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Generative AI in Entrepreneurship Education: Enhancing Faculty's Instructional Design and Pedagogical Capacities

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Abstract

Generative artificial intelligence (GenAI) is reshaping entrepreneurship education by supporting faculty in instructional design and pedagogical practice. This conceptual review integrates recent literature (2022-2025) to develop a theoretical framework examining how GenAI enhances faculty capacities across instructional design (course development, case creation, activity design, assessment) and pedagogical competencies (innovative teaching, personalization, reflective practice). Drawing on the Technology Acceptance Model, AI-TPACK framework, and entrepreneurship pedagogy literature, this study reconceptualizes GenAI as a capacity development mediator rather than merely an efficiency tool. While early experimental studies suggest potential time savings, realizing these benefits requires integration with professional judgment, as quality concerns—including fabricated citations and context adaptation needs—underscore the indispensable role of faculty expertise. Four key contributions emerge: (1) a dual-dimensional framework for GenAI-mediated capacity development; (2) identification of four distinct faculty adoption profiles requiring differentiated support; (3) critical challenges spanning academic integrity, ethics, digital equity, and training deficits; and (4) evidence-based multi-level intervention recommendations. This framework has significant implications for teacher education programs and institutional policies governing AI integration in entrepreneurship education.

Keywords
Generative Artificial Intelligence; Entrepreneurship Education; Instructional Design; Pedagogical Capacity; Faculty Development

1. Introduction

The emergence of generative artificial intelligence (GenAI) marks a paradigm shift in higher education unseen since the advent of the internet (Winkler et al., 2023). ChatGPT's release in November 2022 catalyzed unprecedented attention, accumulating 100 million monthly users within two months—the fastest adoption rate in internet history (Ratten & Jones, 2023). For entrepreneurship education, this technological transformation carries particular significance: as 70% of future startups are projected to operate on digital platforms (Bell & Bell, 2023), entrepreneurship faculty face dual imperatives of preparing digitally literate entrepreneurs while enhancing their own digital pedagogical capacities.

Entrepreneurship education distinctively emphasizes experiential learning, case-based instruction, and business plan development—pedagogical approaches requiring substantial faculty time and expertise (Pita et al., 2021). High-quality instructional design demands extensive investment in content curation, case development, activity planning, and assessment creation. GenAI's potential to augment these processes has generated considerable interest, with ChatGPT becoming the most discussed technological tool among management educators (Ratten & Jones, 2023).

Despite growing research on GenAI in education, a critical gap persists: Chen et al. (2024) revealed that 65% of studies focus on student learning applications, with only 35% examining faculty professional development. This imbalance reflects insufficient scholarly attention to the fundamental question: How can entrepreneurship faculty leverage GenAI to enhance their instructional design and pedagogical capacities? This gap is particularly problematic given that teacher capabilities constitute the prerequisite for effective technology-enhanced student learning.

The present review addresses this gap through conceptual integration of recent literature (2022-2025), developing a theoretical framework for understanding how GenAI tools may transform entrepreneurship faculty capacities. Unlike existing reviews emphasizing student outcomes or technical capabilities, This review adopts a faculty-centric perspective to examine three interrelated questions: (1) How might GenAI support entrepreneurship faculty's instructional design work, and what evidence exists regarding these applications? (2) Through what theoretical mechanisms could GenAI enhance faculty pedagogical competencies? (3) What challenges complicate GenAI integration, and what strategies might address these challenges? This study approach is conceptual rather than systematic. We draw selectively on illustrative empirical studies to ground theoretical propositions, prioritizing recent high-impact publications and diverse methodological approaches (experimental studies, case analyses, conceptual frameworks) that illuminate different facets of faculty-AI interaction. This selective integration enables deeper engagement with theoretical nuances and practical complexities than comprehensive systematic reviews typically afford.

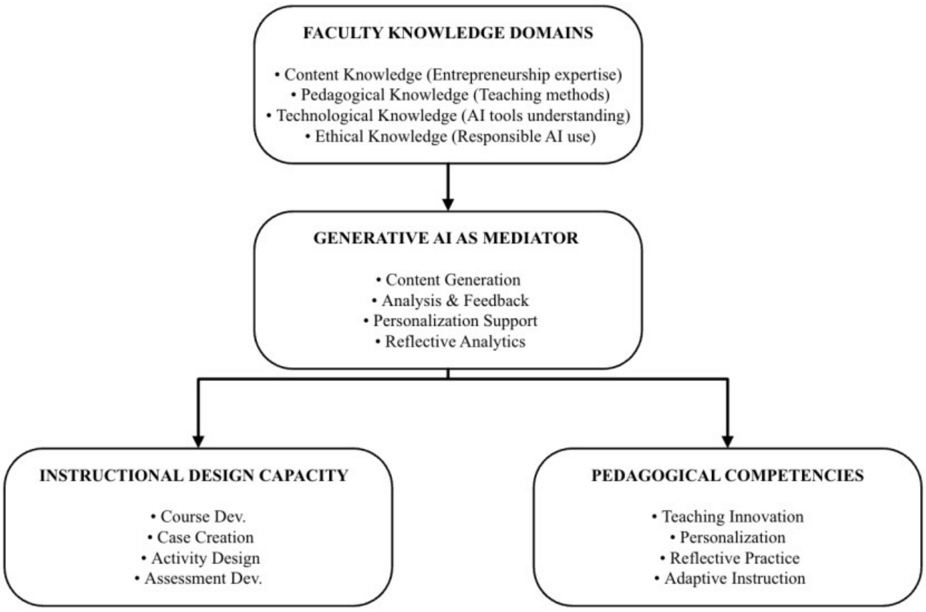

Figure 1 Conceptual framework - GenAI as mediator of faculty capacity development

Our inquiry is theoretically grounded in the AI-TPACK (Technological Pedagogical Content

Knowledge) framework (Celik, 2023; Wang et al., 2024), which posits that effective AI integration requires sophisticated interplay among technological knowledge, pedagogical expertise, content mastery, and ethical judgment. This framework conceptualizes GenAI not as a replacement for faculty expertise but as a mediating tool that, when properly integrated, can amplify instructional design capabilities and pedagogical competencies. Figure 1 presents our conceptual framework positioning GenAI as a mediator between faculty knowledge domains and enhanced teaching capacities.

This review makes three primary contributions to entrepreneurship education scholarship. Building upon the AI-TPACK framework (Celik, 2023; Wang et al., 2024), Existing theory is extended through: (1) specifying the dual-dimensional structure of faculty capacity development in entrepreneurship education contexts—distinguishing instructional design capabilities from pedagogical competencies; (2) identifying four types of augmented expertise (verification, pedagogical evaluation, prompt engineering, contextualization) required for effective GenAI integration, which current TPACK models do not adequately capture; and (3) proposing differentiated intervention strategies aligned with distinct faculty adoption profiles. Rather than claiming a wholly new framework, this study offers a domain-specific elaboration that addresses entrepreneurship education's unique pedagogical demands—particularly the tension between AI's pattern-recognition strengths and entrepreneurship's emphasis on uncertainty management and tacit knowledge.

While this review adopts a conceptual rather than systematic approach, our literature selection followed deliberate criteria to ensure theoretical coherence and empirical grounding. Searches were conducted in Web of Science, Scopus, and Google Scholar using keywords: ("generative AI" OR "ChatGPT" OR "large language model") AND ("entrepreneurship education" OR "faculty development" OR "instructional design") AND (2022-2025). From the initial pool of 287 articles, Priority was given to: (1) peer-reviewed journal articles and high-impact conference proceedings; (2) studies directly addressing faculty capabilities rather than student outcomes; (3) diverse methodological approaches (experimental, qualitative, conceptual) to triangulate insights; and (4) publications demonstrating theoretical advancement beyond descriptive accounts. This purposive sampling yielded 45 core sources, supplemented by seminal works on TPACK and technology acceptance theory. It is acknowledged that this selective approach limits generalizability but enables deeper theoretical engagement with emerging phenomena where systematic evidence remains sparse.

2. Theoretical Foundations

Effective GenAI integration in entrepreneurship education requires theoretical frameworks explaining how technology adoption translates into capacity enhancement. This framework builds upon two foundational theories: Technology Acceptance Model (TAM) explaining adoption decisions, and AI-Technological Pedagogical Content Knowledge (AI-TPACK) framework elucidating integration competencies.

2.1 Technology acceptance and faculty profiles

The Technology Acceptance Model (Davis, 1989) identifies perceived usefulness and ease of use as primary adoption determinants. Recent research extends TAM to GenAI contexts: Shata and Hartley (2025) found that perceived usefulness is the strongest predictor of faculty attitudes toward GenAI adoption, with trust and social reinforcement serving as critical mediators. This finding carries practical implications: professional development programs should emphasize demonstrating GenAI's concrete value for specific teaching tasks rather than merely showcasing technical sophistication.

