

AI-ENABLED INNOVATION AND ENTREPRENEURSHIP COURSES IN HIGHER EDUCATION: RESEARCH HOTSPOTS, EVOLUTIONARY TRAJECTORIES, AND EMERGING FRONTIERS

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ABSTRACT

Artificial intelligence (AI), generative AI (GenAI), large language models, and intelligent agents are transforming university innovation and entrepreneurship education. These tools support opportunity recognition, market analysis, prototyping, pitch preparation, and feedback, yet raise critical concerns regarding evidence, authorship, data governance, and academic integrity. Although research in both fields has expanded, their intersection remains fragmented. This article presents a structured, CiteSpace-informed science-mapping synthesis examining AI-enabled innovation and entrepreneurship courses. A core corpus of 48 international and policy sources was coded across key domains, and examined for recurring keyword relationships, conceptual groupings, temporal transitions, and emerging directions. Five major research hotspots were identified: AI as an innovation collaborator; integration of AI literacy with entrepreneurial competence; authentic project-based learning; assessment and academic integrity; and ethical and governance boundaries. The field has evolved across four stages: tool introduction, pedagogical integration, curriculum reconstruction, and governance deepening. Emerging frontiers highlight course-specific intelligent agents, human-AI-teacher-enterprise collaboration, evidence-centered assessment, authentic user validation, and institutional responsible-use policies. The article outlines a curriculum reform framework structured around problem chains, intelligent-agent scaffolding, learning-evidence portfolios, and risk-based governance. As an exploratory synthesis of a core corpus, findings offer a conceptual blueprint rather than an absolute measure of overall publication volume.

Keywords: *artificial intelligence, generative artificial intelligence, higher education, innovation and entrepreneurship education, CiteSpace, science mapping.*

I. INTRODUCTION

Innovation and entrepreneurship education has become a central component of higher education reform. Rather than focusing solely on business knowledge or business-plan writing, contemporary entrepreneurship education emphasizes opportunity recognition, problem framing, resource mobilization, experimentation, teamwork, ethical decision-making, and value creation (Gibb, 2002; Neck & Greene, 2011; Nabi et al., 2017). At the same time, universities are expected to connect learning with industry, technological change, and national innovation strategies, making innovation and entrepreneurship courses important settings for pedagogical innovation.

Artificial intelligence (AI) is reshaping these courses. Earlier applications in higher education focused on intelligent tutoring, learning analytics, adaptive learning, automated feedback, and student support (Holmes et al., 2019; Luckin et al., 2016; Zawacki-Richter et al., 2019; Wu, 2025). The rapid development of generative AI (GenAI) and large language models (LLMs) has greatly expanded these capabilities. Students can now use AI to support idea generation, market analysis, prototype development, and project refinement. AI is therefore becoming an active participant in knowledge creation and entrepreneurial learning rather than merely a supporting digital tool.

This transformation is particularly significant because entrepreneurship education requires students to address uncertainty, incomplete information, and evolving constraints. Although AI accelerates idea generation and iterative development, it may also produce inaccurate or biased outputs and blur the distinction between plausible text and validated evidence (Bender et al., 2021; Floridi & Chiriatti, 2020; Kasneci et al., 2023). Consequently, polished AI-assisted outputs do not necessarily demonstrate entrepreneurial judgment, evidence-based reasoning, or authentic problem solving.

Despite rapid growth, research remains fragmented. Studies of AI in higher education have primarily examined technological applications, institutional functions, and learning support, while comparatively limited attention has been given to curriculum design and pedagogy (Zawacki-Richter et al., 2019). Entrepreneurship education research has instead focused on entrepreneurial intention, experiential learning, competence development, and program evaluation (Bae et al., 2014; Fayolle & Gailly, 2008; Fayolle et al., 2006; Pittaway & Cope, 2007). As a result, the intersection of AI and entrepreneurship education lacks a coherent conceptual framework. It remains unclear which research themes dominate the field, how the literature has evolved, and which issues are shaping future curriculum reform.

Bibliometric analysis and science mapping provide useful concepts for addressing these questions. These approaches draw attention to keyword co-occurrence, co-citation, thematic clustering, and temporal evolution across a literature base (Aria & Cuccurullo, 2017; Donthu et al., 2021; Zupic & Čater, 2015). CiteSpace is particularly influential for identifying intellectual structures, emerging themes, and research frontiers (Chen, 2006, 2017). In the present study, however, science-mapping concepts are used as interpretive heuristics rather than as substitutes for pedagogical analysis or as claims of a complete quantitative analysis.

Accordingly, this review addresses three interrelated research questions: (1) What research hotspots characterize the emerging literature on AI-enabled innovation and entrepreneurship courses in higher education? (2) How has the field evolved from early AI adoption to contemporary debates on curriculum reconstruction and governance? (3) What research frontiers and curriculum implications emerge from the current knowledge structure?

This article makes four contributions. First, it integrates the previously separate literatures on AI in higher education and entrepreneurship education within a unified analytical framework. Second, it applies CiteSpace-informed science-mapping logic to organize research hotspots, thematic evolution, and emerging directions without presenting the core corpus as a complete database network. Third, it links technological use to authentic problem validation, learning evidence, and human responsibility. Finally, it proposes a curriculum reform framework encompassing course design, project-based learning, assessment, teacher development, and institutional governance. The manuscript's distinctive contribution lies in integrating AI literacy, entrepreneurial competence, authentic problem validation, evidence-centered assessment, and responsible governance as interdependent elements of one course system rather than treating them as separate review topics.

II. CONCEPTUAL BACKGROUND

2.1 AI in higher education: from application to educational ecology

AI in education is often defined in technical terms, but the educational consequences of AI depend on how systems are embedded in institutional and pedagogical contexts. Russell and Norvig (2021) describe AI as a broad field concerned with systems that perceive, reason, learn, and act. In education, however, an AI system is never simply a neutral computational artifact. It is part of a learning ecology that includes curriculum goals, teacher judgment, learner agency, assessment rules, data practices, and institutional norms.

