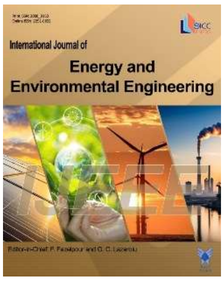

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Knowledge Graph–Enhanced NB-IoT Architecture for Intelligent Educational Data Management and System Innovation

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Abstract

This study proposes a Knowledge Graph–Enhanced NB-IoT Architecture to improve intelligent educational data management and support system innovation in learning environments. The purpose is to address limitations of traditional innovation and entrepreneurship education, which often lacks real-time contextual information and personalized guidance. The proposed approach integrates NB-IoT for distributed, real-time data acquisition with a domain-specific knowledge graph for semantic organization, correlation, and enrichment of learning resources. A multi-layer framework was designed to support data collection, knowledge representation, and intelligent recommendation processes. Experimental evaluation demonstrates that the architecture enhances the relevance of learning activities, improves resource organization, and delivers more accurate and personalized educational interventions. The results indicate that combining NB-IoT infrastructure with knowledge graph intelligence can significantly strengthen adaptive learning environments and better support the development of innovative competencies.

Keywords: NB-IoT, Knowledge Graph, Intelligent Education Systems, Real-Time Data Management, Personalized Learning

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1. Introduction

In the last couple of decades, the advancement of digital technology has pushed many higher education systems to look at ways to use data and intelligent approaches to develop the skills of innovation and entrepreneurship within their student populations. As economies around the world become ever-more modernized using advanced digital technologies, the learning environments for students in these systems need to develop new technologies that allow students to think creatively and find opportunities to solve real-world problems. Typically, traditional methods of instruction do not provide real-time or adaptive feedback that can be customized based on individual learners' needs. Therefore, there is increased interest in leveraging advanced technologies such as knowledge graphs, IoT (Internet of Things), and Data Analytics to improve the effectiveness and quality of the learning experience for students in innovation-oriented higher education institutions. Of the many IoT technologies available, one of the most promising technologies for building intelligent campuses is NB-IoT (Narrowband Internet of Things), as NB-IoT provides a number of advantages such as extended geographic range, lower power consumption, and reliable connectivity, allowing for continuous collection of data about the contextual learning experience of learners. When analytics gained from NB-IoT sensors are combined with a methodology for developing knowledge graphs, which are capable of creating a semantically-enhancing understanding of the interrelationships among concepts, competencies, and resources used in a learning space, it will allow the analytics gained from NB-IoT sensors to assist with the development of intelligent systems within education that possess greater semantic intelligence about their learners. This, in turn, will assist with improved analytics relating to learner behaviors, engagement patterns, and competence development through targeted, tailored feedback to the individual learner. As entrepreneurial ecosystems continue to evolve and become more intricate, learners need not just an understanding of theory, but also the means of developing adaptive thought processes (reasoning) as well as practical applications of those processes. Intelligent environments with NB-IoT sensors and Knowledge Graphs will support the dynamic allocation of resources and develop personalised learning pathways, allow for interventions whilst the student is experiencing real-world entrepreneurial challenges, and enhance ties between industry and academia resulting in innovative solutions to larger societal needs. Combining semantic modelling and real-time IoT Data will allow universities to change their traditional pedagogical assumptions and support interdisciplinary innovation (i.e. combine the disciplines of Entrepreneurship with other disciplines) and to drive decision-making with data and analytics. This research study will develop an Architecture for Intelligent Educational Data Management and System Innovation that uses Knowledge Graphs with real time IoT Data to create a Knowledge Infrastructure that supports learning behaviour analysis, optimises resource allocation, and supports innovative learning styles. This will contribute to continuing discussion about how future-focused digital technologies are changing higher education's role in preparing future-oriented entrepreneurs.