Mah and Groß (2024) revealed faculty heterogeneity in GenAI adoption through latent class analysis, identifying four distinct profiles: (1) Optimistic (33.5%) embrace AI enthusiastically, viewing it as transformative; (2) Critical (27.3%) maintain skepticism about educational value; (3) Critically-reflective (33.9%) acknowledge potential while maintaining cautious stance; (4) Neutral (5.3%) lack formed opinions. Notably, 78.5% expressed interest in AI professional development regardless of profile, suggesting recognition of skill necessity despite attitudinal differences. These profiles imply that one-size-fits-all training approaches will prove ineffective; instead, differentiated strategies addressing each profile's concerns and readiness levels are required.

2.2 AI-TPACK: Integrative framework for competency development

Traditional TPACK framework (Mishra & Koehler, 2006) posits that effective technology integration requires synthesis of Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). AI's emergence necessitates framework evolution. Celik (2023) proposed Intelligent-TPACK, incorporating AI-specific ethical knowledge as an essential fourth dimension. Empirical analysis revealed that Technological-Pedagogical Knowledge (TPK)—understanding how to deploy AI tools in specific instructional contexts—proves most critical for effective integration, with ethical evaluation capacity exhibiting comparable importance to TPK in predicting overall AI-TPACK levels.

Wang et al. (2024) further refined this framework, delineating seven interrelated AI-TPACK components: PK, CK, AI-TK, Pedagogical-Content Knowledge (PCK), AI-Technological-Content Knowledge (AI-TCK), AI-Technological-Pedagogical Knowledge (AI-TPK), and integrated AI-TPACK. Structural equation modeling demonstrated significant interactions among dimensions, with AI-TPK (understanding AI tool deployment in pedagogical contexts) contributing most substantially to overall AI-TPACK. Critically, Wang et al. (2024) found that informal self-directed learning proves insufficient for developing comprehensive AI-TPACK; systematic training is essential. This finding provides empirical justification for institutional investment in structured faculty development programs.

2.3 Entrepreneurship pedagogy considerations

Entrepreneurship education's distinctive characteristics necessitate discipline-specific theoretical considerations. Fox et al. (2024) proposed the AIEE (Artificial Intelligence in Entrepreneurship Education) framework, distinguishing five learning task phases (preparation, execution, monitoring, reflection, integration) and specifying AI's appropriate roles (leader, collaborator, supporter) in each phase. This framework helps faculty understand that AI is not a universal solution but requires strategic deployment aligned with pedagogical objectives and learning stages.

For instance, in business plan initial drafting (preparation/execution phases), AI may serve as content framework leader; however, in critical decision-making and value judgment moments (monitoring/reflection phases), human faculty must retain leadership. This nuanced understanding prevents both over-reliance on AI and unnecessary resistance to potentially beneficial applications.

Lyu et al. (2023) distinguished theory-oriented from practice-oriented entrepreneurship pedagogy, finding practice-oriented approaches contribute more strongly to entrepreneurial processes (from opportunity identification to venture creation), while theory-oriented pedagogy exerts greater impact on opportunity development stages. This differentiation implies that GenAI applications should vary by pedagogical approach: in practice-oriented contexts emphasizing hands-on experimentation, AI serves as real-time feedback and iterative optimization tool; in theory-focused instruction, AI provides diverse explanatory perspectives and case materials. Table 1 synthesizes key theoretical constructs and their implications for entrepreneurship faculty development.

Table 1 Theoretical foundations and faculty development implications

Theoretical Framework	Key Constructs	Core Findings	Faculty Development Implications
Technology Acceptance Model (TAM)	Perceived Usefulness, Ease of Use, Trust	Usefulness is strongest predictor; trust mediates adoption (Shata & Hartley, 2025)	Demonstrate concrete value for specific teaching tasks; build trust through transparent AI capabilities/limitations
Faculty Profile Theory	Optimistic, Critical, Critically-reflective, Neutral	Four distinct profiles with 78.5% interested in PD (Mah & Groß, 2024)	Design differentiated training addressing each profile's concerns; avoid one-size-fits-all approaches
AI-TPACK Framework	AI-TK, PK, CK, AI-TPK, Ethical Knowledge	AI-TPK most critical; informal learning insufficient (Wang et al., 2024; Celik, 2023)	Provide systematic training integrating technology, pedagogy, content, ethics; emphasize contextual application
AIEE Framework	Five learning phases; Three AI roles (leader, collaborator, supporter)	AI role must align with learning phase and pedagogical objective (Fox et al., 2024)	Train faculty to strategically deploy AI based on task phases; avoid blanket adoption or rejection
Entrepreneurship Pedagogy Theory	Theory-oriented vs. Practice-oriented approaches	Practice-oriented pedagogy has stronger impact on venture creation (Lyu et al., 2023)	Customize AI applications to pedagogical approach; use AI differently in theory vs. practice contexts

3. GenAI Enhancement of Instructional Design Capabilities

Instructional design capability—encompassing course development, case creation, learning activity design, and assessment tool development—constitutes a core dimension of faculty professional competence. This review proposes that GenAI transforms these capacities through three interrelated theoretical mechanisms: efficiency amplification through automation of routine tasks, creative expansion through rapid prototyping and iteration, and quality mediation through the dialectic between AI generation and faculty refinement. However, each mechanism operates within constraints requiring sophisticated faculty judgment, which conceptualized as augmented expertise.

This section analyzes how these mechanisms manifest across four instructional design dimensions, drawing on illustrative empirical studies to ground theoretical propositions. This analysis argues that GenAI functions most effectively not as a replacement for faculty expertise but as a mediator amplifying capabilities when integrated with professional judgment. Figure 2 illustrates the AI-assisted course development workflow scholar propose, emphasizing critical faculty judgment checkpoints throughout the design process.

GenAI demonstrates potential for substantial efficiency gains in course development tasks. Experimental evidence provides preliminary support: Choi et al. (2024) found professional instructional designers using ChatGPT completed course mapping 65% faster than manual approaches in controlled settings (n=24, comparative experiment). Importantly, AI-assisted designers produced more iterative versions within equivalent timeframes, enabling enhanced refinement opportunities—suggesting efficiency gains may translate to quality improvements when faculty reinvest saved time in revision cycles.

However, this efficiency dividend accompanies significant quality risks that necessitate expert oversight. The same Choi et al. (2024) study identified that 40% of AI-generated content contained fabricated citations—"hallucinations" presenting fictitious references as authentic. This finding underscores a critical principle: GenAI outputs must be treated as drafts requiring expert validation rather than finished products. Domain expertise in content verification remains irreplaceable, highlighting the first dimension of augmented expertise: verification capacity.

GenAI supports multiple course development tasks, each requiring specific faculty competencies. For learning objective brainstorming, Luo et al.'s (2024) study found instructional designers using GenAI-assisted brainstorming achieved 47% greater idea diversity measured through semantic analysis. However, translating quantity to quality requires faculty applying pedagogical frameworks like Bloom's Taxonomy to select and refine objectives ensuring appropriate cognitive levels and measurability. This exemplifies the second dimension of augmented expertise: pedagogical evaluation capacity.

For module outlines and content frameworks, Ruiz-Rojas et al. (2023) demonstrated that structured instructional design frameworks significantly improve AI output quality. The 4PADAFE matrix integrating Pedagogical objectives, Activities, Assessment, Digital resources, Feedback, and Evaluation guides AI generation toward systematically coherent outputs aligned with instructional design principles. Compared to simple open-ended prompts such as "help me design an entrepreneurship course," structured prompting yields more comprehensive, pedagogically sound content. This illustrates the third dimension of augmented expertise: prompt engineering capacity grounded in instructional design knowledge.

Nevertheless, Hu et al. (2024) found that 78% of GPT-4 generated lesson plans required substantial adaptation to local standards and learner contexts when implemented by 156 teachers in authentic classrooms, indicating AI outputs demand expert review and localization rather than direct implementation. This adaptation necessity reflects AI's training on predominantly Western, English-language data, requiring faculty to apply cultural competence and contextual knowledge in customization—the fourth dimension of augmented expertise: contextualization capacity.

