Journal of Global Information Management
Volume 34 • Issue 1 • January-December 2026

Perceived Barriers of Gen AI Integration in Entrepreneurship Education:

Implications for Information Systems Scholars and Practitioners

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Received: July 9th, 2025 | **Accepted:** January 16th, 2026

ABSTRACT

Generative AI can enhance venture creation education, yet faculty adoption remains limited. This study explores why through a three-stage mixed-methods approach. Stage 1 reviewed 2020–25 literature to identify 23 barriers across pedagogical, technical, institutional, and ethical domains. Stage 2 involved interviews with experienced entrepreneurship educators, refining and reducing the list to 15 context-specific challenges. Stage 3 used a fuzzy-DEMATEL survey to capture expert causal judgments, while thematic coding of interviews added narrative depth. The resulting influence map highlights a clear hierarchy: lack of staff training, unclear governance, and weak technical support are key upstream barriers, while concerns like plagiarism and over-reliance are downstream effects. Cluster analysis groups drivers into pedagogical, organisational, and infrastructural clusters, suggesting a phased response: begin with training and transparent policy, then invest in tools and assessments.

KEYWORDS

Generative Artificial Intelligence, Entrepreneurship Education, Faculty Perceived Barriers, Fuzzy DEMATEL, Thematic Analysis

INTRODUCTION

Besides being the main driver of the revolution in businesses, artificial intelligence (AI) is widely used in the educational sector (Bollaert, 2025; Clegg & Sarkar, 2024; Hughes et al., 2025). The use of generative large language models as tools that can produce complex writings, as well as

DOI: 10.4018/JGIM.400249

the use of multimodal engines that can turn the simplest of drawings into highly detailed visuals, is transforming the educational setting (Hódosi et al., 2023; Ramos, et al., 2024). The transition from using traditional methods to technology that supports learning is witnessed in entrepreneurship education in which the main goal is to develop the creative potential of learners and teach them how to solve problems through questioning and learning by doing (Ali et al., 2025). Although the promise of AI in entrepreneurship education is exciting, the current state of AI use in education is challenging and fragmented (Ali et al., 2025; Zambonino Torres et al., 2025). Educators are concerned about the danger of large language models providing inappropriate attributions for use during feasibility studies, design tools importing copyrighted materials, and image generators creating culturally insensitive images during branding exercises (Ding & Xue, 2025; Rasul et al., 2024).

This concern presents an intriguing paradox. Educators are hopeful that AI will expedite learning and democratize resources, but they are not yet convinced enough to be on the bandwagon (Deep et al., 2025). Excessive dependence on AI might suppress student creativity, threaten academic integrity, or put institutions at risk of legal repercussions (Henadirage & Gunarathnek, 2025; Ramos et al., 2024; Trindade et al., 2025). Adding to these woes is that entrepreneurship programs are complex. Innovation projects are inherently multidisciplinary in nature; students must be able to multitask, gather customer insights, perform financial modeling, and undertake legal analysis (Ali et al., 2025). A well-designed AI tool should be able to perform these multiple roles, thus minimizing cognitive load and inconsistencies in problem solving (Alsakhen et al., 2024; Preuss et al., 2024).

Entrepreneurial education requires solving practical problems and interdisciplinary application of knowledge; it also requires industry-oriented curricula to develop creativity and problem-solving skills of students (Bell & Bell, 2023; Lokce & Sulejmani, 2024; Mu & Zhao, 2024). An overreliance on AI poses a danger of becoming overdependent on AI for various tasks, resulting in the risk of stifling resourcefulness and critical thinking, both of which are essential skills required to navigate the entrepreneurship journey (Berke, 2023; Vecchiarini & Somia, 2023; Zhang, 2025). Assessments in an entrepreneurship course represent a high-stake dimension requiring presentation of opportunity identification and elaborate discussion of plans for transforming uncertainty into opportunity (Berde et al., 2024; Bolzani & Luppi, 2021; Tiberius et al., 2023). The expectations surrounding investor presentations or crowdfunding campaigns mean that any AI-related error could prove costly on a reputational level for both the student and the educational institution (Clegg & Sarkar, 2024; Zhao, 2024). At the same time, rapidly changing industrial expectations—for example, the shift toward circular economy models in sectors like the automotive industry—emphasize the need for graduates who can combine technological competence with critical judgment and sustainable thinking (Imre & Remsei, 2023; Rejeb, Rejeb, Keogh, & Süle, 2025; Remsei et al., 2023).

Although most researchers show increasing academic interest in the use of AI in education, the research in the domain of entrepreneurship education is limited and inconsistent (Fischer & Dobbins, 2023; Rejeb et al., 2024). Existing literature mostly discusses the acceptance of AI by students (Park & Kim, 2025; Qasem et al., 2023), the features of AI technology (Alsakhen et al., 2024; Mittal et al., 2024; Vinkóczi et al., 2024; Xu & Babaian, 2021), or more generic ethical and governance frameworks (Aure, 2025; Dalalah & Dalalah, 2023; Rasul et al., 2024). Use of AI in entrepreneurship courses is largely fragmented and tends to overlook the views and experiences of educators who serve as mediator of curricular innovation (Ala et al., 2022). Although general educational technology (EdTech) surveys have identified common barriers to adopting technologies, such as skills gap and data privacy issues (Gupta & Bhaskar, 2020; Hughes et al., 2025), these surveys present generalized reports. For example, simply stating that technical unreliability is an obstacle ignores the causal factors. Technical issues can manifest as server latency, low institutional investment in technology, or lack of knowledge of the faculty about AI systems (Deep et al., 2025; Ding & Xue, 2025; Ramos et al., 2024; Ratten & Jones, 2023).

In this study we address three research questions:

- RQ1: Which are the causal relationships and dependencies between critical barriers of AI in entrepreneurship education?
- RQ2: What are the most influential critical barriers?
- RQ3: What are the implications for scholars and practitioners?

We first introduce a taxonomy of adoption barriers specific to entrepreneurship education. Second, by using a mixed-method framework, we minimize the biases of the single-method methodologies (Gupta & Bhaskar, 2020; Mustopa et al., 2024). Third, by grounding our understanding in expert perspectives and building a collaborative framework for implementation, we provide actionable interventions for practitioners engaged in developing and/or using technology for entrepreneurship studies. This study follows a three-phased mixed-methods research methodology that integrates a qualitative thematic analysis with a quantitative decision-making trial and evaluation laboratory (DEMATEL) technique. By applying this methodology, we can visualize and understand the intricate relationships between barriers to adopting AI in entrepreneurship education.

In the subsequent sections, we first discuss the available literature on barriers to AI adoption and then provide details of our research design, results, and the implications of our findings to both theory and practice.

LITERATURE REVIEW

Despite advancements in large language models, many entrepreneurship educators are reluctant to integrate generative AI (GenAI) in their entrepreneurship courses (Dalalah & Dalalah, 2023). In addition to the apprehensions of educators, prior studies have reported problems related to governance, infrastructure alignment, and faculty capabilities (Dolmark et al., 2022). An overview of GenAI barriers noted from existing literature is presented in Table 1.

Table 1. An Overview of Generative Artificial Intelligence Barriers Observed From Literature

Category	Barrier	Key insight	Source
Cognitive & pedagogical constraints	Problem-solving	Abstract reasoning of AI, students' problem-solving abilities weaken and lose out on problem framing, assumption testing, and learning from mistakes.	Ramos et al. (2024)
	Avoidance	Students outsource ideation to ChatGPT, skipping creative struggle	Busso (2024)
	Overreliance on AI	Cut-and-paste culture undermines original Thinking	Farooq et al. (2024)
	In depth analysis	Shallow business models collapse under scrutiny	Fernández Miranda et al. (2024)
			Aure (2025)
			Dalalah and Dalalah (2023)
	Entrepreneurial thinking	Rapid AI answers dilute effective reasoning skills	Zambonino Torres et al. (2025)
			Xu et al. (2021)
	Limited guidance	Few prompt libraries exist for entrepreneurial tasks	Fernández Miranda et al. (2024)
	Limited simulation environment	In the absence of genuine sandboxes, students can end up "talking to AI" instead of conducting true experiments.	Ramos et al. (2024)
			Trindade et al. (2025)
			Park and Kim (2025)
	Student entrepreneurial competencies	Mismatch between AI advice and resilience training	Oyetade (2025) & Zuva
	Communicate product ideas clearly	Mixed human/AI voice dilutes investor messaging	Ramos et al. (2024)
	Design (presentation)	Polished AI slides can mask weak concepts and confuse aesthetics with substance.	Busso (2024)
	Emphasizing ideation over experience	Rapid idea generation crowds out fieldwork, prototyping, and user iteration.	Zambonino Torres et al. (2025)

