Scientific Research Publishing

Advances in Applied Sociology, 2026, 16(1), 38-47
https://www.scirp.org/journal/aasoci
ISSN Online: 2165-4336
ISSN Print: 2165-4328

The Advantages and Constraints of LLM-Augmented Knowledge Graphs in University Innovation and Entrepreneurship Education

Bingqi Liu, Zhi Weng, Ayinhu*

School of Electronic Information Engineering, Inner Mongolia University, Hohhot, China
Email: *ayinhu@imu.edu.cn

How to cite this paper: Liu, B. Q., Weng, Z., & Ayinhu (2026). The Advantages and Constraints of LLM-Augmented Knowledge Graphs in University Innovation and Entrepreneurship Education. *Advances in Applied Sociology, 16,* 38-47.
https://doi.org/10.4236/aasoci.2026.161003

Received: October 6, 2025
Accepted: January 10, 2026
Published: January 13, 2026

Abstract

This paper investigates the integration of Large Language Models with Knowledge Graphs (LLM-KGs) into the pedagogical framework of higher education, specifically within innovation and entrepreneurship programs. It argues that this synergy can catalyze a shift toward more intelligent and data-informed educational practices. However, the implementation is scrutinized through a critical lens, revealing significant constraints in data governance, a growing digital divide among faculty, and systemic institutional inertia. In response, the study proposes a set of strategic interventions designed to provide both a conceptual foundation and actionable guidance for the effective adoption of LLM-KG systems in university settings.

Keywords

Large-Scale Models, Knowledge Graph, Innovation and Entrepreneurship Education, Constraints

1. Introduction

Since 2023, the dual-engine strategy of "Educational Large Models + Knowledge Graphs" has emerged as a new focal point for the digital transformation of higher education institutions. The Ministry of Education's *2024 Work Points for Education Digitization Strategy Action* explicitly listed "constructing knowledge graphs in the field of innovation and entrepreneurship education" as a key task for the first time. In April 2024, the General Office of the Ministry of Education issued the *National Education Digitization Strategy Action 2024 Work Points*, which clearly stated the need to precisely empower high-quality teaching and learning, expand disciplinary and professional skill knowledge graphs, and support personalized student learning. This series of policy initiatives indicates that the collaborative application of Large Models and Knowledge Graphs in university innovation and entrepreneurship education has ascended to the level of national strategy, possessing significant practical significance and strategic value.

Currently, the rapid development of artificial intelligence technology has placed higher demands on talent cultivation in universities; fostering high-quality talent with both innovative spirit and entrepreneurial ability has become a crucial task for higher education. As a key component of the higher education system, innovation and entrepreneurship education urgently needs to optimize teaching effectiveness by introducing cutting-edge technologies and innovative methods. Large Language Models (LLMs) and Knowledge Graphs (KGs) are both methods for storing and utilizing knowledge. In terms of form, the former implicitly stores knowledge through network parameters, while the latter explicitly stores knowledge through triples. Specifically, LLMs are capable of completing complex generation tasks and can be applied to open-domain understanding tasks; in few-shot and zero-shot scenarios, their knowledge representation capabilities even surpass those of supervised models (Zhao et al., 2024). Applying LLMs to Knowledge Graph construction offers several benefits: first, it effectively extracts structured knowledge from multi-source heterogeneous data to update the KG; second, it improves construction quality by characterizing entities and their relationships to reason, complete, or correct graph content; and third, it accurately identifies user intent from various query forms to narrow the recall scope, thereby enhancing the accuracy of knowledge retrieval (Hadi et al., 2023; Kaddour et al., 2024).

The application of LLM-Knowledge Graph (LLM-KG) collaboration offers a promising technological pathway. Leveraging their powerful language understanding and generative capabilities, large language models can efficiently process massive volumes of textual data. Meanwhile, knowledge graphs tools that visualize the structure and interconnections of knowledge can help students better comprehend and master complex knowledge systems (Wang & Shen, 2025). By modeling relationships across diverse domains, they provide targeted information and resources that facilitate innovation and entrepreneurship (Li et al., 2024). The synergy between the two exhibits significant advantages in areas such as personalized and adaptive teaching, intelligent learning management, and dynamic construction of educational resources.