Figure 2 illustrates our proposed workflow integrating AI capabilities with faculty judgment at critical checkpoints. The workflow operates in three stages, each with distinct faculty responsibilities. In Stage 1, faculty provide course topics, learning outcomes, and constraints as input. AI then generates draft objectives and outlines. At Faculty Judgment Checkpoint 1, educators evaluate outputs by determining whether cognitive levels are appropriate through applying Bloom's Taxonomy, verifying alignment with intended outcomes, checking content accuracy including facts and citations, and detecting fabricated references. In Stage 2, faculty provide revision prompts specifying local context, cultural adaptation needs, and specific examples. AI regenerates content incorporating faculty guidance. At Faculty Judgment Checkpoint 2, quality is assessed through examining cultural appropriateness for target student populations, local relevance to institutional standards and regional contexts, and alignment with student prerequisites. In Stage 3, faculty synthesize their professional expertise, pedagogical judgment, contextual knowledge, and ethical considerations to produce the final implementation-ready course design.

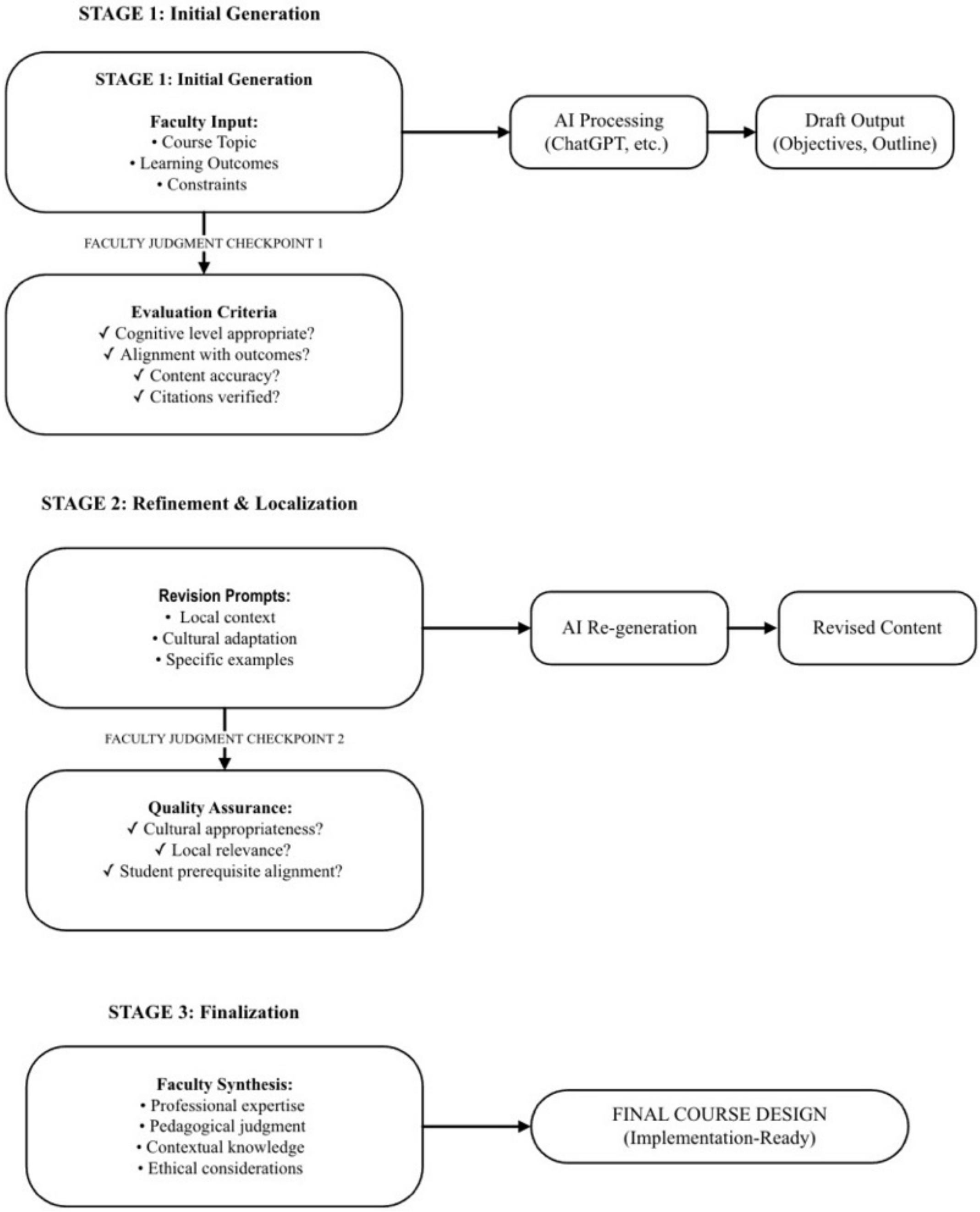

Figure 2 AI-assisted course development workflow

This workflow embodies our central theoretical argument: effective AI integration requires active faculty mediation at each stage rather than passive acceptance of AI outputs. The checkpoints represent moments where augmented expertise proves indispensable.

Case-based pedagogy represents a cornerstone of entrepreneurship education, yet high-quality case development has historically been time-intensive, requiring extensive primary data collection and narrative crafting. GenAI offers innovative solutions for rapid case generation while raising authenticity questions that require careful theoretical and practical consideration. Short and Short (2023) demonstrated ChatGPT’s ability to emulate prominent entrepreneurs’ communication styles, successfully generating content mimicking Elon Musk, Indra Nooyi, Tony Hsieh, and Lisa Su. Expert review validated stylistic similarity, revealing GenAI's potential for creating diverse entrepreneurial communication cases, investor pitch simulations, and business negotiation dialogues.

However, researchers cautioned that AI-generated content, while stylistically accurate, may lack authentic contextual nuances and non-verbal elements characterizing real situations. This distinction between stylistic emulation and substantive authenticity represents a critical theoretical insight: AI excels at pattern reproduction but struggles with contextual depth and tacit knowledge embedded in authentic cases. Consequently, such materials better serve introductory practice exercises rather than replacing in-depth authentic case analysis requiring students to grapple with genuine complexity and ambiguity.

George-Reyes et al. (2024) provided methodological guidance through quasi-experimental research integrating ChatGPT into scientific entrepreneurship education via the i4C method: Identify, Conceive, Invent, and Communicate. Among 105 Ecuadorian graduate students, significant improvements in scientific entrepreneurship knowledge acquisition were achieved, with pre-post test differences statistically significant at $p<0.001$. This study demonstrated that AI not only assists narrative script creation but supports real-time feedback and iterative optimization in business plan development—embodying our theoretical mechanism of creative expansion through rapid iteration. Faculty can adapt this framework to develop narratively engaging entrepreneurship scenario cases by providing AI with industry background, venture challenges, and key stakeholder information to generate initial case narratives, then applying pedagogical expertise to refine plot structure, conflict points, and decision dilemmas.

Darnell et al. (2024) emphasized practical application, providing reusable teaching activity templates such as using large language models to create pros-cons analyses of Lean Startup versus Design Thinking methodologies. For entrepreneurship faculty, this means rapidly generating case materials reflecting current market dynamics and industry trends, overcoming traditional case repositories' update lags. When emerging technologies such as Web3, blockchain, or sustainable energy spark entrepreneurial waves, faculty can immediately generate relevant cases rather than awaiting formal publication.

However, effective case creation using AI requires what this review terms authenticity judgment capacity—the ability to distinguish between surface-level plausibility and genuine authenticity, to identify where AI-generated scenarios oversimplify complex stakeholder dynamics, and to recognize when fabricated elements undermine pedagogical value. This represents a sophisticated expertise dimension potentially more demanding than creating cases manually, as faculty must simultaneously evaluate AI output quality while envisioning how students will engage with materials.

Business simulations and design thinking exercises constitute popular entrepreneurship teaching activities. Silitonga et al. (2024) confirmed through quasi-experimental research that business simulation games significantly enhance students' cognitive and non-cognitive entrepreneurial competencies, with Cohen's d effect sizes ranging 0.62-0.85 representing medium to large effects, and strengthen entrepreneurial intentions. GenAI can enhance simulation adaptivity and personalization in ways traditional systems cannot. Traditional simulation systems operate on preset rules and parameters, presenting identical scenarios to all students. AI-driven simulations can dynamically adjust difficulty levels and contextual parameters based on students' decision history, performance, and learning styles—embodying our theoretical mechanism of personalization scaling.

Faculty might design AI-powered virtual mentor systems providing differentiated hints and challenges during simulations: introducing more complex market changes or competitive threats for advanced students, offering more guided prompts and resources for struggling students. This adaptive scaffolding can address a persistent challenge in entrepreneurship education: accommodating heterogeneous student populations with varying prior business knowledge, risk tolerance, and entrepreneurial experience.