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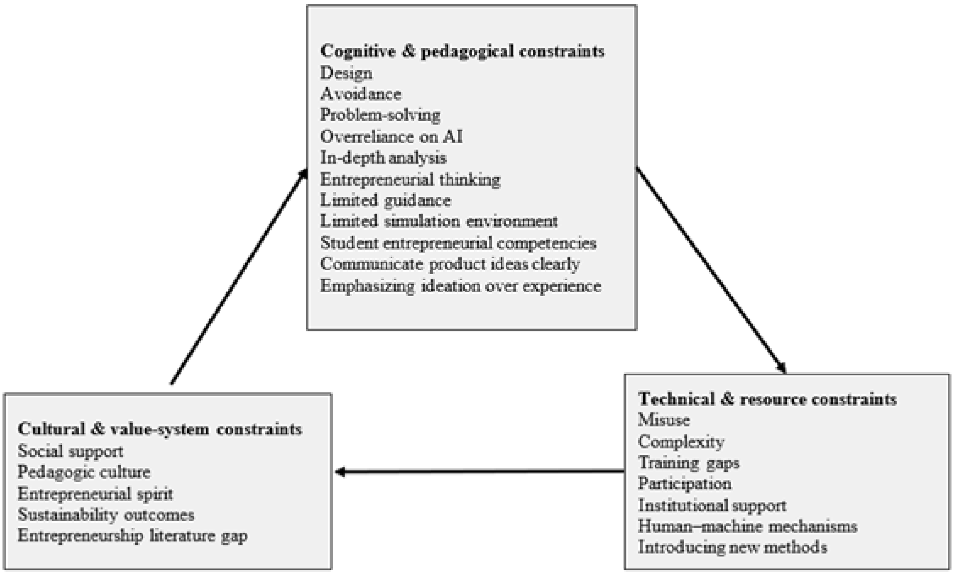
Table 1. Continued

Category	Barrier	Key insight	Source
Technical & resource constraints	Complexity	Layered plug-ins and licences overwhelm staff	Arranz García et al. (2025) Hódosi et al. (2023)
	Training gaps	If faculty and students are not given structured training, poor prompting and over-trust persist.	Zambonino Torres et al. (2025)
			Clegg and Sarkar (2024)
			Rejeb et al. (2024)
	Participation	AI use reduces discussion, critique, and peer learning unless activities enforce collaboration.	Oyetola et al. (2024)
	Institutional support	Slow help desks interrupt classroom adoption.	Mariyono (2025)
	Human–machine mechanisms	Accountability for hallucinations remains constant.	Alshorman (2024) Rejeb, Rejeb, Simske and Süle (2025) Rejeb, Rejeb, Zrelli, and Süle (2025)
	Misuse	Shortcutting and unattributed AI text threaten assessment integrity and learning value.	Saar (2024)et al.
	Introducing new methods	AI-aware rubrics and assignments require time-intensive redesign efforts.	Gupta and Bhaskar (2020)
			Rasul et al. (2024)
			Vecchiarini and Somia (2023)
Cultural & value system constraints	Entrepreneurship literature gap	Limited empirical guidance forces reliance on trial-and-error pedagogy.	Ahmed et al. (2022)
	Social support	Peer and mentor norms can either normalize shortcuts or model ethical experi-mentation.	AbuJarour & AbuJarour (2023)
	Entrepreneurial spirit	Predictable AI outputs dull initiative, grit and founder identity.	Dolenc & Brumen (2024)
	Sustainability outcomes	Optimization for quick wins leads students to underweight environmental and social impacts.	Thangavel et al. (2025)
	Pedagogic culture	Grade-and-coverage mindsets impede reflective, responsible AI integration.	Aluko et al. (2025)

Note. AI = artificial intelligence.

In this study, we report the barriers in adoption of AI in entrepreneurship education as three thematic blocks (Figure 1); namely, cognitive and pedagogical constraints, technical and resource constraints, and cultural and value system constraints. Thereafter, we present an account of the theories used in prior studies regarding the barriers in AI use in education.

Figure 1. Overview of Generative Artificial Intelligence Barriers in Entrepreneurship Education



Note. AI = artificial intelligence.

Cognitive and Pedagogical Constraints

The success of entrepreneurship education is evaluated based on its capacity to inculcate the skill of opportunity identification, trial and error, and articulation of value of a venture (Zhang et al., 2018). Educators often refrain from using technological interventions in their courses when they observe GenAI tools compromising the fundamental learning outcomes (Zhao, 2024). A primary concern of educators is the loss of problem-solving abilities of learners who might opt to copy and paste AI-generated responses instead of attempting to find answers by analyzing actual market data (Zhao, 2024). It is closely associated with avoidance behavior, where students transfer cognitive processes, such as ideation or financial modeling, to GenAI, thereby bypassing tasks that develop entrepreneurial persistence and perseverance (Qasem et al., 2023).

The excessive dependence of students on AI is echoed in several prior studies (Morales-García et al., 2024; Zhang et al., 2024). Farooq et al. (2024) reported that students unconsciously use GenAI to search for elevator pitch ideas without attempting to develop their own concept. The outcome of such an approach is usually a lack of deep analysis wherein plans that look well on paper fall apart upon deeper scrutiny and analysis (Farooq et al., 2024). For educators who prioritize and value sound effectual thinking, the mindless use of GenAI is a pedagogical sabotage (Zambonino Torres et al., 2025). Educators have another anxiety related to the use of GenAI: an overemphasis on ideation using machine learning, in comparison to students experiencing the nuances of developing business ideas grounded in the actual customer needs (Vecchiarini & Somia, 2023; Zambonino Torres et al., 2025;).

Limited institutional guidance and restricted simulation settings compound the pedagogical issues in delivering entrepreneurship courses using GenAI (Dwivedi, 2025; Lim et al., 2023). Furthermore, many universities do not possess curated prompt libraries or vetted datasets required to teach entrepreneurship, forcing faculty to "learn on the fly," thereby resulting in superficial use of AI (Hughes et al., 2025). Educators also complain of the inability of students using AI to convince investors during idea presentations, owing to the challenges of defending the machine-generated text during such presentations (Ramos et al., 2024). Finally, educators are concerned about the mismatch between AI-generated advice and the development of students' core entrepreneurial competencies, especially when the "black box" of an AI-generated mechanism yields conclusive-sounding solutions in no time, putting the process of critical and independent entrepreneurial thinking at risk (Mittal et al., 2024; Yan et al., 2025).

Technical and Resource Constraints

Studies report that even the most zealous educators become overwhelmed while handling technical and resource-related challenges (Ates & Polat, 2025; Govender & Mpungose, 2022). Studies on adoption of technology in higher education have indicated that bottlenecks such as poor training, limited computing power, and nontransparent interfaces often sabotage ambitious targets of integration of technology in dissemination of knowledge (Huo & Siau, 2024; Mustopa et al., 2024).

The complexity of integrating available technological tools in education is a significant deterrent for educators (Alenezi et al., 2023; AlGerafi et al., 2023). A bewildering environment composed of overlapping learning management system extensions, complicated privacy dashboards, and elaborate licensing requirements can deter the adoption of AI by educators (Rehan, 2023). The resistance of educators to integrate AI in their courses is also attributed to their perceptions of high setup time and efforts required that often outweigh the pedagogical benefits (Machado et al., 2025). Although the most apparent way to overcome educator resistance is training, most training workshops are either too general to provide any practical value or are presented as a single event resulting in insufficient transfer of knowledge and skills (Al-Mughairi & Bhaskar, 2025). Such digital skills boot camps can boost confidence that is often short-lived, and the effect disappears amid the pressures of teaching and assessments (Zambonino Torres et al., 2025). The introduction of digital twin-based and multi-attribute decision support systems in the corporate environment is often hindered by user technology overload, system complexity, and a lack of appropriate, practical forms of support (Hódosi et al., 2023). These issues, together with a deficit in grant funding, may result in the widespread feeling of pilot fatigue (Duan & Zhao, 2024).

Educators from nontechnical disciplines, such as those teaching entrepreneurship courses, feel marginalized when AI-integrated projects require assistance of computer science departments, and this scaffolding required to integrate AI tools into entrepreneurial learning might delay the adoption of AI (Alsakhen et al., 2024; Farkas et al., 2015; Patra et al., 2025). Furthermore, a delayed response from helpdesks and vague data retention policies only worsen the issue, leaving the faculty unsupported and confused (Priya et al., 2025). During instances of AI hallucination in student submissions, educators lack adequate support and assistance to troubleshoot the problem; thus, this issue adds to their feelings of vulnerability and inability to question the accuracy and trust of AI-generated content (Elsayed, 2024; Kamel, 2024). This ambiguity causes much anxiety, especially in a high-stakes environment, such as entrepreneurship (Deep et al., 2025). Finally, introduction of innovative teaching pedagogy is stifled by institutional bureaucracy wherein the curriculum approval process can be time-consuming (Barkov et al., 2024; Humes, 2022). Such an institutional setup is incompatible with the fast development of AI technology (Gupta et al., 2023; Kremantzis et al., 2025).

