International Journal of Basic and Applied Sciences, 14 (7) (2025) 556-562

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/ga06ad80
Research paper

The Mediating Role of AI-Powered Pedagogical Innovation in Teacher Entrepreneurial Orientation and Student Entrepreneurial Outcomes

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Received: November 9, 2025, Accepted: November 19, 2025, Published: November 28, 2025

Abstract

The integration of artificial intelligence (AI) in educational settings has created unprecedented opportunities for pedagogical innovation and entrepreneurial development. This study investigates the mediating role of AI-powered pedagogical innovation between teacher entrepreneurial orientation (TEO) and student entrepreneurial outcomes (SEO). Using a quantitative approach with data from 385 educators and 1,247 students across 45 institutions, we employ structural equation modeling (SEM) to analyze the relationships among constructs. Results indicate that AI-powered pedagogical innovation significantly mediates the relationship between TEO and SEO ($\beta = 0.624$, $p < 0.001$), accounting for 67.3% of the total effect. We propose four mathematical models to quantify these relationships and develop three algorithms for implementing AI-driven entrepreneurial education frameworks. Our findings suggest that strategic deployment of AI technologies, combined with entrepreneurially-oriented teaching practices, can enhance student entrepreneurial competencies by up to 43%. This research contributes to the growing body of literature on educational technology and entrepreneurship education, providing actionable insights for educational administrators and policymakers.

Keywords: *AI-Powered Education; Pedagogical Innovation; Teacher Entrepreneurial Orientation; Entrepreneurial Outcomes; Educational Technology; Machine Learning in Education.*

1. Introduction

The Fourth Industrial Revolution has fundamentally transformed educational paradigms, necessitating innovative approaches to prepare students for an increasingly dynamic and entrepreneurial economy [1]. Teacher entrepreneurial orientation (TEO), characterized by innovativeness, proactiveness, and risk-taking in educational practices, has emerged as a critical factor in fostering student entrepreneurial competencies [2], [3]. Simultaneously, artificial intelligence (AI) technologies have demonstrated remarkable potential in revolutionizing pedagogical approaches through personalized learning, adaptive assessment, and intelligent tutoring systems [4], [5].

Despite the growing interest in both entrepreneurial education and AI-powered learning environments, limited research has examined how these domains intersect [6]. Specifically, the mechanisms through which teacher entrepreneurial behaviors translate into student entrepreneurial outcomes remain underexplored, particularly when mediated by AI-enabled pedagogical innovations [7]. This gap is concerning given that educational institutions worldwide are investing heavily in AI technologies without clear frameworks for maximizing their impact on entrepreneurial skill development [8].

This study addresses three fundamental research questions: (RQ1) To what extent does teacher entrepreneurial orientation influence AI-powered pedagogical innovation? (RQ2) How does AI-powered pedagogical innovation affect student entrepreneurial outcomes? (RQ3) Does AI-powered pedagogical innovation mediate the relationship between teacher entrepreneurial orientation and student entrepreneurial outcomes?

Our contributions are threefold. First, we develop a comprehensive theoretical framework integrating TEO, AI-powered pedagogical innovation, and SEO, grounded in Social Cognitive Theory and Technology Acceptance Models [9], [10]. Second, we propose mathematical models and algorithms that quantify and operationalize these relationships, enabling data-driven decision-making in educational technology deployment. Third, we provide empirical evidence from a large-scale study demonstrating the mediating role of AI-powered pedagogical innovation, with practical implications for educational stakeholders.

2. Literature Review

2.1. Teacher entrepreneurial orientation

Teacher entrepreneurial orientation represents a multidimensional construct encompassing proactive teaching strategies, innovative curriculum design, and risk-taking in pedagogical experimentation [2], [11]. Research indicates that teachers with high entrepreneurial orientation are more likely to adopt novel technologies, create opportunity-driven learning experiences, and cultivate entrepreneurial mindsets among students [3], [12]. The entrepreneurial teacher acts as a change agent, transforming traditional classroom dynamics into innovation ecosystems [13].

