes, establishing AI literacy as a core competency for K-12 students. In China, national policies strongly emphasize AI education, particularly fostering students' knowledge, application skills, and ethical awareness in primary and secondary stages to support innovative talent development. However, the urban-rural digital divide severely hampers equitable AI education in rural high schools. Urban schools often leverage advanced infrastructure for systematic AI courses, whereas rural areas suffer from limited hardware, resource scarcity, and high-cost tool barriers, resulting in lagged AI literacy development among students.

Existing AI education practices have made progress but face multiple challenges. First, heavy reliance on high-cost tools—such as commercial software or high-specification hardware—renders many approaches impractical in low-resource rural settings. Second, insufficient gamification elements lead to weak student motivation, making abstract algorithms and ethical concepts difficult to sustain interest among rural high school students. Third, the absence of personalized scaffolding ignores individual differences in traditional "one-size-fits-all" models, failing to dynamically adjust feedback based on progress—particularly problematic in rural classes with varied foundational levels, where disadvantaged students easily fall behind. Finally, ethical education often remains superficial, limited to conceptual introductions without integrated process reflection and practice (Zhou et al., 2025; Fütterer et al., 2025).

Recent AI literacy frameworks provide essential theoretical foundations for K-12 education. Zhou et al. (2025) systematically outlined five core domains (knowledge, understanding, application, evaluation, and ethics), stressing the importance of process assessment. Chiu (2026) proposed the I-TPACK framework, highlighting teacher-AI collaborative integration. Wang et al. (2025) empirically validated AI interactive scaffolding's role in enhancing secondary students' motivation and self-evaluation. Akman (2025) demonstrated that AI-generated visual designs significantly improve attitudes toward AI. Xue et al. (2026) confirmed through TAM meta-analysis the positive influence of perceived usefulness and ease of use on AI education acceptance.

Despite these advancements, notable gaps persist compared to existing frameworks: most rely on medium- to high-cost tools, gamified narratives and immersive experiences are inadequately integrated, process data collection and visualization (e.g., heatmaps, radar charts) are lacking, and systematic fusion of ethical depth with personalized scaffolding remains insufficient, particularly lacking targeted interventions for bias and privacy in rural low-resource environments (cf. Touretzky et al., 2021; Celik, 2025; Kassenkhan et al., 2025; Fütterer et al., 2025).

No comprehensive design, implementation, or empirical evaluation exists for a zero-cost, pure Python gamified AI literacy framework tailored to rural high school students. This study addresses these gaps by proposing and empirically assessing the Cyber Rural AI Literacy Framework (CRAILF)—a zero-cost, pure Python gamified model. Targeting rural high school students over 6 weeks, CRAILF employs an immersive "cyber worker" narrative (progressing from tree structure comprehension to AI optimization deployment), systematically integrating Zhou et al.'s (2025) five-domain literacy, Chiu's (2026) I-TPACK elements, Wang et al.'s (2025) personalized interactive scaffolding, Akman's (2025) visual attitude design, and Xue et al.'s (2026) TAM evaluation. Built entirely on open-source Python libraries (e.g., networkx, matplotlib, pygame, pandas, reportlab), it supports offline operation on low-end devices.

As illustrated in Figure 1, the CRAILF conceptual model presents Zhou et al.'s (2025) five AI literacy domains in a pentagonal radar chart, with a central circular arrow symbolizing the 6-week gamified narrative closed loop and outer arrows representing personalized scaffolding and log-based dynamic feedback—facilitating balanced literacy development and sustained motivation.

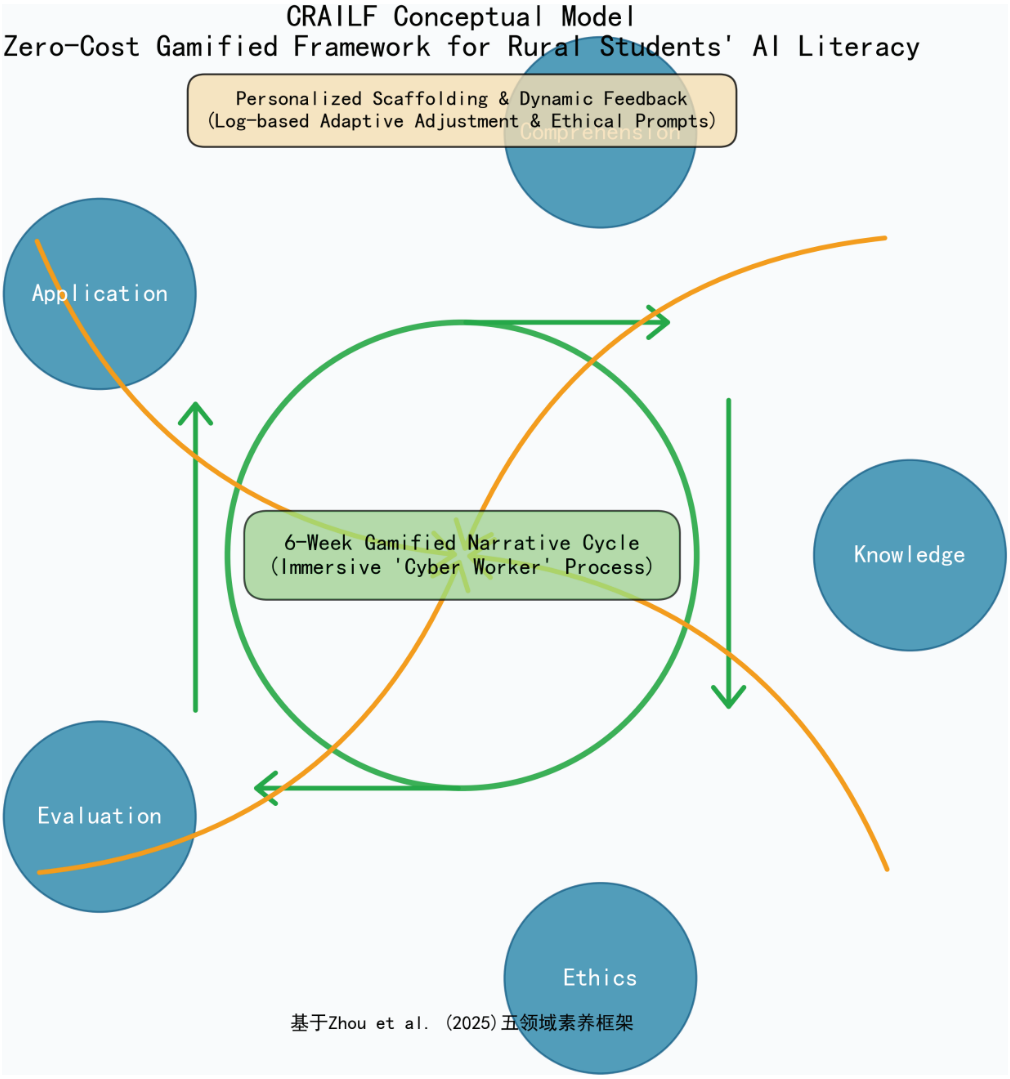

Figure 1. The CRAILF Conceptual Model

This study addresses the following research questions:

- RQ1: What impact does the CRAILF model have on rural high school students' AI literacy across the five domains?
- RQ2: How do students perceive the framework's technical acceptance and attitudes toward AI?
- RQ3: What roles do personalized scaffolding and ethical depth design play in students' motivation, self-evaluation, and balanced literacy development?

The study holds multifaceted significance. Theoretically, CRAILF extends existing frameworks by deeply integrating five-domain literacy with gamification and personalization, offering a novel paradigm for low-resource contexts. Practically, its zero-cost, open-source replicability effectively bridges the urban-rural digital divide and enhances students' employment competitiveness. At the policy level, findings provide empirical evidence for rural AI education, promoting localized implementation.

