ISSN 2529-9824

Research article

Integrating Task-oriented and Affective-support Instruction to Enhance AI Literacy: a Mixed-method Study among Non–CS(Computer Science) Students in Higher Education

Integración de instrucción orientada a tareas y de apoyo afectivo para mejorar la alfabetización en AI: un estudio de métodos mixtos entre estudiantes de educación superior que no se especializan en informática

Yuh-Tyng Chen: Tainan University of Technology, Taiwan.
t00137@gm.tut.edu.tw
Sheau-Ming Chen[1]: Kainan University, Taiwan.
jeffchen@gapps.knu.edu.tw

Date of Receipt: 18/06/2026

Acceptance Date: 21/07/2026

Anticipated Publication Date: 27/07/2026

Publication Date: 01/01/2027

How to cite the article

Chen, Y. T. & Chen, S. M. (2027). Integrating Task-oriented and Affective-support Instruction to Enhance AI Literacy: a Mixed-method Study among Non–CS(Computer Science) Students in Higher Education [Integración de instrucción orientada a tareas y de apoyo afectivo para mejorar la alfabetización en AI: un estudio de métodos mixtos entre estudiantes de educación superior que no se especializan en informática]. *European Public & Social Innovation Review*, 12, 01-16. https://doi.org/10.31637/epsir-2027-3010

[1] **Corresponding author:** Sheau-Ming Chen. Kainan University (Taiwan).

Abstract
Introduction: Given rapid advancement of artificial intelligence (AI) in higher education, AI literacy has become a core skill for students to meet the demands of digital societies. This study examined the effectiveness of an instructional model combines task-oriented learning and emotional support to improve AI literacy among non–CS (Computer Science) students. **Methodology:** A quasi-experimental design was employed with 97 freshman students from various fields (business, finance, fine arts) at a Technology University in Taiwan. The experimental group (n = 53) received instruction based on task-oriented and emotional support principles while the control group (n = 44) received traditional lecture-based instruction. **Results:** It showed the experimental student group scored significantly higher AI literacy and self-efficacy experienced lower digital learning anxiety. No significant differences were observed in motivation to learn. **Discussions:** Mediation analyses confirmed self-regulatory confidence partly mediated the relationship between anxiety and achievement with fully mediated to link between motivation and achievement. Qualitative data further highlighted a psychological transformation pathway: Anxiety → Support → Confidence → Engagement → Achievement. **Conclusions:** It provides empirical evidence integrating task-oriented and emotional-supportive strategies can effectively improve AI literacy among non-CS majors, offering practical insights into AI curriculum and higher education policy.

Keywords: AI; Task-oriented; Affective support; Digital learning anxiety; Self-regulation.

Resumen
Introducción: Este estudio examinó la efectividad de un modelo de instrucción que combina el aprendizaje orientado a tareas y apoyo emocional para mejorar la alfabetización en AI entre estudiantes que no son de informática. **Metodología:** Se empleó un diseño cuasiexperimental con 97 estudiantes de primer año de diversos campos en una Universidad Tecnológica. El grupo experimental (n = 53) recibió instrucción basada en principios de apoyo emocional y orientado a tareas mientras que el grupo de control (n = 44) recibió instrucción tradicional basada en conferencias. **Resultados:** Mostró que los estudiantes del grupo experimental obtuvieron puntuaciones significativamente más altas en alfabetización en AI y la autoeficacia experimentaron una menor ansiedad por el aprendizaje digital. **Discusión:** Los análisis de mediación confirmaron que la confianza en la autorregulación mediaba en parte la relación entre la ansiedad y el logro y totalmente mediada en el vínculo entre la motivación y el logro. Los datos cualitativos destacaron aún más un camino de transformación psicológica: Ansiedad → Apoyo → Confianza → Compromiso → Logro. **Conclusiones:** Proporciona evidencia empírica que integra estrategias orientadas a tareas y de apoyo emocional que pueden mejorar efectivamente la alfabetización en AI entre estudiantes que no se especializan en informática.

Palabras clave: AI; Orientado a tareas; Apoyo afectivo; Ansiedad por el aprendizaje digita; Autorregulación.

1. Introduction

The rapid digital transformation in higher education has positioned artificial intelligence (AI) as a driving force, reshaping both industrial structures and educational paradigms. As AI technologies permeate everyday life, AI literacy has emerged as a foundational competence for students to adapt to the demands of a technology-driven society. Beyond technical skills, AI literacy encompasses critical thinking, algorithmic understanding, cross-disciplinary application, and ethical awareness (Ng, 2012; Long & Magerko, 2020). Accordingly, universities worldwide have incorporated AI literacy into general education curricula to ensure that students across diverse disciplines acquire this essential capability (Zawacki-Richter et al., 2019).