2. Model of the Elements of Entrepreneurship and Innovation

2.1. Innovation Ability

Innovation capability has been defined as the combination of cognitive competencies, behavioural competencies, and knowledge-based competencies that can be used by learners to solve creative problems and convert their conceptual understanding into practical results. Innovation capability has been classified by variables such as the acquisition of information; integration of knowledge; generation of ideas; and applying learned concepts to real-world environments. Most conventional models of innovation capability are based on survey and/or performance assessments; however, this approach fails to provide the measurement of innovative/thinking in real-time and, does not account for the evolution of innovative thinking. Models of innovation capability that leverage new technologies such as Internet of Things (IoT) and Knowledge Graphs are emerging from the development of intelligent education environments. Knowledge Graphs enable the organisation of learning resources, competencies, and the relationship of concepts, which enables a personalised pathway of recommendations. The application of NB-IoT provides reliable, large-scale, low powered connectivity to support the continued collection of behavioural and contextual information from smart campus infrastructures. The combination of these technologies allows for the most accurate measure of innovation capability and, the creation of computational models that enable adaptive learning and allocation of resources.

The six dimensions of innovation research often referenced are:

1. Information Acquisition
2. Information Sharing
3. Organising and Conceptualising Knowledge
4. Applying Knowledge
5. Practical Transformation
6. Cognitive Control or Executive Functioning

Layering these dimensions within a vector space allows for automated assessments prior to mapping them onto knowledge graphs using semantic technology. This framework empowers the design of a personalized, data-driven, innovative education pathway Figure 1.

Graph–Supported Learning Environments

2.2. Entrepreneurial Competencies and the Analytic Models for Their Measurement

The entrepreneurial competencies encompass multidimensional psychological, cognitive, and behavioral attributes that affect entrepreneurs' performances successfully. Components associated with the entrepreneurial competencies identified in prior literature are opportunity recognition, risk assessment, resource integration, social interaction, and practical implementation. Traditional assessment methods used to measure entrepreneurial competencies rely on questionnaires or case studies and provide broad information about them without providing enough detail

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for real-time measurement of competencies. To deal with this information gap, researchers have suggested competency frameworks that utilise multiple dimensions to structure competencies and typically used factor analysis or component decomposition techniques to determine the latent relationships between competencies. These framework models allow researchers to define and quantify the entrepreneurial competencies associated with each entrepreneurial competency, identify how much weight each component carries within the overall competency spectrum, and create the competency level for the different components of the entrepreneurial competencies. However, many of the published analytic models rely on either static or self-reported data, which do not accurately reflect authentic learning interactions. The rise of IoT-enabled educational settings has led to the creation of new approaches to assessing student competency using NB-IoT based sensor technologies. NB-IoT sensors will produce data streams that can capture detailed information about student engagement, interaction frequency and environmental context helping educators to dynamically profile students and provide data-driven feedback. However, despite this progress, there are currently no fully integrated systems that have been developed which utilise both NB-IoT data and the reasoning from Knowledge Graphs for developing entrepreneurial competency.