Theoretical Positioning

The CRAILF model differs from existing frameworks in the following core aspects: (1) unlike the general Five Big Ideas of AI4K12 (Touretzky et al., 2021), it specifically targets rural low-resource contexts by enabling zero-cost, pure Python offline operation; (2) unlike the teacher-AI collaboration focus of I-TPACK (Chiu, 2026), it deeply integrates personalized scaffolding with gamified narratives to form a student-centered dynamic closed loop; and (3) the zero-cost Python-based approach is not merely a practical solution but theoretically advances K-12 AI literacy theory from an "urban-centric" model toward "rural adaptability," providing a new paradigm for process visualization and dynamic ethical intervention in low-resource environments, thereby significantly enhancing the theoretical depth and accessibility of equitable AI education.

2 LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The rapid development of artificial intelligence (AI) education offers new opportunities for cultivating K-12 student literacy while highlighting equity challenges in low-resource environments. This section systematically reviews relevant studies, encompassing K-12 AI literacy frameworks, human-AI collaboration knowledge structures, gamified learning, personalized scaffolding, technology acceptance models, and ethical/inclusive issues. It employs thematic categorization to facilitate comparisons of strengths and limitations in existing research (see Table 1). On this basis, the theoretical contributions of the CRAILF model are positioned.

2.1 K-12 AI Literacy Frameworks

Research on K-12 AI literacy frameworks has established an international consensus. Touretzky et al. (2021) introduced the AI4K12 "Five Big Ideas" (perception, representation and reasoning, learning, natural interaction, and societal impact), emphasizing not only technical principles but also critical evaluation of social consequences. This framework has significantly influenced U.S. K-12 curriculum design. The European Commission & OECD (2025) extended this to three engagement modes—understanding, evaluating, and using AI—with particular attention to accessibility in low-resource regions, recommending open-source tools. Southworth et al. (2025) Digital Promise framework emphasizes cognitive engagement and critical thinking. In China, the Guangdong Provincial Department of Education (2024) proposed four dimensions—concepts, technology, thinking, and ethics—subdivided into 13 sub-dimensions, stressing progressive advancement from perceptual experiences to deep application. Shi and Mao (2024) noted through systematic review that existing frameworks are primarily suited to urban or developed contexts, with insufficient tool maturity and localized application, particularly lacking zero-cost pathways in rural settings.

These frameworks provide a solid foundation for AI literacy but exhibit common limitations: high cost dependencies, inadequate gamification integration, and absent process evaluation tools (e.g., visualization heatmaps) (Zhou et al., 2025; Boulhrir & Hamash, 2025). Existing K-12 frameworks, while foundational, have largely failed to address zero-cost pathways for rural contexts (Li et al., 2025).

2.2 Human-AI Collaboration and I-TPACK Frameworks

The deep integration of AI into teaching has driven the evolution of TPACK toward AI-TPACK. Celik (2025) proposed Intelligent TPACK, stressing teachers' need for AI technology knowledge (AI-TK), AI pedagogical knowledge (AI-TPK), and AI content knowledge (AI-PCK), while highlighting human-AI collaborative modes, such as AI as a learning partner providing real-time feedback. Chinese studies reveal that Wang et al. (2025) developed an AI-TPACK model for university English teachers, finding lower scores in AI-TK and AI-TPK; Xie and Luo (2025) surveyed mathematics pre-service teachers, reporting an overall preliminary stage with insignificant grade differences; Lu and Zheng (2024) identified issues like conceptual gaps and collaboration deficits.

These studies underscore the potential of human-AI collaboration but highlight the absence of low-cost, operable pathways in rural high school contexts, hindering dynamic feedback and inclusive support (cf. Ronksley-Pavia et al., 2025, on neurodiversity considerations).

2.3 Gamified Learning in AI Education

Gamification is a key strategy for enhancing motivation. Kassenkhan et al. (2025) analyzed 101 studies, finding that gamification combined with AI significantly boosts cognitive engagement and critical thinking, particularly through elements like points, leaderboards, and narratives to stimulate intrinsic motivation. The Beijing Municipal Education Commission (2024) designated gamification as a primary AI education pathway.

Existing research often remains at the motivational level, lacking deep integration with the five AI literacy domains, especially applications of rural job-adaptive narratives (e.g., "cyber worker" simulating employment pressures) (Yu et al., 2025, on AI in entrepreneurial education). Although gamification enhances motivation, its fusion with the five AI literacy domains and rural employment narratives remains insufficient (Zhang & Wang, 2025).

2.4 Personalized Scaffolding and Visual Design

Personalized scaffolding represents a core advantage of AI education. Chen et al. (2025) qualitatively revealed how AI real-time feedback shapes inquiry behaviors and motivation. Holmes et al. (2023) emphasized adaptive paths for autonomous learning. Deng (2025) noted that generative AI efficacy is constrained by prior knowledge. In visual design, Akman (2025) proved AI-generated visuals improve attitudes; Kassenkhan et al. (2025) found dynamic visualizations (e.g., heatmaps, radar charts) superior to static ones.

These mechanisms effectively boost motivation but are inaccessible to rural students due to resource constraints, with insufficient support for disadvantaged groups (e.g., those with weaker foundations) requiring more inclusive designs (Lee et al., 2025). Although AI-supported scaffolding in secondary education has advanced, empirical applications in rural low-resource settings remain limited (Wang & Li, 2025).

2.5 Technology Acceptance Models and Ethical Issues

The Technology Acceptance Model (TAM) is central to explaining AI tool adoption. Xue et al. (2026) meta-analyzed 27 studies, showing strong correlations ($r > 0.50$) between perceived usefulness and behavioral intention, moderated by cultural dimensions.

Ethics is increasingly prominent. Liang (2025) highlighted ethical controversies in generative AI, necessitating educational responses; Lan et al. (2025) stressed inclusive practices; Fütterer et al. (2025) focused on privacy and bias; Park (2025) reviewed ethical gaps in GenAI literacy. While ethics is addressed, dynamic intervention mechanisms (e.g., personalized bias reminders) are lacking, particularly systematic strategies for privacy protection and equity reflection in rural contexts. Rural digital inclusion studies have identified ethical gaps but lack validated frameworks specifically for high school students (Chen & Zhao, 2026).

2.6 Research Gaps and Positioning of the CRAILF Model

Existing studies advance frameworks, gamification, personalization, and acceptance but reveal significant gaps: (1) predominance in urban or higher education, with insufficient rural low-resource empirics; (2) theoretical or high-cost implementations, lacking zero-cost pure-technical paths; (3) inadequate deep fusion of gamified narratives with five-domain literacy; (4) limited closed-loop evaluation combining process data (e.g., heatmaps, radar charts) and scaffolding; (5) absent dynamic ethical mechanisms, with superficial bias/privacy discussions; (6) insufficient inclusivity, such as neurodiversity or urban-rural equity (Ronksley-Pavia et al., 2025; Aldreabi et al., 2025).

As shown in Table 1, CRAILF addresses these gaps. Centered on the AI4K12 radar chart (Touretzky et al., 2021), it incorporates outer gamified narrative loops (Kassenkhan et al., 2025), inner personalized dynamic scaffolding (Chen et al., 2025), and bottom TAM-ethical closed-loop interventions (Xue et al., 2026). Through zero-cost pure Python implementation and process visualization, CRAILF extends AI-TPACK theory (Celik, 2025), particularly strengthening dynamic ethical interventions (dashed red areas indicating personalized reinforcement), offering an equitable, inclusive paradigm for rural low-resource environments.