Cultural and Value System Constraints

Although technical and resource limitations defer the adoption of AI in education, cultural impediments are usually more inherent and harder to overcome (Hangl et al., 2023). Another significant dimension is the gap between AI proficiency and knowledge of entrepreneurship literature (Giuggioli & Pellegrini, 2023). Entrepreneurship educators trained in effectuation theory or lean start-up methodology have expressed concerns that GenAI tools are not grounded in these concepts and instead function like a black box unrelated to the pedagogical tradition (Henadirage & Gunarathne, 2025). These educators think that the excessive use of AI applications will end up depleting, instead of fueling, the creative and strong-willed spirit of their students (Ding & Xue, 2025).

The role of social support is equally important. Institutions where the deans and heads of departments are highly proactive in promoting the use of AI witness high success rates of pilot projects (Khairullah et al., 2025). Conversely, under circumstances of ambivalent leadership, the momentum stalls within a short time, and there is less likelihood of faculty taking risks (Rahimi & Oh, 2024).

Finally, the risk-taking appetite in the teaching-learning environment is highly influenced by the prevailing pedagogic culture (Henriksen et al., 2021). In academic contexts where the power hierarchy is very pronounced and there is a strong focus on standard mechanical evaluations, teachers are not very willing to give up their authority to an algorithm-based “co-teacher” (Bollaert, 2025). The generalized, unpredictable characteristics of GenAI clash with syllabi designed for predictable learning outcomes, thereby reinforcing the conservative teaching methodology.

Theoretical Background

Researchers in prior studies have extensively used the unified theory of acceptance and use of technology model to study the adoption of e-learning technologies; these researchers reported that effort expectancy and facilitating conditions were the strongest inhibitors, while perceived data-security risk surfaced as an informal barrier (Abdou & Jasimuddin, 2020; Al-Mughairi & Bhaskar, 2025; Ates & Polat, 2025). Ala et al. (2022) used activity theory and reported that instructors experienced a “black-box anxiety” (low algorithmic transparency) and “workflow fragility” (lack of plug-and-play integration). Furthermore, organizational misalignment (assessment policies, intellectual property ownership) was a larger barrier of adoption than any single technical shortcoming. Scholars viewing AI through diffusion of innovation and technology-organization-environment lenses have reported infrastructure gaps (bandwidth, device access), limited faculty digital skill, and “cultural inertia” (a preference for face-to-face pedagogy) as barriers of use of AI by educators (Alenezi et al., 2023; Ates & Polat, 2025).

Ali et al. (2025) used self-regulated learning theory, coupled with constructivist learning principles, and reported that data-privacy uncertainty and opaque adaptive algorithms led faculty to “gate” or throttle AI use. In studies based on experiential learning theory (Aure, 2025) and bureaucracy theory (Barkov et al., 2024), researchers have reported that “innovation bureaucracy” (excessive approval loops) and slow procurement of AI services, create a temporal adoption barrier even when faculty readiness is high. Bell and Bell (2023) used opportunity recognition theory and noted that academic-integrity fears of educators, such as plagiarism and hallucinations, deterred AI adoption.

Researchers using socio-materiality and activity theory to frame human–AI work systems reported that poorly designed human-machine workflows erode trust, over-automation risks displace reflective learning, and faculty fear of “de-skilling” limits experimentation (Clegg & Sarkar, 2024). Scholars have also supported job demands–resources theory (Deep et al., 2025), absorptive-capacity theory (Dolmark et al., 2022), and self-determination theory (Duan & Zhao, 2024).

The implementation of GenAI in the education sector is increasingly being analyzed using digital transformation and institutional theory to explain the manner and reasons behind the way higher education institutions (HEIs) are reacting to this technological disruption. Digitization in HEIs is considered a critical process that guarantees revolution of the traditional educational paradigm, and in recent studies, scholars have attempted to investigate the driving factors and its further consequences on the adoption of AI (Thakur & Bhavani 2025). This technical change is a complicated combination of organizational, technological, and environmental influences, such as institutional preparedness, competitive forces, and perceived worth of AI (Erdmann & Toro-Dupouy, 2025; Rejeb, Rejeb, Süle et al., 2025).

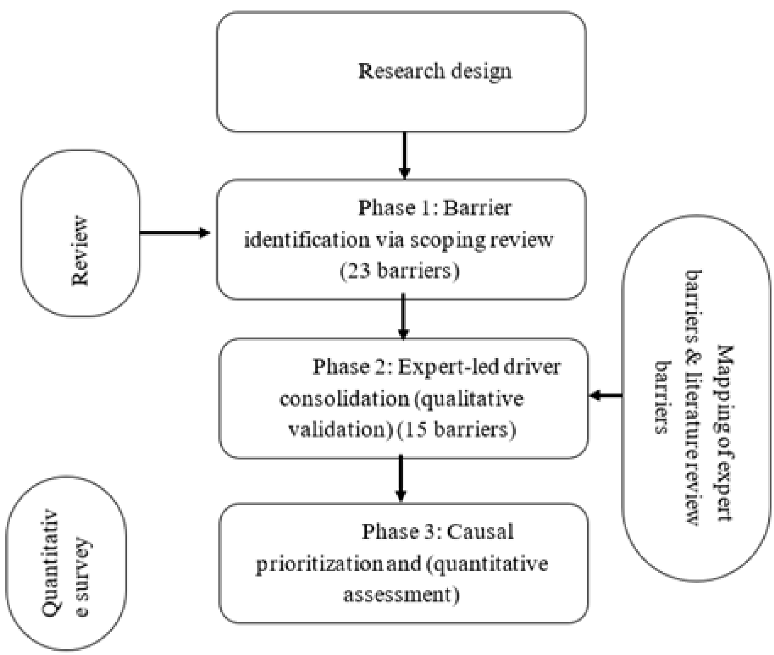
Regarding the organizational approach, GenAI is viewed as an essential source of digital transformation, compelling universities to formulate strategies to remain relevant (Gering et al., 2025; Miklós & Lukács, 2024; Okunlaya et al., 2022). These adaptive reactions can be explained by using institutional theory (Rudko et al., 2025). Gering et al. (2025) used the notion of institutional isomorphism to describe how HEIs tend to operate by emulating the approaches of the best universities in reaction to the pressure of technological changes. In the same vein, the “institutional environment” is a concept that is applied to determine the prerequisites and value drivers that determine the adoption of AI in universities (Erdmann & Toro-Dupouy, 2025). The AI transformation of an HEI can be viewed as a complex web of feedback loops wherein institutions invest in AI to enhance fundamental functionalities, such as learning, research, and administration, and simultaneously adapt to the changes in the job market while addressing internal challenges of academic integrity (Katsamakas et al., 2024).

Although the barriers to adoption of GenAI in education have been examined using different theoretical lenses, authors of these studies have simply listed various barriers and have not delved into understanding the cause-effect relationships. In contrast, our study, anchored in digital transformation and institutional theory, reports the cause-effect relationship through a three-phase mixed-method research design using a DEMATEL technique.

RESEARCH METHODOLOGY

To go beyond a list of barriers, we used three-phase mixed-method research that methodically funnels a wide range of literature-based barriers into a prioritized, causally modeled hierarchy. This approach was aimed at identifying the prominent barriers such that interventions to remove or reduce those barriers would yield significant impact. By doing so, we ensured that our results were not just based on the existing body of literature but also supported and contextualized to the experiences of educators. The sequence, illustrated in Figure 2, progresses from qualitative identification to expert-led refinement and finally to quantitative causal analysis, creating a transparent and rigorous chain of inference.