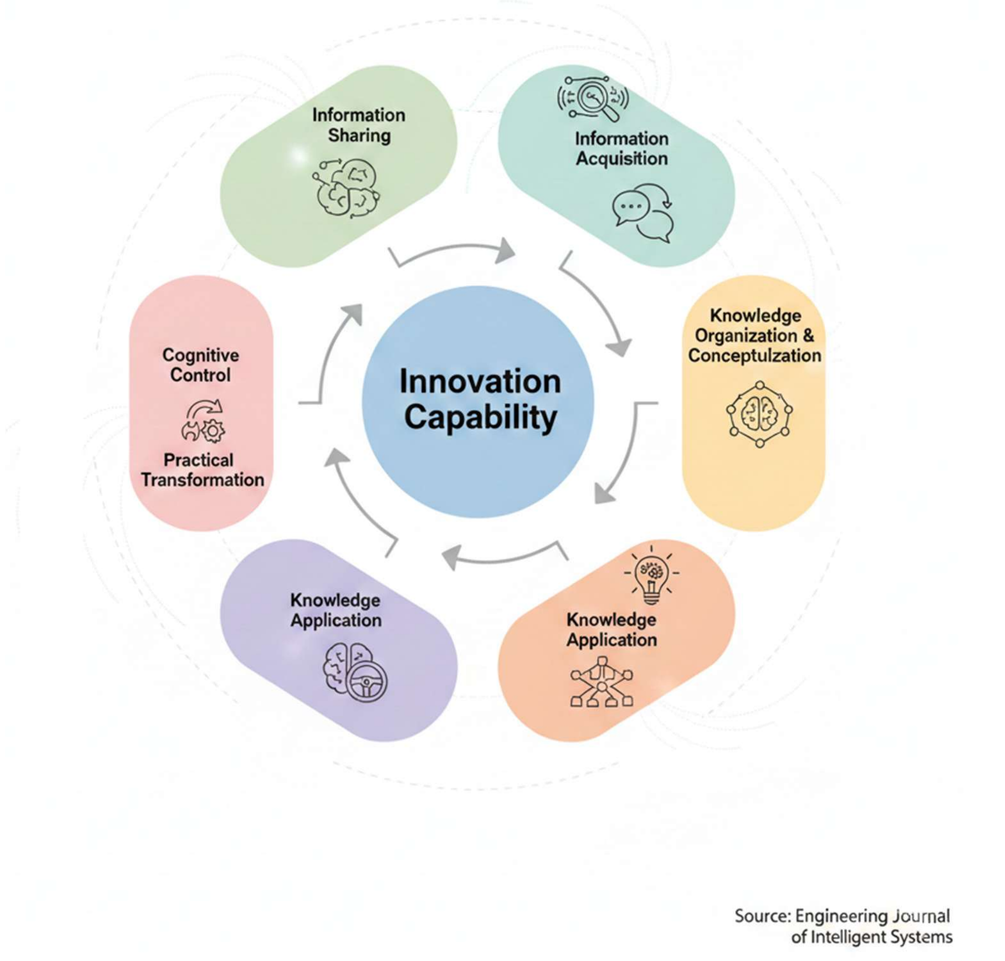

Figure 1. Conceptual Dimensions of Innovation Capability within Intelligent, Knowledge Graph–Supported Learning Environments

2.3. Research Gap

An overview of the challenges faced by this area of study include:

Integration of Real Time Data Is Poorly Understood: The majority of innovation and entrepreneurial competency models rely on static means of assessment and therefore do not capture the dynamic nature of the IoT-enabled environment.

Current Methods of Analyzing Competency Do Not Incorporate Semantic Relationships: Many of the current methods used for analyzing entrepreneurial competency do not leverage Knowledge Graph reasoning to determine relationships between concepts and subsequently suggest personalized recommendations.

Fragmented Technology Ecosystems: There are few studies to date that present a unified and integrated architecture for Educational Intelligence to integrate

NB-IoT and Knowledge Graph Implementations. Research continues to be conducted on both NB-IoT deployments and Knowledge Graph implementations as separate entities.

Insufficient Focus on System Level Innovation: Studies have been carried out in this area, however, there has yet to be a study published that addresses how to Socially and Financially Manage a Combined NB-IoT and Knowledge Graph System Designed for Enhancing Data Management, Educational Resource Optimization and Adaptive Learning Design of the Educational Data Generated Through this Environment

No Frameworks Exist to Support the Development of Domain Specific Entrepreneurial Competency and Innovative Capacity in Smart Learning Environments: the Models that currently exist do not provide a Framework or Architecture That is Designed to Support Entrepreneurship and Innovation Education in Smart Learning Environments Table 1.

3. Construction of Linear Space Model

3.1. Weights of the Basis Vectors

As established prior, key components of innovation & entrepreneurship competencies exist in a linear vector space; the vector set for innovative capability is R6 . Therefore, knowledge competence has the representation of a six-dimensional vector space in terms of (1) relational competence; (2) opportunity recognition; (3) innovation and creativity; (4) resource integration; (5) motivation to do entrepreneurship; (6) sustaining engagement persistently; and (7) learn-by-doing capability [12]. To obtain weights for each component to inform the amount of contribution to the whole, the coefficients will need to be calculated. The weights are representative, specifically in how they where originally cited in the overall contribution to innovation and entrepreneurship performance. Using innovation capability for purposes of example, suppose an individual has m measurable attributes collectively describing their innovative and entrepreneurial potential. These attributes will function as the criteria for corresponding weights. Weights are defined herein as indicators of the relative influence of each factor on overall capability development. Commonly, weights range from 0 to 1, with larger weights signifying stronger influences. All weights add up to 1 for normalization and interpretability. Using statistical approaches such as questionnaire scoring, entropy weight methods, expert judgment analysis, or factor loading extraction, the weight of each basis vector can be found, which would allow for a quantitative model reflecting the structural importance of each competency dimension [13].