Despite this global movement, non–computer science (non-CS) students—particularly first-year undergraduates—continue to face significant challenges in learning about AI. Their prior digital experiences are often limited to document processing or social media use, leaving them underprepared for programming, data reasoning, and computational thinking. This skill gap often leads to digital learning anxiety, low self-efficacy, and suboptimal learning performance (Tsai & Chai, 2012; Abd Aziz et al., 2023).

International research further reveals that even "digital natives" exhibit substantial disparities in digital competence, and non-CS students remain particularly disadvantaged in AI literacy development (Margaryan et al., 2011; Voogt & Roblin, 2012; Gkrimpizi et al., 2023). These findings highlight a critical need for replicable and empirically validated instructional designs that not only enhance cognitive understanding but also address affective barriers such as anxiety and motivation. Strategies that connect structured learning tasks with emotional support mechanisms may help non-CS learners reduce learning anxiety, strengthen confidence, and improve learning engagement.

1.1. Theoretical Foundation and Research Purpose

Drawing upon Bandura's Triadic Reciprocal Determinism, TRD (Bandura, 1986) this study conceptualizes learning as the dynamic interaction among environmental design, personal factors, and behavioral outcomes. Within this framework, integrating task-oriented learning and effective support strategies offers a theoretically grounded approach to improving students' emotional regulation, motivation, and learning achievement.

Such integration may also serve as a sustainable instructional model for promoting equitable and effective AI learning experiences among non-CS students. Accordingly, this study aims to evaluate the effectiveness of task-oriented and effective-support teaching on AI literacy outcomes, as well as the mediating mechanisms linking learners' psychological factors to their performance.
Specifically, the purposes of this study are as follows:

1. To examine the effects of task-oriented and effective-support instruction on AI literacy and learning achievement among non-CS students.

2. To explore the roles of digital learning anxiety, learning motivation, and self-efficacy in AI literacy learning.

3. To test whether self-efficacy mediates the relationships among anxiety, motivation, and learning achievement.

4. To provide empirical implications for curriculum design and educational policy that support AI literacy development in higher education.

2. Literature Review

2.1. AI Literacy in Higher Education

As artificial intelligence (AI) becomes increasingly integrated into social, industrial, and educational systems, AI literacy has emerged as an essential competency for 21st-century learners (Ng, 2012; Long & Magerko, 2020).

Unlike traditional digital literacy, which primarily focuses on tool operation and information retrieval, AI literacy emphasizes the ability to understand, evaluate, and apply AI technologies critically and ethically (Zawacki-Richter et al., 2019).

Recent frameworks define AI literacy as a multidimensional construct involving conceptual understanding, practical application, and ethical reflection (Lin et al., 2023). Conceptually, it requires an understanding of how algorithms, data, and machine learning function; practically, it involves the ability to utilize AI tools to solve real-world problems; ethically, it demands awareness of bias, accountability, and human–AI interaction.

Higher education institutions worldwide have responded to this need by embedding AI literacy into general education or interdisciplinary curricula (Holmes & Tuomi, 2022). However, challenges persist, particularly among non–computer science (non-CS) students who lack prior exposure to programming or data analysis.

Studies indicate that without sufficient instructional scaffolding, these learners often exhibit higher cognitive load, lower confidence, and greater anxiety in AI-related learning environments (Gkrimpizi et al., 2023). Hence, fostering AI literacy effectively requires not only cognitive skill development but also effective and motivational support mechanisms that sustain learners' engagement throughout the learning process.

2.2. *Affective Factors in AI Learning:*

Affective factors have been increasingly recognized as key determinants of successful learning in digital and AI-integrated contexts (Shao et al., 2019). Among them, learning anxiety, motivation, and self-efficacy have been identified as pivotal psychological constructs influencing learners' engagement and performance. Digital learning anxiety refers to the apprehension or tension experienced when interacting with unfamiliar technologies or performing computer-based tasks (Abd Aziz et al., 2023).

Elevated anxiety consumes cognitive resources, reducing working memory efficiency and thereby impeding task performance (Eysenck et al., 2007). In AI learning contexts, non-CS students often report higher levels of anxiety when faced with algorithmic reasoning or coding exercises, which can diminish confidence and persistence. In contrast, learning motivation—both intrinsic and extrinsic—serves as a driving force that sustains attention and effort (Deci & Ryan, 2000). Motivation not only influences persistence but also facilitates self-regulatory learning behaviors' such as goal setting and reflection (Zimmerman, 2000).

