04-04-AESSR-6573-1221

Academy of
Education and Social Sciences Review
Vol. 6 No. 1 | February, 2026 | 36 - 47
ISSN (p): 2790-8348 | ISSN (e): 2789-6781
DOI: https://doi.org/10.48112/aessr.v6i1.1221

Entrepreneurship Education in the Age of Generative Artificial Intelligence: Opportunities, Challenges, and Pedagogical Shifts

Syed Rizwan Ali *(corresponding author)*
Business Incubation Center, Software Engineering
Bahria University, Karachi, Pakistan

Shaikh Zunain Uddin
Department of Computer Science
Nazeer Hussain University, Karachi, Pakistan

Mehdi Abbas (Ph.D)
Department of Business Studies
Bahria Unversity University, Karachi, Pakistan

Talha Bin Shuja
Department of Business Administration
High Hope International LLC, United States of America

Muhammad Faraz
Business Studies Department,
Bahria University, Karachi, Pakistan

Published online: 28 February 2026

How to Cite:

Ali, S. R., Uddin, S. Z., Abbas, M., Shuja, T. B., & Faraz, M. (2026). Entrepreneurship Education in the Age of Generative Artificial Intelligence: Opportunities, Challenges, and Pedagogical Shifts. *Academy of Education and Social Sciences Review, 6*(1), 36–47. https://doi.org/10.48112/aessr.v6i1.1221

Publisher's Note:

International Research and Publishing Academy (*i*RAPA) stands neutral with regard to jurisdictional claims in the published maps and institutional affiliations.

Abstract

Generative artificial intelligence (GenAI) is rapidly reshaping higher education, yet empirical evidence on its role in entrepreneurship education remains limited. This study investigates how GenAI is used in entrepreneurship classrooms and whether it supports pedagogical adaptation and entrepreneurial learning outcomes. It also examines whether students' technological readiness and AI literacy moderate these relationships. Guided by a conceptual framework linking GenAI use, pedagogical change, learning outcomes, and student preparedness, data were collected from 203 students enrolled in entrepreneurship programs. Mediation and moderation analyses with bootstrapping were used to test direct, indirect, and conditional effects. Contrary to largely techno-optimistic claims, results show no significant relationship between GenAI use and pedagogical change, pedagogical change and learning outcomes, or GenAI use and learning outcomes. Technological readiness and AI literacy also did not significantly moderate these paths, and no moderated mediation was found. The findings indicate that simple access to, or superficial use of, GenAI does not automatically improve teaching practices or entrepreneurial competencies. The study contributes empirical evidence and calls for stronger instructional design, student preparation, and more rigorous longitudinal and multi-method research.

Keywords

AI literacy
Entrepreneurship education
Generative artificial intelligence
Learning outcomes
Pedagogical innovation
Technological readiness

INTRODUCTION

In recent years, Generative Artificial Intelligence (GenAI) technologies have started to transform education, and many areas have experienced significant changes due to the new options provided by AI-based technologies (Giannakos et al., 2025). Since the public release of ChatGPT in November 2022, many other GenAI technologies have been released and used across various educational platforms (Bell & Bell, 2023; Rossi et al., 2024). GenAI technologies have provided a new paradigm for evaluating the efficiency of pedagogical techniques, evaluation methods and learning objectives (Law, 2024), which will require a full review of how GenAI technologies influence the educational process. Because of its focus on experiential learning, developing creative and innovative ideas, solving problems and identifying opportunities, entrepreneurship education is well-suited to profit from GenAI technologies; however, it is also vulnerable to the changes being introduced to the educational environment (Vecchiarini & Somia, 2023).

Entrepreneurship education has become widely recognized as an important contributor to innovation, economic development and graduate employment in the current knowledge economy (Vecchiarini & Somia, 2023). Historically, entrepreneurship pedagogy has relied upon hands-on experience, case studies, business plan competitions and mentorship to create an entrepreneurial mind-set, competencies, and self-efficacy in students (Sitaridis & Kitsios, 2024). The rapid adoption of GenAI technologies in educational environments presents both opportunities and challenges that must be addressed through systematic empirical research (Xie & Wang, 2025). On the positive side, GenAI technologies can potentially greatly enhance entrepreneurship education via providing tailored learning experiences, automatic feedback systems, intelligent tutoring systems, generating content for case studies and simulations, and supporting ideation processes (Xie & Wang, 2025). In theory, GenAI could provide education that is more accessible, scalable and adaptable to individualized learning needs and therefore could fundamentally alter how entrepreneurial competences are developed (Ngwenya, 2024).