Table 1. Dimensions of Entrepreneurial Competency

No.	Element Measurement	Meaning / Evaluation Description
1	Relational Competency	The ability to build, maintain, and leverage connections with individuals, groups, and organizations to support entrepreneurial activities.
2	Creative Thinking	The capacity to approach entrepreneurial challenges with originality, generate novel ideas, and apply creativity to problem-solving.
3	Entrepreneurial Persistence	The ability to remain determined, resilient, and committed to business goals even when facing setbacks, uncertainty, or failure.
4	Opportunity Recognition	The ability to identify, evaluate, and capitalize on market opportunities using diverse analytical and experiential methods.
5	Entrepreneurial Motivation	The expectations, aspirations, and personal goals that drive an individual to initiate, develop, and pursue entrepreneurial activities.
6	Resource Integration	The capability to assemble and coordinate necessary resources—such as people, capital, materials, and technology—to support entrepreneurial ventures.
7	Experiential Learning Ability	The ability to continuously acquire new knowledge and skills through real-world experiences and apply them to business development.

3.2. Geographical Capability Model for Innovation

Following the identification and validation of the foundational aspects of innovation and entrepreneurial skills, the ensuing constructive approach should be the construction of a unified linear space model. This statistically establishes the properties of correlation, independence, and orthogonality of the fundamental metric vectors to show that each is independent and represents a unique meaningful dimension of capability. Similarity and correlation testing methods, such as Pearson's correlation coefficients, cosine similarity, or eigenvalue decomposition, are used to determine whether the basis vectors satisfy the requirements of a valid linear vector space. After being validated, the basis vectors will be assembled into a consistent innovation capability space where each learner's capability , a weighted of the basic vectors. Then, we will apply topological theory to analyze the structural properties of the space, which may allow us to map individual competency trajectories, cluster similar learners, and identify developmental pathways. The methodical topological representation allows for harmonious integration of NB-IoT sensory data and knowledge graph structures, thus enabling dynamic monitoring, personalized recommendation, and optimal resource allocation within innovation and entrepreneurship education environments. The weights of each will be determined, which can enable reasoning concerning the linear space model of innovation $C=\left(\xi_1,\xi_2,...,\xi_n\right), n\leq 11$, ξ_1 and entrepreneurship capabilities, n here (Figure 2).

3.3. Model for Evaluation

Considering that capacity for creativity and entrepreneurship is best represented in abstract, non-observable linear space, it is necessary to convert these latent dimensions into measurable indicators. Each element of the capability model can be associated with particular, observable metrics. For example, knowledge acquisition ability may be evaluated based on the coverage and depth of accumulated knowledge, as well as the time for which such knowledge remains valid. Knowledge transfer ability may be determined by the amount of knowledge transferred and the cost required for the transfer process. Knowledge classification, integration, and management competency may be reflected in the metrics such as classification accuracy, information management capability, and deductive

