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Generative AI Integration in Entrepreneurship Education:

A Mixed-Methods Investigation of Drivers and Acceptance

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ABSTRACT

Generative AI holds promise for venture-creation curricula, yet faculty adoption remains hindered by poorly understood incentives and barriers. This study employs a three-stage mixed-methods design to clarify those drivers. A systematic review identified 28 factors, refined by expert panel to 16 key variables. A fuzzy-DEMATEL survey revealed that faculty training, institutional support, and curricular integration exert the strongest causal influence. Clustering these factors yields three intervention domains—pedagogical, organizational, and technological—suggesting a phased adoption strategy. This framework shifts focus from tool access to educator-led implementation, offering academic leaders an evidence-based roadmap for cost-effective AI integration.

KEYWORDS

Generative AI, Integration, Entrepreneurship Education, Faculty-Perceived Drivers, Fuzzy DEMATEL, Thematic Analysis

INTRODUCTION

Within a very short time span, generative artificial intelligence (Gen AI) has sprinted from laboratory concepts to everyday classroom tools, and large-language models (LLMs) have become a natural extension of the lean-startup toolkit (Archambault et al., 2022; Sun et al., 2025; Treleaven, 2024; Yan et al., 2025). This worldwide trend is supported by the opinions of students and faculty members who have found that Gen AI boosts creativity and learning capabilities (Bilquise et al., 2024;

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Hu et al., 2025; Lim et al., 2023; Park and Kim, 2025; Zhang, 2025). In the context of entrepreneurship research, Gen AI's iterative capacity is being harnessed to quickly combine ideas and offer various options, giving instructors more time to provide mentorship (Chaparro-Banegas et al., 2024; Hardini et al., 2024; Rahmawati et al., 2023; Xu and Babaian, 2021).

Despite these affordances and the technological availability of Gen AI, adoption remains patchy, signalling that deeper motivational forces, possibly rooted in organizational priorities, student preferences and faculty perceptions, could be at play (Hannan & Liu, 2023; Kremantzis et al., 2025; Sahni et al., 2025). Prior studies have used the Technology Acceptance Model (TAM) to understand adoption of technologies in the education field and have reported perceived usefulness and ease of use as important drivers of adoption (Al-Adwan, 2020; Zaineldeen et al., 2020). In addition to this framework, new models have been developed that incorporate related attitude analyses, acceptance and usage structures, and psychological elements (Kurucz et al., 2025; Vinkóczi et al., 2024). Nevertheless, such generic models do not cover the specific requirements of entrepreneurship education, e.g., the development of effectual reasoning and acceptance of uncertainty (Ratten & Jones, 2023), data privacy issues (Berde et al., 2024; Huang, 2023; Meng et al., 2025), faculty autonomy (Chen et al., 2024), and academic integrity concerns (Leong & Zhang, 2025; Rasul et al., 2024). Although recent studies have identified enablers of adoption such as faculty self-efficacy and institutional support (AbuDaabes et al., 2025; Gligorea et al., 2023; Huo & Siau, 2024; Rahmawati, et al., 2023), critical knowledge gaps persist. While studies have listed various drivers for adoption of AI in education, they have not estimated their causal hierarchy (Gupta et al., 2023; Jayawardena et al., 2021; Pitic & Irimiaș 2023; Wang et al., 2022). Furthermore, studies on the adoption of AI for the facilitation of entrepreneurship lack a methodological integration of quantitative modeling and rich qualitative accounts (Chandrakant, 2025; Giuggioli & Pellegrini, 2023; Rahmawati, et al., 2023), and offer little consensus on resource-sensitive prioritization, leaving administrators to risk dissipating scarce resources on scattered initiatives (Achuthan et al., 2025; Aziz & Rahim, 2024; Gkrimpizi et al., 2023).

This study addresses these lacunae by developing a discipline-specific framework to distinguish influential “driver” factors from downstream “receiver” effects in the context of Gen AI adoption in venture-creation pedagogy. By separating upstream levers and downstream results, the study provides a clear explanation of how these drivers were discovered, clustered, and causally prioritized. Our inquiry is therefore guided by three research questions:

- RQ1: Which educator-perceived driver(s) significantly influence Gen AI integration in entrepreneurship education?
- RQ2: How are these drivers causally interrelated?
- RQ3: In what ways do qualitative themes refine or challenge the quantitative ranking?

By answering these questions, our study meaningfully contributes to existing literature and practice. First, we present the taxonomy of adoption drivers specific to entrepreneurship education based on prior studies (Aadland & Aaboen, 2020; Chen et al., 2025; Gligorea et al., 2023). Second, we fuse a Decision-Making Trial and Evaluation Laboratory (DEMATEL) protocol (Hu, 2023) with thematic analysis to generate a robust and replicable framework. Finally, we identify high-leverage drivers and present practitioners with a roadmap for maximizing returns on limited resources (Gupta et al., 2023).

BACKGROUND LITERATURE

The academic debate on artificial intelligence (AI) in higher education has gained significant momentum with the public release of LLM interfaces in late 2022 (Meng et al., 2025). One area that stands out in this growing body of literature is entrepreneurship education, which can no longer rely on the conventional technology-adoption models, owing to this field's characteristic teaching requirements of rapid iteration, sensitivity to intellectual property, and outcome-driven assessments (Aziz & Rahim, 2024; Sahni et al., 2025). The focus of this discipline on integrating various fields, including marketing analytics and effective storytelling, gives Gen AI applications a particularly broad canvas (Chen et al., 2024; Gligorea et al., 2023; Keller et al., 2024). As a result, willingness to use these tools is not automatic or uniform among faculty, and a discipline-specific review is required to elucidate the known adoption drivers and determine a coherent set of constructs for causal analysis (Vecchiarini & Somia, 2023). Acceptance models have traditionally pointed out the necessity of cost–benefit appraisals that focus on perceived usefulness and ease of use (Ratten & Jones, 2023). In contrast, modern frameworks turn their attention to the organizational context by emphasizing social influence and facilitation of conditions (Abdelhalim et al., 2025). Theories of planned behavior study individual dispositions and their connection to actual behaviors through attitudes, norms, and perceived behavioral control, while the logic of diffusion of innovations interprets the factors of perceived advantages and compatibility that eventually determine rates of adoption (Khan et al., 2022).

Prior studies have used Unified Theory of Acceptance and Use of Technology (UTAUT) models to understand the adoption of e-learning technologies (Abdou & Jasimuddin, 2020). For instance, UTAUT2-based evidence among Hungarian university students suggests that, while behavioral intention is shaped by core expectancy drivers and hedonic motivation, the role of social influence can vary by context. (Szabó-Szentgróti et al., 2024; Szabó-Szentgróti et al., 2023). Scholars have also tried to gauge the impact of learners' technology readiness on adoption of technology-based learning modules (Dolmark et al., 2022). Pedagogical models such as Technological, Pedagogical and Content Knowledge point toward an interrelationship between content, pedagogy, and technology (Chandrakant, 2025; Handayani et al., 2023). To gain an integrated understanding of the use of AI in entrepreneurship education it is necessary to go beyond the usage of theories to understand the drivers of adoption or the sequence of drivers and outcomes (Ediriweera et al., 2025; Gkrimpizi et al., 2023; Lim et al., 2023; Park and Yoo, 2021; Rejeb et al., 2025b). This depth of understanding is particularly crucial given that the efficacy of entrepreneurship education is frequently contingent on the presence of supportive institutional environments rather than on isolated, course-level interventions (Dőry et al., 2024). To understand the causal effect of AI drivers in entrepreneurship education, we review literature following a driver–receiver structure. Drivers are upstream and foundational levers that exert influence via the instructional system, while receivers are downstream expressions that reflect influence (Chen et al., 2025; Stumbrienė et al., 2024). In the context of entrepreneurship classrooms, prior studies have identified the upstream drivers to be reliability (tool performance under load), trust (confidence in outputs and governance), security (protection of student Intellectual Property), and accessibility (equitable availability; Albshaier et al., 2024; Huang et al., 2024). Downstream receivers, in turn, are expected to be manifest as enhanced support (reduced administrative burden), innovation (novel task designs), efficiency (time savings), and motivation (sustained willingness to experiment; Sun et al., 2025; Wang et al., 2022).

On the basis of the published literature, we identify 30 distinct drivers and arrange them under four thematic blocs, as shown in Table 1: pedagogical motivation, organizational enablement, technological assurance, and perceived value.