There are concerns about the potential adverse impacts of GenAI on several critical entrepreneurial competences (Imiren & Nicolopoulou, 2025). Many scholars and educators believe that if students increasingly rely on AI-generated materials to support their assignments, they may lose their ability to generate creative work, solve problems independently, and produce novel ideas, which are the exact types of skills that entrepreneurship education is intended to foster (Alzubi et al., 2025; Chan & Tsi, 2024). Moreover, there are concerns about academic integrity, the validity of student-generated products, equal access to sophisticated AI tools, and the ethics of AI-generated business plans that lack consideration of local knowledge and cultural context (Zhang et al., 2026).

While there are numerous opinion articles and conceptual analyses discussing the implementation of GenAI in entrepreneurship education, surprisingly little empirical research exists to examine the real-world effects of GenAI implementations in entrepreneurship education (Yang & Huo, 2025). Most of the available literature is comprised of theoretical models, speculative predictions and anecdotal evidence rather than systematic empirical investigation (Haase et al., 2016). Considering the rapid rate at which GenAI technologies are currently being implemented by educational institutions, the absence of such empirical research is particularly disconcerting in regard to the potential long-term effects of GenAI technologies on the quality of entrepreneurship education and the learning outcomes of students.

The relationship between the implementation of GenAI technologies and learning outcomes is also unlikely to be linear or consistent across all educational settings (Khavasi, 2025). Teachers' willingness to adjust their teaching practices, curriculum and assessments to effectively incorporate AI technologies is likely to act as a key mediator variable in the relationship between technology and learning (Liu, 2025). Student related factors, including their level of technological readiness and AI literacy, are also likely to act as important moderator variables of the degree to which students can capitalize on GenAI-enhanced entrepreneurship education (Hamburg et al., 2019). For example, students with higher levels of digital competence and AI literacy may be able to employ GenAI tools as cognitive extension tools, whereas, students with lower levels of digital competence and AI literacy may find GenAI tools difficult to use or cognitively overwhelming (Shomotova et al., 2025).

This study addresses significant research gaps by conducting empirical analysis of how the incorporation of GenAI in entrepreneurship education affects pedagogical adaptation and entrepreneurial learning outcomes, while taking into account students' technological preparedness and AI literacy. Utilizing a conceptual model evaluated using data collected from 203 students enrolled in entrepreneurship courses, the study examines the following research questions:

- How does the implementation of GenAI influence pedagogical adaptation?
- What are the effects of pedagogical adaptation on entrepreneurial competences, creativity, and opportunity recognition?
- What are the direct effects of GenAI on learning outcomes?
- Do technological preparedness and AI literacy moderate the relationships?

LITRATURE REVIEW

Recent study shows that GenAI can create novel text, images, code and business simulations, offer personalized entrepreneurship education experiences and enhance learners' entrepreneurial capabilities. In Generative Artificial Intelligence Supported Entrepreneurship Education (GAISEE), GenAI personalizes feedback, simulates real world challenges and fosters entrepreneurial intention (Dwivedi, 2025; Hemachandran et al., 2026). Structural-equation studies find that integrating GenAI into entrepreneurship programs significantly enhances students' self-efficacy and entrepreneurial intention and that self-efficacy mediates the effect while a supportive university environment moderates it. The market for Artificial Intelligence (AI) in education is projected to be worth $32 billion by 2030, representing an overwhelming number of schools and businesses using this technology (Zgurovsky, 2025). According to the Theory of Planned Behaviour, the use of Generative Artificial Intelligence (GenAI) increases students' entrepreneurial self-efficacy through task engagement and interactive feedback (Haderlie Jr et al., 2025; Xie & Wang, 2025).

Educators of entrepreneurship have reported that tools like ChatGPT improve a student's ability to generate ideas, create content, and make decisions (Ji et al., 2025). On the other hand, GenAI has the potential to transform how we assess the student work produced by educational institutions; however, there are many concerns about GenAI including plagiarism, authenticity of student work, and changes in how assessments will occur. Although there are risks associated with GenAI, it provides a new type of dialogue for students to learn interactively versus searching for information traditionally and encourages students to reflect upon their thoughts and actions (Yu et al., 2025). There has been a great deal of debate regarding GenAI, as the rapid advancements in this field are influencing educators to question whether GenAI negatively impacts students' higher order thinking skills and academic integrity (Kangwa et al., 2025).