Despite recognizing the integrative trend of these technologies, the academic discourse remains underdeveloped in its theoretical modeling of coordination and its empirical scrutiny of pedagogical integration. A significant research gap exists in understanding precisely how large models and knowledge graphs operationalize competency diagnosis and formative feedback. The literature, predominantly descriptive, offers catalogs of outcomes but lacks the analytical rigor of technical taxonomy or comparative dataset benchmarking. This theoretical and methodological deficit has impeded the emergence of scalable, replicable paradigms in education. Thus, a pivotal challenge confronts innovation and entrepreneurship education: the need to conceptualize a technology-enhanced framework that is not only synergistic but also fundamentally congruent with the pedagogical tenets of project-based learning.

This paper investigates the practical application of LLM-KG in higher education innovation and entrepreneurship, analyzes their educational advantages and constraints, and explores coordination mechanisms that combine institutional design with technological implementation. The goal is to better leverage the collaborative potential of LLMs and knowledge graphs, providing actionable pathways for the intelligent transformation of innovation and entrepreneurship education in universities.

2. Application Scenarios of LLM-KG in University Innovation and Entrepreneurship Education

2.1. Generative AI-Driven Course Co-Creation

In the field of innovation and entrepreneurship education, entrepreneurial case studies and business plans serve as core teaching resources, and their adaptability is crucial to the effectiveness of instruction. Traditional teaching models often rely on standardized case databases and fixed templates, which fail to accommodate the diverse learning needs and cognitive differences among students.

In contrast, the generative AI course co-creation model based on LLM-KG dynamically generates highly customized entrepreneurial cases and business plan templates aligned with students' learning interests and goals. By engaging students in the iterative optimization of these templates, this approach significantly enhances learning engagement and instructional relevance, while promoting a systematic understanding of the entrepreneurial process and business model logic. It also strengthens the joint cultivation of students' innovative thinking and practical competencies.

In practical application, students can iteratively adjust and refine the AI-generated templates according to their own creative ideas, thereby deepening their mastery of key entrepreneurial elements within a closed practice loop. This facilitates the effective transformation from knowledge acquisition to internalized capability development.

2.2. University-Enterprise-Government Resource Synergy

The effectiveness of innovation and entrepreneurship education in universities is influenced by multiple factors, including those at the governmental, institutional, corporate, and individual levels (Wang & Shen, 2021). Among these, the university-enterprise-government synergy mechanism serves as a key driver for enhancing students' innovation and entrepreneurship capabilities.

On one hand, by integrating knowledge graph technologies with external data resources such as the National Intellectual Property Administration patent database and corporate databases like Tianyancha, a Chinese corporate database, universities can establish real-time correlations among technological evolution, market dynamics, and capital flows. This enables the provision of accurate and dynamic innovation and entrepreneurship information for students.

On the other hand, through collaborative mechanisms, universities and enterprises can jointly transform students' innovative outcomes into market-oriented products, while government departments accelerate project incubation through policy guidance and financial support. Together, these interactions foster a multi-stakeholder, closed-loop innovation and entrepreneurship ecosystem.

The core advantages of this synergy model are twofold:

1) Students can leverage the structured knowledge networks within knowledge graphs to obtain timely insights into frontier patent technologies, market demand shifts, and corporate trends, effectively identifying high-potential entrepreneurial opportunities; and

2) universities, enterprises, and government agencies can promote deep integration of industry, academia, and research through resource sharing and collaborative project development.

3. Advantages of LLM-KG in University Innovation and Entrepreneurship Education

3.1. Precision and Personalization in Teaching

The essence of innovation and entrepreneurship education lies in cultivating entrepreneurial talents through more practical, diverse, and creative learning approaches (Mi, Xu, & Luo, 2018). In higher education, each student exhibits distinct learning needs and competency levels. Traditional learning path recommendation models, typically based on simple feature matching, struggle to accurately capture individual learning preferences and cognitive variations.

By contrast, the LLM-KG driven conversational learning assistant conducts deep analyses of students' goals, interests, and capability gaps through interactive dialogue, dynamically optimizing personalized learning paths. For instance, when a student expresses entrepreneurial intent in a specific technological domain, the system can instantly integrate data on patent evolution, market demand trends, and successful case databases to generate a customized learning plan that includes both knowledge-linked pathways and practical tasks. This dynamic matching substantially enhances the alignment between instructional content and students' developmental needs.

3.2. Intelligent Teaching Management

Within the innovation and entrepreneurship education ecosystem, teaching management, which encompasses project allocation, mentor guidance, and funding support, directly determines the quality of talent cultivation. Traditional management approaches, limited by experience-based static matching logic, cannot achieve real-time optimization of educational resources.

By introducing an LLM-KG based KG-Attention Multilateral Matching Algorithm, the system deeply analyzes the multidimensional relational networks embedded within knowledge graphs (Zhai et al., 2025). It intelligently evaluates project attributes, mentor expertise, and funding eligibility conditions to construct a high-precision resource allocation model.