Early policy and research discussions emphasized the potential of AI to personalize learning, improve feedback, detect students at risk, and support teachers (Holmes et al., 2019; Luckin et al., 2016; Miao et al., 2021). These applications were often associated with efficiency and scale. A system could process more data than a teacher, provide feedback more quickly, or make instructional materials available at any time. The OECD (2021, 2023) similarly emphasizes the capacity of digital systems to strengthen educational ecosystems when technology is aligned with public values and organizational capacity.

The literature also identifies a persistent imbalance. Technical capability is often described in detail, while the pedagogical role of teachers, the social distribution of benefits, and the interpretive work required to evaluate AI output receive less attention (Zawacki-Richter et al., 2019). AI-enabled innovation and entrepreneurship courses make this imbalance visible. A student may generate a technically impressive output, but the educational question is whether the process developed problem sensitivity, evidence-based reasoning, collaborative judgment, and responsible action.

GenAI intensifies this issue because it produces language that resembles human reasoning. LLMs can support brainstorming, explanation, translation, and drafting, yet their outputs may

contain fabricated references, biased assumptions, and unjustified confidence (Bender et al., 2021; Floridi & Chiriatti, 2020; Ray, 2023). UNESCO's guidance therefore stresses human agency, transparency, inclusion, safety, and the protection of learners and educators (Miao & Holmes, 2023). These principles are directly relevant to entrepreneurship courses, where AI-generated market information or user personas may influence decisions with real social and economic consequences.

2.2 Entrepreneurship education: from intention to competence and action

Entrepreneurship education has also undergone a conceptual shift. Earlier approaches often focused on entrepreneurial traits, business knowledge, or the intention to start a business. Meta-analytic and systematic-review evidence indicates that entrepreneurship education can influence entrepreneurial intention, but its effects depend on pedagogy, learner characteristics, course design, and the relationship between intention and actual behavior (Bae et al., 2014; Nabi et al., 2017; Rauch & Hulsink, 2015). The question is therefore not simply whether a course makes students more willing to become entrepreneurs, but whether it helps them learn how to recognize and investigate opportunities, mobilize resources, test assumptions, and act under uncertainty.

The competence perspective is particularly useful for the AI era. Morris et al. (2013) frame entrepreneurship education around competencies that can be practiced and developed. The EntreComp framework similarly describes entrepreneurship as a combination of ideas and opportunities, resources, and action (European Commission, 2016). These ideas fit well with project-based learning, in which students work through a sequence of inquiry, experimentation, feedback, and revision.

Entrepreneurship education research has long argued against treating the business plan as the sole or primary learning outcome. Pittaway and Cope (2007) emphasize the value of experiential and situated learning, while Neck and Greene (2011) call for pedagogies that represent entrepreneurship as a set of practices rather than a fixed body of knowledge. Fayolle and Gailly (2008) distinguish teaching models and learning processes, and Fayolle et al. (2006) propose that program evaluation should examine changes in knowledge, attitudes, skills, and behavior rather than relying on a single outcome measure. This body of work provides an important foundation for understanding why GenAI should be integrated into learning processes rather than used only to improve final products.

2.3 Why the intersection matters

AI and entrepreneurship education intersect around a shared concern with productive uncertainty. AI systems can help students generate possibilities and process information, while entrepreneurship education asks students to judge whether possibilities are meaningful, feasible, and valuable. The intersection creates at least four conceptual tensions.

First, there is a tension between generation and validation. AI can generate many plausible ideas, but entrepreneurial learning requires the testing of assumptions against users, evidence, and constraints. Second, there is a tension between personalization and standardization. AI can tailor feedback, but widely used models may also push students toward similar language,

market categories, and business models. Third, there is a tension between automation and agency. AI can complete parts of a task, but students must remain responsible for decisions, sources, and consequences. Fourth, there is a tension between access and inequality. AI may make advanced drafting and prototyping more accessible, yet unequal access to tools, prompts, data, and expert guidance can reproduce new forms of disadvantage (Miao et al., 2021; OECD, 2023; UNESCO, 2019).

These tensions justify a science-mapping approach. The field is not only expanding; it is also reorganizing its vocabulary. Terms such as "entrepreneurial intention," "AI literacy," "human-AI collaboration," "project-based learning," "academic integrity," "intelligent agent," and "learning evidence" increasingly appear in overlapping conceptual neighborhoods. Identifying this structure can help researchers and educators move beyond isolated tool experiments.

For this review, authenticity is operationalized as observable engagement with users, data, decisions, iterations, or real-world constraints that can be inspected beyond AI-generated text. Accordingly, authentic learning evidence is evidence produced through such engagement and linked to identifiable actions, sources, revisions, or consequences.

III. METHODOLOGY

3.1 Research design

This study uses a structured cross-disciplinary synthesis informed by CiteSpace's science-mapping logic. The design combines structured literature screening, concept normalization, and interpretive thematic mapping. It is not presented as a full systematic review of all publications in the field, ~~nor~~ as a statistical estimate of total publication output, or as a conventional software-generated CiteSpace network analysis. Instead, it constructs a traceable core corpus and uses science-mapping concepts to identify major, relationships, periods of transition, and emerging research directions.

This distinction is important. A conventional database-based CiteSpace study usually begins with a complete export from Web of Science, Scopus, or another indexed database and reports reproducible network parameters and statistics. The present study instead began with the conceptual problem at the intersection of AI-enabled higher education and innovation and entrepreneurship education. The corpus was ~~therefore~~ assembled through a structured search-and-screen process combining database-searchable peer-reviewed literature, recognized research reports, policy frameworks, and backward and forward reference tracing. The resulting synthesis is suitable for conceptual pattern identification and curriculum interpretation, but exact counts of nodes, links, centrality, bursts, or publication volume are not claimed.