Furthermore, self-efficacy, defined as an individual's belief in their capacity to perform specific tasks (Bandura, 1997), acts as a mediating mechanism between affective states and performance outcomes. High self-efficacy enables learners to approach challenges with resilience and adaptive strategies, while low self-efficacy exacerbates avoidance behavior and anxiety (Schunk & DiBenedetto, 2020).

Collectively, these affective variables interact dynamically—anxiety dampens motivation and confidence, while strong self-efficacy buffers negative emotions and promotes persistence—forming a complex psychological ecosystem that critically shapes AI learning experiences.

2.3. Task-Oriented and Affective-Support Instruction: Theoretical and Empirical Perspectives

The integration of task-oriented learning and affective support has gained increasing attention as an effective pedagogical approach in technology-enhanced education (Lee, 2016; Tejedor Mardomingo et al., 2024). Task-oriented learning, rooted in constructivist and experiential learning theories, emphasizes authentic, goal-directed activities that engage learners in meaningful problem-solving (Nunan, 2004). By structuring learning tasks progressively, this approach promotes cognitive engagement, autonomy, and the development of transferable skills.

However, cognitive engagement alone is insufficient for sustaining long-term motivation, particularly among learners with high anxiety or low confidence. Thus, affective support, which includes encouragement, empathy, and emotional scaffolding, serves as a critical complement. Affective-supportive teaching helps reduce anxiety, enhances confidence, and strengthens the learner–teacher relationship (Meyer & Turner, 2002; Xie et al., 2022).

Building upon Bandura's Triadic Reciprocal Determinism (Bandura, 1986), the combined use of task-oriented and affective-support strategies aligns with the interaction among environment (instructional design), personal factors (emotions, motivation, self-efficacy), and behavior (learning outcomes). Empirical studies have shown that integrating emotional scaffolding into task-based learning environments leads to increased self-efficacy, reduced anxiety, and improved achievement (Shao et al., 2019; Chen & Tsai, 2021).

Therefore, theoretical and empirical literature support the need for an integrated instructional model that unites cognitive and affective dimensions, particularly in AI literacy education, where non-CS learners face complex emotional and technical challenges.

3. Methodology

3.1. Research Design

This study employed a pretest–posttest quasi-experimental design with a control group to investigate the impact of task-oriented and affective-support instruction on the AI literacy of non–computer science (non-CS) students. The design was grounded in Bandura's Triadic Reciprocal Determinism, TRD (Bandura, 1986), which posits that learning outcomes are shaped by the dynamic interaction among environmental design (instructional context), personal factors (anxiety, motivation, self-efficacy), and behavioral outcomes (AI literacy and achievement).To ensure comparability, both groups received identical content and contact hours, while the instructional approach differed. Pretest scores were treated as covariates in subsequent analyses to control baseline differences, thus enhancing internal validity.

3.2. Participants

Participants were 97 first-year undergraduates enrolled in a general education course titled AI Programming and Digital Life at a university of technology in southern Taiwan. They represented various majors such as business administration, finance, and fine arts, all classified as non-CS disciplines. The participants were randomly assigned by class section to the experimental group (n = 53), which received task-oriented and effective support instruction, and the control group (n = 44), which received traditional lecture-based teaching. All participants provided informed consent, and the study was reviewed and approved by the University's Research Ethics Committee to ensure compliance with ethical standards.

3.3. Instruments

Four instruments were used in this study: the AI Literacy Achievement Test, the Digital Learning Anxiety Scale, the Learning Motivation Scale, and the Self-Efficacy Scale. All demonstrated satisfactory reliability and validity, with Cronbach's α ranging from 0.83 to 0.92 and KMO = 0.86 ($p < 0.001$), as confirmed through exploratory factor analysis. The AI Literacy Achievement Test consisted of 50 multiple-choice application items that assessed students' conceptual knowledge, problem-solving skills, and practical application of AI tools. The Digital Learning Anxiety Scale, adapted from Huang (Huang et al., 2022), is a 20-item scale measuring three dimensions: technical anxiety, error fear, and learning helplessness.

Higher scores indicate greater anxiety. The Learning Motivation scale, based on Pintrich (Pintrich et al., 1991), Deci and Ryan (Deci & Ryan, 2000), is a 25-item instrument that evaluates intrinsic motivation, extrinsic motivation, and task value. The Self-Efficacy Scale, based on Zimmerman (Zimmerman, 2000), Schunk and DiBenedetto (Schunk & DiBenedetto, 2020), is a 10-item scale that evaluates students' confidence in managing AI-related learning tasks. All items were rated on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicated stronger confidence, motivation, or perceived competence.