However, Krushinskaia et al. (2024) warned of significant risks. Their study found that 40% of instructional designers accepted AI suggestions without sufficient adjustment, resulting in decreased course creativity. This finding indicates faculty must maintain critical thinking when using AI for activity enhancement, ensuring AI intervention genuinely serves pedagogical goals rather than oversimplifying learning complexity. The theoretical insight here involves what this review terms the complexity preservation imperative: GenAI's tendency toward pattern-based solutions may inadvertently reduce the productive struggle and ambiguity that characterize effective entrepreneurship education. Faculty augmented expertise must include capacity to recognize when AI suggestions, while technically competent, pedagogically undermine learning objectives by removing necessary complexity.

For Design Thinking—another core entrepreneurship methodology—GenAI supports multiple stages: analyzing user interview data to identify key pain points during empathy phase; assisting problem statement refinement for focus and feasibility during definition phase; generating numerous creative solutions to stimulate divergent thinking during ideation phase; producing initial concept sketches or interface prototypes during prototyping phase. Wannamakok et al. (2023) confirmed that Design Thinking-based online learning effectively enhances entrepreneurial intention, with peer interaction and guest sharing significantly impacting outcomes. GenAI can augment these processes without replacing the fundamentally social and collaborative nature of effective Design Thinking pedagogy—provided faculty maintain focus on human interaction as central rather than peripheral to learning.

Assessment design constitutes among faculty work's most challenging aspects, requiring balance among validity, reliability, fairness, and feasibility. GenAI demonstrates significant efficiency potential while raising assessment authenticity concerns that require careful theoretical analysis. Cheng et al. (2024) developed the TreeQuestion system illustrating AI breakthroughs in objective item generation. Utilizing large language models for automatic multiple-choice question generation, the system reduced generation time by 95%, achieving 300% assessment volume increase without compromising rigor. Employing "knowledge tree" architecture ensures generated items cover all course content knowledge points, with automatic distractor quality analysis maintaining item quality.

Research demonstrated effective conceptual learning outcome assessment capability, though limitations persist in evaluating higher-order cognitive abilities like creative thinking—a critical concern for entrepreneurship education emphasizing innovation, opportunity recognition, and adaptive problem-solving. Researchers emphasized that expert oversight remains indispensable for ensuring cognitive objective alignment—faculty must review whether AI-generated items genuinely measure intended outcomes and contain no ambiguities or cultural biases.

Chiu et al. (2024) conducted a scoping review on how GenAI transforms higher education assessment, arguing assessment must transform to cultivate students' self-regulated learning skills, with responsible learning and academic integrity as core concerns. They recommended integrating assessment redesign with AI literacy training in faculty professional development, while strengthening faculty belief clarification regarding human versus AI assessment roles. For entrepreneurship faculty, this necessitates reconceptualizing core assessment tasks like business plan evaluation, entrepreneurial pitch scoring, and reflection report review. Rather than asking “How can AI grade this assignment?”, the more productive question becomes “How should we redesign assessments to measure capabilities AI cannot replicate?”—focusing on higher-order thinking, authentic performance, and situated judgment that require human evaluation.

This leads to what Chiu et al. (2024) termed “AI-resistant assessment” concepts, emphasizing assessment should measure higher-order cognitive abilities and authentic context performance. Specific strategies include increasing process assessment weight by requiring students to document thinking journals and decision processes, which AI cannot forge authentically; designing tasks based on authentic enterprise engagement requiring first-hand data from interviews or field research that AI cannot generate; adopting oral defense formats examining students’ deep understanding of and critical reflection on their work through dialogic reasoning AI cannot replicate; and designing complex synthesis tasks requiring integration of multiple information sources across modalities where AI limitations persist in multi-modal, cross-contextual integration.

Effective assessment development using AI requires what this review terms construct validity preservation capacity—ensuring that efficiency gains from AI-generated items do not come at the cost of measuring what we intend to measure. Faculty must develop sophisticated ability to evaluate whether AI-generated assessments genuinely capture entrepreneurial competencies such as opportunity recognition, effectual reasoning, resource mobilization, and tolerance for ambiguity versus merely testing factual recall or surface-level comprehension.

Table 2 GenAI applications in instructional design: efficiency, quality, and faculty judgment

Design Dimension	GenAI Application	Efficiency Gains	Quality Concerns	Needed Faculty Expertise
Course Development	Learning objectives; Outlines; Module design	Faster design; Higher idea diversity	Fabricated citations; Western bias; Requires major classroom adaptation	Error checking; Pedagogical alignment; Local contextualization
Case Creation	Scenario writing; Stakeholder dialogue	Rapid case generation; Supports iterative planning	Lacks contextual nuance; Stereotypes; Oversimplifies complexity	Authenticity judgment; Cultural competence; Narrative design
Activity Design	Simulation personalization; Design Thinking scaffolds; Adaptive difficulty	Personalized learning paths; Improved competency outcomes	Overreliance on AI suggestions; Reduced creativity; Oversimplified struggle	Maintain cognitive complexity; Ensure alignment with learning goals
Assessment Development	MCQ generation; Rubrics; Distractors	Major time savings; High item volume	Weak on higher-order skills; Limited authenticity; Cultural/language biases	Validate constructs; Calibrate cognitive levels; Detect bias

Table 2 synthesizes GenAI applications across instructional design dimensions, specifying efficiency gains reported in experimental studies, quality considerations documented across research, and required faculty judgment capacities constituting augmented expertise. Critically, this table illustrates this study central theoretical argument: GenAI enhances faculty instructional design capabilities not by replacing expertise but by requiring new forms of sophisticated judgment mediating between AI capabilities and instructional quality.

Across all four instructional design dimensions, a consistent pattern emerges: AI outputs function most effectively as starting points requiring expert refinement rather than finished products. The faculty role shifts from pure content creation to a more complex responsibility encompassing content generation facilitation, critical evaluation, context-specific adaptation, and quality assurance. This shift arguably requires higher-level capabilities than traditional instructional design, as faculty must simultaneously understand AI capabilities and limitations, maintain pedagogical vision, apply domain expertise, and exercise ethical judgment—embodying augmented expertise as integration of technological, pedagogical, content, and ethical knowledge dimensions consistent with AI-TPACK framework (Celik, 2023; Wang et al., 2024).

4. GenAI Enhancement of Pedagogical Competencies

Beyond instructional design efficiency, GenAI fundamentally enhances faculty pedagogical competencies—teaching innovation capacity, personalization capability, and reflective practice—transforming how faculty conceptualize and enact their professional roles.

4.1 Teaching innovation capacity: expanding pedagogical possibilities

Teaching innovation capacity reflects faculty ability to continuously improve methods, develop novel activities, and integrate frontier knowledge. Bell and Bell (2023) noted that AI tools enable faculty to rapidly acquire and integrate cross-domain knowledge, overcoming individual experience limitations. For many entrepreneurship faculty whose professional backgrounds may be confined to specific industries or functional areas, yet entrepreneurship education demands multi-faceted knowledge spanning technology, markets, finance, and operations, AI serves as a “knowledge bridge” facilitating rapid familiarization with unfamiliar domains’ foundational knowledge.

Lim et al. (2023) employed paradox theory to reconcile educational tensions surrounding GenAI, proposing a framework positioning AI as transformative resource coexisting with educators. This theoretical perspective helps faculty transcend binary thinking (complete embrace versus complete resistance), exploring organic integration models combining AI with traditional teaching methods.

Neergård and Roald (2025) revealed that many faculty position themselves as “entrepreneurship outsiders,” perceiving themselves as lacking entrepreneurship teaching capability. GenAI tools can help such faculty bridge knowledge gaps by accessing entrepreneurship cases, industry trends, and teaching resources. However, Ding et al. (2024) demonstrated that case-based AI professional development proves more effective than abstract technical training, with ill-structured problems promoting superior knowledge application, though model cases should precede ill-structured problem-solving.

4.2 Personalization capacity: scaling individualized instruction

Personalized instruction represents a core educational technology goal. Ali et al. (2025) systematically reviewed confirming AI significantly optimizes educational outcomes through customized content and feedback, with adaptive learning systems enhancing student engagement. For entrepreneurship faculty, this enables differentiated learning paths based on students’ entrepreneurial interest domains, learning styles, and competency levels.

Chen et al. (2024) identified four primary AI application domains: personalized and adaptive instruction, simulation-based entrepreneurship training, ethical and psychological concerns, and ecosystem integration through intelligent systems, providing a clear roadmap for developing personalization capacity. Faculty can utilize AI to analyze students' business plan drafts for targeted improvement suggestions; generate customized case materials based on students' industry interests; design modular content adapting to different learning paces.

However, achieving genuinely effective personalized instruction requires faculty to possess four critical competencies: (1) Data literacy—interpreting AI-provided learning analytics data to identify authentic needs beyond surface characteristics; (2) Pedagogical knowledge—understanding different personalization strategies' (content differentiation, process differentiation, product differentiation) appropriate contexts; (3) Technical integration capability—configuring and adjusting AI system parameters for outputs aligned with pedagogical objectives; (4) Humanistic care—recognizing that not all student needs can be met through technological means, with certain situations requiring irreplaceable face-to-face teacher-student interaction.