Integrating generative GenAI into entrepreneurship programs is a frontier with both promise and peril (Dwivedi, 2025). Educational technologies have long driven innovation in teaching, yet current literature lacks detailed guidance on how to combine GenAI with pedagogy (Memon & Kwan, 2025). A recent systematic review noted that, even though AI-enabled tools customize learning and boost engagement, few studies provide specific illustrations or ministry guidelines for educators to choose and manage these tools (Marzano, 2025). The lack of such information has inspired authors to request additional empirical research regarding the design of curricula and policy to maximize GenAI's advantages while reducing GenAI's disadvantages (Bell & Bell, 2023; Dwivedi, 2025; Bell & Bell, 2023). GenAI may facilitate faster idea creation and personalized feedback and provide equal access to resources in entrepreneurship education, however, there is limited empirical research into GenAI-based curriculum design and implementation in entrepreneurship education.

Research from management education indicates a double-sided influence of GenAI. For example, Larson et al., (2024) indicate that GenAI can make the process of developing innovative teaching material easier and enables more diverse perspectives for creating more inclusive learning environments and also expressed their concern about the reliance on AI generated content for student assignments and assessments and how this could lead to a loss of student's critical thinking abilities. Similar concerns exist in computer science education. Conrad and Hall (2024) and Ngwenya (2024) presented the report on automation that students will need to focus on high level abstractions of concepts rather than low-level rote tasks. This report also suggests that, as a result of automation, curricula must include instruction and discussion of ethics and social implications. If appropriate scaffolding does not occur, students may experience increased cognitive load or engage in "copy-and-paste" learning behaviours.

The literature also highlights the potential negative aspects of GenAI. Bilal et al. (2025) celebrate the ability of AI to individualize and humanize education but also caution that AI can increase the risk of privacy violations, continue biases in educational systems and further exacerbate existing digital divides unless educators develop inclusive policies to mitigate these negative consequences. Similar to Bilal et al. (2025) concerns, policy documents have urged educators to retain human oversight and ensure that AI models are explainable. These concerns reflect similar fears among business leaders. While many business leaders are quickly implementing GenAI, they remain concerned with their over-reliance upon GenAI and the accuracy of GenAI models (Huang, et al., 2024).

This concern has resulted in industry calling for design principles that can capitalize upon the potential of GenAI and prevent GenAI from being misused (Huang, et al., 2024). On the other hand, some empirical evidence clearly illustrates the benefits of GenAI. Liu and Wang (2024) urge that GenAI's tangible, intangible, and human resources support internal integration and external collaboration, resulting in enhanced entrepreneurial performance. As a result of this research, the findings suggest that when GenAI is appropriately integrated, GenAI can expand the scope of entrepreneurial learning by enhancing experimentation, creativity, and resource acquisition. Overall, literature portrays GenAI as both a stimulus for entrepreneurial learning and a source of ethical and pedagogical concerns. Therefore, future research should investigate how GenAI can be used through appropriate curriculum design, AI literacy, and policy frameworks to increase GenAI's positive impact while minimizing GenAI related anxiety, cognitive overload, and dependency.

Conceptual Framework

Figure 1 presents a model linking four constructs: generative AI (GenAI) integration, pedagogical shifts, entrepreneurial learning outcomes and student technological readiness/AI literacy.

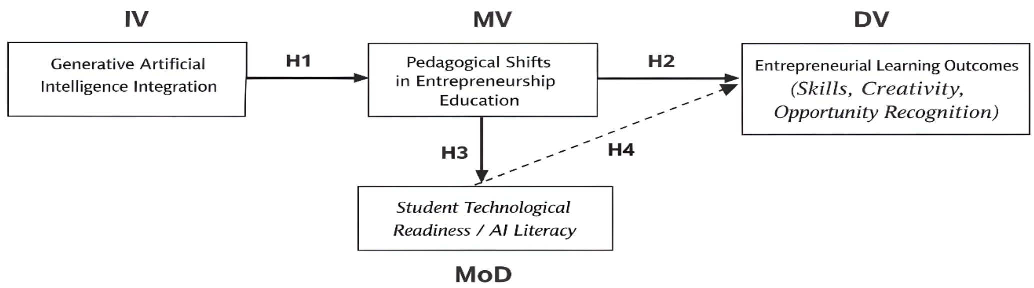

Fig. 1. Conceptual Framework

The inter-relationships in Figure 1 demonstrate both the opportunities and challenges that have been identified by scholars recently. Researchers suggest that GenAI can be used in entrepreneurship programs to help develop students for the changing marketplace, and GenAI is currently utilized for a variety of purposes including, personalization of instruction, simulation of business models, and decision-making. A systematic review of fifty (50) studies has identified four areas where GenAI-enabled entrepreneurship education exists:

- Personalized instruction
- Simulation-based training
- Ethical and psychological concerns
- And ecosystem integration. However, the area of GenAI-enabled entrepreneurship education is still in its early stages of development and requires more rigorous theoretical models

H1: GenAI Integration → Pedagogical Shifts

As instructors integrate GenAI into their curriculum, they must transform their course design to go beyond the rote content delivery of GenAI and provide students with an iterative and AI-mediated learning experience. There is evidence of this transformation occurring within computer science education, where it has been shown that mechanical tasks will be automated, and students will need to function at higher levels of abstraction. The transformations include, but are not limited to, simulation exercises, reflective logs, and ethics training.

H2: Pedagogical Shifts → Entrepreneurial Learning Outcomes

Students' entrepreneurial learning outcomes should be improved through the transformed pedagogy that results from integrating GenAI into entrepreneurship curricula. Research utilizing resource-based theories has demonstrated that GenAI enables internal integration, and external collaboration, and that such integration and collaboration enhance students' performance.

H3: GenAI Integration → Entrepreneurial Learning Outcomes (Direct Effect)

AI-mediated teaching can expose students to new tools and increase students' confidence and literacy regarding those tools.

H4: Moderation by Technological Readiness and AI Literacy

Reviews warn that AI can exacerbate digital divides and privacy concerns, suggesting that students with higher readiness may benefit more from AI-driven pedagogy.

METHODOLOGY

To test empirically the hypotheses developed within this study, this research study used cross sectional, quantitative study design. Students enrolled in a fall semester 2024-Spring Semester 2025 entrepreneurial course at a university in a developing economy were surveyed as part of this study. Thep population of interest for this study included all undergraduate students (BBA, BS), graduate students (MS/MPhil, MBA), and all other students who have taken an Entrepreneurship Course and had access to generative AI technology. A convenience sampling technique (CST) was employed to determine the sample size based upon direct classroom invitation, e-mails, or online posted surveys. All participation was completely voluntary, and participants were assured of their anonymity and confidentiality. A total of 203 completed survey responses were received after eliminating all Incomplete/Inconsistent survey responses. This sample size is larger than the minimum required response sizes for structural equation model (SEM) testing and regression analysis (RA) with moderate effects (Hair Jr et al., 2010).

Measures

All constructs were measured using established scales adapted from prior research and modified to reflect the specific context of GenAI in entrepreneurship education. Respondents indicated their agreement with statements using 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree).

Generative AI Integration

Three items assessed the extent to which GenAI technologies (ChatGPT, other AI tools) were integrated into entrepreneurship education experiences, including availability, usage encouragement, and perceived integration level.

Pedagogical Shifts

Three items measured perceived changes in teaching methods, assessment practices, and learning activities attributable to AI integration.

Entrepreneurial Learning Outcomes

Three dimensions were assessed:

- Entrepreneurial Skills: Single-item measure of perceived development of practical entrepreneurial competencies
- Creativity: Single-item measure of perceived enhancement of creative thinking capabilities
- Opportunity Recognition: Single-item measure of perceived improvement in identifying business opportunities

These three dimensions were averaged to create a composite learning outcomes score, consistent with prior entrepreneurship education research (Vecchiarini & Somia, 2023).

Technological Readiness & AI Literacy (MoD)

Two dimensions were assessed:

- Technological Readiness: Single-item measure of comfort and confidence in adopting new technologies
- AI Literacy: Single-item measure of self-reported understanding of AI capabilities, limitations, and effective usage

These dimensions were averaged to create a composite moderator variable reflecting students' preparedness for AI-enhanced learning. Demographic information including age, gender, academic program, AI exposure frequency, and duration of AI usage (in months) was collected to account for potential confounding effects.