For example, when dealing with technologically innovative projects, the system can recommend interdisciplinary expert teams by referencing mentors' academic trajectories and project experience profiles represented within the knowledge graph. Simultaneously, by aligning project incubation characteristics with funding requirements, it can automatically match suitable venture capital or special-purpose funds. This significantly improves the efficiency and responsiveness of teaching management, providing robust technological support for refined, data-driven governance in innovation and entrepreneurship education.

3.3. Dynamic Textbook and Resource Development

Digital learning materials encompass diverse and rich educational resources that empower students' active learning far more effectively than traditional textbooks (Li, 2005). In innovation and entrepreneurship education, the timeliness and adaptability of instructional resources are essential to maintaining teaching quality. Traditional textbooks, with long update cycles, often fail to keep pace with rapid knowledge evolution, leading to a disconnect between academic content and real-world industry developments.

LLM-KG driven digital textbooks leverage the semantic understanding capacity of large models and the structural representation strengths of knowledge graphs to establish an intelligent content update mechanism. When new knowledge points, exemplary cases, or policy regulations emerge, the system can automatically refresh and adjust the instructional materials in real time.

This dynamic updating mechanism not only ensures the cutting-edge accuracy of teaching content but also, through the intelligent structuring of knowledge graphs, enables students to systematically grasp the evolving logic and trajectory of the innovation and entrepreneurship knowledge system.

4. Constraints of LLM-KG in University Innovation and Entrepreneurship Education

Although LLM-KG demonstrate remarkable advantages in innovation and entrepreneurship education, their practical implementation still faces multiple challenges. These challenges extend beyond technical constraints to encompass issues related to educational philosophy, institutional support, and governance mechanisms.

4.1. Data Governance Risks

Data governance represents a critical concern in the application of LLM-KG.

Large models are inherently influenced by inaccuracies or biases embedded in their training data. When generating outputs based on statistical patterns, models may produce responses that sound plausible but deviate from factual or domain-specific knowledge, commonly known as factual errors (Luo & Zhang, 2023). Such phenomena can compromise the accuracy and reliability of the knowledge graph.

Since knowledge graph information directly informs students' understanding of industry knowledge, business models, and policy frameworks, factual inaccuracies can not only undermine the credibility of instructional content but also mislead students in crucial areas such as entrepreneurial decision-making and business planning. Consequently, establishing effective mechanisms for data monitoring, validation, and continuous quality assurance is a prerequisite for ensuring the sustainable and trustworthy application of LLM-KG technologies in educational contexts.

4.2. Widening of the Teacher Digital Divide

As technology continues to evolve, the application of LLM-KG in university innovation and entrepreneurship education is becoming increasingly widespread. The structural improvement of teachers' digital literacy has become a core factor constraining the release of technological efficacy. Currently, local universities exhibit significant imbalances in the construction of teacher digital skills training systems and technical resource support platforms. Issues such as the uneven universalization of urban and rural networks, as well as distinct disparities in network speed, stability, and digital teaching resources across different regions, are prevalent. Consequently, the primary contradiction of the educational digital divide has shifted toward a literacy divide (Liu & Dai, 2025). This results in the improvement rate of teachers' digital literacy failing to match the pace of technological development, further restricting the balanced regional development of innovation and entrepreneurship education quality. Therefore, constructing a teacher digital literacy support system that aligns with the actual needs of local universities has become a critical path for promoting the high-quality popularization of LLM-KG technology in innovation and entrepreneurship education.

4.3. Institutional Lag

In the educational application of LLM-KG technology, the absence of data security and privacy protection mechanisms has become a key factor constraining its large-scale implementation. In innovation and entrepreneurship education, core data submitted by students—such as business plans, technical proposals, and market analyses—constitute highly sensitive commercial information. A leak could not only lead to intellectual property risks but also damage the market competitiveness of student entrepreneurial projects. However, current institutions and regulations exhibit a delay in this regard. On one hand, there is a lack of a refined classification standard system for innovation and entrepreneurship education data, making it difficult to distinguish the protection levels required for general learning data versus commercially sensitive data. On the other hand, existing privacy protection regulations fail to fully consider the specificities of data flow in educational scenarios, leading to compliance risks in links such as knowledge graph construction and model training. Therefore, universities need to start from multiple aspects, including classified management of data resources, institutional improvement, technological innovation, implementation of responsibilities, and security education, to build a comprehensive data security protection system (Wang et al., 2021; Liu, 2021). Constructing a data security governance framework that fits the characteristics of innovation and entrepreneurship education has become an urgent task for promoting the standardized application of LLM-KG technology in the field of higher education.