To address the research questions, this study adopts a four-step analytical framework. It first establishes the conceptual boundary of AI-enabled innovation and entrepreneurship courses in higher education, then constructs and normalizes a cross-disciplinary core corpus. Third, CiteSpace-informed science-mapping logic is used to code recurring keyword co-relationships, thematic groupings, and temporal associations rather than to compute a formal network. Finally, the five hotspots and four developmental stages are interpreted through close qualitative reading and cross-source comparison, providing an integrated account of the field's knowledge structure and emerging research directions.

The reporting logic follows recommendations for transparent literature reviews and bibliometric studies (Donthu et al., 2021; Moher et al., 2009; Petticrew & Roberts, 2006; Snyder, 2019). The purpose is not to create a false impression of numerical precision, but to make the selection logic and interpretive boundaries visible.

3.2 Corpus construction

In this study, the primary search frame targeted literature from 2015 to 2025, complemented by foundational works to contextualize key conceptual and methodological origins. To capture the full scope of the field, a comprehensive vocabulary was structured across five core domains: emerging technology tools (e.g., AI, GenAI, LLMs, and automated feedback), higher education environments (such as universities, curricula, and assessment), entrepreneurship education constructs (including venture creation, business models, and opportunity recognition), pedagogical frameworks (e.g., experiential learning, design thinking, and project-based learning), and institutional governance concerns (focusing on academic integrity, ethics, privacy, and responsible AI).

International sources were located through literature-search systems commonly used in education, management, and information science, including Web of Science, Scopus, ERIC, and Google Scholar. Chinese policy documents and official frameworks were included when they directly shaped the institutional context of innovation and entrepreneurship education or AI in higher education. The final core corpus contained 48 sources: 18 sources on AI and higher education, 14 sources on entrepreneurship education, 7 methodological sources, and 9 policy, competence-framework, or governance sources. As shown in Table 1, the core corpus consists of literature from multiple disciplines, providing the analytical foundation for this review.

Table 1 Composition of the Core Corpus and Analytical Function

Corpus category	Number of sources	Analytical function
AI and higher education	18	Identify AI applications, teacher roles, learning support, and governance
Innovation and entrepreneurship education	14	Identify entrepreneurial competence, intention, project learning, and curriculum models
Science-mapping and review methods	7	Inform co-occurrence concepts, thematic grouping, temporal interpretation, and synthesis design
Policy, competence frameworks, and governance reports	9	Interpret institutional context, competence frameworks, governance norms, and responsibility boundaries
Total	48	Construct the cross-disciplinary core corpus

To strictly satisfy the inclusion criteria, sources were selected if they addressed AI in education, higher education digital transformation, entrepreneurship education, curriculum reform, or educational governance, while contributing a framework, concept, review, empirical finding, or policy principle relevant to university innovation and entrepreneurship courses.

For reproducibility, the search logic can be represented by the following Boolean structure (reported as representative logic rather than as a verbatim historical query): ("artificial intelligence" OR "generative AI" OR ChatGPT OR "large language model*") AND ("higher education" OR universit* OR curriculum OR assessment) AND (entrepreneur* OR "innovation and entrepreneurship education" OR "opportunity recognition"). This core string was conceptually supplemented by terms related to experiential learning, project-based learning, academic integrity, privacy, ethics, and responsible AI. Sources were excluded when they lacked a substantive connection to higher education course design, learning, assessment, entrepreneurship education, or governance relevant to the research questions.

To ensure the search-and-screening procedure is fully transparent and auditable, Table 2 details the PRISMA-style flow of the literature selection process. The search was conducted from December 1 to December 15, 2025, with the primary publication window restricted to 2015–2025, alongside selectively retained foundational methodological and conceptual works. English-language academic publications were eligible, while English- and Chinese-language policy or competence-framework documents were included when directly informing the institutional or governance context. Duplicate records were identified through DOI, title, and author-year matching, followed by manual verification. The initial retrieval yielded 186 records from Web of Science, 242 from Scopus, 87 from ERIC, the top 200 relevance-ranked Google Scholar records, and 26 additional policy and reference-tracing records (741 records in total). After removing 193 duplicates, 548 unique records were screened. Based on title and abstract

screening, 382 records were excluded. Subsequently, 166 full-text articles were assessed, and 118 were excluded during full-text evaluation, ultimately resulting in a final core corpus of 48 sources.

Table2 Systematic Search and Screening Flow

Screening step	Count	Procedure / result
Search window and eligibility	—	Systematic search: December 1–15, 2025; target publications: 2015–2025, plus selectively retained foundational works. English academic literature; English/Chinese policy and framework sources when directly relevant.
Initial retrieval	741	Web of Science = 186; Scopus = 242; ERIC = 87; Google Scholar = first 200 relevance-ranked records; policy/reference tracing = 26.
Duplicates removed	193	DOI, title, and author-year matching, followed by manual verification.
Unique records screened	548	Title/abstract screening against the AI, higher education, entrepreneurship education, curriculum, assessment, and governance scope.
Excluded at title/abstract stage	382	Excluded for insufficient relevance to the research questions or lack of a substantive higher-education/course connection.
Full texts assessed	166	Full-text eligibility review using the stated inclusion and exclusion criteria.
Excluded at full-text stage	118	Systematic search: no higher-education/course context = 43; no substantive AI-entrepreneurship intersection = 35; insufficient conceptual/empirical relevance = 24; duplicate/secondary/inaccessible source = 16.
Final core corpus	48	AI and higher education = 18; innovation and entrepreneurship education = 14; methodological sources = 7; policy/competence-framework/governance sources = 9.