Mulaudzi and Hamilton (2025) explored AI's role in personalized learning from teacher perspective, finding attitudes ranging from skepticism to cautious optimism, with initially negative attitudes often transforming into recognition of AI brainstorming utility following direct value experience. This finding carries important implications for training programs: progressive exposure and guided practice should help faculty overcome initial concerns while sharing appropriate AI integration success cases.

4.3 Reflective practice capacity: evidence-based professional growth

Reflective practice constitutes a core dimension of teacher professional development. Yik et al. (2023) distinguished three reflection levels: surface reflection (descriptive event recording), pedagogical reflection (analyzing relationships between teaching strategies and learning outcomes), and critical reflection (examining one's teaching beliefs and values). Research demonstrated that technology-driven methods (video analysis, blog writing, online discussion) can support reflection activities across levels, with GenAI providing novel reflection tools—faculty can use AI to analyze teaching video transcript texts, obtaining insights regarding questioning strategies, feedback patterns, and classroom interaction.

Li and Walsh (2023) demonstrated how Video-Enhanced Observation (VEO) supports dialogic reflection, proving reflective practice develops progressively over time with evidence-based reflection playing crucial roles in cognitive and practice development. GenAI can enhance this process: through natural language processing analysis of classroom dialogue, AI can identify teachers' question type distributions (closed versus open questions), wait time patterns, differential attention across students. These quantitative data provide faculty a "mirror" for reflection, helping discover previously unrecognized teaching patterns.

Mai et al. (2024) employed Biggs' Presage-Process-Product (3P) model to systematically review ChatGPT applications, identifying 13 advantages and 10 disadvantages. This structured analytical framework can be applied by faculty for reflecting on their own AI integration practices—reflecting on how AI assists course material development in presage stage, how AI supports personalized instruction in process stage, how AI affects learning outcomes and academic integrity in product stage.

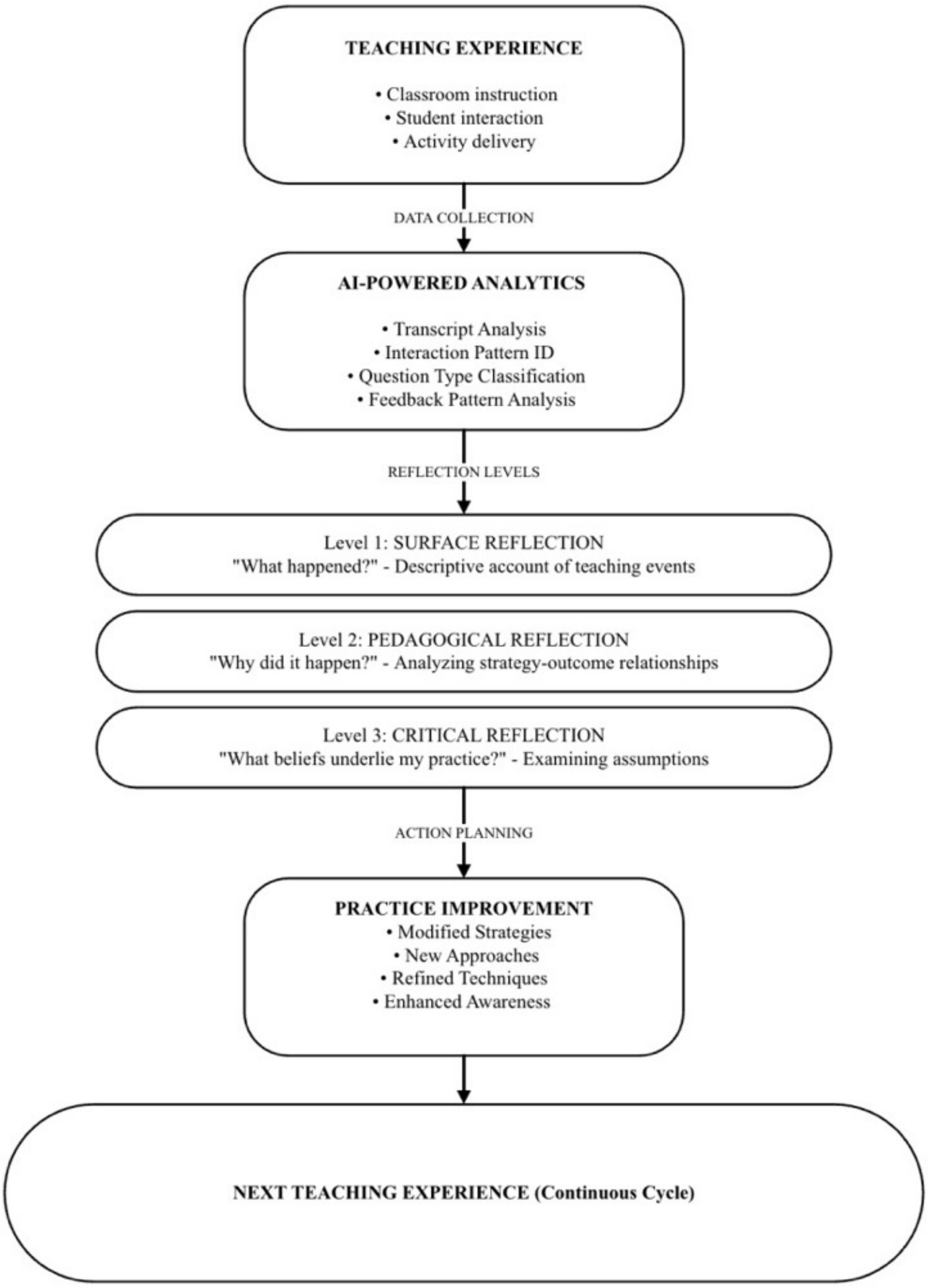

Figure 3 GenAI-enhanced reflective practice cycle for faculty development

5. Challenges and Strategic Responses

Despite GenAI's transformative potential, entrepreneurship faculty encounter multiple challenges in integration, spanning academic integrity concerns, ethical considerations, digital inequities, and professional development deficits. Addressing these challenges requires coordinated efforts across policy, institutional, and individual levels.

5.1 Academic integrity and assessment authenticity

When students can readily use AI to generate business plans and case analyses, traditional assessment methods face fundamental validity challenges. Ratten and Jones (2023) emphasized ChatGPT's transformative capability in changing assessment implementation and grading, necessitating urgent policies regarding ChatGPT and subsequent GenAI. However, policy formulation faces dilemmas: complete AI prohibition proves both unrealistic (difficult to monitor effectively) and unreasonable (depriving students of learning future professional tools); complete permission may foster over-reliance, hindering authentic capability development.

More viable strategies involve assessment task redesign rendering them less amenable to complete AI replacement. Chiu et al. (2024) proposed “AI-resistant assessment” concepts, emphasizing assessment should measure higher-order cognitive abilities and authentic context performance. Specific strategies include: increasing process assessment weight, requiring students to document thinking journals and decision processes (AI cannot forge cognitive processes); designing tasks based on authentic enterprise interviews or field research, requiring first-hand data submission (AI cannot generate original field data); adopting oral defense formats examining students’ deep understanding of and critical reflection on AI-generated content; designing complex tasks requiring synthesis of multiple information sources (AI limitations persist in multi-modal, cross-contextual information integration).

5.2 Ethical considerations and digital equity

Ethical considerations permeate AI teaching applications. Celik (2023) demonstrated ethical evaluation capability constitutes an indispensable component of teachers’ AI integration knowledge. Hodges and Kirschner (2024) warned that AI-driven systems, without careful monitoring, may amplify existing inequalities. Bolick and da Silva (2024) found 28% of AI image outputs perpetuated stereotypes, such as over-representing white males when generating “successful entrepreneur” images.

Digital divides constitute another ethical challenge. Though GenAI tools claim universal accessibility, actual usage effectiveness depends heavily on users’ digital literacy, English proficiency, and high-quality network access. Acosta-Enriquez et al. (2024) found knowledge deficiency and distrust constitute primary AI adoption obstacles. For students from educationally under-resourced backgrounds, they may lack prerequisite knowledge and skills for effective AI tool use, placing them at greater disadvantage in AI-enhanced teaching environments. Faculty must recognize this digital inequality and adopt measures narrowing gaps, such as providing AI tool usage foundational training, designing alternative learning paths not entirely dependent on AI, ensuring assessment standards are fair to all students.