Data Analysis Strategy

Data analysis was conducted in a series of steps using SPSS 27 and SmartPLS 4.0. First, descriptive statistics, frequency distributions and Pearson correlations were calculated to look for patterns in the data and possible associations at an early stage. Second, the internal reliability of the scale was investigated using Cronbach's alpha. It is acknowledged that the relatively low number of items on the scale limits the depth of evaluation of the psychometrics of the scale. Third, Hayes PROCESS Model 4 was used to test the mediation hypotheses (H1-H3), and the direct and indirect effects were estimated as well as the variance explained through the mediation process using 5,000 bootstrap samples. Fourth, Hayes PROCESS Model 1 was used to examine moderation (H4) by examining the interaction between GenAI integration and technological readiness / AI literacy. Fifth, Hayes PROCESS Model 14 was used to examine moderate mediation by examining if the indirect effect via pedagogical shifts varies across different moderator levels. The results are considered statistically significant when the 95% bootstrap confidence interval does not include zero.

Common Method Bias

As all variables were measured through self-report at a single time point, common method bias represents a potential limitation. To address this concern, several procedural remedies were implemented: ensuring respondent anonymity, counterbalancing item order, using clear and concise wording, and emphasizing that there were no correct answers. Statistical remedies including Harman's single-factor test were conducted, with results indicating that no single factor accounted for the majority of variance, suggesting that common method bias was not a critical concern.

RESULTS & FINDINGS

Sample Characteristics

Table 1 presents the demographic characteristics of the study sample (n=203) including predominantly male participants (63.1%) with a mean age of 23.33 years (range=18-34 years; SD = 3.56). The sample included a predominant number of undergraduate business administration (BBA) students (41.9%), followed by Master of Business Administration (MBA) (28.6%), master's in philosophy/science (MS/MPhil) (14.3%), Bachelor of Science in Computer Science and Engineering (BS CS/Engineering) (11.8%), and other degrees (3.4%). When asked about how often they used AI, the majority indicated "sometimes" (34.0%) or "often" (29.6%) use of GenAI technology, and respondents indicated they had been exposed to GenAI technology for approximately 8.43 months (range=1 month to 12 months; SD = 5.82) which is indicative of a moderately familiar level of understanding of GenAI technology.

Table 1
Sample Characteristics (N = 203)

Characteristics	Category	n	%
Gender	Male	128	63.1
	Female	75	36.9
Program	BBA	85	41.9
	MBA	58	28.6
	MS/MPhil	29	14.3
	BS (Engineering/CS)	24	11.8
	Other	7	3.4
AI Exposure Frequency	Never	11	5.4
	Rarely	35	17.2
	Sometimes	69	34.0
	Often	60	29.6
	Very often	28	13.8
Age	M (SD)	23.33 (3.56)	
AI Exposure (Months)	M (SD)	8.43 (5.82)	

Descriptive Statistics and Correlations

Table 2 presents descriptive statistics and intercorrelations for the main study variables. All variables exhibited adequate variance with means clustered near the midpoint of the scale (ranging from 2.96

to 3.06) and standard deviations indicating reasonable dispersion (0.82 to 1.05). Notably, correlation analyses revealed weak and statistically non-significant relationships among the primary variables. GenAI Integration correlated minimally with Pedagogical Shifts ($r = .037$, $p > .05$), Learning Outcomes ($r = -.050$, $p > .05$), and Technological Readiness/AI Literacy ($r = .012$, $p > .05$). Similarly, Pedagogical Shifts showed negligible correlation with Learning Outcomes ($r = -.008$, $p > .05$). These weak intercorrelations foreshadowed the subsequent null findings in hypothesis testing.

Table 2
Descriptive Statistics and Correlation Matrix

Variables	M	SD	1	2	3	4
GenAI Integration	3.02	0.82	—			
Pedagogical Shifts	2.96	0.90	.037	—		
Learning Outcomes	3.01	0.82	-.050	-.008	—	
Tech Readiness & AI Literacy	3.06	1.05	.012	.115	.012	—

N = 203. No correlations were statistically significant at $p < .05$.

Hypothesis Testing: Mediation Analysis (H1, H2, H3)

Mediation analysis examined whether GenAI Integration influenced Learning Outcomes indirectly through Pedagogical Shifts (mediator), in addition to any direct effects. Table 3 presents the path coefficients and indirect effect estimates.