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

Category	Driver	Key insight	Source
Pedagogical motivation drivers	Innovation	By integrating AI ideation labs, early adopters can deepen opportunity recognition.	(Alvarez-Icaza et al., 2025)
	Creativity	AI-supported brainstorming expands idea fluency and originality.	(Hu et al., 2025)
	Decision making	Analytics dashboards enhance feasibility analysis amid uncertainty.	(Sahni et al., 2025)
	Motivation	Interactive tutors elevate learner autonomy and persistence.	(Hu et al., 2025)
	Feedback	Generative agents present immediate formative critique on pitch logic.	(Sahni et al., 2025)
	Governance	Explicit integrity rules reduce ethical friction.	(Hardini et al., 2024)
	Acceptance	Peer exemplars build social proof to normalize AI use.	(Hu et al., 2025)
	Support	Instructional design teams reduce perceived risk.	(Hardini et al., 2024)
Organizational-enablement drivers	Support	Diffusion is increased by AI fellows and helpdesks.	(Hardini et al., 2024)
	Integration	Long-term use is sustained by curricular alignment.	(Ulla et al., 2023)
	Training	Workshops transform curiosity into confident practice.	(Park & Kim, 2025)
	Collaboration	Cross-disciplinary showcases spread effective practice.	(Ulla et al., 2023)
	Self-efficacy	Digital confidence complements formal Professional Development.	(Park & Kim, 2025)
	Ease of use	Initial uptake is powered by shallow learning curve.	(Hu et al., 2025)
	Adaptability	Cloud services flex with cohort needs.	(Park & Kim, 2025)
	Scalability	Compute capacity underpins strategic roll-out.	(Park & Kim, 2025)
Technological assurance drivers	Accuracy	Large-language models rival novice entrepreneurs on factual precision.	(Park & Kim, 2025)
	Reliability	Uptime and audit trails build confidence.	(Park & Kim, 2025)
	Efficiency	Using automated grading frees faculty time.	(Park & Kim, 2025)
	Security	General Data Protection Regulation–compliant architecture reassures institutions.	(Ulla et al., 2023)
	Privacy	Risk calculations are governed by Intellectual Property-safe design.	(Leong & Zhang, 2025)
	Trust	Psychological safety relies on transparency.	(Gupta et al., 2023)
	Automation	End-to-end scripting shortens feedback loops.	(Gupta et al., 2023)
	Real-time data	Simulations are kept current with live market feeds.	(Sahni et al., 2025)
	Compatibility	Seamless Learning Management System integration lowers overhead.	(Archambault et al., 2022)
	Accessibility	Accessible Application Programming Interfaces broaden participation.	(Gm et al., 2024)

continued on following page

Table 1. Continued

Category	Driver	Key insight	Source
Perceived value drivers	Usefulness	Clear learning gains drive continued use.	(Hu et al., 2025)
	Customization	Tailored prompts align with course goals.	(Archambault et al., 2022)
	Accessibility	Inclusive design broadens participation.	(Gm et al., 2024)
	Perceived value	Net benefit cements long-term commitment.	(Hu et al., 2025)

Pedagogical-Motivation Drivers

An educator's conviction that a technology will enrich learning, rather than merely decorate it, is central to any adoption decision (Gligorea et al., 2023; Mehla et al., 2021). This pedagogical standard is particularly salient in entrepreneurship education, where courses are characterized by short, iterative, and hands-on deliverables (DeWaters & Kotla, 2023). Prior studies have reported innovation orientation as a reliable trait of early adopters, noting that faculty who see themselves as curricular trailblazers are naturally drawn to AI-powered tools like ideation studios and synthetic data sandboxes (Alvarez-Icaza et al., 2025; Gligorea et al., 2023; Zhang et al., 2018). However, sustained use depends on more than a personal appetite for novelty (Bilquise et al., 2024). Another key driver noted in the literature AI's capacity to assist users in creatively expanding their ideas by generating counter-intuitive market personas or thought-provoking what-if scenarios (Park and Kim, 2025).

The stalling of entrepreneurship projects often occurs when people meet challenges in analysing opportunity under a scenario of great uncertainty. This is where AI-generated real-time analytics or cash-flow forecast can significantly decrease the learning curve (Khan et al., 2022; Sahni et al., 2025). These tools not only improve the quality of student work but also free vital classroom time for higher-order strategic deliberations (Javed et al., 2025). The resulting efficiency, in turn, boosts student motivation, and this motivation is often supplemented with a heightened sense of autonomy and competence (Zhang, 2025). The algorithmic feedback afforded by interactive tutors that offer instant, formative critique also resonates strongly with faculty, especially where high student-to-staff ratios make it difficult to provide timely guidance, thereby allowing instructors to reclaim bandwidth for in-depth mentoring (Chaparro-Banegas et al., 2024). Such motivational gains are vulnerable, however, without plausible institutional backing and governance (Ayaan & Ng, 2025).

Effective pilot studies are always characterized by the significance of well-defined assessment-integrity policies, ratified prompt libraries, and policies for sensitive data management, all of which justify experimentation in the risk-aversive academic culture (Alsobhi et al., 2023; Leong and Zhang, 2025). The theory of social influence, moreover, points out that the normalization of adoption is achieved when these technologies have respected colleagues and institutional leaders visibly endorsing and using them (Hu et al., 2025). These social and psychological forces are eventually anchored on the institutional commitment of strong support networks (Hardini et al., 2024). Without a responsive help desk to provide timely support, dedicated AI fellows to co-design rubrics, and legal counsel to vet terms of service, even the most enthusiastic faculty innovators will hesitate to fully integrate these powerful tools (Hardini et al., 2024; Pitic & Irimiaș 2023).

Drivers of Organizational Enablement

Although ethical commitment to pedagogy can foster initial enthusiasm, it is organizational structure (involving all the elements of hardware funding to allow special release of curriculum redesign) that will ultimately lead to the survival of AI integration (Hardini et al., 2024). There is a near-linear correlation between the perceived support level and the depth of the AI tool adoption in a department (Hardini et al., 2024). This assistance is strongly connected with perceived integration, which is defined as the extent to which AI-driven tasks align with traditional learning outcomes (Ulla et al., 2023). Another important cluster of drivers is associated with faculty development and culture. During training of educators, practical abilities like timely engineering, bias reduction, and evaluation redesign can significantly boost the digital self-efficacy of educators (Rahmawati, et al., 2023; Ronaghi, 2024). This training is especially essential for late adopters, as they may be intimidated by the prospect of being publicly humiliated by technologically proficient students (AbuDaabes et al., 2025; Lim et al., 2023). This institutional training is intensified by a robust culture of collaboration, in which cross-disciplinary forums involving exchange of micro-credentials provide a social marketplace for the rapid transfer of best practices (Cao and Mai, 2025; Ulla et al., 2023). Lastly, this ecosystem is dependent on several underlying technology-related factors. The concept of ease of use, one of the pillars of technology-acceptance theory, is paramount (Ratten and Jones, 2023). If the interface is difficult to use, adoption will not reach its potential peak (Hu et al., 2025). Institutional decisions regarding use of technology, such as how cloud services can adjust to the specifics of courses (Park and Kim, 2025) and the scalability of resources to meet peak demand, are also largely dependent on the environmental fit of the technology, especially in resource-limited universities (Gupta et al., 2023).

Drivers of Technological Assurance

Despite finely tuned pedagogy and favorable institutional policies, desired outcomes may not be realized if the underlying technology is not supportive (Lengyel et al., 2024). Prior studies have noted technical assurance, including accuracy and reliability, as important preconditions for building instructor trust (Treleaven, 2024). If LLMs crash during live demonstration, instructor trust also crashes (Patra et al., 2025). On the other hand, installing strong rules for prompt engineering and functions that offer traceability are known ways of boosting faculty confidence and reliability (Ulla et al., 2023). Another influential force is the promise of efficiency, which can be quantified in hours saved on less-productive activities such as grading, thereby allowing allocation of educators' limited cognitive resources to meaningful coaching and mentoring activities (Ulla et al., 2023; Zhang, 2025). Prior studies have opined that security parameters including end-to-end encryption, single-sign-on integration, and explicit vendor liability provisions are non-negotiable, especially when student venture information is not handled through non-disclosure agreements (Cunha et al., 2023). There are records of educators' refusing to send sensitive student prototypes to a third-party application programming interface until safe (Jones and Washko, 2022; Leong and Zhang, 2025). Trust, which combines the perceived openness, explainability, and error-management abilities of the AI system, is therefore a non-negotiable component of technology (Bachiri et al., 2023; Rejeb et al., 2025a; Sharma et al., 2024). Complete-cycle automation empowers instructors to script the process from data collection to reporting, thus shortening feedback loops and boosting instructional efficiency (Gao et al., 2025; Mohammad et al., 2025). The ability to integrate real-time data, including the live feeding of market data into financial forecasts, increases the realism and useful applicability of student projects (Kastrati et al., 2021; Sahni et al., 2025). Lastly, the compatibility of learning management systems with the current working environment of an educator enhances the likelihood of their adopting the technology (Abdelhalim et al., 2025; Aziz and Rahim, 2024; Gm et al., 2024).