5.3 Faculty training deficits and professional development needs

Current most severe challenge is critically insufficient faculty training. Chen et al. (2024) revealed research imbalance—only 35% of studies explore AI for teacher professional development, reflecting policymakers’ and educational institutions’ insufficient attention to teacher-side needs. Many faculty are thrust to “AI integration” frontlines without adequate training, facing technical operation challenges, managing student AI usage pedagogical issues, and contemplating AI’s deep pedagogical implications.

Mah and Groß (2024) found 78.5% of faculty expressed interest in AI teaching professional development, yet existing training programs manifest three problems: (1) overemphasizing technical operations (how to use) while neglecting pedagogical integration (how to teach with) and critical reflection (when and why to use); (2) adopting “one-size-fits-all” training models failing to accommodate different disciplines’ and teaching contexts’ differential needs; (3) lacking continuity support, with faculty lacking ongoing practice, feedback, and improvement mechanisms after initial training.

Future faculty professional development programs should adopt these strategies: First, employ differentiated training models, providing customized support based on faculty AI familiarity, disciplinary backgrounds, and teaching contexts. Ding et al. (2024) demonstrated case-based AI professional development proves more effective than abstract technical training because cases exhibit concrete situations and decision processes for AI integration. Second, establish "community of practice" mechanisms supporting peer learning and experience sharing among faculty. Yang and Stefaniak (2025) revealed faculty attitudes became more positive and usage strategies more mature following AI integration experience exchanges with colleagues. Third, provide continuous technical and pedagogical support rather than one-off workshops. Kumar et al. (2024) noted instructional designers play critical bridging roles in faculty AI integration processes, yet many institutions lack such professionals, leaving faculty without assistance channels when encountering problems. Figure 4 presents a comprehensive framework for addressing GenAI integration challenges through multi-level strategies.

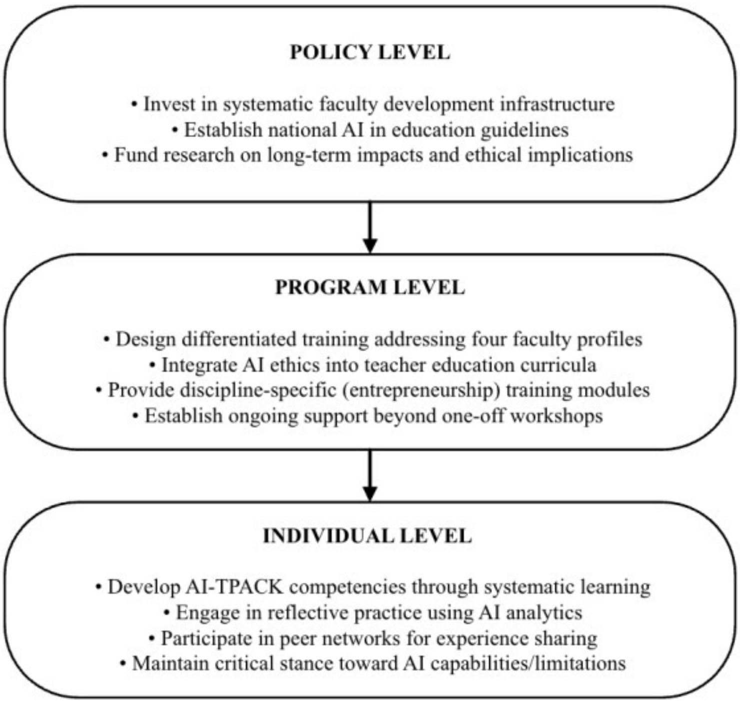

Figure 4 Multi-level strategies for addressing GenAI integration challenges

6. Discussion

This review's primary theoretical contribution lies in systematically articulating GenAI's paradigm shift from "teaching tool" to "capacity development mediator." Traditional educational technology research typically focuses on technology features' direct impacts on learning outcomes (Chiu et al., 2024), whereas this review reveals a more complex process: GenAI tools, through restructuring faculty workflows, cognitive processes, and professional practices, indirectly foster systematic enhancement of instructional design capabilities and pedagogical competencies.

The AI-TPACK framework evolution (Celik, 2023; Wang et al., 2024) provides theoretical foundations for understanding this process, yet this review further indicates that entrepreneurship education field's AI integration exhibits distinctiveness. Entrepreneurship teaching emphasizes uncertainty management, opportunity identification, and action orientation (Fox et al., 2024), creating tension with AI tools' strengths in pattern recognition and structured task processing. Consequently, entrepreneurship faculty AI capacity development cannot simply adopt generic educational technology frameworks but requires establishing discipline-specific theoretical models. This study proposed "instructional design capacity-pedagogical competencies" dual-dimensional analytical framework represents an initial response to this theoretical gap.

Moreover, this study analysis challenges the common assumption that efficiency gains automatically translate to quality improvements. While GenAI reduces course planning time by 65% and assessment generation by 95%, 78% of outputs require substantial adaptation (Hu et al., 2024) and 40% accept AI suggestions without adjustment leads to decreased creativity (Krushinskaia et al., 2024). These findings underscore that efficiency must be coupled with enhanced professional judgment—a sophisticated capacity requiring intentional development through systematic training and reflective practice.

This study identification of four distinct faculty profiles (Mah & Groß, 2024)—optimistic, critical, critically-reflective, neutral—carries profound practical implications. The finding that 78.5% express professional development interest despite attitudinal differences suggests that resistance often stems from insufficient understanding or concerns about pedagogical fit rather than fundamental opposition to technology. This insight shifts the professional development challenge from "convincing skeptics" to "addressing heterogeneous needs."

For optimistic faculty, advanced application training exploring innovative integration models proves most valuable. For critical faculty, case-based workshops demonstrating concrete educational value and addressing specific concerns (e.g., academic integrity, student dependency) may prove persuasive. For critically-reflective faculty, peer learning platforms facilitating experience exchange and rational discourse support their balanced perspective. This differentiated approach aligns with adult learning theory principles emphasizing relevance, autonomy, and experiential foundations.

The emphasis on reflective practice (Yik et al., 2023; Li & Walsh, 2023) as central to AI-era faculty development represents another key practical contribution. AI tools can provide teaching practice "data mirrors," but translating data into insights and insights into action improvements requires active faculty reflection and professional judgment. Professional development programs should integrate technical training with reflective practice workshops, helping faculty establish "use AI-analyze data-reflect and improve" continuous development cycles.

This conceptual literature review approach affords advantages in systematically surveying research landscapes yet manifests clear limitations. First, existing literature predominantly comprises conceptual discussions or short-term intervention studies, lacking longitudinal research tracking faculty AI capacity development trajectories. Future research should employ mixed-methods designs combining quantitative tracking (e.g., periodic AI-TPACK scale measurements) with qualitative depth description (e.g., in-depth interviews revealing teacher experiences), unveiling capacity development dynamic processes and critical turning points.

Second, reviewed studies derive primarily from high-income Western countries, with extremely scarce research on developing countries and non-English nations. AI tool accessibility, educational cultural differences, and digital infrastructure may significantly influence AI integration effects and challenges. Chen et al. (2024) similarly identified this research gap. Future research should strengthen cross-cultural, cross-contextual comparative research, exploring GenAI-enabled teaching's universal principles and localization strategies.

Third, current research predominantly focuses on individual faculty capacity development while neglecting organizational and institutional level influencing factors. Kumar et al. (2024) noted instructional designers' bridging roles in AI integration, yet many institutions lack such professional support. Future research should examine faculty AI capacity development from ecosystem perspectives, analyzing multi-level factor interactions including institutional policies, technical support, peer networks, and disciplinary cultures.

Fourth, this study review acknowledges citation limitations. While this study prioritized peer-reviewed sources, some citations reflect secondary rather than primary sources due to access constraints, and publication lag means cutting-edge 2025 developments may be underrepresented. Future systematic reviews should employ comprehensive database searches with explicit inclusion/exclusion criteria and quality appraisal protocols.

A critical yet frequently overlooked issue this review reveals: GenAI-enabled teaching's ethical dimensions should not merely be viewed as "risks requiring avoidance" but must become core components of faculty professional capacity. Celik (2023) incorporated ethical evaluation capability into Intelligent-TPACK framework, yet current teacher training often marginalizes ethical issues to "precaution checklists."

Authentic ethical capacity development requires faculty to identify three ethical problem levels: technical level (e.g., AI hallucinations, data privacy), pedagogical level (e.g., assessment fairness, academic integrity), and societal level (e.g., algorithmic bias, digital divide). Bolick and da Silva (2024) found 28% of AI image outputs perpetuate stereotypes; Hodges and Kirschner (2024) warned AI may amplify inequalities. These findings remind us that entrepreneurship education faculty, as future business leaders' cultivators, bear responsibility for helping students establish technological ethical consciousness and social responsibility awareness.