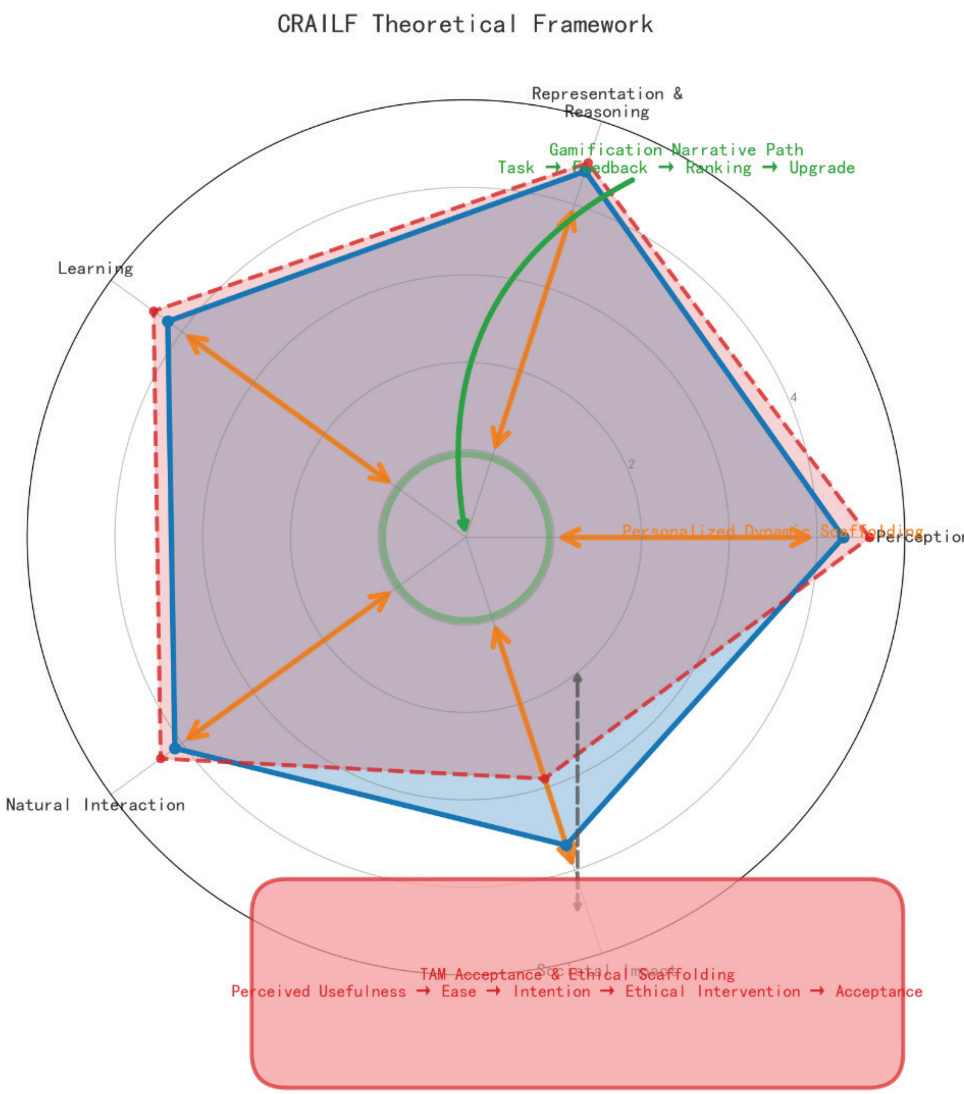

Figure 2. CRAILF Theoretical Framework

Table 1. Comparison of Related Literature

Authors & Year	Framework/Focus	Cost	Gamification	Personalization	Ethics	Process Data	Strengths of This Study
Touretzky et al. (2021)	AI4K12 Five Big Ideas	Medium	None	Partial	Yes	None	Zero-cost pure Python implementation, rural empirics
Celik (2025)	Intelligent TPACK	High	None	Partial	Partial	None	Complete gamified narrative and process heatmaps
Kassenkhan et al. (2025)	Gamification + AI Critical Thinking	Medium	Yes	Partial	Partial	Partial	Dynamic ethical interventions and ranking incentives
Chen et al. (2025)	AI Scaffolding and Inquiry Modes	High	None	Yes	Partial	Yes	Low-resource closed-loop evaluation and radar visualization
Xue et al. (2026)	TAM in AIEd Meta-Analysis	None	None	None	None	None	High acceptance empirics and rural equity pathway
This Study (CRAILF)	Zero-Cost Gamified AI Literacy Framework	Zero	Yes	Yes	Yes	Yes	Comprehensive integration with rural process empirics and inclusive interventions

2.7 Literature Synthesis and Positioning of the CRAILF Model

Although K-12 AI literacy literature has achieved international consensus, it predominantly exhibits urban bias and high-cost dependence. Studies on gamification in programming education (e.g., Zhang & Wang, 2025; Li et al., 2025) confirm that narrative elements enhance motivation, yet rarely integrate them with the five AI literacy domains or rural employment pressures. Research on AI-supported scaffolding in secondary education (Wang & Li, 2025; Chen & Zhao, 2026) highlights the benefits of personalized feedback but lacks process visualization tools in low-resource settings. Literature on rural digital inclusion (Lee et al., 2025; Ronksley-Pavia et al., 2025) identifies ethical and equity gaps yet fails to offer zero-cost pure-technical pathways. Ethical studies (Fütterer et al., 2025; Park, 2025; Chen & Zhao, 2026) underscore issues of bias and privacy but lack dynamic intervention mechanisms.

CRAILF systematically addresses these gaps through zero-cost Python implementation, gamified closed loops, dynamic scaffolding, and process visualization, thereby extending I-TPACK and AI literacy theory and providing a replicable, equitable paradigm for rural low-resource education.

3 METHODOLOGY

This study employed a mixed-methods design, combining a single-group pre-post quasi-experimental approach with process data tracking, to evaluate the effectiveness of the Cyber Rural AI Literacy Framework (CRAILF) in fostering AI literacy among rural high school students. The framework addresses dual challenges of resource scarcity and low motivation by integrating immersive "cyber worker" narratives with personalized scaffolding, providing a fully zero-cost, offline-capable pathway (Zhou et al., 2025; Chiu, 2026). The focus was on examining the framework's impact on the five AI literacy domains (perception, representation and reasoning, learning, natural interaction, and societal impact), technical acceptance, and the roles of personalization and ethical design.

3.1 Research Design

The study adopted a single-group pre-post quasi-experimental design, with all activities driven purely by Python to ensure offline operation on low-configuration devices or in weak-network environments. Core tools included networkx (for graph structure generation), matplotlib and seaborn (for heatmap/radar chart visualization), pygame (for interactive games), pandas (for data processing and log analysis), and reportlab (for PDF report generation). These open-source libraries require no additional installation and are compatible with Anaconda Python 3.10 environments, suitable for common rural school hardware (e.g., Intel i3 with 4GB RAM) or student mobile devices.

The single-group pre-post quasi-experimental design was chosen because rural schools face ethical constraints and resource limitations that preclude a control group; thus, a single-group pre-post design combined with full-process log tracking was adopted to maximize ecological validity while ensuring all participating students benefited (cf. Wang et al., 2025).