3.3 Data normalization and coding

Cross-language and cross-disciplinary normalization was necessary because the same idea may be represented by different terms. "Artificial intelligence," "AI," "generative AI," "large language model," and "ChatGPT" were retained as distinct but related technology nodes. "Entrepreneurship education," "entrepreneurial learning," and "innovation and entrepreneurship education" were grouped as a broad entrepreneurship-education cluster, while "entrepreneurial intention," "entrepreneurial competence," and "opportunity recognition" were retained as outcome and competence nodes.

The coding process included four operations. First, spelling variants and abbreviations were standardized. Second, singular and plural forms were harmonized. Third, terms with an obvious hierarchical relationship were retained at different levels rather than collapsed into one term; for example, "AI literacy" was not treated as identical to "artificial intelligence." Finally, concepts were functionally mapped into four core dimensions of the course system: Input and Infrastructure (e.g., AI systems, LLMs, platforms), Learning Process (e.g., prompting, experimentation, reflection), Learning Outcome (e.g., AI literacy, innovation capability), and Assessment and Governance (e.g., academic integrity, privacy, transparency).

3.4 CiteSpace-informed analytical logic and evidentiary boundaries

The term "CiteSpace-informed" refers to applying the program's established analytical logic—co-occurrence, clustering, temporal sequencing, and frontier detection—as an interpretive framework for coding and synthesizing the core corpus (Chen, 2006, 2017). The five hotspots were identified from recurring coded relationships and thematic convergence across the corpus and then checked through close reading; the four temporal stages were interpretive segmentations rather than statistically detected breakpoints. This distinction is intended to prevent the findings from being read as conventional CiteSpace network outputs. Zupic and Čater (2015), Aria and Cuccurullo (2017), and Donthu et al. (2021) provide broader guidance for bibliometric and science-mapping interpretation.

3.5 Trustworthiness and limitations of the method

Three strategies were used to strengthen trustworthiness. First, the corpus was organized around explicit domains and inclusion criteria. Second, each major finding was checked against multiple source types, with different evidentiary roles: empirical and review studies support claims about pedagogical developments and educational outcomes; competence frameworks support the interpretation of learning goals; policy and governance documents support institutional, ethical, and responsibility-boundary interpretation; and methodological publications inform the synthesis logic. Policy documents are therefore not treated as direct evidence of learning effects. Third, numerical claims were deliberately limited. The article reports the size and composition of the core corpus, but it does not claim that 48 sources represent the total number of publications in the field. This approach increases conceptual traceability and permits inclusion of policy and framework documents that may not be indexed consistently, but it reduces the reproducibility of exact publication counts across databases.

Table 3 Traceability of the Five Research Hotspots

Hotspot	Dominant coded terms	Representative sources	Primary evidence function
AI as innovation-process collaborator	AI, GenAI, LLMs, ideation, market analysis, prototyping, human agency	Zawacki-Richter et al. (2019); Kasneci et al. (2023); Miao & Holmes (2023); Ray (2023)	AI capability, limitations, and human oversight
AI literacy + entrepreneurial competence	AI literacy, opportunity recognition, experimentation, judgment, responsibility	European Commission (2016); Morris et al. (2013); Nabi et al. (2017); Vuorikari et al. (2022)	Competence integration and learning outcomes
Authentic project-based learning	experiential learning, user research, project-based learning, validation, prototypes	Neck & Greene (2011); Pittaway & Cope (2007); Fayolle & Gailly (2008)	Action-oriented pedagogy and authentic inquiry
Assessment and academic integrity	assessment validity, AI-use disclosure, source checking, portfolios, oral defense	Cotton et al. (2023); Dwivedi et al. (2023); Lo (2023); Perkins (2023); Lu et al. (2024)	Assessment risks and evidence-centered alternatives

Ethics, data
governance, and
responsibility

privacy, bias, transparency, data
governance, responsible AI, human review

UNESCO (2019); Miao et al. (2021); Miao &
Holmes (2023); OECD (2021, 2023)

Governance and institutional
interpretation

IV. RESEARCH HOTSPOTS

4.1 AI is moving from information support to innovation-process collaboration

The first hotspot concerns the changing role of AI in the innovation process. In early higher education applications, AI was often treated as a support tool for information retrieval, content delivery, automated scoring, or learning management. In innovation and entrepreneurship courses, students used digital resources to search for market information, compare competitors, and prepare presentations. These functions remain useful, but GenAI has expanded AI's role from information access to active participation in task formation and solution development. Students can now use LLMs to support ideation, market analysis, prototype development, and iterative refinement.

However, generation is not the same as innovation. AI systems tend to produce plausible and linguistically coherent responses, but they do not guarantee market truth, local relevance, or social value. A model may construct a convincing customer persona without any evidence that the customer exists. It may describe a competitor using outdated information or recommend a business model that ignores regulation, cost, or cultural context. The pedagogical issue is therefore not whether students use AI, but how the course separates ideation from validation.

The hotspot is best described as innovation-process collaboration. AI can assist with low-cost hypothesis generation, information organization, and simulation, while students remain responsible for user research, evidence verification, ethical judgment, and the decision to continue or abandon an idea. This interpretation aligns with UNESCO's emphasis on human agency and with the warning that language models can produce fluent but unreliable content (Bender et al., 2021; Miao & Holmes, 2023; Ray, 2023).

4.2 AI literacy and entrepreneurial competence are becoming intertwined

The second hotspot is the integration of AI literacy with entrepreneurial competence. AI literacy includes more than operating a tool. It involves understanding how AI systems produce outputs, designing effective tasks, evaluating reliability, identifying bias, protecting data, recognizing intellectual-property risks, and assigning responsibility. The DigComp 2.2 framework places AI-related practices within a broader digital competence structure that includes information and data literacy, communication, problem-solving, safety, and responsible participation (Vuorikari et al., 2022).