This requires teacher training to not only transmit technical operation skills but cultivate "critical technology consciousness"—understanding technology as non-neutral tools embedded with power relations and value orientations constituting social products. Entrepreneurship faculty should guide students thinking: In AI-driven entrepreneurial practice, how to balance efficiency with equity, innovation with responsibility, commercial value with social value?

Looking forward, GenAI's role in entrepreneurship education will evolve from "auxiliary tool" to "collaborative partner." Fox et al. (2024) proposed AIEE framework presaging this trend: relationships among AI, faculty, and students will become more dynamic with increasingly blurred role boundaries. This necessitates reconsidering entrepreneurship education's essential objectives.

Bell and Bell (2023) distinguished three entrepreneurship education paradigms: teaching about entrepreneurship (knowledge transmission), teaching for entrepreneurship (capability cultivation), and teaching through entrepreneurship (experiential learning). AI tools impact the first paradigm most (because knowledge transmission is readily automated), yet in latter two paradigms, AI may conversely become powerful tools for reinforcing experiential learning and cultivating entrepreneurial thinking. Future entrepreneurship education may manifest "human-AI co-creation" forms: faculty design authentic entrepreneurial challenges, AI provides real-time data and feedback, students learn decision-making and action in dynamic contexts.

However, realizing this vision requires overcoming current systemic obstacles. Policymakers need to invest in teacher professional development infrastructure rather than merely demanding faculty "embrace AI." Educational institutions need to establish cultures supporting innovation and error tolerance, allowing faculty to experiment and learn in AI integration. Technology developers need to deeply collaborate with educators, developing tools genuinely serving pedagogical objectives rather than pursuing technological showmanship. Researchers need to continuously track AI's long-term impacts on faculty capabilities, student learning, and entrepreneurial ecosystems, providing evidence-based foundations for policymaking and practice.

7. Critical Reflection

While this review identifies GenAI's potential benefits, we must critically examine potential hidden costs that current enthusiasm may obscure.

First, the efficiency narrative risks de-skilling faculty over time. If instructors increasingly rely on AI for course design, their tacit design knowledge—developed through years of iterative refinement—may atrophy. Carr's (2014) "automation paradox" warns that as systems become more automated, operators' skills deteriorate precisely when expert intervention is most needed during system failures. For entrepreneurship faculty, this could manifest as diminished ability to create compelling cases or design activities when AI tools are unavailable or inappropriate.

Second, AI integration may amplify existing inequalities between well-resourced and under-resourced institutions. Effective GenAI use requires not just technology access but significant professional development infrastructure, instructional design support, and time for experimentation—resources disproportionately available at elite universities. This could widen quality gaps in entrepreneurship education rather than democratizing access to high-quality pedagogical resources.

Third, the emphasis on AI-assisted efficiency may inadvertently shift faculty attention from relational dimensions of teaching—mentor-student bonds, empathetic guidance through entrepreneurial setbacks, embodied modeling of entrepreneurial identity—toward optimizing content delivery. Entrepreneurship education's transformative power often derives from affective and relational elements that resist quantification or automation (Neck & Corbett, 2018).

Fourth, widespread AI adoption may produce pedagogical homogenization. If faculty globally use similar AI tools trained on similar datasets, entrepreneurship education may lose valuable diversity in pedagogical approaches, cultural perspectives, and local contextualization that currently enriches the field.

These concerns do not invalidate GenAI's potential value but underscore that integration decisions involve value trade-offs rather than purely technical optimizations. Future research must track these potential negative consequences alongside efficiency gains.

8. Conclusion

Generative artificial intelligence presents entrepreneurship education faculty with both unprecedented opportunities and significant challenges. This review developed a conceptual framework positioning GenAI not as a simple efficiency tool but as a mediator of faculty capacity development, operating through three mechanisms: efficiency amplification, creative expansion, and quality mediation. However, each mechanism's success depends fundamentally on faculty augmented expertise—the sophisticated integration of domain knowledge, pedagogical judgment, and AI literacy. This study analysis yields a central theoretical insight: effective AI integration paradoxically requires higher-level skills than AI replacement might suggest, potentially widening rather than narrowing faculty capability gaps. This challenges assumptions underlying many institutional AI adoption initiatives and underscores the need for substantial, sustained investment in faculty professional development. Moving forward, entrepreneurship education must navigate tensions between AI's potential and its limitations, between efficiency gains and quality preservation, between standardization pressures and contextualization requirements. Success requires not passive technology acceptance but active shaping of technology-pedagogy relationships, ensuring AI genuinely serves the fundamental objective of cultivating future entrepreneurs with innovative thinking, social responsibility, and critical consciousness. The path forward demands multi-stakeholder coordination: policymakers investing in faculty development infrastructure, institutions establishing supportive cultures for experimentation, technology developers collaborating deeply with educators, and researchers tracking long-term impacts. Only through such coordinated efforts can entrepreneurship education harness AI's transformative potential while mitigating its risks.

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Ethics Statement

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References

Acosta-Enriquez, B. G., Reynoso-Ibarra, O. I., Vega-Lebrún, C. A., & Quezada-Carreón, A. E. (2024). Acceptance of artificial intelligence in university contexts: A conceptual analysis based on UTAUT2 theory. *Heliyon*, *10*(19), e38315. https://doi.org/10.1016/j.heliyon.2024.e38315

Ali, O., Murray, P. A., Momin, M., Dwivedi, Y. K., & Malik, T. (2024). The effects of artificial intelligence applications in educational settings: Challenges and strategies. *Technology Forecasting and Social Change*, 199, 123076. https://doi.org/10.1016/j.techfore.2023.123076

Barrot, J. S. (2024). Using ChatGPT for second and foreign language learning: A scoping review and meta-analysis of its efficacy and user perceptions. *Computers & Education*, 224, 105224. https://doi.org/10.1016/j.compedu.2024.105224

Bell, R., & Bell, H. (2023). Entrepreneurship education in the era of generative artificial intelligence. *Entrepreneurship Education*, *6*(3), 229-244. https://doi.org/10.1007/s41959-023-00099-x

Bolick, A. D., & da Silva, R. L. (2024). Exploring artificial intelligence tools and their potential impact to instructional design workflows and organizational systems. *TechTrends*, *68*(1), 91-100. https://doi.org/10.1007/s11528-023-00894-2

Cabero-Almenara, J., Gutiérrez-Castillo, J. J., Guillén-Gámez, F. D., & Gaete-Bravo, A. F. (2024). The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2. *Frontiers in Artificial Intelligence*, 7, 1497705. https://doi.org/10.3389/frai.2024.1497705

Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Computers in Human Behavior*, 138, 107468. https://doi.org/10.1016/j.chb.2022.107468

Chalmers, D., MacKenzie, N. G., & Carter, S. (2021). Artificial intelligence and entrepreneurship: Implications for venture creation in the fourth industrial revolution. *Entrepreneurship Theory and Practice*, *45*(5), 1028-1053. https://doi.org/10.1177/1042258720934581

Chen, L., Ifenthaler, D., Yau, J. Y., & Sun, W. (2024). Artificial intelligence in entrepreneurship education: A scoping review. *Education + Training*, *66*(6), 589-608. https://doi.org/10.1108/ET-05-2023-0169

Cheng, S., Liu, Q., Chen, X., Bao, H., & Zhang, J. (2024). Assessing conceptual learning outcomes with large language model-generated multiple-choice questions: a validity study. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW2), 1-28. https://doi.org/10.1145/3686970

Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence*, 6, 100197. https://doi.org/10.1016/j.caeai.2024.100197

Chiu, T. K. F., & Rospigliosi, A. (2025). Developing intelligent-TPACK (I-TPACK) framework from unpacking AI literacy and competency: implementation strategies and future research direction. *Interactive Learning Environments*, 1-22. https://doi.org/10.1080/10494820.2025.2545053

Choi, J., Jung, Y., & Kim, S. (2024). Utilizing generative AI for instructional design: Exploring strengths, weaknesses, opportunities, and threats. *TechTrends*, *68*(6), 1046-1059. https://doi.org/10.1007/s11528-024-00967-w

Darnell, J. A., & Gopalkrishnan, S. (2024). Entrepreneurship teaching exercises: Integrating generative AI. *Discover Education*, *3*(1), 261. https://doi.org/10.1007/s44217-024-00261-0

Ding, Y., Zhang, L., Wang, X., & Liu, Q. (2024). Enhancing teacher AI literacy and integration through different types of cases in teacher professional development. *Computers and Education: Open*, 6, 100178. https://doi.org/10.1016/j.caeo.2024.100178