3.4. Intervention Procedure

The intervention lasted 18 weeks (one academic semester). Both groups followed the same syllabus and learning objectives, differing only in instructional approach. The experimental group received instruction that integrated task-oriented learning and affective support, designed according to the Bandura's TRD framework at 1986:

- Environmental dimension: Structured AI projects and real-world problem-solving tasks.

- Personal dimension: Emotional scaffolding and motivation-boosting activities.

- Behavioral dimension: Reflective learning logs and peer collaboration.

In each session, students participated in task-based activities that utilized AI tools, accompanied by ongoing affective feedback and reflection prompts designed to build confidence and reduce anxiety. The control group was taught through traditional lecture-based methods, focusing on teacher explanation and individual exercises without effective or collaborative scaffolds. Both groups completed the same assignments and assessments.

3.5. Data Analysis

Data were analyzed using SPSS 26.0 and the PROCESS Macro (Hayes, 2022). Descriptive statistics and reliability tests were initially conducted to assess normality and internal consistency. ANCOVA was used to compare posttest AI literacy scores between groups while controlling pretest differences. Pearson correlations were used to examine the relationships among digital learning anxiety, motivation, self-efficacy, and achievement.

To test the mediation hypotheses, PROCESS Model 4 with 5,000 bootstrap samples and 95% bias-corrected confidence intervals was applied. An indirect effect was deemed significant if the confidence interval did not include zero. For qualitative data, including reflection logs, interviews, and classroom observations, thematic analysis was conducted (Braun & Clarke, 2006).

Two independent coders identified themes related to learners' emotional and motivational changed, with inter-coder reliability assessed using Cohen's κ, which exceeded 0.80. Triangulation across data sources helped ensure the trustworthiness and credibility of the findings.

4. Results

4.1. Descriptive Statistics and Scale Reliability

Table 1 presents the descriptive statistics for key variables of the experimental group (n = 53) and the control group (n = 44). The two groups exhibited similar pretest scores for learning achievement (26.87 vs. 26.05), with no significant difference (t (95) = 0.35, p = 0.73), indicating baseline equivalence. Compared with the control group, the experimental group showed: (1) lower digital learning anxiety (M = 79.26, SD = 19.69 vs. M = 91.61, SD = 24.27); (2) higher self-efficacy (M = 101.96, SD = 16.49 vs. M = 97.48, SD = 15.77); (3) comparable learning motivation (M = 22.66 vs. M = 21.66); and (4) significantly higher posttest learning achievement (M = 79.43, SD = 13.30 vs. M = 55.73, SD = 15.07). These findings suggest that the task-oriented and effective-support instructional intervention effectively reduced learning barriers and improved AI literacy performance.

Table 1.

Descriptive Statistics of Key Variables by Group (M, SD, N)

Variable	Group (N)	M	SD
Digital Learning Anxiety	Experimental (53)	79.26	19.69
	Control (44)	91.61	21.27
Self-Efficacy	Experimental (53)	101.96	16.49
	Control (44)	97.48	15.77
Learning Motivation	Experimental (53)	22.66	6.15
	Control (44)	21.66	5.66
Learning Achievement (Pre-test)	Experimental (53)	26.87	11.75
	Control (44)	26.05	11.15
Learning Achievement (Post-test)	Experimental (53)	79.43	13.30
	Control (44)	55.73	15.07

Source: Own elaboration.

4.2. Intervention Efficacy (ANCOVA)

Table 2 presented that ANCOVA was conducted using pretest scores as a covariate to control baseline differences. The main effect of group was significant, $F(1, 94) = 67.03$, $p < .001$, partial $\eta^2 = .416$. The adjusted means showed that the experimental group outperformed the control group by 23.6 points on the posttest achievement. This result supports H1 and confirms that the task-oriented and effective support instruction significantly enhanced AI literacy and learning achievement.

Table 2.

ANCOVA Results for Learning Achievement after Controlling for Pre-test cores

Source	Type III Sum of Square	df	Mean Square	F	P	Partial η²
Corrected Model	13,719.76	2	6,859.88	34.38	.000	.422
Intercept	62,115.20	1	62,115.20	311.32	.000	.768
Pretest	208.41	1	208.41	1.05	.309	.011
Group	13,373.31	1	13,373.31	67.03	.000	.416

***p < 0.001; **p < 0.01; p < 0.05

Source: Own elaboration.