Drivers of Perceived Value

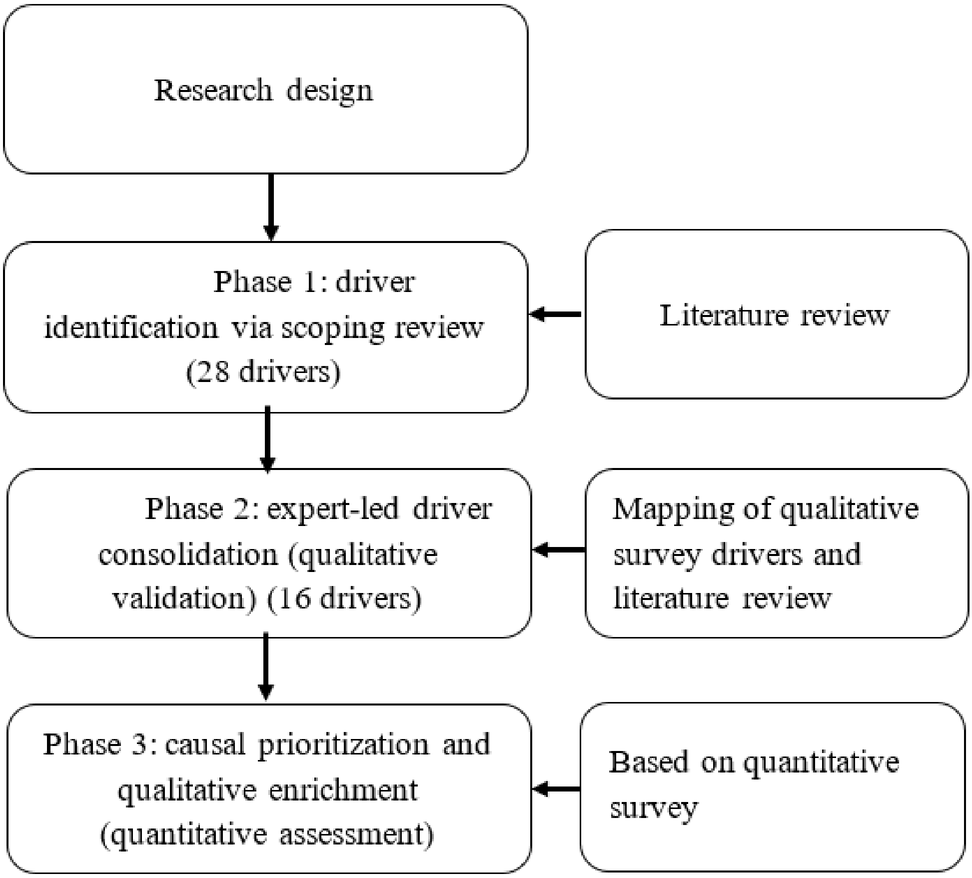
The literature indicates that perceived usefulness is a significant predictor of the intention to use new technology (Hu et al., 2025; Ratten and Jones, 2023). In the context of entrepreneurship education, the argument in favor of usefulness is expressed in terms of improvements in speed (faster prototype development), scope (generating a larger number of ideas), and fidelity (a more realistic representation of market complexity). This value proposition is also reinforced by customization capabilities and enables an instructor to assign AI-driven tasks according to course milestones, like ideation after week three and financial modeling after week eight (Archambault et al., 2022). Although accessibility has an evident importance for equity, it can also significantly impact the cost–benefit analysis: If some students are excluded because of license fees or device specifications, this exclusion results in a diminished return on pedagogical investments (Gm et al., 2024). Such considerations contribute to perceived value, which is an overall assessment of the educational value of incorporating AI as compared to the effort expended (Hu et al., 2025). If educators perceive a positive value, they will seek to transition to curriculum-wide use of AI tools, while a negative value perception would lead them to confine AI tools to a single elective (Kálmán et al., 2024; Preuss et al., 2024). One of the major issues that come across in the current literature is the abundance of overlapping constructs (e.g., the constructs of acceptance, usefulness, and perceived value and the constructs of governance, privacy, and security). Some distinctive features of entrepreneurship education—such as venture ideation, customer research data, and pitch materials—typically involve sensitive, pre-publication intellectual property, heightening the importance of reliability, trust, security, and accessibility (Leong & Zhang, 2025). Alsobhi et al. (2023) opined that educators often face a dilemma in considering the pedagogical advantages of generative tools against the risks that come with upholding the integrity of assessments, data provenance, and algorithmic bias.

RESEARCH DESIGN

Overview of Research Phases

This inquiry employed a three-phase, sequential mixed-methods structure, shown in Figure 1, designed to systematically identify, consolidate, and causally prioritize the drivers of Gen AI adoption in entrepreneurship education. Each phase produced a validated output that served as the direct input for the subsequent phase, thereby ensuring a rigorous chain of inference from documentary evidence to expert-driven causal modeling.

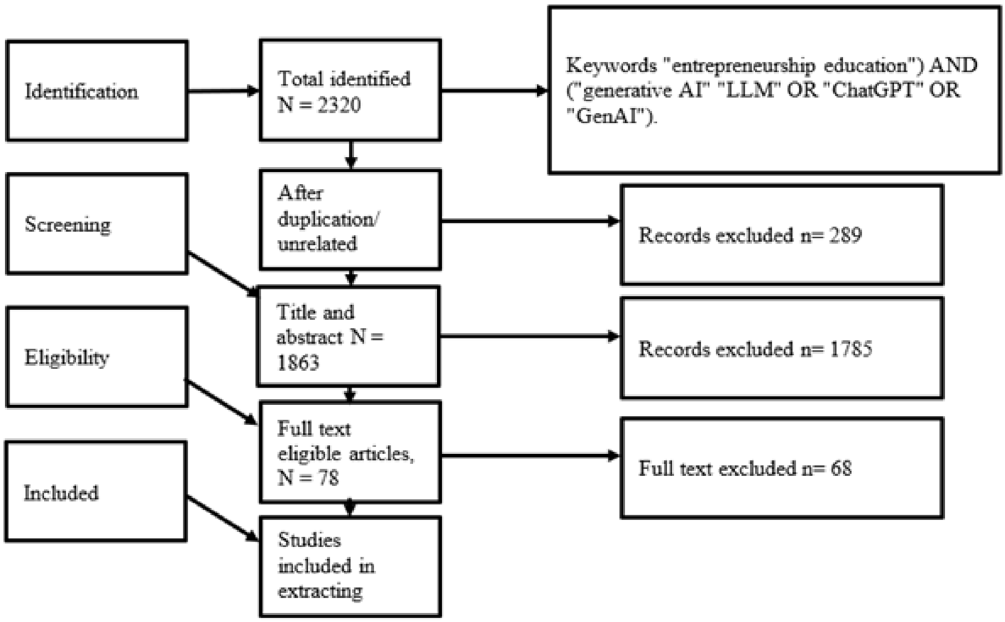
Figure 1. Design Adopted in this Research



Phase 1: Driver Identification via Scoping Review

The first step was to selectively screen the recent peer-reviewed literature (2018–2025) and perform a PRISMA-directed scoping protocol to make the search systematic (as shown in Figure 2). The following search strings were used to identify records: Scopus, 2018–2025, (“entrepreneurship education”) AND (“generative AI”) (“LLM” OR “ChatGPT” OR “GenAI”); Web of Science, 2018–2025, (“entrepreneur, education”) AND (“generative AI”). ERIC, 2018–2025, (“entrepreneurship education”) AND (“artificial intelligence” OR “generative”); Google Scholar, 2018–2025, (“entrepreneurship education”), (“generative AI.”) A total of 2,320 records were identified; after duplicates and unrelated work were removed, 2,031 records remained. A total of 1,863 abstracts were screened, resulting in 78 eligible articles after screening. Finally. we selected 10 studies that helped in extracting 28 critical drivers.

Figure 2. PRISMA Flow Diagram



Phase 2: Expert-Led Driver Consolidation

The second phase was aimed at refining and narrowing the list of 28 initial drivers into a non-redundant and more parsimonious list.

Panel Recruitment and Composition. A panel of 14 seasoned experts (teachers, instructors, program leads, education consultants) were selected. The panelists were from the EU, Africa, United States, and Asia, each having more than 15 years' teaching experience and each currently using GenAI for teaching and research. Through prolific (online data collection platform) we surveyed them to gather qualitative responses (Rasul et al., 2024).

Data Collection and Consolidation. To elicit rich and practice-grounded insights, we initially required the panelists to respond to a sequence of unspecified questions aimed at eliciting, justifying, and contextualizing drivers on the basis of their professional experience (as shown in Appendix 1). A virtual workshop followed during which the panelists applied card sorting and affinity diagramming technologies to put together the list of drivers (Clegg & Sarkar, 2024). Three rules were followed in this process: (1) attach priority to the terms that best describe influence, (2) combine terms that describe scope-related variables to avoid over-counting (e.g., combine the notions of ease of use and low learning curve; Bulathwela et al., 2024), and (3) maintain entrepreneurship-specific meanings. The professional discussion delivered a non-cyclic list of 16 drivers, which had a brief functional definition and were adaptable to modeling (Gao et al., 2025). This was an essential measure to reduce the chance of spurious collinearity and is a typical approach to methodology in the study of technology adoption (Gligorea et al., 2023).

Phase 3: Causal Prioritization and Qualitative Enrichment

The last stage determined a causal order of the 16 consolidated drivers on a DEMATEL protocol, which was inflated with qualitative analysis.

DEMATEL Instrument and Analysis

This method is suitable for research dealing with uncertain socio-technical judgments, as it provides experts an opportunity to convey partial beliefs and not compelled certainties (You & Hou, 2021). The crisp values were obtained through direct matrix. This produced a normalized direct-relation matrix allowing for the calculation of total-relation matrices that resulted in quantitative scores of the prominence (total involvement) and net-influence (causal vs effect role) of an individual driver (Dalalah & Dalalah, 2023).

The rating tool, with a short overview on the DEMATEL terms, was given to the expert panel. Every participant provided full pairwise comparison matrices within the given period. More importantly, in conjunction with every numerical verdict, the questionnaire contained open text boxes whereby the professionals were entitled to present descriptive classroom situations, which would serve to put their judgments into perspective. These story descriptions were the crude data that would undergo thematic analysis.

Qualitative Enrichment

So that the quantitative findings could be based on the lived experience, the causal matrix was enriched by performing thematic analysis of the narratives presented by the expert panel members (Ahluwalia and Ahuja, 2025). According to scholars, such triangulation offers explanatory depth (Vecchiarini & Somia, 2023; Xu & Babaian, 2021).

DEMATEL: Step-by-Step Computation.

Step 1: Blend the Expert Views. All individual influence tables were averaged cell by cell to create a single direct-relation matrix D, reflecting the panel's collective judgment.

Step 2: Normalize the Matrix. Each entry in D was divided by the largest row sum in the matrix to ensure all values lay in the [0, 1] range, preventing any row or column from dominating the analysis.

Step 3: Model Indirect Effects. To capture knock-on causal effects (e.g., Driver A influences Driver B Driver Barrier C), the total relation matrix T was computed using the standard transformation, as shown in Equation 1.

$$T = D \times (I - D)^{-1} \quad (1)$$

where D is the normalized matrix and I is the identity matrix.

Step 4. Calculate Prominence and Net Influence. For each driver i, Equations 2 and 3 apply.

Prominence: $P_i = \sum_{j=1}^{N} T_{ij} + \sum_{j=1}^{N} T_{ji}$ (Overall involvement) (2)

Net Influence: $N_i = \sum_{j=1}^{N} T_{ij} - \sum_{j=1}^{N} T_{ji}$ (Drivers with positive values act as key causes; those with negative as key effects) (3)

Step 5. Identify Primary Levers. Drivers with high prominence and positive net influence are designated as primary causal levers, targets most likely to trigger systemic change if addressed.