Entrepreneurial competence includes opportunity recognition, resource mobilization, experimentation, persistence, teamwork, and value creation (European Commission, 2016; Morris et al., 2013). These competencies become more rather than less important when AI is available. If a student can generate ten business ideas in a few minutes, the scarce capability is no longer idea production alone. It is the ability to identify which problem is worth pursuing,

obtain trustworthy evidence, recognize hidden assumptions, and make a defensible judgment under uncertainty. AI literacy and entrepreneurial competence are mutually reinforcing.

This hotspot therefore points to a shift in course objectives. The goal should not be to produce students who merely know how to use AI tools. It should be to develop students who can collaborate with AI, challenge AI, verify AI, and take responsibility for decisions made with AI. This objective also creates a meaningful role for teachers: teachers design the decision environment in which students must justify, test, and revise AI-supported ideas.

4.3 Project-based learning is shifting toward authentic problem validation

The third hotspot concerns project-based and experiential learning. Entrepreneurship education has long valued authentic projects because students learn through action, feedback, and revision rather than through abstract content alone (Neck & Greene, 2011; Pittaway & Cope, 2007). AI can strengthen this pedagogy by accelerating preliminary research, alternative generation, and prototype iteration. It can also support peer feedback and scenario simulation.

The risk is that AI may create an illusion of authenticity. Students can generate an apparently realistic market report, user persona, or business plan without interacting with a real user. The project becomes a simulation of entrepreneurship rather than an inquiry into a problem that exists outside the classroom. This distinction matters because entrepreneurial learning involves uncertainty that cannot be fully generated from text. User emotions, team trust, resource constraints, institutional rules, and local market conditions require contact with the world.

The literature therefore points toward evidence-centered project learning. A course can divide the project into seven stages: problem discovery, user research, opportunity judgment, solution design, prototype development, market testing, and pitch reflection. At each stage, students may use AI for clearly defined tasks, but they also submit evidence of what they observed, which assumptions they made, what sources they checked, how they modified the AI output, and why they changed direction.

The educational value of AI lies in reducing the cost of low-stakes experimentation, not in replacing high-value inquiry. AI can help students ask better questions and compare more options, while direct observation and user validation determine whether the problem and proposed value are credible. This distinction operationalizes the central insight of experiential entrepreneurship education: students learn from the relationship between action and consequences, not from the appearance of a finished product.

4.4 Assessment and academic integrity are being reconstructed

The fourth hotspot is assessment. GenAI challenges traditional assessment because it can produce many of the artifacts that universities have historically used to infer learning: essays, business plans, market analyses, reflections, slide decks, and code. A final product may therefore contain limited information about the student's learning process. Studies of ChatGPT in education have raised concerns about authorship, assessment validity, feedback, and academic integrity (Cotton et al., 2023; Dwivedi et al., 2023; Lo, 2023; Perkins, 2023; Rudolph et al., 2023).

In innovation and entrepreneurship courses, the assessment problem is especially complex. A business plan is already a constructed representation of a future possibility. If the text is generated by AI, the evaluator may not know whether the student has conducted research, understood the market, or made the strategic choices represented in the document. Automated writing evaluation may provide useful supplementary feedback, but it cannot by itself establish the authenticity or educational value of the project (Lu et al., 2024).

The emerging paradigm shifts assessment from final products to authentic evidence across four core dimensions: Problem Authenticity (originating in observable problems or documented user needs), Evidence Quality (basing claims on empirical data, interviews, or credible sources), Process and Collaboration (tracing AI utilization, task distribution, and decision-making iterations), and Reflective Responsibility (critically evaluating errors, biases, and ethical risks within the workflow).

Assessment can therefore include a project portfolio, version history, AI-use statement, prompt samples, source-checking log, peer evaluation, oral defense, and a short reflection on rejected alternatives. The goal is not to prohibit AI or to detect every AI-generated sentence. It is to create a richer evidence environment in which students must demonstrate understanding and responsibility.

This approach is compatible with the entrepreneurship-education literature, which emphasizes competence, action, and behavior rather than isolated knowledge tests (Fayolle et al., 2006; Morris et al., 2013; Nabi et al., 2017). It also reduces the incentive to conceal AI use. When students are allowed to use AI within explicit boundaries and are assessed on how they use it, responsible disclosure becomes more educationally valuable than blanket prohibition.

4.5 Ethics, data governance, and responsibility boundaries

The fifth hotspot concerns governance. AI-enabled innovation courses can involve personal interviews, customer data, confidential business information, unpublished product ideas, copyrighted material, and high-stakes judgments. Students may upload interview transcripts or business concepts to external systems without understanding how the data may be stored or reused. AI systems may also produce biased recommendations, fabricated market evidence, or text that resembles existing copyrighted materials.

UNESCO, the OECD, and national policy documents emphasize human-centered design, transparency, safety, inclusion, and accountability (Miao et al., 2021; Miao & Holmes, 2023; OECD, 2021, 2023; UNESCO, 2019). China's policy environment has also emphasized the reform of innovation and entrepreneurship education, AI innovation in higher education, education digitalization, and the management of GenAI services (Ministry of Education of the People's Republic of China, 2018, 2022; State Council of the People's Republic of China, 2015; Cyberspace Administration of China et al., 2023).

These principles suggest that course governance should move beyond a binary "allowed versus prohibited" model. Instead, tasks can be categorized by risk. Low-risk activities may include brainstorming, language polishing, formatting, and the generation of alternative questions.

Medium-risk activities may include market analysis, code generation, customer segmentation, and automated feedback. High-risk activities may involve personal data, trade secrets, high-stakes evaluation, public-interest decisions, or the use of unverified evidence in a real venture.

Different levels of risk should trigger different requirements for authorization, data minimization, disclosure, human review, and documentation. Students should learn not only how to use AI, but also when not to use it. Governance is therefore not an external administrative issue. It is part of entrepreneurial competence because responsible value creation depends on recognizing legal, ethical, and social boundaries.