4.3. *Correlation Analysis of Core Variables*

Pearson correlation analysis, as shown in Table 3, revealed that digital learning anxiety was negatively correlated with self-efficacy ($r = -.569$, $p < .01$), learning motivation ($r = -.406$, $p < .01$), and learning achievement ($r = -.562$, $p < .01$). Self-efficacy was positively correlated with learning motivation ($r = .712$, $p < .01$) and achievement ($r = .636$, $p < .01$), and learning motivation was positively correlated with achievement ($r = .424$, $p < .01$). These findings align with Bandura's social cognitive theory that emotional states affect behavior through efficacy beliefs (Bandura, 1997).

Table 3.

Correlation Matrix among Digital Learning Anxiety, Self-Efficacy, Learning Motivation and Post-test Learning Achievement

Variable	1	2	3	4
1. Digital Learning Anxiety	1	-.569**	-.406**	-.562**
2. Self-Efficacy		1	.712**	.636**
3. Learning Motivation			1	.424**
4. Learning Achievement				1

***p < 0.001; **p < 0.01; p < 0.05

Source: Own elaboration.

4.4. *Mediation Analysis*

To examine how emotional and motivational factors influenced learning achievement through self-regulation, the mediation hypotheses were tested using PROCESS Model 4 with 5,000 bootstrap samples and 95% bias-corrected confidence intervals (Hayes, 2022).

4.4.1. Direct Effects Overview.

Preliminary regression results confirmed that digital learning anxiety negatively predicted learning achievement ($\beta = -0.296$, $p < .01$), while self-efficacy positively predicted it ($\beta = 0.512$, $p < .001$). Learning motivation alone did not significantly predict achievement ($\beta = -0.061$, $p = .574$). These direct effects established the foundation for subsequent mediation testing, as shown in Table 4.

Table 4.

Summary of Direct Effects and Path Coefficients (PROCESS Model 4)

Predictor → Outcome	Path	β	SE	p	Interpretation
Digital Learning Anxiety → Self-Regulation	a1	-0.331	0.051	<.001	Negative direct path
Learning Motivation → Self-Regulation	a2	0.562	0.081	<.001	Positive direct path
Self-Regulation → Achievement	b	0.512	0.071	<.001	Significant mediating path
Digital Learning Anxiety → Achievement (direct)	c'_1	−0.296	0.075	.002	Partial mediation
Learning Motivation → Achievement (direct)	c'_2	0.234	0.090	.012	Partial mediation

Source: Own elaboration.

4.4.2. Indirect (Mediation) Effects.

As shown in Table 5, both emotional and motivational pathways demonstrated significant indirect effects through self-regulation.

- For the emotional pathway, digital learning anxiety indirectly and negatively affected achievement (β_indirect=- 0.171, 95% CI [-0.265, -0.095]), indicating partial mediation.

- For the motivational pathway, learning motivation indirectly and positively influenced achievement (β_indirect=0.266, 95% CI [0.154, 0.392]), also indicating partial mediation.

Table 5.

Indirect Effects and Confidence Intervals (PROCESS Model 4)

Path	Indirect Effect (a x b)	SE	95% x CI (LLCI, ULCI)	Mediation Type
Anxiety → Self-Regulation → Achievement	−0.171	0.045	[−0.265, −0.095]	Partial
Motivation → Self-Regulation → Achievement	0.266	0.062	[0.154, 0.392	Partial

Source: Own elaboration.

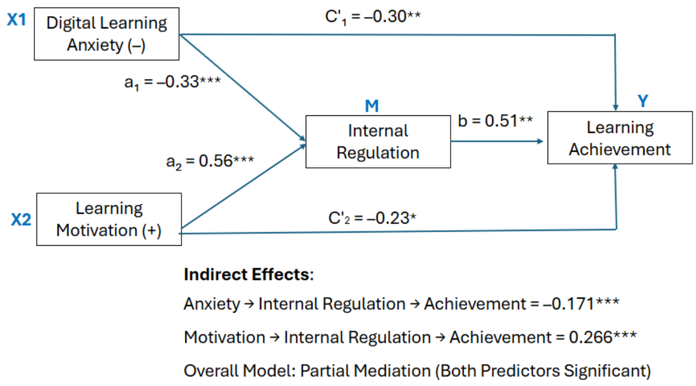
4.4.3. Effects of Mediation

The results confirm that self-regulation serves as a significant mediator connecting personal affective factors to learning outcomes. Specifically, anxiety undermines self-regulatory confidence, leading to decreased performance, while motivation enhances self-regulation and persistence, resulting in improved achievement. This dual-path pattern supports Bandura's Triadic Reciprocal Determinism at 1986, emphasizing that personal factors (emotion and motivation) influence behavioral outcomes (achievement) through self-regulatory mechanisms.