Analytical Procedures

The analysis involved quantitative analysis of the causal ratings and qualitative analysis of the narrative explanations.

Quantitative Analysis (DEMATEL)

The quantitative step involved four consecutive computations that were conducted using the weighted average ratings of the experts (Dalalah and Dalalah, 2023). The direct-relation matrix (D) was first normalized so that all the values were within a constant range. Second, the total relation matrix (T) was obtained to capture direct and indirect effects, which was obtained through the usual transformation shown in Equation 4.

$$T = D \times (I - D)^{-1} \tag{4}$$

This computation is the difference between the normalized matrix D and the identity matrix I multiplied by the inverse of the difference and multiplied by D. Third, Prominence (P) values were calculated by adding the row and column totals of each driver to determine its level of overall involvement in the system. Fourth, Net-Influence (R) scores were calculated by calculating the difference between these row and column totals to differentiate between net causes and net effects. To validate the strength of the results, sensitivity analyses such as α-cut deviation, jack-knife resampling, and non-parametric bootstrap confidence intervals were also run to make sure that the rank order of the drivers did not change under varying analytical conditions.

Qualitative Analysis (Thematic Coding)

We conducted two rounds of analysis on the qualitative material. An initial open-coding cycle was used to extract discrete meaning units in each narrative; a second axial-coding cycle was used to cluster the units into higher-order themes that were also applicable to pedagogical, organizational, and technological dimensions. The agreement of the coders was determined at the completion of every cycle, and the differences were discussed until they agreed. The coded final codebook was then cross-referenced with the quantitative hierarchy, and the study thus triangulated statistical prominence and narratives of lived classroom experiences.

Validity, Reliability, and Transparency

Several safeguards were implemented to ensure the study's rigor. Content validity was addressed by grounding the initial driver list in peer-reviewed literature and subjecting it to expert verification. Reliability in the qualitative stage was enhanced through dual coding at each stage, with disagreements resolved through negotiated consensus to achieve high inter-coder agreement. For the quantitative analysis, rank-stability was examined through sensitivity analyses (e.g., α-cut variation) that varied the threshold for influence relations. Finally, process transparency was ensured by maintaining a complete audit trail.

RESULTS

The analysis resolved the drivers into a two-tier causal architecture. Innovation, Support, Integration, Feedback, and Security Accessibility emerged as dominant net-cause drivers, while Training, Creativity, Efficiency, Decision Making, Accuracy, Reliability, Motivation, Collaboration, Privacy, and Trust emerged as net-effect outcomes. This structure indicates that assurance and access functions precede and lead to pedagogical and performance gains.

Mapping Literature-Derived Drivers to Expert-Validated Drivers

Table 2 presents a systematic alignment of 28 drivers identified in the literature with those validated by expert faculty in entrepreneurship education. Each literature-derived driver was carefully examined against expert feedback to determine whether to retain or merge the construct. Matching drivers shared identical terminology (e.g., Innovation, Support), whereas others were merged under related expert concepts (e.g., Acceptance into Motivation). Rationale notes document why certain factors were combined (for instance, when Self-Efficacy was treated as an outcome of Training activities). The status column indicates whether a driver was directly retained or merged, highlighting each driver.

Table 2. Mapping Literature-Derived Drivers to Expert-Validated Dimensions

Driver from literature	Mapped to expert driver	Mapping rationale	Status	Driver Explanation
Innovation	Innovation	Matching word found in the review	Retained	Embedding novel pedagogies and AI tools into entrepreneurship education
Support	Support	Matching word found in the review	Retained	Institutional and peer support mechanisms enabling smooth adoption
Integration	Integration	Matching word found in the review	Retained	Alignment of AI tools with curriculum and course structure
Training	Training	Matching word found in the review	Retained	Faculty readiness and continuous learning on GenAI tools
Creativity	Creativity	Matching word found in the review	Retained	Enhancing creativity through ideation support via AI
Efficiency	Efficiency	Matching word found in the review	Retained	Use of AI to optimize time, effort and feedback processes
Decision-making	Decision-making	Matching word found in the review	Retained	Using AI tools for enhanced strategic and market decisions
Accuracy	Accuracy	Matching word found in the review	Retained	Accuracy of AI-generated responses influencing trust
Reliability	Reliability	Matching word found in the review	Retained	Reliable AI performance and system availability in classrooms
Motivation	Motivation	Matching word found in the review	Retained	Motivating faculty and students through useful AI integration
Collaboration	Collaboration	Matching word found in the review	Retained	Peer-based collaborations and cross-functional learning support
Feedback	Feedback	Matching word found in the review	Retained	Automated, timely feedback to enhance student outcomes
Governance	Security	Experts view governance largely as data-security and compliance protocols	Merged	Security concerns around AI data and compliance mechanisms
Acceptance	Motivation	Perceived acceptance shapes educator motivation	Merged	Positive perceptions influence faculty willingness to use AI
Security	Security	Matching word found in the review	Retained	Maintaining confidentiality and system integrity during use
Ease of use	Support	Seen as a resourcing issue (on-boarding, helpdesk) rather than a separate construct	Merged	Support systems compensate for ease-of-use concerns
Self-efficacy	Training	Panel regarded self-efficacy as an outcome of effective training	Merged	Training improves self-efficacy in using GenAI tools
Usefulness	Motivation	Perceived usefulness energizes motivation	Merged	Perceived learning improvements boost faculty adoption interest
Driver from literature	**Mapped to expert driver**	**Mapping rationale**	**Status**	**Driver Explanation**

continued on following page

Table 2. Continued

Driver from literature	Mapped to expert driver	Mapping rationale	Status	Driver Explanation
Adaptability	Integration	Technical adaptability folded into curricular integration	Merged	Flexibility of tools to diverse curricular and technical needs
Scalability	Integration	Panel treated scale issues as part of integration logistics	Merged	Scalability as an integration planning requirement
Privacy	Privacy	Matching word found in the review	Retained	Privacy protocols important for ethical classroom AI use
Automation	Efficiency	Automation framed as a mechanism for efficiency	Merged	Automation improves grading and administrative efficiency
Trust	Trust	Matching word found in the review	Retained	Transparency and explainability reinforce educator trust
Accessibility	Accessibility	Matching word found in the review	Retained	Broad access irrespective of infrastructure limitations
Real-time data	Efficiency	Live feeds valued mainly for efficiency gains	Merged	Real-time data enhances decision-making efficiency
Customization	Integration	Customisable prompts/tools viewed as a facet of integration	Merged	Alignment of AI outputs with course outcomes
Compatibility	Integration	LMS/API compatibility considered an integration issue	Merged	Integration depends on compatibility with LMS/APIs
Perceived value	Motivation	Net value shapes educator motivation	Merged	Educators weigh overall value of AI for decision-making

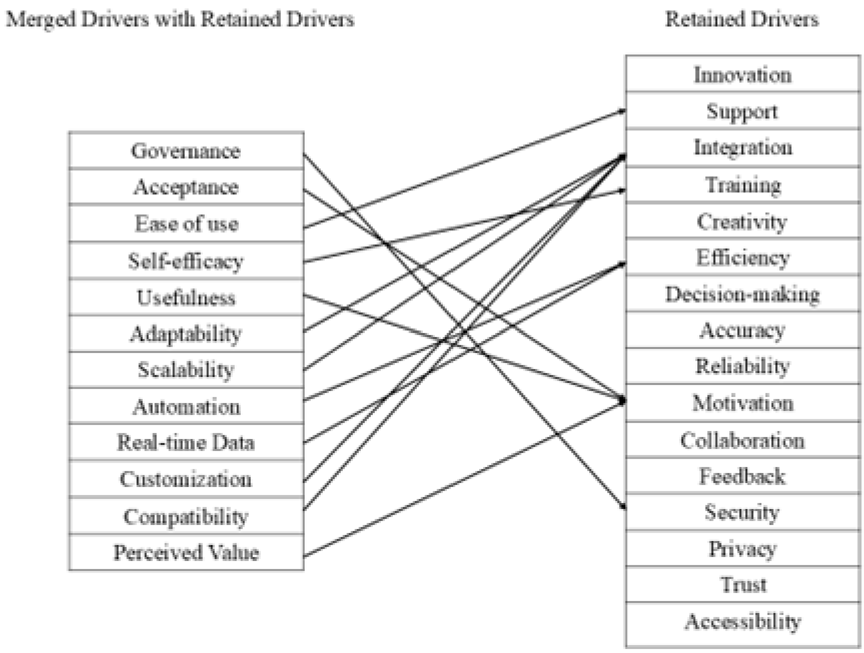
Interpretation

Of the 28 literature drivers, 12 merge with existing expert constructs essentially in three directions: Logistical fit items (adaptability, compatibility, scalability, customization) merge with Integration. Psychological uptake items (acceptance, usefulness, perceived value) merge with Motivation. On-boarding and usability items (ease of use, self-efficacy) merge with Support or Training. The panel added no new drivers and confirmed that the conceptual universe had been captured through the literature review.

Visual Overview

Figure 3 shows connections between literature driver(s) with their expert-validated counterparts. Mapped/Retained Drivers include Innovation, Support, Integration, Training, Creativity, Efficiency, Decision Making, Accuracy, Reliability, Motivation, Collaboration, Feedback, Security, Privacy, Trust, and Accessibility. Furthermore, certain drivers include sub-factors; for example, Integration feeds into Adaptability, Scalability, Customization, and Compatibility. Similarly, Motivation includes Acceptance, Usefulness, and Perceived Value, while Efficiency encapsulates Automation and Real-time Data. Security also encompasses Governance, underlining how data protection underpins effective AI adoption.