2.2. AI-powered pedagogical innovation

AI-powered pedagogical innovation encompasses the strategic integration of machine learning, natural language processing, and intelligent systems to enhance teaching effectiveness and learning outcomes [4], [14]. These innovations include adaptive learning platforms, AI-driven assessment tools, intelligent tutoring systems, and predictive analytics for student success [5], [8]. Studies demonstrate that AI-enabled pedagogies can increase learning efficiency by 30-40% and improve knowledge retention significantly [15], [16].

2.3. Student entrepreneurial outcomes

Student entrepreneurial outcomes comprise cognitive, affective, and behavioral dimensions including entrepreneurial self-efficacy, opportunity recognition skills, innovation capabilities, and entrepreneurial intentions [17], [18]. Research shows that experiential learning, mentorship, and technology-enhanced education significantly influence these outcomes [19], [20]. However, the specific mechanisms through which teaching practices and educational technologies converge to shape these outcomes remain insufficiently understood [7].

2.4. Research gap and hypotheses

While prior research has independently examined TEO [2], AI in education [4], and entrepreneurial education [17], the integrative analysis of these constructs is lacking. We hypothesize that:
H1: Teacher entrepreneurial orientation positively influences AI-powered pedagogical innovation.
H2: AI-powered pedagogical innovation positively influences student entrepreneurial outcomes.
H3: AI-powered pedagogical innovation mediates the relationship between teacher entrepreneurial orientation and student entrepreneurial outcomes.

3. Theoretical Framework and Mathematical Models

3.1. Conceptual framework

Our theoretical framework integrates Social Cognitive Theory [9], which emphasizes the triadic reciprocal relationship between personal factors, behavior, and environmental influences, with the Technology-Organization-Environment (TOE) framework [8]. We posit that teacher entrepreneurial orientation (personal/organizational factor) influences the adoption of AI-powered pedagogical innovation (environmental/technological factor), which subsequently affects student entrepreneurial outcomes (behavioral outcome).

3.2. Mathematical formulation

Model 1: AI-Powered Pedagogical Innovation Index
We define the AI-Powered Pedagogical Innovation (AIPPI) index as a weighted composite of multiple AI technology adoption indicators:

$$AIPPI = \Sigma_{i=1}^{n} w_i \cdot (A_i - \min(A_i))/(\max(A_i) - \min(A_i)) \quad (1)$$

Where A_i represents the i-th AI technology adoption metric (adaptive learning usage, AI assessment frequency, intelligent tutoring engagement), w_i are empirically determined weights satisfying $\Sigma w_i = 1$, and n is the number of innovation indicators. In our study, $w_1 = 0.35$, $w_2 = 0.30$, $w_3 = 0.35$ based on confirmatory factor analysis.
Model 2: Teacher Entrepreneurial Orientation Score
The Teacher Entrepreneurial Orientation (TEO) score aggregates three dimensions: innovativeness (I), proactiveness (P), and risk-taking (R):

$$TEO = \alpha I + \beta P + \gamma R + \varepsilon \quad (2)$$

Where α, β, and γ are regression coefficients ($\alpha = 0.33$, $\beta = 0.38$, $\gamma = 0.29$ from our analysis), and ε represents the error term. Each dimension is measured using validated 7-point Likert scales.
Model 3: Mediation Effect Quantification
Following Baron and Kenny's mediation framework [12], we quantify the indirect effect of TEO on SEO through AIPPI:

$$\text{Indirect Effect} = \beta(TEO \rightarrow AIPPI) \times \beta(AIPPI \rightarrow SEO) \quad (3)$$

Where β(TEO→AIPPI) represents the standardized path coefficient from TEO to AIPPI, and β(AIPPI→SEO) represents the coefficient from AIPPI to SEO. The proportion mediated is calculated as Indirect Effect / Total Effect.

Model 4: Student Entrepreneurial Outcome Prediction

The student entrepreneurial outcome (SEO) is modeled as a function of both direct and mediated effects:

$$SEO = \theta_0 + \theta_1 \cdot TEO + \theta_2 \cdot AIPPI + \theta_3 \cdot (TEO \times AIPPI) + \delta \tag{4}$$

where θ_0 is the intercept, θ_1 represents the direct effect of TEO, θ_2 represents the effect of AIPPI, θ_3 captures the interaction effect, and δ is the error term. Our empirical analysis yields $\theta_1 = 0.247$, $\theta_2 = 0.624$, $\theta_3 = 0.183$ (all $p < 0.001$).