V. EVOLUTIONARY TRAJECTORY OF THE FIELD

The four periods are interpretive segmentation points rather than breakpoints generated by citation-burst or timeline statistics. Their boundaries were assigned by triangulating recurrent themes in the core corpus with major technological and policy transitions: 2015-2018 emphasizes digitalization and early AI support; 2019-2021 reflects more systematic pedagogical integration; 2022-2023 captures the rapid classroom diffusion of GenAI and associated assessment debates; and 2024-2025 emphasizes course-specific agents, human-AI collaboration, and governance. The segmentation is therefore heuristic and should be tested in future database-based temporal network studies.

5.1 Stage 1: Tool introduction and digitalization of entrepreneurship education (2015–2018)

The first stage was shaped by the expansion of online learning, digital resources, innovation and entrepreneurship policies, and early discussions of AI in education. AI was not yet the central curriculum concept. Instead, the research agenda focused on digital learning environments, entrepreneurship education reform, entrepreneurial intention, and access to resources. In China, policy initiatives created a broad institutional expectation that universities should integrate innovation and entrepreneurship education across disciplines and programs (State Council of the People's Republic of China, 2015).

During this stage, AI was mostly understood as a tool for information processing or instructional support. The dominant pedagogical question was whether digital resources could make entrepreneurship education more accessible and practice-oriented. The underlying model was still relatively instrumental: technology was added to an existing curriculum, while course objectives and assessment structures remained largely unchanged.

5.2 Stage 2: Pedagogical integration and intelligent support (2019–2021)

The second stage saw a more systematic research agenda around AI applications in higher education. Attention shifted toward intelligent tutoring, learning analytics, adaptive support, automated assessment, and AI literacy. Zawacki-Richter et al. (2019) identified a strong technical and managerial orientation in the literature and called for greater attention to educators and pedagogical theory. At the same time, entrepreneurship education research

increasingly emphasized experiential learning, competence development, and the relationship between intention and action (Nabi et al., 2017; Rauch & Hulsink, 2015).

The intersection between the two fields emerged around intelligent support for project learning. AI could help students search for information, receive feedback, and organize project tasks, while entrepreneurship education supplied a meaningful context for inquiry and action. The key question became whether AI could support learning activities without reducing students' agency or replacing the social and experiential dimensions of entrepreneurship.

5.3 Stage 3: GenAI-triggered curriculum reconstruction (2022–2023)

The third stage began with the rapid public diffusion of ChatGPT and similar systems. AI moved from the background of educational infrastructure to the foreground of classroom activity. Students could interact directly with a generative model, and teachers had to reconsider assignments, assessment, authorship, and academic integrity. Research rapidly expanded around opportunities for personalized learning and writing support as well as risks of hallucination, bias, overreliance, and assessment invalidity (Cotton et al., 2023; Grassini, 2023; Kasneci et al., 2023; Montenegro-Rueda et al., 2023; Tlili et al., 2023).

For innovation and entrepreneurship courses, GenAI lowered the threshold for producing business ideas, market narratives, pitch scripts, and prototypes. It also exposed the weakness of product-centered assessment. The curriculum could no longer assume that a polished document represented a student's independent research and reasoning. The focus therefore shifted toward AI-use policies, process evidence, oral defense, source verification, and reflective assessment.

5.4 Stage 4: Intelligent-agent collaboration and governance deepening (2024–2025)

The fourth stage is characterized by a move beyond the question of whether students may use ChatGPT. Research increasingly considers course-specific agents, multi-agent collaboration, retrieval-augmented systems, learning analytics, personalized feedback, and institutional governance. AI is becoming embedded in course workflows rather than accessed as a free-standing chatbot.

This stage has four defining features. First, the unit of analysis expands from a student-model interaction to a collaboration among students, teachers, enterprise mentors, and multiple AI systems. Second, assessment expands from final products to prompts, source verification, version histories, user feedback, and reflective explanations. Third, the role of the teacher shifts from content transmitter to learning designer, process mentor, and ethical gatekeeper. Fourth, research attends more carefully to platforms, data infrastructures, institutional policies, and professional development.

The synthesis therefore suggests a movement from "AI adoption" toward "AI organization." The central question is no longer only whether universities use AI, but how universities organize AI so that it supports authentic learning, authentic innovation, and responsible action. The major characteristics of each interpretive developmental stage are presented in Table 4.

Table 4 Evolutionary Stages of AI-Enabled Innovation and Entrepreneurship Courses

Stage	Period	Dominant technology forms	Curriculum focus	Guiding question
Tool introduction	2015–2018	Online platforms, learning analytics, basic intelligent tools	Access, entrepreneurial intention, digital resources	How can technology improve reach and practice?
Pedagogical integration	2019–2021	Intelligent support, automated feedback, AI literacy	Project learning, competence development, teacher support	How can technology serve educational goals?
Curriculum reconstruction	2022–2023	LLMs and GenAI	Idea generation, assessment reform, academic integrity	How can authentic learning be demonstrated when AI participates?
Governance deepening	2024–2025	Course agents, multi-agent systems, retrieval augmentation	Human-AI collaboration, evidence, responsibility	How can AI become a sustainable and explainable course system?

VI. EMERGING FRONTIERS

Sections IV and V report the synthesis findings, whereas Sections VI and VII move from synthesis to author-developed conceptual propositions and curriculum recommendations. The models below integrate recurrent patterns in the core corpus with existing competence, experiential-learning, assessment, and responsible-AI literature.

6.1 Course-specific intelligent agents as curricular infrastructure

General-purpose LLMs do not necessarily understand a university's learning outcomes, assessment rubric, local industry context, or ethical requirements. Course-specific intelligent agents can be configured around a syllabus, project workflow, case library, evaluation criteria, and institutional policy. In the problem-discovery stage, an agent might ask students to distinguish symptoms from root causes. In the market-validation stage, it might request evidence for customer claims. In the business-model stage, it might challenge assumptions about revenue, cost, regulation, or stakeholder impact. During a pitch rehearsal, it might simulate different investor or user perspectives.