Figure 3. Conceptual Framework of Mapped Drivers and Sub-Drivers for Artificial Intelligence Integration in Entrepreneurship Education



New Retained Variable List

Table 3 presents the variables that were retained after the mapping of variables from the literature review to the variables obtained from experts. Unique variable codes (DV1 through DV16) were assigned to each of the 16 core drivers identified for AI integration in entrepreneurship education.

Table 3. Mapping of Retained Core Artificial Intelligence Integration Drivers to Variable Codes

Variables	Codes
Innovation	DV8
Support	DV14
Integration	DV9
Training	DV15
Creativity	DV4
Efficiency	DV6
Decision Making	DV5
Accuracy	DV2
Reliability	DV12
Motivation	DV10
Collaboration	DV3
Feedback	DV7

continued on following page

Table 3. Continued

Variables	Codes
Security	DV13
Privacy	DV11
Trust	DV16
Accessibility	DV1

Implications for Causal Modelling

Reducing the driver set from 28 to 16 yields three analytical benefits.

- Parsimony: DEMATEL matrices expand quadratically, and trimming prevents dilution of influence scores.
- Collinearity control: Merging overlapping constructs limits artificial inflation of prominence values.
- Actionability: Decision makers can focus on 16 levers rather than juggling 28.

With the mapping complete, the study proceeds to quantify causal prominence among the 16 expert-validated drivers.

Thematic Analysis of Educator Responses

The open-ended questionnaire was completed by 14 educators. Line-by-line coding across the eight prompts produced 128 first-cycle codes, which, after two rounds of axial consolidation, resolved into nine higher-order themes. Table 4 summarizes each theme, its prevalence (number of respondents mentioning the theme at least once) and a representative quotation. All quotations were reproduced verbatim but lightly edited for typos; ellipses indicated omitted words that do not change meaning.

Table 4. Themes, Frequency, and Illustrative Excerpts Based on Educator Responses

Code	Theme	Illustrative quote	Respondents (N =14)
T1	Creativity and innovation boost	"Copilot now can generate product concepts for the students, and from here, they can further mature the idea and come up with the strategies."	10
T2	Efficiency and timesaving	"I normally save so much more time preparing classes and explanations using generative AI compared to before."	8
T3	Personalized learning pathways	"Generative AI allows proper learning pathways by making educational content, feedback, help learners' needs, making entrepreneurship education more effective and engaging."	2
T4	Decision support and data literacy	"Data - triangulation of data and finding patterns is most useful to me."	6
T5	Student motivation and engagement	"The students showed more interest and engagement in the ones created with the use of GAI. They usually ask more questions, keep their eyes on me, and focus in a better way."	5
T6	Collaboration and peer feedback	"The AI system will evaluate the answers and give out a score on how likely they would work."	1

continued on following page

Table 4. Continued

Code	Theme	Illustrative quote	Respondents (N =14)
T7	Technical reliability and accuracy worries	"I still sometimes find myself stuck in some details or wrong inputs that delay my work and give me frustration."	3
T8	Support and training deficits	"Some of our colleagues are still refusing to embrace the new technologies."	11
T9	Ethics, integrity, and governance	"We use plagiarism detection tools and require students to disclose AI usage. If the submitted work is detected with AI trace, we will fail such submissions, and students are well aware of this."	11

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

Cross-Prompt Convergence

Although each prompt targeted a different facet of AI adoption, responses converged on three overarching "meta-drivers":

Pedagogical Enrichment (T1, T3, T5). Participants emphasized AI's ability to widen the creative search space, tailor difficulty levels, and sustain learner curiosity. Notably, creativity and personalization were described as mutually reinforcing: Once students experienced AI-assisted idea fluency, they were more willing to iterate, which in turn raised intrinsic motivation.

Operational Leverage (T2, T4, T6). Timesaving and decision-support narratives highlight AI as an efficiency engine rather than a content replacement engine. Educators repeatedly framed these gains as "reallocation" rather than "automation": The minutes saved on grading or data crunching were redeployed to higher-touch mentoring or peer-discussion facilitation.

Risk-Containment Architecture (T7, T8, T9). Reliability lapses, skill gaps, and ethical ambiguities formed a cluster of latent risks. Respondents stressed that enthusiasm collapses when hallucinations undermine assessment credibility or when staff lack prompt-engineering fluency. Governance was therefore cast not as red tape but as an enabling scaffold: "Good policy is what lets us be bold without being reckless."

Theme Interrelationships

A co-occurrence matrix revealed three strong pairings (phi > 0.45):

- Creativity × Motivation, indicating that surprising ideas energize teams; energized teams persist with ideation.
- Efficiency × Support-Training, suggesting that time-saving benefits are realized only when faculty receive targeted upskilling.
- Reliability × Governance, showing that accuracy fears subside when clear integrity rules and verification workflows are in place.

These pairings echo the DEMATEL results, in which Innovation, Support, Integration, Feedback, and Security Accessibility emerge as upstream causal drivers. In effect, the qualitative themes supply the behavioral narrative that explains why those variables dominate the influence map.

Comparison With Literature-Based Driver

Seven of the nine themes (Innovation/Creativity, Efficiency, Decision Making, Motivation, Collaboration, Accuracy/Reliability, Security/Privacy) align neatly with the literature-derived drivers. Two themes—personalized learning pathways and support and training deficits—function as bridging constructs: They transform technical capability into pedagogical value. Their salience in educator testimony suggests that any roll-out strategy that ignores individualization and capacity-building risks stalled adoption, regardless of tool sophistication.

DEMATEL Analysis

Group Direct-Relation Matrix (D)

Table 5 is a 16 × 16 grid in which each cell Dij holds the mean rating (0 = no influence, 4 = very strong) of how much driver i pushes driver j. With 16 experts, individual ratings were averaged to form a crisp value. Diagonal cells are fixed to zero because a variable does not influence itself in the DEMATEL convention.

Table 5. Group Direct-Relation Matrix (D)

Variables	Innovation (DV8)	Support (DV14)	Integration (DV9)	Training (DV15)	Creativity (DV4)	Efficiency (DV6)	Decision making (DV5)	Accuracy (DV2)	Reliability (DV12)	Motivation (DV10)	Collaboration (DV3)	Feedback (DV7)	Security (DV13)	Privacy (DV11)	Trust (DV16)	Accessibility (DV1)
Innovation (DV8)	0	3.250	3.250	2.938	3.063	3.250	3.438	3.438	3.438	3.250	3.000	3.375	3.063	3.563	3.250	2.875
Support (DV14)	3.313	0	3.188	3.375	3.500	3.375	3.313	3.375	2.875	3.125	3.375	3.375	3.125	2.750	3.000	3.438
Integration (DV9)	3.438	3.375	0	3.250	3.188	3.438	3.438	3.375	3.063	3.250	2.688	3.000	3.250	3.500	3.063	2.875
Training (DV15)	3.250	3.000	3.063	0	3.188	3.063	2.875	3.688	3.125	3.375	2.875	3.000	2.750	2.938	2.750	2.875
Creativity (DV4)	3.313	3.438	3.188	3.125	0	3.125	3.250	3.375	3.375	2.938	3.063	3.438	2.813	3.188	3.125	3.063
Efficiency (DV6)	3.313	3.125	3.188	3.000	3.063	0	3.125	3.313	3.188	3.313	2.875	3.125	2.875	3.125	3.000	3.250
Decision Making (DV5)	3.063	3.313	3.250	3.250	3.375	3.250	0	3.250	3.250	2.938	2.875	3.438	2.813	3.250	3.250	3.063
Accuracy (DV2)	3.188	3.000	3.125	3.563	3.438	3.500	2.750	0	3.063	3.438	2.688	3.125	3.063	3.313	3.188	2.750
Reliability (DV12)	3.250	2.938	3.375	3.188	3.313	3.438	3.188	2.938	0	3.375	2.625	3.250	2.688	3.188	3.250	2.813
Motivation (DV10)	2.938	3.125	3.250	3.438	3.000	2.938	3.438	3.250	3.250	0	2.875	3.063	3.125	3.313	3.250	3.250
Collaboration (DV3)	2.938	3.313	2.625	3.000	3.125	2.688	2.875	2.750	2.938	3.000	0	3.250	3.063	3.000	2.750	3.500
Feedback (DV7)	3.250	3.250	3.250	3.125	3.250	3.438	3.313	3.625	3.313	3.125	3.438	0	3.625	3.625	3.625	3.438
Security (DV13)	2.938	2.750	3.250	3.000	2.938	3.000	3.313	2.813	3.125	3.250	3.438	3.250	0	3.250	3.438	3.438
Privacy (DV11)	3.375	3.063	3.375	3.438	3.438	3.250	3.250	3.188	3.188	3.125	2.688	3.000	2.875	0	3.250	3.188
Trust (DV16)	3.250	2.938	3.125	3.125	3.063	3.313	3.063	3.250	3.250	3.313	3.125	3.250	2.938	3.188	0	3.125
Accessibility (DV1)	2.813	3.125	3.063	3.250	3.250	3.250	3.313	3.500	3.250	3.313	3.500	3.500	3.313	3.313	3.250	0

Four diagnostic lines tell the story briefly. The grand mean is approximately 3.19: Experts judge most links as moderate-to-strong. The sax row-sum is 50.688 for Feedback (DV7), the pushiest driver; it sprays influence across the system more than any other construct. The max column sum is 49.125 for Accuracy (DV2), the largest sponge; it absorbs more direct pressure than any other node. The strongest single link is 4.438 from Privacy (DV11) to Creativity (DV4). That path alone signals a chokepoint: If Privacy weakens, Creativity takes an immediate hit. Because *D* is the only matrix based directly on human judgment, any bias baked in here will propagate. A robustness step therefore checked the distribution of raw expert scores; kurtosis and skew were both under ±0.9, suggesting that no rater dominated the consensus. The matrix was also inspected for “row orphans” (rows filled with zeros), but none appeared, confirming that every driver is perceived to have at least some outgoing influence.