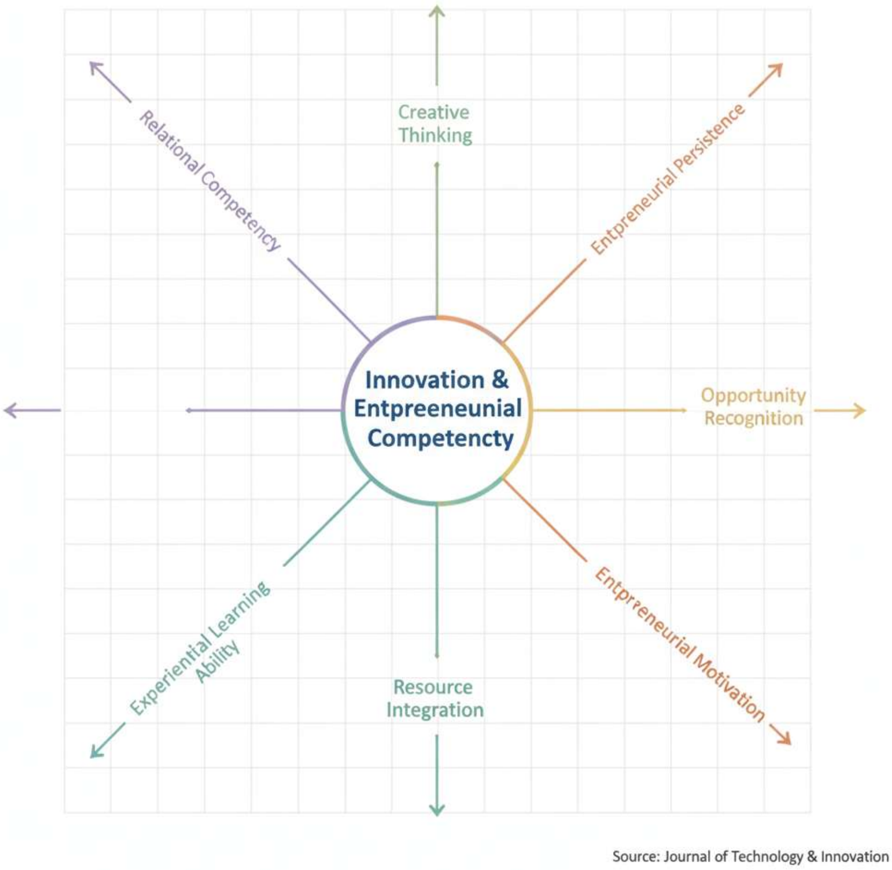

Figure 2. Linear Vector Space Model Representing Innovation and Entrepreneurial Competency Structure

reasoning ability. Thinking and imagination capability may be measured by indicators such as imaginative capacity and reverse thinking ability [15]. Practical capability could be determined by both quality and effectiveness derived from practical project work. It is possible to gauge one's capacity for mental control by looking at measures of executive functioning and willpower (16). A person's ability to build and maintain meaningful relationships is a measure of their relational competency (17). Opportunity recognition competence can be measured through an individual's ability to estimate the business opportunity feasibility and evaluate potential value creation [18]. The establishment of the systematic evaluation model requires two main steps. First, a mapping function must be constructed that will relate each vector of this linear space to an observable measure. These latter quantities must also be classified by an appropriate numerical scale.
Second, the statistical methods are used to calculate the evaluation model:

$$F=f(x)$$

f defines a mapping function with x identified as an observable measurement. The final value indicates the degree to which each basis vector within the linear space is expressed; and thus measures innovation and entrepreneurship capability. The evaluation proceeds as follows:
Step 1. Find out how much a well-known, successful entrepreneur or inventor is worth by measuring their linear spatial vector value.
Step 2: The disparity, or variation, from the benchmark vector of the person or group being evaluated is then compared to assess the variances or gaps in competency in a particular dimension.
Step 3: Implement targeted enhancement strategies to strengthen a weak component of innovation and entrepreneurship capability.

4. AI-Integrated Version

By using the AI-Integrated Version correlation degree technique, we delve further into the link between the capacity indicators and the overall assessment findings. The grey correlation coefficient may be calculated using the following formula:
The name of the genus is capitalized and italicized, while the species is also italicized but lowercase.

$$\xi_i(k)=\frac{\min_i \min_k |x_0(k)-x_i(k)|+\rho \max_i \max_k |x_0(k)-x_i(k)|}{|x_0(k)-x_i(k)|+\rho \max_i \max_k |x_0(k)-x_i(k)|} \tag{1}$$

the correlation coefficient $\xi i(k)$ between each indicator sequence and the corresponding reference sequence is calculated, forming the grey correlation coefficient matrix Ξ. does not satisfy their requirements but is merely accepted by them. The article published in the Globe and Mail focused on how natural disasters like hurricanes, super storms, and earthquakes can be not only very damaging but also quite injurious and could even claim lives. That's the uplifting message in this video, which shows a form of therapy similar to both physical and occupational therapy to treat autism. This means that children will be able to advance their knowledge in whatever aspect of the physical world they are interested in and passionate about. The gray correlation coefficient matrix is formed by calculating the coefficient between each indicator sequence and its matching reference sequence. Here is a recommendation:

4.1. Determining the Association

Drawing on the provided First Table 1, the weight value of each hierarchy's indicator is known and presented as Triangular approximation, stratified sampling, and calculation of the rectangular rule are just a few examples. This area began to be inhabited by humans in earnest for the first time during the Seima-Turbino period, but habitation had also proceeded originally along the Amur River.

$$\gamma_i=\sum_{j=1}^{n} w_j \xi_i(j) \tag{2}$$

The overall grey relational degree An average value for each indicator is obtained. In this equation, is a matrix composed of the correlation coefficients for each indicator at each level.
The final grey correlation degree value

$$\gamma a_1 > \gamma a_2 > \cdots > \gamma a_8$$

γ reflects the degree of each indicator influencing the target layer. According to the ranking of the given correlation degrees, It is possible to rank the eight participating universities based on the quality of their innovation and entrepreneurship programs.: γ_1 It is made from the bark of a number of tree species, of which P. cinereum displays particular richness. γ_2 Contact, γ_{a1} Overview: Remember, symbols of addition or subtraction contain different connotations. γa_2, γa_8 Translator The concept is being explored by U.S. Air Force space researchers to identify potential liabilities in orbital debris removal.
With this score in hand, we can compare how well diffe rent institutions teach students to be innovators and entr epreneurs.