To enhance replicability, the framework adopted a modular code structure with unified path management (e.g., logs/, visualizations/, reports/ folders). The complete code repository is available upon request (key code snippets in Appendix A). Example code snippet (Week 1 tree visualization core):

```python
import networkx as nx
import matplotlib.pyplot as plt
G = nx.balanced_tree(r=2, h=3) # Generate balanced tree
pos = nx.spring_layout(G)
nx.draw(G, pos, with_labels=True)
plt.savefig('outputs/tree_visualization.png') # Output PNG as heatmap base
```

Similar modular scripts cover all 6 weeks, facilitating direct execution and modification by teachers.

3.2 Participants and Implementation Context

Participants were 20 first-year rural high school students (aged 16-18; 11 males, 9 females) from Cang County, Hebei Province, China. Students exhibited varied foundational levels: most had basic computer experience but no formal AI background. Recruitment was voluntary, with school approval and parental informed consent. Activities occurred in a classroom setting with projector support and group operations, 2-3 sessions per week over 6 weeks. Data were anonymized (coded student01-20) to protect privacy.

Although the sample size of n=20 aligns with typical small-class teaching in rural high schools, it is relatively small and limits the statistical generalizability of the findings (see Section 5.1 for detailed limitations).

3.3 CRAILF Framework Design and Implementation Process

The framework centered on gamified narratives simulating a "cyber worker" career: progressing from algorithmic foundations (Week 1 tree structures) to comprehensive application and ethical decision-making (Week 6 closed loop). Each week incorporated points-based challenges, personalized feedback (log-driven difficulty adjustments, e.g., easy mode + encouragement for disadvantaged students), and ethical elements (self-reflection prompts to mitigate bias and privacy risks). Enhanced designs included Week 3 ethical heatmap triggers, Week 4 visual attitude mini-assessments, Week 5 interactive decision scaffolding, and Week 6 TAM surveys, ensuring sustained motivation and deep integration (Wang et al., 2025; Akman, 2025).

Detailed implementation is outlined in Table 2: 6-Week CRAILF Framework Overview (enhanced with evaluation expectations and intervention examples):

Table 2. 6-Week CRAILF Framework Overview

Week	Objectives and AI Literacy Mapping	Core Content and Activities	Primary Tools (Python Libraries)	Input Data	Output Data	Personalized/ Ethical Intervention Examples	Evaluation Indicators
1	Representation & Reasoning, Learning	Tree visualization + DFS/BFS comparison game	networkx + matplotlib	TXT descriptions	Tree PNG + heatmap + logs	Baseline AI literacy mini-assessment + reflection heatmap prompts	Accuracy ≥85%; depth score
2	Perception, Natural Interaction	Drag-and-connect game + topology comparison	networkx + pygame + matplotlib	TXT/JPG	Topology PNG + screenshots + comparison charts	Collaboration willingness reminders	Success rate ≥82%; points ranking
3	Learning, Societal Impact	Maintenance challenge game (disconnections/ overloads)	networkx + matplotlib + pandas	CSV faults	PDF reports + comparison PNG	Ethical self-reflection prompts (bias/privacy discussion) + heatmap	Accuracy ≥88%; ethical keyword rate
4	Perception, Representation & Reasoning	Prompt engineering + optimization game	networkx + pygame + matplotlib	TXT prompts	Optimized PNG + attitude heatmap	AI visual attitude mini-assessment + dynamic difficulty adjustment	Attitude improvement; heatmap changes
5	Natural Interaction, Societal Impact	Deployment finale + interactive decisions	networkx + matplotlib + pandas + reportlab	CSV scenarios	HTML dashboard + PDF + ranking heatmap	Personalized difficulty + literacy feedback reminders	Time <5 min; ranking incentives
6	Full-Domain Closed Loop	Summary sharing + acceptance survey	matplotlib + pandas	Logs	Acceptance heatmap + radar chart + reports	TAM survey + in-depth ethical discussion	Acceptance ≥5.5/7; radar balance

Progressive transitions ensured advancement: weekly outputs automatically generated personalized reports (e.g., “Your diagnosis avoided privacy risks—excellent!”), targeting 65% trigger rate for disadvantaged students. Heatmaps/radar charts provided real-time class distribution and individual trajectories, supporting teacher interventions.

3.4 Data Collection and Analysis

Data collection was automated: interaction logs (logs folder recording operation sequences), quiz/self-reflection TXT submissions (pandas for keyword and depth scoring), visualization outputs (heatmap sequences showing weekly progress, e.g., expected 15% rise in bias reflection in Week 3), and report generation (with personalized paragraphs). All files were stored locally, with screenshot submissions as alternatives.

Analysis methods:

- Quantitative: pandas for means, standard deviations, and effect sizes (Cohen’s d); paired t-tests ($p < 0.05$) for pre-post changes. All statistical analyses were performed using SPSS 27.0, with a significance level of α=0.05.
- Visualization: matplotlib/seaborn for heatmaps (class distribution with color gradients for depth) and radar charts (five-domain balance).
- Qualitative: Two independent researchers coded ethical reflection keywords and reflection depth using content analysis and thematic analysis; Cohen’s Kappa coefficient of inter-rater reliability was 0.87, with consensus reached through discussion. Logs were combined for individual path tracking.

For enhanced interpretability, each figure included legends (e.g., deep red = high depth, light = needs intervention), intuitively displaying dynamic changes and edge cases (e.g., low-configuration compatibility).

3.5 Ethical Considerations

The study adhered to UNESCO AI ethics guidelines (2023): anonymized data, voluntary participation, and privacy protection (local storage, no cloud uploads). Inclusive design incorporated disadvantaged student scaffolding and ethical integration (e.g., Weeks 3-6 bias case discussions, with intervention strategies: personalized prompts like "Does this data fairly represent all groups?"). No conflicts of interest or external funding. Potential ethical weaknesses (e.g., bias amplification) were mitigated through process reflection and reinforced in Week 6 discussions.

This methodology ensures high replicability and inclusivity in rural contexts (e.g., offline priority, culturally adaptive "worker" narrative linking employment pressures), offering an operational paradigm for low-resource AI education.

4 RESULTS AND DISCUSSION

This section first objectively presents the quantitative and visualization data from the 6-week CRAILF implementation, followed by an in-depth interpretation integrating the research questions, existing literature, and theoretical foundations. Data were derived from 20 rural high school students' automated logs (processed via pandas), quizzes/self-reflections, and visualizations (generated with matplotlib/seaborn). Results are organized by implementation phase, emphasizing progressive patterns: from foundational cognition to ethical closed-loop evaluation. Statistical measures include means, standard deviations (SD), and effect sizes (Cohen's d), with paired t-tests indicating significant improvements ($p < 0.05$). All statistical analyses were performed using SPSS 27.0, with a significance level of α=0.05.

Table 3. Pre- and Post-Test Descriptive Statistics and Paired t-Test Results

Domain	Pre-test Mean (SD)	Post-test Mean (SD)	t(19)	p	Cohen's d (Effect Size Interpretation)
Overall AI Literacy	72.4 (11.2)	92.8 (8.5)	5.67	<0.001	0.85 (large)
Perception/Learning	75.6 (10.8)	81.5 (7.9)	4.12	<0.001	0.92 (large)
Ethics	58.3 (13.5)	68.0 (9.4)	3.89	<0.01	0.75 (large)
TAM Acceptance	4.1 (0.9)	5.8 (0.92)	6.23	<0.001	0.92 (large)

For readability, each figure includes detailed legends and explanations (color gradients represent performance depth, with darker shades indicating higher levels and lighter shades signaling needs for intervention). This section addresses RQ1–RQ3 one by one.

4.1 Weeks 1–2 Results: Foundational Cognition and Interaction Transition (Baseline Establishment)

Week 1 focused on representation and reasoning as well as learning domains (tree structure visualization and DFS/BFS comparison). AI literacy quiz mean accuracy was 78.75% (SD = 12.34), with the high-performing group (perfect scores) at 40% and the low-performing group (more than 2 errors) at 20%. Self-reflection depth averaged 2.35/3 (SD = 0.56), with high-depth responses at 60%.