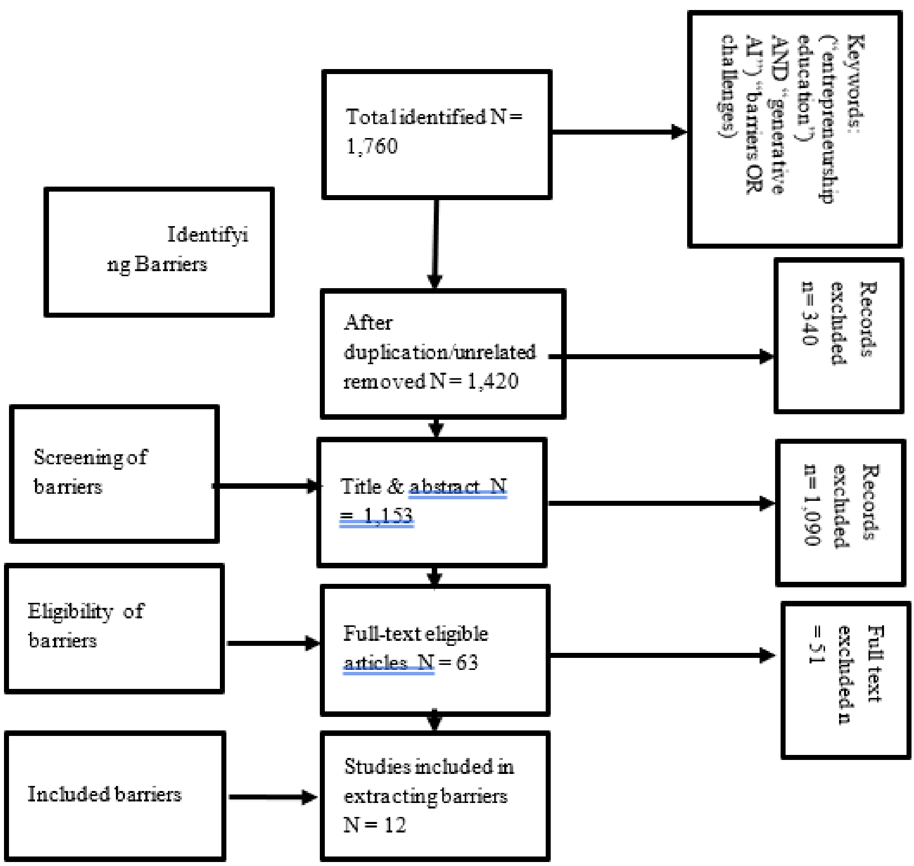
Figure 2. Design of the Adopted Research Methodology



Phase I: Identification of Barriers

We first conducted a systematic search of recent empirical literature (2019–2025) on adoption of AI in entrepreneurship education. To ensure that the search was comprehensive, we adopted the scoping protocol led by preferred reporting items for systematic reviews and meta-analyses (Figure 3). The initial search resulted in generation of 1,760 records. Having filtered out duplicates and screened the titles, abstracts, and full texts to select only the relevant ones, we narrowed the records down to 12 core studies. A critical analysis of these articles enabled us to derive and code 23 different barriers in integrating GenAI.

Figure 3. Flow Diagram Using Preferred Reporting Items for Systematic Reviews and Meta-Analyses



Phase II: Expert Validation and Refinement

In phase II we aimed to filter and consolidate the original list of 23 barriers based on their real-world salience. We assembled a purposive team of 17 experienced professionals (professors, instructional designers, and EdTech managers) who were recruited by professional networks. These professionals were chosen based on their rich experience in teaching and their attempts to apply GenAI to their courses. To elicit rich and practice-grounded insights, the panelists were initially required to respond to a sequence of semi-structured questions aimed at eliciting, justifying, and contextualizing barriers based on their professional experience (see the Appendix).

The panel initially evaluated the 23 barriers (identified from literature) in a validation survey that enabled us to eliminate all those barriers that were not very critical or were rarely experienced (Table 2). The participants were then engaged in a consolidation exercise, where they were prompted with open-ended questions and clustering techniques to combine similar ideas conceptually and remove redundancy (Mittal et al., 2024). For example, training gaps and digital self-efficacy deficits were merged into a stronger construct. This refinement process supervised by the experts played a critical role in generating the final list of barriers that are theoretically and empirically distinct, thereby avoiding the situation of having the same issue being counted twice during the following causal analysis (Farooq et al., 2024).

Table 2. Crosswalk Between Literature-Derived and Expert-Validated Barrier

Barrier in literature review	Mapped to expert barrier	Mapping rationale	Status	Barrier Explanation
Problem-solving	Problem-solving	Matching word found in the review	Retained	Faculty concerned that AI erodes critical thinking and student-led solution generation.
Complexity	Complexity	Matching word found in the review	Retained	Complexity stems from policy ambiguity, IP issues, and infrastructure challenges.
Avoidance	Avoidance	Matching word found in the review	Retained	Avoidance occurs when students use AI to bypass genuine learning.
Training	Training	Matching word found in the review	Retained	Training gaps make faculty and students unprepared for AI-enabled instruction.
Participation	Support	Participation seen as resourcing (e.g., infrastructure)	Merged	Participation barriers often stem from inadequate digital access.
Support	Support	Matching word found in the review	Retained	Support refers to the institutional scaffolding needed for equitable AI use.
Entrepreneurship literature	Pedagogic culture	Disciplinary practices seen as primary barrier	Merged	Scholars viewed gaps as pedagogical culture norms, not knowledge absence.
Overreliance on AI	Overreliance on AI	Matching word found in the review	Retained	Perceived excessive AI use risks displacing entrepreneurial intuition.
In-depth analysis	In-depth analysis	Matching word found in the review	Retained	AI-generated content lacks sufficient depth for market validation.
Thinking in entrepreneur-ship education	Thinking in entrepreneurship education	Matching word found in the review	Retained	AI tools may dilute reflective, process-oriented entrepreneurship thinking.

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Table 2. Continued

Barrier in literature review	Mapped to expert barrier	Mapping rationale	Status	Barrier Explanation
Limited guidance	Limited guidance	Matching word found in the review	Retained	Students often lack guidance in how to refine AI outputs.
Limited simulation environment	Mechanisms between humans and machines	Sandbox gaps seen as orchestration problem	Merged	Lack of simulation tools hampers experiential AI entrepreneurship tasks.
Social support	Support	Subsumed as institutional resourcing	Merged	Support infrastructure overlaps with social scaffolding needs.
Entrepreneurial spirit	Entrepreneurial spirit	Matching word found in the review	Retained	Overdependence on AI may undermine entrepreneurial passion and identity.
Tangible sustainability outcomes	Not matched	No expert agreement; excluded	Omitted	Sustainability not seen as core or specific AI barrier.
Mechanisms between humans and machines	Mechanisms between humans and machines	Matching word found in the review	Retained	AI human interaction challenges include judgment, ethics, and balance.
Misuse	Misuse	Matching word found in the review	Retained	Misuse relates to ethical and ill-informed application of AI tools.
Students' entrepreneurial competencies	Students' entrepreneurial competencies	Matching word found in the review	Retained	Students lack skills to convert AI output into viable ventures.
Communicate product & solution ideas clearly	Design	Communication placed within design barrier	Merged	Clarity in presenting AI-generated ideas seen as a design issue.
Design	Design	Matching word found in the review	Retained	Poorly structured prompts impact depth and originality of AI outputs.
Introducing new methods	Not matched	Viewed as too broad; absorbed in pedagogy	Omitted	Too generic; fails to isolate actionable curriculum barriers.
Pedagogic culture	Pedagogic culture	Matching word found in the review	Retained	Faculty norms and teaching culture act as AI integration resistance.
Emphasizing ideation over experience	Overreliance on AI	Seen as an outcome of over dependence	Merged	Ideation over experience imbalance tied to excessive AI dependency.

Phase III: Causal Modeling and Qualitative Enrichment

Phase III involved mapping the causality between the narrowed down barriers. We used a DEMATEL technique, which is well adapted for capturing the nuanced and often unpredictable judgments of specialists (Priya et al., 2025). The expert panel was requested to indicate the direct effect of each barrier on the other barriers using a calibrated linguistic scale. All these judgments were used for a series of computations to obtain two significant measures on each barrier: (a) prominence

(P), indicating the total level of involvement in the system, and (b) net influence (N), indicating its significance as a causal power (positive value) or as an effect (negative value).

This quantitative analysis helped identify significant barriers that, if removed, would most likely foster a positive change that is systemic in nature (Henadirage & Gunarathne, 2025). We augmented the DEMATEL matrix with a qualitative analysis of the expert views obtained during semi-structured interviews. These narrative data were inductively coded to understand their influence. This mixed method enabled us to examine both the statistical framework of the problem and lived experiences that define it, echoing patterns observed in prior studies (Hughes et al., 2025; Zhao, 2024).

To guarantee the rigor of our study, we applied several safeguards. Content validity was established by grounding our initial barrier list in peer-reviewed literature and expert verification. Process transparency was maintained through a clear audit trail of all instruments and data. Finally, qualitative reliability was enhanced through dual coding and negotiated agreement on thematic categories. By moving systematically from a broad literature scan to expert-driven refinement and finally to an integrated causal analysis, we enabled this methodology to deliver a robust and actionable hierarchy of educator-perceived barriers.

RESULTS

In this section we discuss the results of the multiphase process followed in our study. We first outline the systematic congruence of barriers that emerged in scholarly literature and those of practitioners using an intensive qualitative interview and structured survey response to highlight these issues. This outline is followed by a description of thematic analysis and then, lastly, the detailed quantitative findings of DEMATEL analysis.

Mapping Literature-Derived Barriers to Expert-Validated Constructs

We mapped the barriers to AI adoption stated in prior studies on entrepreneurship education with the practical challenges faced by educators while implementing GenAI into the entrepreneurship education. This step was done to determine whether the conceptual barriers uncovered in the academic literature were also perceived by the domain experts who are actively engaged in teaching and dealing with AI adoption.