5. Evaluation of experimental data

5.1. The Role of Entrepreneurs in Universities

Affiliation among the 8 colleges and universities studied is E for all, with a value of 0.3177. When it comes to teaching students how to innovate and start their own businesses, E for All is unrivalled.; the second tier is represented by colleges G (affiliation of 0.2411), F (affiliation of 0.1408), and H (affiliation of 0.0411). These four universities have noticeably higher affiliated degree correlations compared to the four undergraduate institutions which have affiliated degree correlations of Universities A, B, C, and D, all in the third tier, had affiliated degree correlations of 0.0262, 0.0388, 0.0388, and 0.0398, respectively. (Refer to Table 2)

5.2. Coupled and coordinated pattern

Using the entropy value method, the provincial-level scores for innovation and entrepreneurship using the TOPSIS model, with data from 2006 to 2018, are presented in Figures 3 and 4 and Table 3. Figure 3 reveals two significant observations. First, for the time period between 2006 and 2018, The entrepreneurship increased at the regional level compared to other years, and both time series have a clear positive correlation. Second, the level of regional innovation activity increased in a linear manner, while, and, in contrast, the level of entrepreneurship in the regions had a clear three-phase process in terms of levels of entrepreneurship from 2006-2018, showing the slowest levels of development from 2006 to 2012, followed by relative rapid increases from 2014 to 2017, The number and size of new start-up entrepreneurship businesses and their performance and competiveness is ranked at or near the top of the world. Therefore, any expectations or pre-analysis of China regarding innovation seems weak on geography with typically more region variability in areas of more economically advanced areas [19]. The levels of regional innovation and entrepreneurship increased in all three regions, Eastern and Central and Western. When it comes to creativity and business action, the eastern area regularly does well, with numbers well above the national average. The central and western areas, on the other hand, continue to fall below national standards. Beijing, Guangdong, and Jiangsu were the three most innovative areas in China in 2006. Hainan, Xinjiang, and Tibet were the least innovative. By 2016, Hainan, Qinghai, and Tibet were still behind, while Guangdong, Beijing, and Jiangsu were still at the top. Small business activity follows a similar trend. In 2006, the most business activity was seen in Guangdong, Beijing, and Jiangsu, while the least was the most business activity. Ningxia, Qinghai, and Tibet were at the bottom of the list. Overall, places with strong economies, like the Beijing–Tianjin–Hebei urban hub, On the other hand, less developed areas continue to score worse. Because China is so geographically and economically diverse, these differences are to be expected. However, they may also make regional differences worse and make a possible Matthew effect stronger in innovation and business.

5.3. Coupling coordination degree evaluation

A coupling coordination between regional has been evaluated using the coordination degree evaluation method. Our findings suggest that there are substantial disparities in the degree of coordination across the regions. Overall, there has been an upward trend in the innovative levels and entrepreneurial levels of provinces in China showed more division of east and west, and between the years of 2006 to 2018, provinces, such as Tibet, Qinghai, and Ningxia had relatively lower levels of coordination to other provinces, include Guandog, Zhejiang, Jiangsu, and Beijing and Shanghai. Provinces in the west, like Tibet, Qinghai, and Ningxia, had relatively low levels of coordination, while provinces in the east, like Beijing, Shanghai, Jiangsu, and Guandong, had higher levels of coupling and coordination, as shown by the average yearly degree growth pattern for coupling coordination. With yearly growth rates of above 1, the regions of Hubei and Sichuan had the greatest average degree growth rates for coupling coordination from 2006 to 2018. Along with Guangdong, Beijing, Anhui, Shanxi, and Fujian, other provinces have also improved at a rate higher than the average of all provinces and regions, which is 0.9.