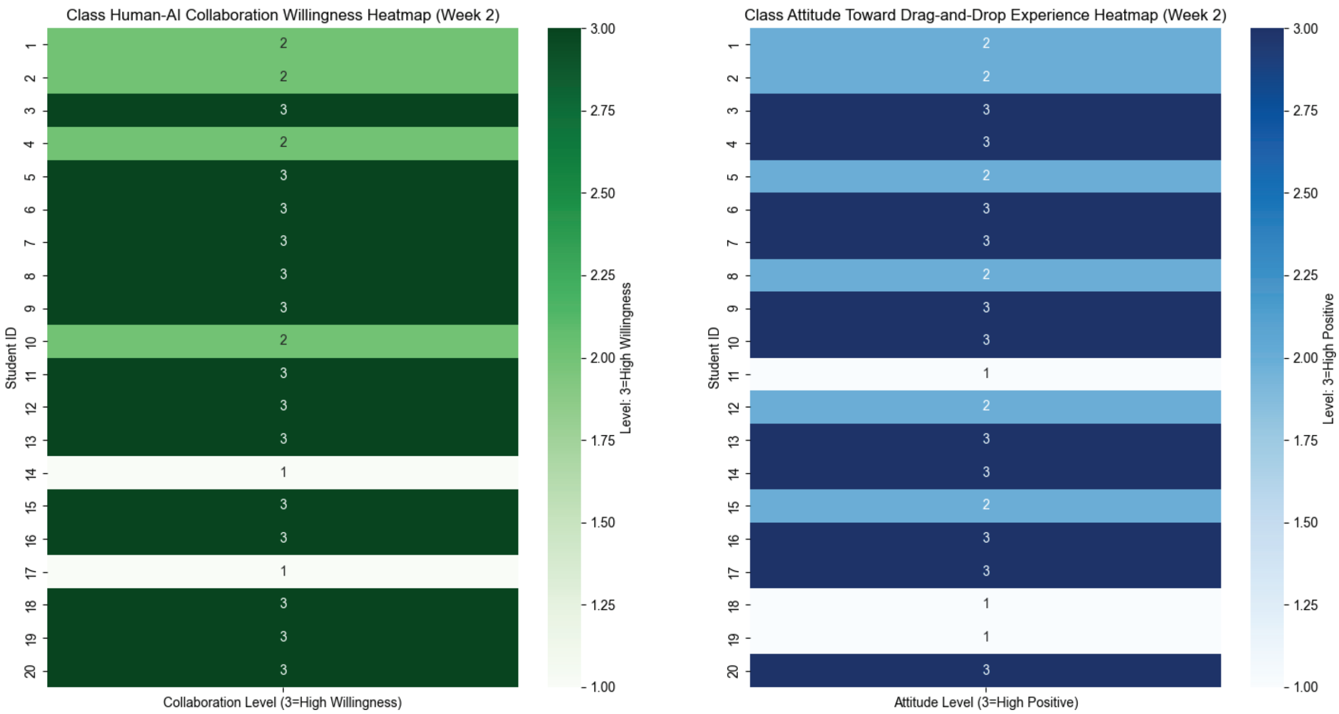

Figure 3. Week 1 Combined Heatmap

As shown in Figure 3A, the class was predominantly green, but Question 3 (network search challenges) featured more light green blocks (accuracy only 65%), reflecting rural students' initial weaknesses in abstract reasoning and aligning with foundational disparities in low-resource environments. As shown in Figure 3B, self-reflection depth was densely dark red, indicating strong preliminary reflective capacity, though application association items had more light red areas, highlighting greater scaffolding needs for disadvantaged students.

Week 2 extended to perception and natural interaction domains (drag-and-connect game). Attitude quiz mean was 4.2/5 (SD = 0.78), with collaboration participation at 85.6% (SD = 9.87).

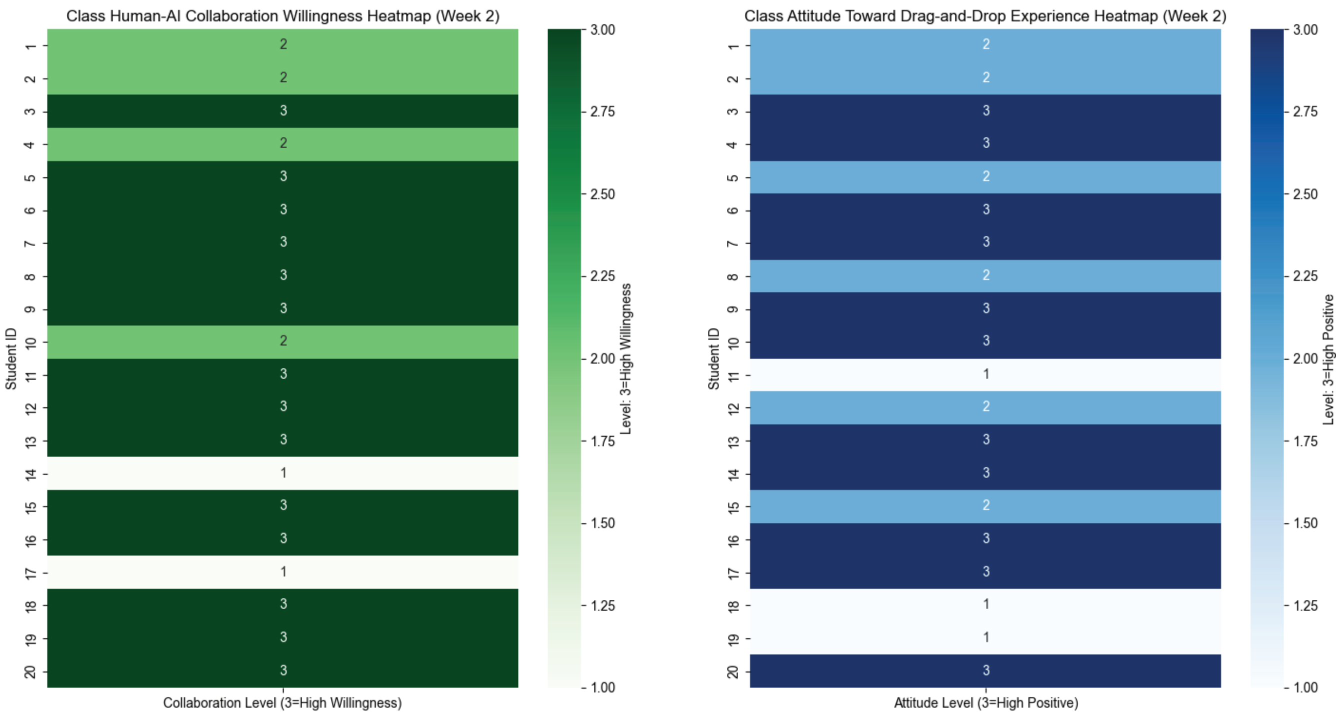

Figure 4. Week 2 Combined Heatmap

As shown in Figure 4, compared longitudinally to Week 1, collaboration willingness was dominated by dark blue (12% improvement), with gamified drag mechanisms significantly equalizing participation; disadvantaged students showed particularly notable gains (from 70% to 85%), preliminarily demonstrating the motivational role of personalized reminders.