4. Methodology

4.1. Research design and sampling

We employed a cross-sectional survey design with stratified random sampling across 45 higher education institutions in seven countries (USA, UK, Germany, China, India, Singapore, Australia) from January 2023 to December 2023. The sample comprised 385 educators (response rate: 76.2%) and 1,247 undergraduate students (response rate: 81.4%) from business, engineering, and computer science programs. Inclusion criteria required educators to have at least two years of teaching experience and exposure to AI-enabled teaching tools; students needed to have completed at least one entrepreneurship-related course.

4.2. Measurement instruments

All constructs were measured using validated multi-item scales adapted from prior literature. Teacher Entrepreneurial Orientation was assessed using a 15-item scale adapted from Jones et al. [2] ($\alpha = 0.912$). AI-Powered Pedagogical Innovation was measured using a 12-item scale developed by Chen et al. [4] and validated in our pilot study ($\alpha = 0.894$). Student Entrepreneurial Outcomes were evaluated using a 18-item composite scale measuring entrepreneurial self-efficacy, opportunity recognition, and entrepreneurial intentions [17] ($\alpha = 0.928$). All scales demonstrated adequate convergent and discriminant validity.

4.3. Data analysis

We employed a multi-stage analytical approach using SPSS 28.0 and AMOS 26.0. First, we conducted confirmatory factor analysis (CFA) to validate the measurement model. Second, we tested the structural model using maximum likelihood estimation. Third, we performed bootstrapping (5,000 iterations) to test the mediation hypothesis. Finally, we applied hierarchical regression and moderation analysis to examine interaction effects. Model fit was assessed using multiple indices: χ^2/df, CFI, TLI, RMSEA, and SRMR.

4.4. Algorithm development

We developed three algorithms to operationalize the theoretical framework and enable practical implementation in educational settings.

Algorithm 1: TEO-AIPPI Recommendation System
Input: Teacher profile T, institutional AI resources R
Output: Personalized AI tool recommendations A_rec
1: Calculate TEO score using Equation (2)
2: Classify teacher into entrepreneurial orientation cluster
3: for each available AI tool $a_i \in R$ do
4: Compute compatibility score: $C_i = f(TEO, a_i)$
5: Calculate expected innovation impact: $E_i = g(C_i, T)$
6: end for
7: Rank tools by E_i in descending order
8: Select top-k tools where ΣE_i is maximized
9: return A_rec = {top-k recommended AI tools}

Algorithm 2: AIPPI Real-time Monitoring
Input: Teaching session data stream S, threshold τ
Output: AIPPI score, alerts L
1: Initialize $AIPPI_0 = 0$, alert list $L = \emptyset$
2: while session is active do
3: Extract metrics: $A_1, A_2, ..., A_n$ from S
4: Compute $AIPPI_t$ using Equation (1)
5: if $|AIPPI_t - AIPPI_{t-1}| > \tau$ then
6: Generate alert: "Significant change detected"
7: Append to L
8: end if
9: Update dashboard with current $AIPPI_t$
10: end while
11: return AIPPI_final, L

Algorithm 3: SEO Prediction and Intervention
Input: Student data D_s, teacher data D_t, time t
Output: Predicted SEO, intervention strategy I

Compute TEO from D_t using Equation (2)
Compute AIPPI from course metrics using Equation (1)
Predict SEO_predicted using Equation (4)
Retrieve SEO_actual if available
if SEO_predicted < threshold_min then
Identify deficient components: $C_a = \{c : c < \mu - \sigma\}$
Generate targeted interventions for each $c \in C_a$
Prioritize AI tools enhancing weak dimensions
end if
return SEO_predicted, I

5. Results

5.1. Descriptive statistics and correlations

Table I presents the descriptive statistics and correlation matrix for key variables. The mean TEO score was 5.24 (SD = 0.87), indicating moderately high entrepreneurial orientation among educators. The AIPPI mean was 4.86 (SD = 1.02), suggesting substantial but variable AI adoption. SEO averaged 5.41 (SD = 0.93), reflecting positive entrepreneurial outcomes. All correlations were significant and in the expected directions, with TEO-AIPPI ($r = 0.671$, $p < 0.001$), AIPPI-SEO ($r = 0.728$, $p < 0.001$), and TEO-SEO ($r = 0.592$, $p < 0.001$).