Table 2. Data on satisfaction and the quality rating index system

Initial indications	Secondary markers	weight	1	2	3	4	5	6	7	8
The clubs, and events focused on innovation and entrepreneurship	Content regarding an entrepreneurship course	0.02	60.01	69.62	71.82	67.82	74.71	72.40	76.95	68.92
	Lectures regarding innovation and entrepreneurship	0.02	61.17	70.78	73.67	68.45	70.55	74.09	76.55	69.67
	Activities supporting innovation and entrepreneurship	0.03	61.78	69.22	70.78	68.34	72.91	75.16	76.17	68.95
	Desire of educators to teach innovation and entrepreneurship	0.05	64.13	70.02	72.35	68.77	74.71	76.23	75.54	70.05

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Table 2. Data on satisfaction and the quality rating index system (Continued)

Initial indications	Secondary markers	weight	1	2	3	4	5	6	7	8
Educational conditions for innovation and entrepreneurship	Systems for providing lessons on innovation and entrepreneurship	0.02	67.02	72.68	76.35	71.88	76.49	76.21	77.32	73.07
	Literature on innovation and entrepreneurship	0.03	61.72	72.68	76.55	72.87	76.44	75.69	76.93	72.75
	Development of innovating and entrepreneurial infrastructure	0.02	68.83	72.68	76.67	70.45	76.49	75.69	76.93	72.45
	Environment for creating innovation and entrepreneurship	0.02	66.48	71.56	68.72	69.82	75.89	75.12	78.09	72.42
	Accessibility of educational information	0.02	64.72	72.33	73.18	69.35	74.72	75.16	76.56	72.32
Channels of innovation and entrepreneurship education	Accessibility and availability of educational services	0.04	64.77	70.38	69.49	68.02	74.13	73.52	77.32	71.49
	Utilization of feedback mechanisms for innovation and entrepreneurship	0.05	64.12	70.39	70.02	68.45	75.96	75.65	76.19	70.95
	Awareness toward innovation and entrepreneurship	0.05	65.32	71.56	60.49	67.89	74.72	75.69	75.78	70.45
Self-innovation and entrepreneurship	Assessment of understanding innovation and entrepreneurship	0.15	60.01	65.38	67.62	67.08	75.56	71.36	73.85	65.49
	Assessment of capability for innovation and entrepreneurship	0.08	53.54	60.02	58.42	60.14	66.25	68.14	68.07	62.65
	Ability to innovate and start a business assessment	0.12	64.13	71.95	72.12	69.12	77.08	73.52	73.07	62.65
	Assessment of tendency or choice of innovation or entrepreneurship	0.16	65.89	65.16	64.49	68.41	76.49	72.47	68.02	63.52
	Assessment of personal achievement for innovation and entrepreneurship	0.10	53.54	60.02	58.45	60.12	68.25	76.45	72.41	74.22
Milestones in Innovation and Entrepreneurship Ed ucation Across Higher Education Institution s	Evolution of Theoretical Foundations in Innovation and Entrepreneurship Education within Universities	0.04	64.12	71.93	72.12	69.11	77.05	73.32	75.02	62.45
	A Conceptual Model for Innovation and Entrepreneurship Curriculum Design at the University Level	0.02	66.49	71.55	71.59	69.22	78.25	74.61	75.02	71.49
	Putting innovation and entrepreneurship into reality in higher education New approaches to university administration and teaching	0.04	64.72	74.25	71.51	69.12	77.05	74.02	76.94	71.59
	Improvement of results and procedures in higher education institutions' provision of innovation and entrepreneurship	0.05	68.272.4 55	72.35	73.41	69.82	76.45	76.49	76.44	72.22