5. Improvement Measures

To address the constraints and challenges of applying LLM-KG in university innovation and entrepreneurship education, a systematic solution can be developed from the following dimensions.

5.1. Reducing Model Hallucination through RLHF and Collaborative Review

Reinforcement Learning from Human Feedback (RLHF) refers to optimizing a model's learning and decision-making process through interaction with and feedback from human experts (Bai et al., 2022). This method enables the large model to continuously learn and correct its knowledge generation biases by building a "human feedback-model optimization" closed-loop mechanism. RLHF combines reinforcement learning with high-quality manually annotated data to optimize the model's behavioral strategy. By integrating the training effects of three stages—supervised fine-tuning models, reward model training, and reinforcement learning fine-tuning models—it aligns the large language model's output more closely with human preferences and expectations (Hu, 2024). specifically, the system first collects preferences from teachers and industry experts regarding model-generated content to form a dataset; subsequently, it trains a model to quantify and evaluate the content's accuracy, pedagogical applicability, and industry currency; finally, it uses reinforcement learning algorithms (such as PPO) to iteratively optimize the model, ensuring the output meets practical needs. Simultaneously, a "human-machine collaborative audit" mechanism is introduced to combine expert review with automated verification: knowledge relationships generated by the large model are first screened via preset industry standards, followed by manual verification by education experts, forming a two-tier audit process of "machine preliminary screening + expert review". This mechanism not only reduces the rate of factual errors in the knowledge graph but also keeps the content synchronized with the latest developments in innovation and entrepreneurship education through continuous feedback loops, providing a more reliable knowledge support system for universities.

5.2. Enhancing Teachers' Digital Literacy

Between 2024 and 2025, the Ministry of Education (MoE) issued a series of key policies aimed at building a teacher support system centered on digital competency development. In 2024, the official National Standards for Teachers' Digital Literacy were released, refining digital literacy into multiple dimensions and embedding them into teacher qualification certification and professional title evaluations, thus ensuring institutionalized and continuous capacity enhancement.

The "AI-Empowered Education Action Plan", launched in early 2024, focuses on the practical promotion of intelligent teaching assistants and discipline-specific AI tools. Concurrently, the National Smart Education Platform continues to optimize resource supply by integrating emerging tools such as subject-specific knowledge graphs to support precision teaching.

Local education authorities should proactively implement MoE directives by establishing regional teacher digital competency certification centers within the national platform framework and by developing LLM-KG based application courses tailored to local innovation and entrepreneurship education contexts. Initiatives such as organizing faculty exchange programs, where educators from developed regions conduct demonstration teaching in local universities and setting up LLM-KG Innovation Labs can provide teachers with authentic, hands-on environments for digital pedagogy practice. These measures collectively foster balanced regional development in digital education capacity.

5.3. Institutional Modernization

To provide more robust institutional safeguards for the application of LLM-KG in higher education innovation and entrepreneurship programs, policies should be established to regulate the construction, application, and management of educational knowledge graphs. These should define technical standards and operational requirements for data collection, knowledge modeling, and instructional integration.

In terms of data security, a three-tier desensitization mechanism can be implemented:

Primary desensitization removes direct identifiers from business plans and related materials; Intermediate desensitization blurs key commercial data; Advanced desensitization generates simulated datasets for teaching purposes. Each desensitization level should have clearly defined application contexts, user permissions, and validity periods. Additionally, a Higher Education Innovation and Entrepreneurship Data Security Evaluation Index System should be established to incorporate data compliance into teachers' digital literacy assessment. This will promote the standardized, secure, and sustainable adoption of LLM-KG technologies in educational contexts.

6. Conclusion

The Large Model-augmented Knowledge Graph (LLM-KG) provides precise, intelligent, and dynamic technical support for innovation and entrepreneurship education in higher education institutions, demonstrating significant advantages in areas such as curriculum co-creation and resource synergy. However, constrained by regional economic development levels and inherent technical limitations, its application in entrepreneurship education still faces limitations regarding data hallucinations, the digital divide, and institutional lag. Future efforts should focus on strengthening collaborative audit mechanisms, improving digital literacy training systems, and perfecting data security and institutional regulations. By promoting the deep integration of technology, education, and policy, and constructing a synergistic development path of "Technology-Talent-Institution", we can fully unleash the potential of LLM-KG in cultivating innovative talent and facilitate the high-quality development of innovation and entrepreneurship education in domestic universities.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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