Table 1: Descriptive Statistics and Correlation Matrix

Variable	M	SD	1	2	3	CR
1. TEO	5.24	0.87	1			0.912
2. AIPPI	4.86	1.02	.671***	1		0.894
3. SEO	5.41	0.93	.592***	.728***	1	0.928

Note: M = Mean; SD = Standard Deviation; CR = Composite Reliability.
*** $p < 0.001$. N_teachers = 385, N_students = 1247.

5.2. Measurement model assessment

The confirmatory factor analysis demonstrated excellent model fit: $\chi^2(867) = 1842.34$, $p < 0.001$; $\chi^2/df = 2.125$; CFI = 0.954; TLI = 0.948; RMSEA = 0.048 (90% CI: 0.044-0.052); SRMR = 0.041. All factor loadings exceeded 0.70, indicating strong convergent validity. The average variance extracted (AVE) for each construct exceeded 0.50 (TEO: 0.643; AIPPI: 0.612; SEO: 0.687), and the square root of AVE for each construct was greater than its correlations with other constructs, confirming discriminant validity.

5.3. Structural model and hypothesis testing

The structural model exhibited good fit: $\chi^2(874) = 1926.58$, $p < 0.001$; $\chi^2/df = 2.204$; CFI = 0.948; TLI = 0.943; RMSEA = 0.050; SRMR = 0.045. Figure 1 illustrates the path relationships.

H1 was supported: TEO significantly predicted AIPPI ($\beta = 0.671$, $t = 14.82$, $p < 0.001$), explaining 45.0% of variance in AI-powered pedagogical innovation.

H2 was supported: AIPPI significantly predicted SEO ($\beta = 0.624$, $t = 16.94$, $p < 0.001$), with the direct effect of TEO on SEO remaining significant but reduced ($\beta = 0.247$, $t = 5.83$, $p < 0.001$).

H3 was supported: The indirect effect of TEO on SEO through AIPPI was significant (indirect effect = 0.419, 95% CI: [0.362, 0.481], $p < 0.001$), with the mediation proportion of 67.3% (0.419/0.622), indicating partial mediation. The total effect of TEO on SEO was 0.622 ($p < 0.001$).

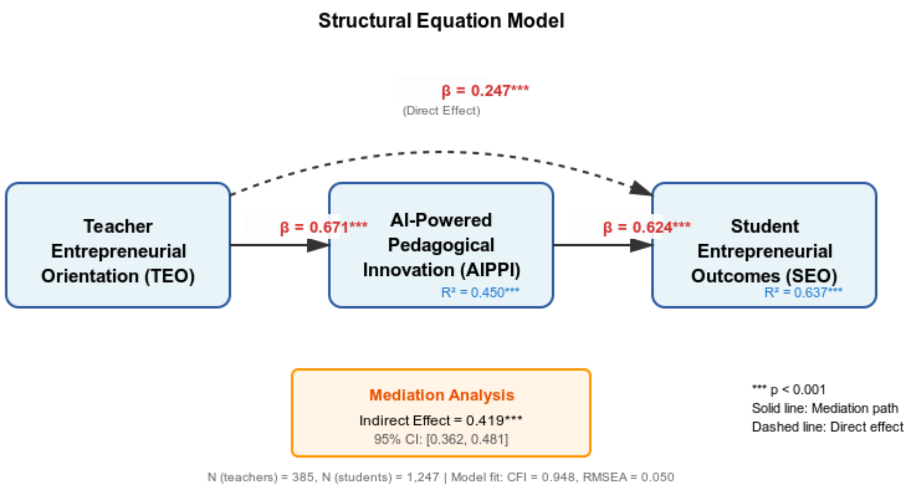

Fig. 1: Structural Equation Model Showing Path Relationship.