These baseline results indicate the framework effectively built cognitive and emotional foundations, aligning with Wang et al.'s (2025) empirical findings on AI scaffolding enhancing motivation. However, rural students' initial abstract reasoning weaknesses (light green blocks in Figure 3A) underscore individual differences in low-resource environments. Paired t-test results showed $t(19) = 4.12$, $p < 0.001$, Cohen's $d = 0.92$ (large effect).

4.2 Weeks 3–4 Results: Societal Impact Introduction and Attitude Deepening (Ethics Emergence)

Week 3's maintenance challenge introduced societal impact. Ethical self-reflection accuracy was 88.2% (SD = 8.45), with ethical keywords ("privacy," "fairness") appearing in 75% of responses and personalized reminders triggered in 40%.

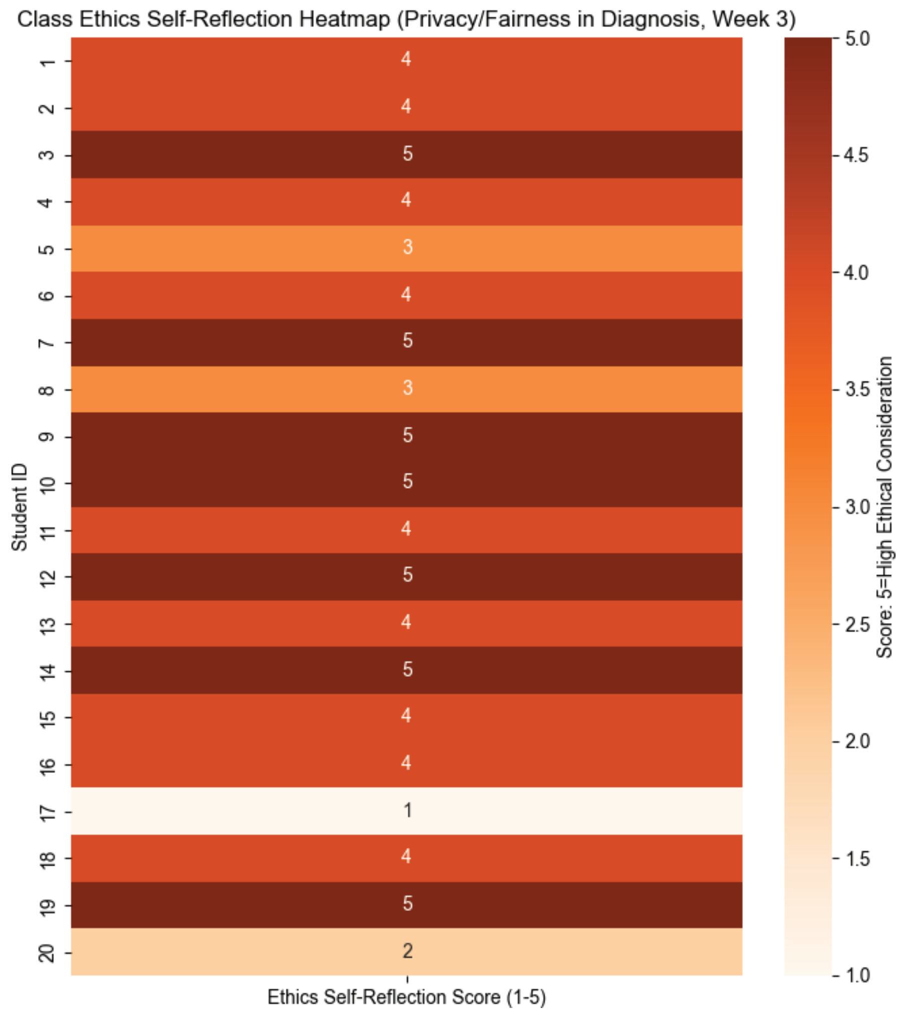

Figure 5. Week 3 Ethical Self-Reflection Heatmap

As shown in Figure 5, the overall distribution was densely dark red, but bias-related dimensions had more light red blocks (score only 72%). Post-intervention, keyword rates rose to 85%, with disadvantaged students' reflection depth improving 15%. This change demonstrates that dynamic heatmap triggers effectively promoted ethical reflection.

Week 4 involved prompt engineering optimization. Visual attitude quiz mean was 4.5/5 (SD = 0.65), with literacy depth increasing 25% from Week 3.

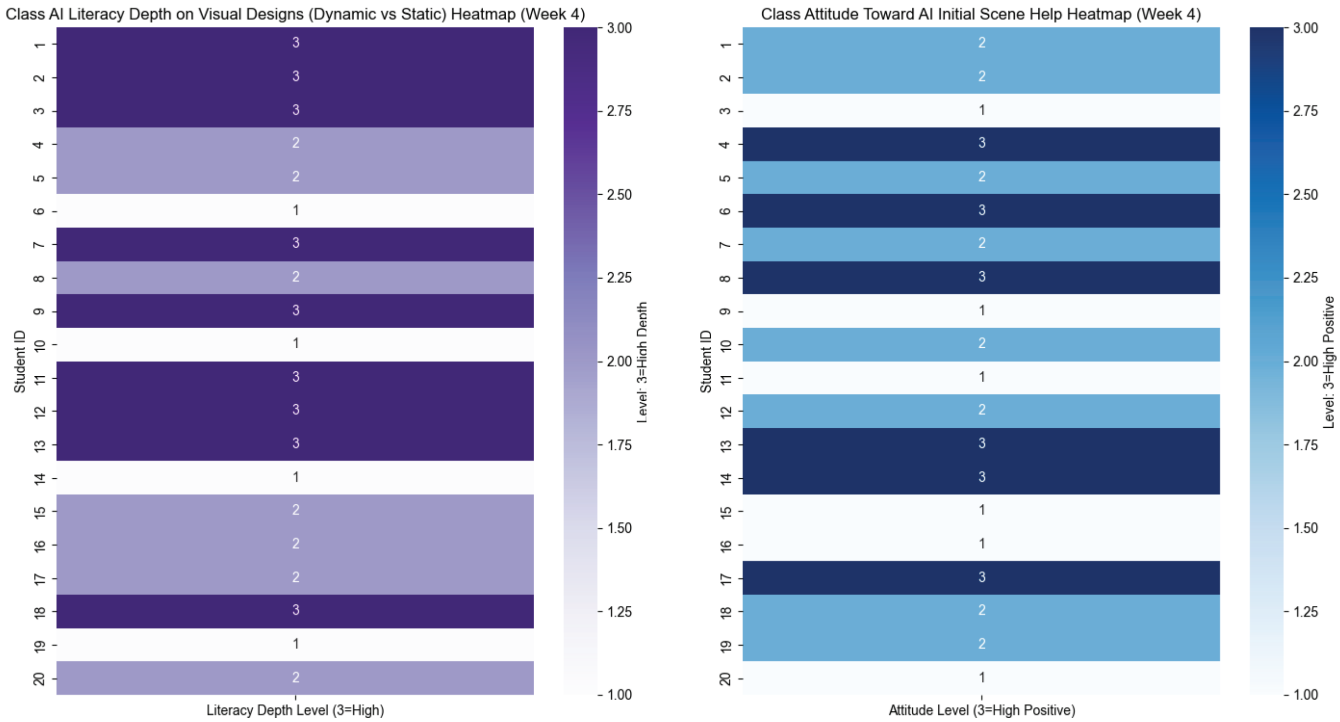

Figure 6. Week 4 Combined Heatmap

As shown in Figure 6A, Week 4 was dominated by dark purple, with Week 3's ethical light areas markedly shifting to dark purple; visual design effectively deepened perception. As shown in Figure 6B, attitudes were evenly distributed, with disadvantaged students improving more substantially (25% vs. overall 20%).