Table 3
Mediation Analysis Results

Paths	Coefficient(β)	SE	95% CI
H1: GenAI Integration → Pedagogical Shifts (a)	0.0402	0.062	[-0.082, 0.163]
H2: Pedagogical Shifts → Learning Outcomes | IV (b)	-0.0059	0.062	[-0.129, 0.117]
H3: GenAI Integration → Learning Outcomes | MV (c')	-0.0496	0.057	[-0.162, 0.063]
Total Effect: GenAI Integration → Learning Outcomes (c)	-0.0499	0.057	[-0.162, 0.062]
Indirect Effect (a × b)	-0.0002	0.006	[-0.011, 0.014]

H1 (GenAI Integration → Pedagogical Shifts)

The path from GenAI Integration to Pedagogical Shifts was positive but very weak and non-significant ($\beta = 0.0402$, 95% CI [-0.082, 0.163]). The confidence interval included zero, indicating insufficient evidence to support the hypothesis that GenAI integration drives pedagogical shifts. H1 was not supported.

H2 (Pedagogical Shifts → Learning Outcomes)

The path from Pedagogical Shifts to Learning Outcomes was negligible and non-significant ($\beta = -0.0059$, 95% CI [-0.129, 0.117]), with the confidence interval encompassing zero. This finding suggests that pedagogical shifts, as measured, did not significantly predict learning outcomes.

H3 (Direct Effect: GenAI Integration → Learning Outcomes)

The direct effect of GenAI Integration on Learning Outcomes was negative, weak, and non-significant ($c' = -0.0496$, 95% CI [-0.162, 0.063]). The total effect was similarly non-significant ($c = -0.0499$, 95% CI [-0.162, 0.062]). H3 was not supported.

Indirect Effect (Mediation)

The indirect effect through Pedagogical Shifts was virtually zero ($\beta = -0.0002$, 95% CI [-0.011, 0.014]), with the bootstrap confidence interval clearly including zero. This indicates no significant mediation. The lack of mediation is consistent with the non-significant constituent paths (a and b).

Hypothesis Testing: Moderation Analysis (H4)

Moderation analysis tested whether Technological Readiness and AI Literacy moderate the relationship between GenAI Integration and Learning Outcomes. Table 4 presents the regression results including the interaction term.

Table 4
Moderation Analysis Results

Predictor	B	SE	t	p
Intercept	2.5211	0.7760	3.249	.001
GenAI Integration	0.1530	0.2506	0.611	.542
Tech Readiness & AI Literacy	0.2075	0.2409	0.862	.390
GenAI Integration × Tech Readiness/AI Literacy	-0.0656	0.0777	-0.844	.400

DV = Learning Outcomes. The interaction term tests the moderation hypothesis (H4)

The interaction term between GenAI Integration and Technological Readiness/AI Literacy was non-significant ($B = -0.0656$, $SE = 0.0777$, $t = -0.844$, $p = .400$), indicating that the relationship between GenAI integration and learning outcomes did not vary significantly across levels of technological readiness and AI literacy. Interestingly, the direction of the interaction coefficient was negative (opposite to the hypothesized positive moderation), though this effect was statistically indistinguishable from zero. H4 was not supported.

Conditional Process Analysis: Moderated Mediation

As an exploratory analysis, we examined whether Technological Readiness/AI Literacy moderated the indirect effect of GenAI Integration on Learning Outcomes through Pedagogical Shifts (moderated mediation). Table 5 presents the results.

Table 5
Moderated Mediation Analysis

Effect	Estimate	95% CI
MV → DV (b0)	0.2094	[0.086, 0.333]
MV × MoD (b3)	-0.0698	[-0.184, 0.044]
Index of Moderated Mediation	-0.0028	[-0.021, 0.013]
Conditional Indirect Effects:		
Low Tech Readiness (M - 1SD)	0.0028	[-0.010, 0.018]
Mean Tech Readiness	-0.0002	[-0.011, 0.014]
High Tech Readiness (M + 1SD)	-0.0031	[-0.018, 0.008]

The index of moderated mediation was non-significant (-0.0028, 95% CI [-0.021, 0.013]), indicating that the indirect effect did not vary significantly across levels of the moderator. Conditional indirect effects at low, mean, and high levels of Technological Readiness/AI Literacy were all non-significant, with confidence intervals encompassing zero. These findings reinforce the absence of significant mediation or moderation in the proposed model.