Expert respondents were presented with 23 variables based on literature and the responses provided helped us refine the variables through retention, merging, or elimination. After the consolidation step of retaining, merging, and omitting, 15 nonoverlapping barriers (RV1–RV15) were retained for the DEMATEL phase. Such evidence-based reduction not only eliminated redundancy and interpretive ambiguity but also enhanced the analytical accuracy of the analysis.

The consolidation exercise included the following steps:

- Resource-centered fusion: Items like “participation” and “social support” were included in the larger item “support.” Experts suggested that low participation of students is not because of lack of motivation, but rather, it is usually because of a hardware shortage, a patchy Wi-Fi connection, or a license bottleneck. When such infrastructural shortcomings are addressed, attendance increases by default. Likewise, the “social support networks,” “peer mentoring,” and “help desk chat” were positioned as the variants of the institutional support instead of the independent obstacles.
- Pedagogical reframing: Two concepts mentioned in prior studies (i.e., “entrepreneurship literature” and “introducing new methods”) were interpreted by the experts as the expression of “pedagogic culture.” Respondents explained that the barrier to AI adoption was not so much for the entrepreneurship content as for the established pedagogy, like the use of case studies and nonflexible evaluation rubrics, that poorly adapt to the fluidity of AI-aided work and lengthy risk-averse course approval processes.

- Downstream subsumption: A small set of barriers was judged consequential, but ultimately derivative of other, more primary issues. The fear that AI "emphasizes ideation over experience," for instance, was merged into "overreliance on AI." Experts believed that once overdependence is tamed through scaffolded prompts or "AI last" submission rules, the experience–ideation balance corrects itself. Likewise, the scarcity of sandbox simulation environments was seen as just one symptom of fragile mechanism between humans and machines and a robust orchestration strategy involving clear data flows and human checkpoints would naturally specify safer sandboxes.

During the validation process, the expert panel determined that two barriers initially identified in the literature were not true obstacles, leading to their removal from the study. The first, "tangible sustainability," was eliminated because the instructors on the panel, although agreeing that sustainability outcomes are desirable, believed that these concerns were peripheral to the immediate struggle of adopting GenAI. In their view, it wasn't an actual barrier preventing them from moving forward. Similarly, the second barrier, "introducing new methods," was also removed. The panel argued that a method's novelty is just the way of expressing a situation, not a barrier. The real trouble, they stated, was the non-encouraging culture and insufficient institutional backing for the implementation of new methods. This evidence-based reduction played a crucial role in enhancing the accuracy of our study analysis by ensuring that the conceptual redundancies were eliminated and that the chances of multicollinearity were reduced during the later DEMATEL.

Retained Variable

Table 3 provides the list of the variables that were retained after mapping of variables from literature review to the variables obtained from experts.

Table 3. List of Retained Variables With Codes

Variable names	Codes
Avoidance	RV1
Complexity	RV2
Design	RV3
Entrepreneurial spirit	RV4
In-depth analysis	RV5
Limited guidance	RV6
Mechanisms between humans and machines	RV7
Misuse	RV8
Overreliance on AI	RV9
Pedagogic culture	RV10
Problem-solving	RV11
Students' entrepreneurial competencies	RV12
Support	RV13

continued on following page

Table 3. Continued

Variable names	Codes
Thinking in entrepreneurship education	RV14
Training	RV15

Note. RV = retained variable.

Thematic Analysis: The Voice of the Faculty

To add rich human context to our quantitative models, we performed a thematic analysis of the qualitative study conducted with 17 educators (Table 4). The analysis yielded 142 initial codes, which were refined to 11 axial codes and finally clustered into three distinct meta-domains (Note: In the bulleted text, T1, T2, etc., correspond to the themes listed in Table 4):

- capability shortfalls: Training and support deficits (T1) and student competency gaps describe missing skills that stall responsible adoption.
- curricular disruption: Problem solving erosion (T2), overreliance (T3), and assessment design strain (T5) capture how AI upends long-standing pedagogical routines.
- institutional friction: Integration complexity (T4), governance gap (T7), and resource constraints (T8) portray structural bottlenecks outside the educator's direct control; reliability (T9), entrepreneurial mindset dilution (T10), and human AI balance (T11) work as cross-cutting "risk amplifiers" because they intensify capability and curricular problems whenever institutional friction lingers.

Table 4. Thematic Analysis of 17 Expert Respondents

Theme	Respondents (*N* = 17)	Illustrative excerpt
T1: Training & support deficits	16	Improper training could lead professors to either overuse or underuse these tools.
T2: Erosion of problem-solving skills	15	Students could misuse GAI resources to produce case solutions, presentation decks, or business ideas, hence compromising uniqueness and critical thinking.
T3: Overreliance & assessment avoidance	6	This causes pupils to rely too much on AI and prevents them from learning how to think methodically or experiment with other concepts.
T4: Integration complexity	7	Educators want to integrate AI and teach students how to use it properly, but it's so easy to overdo it and for students to abuse it.
T5: Assignment & assessment redesign strain	1	Educators also need proper ethical guidelines to be presented in the rubrics; people should know how to express their use of AI and what is the boundary there.
T6: Ethical misuse & academic integrity risk	8	Ethical and academic integrity issues: Students could misuse GenAI resources to produce case solutions, presentation decks, or business ideas, compromising uniqueness and critical thinking.
T7: Institutional policy & governance gap	14	First, there should be guidelines on ethical AI use.

continued on following page

Table 4. Continued

Theme	Respondents (N = 17)	Illustrative excerpt
T8: Resource constraints (hardware/licenses)	6	Additionally, integrating GenAI into existing curricula, managing technological infrastructure, and assessing student learning outcomes pose challenges.
T9: Technical reliability & accuracy worries	4	Factors contributing to the complexity of using GenAI in teaching include ensuring academic integrity, addressing bias and fairness, and navigating intellectual property rights.
T10: Dilution of entrepreneurial spirit	7	Some students from different backgrounds also struggled to provide good prompts, which led to generic results without originality or relevance.
T11: Human-AI balance in judgment	1	Balancing human judgment with AI-driven insights adds further complexity.

Note. AI = artificial intelligence; GenAI = generative artificial intelligence.

Jaccard co-occurrence analysis revealed three strong pairings (J > 0.45):

- training deficits × overreliance: A lack of prompt literacy prompts dependency on copy paste.
- integration complexity × governance gap: Unclear policy prolongs technical approval cycles, compounding complexity.
- problem-solving erosion × assessment design strain: When reasoning evaporates, educators rush to redesign assignments.

DEMATEL Analysis

Quantitative analysis using the DEMATEL analysis helped us to map the causal structure of the 15 validated barriers. For the analysis we provided formal nomenclature to each validated barrier using compact variable codes (RV1–RV15). This structured renaming ensured clarity during matrix computations and causal diagram generation. Each code represents a barrier validated by faculty-perceived barrier that was retained after literature-expert mapping and now serves as an input for influence analysis.

Group Direct-Relation Matrix

The analysis began by aggregating the judgments of all 17 experts into a single group direct-relation matrix (D). Table 5 shows the panel's collective assessment of the direct causal influence of each barrier *i* on every other barrier *j*, based on a 5-point Likert scale (0 = no influence, 4 = very strong). Each cell D_{ij} therefore reports the mean strength, which is calculated using the formula shown in equation (1).

$$D_{ij} = (1/m) \sum_{i} d_{ij}\hat{}(k) \quad (1)$$

In this equation, m is the number of experts.

Table 5. Group Direct-Relation Matrix

Variables	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10	RV11	RV12	RV13	RV14	RV15
RV1	0	2.40	2.60	2.73	3.00	2.60	2.87	3.00	3.00	2.73	2.80	2.67	2.80	2.73	3.20
RV2	2.93	0	3.07	3.40	3.00	2.60	3.13	3.00	3.07	2.67	3.07	3.13	3.00	3.20	3.13
RV3	2.73	2.93	0	2.80	2.60	2.07	2.87	2.07	2.53	2.53	3.20	2.27	3.00	2.87	2.80
RV4	2.60	3.27	3.20	0	3.27	2.67	3.13	2.53	3.27	3.00	3.40	3.53	3.33	3.47	2.87
RV5	2.60	3.00	2.60	3.00	0	2.33	3.27	2.33	3.13	2.80	2.80	2.87	3.47	3.40	3.00
RV6	3.20	2.87	2.80	2.67	2.67	0	2.60	2.67	0.00	2.60	2.53	2.73	2.53	2.80	2.93
RV7	2.60	3.27	3.20	3.20	3.20	3.07	0	2.80	3.00	2.93	3.13	3.13	3.33	3.13	2.93
RV8	3.40	3.00	2.47	2.87	3.07	2.87	2.87	0	3.20	3.07	3.00	3.13	2.87	2.73	2.73
RV9	2.87	3.07	3.00	3.00	3.27	2.67	3.00	3.00	0	2.73	3.00	3.13	3.33	3.20	3.20
RV10	3.27	3.27	2.93	3.53	3.13	3.13	3.07	3.00	3.13	0	2.93	3.33	3.00	3.27	2.87
RV11	2.60	3.27	3.13	3.33	3.47	2.93	3.33	2.33	3.07	2.47	0	3.27	2.87	3.00	3.07
RV12	3.07	3.13	2.80	3.47	3.40	2.67	3.13	2.60	3.53	3.20	3.47	0	3.00	3.27	3.20
RV13	2.67	3.40	3.00	2.87	3.47	3.13	3.13	2.40	3.07	2.33	3.67	3.33	0	3.00	3.27
RV14	2.20	2.73	2.73	3.27	3.20	2.53	3.07	2.87	2.80	2.87	3.53	2.87	3.33	0	2.80
RV15	2.53	3.33	3.20	3.27	3.20	2.87	3.47	3.00	3.13	2.47	3.07	3.20	3.20	3.47	0