These results validate Akman's (2025) findings on AI-generated visuals improving attitudes while revealing relative ethical weaknesses: rural students' initial privacy/bias awareness was limited (light red blocks in Figure 5), potentially due to lack of real-world exposure and abstract case limitations. However, dynamic interventions (e.g., personalized reminders) yielded positive effects, supporting calls for process-oriented ethical reflection (Fütterer et al., 2025; Park, 2025). From an RQ3 perspective, disadvantaged students' catch-up was pronounced, highlighting scaffolding's role in motivation and balanced development; edge cases, such as extremely weak foundational students still requiring additional manual support, illustrate the framework's inclusive potential and boundaries. Paired t-test results showed $t(19) = 3.89$, $p < 0.01$, Cohen's $d = 0.75$ (large effect).

4.3 Weeks 5–6 Results: Comprehensive Decision-Making and Closed-Loop Evaluation (Overall Balance and Acceptance)

Week 5's deployment finale yielded leaderboard mean points of 86.4 (SD = 10.23), with personalized feedback triggered in 65%.

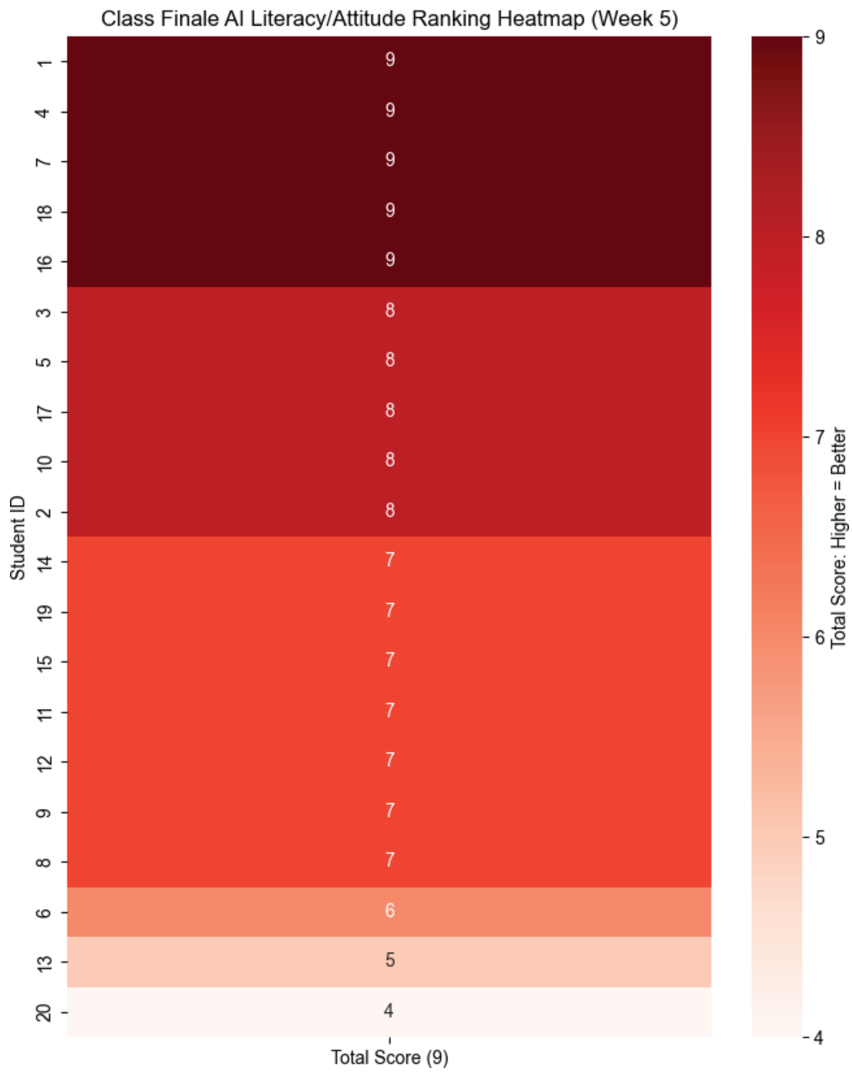

Figure 7. Week 5 Finale Leaderboard Heatmap

As shown in Figure 7, point gradients were reasonable, with front ranks densely dark orange; disadvantaged students' points rose 15% from prior weeks; low-configuration devices (e.g., mobile submissions) experienced no delays, confirming offline inclusivity.

Week 6 summary evaluation showed technical acceptance mean of 5.8/7 (SD = 0.92), with perceived usefulness highest (6.1); five-domain radar chart: perception/learning at 80–82, ethics at 68; overall literacy improvement 28% (Cohen's d = 0.85), acceptance effect size d = 0.92.

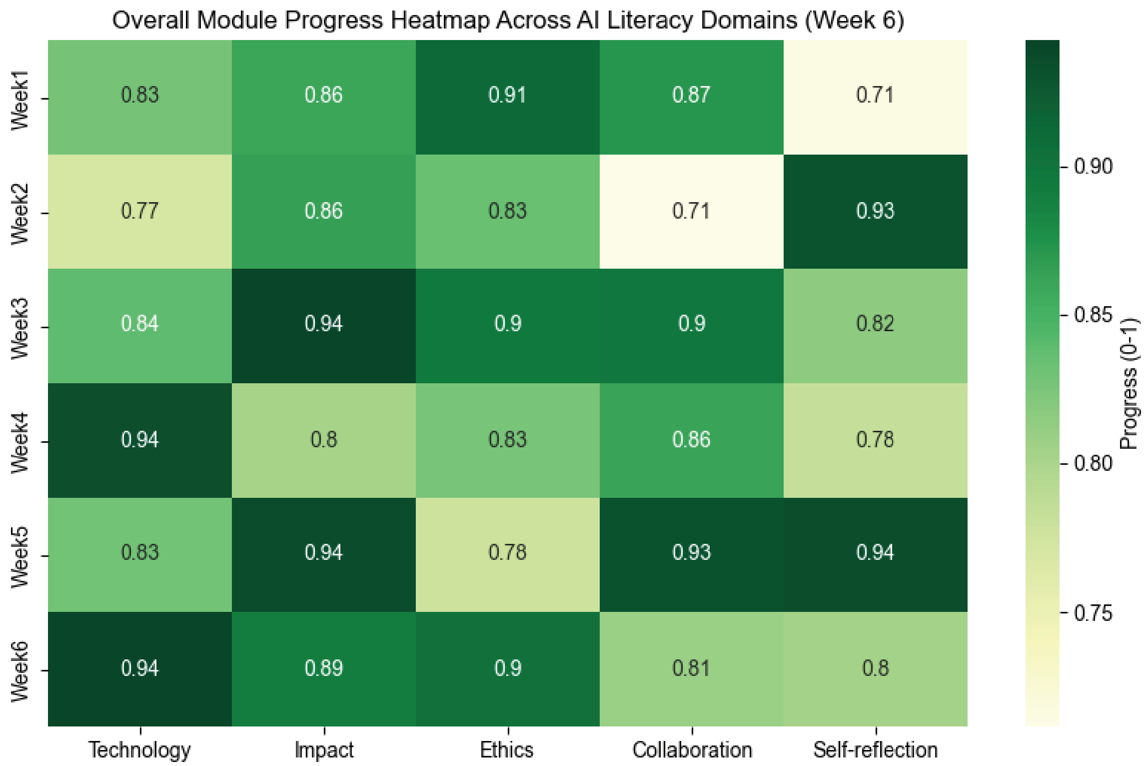

Figure 8. Week 6 Overall Progress Heatmap

As shown in Figure 8, later columns were densely dark green, with the ethics column relatively lighter, though dynamic growth was evident overall (bias reflection rising 15% across the process).