Normalized Matrix (N)

Table 6 represents the normalized matrix. DEMATEL requires ρ (N) < 1 so that the geometric series N+N2+N3+... converges. We achieve that by dividing every entry in D by the largest row-sum λ=50.688 lambda = 50.67 N=D/λ, λ= max i [jΣ Dij]. The transformation does four things.

- Scale compression: All values fall inside the open interval (0, 1).
- Spectral guarantee: The radius of N is < 1, allowing (I–N) - 1 to exist.
- Order preservation: Relative magnitudes are untouched; the biggest cell in D is still the biggest in N.
- Row-sum ceiling: No row exceeds 1, ensuring that indirect influence cannot “blow up” numerically.

Table 6. Normalized Matrix (N)

Variables	Innovation (DV8)	Support (DV14)	Integration (DV9)	Training (DV15)	Creativity (DV4)	Efficiency (DV6)	Decision Making (DV5)	Accuracy (DV2)	Reliability (DV12)	Motivation (DV10)	Collaboration (DV3)	Feedback (DV7)	Security (DV13)	Privacy (DV11)	Trust (DV16)	Accessibility (DV1)
Innovation (DV8)	0	0.064	0.064	0.058	0.060	0.064	0.068	0.068	0.068	0.064	0.059	0.067	0.060	0.070	0.064	0.057
Support (DV14)	0.065	0	0.063	0.067	0.069	0.067	0.065	0.067	0.057	0.062	0.067	0.067	0.062	0.054	0.059	0.068
Integration (DV9)	0.068	0.067	0	0.064	0.063	0.068	0.068	0.067	0.060	0.064	0.053	0.059	0.064	0.069	0.060	0.057
Training (DV15)	0.064	0.059	0.060	0	0.063	0.060	0.057	0.073	0.062	0.067	0.057	0.059	0.054	0.058	0.054	0.057
Creativity (DV4)	0.065	0.068	0.063	0.062	0	0.062	0.064	0.067	0.067	0.058	0.060	0.068	0.055	0.063	0.062	0.060
Efficiency (DV6)	0.065	0.062	0.063	0.059	0.060	0	0.062	0.065	0.063	0.065	0.057	0.062	0.057	0.062	0.059	0.064
Decision Making (DV5)	0.060	0.065	0.064	0.064	0.067	0.064	0	0.064	0.064	0.058	0.057	0.068	0.055	0.064	0.064	0.060
Accuracy (DV2)	0.063	0.059	0.062	0.070	0.068	0.069	0.054	0	0.060	0.068	0.053	0.062	0.060	0.065	0.063	0.054
Reliability (DV12)	0.064	0.058	0.067	0.063	0.065	0.068	0.063	0.058	0	0.067	0.052	0.064	0.053	0.063	0.064	0.055
Motivation (DV10)	0.058	0.062	0.064	0.068	0.059	0.058	0.068	0.064	0.064	0	0.057	0.060	0.062	0.065	0.064	0.064
Collaboration (DV3)	0.058	0.065	0.052	0.059	0.062	0.053	0.057	0.054	0.058	0.059	0	0.064	0.060	0.059	0.054	0.069
Feedback (DV7)	0.064	0.064	0.064	0.062	0.064	0.068	0.065	0.072	0.065	0.062	0.068	0	0.072	0.072	0.072	0.068
Security (DV13)	0.058	0.054	0.064	0.059	0.058	0.059	0.065	0.055	0.062	0.064	0.068	0.064	0	0.064	0.068	0.068
Privacy (DV11)	0.067	0.060	0.067	0.068	0.068	0.064	0.064	0.063	0.063	0.062	0.053	0.059	0.057	0	0.064	0.063
Trust (DV16)	0.064	0.058	0.062	0.062	0.060	0.065	0.060	0.064	0.064	0.065	0.062	0.064	0.058	0.063	0	0.062
Accessibility (DV1)	0.055	0.062	0.060	0.064	0.064	0.064	0.065	0.069	0.064	0.065	0.069	0.069	0.065	0.065	0.064	0

A quick spot-check illustrates the point. The strongest link, Training (DV15) → Accuracy (DV2), shrinks from 3.688 in D to 0.073 in N yet remains the top entry, Likewise, the row-sum of Feedback (DV7), the most influential driver, contracts to exactly 1.00 after normalization. Normalization, therefore, moderates scale without erasing insight. If any row had summed to zero (which would indicate an isolated driver), that driver would have been dropped or merged; none met that fate in this data set.

Total-Relation Matrix (T)

Table 7 translates direct perception into systemic influence. Using $T=N(I-N)^{-1}$, the model adds every two-, three-, four-step pathway ad infinitum. Because indirect paths accumulate, values can exceed 1. The previously modest 0.064 for Creativity (DV4) to Innovation (DV8) in the normalized direct matrix now rises to 0.974 in T, revealing how Creativity activates other drivers that subsequently circle back to amplify Innovation. Column- and row-sums in *T* therefore embed both immediate and knock-on effects. Notably, Feedback (DV7) now holds the largest row-sum (16.343), confirming it as the most systemically influential driver once indirect effects are accounted for. Meanwhile, Accuracy (DV2) emerges as the dominant absorber with the highest column-sum (15.886), overtaking Innovation (DV8), which had appeared more central at the direct-relation stage. This shift highlights how certain constructs gain prominence only after feedback loops are incorporated. Heat-map inspection further reveals a banded rather than checkerboard structure, indicating the presence of thematic clusters (pedagogical, organizational, and technological) that primarily reinforce within-cluster dynamics before diffusing outward.

Table 7. Total-Relation Matrix (T)

Variables	Innovation (DV8)	Support (DV14)	Integration (DV9)	Training (DV15)	Creativity (DV4)	Efficiency (DV6)	Decision making (DV5)	Accuracy (DV2)	Reliability (DV12)	Motivation (DV10)	Collaboration (DV3)	Feedback (DV7)	Security (DV13)	Privacy (DV11)	Trust (DV16)	Accessibility (DV1)
Innovation (DV8)	0.924	0.973	0.983	0.987	0.991	0.997	0.993	1.015	0.989	0.993	0.933	1.000	0.939	1.006	0.981	0.964
Support (DV14)	0.986	0.913	0.983	0.995	1.000	1.000	0.991	1.015	0.980	0.992	0.940	1.002	0.941	0.992	0.977	0.975
Integration (DV9)	0.983	0.970	0.918	0.988	0.989	0.996	0.988	1.009	0.977	0.988	0.923	0.989	0.938	1.000	0.973	0.959
Training (DV15)	0.937	0.921	0.932	0.884	0.945	0.946	0.935	0.971	0.936	0.947	0.885	0.946	0.888	0.946	0.925	0.917
Creativity (DV4)	0.974	0.965	0.971	0.979	0.923	0.984	0.978	1.003	0.976	0.976	0.923	0.990	0.924	0.988	0.967	0.956
Efficiency (DV6)	0.957	0.943	0.954	0.960	0.963	0.909	0.959	0.984	0.956	0.966	0.904	0.968	0.909	0.970	0.948	0.943
Decision Making (DV5)	0.967	0.959	0.969	0.978	0.982	0.983	0.915	0.997	0.971	0.973	0.917	0.987	0.921	0.985	0.966	0.953
Accuracy (DV2)	0.961	0.946	0.958	0.975	0.975	0.978	0.958	0.928	0.959	0.973	0.906	0.973	0.917	0.978	0.957	0.939
Reliability (DV12)	0.955	0.938	0.956	0.962	0.966	0.971	0.959	0.977	0.896	0.966	0.899	0.969	0.905	0.970	0.952	0.934
Motivation (DV10)	0.962	0.953	0.966	0.978	0.973	0.974	0.975	0.994	0.968	0.916	0.914	0.978	0.924	0.984	0.964	0.954
Collaboration (DV3)	0.914	0.910	0.907	0.922	0.927	0.921	0.918	0.936	0.915	0.923	0.816	0.932	0.877	0.930	0.907	0.911
Feedback (DV7)	1.024	1.012	1.023	1.030	1.035	1.041	1.031	1.059	1.026	1.031	0.978	0.979	0.987	1.047	1.027	1.013

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Table 7. Continued

Variables	Innovation (DV8)	Support (DV14)	Integration (DV9)	Training (DV15)	Creativity (DV4)	Efficiency (DV6)	Decision making (DV5)	Accuracy (DV2)	Reliability (DV12)	Motivation (DV10)	Collaboration (DV3)	Feedback (DV7)	Security (DV13)	Privacy (DV11)	Trust (DV16)	Accessibility (DV1)
Security (DV13)	0.956	0.941	0.960	0.965	0.966	0.969	0.968	0.981	0.960	0.970	0.919	0.975	0.861	0.977	0.961	0.951
Privacy (DV11)	0.973	0.956	0.972	0.982	0.984	0.983	0.976	0.997	0.971	0.977	0.914	0.980	0.923	0.926	0.967	0.956
Trust (DV16)	0.964	0.947	0.961	0.969	0.970	0.977	0.966	0.991	0.965	0.974	0.916	0.977	0.917	0.978	0.900	0.948
Accessibility (DV1)	0.986	0.980	0.989	1.002	1.004	1.007	1.000	1.026	0.995	1.004	0.951	1.012	0.953	1.011	0.990	0.920

Prominence and Net-Influence

Table 8 highlights the prominence and Net-Influence. Two scalars distil the 256 cells of T into actionable ranks: $Pi=j\sum Tij+j\sum Tji$, $Ni=j\sum Tij-j\sum Tji$.