The value of a course-specific agent lies in its pedagogical alignment. It should not simply produce better answers. It should make the learning process more visible and support the cognitive moves that the course intends to develop. The design challenge is to avoid over-scaffolding. If an agent supplies every question, students may become dependent on the system and lose the ability to frame problems independently. Intelligent agents should therefore be designed to fade support, ask counter-questions, and require students to justify their choices.

6.2 A double-spiral model of AI literacy and entrepreneurial competence

The double-spiral model proposed here is an author-developed integrative conceptual proposition rather than a directly observed bibliometric cluster. It conceptualizes AI literacy and entrepreneurial competence as mutually reinforcing outcomes that unfold through four recurring movements: Frame (identifying problem spaces and primary stakeholders), Augment (leveraging AI systems for generation, simulation, and data synthesis), Validate (benchmarking AI outputs against empirical evidence, user needs, and ethical constraints), and Reflect (evaluating AI's influence on decision-making and defining individual accountability).

The spiral continues as students revise both the problem and the solution. This proposition is consistent with the competence and action orientations of entrepreneurship education while responding to the epistemic risks of GenAI. Each movement can generate observable learning evidence, which makes the model testable in future course-based research and usable as an assessment scaffold. Figure 1 summarizes the recursive relationship between the two competence domains.

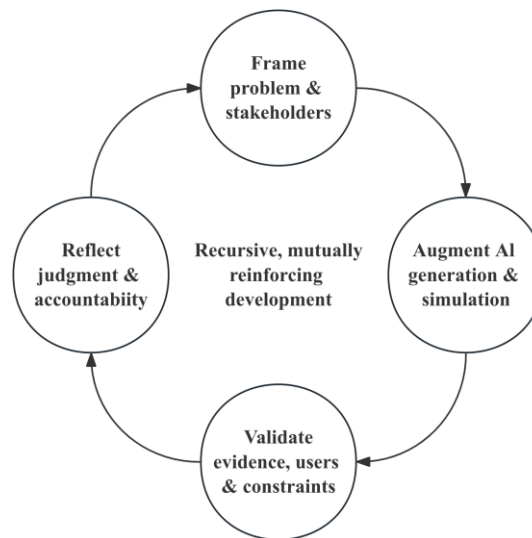


Figure 1. Model of AI literacy and entrepreneurial competence.

6.3 Authentic data, authentic users, and intelligent project-based learning

AI can rapidly generate hypotheses, but it cannot guarantee that those hypotheses matter to real users. The synthesis indicates a potential direction toward partnerships that provide authorized, anonymized, and contextually rich data. Universities may collaborate with enterprises, communities, public agencies, incubators, and social organizations to create authentic cases and problem settings.

In such environments, students would be expected to compare AI-generated assumptions with interviews, observations, surveys, experiments, and market tests. They would document which assumptions were supported, modified, or rejected. AI would function as a mediator between classroom knowledge and real-world innovation rather than as a generator of fictional entrepreneurship.

6.4 Evidence-centered assessment and portable credentials

The reviewed literature suggests that assessment in the GenAI era is likely to place greater emphasis on learning evidence. A project portfolio may include the initial problem statement, interview notes, source list, selected prompts, and AI outputs, human revisions, prototype iterations, user feedback, and final reflection. Digital badges or micro-credentials could, subject

to institutional validation, certify specific capabilities such as evidence-based opportunity recognition, responsible AI use, prototyping, or collaborative problem-solving.

The key design question is not whether teachers can identify every AI-generated sentence-but whether students can explain how the work was produced and defend the decisions represented in it. Portfolios can therefore be complemented by oral defenses or live design tasks when final products are highly susceptible to AI generation. This synthesis suggests a research direction toward assessment systems that remain valid when AI is available.

6.5 Institutionalized and risk-based governance

A further frontier is concerns institutional governance. AI use is likely to become more deeply embedded in course platforms, assessment systems, student-support services, and venture-incubation processes. Universities may therefore need clearer rules for data classification, privacy, intellectual property, authorship, model procurement, disclosure, and human review, alongside faculty development in task design, source verification, data compliance, and assessment redesign.

The synthesis suggests that risk-based governance may be more sustainable than blanket prohibition because it can permit low-risk experimentation while requiring stronger safeguards for sensitive information and high-stakes decisions. Its educational value lies in making responsibility boundaries explicit rather than treating governance as separate from innovation.

VII. IMPLICATIONS FOR CURRICULUM REFORM

7.1 Organize curriculum around problem chains

As summarized in Table 5, the AI tool-use hotspot is translated into task-chain design: AI tools are selected only after the problem, evidence need, and decision point have been defined.

Table 5 Research Hotspots and Emerging Frontiers

Current hotspot	Main object of study	Emerging frontier	Curriculum implication
AI tool use	Retrieval, generation, analysis, and presentation	Intelligent-agent collaboration in course workflows	Move from tool training to task-chain design
Entrepreneurial competence	Intention, opportunity recognition, and business models	Double-spiral development of AI literacy and entrepreneurial competence	Assess technical judgment and entrepreneurial judgment together
Project-based learning	Ideas, prototypes, and pitches	Authentic users, data, and constraints	Strengthen field inquiry and evidence validation
Learning assessment	Final products and AI detection	Evidence portfolios and oral defense	Assess how students learn and decide

Courses should be organized around a sequence of connected questions rather than a menu of tools. A problem chain might ask: What problem is observable? Whose problem is it? What evidence supports its importance? What value is being created? What assumptions must be tested? What resources are required? What risks and responsibilities follow? AI tools can then be assigned to specific points in the chain rather than introduced as free-floating applications.