Fox, J. D., Pittaway, L., & Uzuegbunam, I. (2024). Artificial intelligence as a dynamic copilot in entrepreneurship education. Entrepreneurship Education and Pedagogy. Advance online publication. https://doi.org/10.1177/25151274241256307

George-Reyes, C. E., Avello-Martínez, R., & Duarte, J. E. (2024). Developing scientific entrepreneurship and complex thinking skills: Creating narrative scripts using ChatGPT. *Frontiers in Education*, 9, 1378564. https://doi.org/10.3389/feduc.2024.1378564

Heung, C. M., & Chiu, T. K. F. (2025). How ChatGPT impacts student engagement: A systematic review and meta-analysis study. *Computers and Education: Artificial Intelligence*, 8, 100361. https://doi.org/10.1016/j.caeai.2025.100361

Hodges, C. B., & Kirschner, P. A. (2024). Innovation of instructional design and assessment in the age of generative artificial intelligence. *TechTrends*, *68*(1), 195-199. https://doi.org/10.1007/s11528-023-00926-x

Hu, X., Chen, Z., & Davison, R. M. (2024). Teaching plan generation and evaluation with large language models. *IEEE Transactions on Learning Technologies*, 17, 1885-1899. https://doi.org/10.1109/TLT.2024.3384765

Krushinskaia, I., Holstein, K., & Aleven, V. (2024). *Effects of generative AI on instructional design outcomes: An exploratory study comparing novice and experienced designers*. In A. M. Olney et al. (Eds.), Artificial Intelligence in Education (pp. 564-576). Springer. https://doi.org/10.1007/978-3-031-64312-5_49

Kumar, S., Martin, F., & Ritzhaupt, A. D. (2024). The role of instructional designers in the integration of generative artificial intelligence in online courses. *Online Learning*, *28*(3), 1-26. https://doi.org/10.24059/olj.v28i3.4501

Li, Y., & Walsh, S. (2023). Technology-enhanced reflection and teacher development: A student teacher's journey. *RELC Journal*, *54*(3), 625-641. https://doi.org/10.1177/00336882231161153

Lim, T., Gottipati, S., & Cheong, M. L. F. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. *The International Journal of Management Education*, *21*(2), 100790. https://doi.org/10.1016/j.ijme.2023.100790

Luo, Y., Hwang, G. J., Fernández-Cárdenas, J. M., & Chen, S. C. (2024). Exploring instructional designers' utilization and perspectives on generative AI tools: A mixed methods study. *Educational Technology Research and Development*, *72*(6), 3481-3509. https://doi.org/10.1007/s11423-024-10437-y

Lyu, Y., Zhu, H., Ye, Y., & Chen, J. (2023). The impact of entrepreneurship pedagogy on nascent student entrepreneurship: An entrepreneurial process perspective. *Studies in Higher Education*, *48*(11), 1747-1763. https://doi.org/10.1080/03075079.2023.2220722

Machost, H., & Stains, M. (2023). Reflective practices in education: A primer for practitioners. *CBE—Life Sciences Education*, *22*(2), ar23. https://doi.org/10.1187/cbe.22-07-0148

Mah, D. K., & Groß, N. (2024). Artificial intelligence in higher education: Exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *International Journal of Educational Technology in Higher Education*, 21, 58. https://doi.org/10.1186/s41239-024-00490-1

Mai, S., Hu, X., & Wang, C. (2024). The use of ChatGPT in teaching and learning: A systematic review through SWOT analysis approach. *Frontiers in Education*, 9, 1328769. https://doi.org/10.3389/feduc.2024.1328769

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, *108*(6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x

Mulaudzi, T., & Hamilton, M. (2025). Lecturer's perspective on the role of AI in personalized learning: Benefits, challenges, and ethical considerations in higher education. *Journal of Academic Ethics*, *23*(1), 45-62. https://doi.org/10.1007/s10805-025-09615-1

Neergård, H., & Roald, J. (2025). Competent to teach? Educators' perceptions of entrepreneurship competences in higher education. *International Journal of Entrepreneurial Behavior & Research*, *31*(8), 2027-2048. https://doi.org/10.1108/IJEBR-08-2024-0987

Ng, D. T. K., Tan, S. C., Lee, M. F. I., Chu, S. K. W., & Zheng, C. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, *55*(3), 1082-1104. https://doi.org/10.1111/bjet.13411

Pita, M., Costa, J., & Moreira, A. C. (2021, February). *Entrepreneurial Ecosystems and Sustainable Entrepreneurship: Challenges Towards More Social Entrepreneurial Orientation*. In International Joint conference on Industrial Engineering and Operations Management (pp. 559-567). Cham: Springer International Publishing.

Ratten, V., & Jones, P. (2023). Generative artificial intelligence (ChatGPT): Implications for management educators. *The International Journal of Management Education*, *21*(3), 100857. https://doi.org/10.1016/j.ijme.2023.100857

Rodrigues, A. L., Costa, J., & Moreira, A. C. (2023). Entrepreneurship education pedagogical approaches in higher education: A systematic literature review. *Education Sciences*, *13*(9), 940. https://doi.org/10.3390/educsci13090940

Ruiz-Rojas, L. I., Hernández-Méndez, S., & Peralta-Martínez, E. (2023). Empowering education with generative artificial intelligence tools: Approach with an instructional design matrix. *Sustainability*, *15*(15), 11524. https://doi.org/10.3390/su151511524

Sarooghi, H., Sunny, S., Hornsby, J., & Fernhaber, S. (2019). *Design thinking and entrepreneurship education: Where are we, and what are the possibilities? Journal of Small Business Management*, *57*(S1), 78-93. https://doi.org/10.1080/00472778.2019.1594218

Shata, A., & Hartley, K. (2025). Artificial intelligence and communication technologies in academia: Faculty perceptions and the adoption of generative AI. *International Journal of Educational Technology in Higher Education*, 22, 14. https://doi.org/10.1186/s41239-025-00511-7

Shepherd, D. A., & Majchrzak, A. (2022). Machines augmenting entrepreneurs: Opportunities (and threats) at the nexus of artificial intelligence and entrepreneurship. *Journal of Business Venturing*, *37*(4), 106227. https://doi.org/10.1016/j.jbusvent.2022.106227

Short, C. E., & Short, J. C. (2023). The artificially intelligent entrepreneur: ChatGPT, prompt engineering, and entrepreneurial rhetoric creation. *Journal of Business Venturing Insights*, 19, e00388. https://doi.org/10.1016/j.jbvi.2023.e00388

Silitonga, L. M., Dharmawan, B., Murti, A. T., & Wu, T. T. (2024). Promoting entrepreneurial intentions and competencies through business simulation games: A quasi-experimental study. *Journal of Educational Computing Research*, *62*(1), 149-172. https://doi.org/10.1177/07356331231209772

Somià, T., & Vecchiarini, M. (2024). Navigating the new frontier: the impact of artificial intelligence on students' entrepreneurial competencies. *International Journal of Entrepreneurial Behavior & Research*, *30*(11), 236-260. https://doi.org/10.1108/IJEBR-01-2024-0028

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. Interactive Learning Environments. Advance online publication. https://doi.org/10.1080/10494820.2023.2209881

Thanasi-Boçe, M., Rexhepi, G., Manara, G., & Rossi, M. (2023). *Implementing a design thinking approach in entrepreneurship education*. In A. Visvizi et al. (Eds.), Research and Innovation Forum 2022 (pp. 419-431). Springer. https://doi.org/10.1007/978-3-031-42511-0_28

Wang, Y., Liu, C., & Tu, Y. F. (2024). Teachers' AI-TPACK: Exploring the relationship between knowledge elements. *Sustainability*, *16*(3), 978. https://doi.org/10.3390/su16030978

Winkler, C., Hammoda, B., Noyes, E., & Van Gelderen, M. (2023). Entrepreneurship education at the dawn of generative artificial intelligence. *Entrepreneurship Education and Pedagogy*, *6*(4), 579-589. https://doi.org/10.1177/25151274231198799

Xia, Q., Weng, X., Ouyang, F., Lin, T. J., & Chiu, T. K. F. (2024). A scoping review on how generative artificial intelligence transforms assessment in higher education. *International Journal of Educational Technology in Higher Education*, 21, 40. https://doi.org/10.1186/s41239-024-00468-z

Yang, K. B., & Stefaniak, J. (2025). An exploration of instructional designers' prioritizations for integrating ChatGPT in design practice. *Educational Technology Research and Development*, *73*(1), 245-268. https://doi.org/10.1007/s11423-025-10509-7

Yue, X., Jong, M. S. Y., & Ng, D. T. K. (2024). K-12 teachers' TPACK for teaching AI: Findings from a systematic literature review. *Education and Information Technologies*, *29*(16), 22051-22083. https://doi.org/10.1007/s10639-024-12621-2