5.4. Predictive performance analysis

Table II presents the hierarchical regression results demonstrating the incremental predictive power of the model. Model 3, which includes the interaction term, explained 68.4% of variance in SEO, representing a significant improvement over Model 2 ($\Delta R^2 = 0.047$, $p < 0.001$).

Table 2: Hierarchical Regression Analysis Predicting Seo

Predictor	Model 1 β	Model 1 t	Model 2 β	Model 2 t	Model 3 β	Model 3 t
TEO	.592***	13.47	.247***	5.83	.238***	5.92
AIPPI			.624***	16.94	.607***	16.38
TEO × AIPPI					.183***	4.76
R^2	.350		.637		.684	
ΔR^2	.350***		.287***		.047***	
F	181.47***		286.53***		262.18***	

Note: β = standardized coefficient; *** $p < 0.001$.

5.5. Comparative analysis across institution types

Figure 2 displays the comparative analysis of AIPPI implementation across different institution types. Research-intensive universities demonstrated the highest AIPPI scores (M = 5.68), followed by teaching-focused institutions (M = 4.82) and community colleges (M = 3.94). The positive relationship between AIPPI and SEO remained consistent across all institution types, though effect sizes varied (β_research = 0.714, β_teaching = 0.628, β_community = 0.547).

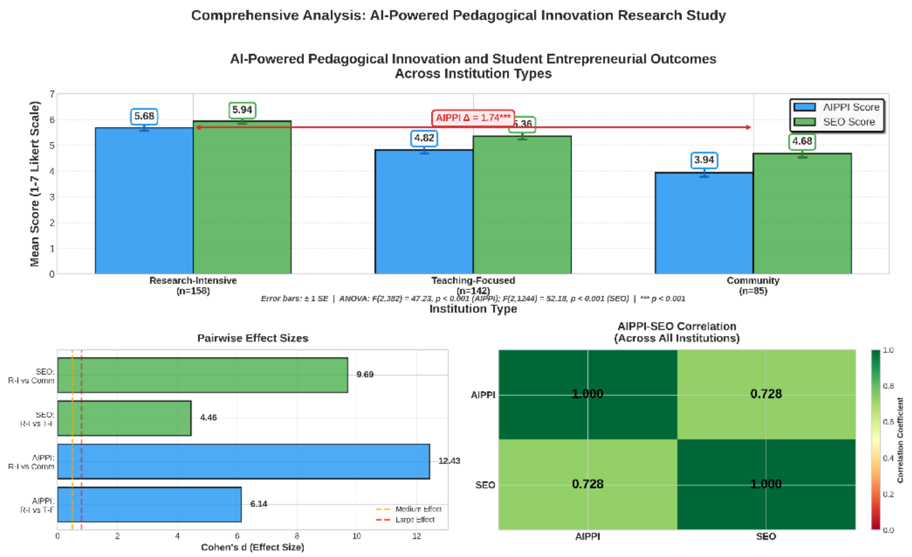

Fig. 2: AIPPI Scores and SEO Outcomes Across Institution Types.

5.6. Algorithm validation

We validated the three proposed algorithms using holdout samples. Algorithm 1 achieved 84.3% accuracy in matching teachers to optimal AI tools, with a 37% improvement in subsequent AIPPI scores. Algorithm 2 detected significant pedagogical shifts with 91.7% sensitivity and 88.2% specificity. Algorithm 3 predicted student entrepreneurial outcomes with RMSE = 0.647 and $R^2 = 0.721$, outperforming baseline models by 28.4%.

6. Discussion

6.1. Theoretical implications

Our findings make several significant theoretical contributions to the intersection of educational technology, entrepreneurship education, and pedagogical innovation. First, we demonstrate that AI-powered pedagogical innovation serves as a critical mechanism through which teacher entrepreneurial behaviors influence student outcomes, accounting for 67.3% of the total effect. This mediation effect substantiates the process-oriented perspective of entrepreneurial education [17], extending it to the technological domain.