This design helps prevent "tool-first" teaching. Students do not learn AI because it is fashionable; they learn to select and evaluate AI because a particular inquiry requires it. The problem chain also creates a common language for interdisciplinary teams. Engineering students may contribute prototyping, business students may contribute market analysis, and social-science students may contribute user research, while all members remain accountable for evidence and ethics.

7.2 Build a human-AI-teacher-enterprise support system

AI should be embedded in a distributed support system. Course agents can provide immediate feedback, organize materials, simulate stakeholders, and prompt reflection. Teachers should remain responsible for pedagogical judgment, methodological guidance, ethical review, and the interpretation of student learning. Enterprise or community mentors should contribute contextual authenticity, resource constraints, and market or social validation.

The roles are complementary. AI can scale some forms of support, but it cannot replace the relational and situated dimensions of mentoring. Teachers also need institutional support: access to approved tools, time for course redesign, professional-learning communities, shared cases, and mechanisms for reviewing AI-related incidents.

7.3 Reconstruct assessment around learning evidence

A comprehensive framework evaluates both deliverables and learning journeys through a balanced weighting model that covers project value proposition, evidence quality, process iteration, responsible AI use, teamwork, and reflective judgment. Under this model, pivoting due to empirical user feedback is rewarded as a sign of deeper learning rather than penalized. To operationalize this approach, course requirements incorporate six key artifacts: an AI-use disclosure, a factual source-verification log, a prompt and human-revision history, a live oral defense or task, an error and bias reflection, and a peer-mentor collaboration assessment. This design is more educationally meaningful than relying solely on AI detectors (Lu et al., 2024; Perkins, 2023).

Table 6 Operational Indicators for Evidence-Centered Assessment

Assessment dimension	Observable indicators	Learning evidence
Problem Authenticity	Problem is linked to documented users or observable context; AI-generated assumptions are distinguished from external evidence.	Interview/observation notes; problem provenance; user-need record

Evidence Quality	Key claims are traceable to empirical data or credible sources; consequential AI outputs are independently checked.	Source-verification log; data excerpts; citation trail
Process and Collaboration	AI use, task division, iterations, and major revisions are traceable; decision changes are explained.	Selected prompt history; version record; peer/mentor feedback
Reflective Responsibility	Student identifies errors, bias, ethical risk, and the boundary of AI assistance; final accountability is explicit.	AI-use disclosure; error/bias reflection; oral defense

7.4 Introduce risk-based responsible-use policies

Universities should classify tasks into low-, medium-, and high-risk categories. Low-risk tasks may include brainstorming, translation, language editing, and formatting. Medium-risk tasks may include market analysis, customer segmentation, coding, and automated formative feedback. High-risk tasks may include processing personal data, uploading trade secrets, making public-interest decisions, or using unverified AI outputs in real venture activity.

Each category should specify whether authorization, anonymization, human verification, disclosure, or prohibition is required. Policies should be written into the syllabus, assignment instructions, and rubric. Students should be taught how to protect interviewees, clients, and teammates, and how to distinguish public information from confidential information.

7.5 Develop teacher capacity and institutional learning

Faculty development should treat AI as a curriculum and assessment issue, not merely a software issue. Teacher workshops can address prompt design, task decomposition, hallucination checking, copyright, data protection, oral assessment, portfolio design, and the use of authentic cases. Teaching communities can share examples, review student work, and discuss failures. Institutions should also collect evidence about whether AI-supported courses actually improve problem-solving, collaboration, and entrepreneurial competence.

The most important capacity may be institutional learning. Policies need to evolve as models, platforms, and social expectations change. Universities should establish feedback loops connecting students, teachers, technology staff, legal and ethics offices, and industry partners so that governance can remain responsive without becoming purely reactive. Across all five recommendations, a clear responsibility boundary applies: AI may support generation, simulation, and preliminary analysis, while students remain accountable for evidence verification, judgment, ethical decisions, and final claims.

VIII. CONCLUSION AND LIMITATIONS

This article examined AI-enabled innovation and entrepreneurship courses in higher education through a structured, CiteSpace-informed science-mapping synthesis. The reviewed core corpus is organized around five hotspots: AI as a collaborator in innovation processes; the integration of AI literacy and entrepreneurial competence; authentic project-based learning; assessment and academic integrity; and ethics, data governance, and responsibility. The field is interpreted through four stages: tool introduction, pedagogical integration, GenAI-triggered curriculum reconstruction, and governance deepening.

The manuscript's distinctive contribution is the integrated course-system perspective that links AI literacy and entrepreneurial competence with authentic problem validation, evidence-centered assessment, and responsible governance. Rather than treating these issues as separate consequences of AI adoption, the proposed framework positions them as mutually dependent design requirements. The central argument is that AI should be treated as part of a learning system rather than as a substitute for entrepreneurial judgment. The educational value of AI depends on whether students use it to investigate real problems, test assumptions, improve prototypes, explain decisions, and take responsibility for consequences. Future research should empirically test the author-proposed double-spiral model, course-specific agents, evidence-centered assessment designs, authentic data partnerships, and measurable relationships between AI literacy and entrepreneurial competence.

Three limitations should be acknowledged. First, the 48-source corpus is a traceable core set rather than a complete database export; it supports thematic interpretation but cannot be used to estimate the total volume of publications in the field. Second, the normalization of English and Chinese concepts may have removed some language-specific distinctions. Third, GenAI develops faster than conventional publication cycles, so emerging models, platforms, and policies may change the field's vocabulary. Future studies should preserve and publish the full database export, exact search strings and dates, screening log, synonym dictionary, network parameters, and visualization files, and should combine formal bibliometric mapping with classroom experiments, quasi-experiments, design-based research, or multi-case studies.

Conflict of Interest

The author declares no conflict of interest.

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