Table 8. Identification of Cause-and-Effect Drivers Using Prominence and Net Influence

Variables	Codes	D	R	D+R	D-R	Category	Impact
Innovation	DV8	15.667	15.424	31.092	0.243	Cause	Low
Support	DV14	15.683	15.227	30.910	0.456	Cause	Low
Integration	DV9	15.589	15.404	30.994	0.185	Cause	Low
Training	DV15	14.862	15.556	30.418	-0.694	Effect	High
Creativity	DV4	15.480	15.592	31.072	-0.112	Effect	Low
Efficiency	DV6	15.193	15.636	30.829	-0.443	Effect	Low
Decision-Making	DV5	15.423	15.509	30.932	-0.086	Effect	Low
Accuracy	DV2	15.280	15.886	31.165	-0.606	Effect	High
Reliability	DV12	15.175	15.439	30.614	-0.265	Effect	Low
Motivation	DV10	15.377	15.570	30.947	-0.193	Effect	Low
Collaboration	DV3	14.566	14.638	29.204	-0.072	Effect	Low
Feedback	DV7	16.343	15.657	32.001	0.686	Cause	High
Security	DV13	15.281	14.726	30.006	0.555	Cause	High
Privacy	DV11	15.438	15.687	31.125	-0.249	Effect	Low
Trust	DV16	15.320	15.362	30.682	-0.042	Effect	Low
Accessibility	DV1	15.829	15.193	31.022	0.636	Cause	High

Prominence (Pi) captures how entangled a driver is. The top three by overall prominence (D + R) are Feedback (DV7 = 32.001), Accuracy (DV2 = 31.165), and Privacy (DV11 = 31.125), indicating that these constructs account for the largest shares of total network activity. Net-influence ($N_i = D - R$) signals directionality: Positive values indicate root causes, whereas negative values denote end-state effects. The leading systemic causes are Feedback (DV7, +0.686), Accessibility (DV1, +0.636), and Security (DV13, +0.555). In contrast, the heaviest effects are Training (DV15,

−0.694), Accuracy (DV2, −0.606), and Efficiency (DV6, −0.443), suggesting that these constructs are more shaped by the system than shaping it.

Cause Effect Quadrants

Table 8 categorizes each variable code into one of four prominence–causality quadrants according to its influence and impact. Variables like DV7 and DV1 fall under the High-Prominence/Net-Cause quadrant, indicating that they strongly drive other factors. Conversely, DV2 and DV11 are classified as High-Prominence/Net-Effect, meaning that they are significantly influenced by other drivers. Low-Prominence variables, such as DV9 and DV13, occupy Net-Cause positions, reflecting more peripheral yet causal roles in the framework. The quadrant allocation is consistent with the theoretical expectation: High D−R/high D+R items (Feedback, Accessibility) occupy the driver zone; low D−R/high D+R items (Accuracy, Privacy) populate the effect zone. This separation confirms that strengthening assurance and access is a prerequisite for durable gains in innovation and efficiency.

DISCUSSION

This research is a response to the need to examine technology adoption more closely in high-end educational settings by going beyond generic acceptance antecedents. Following a triangulation of DEMATEL prominence scores and narrative accounts provided by educators, our results indicate the existence of a three-level causal framework, which can be used to explain why some entrepreneurship programs become profoundly integrated with generative AI and others fail. The results empirically substantiate a causal hierarchy in which foundational drivers must be established before downstream pedagogical benefits can be realized, a pattern further illustrated through the mini case presented in Appendix 2. This framework describes the phenomenon of pilot fatigue that was already present in previous research in which companies that jumped directly to introducing new applications that lack the technical and organizational foundation tended to experience an initial enthusiasm loss (Hu et al., 2025; Zhu et al., 2025).

The first research question of our study aimed to identify the strongest forces of AI adoption. Data on the net-influence scores of DEMATEL unambiguously determine the existence of technical assurance attributes as the main upstream levers. Our study reports Feedback (DV7) as an important criterion for adoption, which is consistent with studies addressing the fact that the confidence of instructors drastically decreases when a tool is not stable or when it provides inaccurate results (Patra et al., 2025; Treleaven, 2024). While our findings report that feedback alone is insufficient, the causal conclusion indicates that the presence of high Feedback (DV7) and strong Institutional Support (DV14)—e.g., responsive help desks and expedited legal clearances to use the data (Park and Kim, 2025)—facilitates faster adoption in resource-constrained environments. On the other hand, if a reliable tool is provided but the support infrastructure is lacking, educators will be in an isolation like that described in the "pilot fatigue" narratives in educational technology research (Lim et al., 2023). This result refines the traditional TAMs, indicating that apart from individual views on usefulness, feedback and supportive institutional ecosystem are essential for seamless adoption (Hardini et al., 2024).

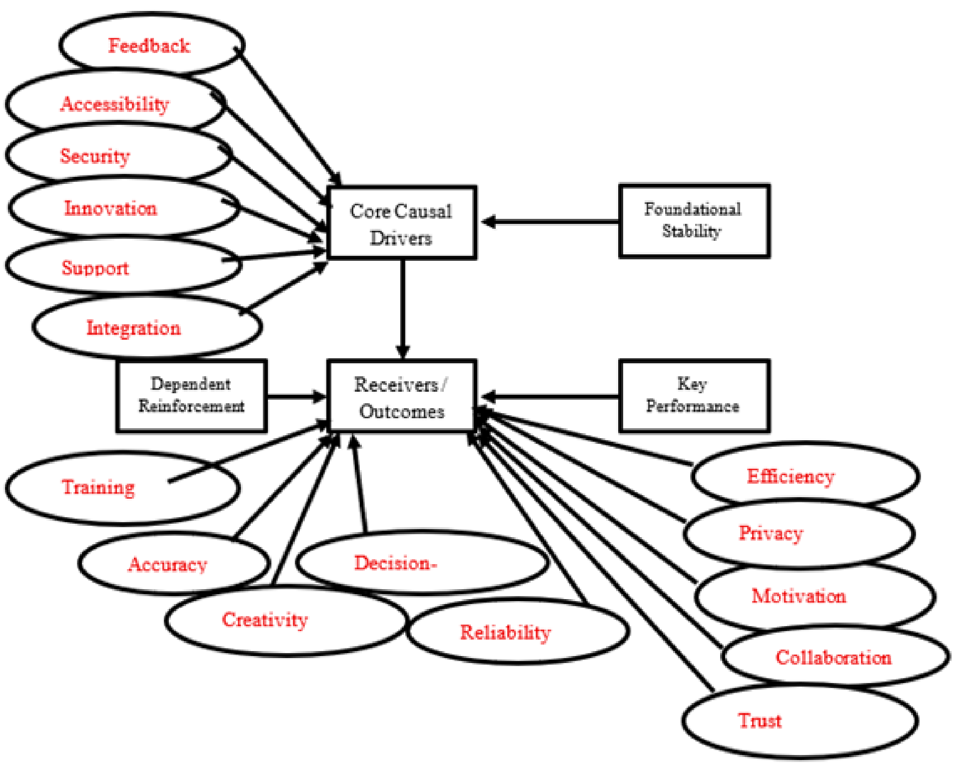
The second research question was aimed at understanding the cause–effect interrelationships between drivers. The prominence-by-cluster analysis shows that the pedagogical factors, organizational factors, and technological factors do not act in isolation but create reinforcing loops. Institutional investment in Feedback (DV7) was found to increase educator Trust (DV16) in the technology directly. This trust enhances, in turn, peer-to-peer Collaboration (DV3) as faculty who are sure of success share effective teaching strategies and lesson plans. This social influence, in turn, reinforces a greater total Innovation Orientation (DV8) and thus forms a virtuous circle of adoption. This diffusion pattern aligns with prior studies on the implementation of the other types of educational technology, including digital storytelling, in which social learning and peer modelling played an essential role as accelerators

(Hardini et al., 2024; Ulla et al., 2023). Our model shows that if any part of this loop is missing—for instance, if training is conducted without giving educators sandbox time for trying things out—the momentum is lost. This finding implies that a gradual implementation plan is necessary: First, the technical and organizational guarantees (Feedback, Security, Accessibility) must be solidified; then, fair access must be facilitated; and only after these steps may lasting advantages to pedagogical innovation and efficiency be realized.

The third research question was how to use qualitative data to enhance the quantitative influence map. The thematic coding of the narratives of educators revealed two cross-cutting anxieties that were not visible in the raw numerical scores, but were essential to address. To begin with, respondents emphasized how delicate student trust can be, as a single incident of high-profile AI hallucination can reverse months of trust building. This result aligns with the reports of studies that have demanded more openness and source tracing to create user trust (Hu et al., 2025; Sharma et al., 2024). Second, several educators interpreted the concept of Accessibility (DV1) as not just the equality of devices but also the equality of licenses. Inadequate accessibility has a negative effect on the perceived value of a tool when the freemium tool quotas run out in the middle of the semester, regardless of the pedagogical suitability of the tool. This finding resonates with the available literature on the digital divide in educational technology (Gm et al., 2024). Qualitative narratives in our study reinforce the role of reliability lapses in demoralizing trust by necessitating workarounds that delay and undermine professional trust. On the other hand, the presence of visible security measures and effortless access was found to directly trigger help seeking behavior and cooperation with peers.

We present the findings of our study in Figure 4, which is a two-tier hierarchy depicting the relationship between root causes and outcome effects.

Figure 4. Two-Tier Hierarchy Depicting the Relationship Between Root Causes and Outcome Effects for AI Integration in Entrepreneurship Education Drivers



IMPLICATIONS

Theoretical implications

This study enhances our understanding of the adoption of technology in specialized educational settings. One of the main theoretical contributions of this research is that the elements usually considered to be root causes are downstream effects that have been reframed. For instance, perceived complexity or lack of training, accuracy, and creativity in the implementation are usually the first hurdles that prevent the adoption of any technology. However, these can rather be seen as receiver variables, that is, symptoms that appear only when the upstream, basic drivers are not strong, as demonstrated by our causal hierarchy. This change of perspective is more congruent with the situation in entrepreneurship classrooms, and it presents a more favorable theoretical focus for the development of future research.