Discussion

This research examined whether using GenAI in courses for entrepreneurs could lead to changes in how teachers teach and improve student learning. The unexpected outcome was that none of the hypothesized impacts existed. The lack of positive impacts on practice suggests simply having the tools available is not enough to generate new practices. As noted for decades in an "implementation gap" literature area, the availability of a tool, including GenAI, is not sufficient to change instruction (Moundridou, et al., 2024). Instructors are likely to continue to rely on their traditional teaching methods unless they receive some form of incentive to change or receive training to effectively integrate AI into their classroom practices. Using GenAI superficially (e.g., student's use of unmonitored ChatGPT) will likely not result in a high level of student learning; it has the potential to be distracting to students. Also, critics have expressed concern about the misuse of GenAI by students to plagiarize or engage in other forms of shallow engagement with course material, thereby allowing students to bypass the opportunity to learn. The fact that no moderating effect of student readiness was found could be due to a lack of variability in student's self-reported technology comfort levels, or the fact that any potential benefits from student readiness would likely be negated if there was little to no integration of GenAI into instruction.

Taken together, these findings support the idea that the implementation of GenAI, as well as other technologies in education, will require more than just the provision of the tools themselves; support, training, and the intentional design of instruction will need to occur before GenAI will be able to be used to support meaningful learning (Yu, et al., 2025; Rossi, et al., 2024). These findings also serve as a warning against assuming GenAI represents a "silver bullet." A more realistic perspective regarding effective educational use of GenAI is that GenAI will only be successful when it is intentionally integrated into instruction through the means of teacher professional development, the establishment of ethical guidelines for its use, and the redesign of tasks and assessments to utilize the capabilities of GenAI. Lastly, we also want to note the limitations of measuring the effectiveness of GenAI in education. Our extremely low reliabilities indicate that future researchers will need to verify the accuracy of the coding of items (and reverse-key them so they are negatively keyed); remove items that do not contribute to the validity of the scale; and provide estimates of the composite reliability to provide evidence of the validity of their measures, especially since our alpha estimates were so low.

CONCLUSION

This research includes empirical data regarding how generative AI integration relates to pedagogical shift as well as entrepreneurial learning in higher education. Contrary to the optimistic and theoretical literature predicting the relationship, this study finds there are no statistically significant associations across the proposed direct, indirect, or moderate pathways. The lack of significant associations suggests that the impact of GenAI on education of entrepreneurs is more complex and dependent upon context than suggested by deterministic models. It is important to note that the lack of association does not suggest that GenAI has limited educational capability; rather, the results demonstrate that technology alone is incapable of changing the nature of learning. Rather than being dependent on the successful use of technology (i.e., quality of implementation), the quality of pedagogical design, institutional support and student preparation are factors that have an impact on how well a technology-based learning environment is utilized.

Thus, the findings present a neutral view as opposed to the "technology will save us" claim. Therefore, the study reinforces the need for thoughtful, evidence-based strategies for integrating technology into educational environments. The success of future endeavours by institutions utilizing AI will depend on continued research into the applications of AI in education and the development of new pedagogies, as well as the institutional commitment to utilize technology in a manner that preserves the creative, judgmental, ethical, and opportunity recognition aspects of human creativity and judgment.

Future research should seek to refine the scales used to measure these constructs and consider the use of alternative theoretical lenses to better understand how GenAI impacts entrepreneurial learning.

Competing Interest

The authors declare no conflict of interest.

Authors' Biography

[1] **Syed Rizwan Ali** is an Assistant Professor at the Business Incubation Center, Software Engineering, Bahria University in Karachi, Pakistan. He obtained his Masters in CAAD from the University of the West of England (UWE) in Bristol, England.

[2] **Shaikh Zunain Uddin** is a Research Scholar at the Department of Computer Science, Nazeer Hussain University in Karachi, Pakistan. He received his Bachelors in Computer Science from Nazeer Hussain

University in Karachi, Pakistan.

[3] **Mehdi Abbas (Ph.D)** is a Sr. Lecturer at the Department of Business Studies, Bahria University Karachi – Pakistan. He received his Master's from Australia and PhD from Universiti Utara Malaysia, Sintok Kedah Darul Aman, Malaysia School of Technology Management and Logistics (STML), College of Business, Universiti Utara Malaysia, Malaysia.

[4] **Talha Bin Shuja** is serving at the Department of Business Administration, High Hope International LLC in the United States of America. He obtained his Masters in Business Administration from SZABIST in Karachi, Pakistan.

[5] **Muhammad Faraz** is a Senior Assistant Professor at the Business Studies Department, Bahria University in Karachi, Pakistan. He obtained his M.Sc. in Industrial Psychology from the University of Karachi in Karachi, Pakistan.

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