Note. RV = retained variable; RV = Avoidance; RV2= Complexity; RV3 = Design; RV4 = Entrepreneurial spirit; RV5 = In depth analysis; RV6 = Limited guidance; RV7 = Mechanisms between humans and machines; RV = 8 Misuse; RV9 = Overreliance on AI; RV10 = Pedagogic culture; RV11 = Problem solving; RV12 = Entrepreneurial competencies; RV13 = Support; RV14 = Thinking in entrepreneurship education; RV15 = Training

The largest single entry is 3.67 for the link RV13–RV11, confirming that a shortage of institutional support significantly impacts the problem-solving abilities of students.

Normalized Matrix

Direct scores were divided by the largest row-sum λ (here $\lambda \approx 43.9$). This step generated a normalized matrix (N) preserving the relative strength of the relationships with values ranging between 0 and 1 and spectral radius < 1 (Table 6). This process of normalization ensures mathematical stability and convergence of the model. After the scores were scaled, the link RV13–RV11 still dominates (weight 0.084), showing that normalization preserves relative ordering during the rescaling of absolute magnitudes.

The formula used for normalization is shown in equation (2).

$$N = D / \lambda \text{ with } \lambda = \max_i \sum_j D_{ij} \quad (2)$$

In equation, 2 N is the normalized matrix.

Table 6. Normalized Matrix

Variables	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10	RV11	RV12	RV13	RV14	RV15
RV1	0	0.055	0.059	0.062	0.068	0.059	0.065	0.068	0.068	0.062	0.064	0.061	0.064	0.062	0.073
RV2	0.067	0	0.070	0.077	0.068	0.059	0.071	0.068	0.070	0.061	0.070	0.071	0.068	0.073	0.071
RV3	0.062	0.067	0	0.064	0.059	0.047	0.065	0.047	0.058	0.058	0.073	0.052	0.068	0.065	0.064

continued on following page

Table 6. Continued

Variables	RV1	RV2	RV3	RV4	RV5	RV6	RV7	RV8	RV9	RV10	RV11	RV12	RV13	RV14	RV15
RV4	0.059	0.074	0.073	0	0.074	0.061	0.071	0.058	0.074	0.068	0.077	0.080	0.076	0.079	0.065
RV5	0.059	0.068	0.059	0.068	0	0.053	0.074	0.053	0.071	0.064	0.064	0.065	0.079	0.077	0.068
RV6	0.073	0.065	0.064	0.061	0.061	0	0.059	0.061	0.000	0.059	0.058	0.062	0.058	0.064	0.067
RV7	0.059	0.074	0.073	0.073	0.073	0.070	0	0.064	0.068	0.067	0.071	0.071	0.076	0.071	0.067
RV8	0.077	0.068	0.056	0.065	0.070	0.065	0.065	0	0.073	0.070	0.068	0.071	0.065	0.062	0.062
RV9	0.065	0.070	0.068	0.068	0.074	0.061	0.068	0.068	0	0.062	0.068	0.071	0.076	0.073	0.073
RV10	0.074	0.074	0.067	0.080	0.071	0.071	0.070	0.068	0.071	0	0.067	0.076	0.068	0.074	0.065
RV11	0.059	0.074	0.071	0.076	0.079	0.067	0.076	0.053	0.070	0.056	0	0.074	0.065	0.068	0.070
RV12	0.070	0.071	0.064	0.079	0.077	0.061	0.071	0.059	0.080	0.073	0.079	0	0.068	0.074	0.073
RV13	0.061	0.077	0.068	0.065	0.079	0.071	0.071	0.055	0.070	0.053	0.083	0.076	0	0.068	0.074
RV14	0.050	0.062	0.062	0.074	0.073	0.058	0.070	0.065	0.064	0.065	0.080	0.065	0.076	0	0.064
RV15	0.058	0.076	0.073	0.074	0.073	0.065	0.079	0.068	0.071	0.056	0.070	0.073	0.073	0.079	0

Note. RV = retained variable; RV1 = avoidance; RV2 = complexity; RV3 = design; RV4 = entrepreneurial spirit; RV5 = in-depth analysis; RV6 = limited guidance; RV7 = mechanisms between humans and machines; RV8 misuse; RV9 = overreliance on AI; RV10 = pedagogic culture; RV11 = problem solving; RV12 = entrepreneurial competencies; RV13 = support; RV14 = thinking in entrepreneurship education; RV15 = training.

Total-Relation Matrix

The total-relation matrix (T) in DEMATEL captures both direct and indirect influences among variables by extending the normalized matrix through matrix inversion. The total-relation matrix (Table 7) reveals the cumulative strength of causal relationships, highlighting how one barrier may indirectly affect others through multiple pathways. The values in this matrix can exceed 1, reflecting the aggregate influence.

The matrix is calculated as shown in equation (3).

$$T = N\,(I - N)^{-1} \tag{3}$$

In this equation, I is the identity matrix.

The RV13–RV11 link, for instance, increases from a direct influence of 0.084 in matrix N to a total influence of 1.24 in matrix T, quantitatively demonstrating how institutional failures cascade through the system to create powerful and far-reaching consequences.

Table 7A. Total-Relation Matrix: RV1–RV5

Variables	RV1	RV2	RV3	RV4	RV5
RV1	0.97	1.11	1.06	1.13	1.14
RV2	1.10	1.14	1.15	1.22	1.23
RV3	0.98	1.07	0.96	1.08	1.09
RV4	1.12	1.24	1.18	1.18	1.26
RV5	1.06	1.16	1.10	1.17	1.12
RV6	0.95	1.02	0.98	1.03	1.04
RV7	1.11	1.22	1.16	1.23	1.25

continued on following page

Table 7A. Continued

Variables	RV1	RV2	RV3	RV4	RV5
RV8	1.09	1.17	1.11	1.18	1.20
RV9	1.10	1.21	1.15	1.22	1.24
RV10	1.14	1.24	1.18	1.26	1.27
RV11	1.09	1.20	1.14	1.21	1.23
RV12	1.14	1.25	1.18	1.27	1.28
RV13	1.11	1.22	1.16	1.22	1.25
RV14	1.05	1.16	1.11	1.18	1.19
RV15	1.12	1.23	1.18	1.25	1.26

Note. RV1 Avoidance; RV2 Complexity; RV3 Design; RV4 Entrepreneurial spirit; RV5 In depth analysis; RV6 Limited guidance; RV7 Mechanisms between humans and machines; RV8 Misuse; RV9 Overreliance on AI; RV10 Pedagogic culture; RV11 Problem solving; RV12 Entrepreneurial competencies; RV13 Support; RV14 Thinking in entrepreneurship education; RV15 Training

Table 7B. Total-Relation Matrix: RV6–RV10

Variables	RV6	RV7	RV8	RV9	RV10
RV1	1.00	1.12	0.99	1.06	1.01
RV2	1.07	1.21	1.07	1.13	1.08
RV3	0.95	1.07	0.93	1.00	0.96
RV4	1.10	1.24	1.08	1.17	1.11
RV5	1.03	1.17	1.02	1.10	1.05
RV6	0.86	1.02	0.90	0.91	0.92
RV7	1.09	1.15	1.07	1.14	1.10
RV8	1.05	1.17	0.98	1.11	1.06
RV9	1.08	1.21	1.07	1.07	1.08
RV10	1.12	1.24	1.10	1.17	1.06
RV11	1.07	1.20	1.05	1.13	1.07
RV12	1.11	1.25	1.09	1.18	1.13
RV13	1.09	1.21	1.06	1.14	1.08
RV14	1.04	1.17	1.03	1.09	1.05
RV15	1.10	1.24	1.09	1.16	1.10