Figure-1 illustrates this integrated self-regulatory model, in which emotional and motivational processes converge through self-regulation to shape learning achievement. The findings suggest that effective instructional design should simultaneously address emotional barriers and motivational drivers to optimize AI literacy learning for non-computer science (non-CS) students.

Figure 1.

Integrated Self-Regulatory Model Linking Emotion and Motivation for Learning Achievement



Source: Own elaboration.

5. Discussion

The qualitative findings—comprising interviews with 12 students and teacher observation logs—provided valuable insights that complement the quantitative findings, illustrating how the task-oriented and affective-support instructional design facilitated students' psychological transformation throughout the AI literacy course.

5.1. Initial Anxiety and Need for Support

At the beginning of the course, students expressed clear tension, fear, and helplessness when facing Python programming tasks:

> *"Every time I saw Python code on the screen, I got nervous- it felt like looking at a foreign language." (Student 3).*

Teacher observations confirmed this anxiety and avoidance behavior:

> *"When I asked students to run a simple Python script, several just stared at the screen, hesitant to touch the keyboard. Some even whispered, 'I don't know how to start." (Teacher Observation, Week 2).*

These early records highlight the prevalence of digital learning anxiety and avoidance among non-CS students.

5.2. Affective Support Alleviates Anxiety

Affective support strategies—such as encouragement, positive feedback, and peer collaboration—effectively reduced students' anxiety and built a sense of safety in learning:

> *"Honestly, when I first saw Python code, I thought, 'I'm doomed, I'll definitely fail" My palms were sweating. But the teacher kept reminding us that making mistakes is normal and encouraged us to discuss problems with classmates. Just knowing that errors wouldn't be punished and that I could always ask for help reduced a lot of stress. Later, I wasn't afraid of red error messages anymore—I saw them as hints for improvement. (Student 9).*

"At first, our group couldn't even install the software and felt so frustrated. But the teaching assistant didn't just fix it for us – he patiently said, 'Let's take it step by step; everyone struggles at first.' That understanding attitude really mattered. If he had said, 'It's easy,' I might've given up. Feeling understood made me want to keep trying." (Student 4).

"When I talked with my teammates about the project, I realized I wasn't the only one struggling. Sharing ideas made me less anxious and more confident." (Student 7).

Teacher reflections also supported these:

"During later group activities, previously quiet students began to speak up when peers encouraged them." (Teacher Observation, Week 6).

These findings demonstrate that affective support created a psychologically safe environment that reduced anxiety and promoted collaborative learning.

5.3. Task Orientation Builds Self-Efficacy and Engagement

Through accomplishing small AI-based projects, students gradually gained tangible evidence of their ability, strengthening their self-efficacy and engagement:

"After completing our mini-AI project, I felt proud. It proved that I could actually code and solve problems." (Student 10).

Peer collaboration further enhanced confidence and perceived competence:

"At first, I thought this course was too difficult. But after working with my teammates and solving problems together, I realized I could really apply AI tools in daily life." (Student 12).

Teacher observations corroborated this:

"By Week 12, some students voluntarily stayed after class to refine their projects, showing stronger persistence and initiative." (Teacher Observation, Week 12).

5.4. Summary of Qualitative Insights

Overall, the qualitative findings depict a clear psychological trajectory → from initial anxiety → affective support → enhanced self-efficacy → improved learning outcomes and AI literacy. This progression aligns with quantitative mediation results, which identified self-regulation as the key mechanism linking emotional and motivational factors to learning achievement. The qualitative evidence thus provides triangulation support for Hypothesis 5 (H5), illustrating how affective support and task orientation jointly foster students' confidence, persistence, and learning success in AI literacy education.

6. Conclusion

Grounded in Bandura's Triadic Reciprocal Determinism (TRD) at 1986, this study investigated the effects of an instructional model integrating task-oriented learning and affective support on non–computer science (non-CS) undergraduates' AI literacy learning outcomes. By combining quantitative and qualitative data, the study yielded the following conclusions:

6.1. Instructional Effectiveness and Literacy Development

AI literacy and learning achievement were significantly improved. Students in the experimental group outperformed those in the control group in AI conceptual understanding, data processing, and Python programming skills. This finding confirms that the proposed instructional model effectively facilitates AI literacy acquisition among non-CS students.

Moreover, digital learning anxiety significantly decreased, particularly in the subdimensions of technical anxiety and error fear. This indicates that effective-support strategies successfully reduced emotional barriers and created a psychologically safe learning environment that promoted participation and persistence.