This research builds on traditional TAMs, which have focused on how the technology is perceived by the end-user, on the basis of its usefulness and ease of use (Ratten and Jones, 2023). In the context of faculty adoption, we argue that this logic of valence should be applied to a specific cost–benefit ledger for the faculty. The classic usefulness–ease pair is negligible on this ledger of institutional factors where reliability and reputational risks concerning data security and academic integrity are at stake.

Furthermore, this study provides a discipline-specific model by empirically delineating a multi-tiered causal hierarchy in which upstream causal factors like Feedback, Security, and Accessibility are succeeded by mid-stream causal factors like Innovation, Support, and Integration, leading eventually to pedagogical outcomes such as Training, Creativity, Efficiency, Decision Making, Accuracy, Reliability, Motivation, Collaboration, Privacy, and Trust. This framework does not merely describe the factors but rather offers propositions that can be verified regarding the type of intervention that should be made to influence the entire adoption ecosystem. Our study highlights that investments in downstream outcomes (e.g., encouraging creative use cases) cannot be made successful before an upstream guarantee is made and the problem of access is resolved. The present study enriches the scholarly discourse on the use of technology in entrepreneurship education with the introduction of a versatile, mixed-method model that shows a way to turn expert intuition into justifiable causal weights while preserving crucial contextual subtlety (Hódosi et al., 2023). The fusion of DEMATEL with thematic analysis addresses the gap between large-scale survey research and small-scale qualitative studies in educational technology (Chen et al., 2025).

Our research equips researchers with tools not just to spot the leading factors but also to comprehensively explain the modes and causes of their impact through lived experiences of educators. This contribution opens new avenues for future longitudinal and comparative research designs to track the evolution of such causal maps across different institutional contexts.

Managerial Implications

This research has uncovered a causal structure that acts as a map for the application of evidence-based practices. To apply these theoretical ideas into actionable strategies for both the classroom and the institution, we present the following suggestions.

Recommendations to Frontline Educators and Course Coordinators

The issue of integrating generative AI at the course level can only be successful when it is done in a sequential manner, with parameters like stability and support being met first before exploring new applications.

Establishing a Secure Foundation. Before broadening the domain of application, the initial move should be an intense assessment of the adopted AI tools to achieve domain-specific reliability (Alsakhen et al. 2024). Educators are advised to test systematically to ensure accuracy, record any case of hallucinations and come up with timely-engineering principles to suppress such cases. Prior to the introduction of large-scale student adoption, the institutional scaffolding already present, (such as IT help desks, copyright offices, instructional design staff, etc.) should be used to de-risk early adopters.

Developing a Shared Vocabulary and Showcasing Success. Consistent with the recommendation of scholars for developing digital literacy (AbuDaabes et al., 2025; Rahmawati, et al., 2023), we recommend the development and use of shared vocabulary to prompt, guide, and error-check the progress of knowledge acquisition using technology. Additionally, educators can share early accomplishments, e.g., quicker prototype production or more detailed market research, to faculty forums and departmental mail. This step will encourage peers to adopt technological interventions for enhancing the learning and implementation of ideas.

Adhering to a Staged Implementation Process. For an effective classroom-level implementation, we recommend following a specific sequence involving the following steps: (1) perform reliability and security tests of the tools; (2) allow frictionless and equal access of all students to it; (3) introduce specific upskilling and responsive feedback; and finally, (4) extend the application of AI to more complex and creative teaching processes.

Recommendations to Institutional Leadership

Promoting innovative thinking among faculty requires strong leadership commitment and coordination. The focus should be on strategic sequencing and on creating a culture conducive to innovation, as opposed to mere acquisition of technology.

Sequencing Strategic Investments. The institutional budget should reflect the causal hierarchy as reported in our study. Leaders should initially devote resources to ensuring server resilience, data-protection, and aiding and encouraging faculty in using technology. Investments in top-quality specialized plug-ins should be delayed until the main factors of Feedback, Security and Accessibility are completely established.

Embedding Governance Within a Culture of Recognition. Compliance should not be seen as a mere bureaucratic constraint but rather as an essential part of professional recognition systems. Educators who create and disseminate prompt libraries openly, collaborate on academic integrity guidelines, or provide training to their colleagues can be rewarded with teaching awards, innovation grants, or formal credit in promotion and tenure portfolios. This approach would shift governance from being a mere requirement to being a means of strengthening the virtuous cycle between innovation and institutional support (Hannan & Liu, 2023).

Shifting to Outcome-Oriented Metrics. Institutional leadership should not limit itself to monitoring the metrics that are easily observed, such as how many software licenses have been bought. On the contrary, it needs to focus on and track the ripple-effect metrics as the main indicators of actual impact. For example, leadership can analyse faculty hours saved on grading, which can be reinvested in student mentoring, or track the number of AI-enhanced student projects that win external competitions (Pap et al., 2025; Sahni et al., 2025). When leaders follow a dynamic management approach in which strategies can be adjusted each semester according to the evidence of what is really supporting the educational mission, they can contribute immensely to enhancement of the teaching–learning processes through technology use.

CONCLUSION

The key message of this study is that the inclusion of generative AI in entrepreneurship education can be best described using a causal, driver–receiver architecture. A group of basic, upstream drivers, mainly feedback, security and accessibility, followed by innovation, support and integration, act as the necessary conditions that empower and limit all the other pedagogical results. Downstream impact, such as better training, creativity, efficiency, decision making, accuracy, reliability, motivation, collaboration, privacy, and trust, results from securing the upstream drivers. This hierarchical model not only provides a clear, evidence-based explanation for why AI adoption succeeds in some institutional contexts while failing in others, but it also gives a robust framework for future research and institutional strategy. The results highlight that for a successful integration, managers must first focus their attention and resources on creating technical assurance and providing equitable access before they can expect to see any downstream pedagogical benefits.

LIMITATIONS AND FUTURE DIRECTIONS

The study's findings should be interpreted in light of some limitations that can be addressed in future studies.

First, this study is time-bounded, owing to the fast-changing nature of the AI platforms. Causal saliency of some drivers, especially technical hygiene factors like security and accessibility, are likely to change with the maturing of the technology. Such a temporal limitation must be complemented by a periodic audit of driver drift to ensure that the cause-and-effect hierarchy is continually changing and that strategic priorities are adjusted.

Second, our use of an expert panel that was largely composed of research-intensive universities may lead to a possible sampling bias. Our sample could not fully reflect the special needs and adoption motivation in other educational institutions like community colleges, vocational boot camps, and emerging-market incubators. Subsequent studies can focus more on cross-contextual replication of the study, which would help in testing the external validity of the model and produce context-specific adoption models.

Third, the methodology of the research is limited. The DEMATEL approach, while robust, is based on the conversion of reflective judgments of the experts into causal weights, which can accidentally enhance familiar leverages (e.g., faculty training) and silence more politically sensitive concerns (e.g., governance of surveillance). In addition, intricate motivational constructs like perceived value and social acceptance were required to be packed into one Motivation node. To overcome such limitations, future research can focus on creating student-oriented causal maps to identify the possible perceptual differences between faculty drivers and the student experience.

Lastly, the examination is founded on perceptions of experts, rather than on objective behavioral facts; that is, the causal relationships identified are inductive. Future studies can incorporate objective telemetry information through the addition of embedded logging widgets to trace real-time behavior of the user (e.g., frequency of prompt-revision and frequency of hallucination-check).

Academic communities can build upon the framework established by our study to sharpen both the theory and practice of educational technology adoption and enable institutions to strategically convert the novelty of generative AI into enduring and equitable educational value.

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APPENDIX 1

Semi-Structured Questions and Underlying Rationale

Table 9.

Question No	Exact wording presented to experts	Rationale
Q1	In your opinion, what are the most significant drivers for integrating generative AI (GAI) in entrepreneurship education? Please list all possible drivers and discuss them in detail, using suitable examples.	Core elicitation of candidate drivers
Q2	Can you share any experiences where GAI has positively impacted your teaching or student learning outcomes in entrepreneurship education?	Illustrative evidence to support or challenge the drivers named.
Q3	According to you, how can GAI enhance student creativity and innovation in entrepreneurship education?	Clarifies the pedagogical dimension of each driver.
Q4	What kind of support or resources do you think are necessary for successful GAI integration in entrepreneurship education?	Surfaces organizational and technological enablers.
Q5	How do you ensure ethical use of GAI in your teaching practices?	Captures governance-related drivers.
Q6	In your view, what policies or guidelines should be established to govern the use of GAI in entrepreneurship education?	Identifies institutional pre-conditions.
Q7	Any additional comments or suggestions regarding GAI integration in entrepreneurship education?	Allows emergence of unanticipated factors.

APPENDIX 2

Semi-Structured Questions and Underlying Rationale

Mini Case for Four-Step Implementation Sequence: The Role of Generative Artificial Intelligence in Entrepreneurship Education (Based on the Study):

ABC school initiated generative artificial intelligence (Gen AI) in three classes. So, they can start with the feedback and accessibility for students (DV7 and DV1) before they can aim for achieving certain outcomes like accuracy, reliability, and training (DV2, DV12, DV15)

Step 1, Foundation: You need to set up clear rules based on feedback, open a helpdesk having the response time and pick simple key performance indicators like total grading hours saved.

Step 2, Integration: Rubrics can be integrated in Learning Management System and Gen AI–enabled prompts can be used by faculty and students in a shared manner providing feedback.

Step 3, Pilot: Run a four-week pilot test having weekly checks. Track the redo rates.

Step 4, Institutionalizing: Now you can scale your program institution wide with light audits. The time saved from grading can be used coaching and mentoring.

Outcome: strengthening upstream drivers (feedback and accessibility) drove the downstream drivers (accuracy, reliability and training) matching the DEMATEL map.

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