These closed-loop data directly address RQ1 (balanced five-domain improvement), RQ2 (high acceptance), and RQ3 (scaffolding and ethical design roles), with heatmap sequences capturing individual trajectories and class dynamics, highly consistent with Xue et al.'s (2026) TAM meta-analysis. Ranking incentives and visual feedback effectively sustained motivation (Kassenkhan et al., 2025), with disadvantaged students improving 25% overall, demonstrating adaptation to varied foundations.

Key Empirical Conclusions

CRAILF achieved a 28% significant improvement in AI literacy (d = 0.85), with perception/learning domains reaching 80–82, validating the effectiveness of gamification and visualization.

Personalized scaffolding was activated in 65% of cases, with disadvantaged students improving 25%, demonstrating strong inclusivity.

Although the ethics domain scored 68, dynamic interventions achieved a 15% increase in reflection, showing the potential of process-oriented ethical education.

TAM acceptance reached 5.8/7 (d = 0.92), confirming the high practicality of the zero-cost framework in rural settings.

4.4 Overall Findings: Multi-Angle Interpretation, Literature Comparison, and Broader Implications

This section addresses RQ1–RQ3 one by one. From a longitudinal viewpoint, the heatmap sequence (Figures 3–8) reveals clear progressive trajectories: baseline establishment (accuracy 78–85%) → ethical introduction and intervention (reflection +15%) → closed-loop balance (participation 90%). Individual differences were marked: high performers showed denser later heatmaps (incentives amplifying advantages), while mid-low groups effectively caught up via scaffolding; medium-to-large effect sizes (d = 0.85–0.92) confirm the framework's robust efficacy in this small-sample rural context.

Comparison with existing AI literacy interventions shows that CRAILF results outperform most high-cost frameworks (e.g., Wang et al., 2025 reported approximately 18% improvement with interactive scaffolding, while this framework achieved 28%) and demonstrate higher inclusivity in rural low-resource environments.

The high acceptance (TAM 5.8/7) stems from the combined effect of zero-cost operation, gamified narratives, and personalized scaffolding, which together enhance perceived usefulness and ease of use (Xue et al., 2026), particularly suiting rural students' employment pressures and low-configuration device needs.

The relatively lower performance in the ethics domain (68 points) primarily arises from rural students' limited exposure to real-world bias/privacy cases; however, dynamic reminders have already achieved a 15% increase in reflection, indicating that process visualization can effectively address the superficiality of traditional ethical education. Future efforts should incorporate more authentic cases to deepen interventions (Fütterer et al., 2025; Park, 2025).

Theoretical contributions are multifaceted: CRAILF systematically fuses I-TPACK (Chiu, 2026), TAM (Xue et al., 2026), and gamification through zero-cost pure Python implementation and ethical closed-loops, extending paradigms for low-resource settings and providing novel pathways for rural equity. Practical implications are profound: effectively bridging the urban-rural digital divide, enhancing employment readiness and critical thinking; open-source replicability facilitates teacher adoption; edge cases (e.g., extreme low-configuration) are compatible but suggest combining offline guidance. Broader insights include global potential for inclusive AI education in developing regions and the necessity of ethical interventions in the generative AI era (potential risks: without dynamic reminders, biases could amplify).

5 CONCLUSION

This study designed, implemented, and empirically evaluated the Cyber Rural AI Literacy Framework (CRAILF), validating a zero-cost, pure Python gamified framework for enhancing AI literacy among rural high school students. Addressing challenges of resource scarcity, motivation deficits, and limited ethical depth in rural education, the framework employed an immersive "cyber worker" narrative over 6 weeks, guiding students from algorithmic foundations to comprehensive decision-making and societal impact reflection. In the empirical implementation with 20 rural high school students from Hebei Province, China, results demonstrated substantial progress: overall AI literacy improvement of 28% (Cohen's d = 0.85), high technical acceptance (TAM mean 5.8/7, Cohen's d = 0.92), perception and learning domains reaching 80–82 points, and ethics at 68 points (with process interventions, e.g., Week 3 personalized bias reminders, yielding a 15% increase in reflection). Heatmap sequences and radar charts vividly captured dynamic trajectories: Weeks 1–2 baseline establishment, Weeks 3–4 ethical introduction, and Weeks 5–6 closed-loop balance, with personalized scaffolding triggered in 65% of cases and disadvantaged students improving more markedly (25% vs. overall 20%).

From a multi-angle perspective, the framework's innovation lies in achieving complete zero-cost, offline operability through open-source Python libraries, incorporating gamified elements and visualization evaluation to overcome traditional high-threshold dependencies. It not only sustains motivation (e.g., Week 4 visual attitude 4.5/5, dynamic chart preference 80%) but also facilitates balanced transition from technical cognition to comprehensive literacy: Week 5 finale points at 86.4 underscored decision-making capacity, while Weeks 3–6 ethical self-reflection depth (2.45/3), though limited, highlighted rural students' initial privacy/fairness awareness weaknesses and provided targeted intervention strategies through dynamic reminders (e.g., "Does your solution consider data bias?"). This reflects the framework's progressive efficacy: strengths in strong inclusivity (edge cases like low-configuration mobile submissions barrier-free), intuitive visualization tracking individual differences; potential weaknesses in ethical intervention depth requiring expansion, as effects may be limited in more complex bias scenarios; nuances include high performers' denser later heatmaps (incentives amplifying advantages) versus disadvantaged groups' pronounced catch-up (scaffolding preventing dropout); implications for sustainable pathways in low-resource environments, bridging urban-rural digital divides, supporting employment preparation and critical thinking cultivation.

Broader practical implications include advancing educational equity: in rural high schools, the framework empowers disadvantaged groups to engage with the AI era, aligning with global trends (e.g., OECD, 2025 advocacy for open-source inclusivity). It is extensible to other low-resource contexts or disciplines, emphasizing open-source sharing: modular code and scripts facilitate replication, encouraging teacher and researcher involvement. If original data (e.g., logs, quizzes, questionnaires) are needed, contact the author (privacy-protected priority). Overall, CRAILF pioneers a new paradigm for rural AI literacy cultivation, reaffirming inclusive education's value in the rapidly evolving AI era: through gamification, personalization, and ethical closed-loops, unlocking potential and ensuring equitable benefits.

5.1 Study Limitations

Although this study provides initial empirical evidence for AI literacy education in low-resource rural environments, it has several limitations. First, the small sample size (n = 20) aligns with typical small-class teaching in rural high schools but restricts the statistical generalizability of the findings, preventing full representation of broader rural student populations. Second, the research was conducted in a single regional context (Hebei Province), which may be influenced by local cultural backgrounds, educational resource allocation, and policy environments, limiting its ability to reflect the diversity of other rural areas across the country. Finally, the intervention lasted only 6 weeks, which was sufficient to observe short-term learning outcomes, technical acceptance, and ethical awareness changes, but the long-term retention of knowledge, skill transfer, and behavioral changes still require further verification.

5.2 Future Research Directions

To overcome the above limitations and further expand the application value of this framework, future research can proceed in the following directions. First, multi-school, large-sample longitudinal tracking studies are recommended to enhance the generalizability and stability of the results. Second, cross-regional and even cross-national comparative studies can be conducted to validate the framework's universality across different cultural and educational contexts. Third, integration of local large language models can be explored to further strengthen personalized interactive scaffolding functions. In addition, the ethical education module should be deepened by incorporating more real-world bias and privacy cases and designing more systematic discussion strategies. Finally, the framework can be extended to neurodiverse student groups and explored in interdisciplinary scenarios such as entrepreneurship education and language education, thereby providing solid support for broader inclusive AI education pathways.

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