Note. RV1 Avoidance; RV2 Complexity; RV3 Design; RV4 Entrepreneurial spirit; RV5 In depth analysis; RV6 Limited guidance; RV7 Mechanisms between humans and machines; RV8 Misuse; RV9 Overreliance on AI; RV10 Pedagogic culture; RV11 Problem solving; RV12 Entrepreneurial competencies; RV13 Support; RV14 Thinking in entrepreneurship education; RV15 Training

Table 7C. Total-Relation Matrix: RV11–RV15

Variables	RV11	RV12	RV13	RV14	RV15
RV1	1.13	1.11	1.12	1.13	1.10
RV2	1.22	1.20	1.21	1.22	1.18

continued on following page

Table 7C. Continued

Variables	RV11	RV12	RV13	RV14	RV15
RV3	1.09	1.05	1.08	1.09	1.05
RV4	1.26	1.23	1.24	1.26	1.21
RV5	1.17	1.15	1.17	1.18	1.14
RV6	1.03	1.01	1.02	1.04	1.01
RV7	1.24	1.21	1.23	1.23	1.19
RV8	1.19	1.17	1.18	1.18	1.15
RV9	1.22	1.20	1.22	1.22	1.18
RV10	1.26	1.24	1.24	1.26	1.21
RV11	1.15	1.19	1.20	1.21	1.17
RV12	1.27	1.17	1.25	1.27	1.22
RV13	1.24	1.21	1.15	1.23	1.19
RV14	1.19	1.15	1.18	1.12	1.14
RV15	1.25	1.22	1.24	1.25	1.14

Note. RV = retained variable; RV1 = avoidance; RV2 = complexity; RV3 = design; RV4 = entrepreneurial spirit; RV5 = in-depth analysis; RV6 = limited guidance; RV7 = mechanisms between humans and machines; RV8 = misuse; RV9 = overreliance on AI; RV10 = pedagogic culture; RV11 = problem-solving; RV12 = entrepreneurial competencies; RV13 = support; RV14 = thinking in entrepreneurship education; RV15 = training.

The Cause-Effect Hierarchy

Prominence and net-influence (Table 8) were calculated using the total-relation matrix to determine each barrier's role in the system. Prominence (P) reflects a barrier's total involvement, indicating its overall importance. It is the sum of the influence it exerts (row sum) and the influence it receives (column sum). Net-influence (N), calculated as the difference between the influence it exerts and receives, is indicative of a barrier's net role as either a primary cause (positive score) or a dependent effect (negative score).

Prominence P_i = row-sum + column-sum (indicating total involvement of barrier *i*). Net influence N_i = row-sum − column-sum (indicating whether barrier *i* acts mainly as a cause [positive] or an effect[(negative]).

Prominence and net influence are calculated using the formulas shown in equations (4) and (5).

$$P_i = \sum_i T_{ij} + \sum_i T_{ji} \tag{4}$$

$$N_i = \sum_i T_{ij} - \sum_i T_{ji} \tag{5}$$

Table 8. Prominence and Net-Influence Scores

Variables	Prominence (D+R)	Net influence (D-R)	Impact	Outcome
RV1	32.312	0.028	Low	Net cause
RV2	35.092	-0.207	Low	Net effect
RV3	32.264	-1.340	High	Net effect

continued on following page

Table 8. Continued

Variables	Prominence (D+R)	Net influence (D-R)	Impact	Outcome
RV4	35.724	0.056	Low	Net cause
RV5	34.826	-1.267	High	Net effect
RV6	30.508	-1.013	High	Net effect
RV7	35.286	-0.040	Low	Net effect
RV8	32.534	1.466	High	Net cause
RV9	34.020	0.910	High	Net cause
RV10	33.852	2.119	High	Net cause
RV11	35.254	-0.595	High	Net effect
RV12	35.565	0.542	High	Net cause
RV13	35.263	-0.162	Low	Net effect
RV14	34.739	-1.044	High	Net effect
RV15	35.095	0.547	High	Net cause

Note. D = ; R = ; RV = retained variable; RV1 = avoidance; RV2 = complexity; RV3 = design; RV4 = entrepreneurial spirit; RV5 = in-depth analysis; RV6 = limited guidance; RV7 = mechanisms between humans and machines; RV8 = misuse; RV9 = overreliance on AI; RV10 = pedagogic culture; RV11 = problem-solving; RV12 = entrepreneurial competencies; RV13 = support; RV14 = thinking in entrepreneurship education; RV15 = training.

DISCUSSION

GenAI has created both opportunities and challenges for higher education. In this study we go beyond enumerating the barriers and present a causal hierarchy of the barriers impacting GenAI integration in this domain of education. Our study used a mixed-methods design that leveraged expert validation and DEMATEL analysis to understand the interdependencies among the barriers. The DEMATEL analysis of GenAI barriers represented as a cause-and-effect structure, presents GenAI barriers as a causal network.

Our first two research questions were aimed at understanding the causal relationships between barriers and finding out which root causes and final impacts were highly significant. Our results indicate that effective introduction of GenAI is less of a technological issue, compared with human capability and intentional institutional design. Our study reports five high-impact/net-cause upstream levers of misuse (RV8), overreliance on AI (RV9), pedagogic culture (RV10), entrepreneurial competencies (RV12) and training (RV15) that have a subsequent impact on the system at large. When these root-level (upstream) problems persist, a whole set of important abilities and conditions start to break down. As a result, instructors and students will: (a) perceive technology to be complicated (RV2—complexity), (b) produce only superficial analyses (RV5—in-depth analysis), (c) have poorly designed ways of working with AI tools (RV7—human-machine mechanisms), (d) lose their capacity for real problem-solving (RV11—problem-solving), (e) receive inconsistent or inadequate help from their institution (RV13—support), (f) experience a distortion of entrepreneurial thinking skills (RV14—entrepreneurial thinking), (g) be unable to design thoughts into actions (RV3—design), and (h) have a scope of limited guidance (RV6—limited guidance). Strengthening of misuse (RV8) and pedagogic culture (RV10) can greatly lessen various challenges of the downstream. Therefore, design (RV3), in- depth analysis (RV5), limited guidance (RV6), problem-solving (RV11), and thinking in entrepreneurship education (RV14) are the most influenced outcome barriers.

The fact that pedagogic culture (RV10) emerged as the main causal factor gives solid empirical support to the previous body of scholarship that points to the fact that educator preparedness and competence are the two prerequisites of any successful adoption of EdTech (Fischer & Dobbins, 2023; Zambonino Torres et al., 2025). We demonstrated that perception of complexity (RV2) is a result of insufficient training (RV15), which in turn, promotes a pedagogical withdrawal leading to reduction in problem-solving (RV11) and a lack of in-depth analysis (RV5). This finding empirically substantiates prior studies (Vecchiarini & Somia, 2023), cautioning that AI, when improperly applied, may negatively impact the bricolage mentalities of entrepreneurs. Our model offers a causal process explaining how institutional failure (RV10—lack of pedagogic culture) effects in-depth analysis (RV5), design (RV3), and thinking (RV14) in entrepreneurship education.

Our analysis showed that issues like avoidance (RV1) and a decline in entrepreneurial spirit (RV4) are not the primary drivers of the problem. Although they are “causes,” their influence is weak. In other words, even though people often talk about these risks, our results revealed that they don’t have a strong domino effect on the rest of the system. On the other hand, poor tool complexity (RV2), mechanisms between humans and machines (RV7), and support (RV13) are classified as “effects,” but with low impact. This finding means they are largely symptoms or outcomes of other, more significant problems.

CONCLUSION

In this study we attempted to go beyond a simple enumeration of obstacles to the adoption of GenAI in the entrepreneurship education discipline and aimed at exposing the cause-effect model that governs it. We were able to map the multifaceted interdependencies among 15 critical barriers with a mixed-method design that incorporated the qualitative expert validation with an additional quantitative DEMATEL analysis.

According to our findings, the obstacles to successful GenAI integration are not technological, but to a large extent human and institutional. In the analysis, we have found two significant net-cause barriers: misuse (RV8) and pedagogic culture (RV10). These two upstream factors are the significant levers in the system. If unaddressed, this issue may initiate a ripple effect of net-effect hindrances, including the deterioration of problem-solving skills (RV11), design (RV3), in-depth analysis (RV5), limited guidance (RV6), and thinking in entrepreneurship education (RV14). We empirically proved that educator preparedness is the key to successful EdTech adoption in our study and how failure to train educators can cause pedagogical failures.

In addition, our cause-effect model reconceptualized the mainstream discourse regarding GenAI use in education. Poor practices such as avoidance (RV1) and entrepreneurial spirit (RV4) were found to be low-impact causes. Similarly, issues like complexity (RV2), mechanisms between humans and machines (RV7), and support (RV13) were identified to be low-impact effect, implying that these challenges are mostly symptoms of more profound underlying causes. Therefore, reactive institutional responses to plagiarism or excessive mindless use of AI cannot be successful; rather, a more active investment in faculty training and a deliberate attempt to enhance entrepreneurial competencies by creating a strong pedagogic culture and avoiding misuse would eliminate most of the downstream problems.