6.2. Verification of Psychological Mechanisms

The mediation analyses verified the crucial mediating role of self-efficacy. Specifically, self-efficacy partially mediated the relationship between learning anxiety and achievement and fully mediated the relationship between motivation and achievement. This suggests that learners' confidence and belief in their capability serve as key psychological mechanisms linking effective and motivational factors to performance.

Qualitative evidence supported this dynamic transformation process. Students' reflections and teacher observations revealed a clear psychological trajectory → reduced anxiety → increased self-efficacy → higher engagement → improved learning outcomes. This process-based evidence provides rich contextual validation for the statistical mediation results.

6.3. Non-Significant Findings on Learning Motivation

Although some interview participants expressed greater appreciation for the value of AI learning, the overall learning motivation did not significantly increase at the group level. This may reflect the limitations of a short-term intervention in altering deep-seated motivational structures. Non-CS students might still view AI literacy as an instrumental rather than intrinsic skill. The result also suggests that affective support alone may not be sufficient to enhance long-term motivation; strategic motivational designs such as goal setting, value relevance, and domain linkages required to achieve lasting impact.

6.4. Pedagogical Implications

Based on the findings, several pedagogical implications are proposed for curriculum design and instructional practice:

6.4.1. Create a supportive, low-anxiety learning environment.

Course design should integrate concrete, task-based experiences with effective-support mechanisms to reduce digital anxiety and foster active participation.

6.4.2. Strategically enhance self-efficacy.

Given its mediating role, instruction should incorporate scaffolded tasks and formative feedback to help students accumulate mastery experiences, thereby strengthening confidence and persistence.

6.4.3. Reinforce learning motivation through goal relevance and value connection.

Motivation can be enhanced through:

- Goal setting and professional linkage: Align AI learning with students' disciplinary and career goals to emphasize relevance.
- Task value emphasis: Demonstrate cross-disciplinary applications to highlight the importance of AI literacy.
- Feedback and gamification: Use learning analytics feedback or gamified systems to gradually shift extrinsic to intrinsic motivation.

6.4.4. Incorporate mixed-method feedback mechanisms.

Qualitative findings—such as reflections and teacher observations—help capture affective and motivational shifts that quantitative measures may miss, offering a fuller picture of learning transformation.

6.5. Suggestions

While the study provides robust empirical evidence, certain limitations remain:

- Duration and motivational sustainability:
  Conducted over one semester (18 weeks), the study may not capture long-term changes in motivation. Future research should adopt longitudinal designs to examine sustained motivational and cognitive development.
- Sample generalizability:
  The participants were non-CS students from a single university. Caution is advised when generalizing the findings to other institutions or contexts.
- Future directions:
  Future studies could conduct cross-institutional comparisons or longitudinal tracking. In addition, integrating motivationally oriented strategies—such as task-value emphasis and goal-setting—into controlled experiments can further validate their efficacy in enhancing AI literacy among non-CS learners.

7. References

Bandura, A. (1986). *Social foundations of thought and action*. Englewood Cliffs, N.J.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *33*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Chen, C. H., & Tsai, C. C. (2021). In-service teachers' conceptions of mobile technology-integrated instruction: Tendency towards student-centered learning. *Computers & Education*, 170, 104224. https://doi.org/10.1016/j.compedu.2021.104224

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry, 111*(4), 227-268. https://doi.org/10.1207/S15327965PLI1104_01

Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: Attentional control theory. *Emotion*, *7*(2), 336-353. https://doi.org/1 0.1037/1528-3542.7.2.336

Gkrimpizi, T., Peristeras, V., & Magnisalis, I. (2023). Classification of barriers to digital transformation in higher education institutions: Systematic literature review. *Education Sciences*, *13*(7), 746.

Hayes, J. (2022). *The theory and practice of change management*. Bloomsbury Publishing.

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European journal of education*, *57*(4), 542-570. https://.doi.org/10.1111/ejed.12533

Huang, R. T., Jabor, M. K., Tang, T. W., & Chang, S. C. (2022). Examine the moderating role of mobile technology anxiety in mobile learning: A modified model of goal-directed behavior. *Asia Pacific Education Review*, *23*(1), 101-113.

Lee, C. (2016). Multilingual resources and practices in digital communication. In Georgakopoulou, A., & Spilioti, T. (Eds.), *The Routledge handbook of language and digital communication* (pp. 18-132). Routledge.

Lin, C. C., Huang, A. Y., & Lu, O. H. (2023). Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review. *Smart Learning Environments, 10*(1), Article 41.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems,* 1-16.

Margaryan, A., Littlejohn, A., & Vojt, G. (2011). Are digital natives a myth or reality? University students' use of digital technologies. *Computers & Education*, *566*(2), 429-440. https://doi.org/10.1016/j.compedu.2010.09.004

Meyer, D K., & Turner, J. C. (2002). Discovering emotion in classroom motivation research. *Educational psychologist*, *37*(2), 107-114.