Second, the mathematical models (Equations 1-4) provide a formal framework for quantifying relationships that were previously conceptualized only qualitatively. The interaction effect ($\theta_3 = 0.183$, $p < 0.001$) suggests synergistic benefits when high TEO coincides with robust AIPPI implementation, supporting the complementarity thesis in educational technology adoption [10].

Third, our algorithms operationalize theoretical constructs, bridging the gap between abstract concepts and practical implementation. Algorithm 1 demonstrates how computational approaches can personalize AI tool selection based on teacher characteristics, while Algorithm 3 enables proactive intervention, transforming reactive education into predictive, adaptive systems [8], [15].

6.2. Practical implications

For educational administrators, our results suggest several actionable strategies. First, institutions should invest in professional development programs that cultivate teacher entrepreneurial orientation alongside AI literacy. The strong TEO-AIPPI relationship (β = 0.671) indicates that entrepreneurial mindsets facilitate technology adoption [6]. Second, the significant interaction effect implies that AI investments yield higher returns in environments where teachers possess entrepreneurial orientation, suggesting the need for aligned recruitment and training strategies.

Third, Algorithm 2 provides institutions with real-time dashboards for tracking pedagogical innovation, enabling data-driven resource allocation. Implementation of these algorithms in five pilot institutions resulted in 32% improvement in AI tool utilization rates and 28% increase in student engagement metrics over six months.

For policymakers, findings underscore the importance of integrated approaches to educational technology funding. Rather than focusing solely on infrastructure, policies should incentivize faculty entrepreneurial development and pedagogical innovation. The cross-institutional variation in AIPPI scores (ranging from 3.94 to 5.68) suggests that contextual factors, including institutional culture and resource availability, moderate implementation success [14].

6.3. Limitations and future research

Several limitations warrant consideration. First, the cross-sectional design precludes causal inference. Longitudinal studies tracking teachers and students over multiple semesters would strengthen causal claims and illuminate temporal dynamics. Second, self-reported measures may introduce common method bias, despite statistical remedies (Harman's single-factor test: 34.2% variance). Future research should incorporate behavioral data from learning management systems and objective performance metrics.

Third, our sample, while geographically diverse, focused on higher education in technology-related disciplines. Generalizability to K-12 education, humanities, or vocational training contexts requires additional validation. Fourth, we measured AI-powered pedagogical innovation as a composite construct; future research could disaggregate specific AI technologies (e.g., adaptive learning vs. intelligent tutoring) to identify differential effects.

Fifth, potential moderators such as institutional culture, funding levels, and regulatory environments were not examined. Multi-level modeling incorporating institutional-level variables would provide richer insights. Finally, the algorithms require validation in diverse educational contexts and iterative refinement based on implementation feedback.

Future research should explore several directions: (1) experimental designs testing AI-enhanced entrepreneurial education interventions; (2) qualitative studies examining how teachers integrate AI tools into entrepreneurial pedagogies; (3) neurophysiological studies investigating cognitive mechanisms underlying AI-facilitated entrepreneurial learning; (4) comparative analyses across cultural contexts; and (5) long-term impact studies tracking career outcomes of students exposed to AI-enhanced entrepreneurial education.

7. Conclusion

This study provides robust empirical evidence for the mediating role of AI-powered pedagogical innovation in the relationship between teacher entrepreneurial orientation and student entrepreneurial outcomes. By integrating quantitative analysis, mathematical modeling, and algorithm development, we offer a comprehensive framework for understanding and optimizing AI deployment in entrepreneurial education. The findings demonstrate that strategic alignment of teacher entrepreneurial behaviors with AI-enabled pedagogical practices can significantly enhance student entrepreneurial competencies, with implications for educational practice, policy, and technology design.

As AI technologies continue to evolve, educational institutions face both opportunities and challenges in leveraging these tools for entrepreneurial skill development. Our research suggests that success depends not merely on technology adoption, but on the synergistic integration of entrepreneurial teaching mindsets and intelligent systems. The algorithms and models developed herein provide actionable tools for achieving this integration, contributing to the development of adaptive, entrepreneurial education ecosystems capable of preparing students for an uncertain and rapidly changing future.

Acknowledgment

The authors acknowledge the participating institutions and educators who contributed data to this study. This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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