This causal knowledge would enable institutions to better distribute their resources, moving beyond a reactive, symptom-focused approach to a strategic, systemic one. By doing so, they will be able to break the barrier to adoption and initiate the vital process of transforming the disruptive potential of the GenAI into the long-lasting, sustainable benefit for the next generation of entrepreneurs.

IMPLICATIONS

Theoretical Implications

Our study presents a detailed understanding of the intricate relationships between barriers to adopting AI in entrepreneurship education. Although prior studies have largely listed the barriers in adoption of GenAI for entrepreneurship education, they have not analyzed the relationship between the barriers. We fill this gap in existing literature by following a mixed-method research design. First, our study establishes that barriers such as misuse and pedagogic culture have a subsequent impact on the entire ecosystem of adopting AI in education. The absence of pedagogic culture and misuse has a negative effect on design, in-depth analysis, guidance, problem-solving, and thinking in entrepreneurship education. Such a cause-effect relationship is not presented in existing studies, and our study thus contributes by reporting the strength of the effect/impact (low/high) of upstream levers. By mapping this causal chain, we provide in this study a granular view of how institutional pressures manifest. Instead of treating “institutional support” as a monolithic factor, we demonstrate how specific institutional failures, like inadequate training programs, misuse, and lack of pedagogic culture, create a domino effect that degrades the entire educational ecosystem—a dynamic often theorized, but rarely demonstrated empirically in the context of GenAI.

Second, we report that issues like avoidance and entrepreneurial spirit are not the root cause of the problem, and their influence as a barrier to AI adoption is weak. Third, we report that complexity, mechanisms between humans and machines, and support are largely symptoms of other, more significant problems. Such a detailed cause-effect relationship is missing in literature in the context of AI in education.

Most of the traditional technology acceptance literature, such as the technology acceptance model and unified theory of acceptance and use of technology, present a predictor of adoption of technology (Abdou & Jasimuddin, 2020; Farooq et al., 2024). In our study we challenge this linear perspective and suggests that a more dynamic and hierarchical relationship exists. The complexity involved in integrating GenAI in education is not essentially an aspect of the technology, but rather, a perception that arises and is largely influenced by the quality of training and the level of entrepreneurship competencies. Technology that may seem complex can be simplified and made easy to comprehend by a layman with well-trained educators possessing entrepreneurial competencies. This hierarchical interpretation aligns with the institutional theory, which states that organizational change cannot be viewed as a direct linear adoption, but a complex negotiation between the old structures, norms, and new external forces such as GenAI. According to our results, digital transformation in education can be achieved successfully only by targeting these capabilities at the institution level, rather than just focusing on individual user acceptance.

Our results regarding impact on mechanisms between humans and machines (RV7) add an important dimension to the literature. Although researchers such as Clegg and Sarkar (2024) have emphasized human-machine interface, our model proves that the lack of pedagogic culture and misuse can lead to systemic failure, wherein “mechanisms” such as the formal and informal procedures, workflows, and governance systems that coordinate human-AI cooperation get severely impacted if educators lack training. This result of our study empirically supports the claims of the institutional theorists that organizational preparedness, which is reflected through trained professionals, is the key element in successful digital transformation (Dolmark et al., 2022; Hughes et al., 2025; Rejeb, Rejeb, Simske, & Süle, 2025). More specifically, our study contributes to institutional theory by moving beyond identifying pressures (e.g., coercive, mimetic) to modeling the internal causal mechanisms through which institutions succeed or fail in their digital transformation efforts. We show that “organizational preparedness” is not a passive state, but an active capability rooted in pedagogic culture, avoiding misuse that directly enables the cocreation of effective human-AI workflows (Rejeb et al., 2025). This finding thus extends the literature on digital transformation by specifying that without foundational investment in human capital, any technological advancement risks being rejected or poorly integrated, thereby reinforcing institutional inertia rather than overcoming it.

Practical Implications for Educators and Administrators

Based on our results we provide suggestions for strategic interventions for practitioners who need to focus on the root cause of the barriers and not simply try fixing the symptoms. To begin, higher education institutions need to invest in their human resource (i.e., educators). The best initial move could be to roll out pedagogy-intensive AI upskilling of educators. This upskilling should not just be simple tool tutorials, but it also should include advanced prompt engineering, knowledge of ethical issues, and hands-on practice and discussion on designing AI-based assignments that foster, rather than erode, critical thinking.

Before the mass adoption of tools, institutions should actively establish well-defined governance, ethical code, and support mechanisms. This process involves the creation of special helpdesks and the development of explicit policies regarding data privacy and academic honesty, as well as the provision of guided materials such as vetted prompt libraries.

Although it is tempting to replace complex AI tools with simpler ones to avoid complexities of application, an attempt should be made to provide training and create a pedagogic culture to avoid misuse on current tools and to increase the know-how and reduce the adoption barrier. Furthermore, educators need to be trained on pedagogical interventions for responsible use of AI for enhancing the engagement of students with these tools without being developing an overreliance on them to generate responses.

With an emphasis on people, pedagogy, and policy, education institutions would be able to create an environment where the problems of overreliance, superficial use, and assessment degradation are proactively mitigated. Such an approach will help to cultivate a culture of responsible innovation, enabling entrepreneurship education to harness the transformative potential of GenAI without compromising pedagogical integrity.

LIMITATIONS AND FUTURE DIRECTION

Although the results of our study provide results that can be useful for both academics and industry, they should be used with reference to some limitations. We also provide suggestions for future research.

First, on one hand, the causal effect of some barriers, especially related to technical aspects, such as perceived complexity (RV2) or design flaws (RV3), might reduce as the technology matures and crosses the initial threshold of adoption. On the other hand, the problem of pedagogical barriers, like the loss of the ability to solve problems (RV11), can increase with increasing dependency of students on GenAI. Hence, our causal model is time-limited by its nature as the GenAI platforms develop quickly. We recommend to periodically audit this shift in barriers of adoption to keep the causal hierarchy pertinent and adjust strategic priorities accordingly.

Second, we collected responses from educators belonging to research-intensive universities, which presents a possible sampling bias. The identified barriers and the perceived magnitude may not be the sole measure of the peculiarities of other learning institutions, like community colleges, vocational training facilities, or accelerators in new markets where limited resources or other pedagogical priorities may change the barriers landscape. Cross-contextual replication of this study will lend external validity to our model and might lead to formulation of more context-specific models.

Third, although the DEMATEL method is useful to identify the cause-effect relationships, it uses the reflective judgment of the experts to translate them into causal weights. This approach would lead to the unintentional amplification of known barriers (e.g. misuse (RV8) and pedagogic culture (RV10) and possibly reduce more politically sensitive or less obvious ones (e.g., data privacy or ethical governance concerns). To address this issue, future studies could use qualitative design approaches, such as ethnographic designs, to reveal subtle and lived experiences of these barriers or create student-centered causal maps that compare their perceptions with the faculty.

Lastly, we based our analysis on the opinion of the experts and not on behavioral facts. The causal relations that we determined are, thus, inductive interpretations of professional opinion. Future research would enhance these results by considering objective telemetry of educational platforms. For example, using embedded logging tools that can follow real-time user activities (e.g., how often they consulted a help guide, how they revised the prompts, how much time was spent on a particular task, etc.), generating quantitative data on how various barriers are operationalized in practice.

CONFLICTING INTERESTS

The authors of this publication declare there are no competing interests

FUNDING STATEMENT

Funding for this research was covered by Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2025R429), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

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APPENDIX A

Semi-Structured Questions for Exploring Barriers to Generative Artificial Intelligence Integration in Entrepreneurship Education

Table 9. Semi-Structured Questions

Code	Verbatim prompt	Purpose
Q1	According to you, what are the most significant barriers or challenges in integrating generative AI (GenAI) in entrepreneurship education?	Core elicitation of candidate barriers.
Q2	Can you share any specific situations where GenAI integration was challenging for you or your students?	Concrete episodes to anchor Q1 statements.
Q3	What support or resources do you think are lacking for effective GenAI integration?	Surfaces missing enablers.
Q4	How do you believe GenAI may negatively impact student problem-solving skills?	Pedagogical dimension.
Q5	What factors contribute to the complexity of using GenAI in your teaching process?	Clarifies the “complexity” construct.
Q6	How do you ensure balanced use of GenAI without causing overreliance among students?	Addresses overdependency concerns.
Q7	How do you foster critical thinking and entrepreneurial spirit despite using artificial intelligence (AI) tools?	Captures strategies that mitigate barriers.
Q8	What policies or guidelines should be established to address barriers to AI adoption in entrepreneurship education?	Institutional dimension.
Q9	Any additional comments or suggestions regarding the challenges of AI integration?	Space for emergent insights.

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