Ng, W. (2012). Can we teach digital natives' digital literacy? *Computers & Education*, *599*(3), 1065-1078. https://doi.org/10.1016/j.compedu.2012.04.016

Nunan, D. (2004). *Task-based language teaching*. Cambridge University press.

Pintrich, P. R. (1991). A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ).

Schunk, D. H., & DiBenedetto, M. K. (2020). Self-efficacy theory in education. In *Handbook of motivation at school*, (pp. 34-54). Routledge.

Shao, K., Pekrun, R., & Nicholson, L. J. (2019). Emotions in classroom language learning: What can we learn from achievement emotion research? *System,* 86, 102121.

Tejedor Mardomingo, M., Gil-Mediavilla, M., Alguacil Sánchez, S., Martínez-Valderrey, V. & Ruiz Ruiz, M. E. (2024). Tecnología educativa y mapas online interactivos para fomentar la movilidad sostenible y las rutas o caminos escolares. *European Public & Social Innovation Review*, 9, 1-18. https://doi.org/10.31637/epsir-2024-931

Tsai, C. C., & Chai, C. S. (2012). The "third-order barrier" for technology integration: Implications for teacher education. *Australasian Journal of Educational Technology*, 288(6), 1057–1060. https://doi.org/10.14742/ajet.810

Voogt, J., & Roblin, N. P. (2012). A comparative analysis of international frameworks for 21st century competences: Implications for national curriculum policies. *Journal of Curriculum Studies*, 444(3), 299-321. https://doi.org/10.1080/00220272.2012.668938

Xie, B., Yuan, L., Li, S., Liu, C. H., Cheng, X., & Wang, G. (2022). Active learning for domain adaptation: An energy-based approach. In *Proceedings of the AAAI conference on artificial intelligence,* 36(8), 8708-8716.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, 166(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zimmerman, B. J. (2000). Self-efficacy: An essential motive to learn. *Contemporary Educational Psychology*, 255(1), 82-91. https://doi.org/10.1006/ceps.1999.1016

AUTHOR CONTRIBUTIONS, FUNDING AND ACKNOWLEDGMENTS

Contributions of the Authors
Conceptualization: Both Authors Yuh-Tyng and Sheau-Ming. **Software:** Yuh-Tyng. **Formal analysis:** Yuh-Tyng. **Data Curation:** Yuh-Tyng; Sheau-Ming. **Preparation of the draft original:** Yuh-Tyng; Sheau-Ming. **Revision and Editing:** Yuh-Tyng; Sheau-Ming. **Supervision:** Sheau-Ming. **Project Management:** Sheau-Ming. **Both Authors have read and accepted the published version of the manuscript:** Yuh-Tyng and Sheau-Ming.

Financing: This research received no external funding.

Acknowledgments: The research is made possible through diversity works assistance by Tainan University of Technology, Yongkang District, Tainan City 710, Taiwan. We shall pay highly thankful to the Institution.

Conflict of interests: Both authors declare that there is no conflict of interests regarding the publication of this paper.

AUTHORS:

Yuh-Tyng Chen
Tainan University of Technology, Taiwan.

Dr. Yuh-Tyng Chen is now an Associate Professor in the Department of Living Services Industry, Tanina University of Technology, Taiwan. Before that, she was a Lecturer, an Assistant then an Associate professor in the Department of Information Management, the same University. She obtained her BA in Tunghai University (Taiwan), MS of Computer Science in New Jersey Institute of Technology (USA) and PhD of Creative Industries Design in National Cheng-Kung University (Taiwan). She is currently focusing research interests on Tech-enhanced learning, Learning behavior analysis, and Information tech. application.
t00137@gm.tut.edu.tw

Sheau-Ming Chen
Kainan University, Taiwan.

Dr. Sheau-Ming Chen is now an Assistant Professor in the School of Tourism and Transportation, Kainan University, Taiwan. His previous positions in the same University were a Lecturer then an Assistant professor of the Center for General Education. And before those, he ever serviced as a Lecturer of Environmental Engineering Department, Kun Shan University, Taiwan, for almost ten years. He received his Undergradute Degree in National Taipei Institute of Technology (now is National Taipei University of Tech.) Taiwan, MS of Environmental Science in New Jersey Institute of Technology (USA) and PhD of Resources Engineering in National Cheng-Kung University (Taiwan). His current research interests are Eco-environmental education, Sustainable development, and Environmental issues.
jeffchen@gapps.knu.edu.tw