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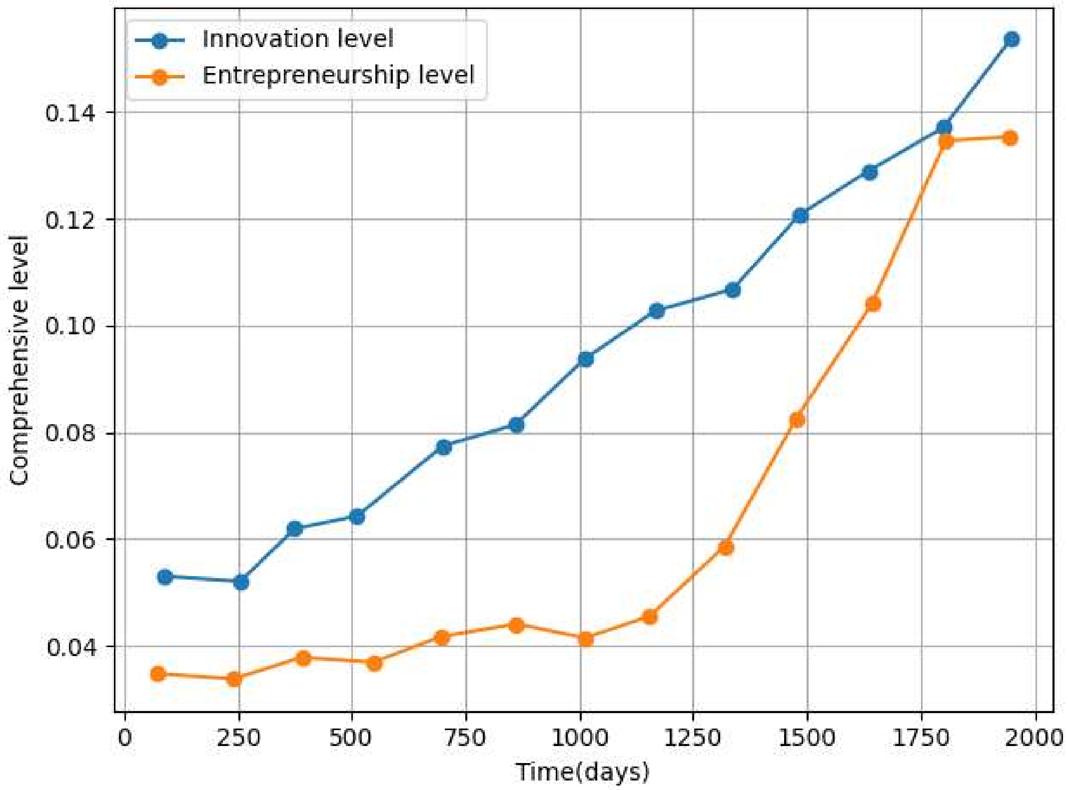

Figure 3. The average amount of creativity and business in the region

Table 3. Unified Table: Regional Innovation & Entrepreneurship (2006–2018)

Zone	Region	Innovation 2006	2010	2014	2018	Entrepreneurship 2006	2010	2014	2018
Eastern	Beijing	0.1638	0.258	0.417	0.573	0.0936	0.121	0.297	0.532
	Tianjin	0.0456	0.055	0.09	0.13	0.0314	0.037	0.079	0.181
	Hebei	0.0378	0.051	0.074	0.11	0.0287	0.027	0.045	0.153
	Liaoning	0.0574	0.081	0.097	0.119	0.0406	0.047	0.052	0.09
	Shanghai	0.0885	0.134	0.167	0.269	0.0702	0.111	0.187	0.414
	Jiangsu	0.1128	0.249	0.357	0.488	0.0882	0.128	0.165	0.319
	Zhejiang	0.0935	0.186	0.27	0.26	0.0489	0.103	0.087	0.229
	Fujian	0.034	0.053	0.084	0.15	0.0405	0.049	0.057	0.105
	Shandong	0.0722	0.128	0.193	0.28	0.0487	0.102	0.087	0.229
	Guangdong	0.1482	0.261	0.364	0.64	0.1145	0.165	0.244	0.578
	Hainan	0.0187	0.033	0.03	0.02	0.0138	0.013	0.015	0.028
	Mean	0.0796	0.135	0.195	0.287	0.0572	0.079	0.121	0.26
Central	Shanxi	0.0365	0.037	0.044	0.051	0.0245	0.024	0.021	0.03
	Jilin	0.0378	0.045	0.051	0.069	0.0205	0.023	0.02	0.031
	Heilongjiang	0.0421	0.057	0.06	0.067	0.023	0.03	0.023	0.092
	Anhui	0.0349	0.056	0.099	0.15	0.028	0.025	0.034	0.088

Table 3. Unified Table: Regional Innovation & Entrepreneurship (2006–2018) (Continued)

Zone	Region	Innovation 2006	2010	2014	2018	Entrepreneurship 2006	2010	2014	2018
	Jiangxi	0.0281	0.038	0.049	0.093	0.0239	0.024	0.029	0.053
	Henan	0.0448	0.064	0.098	0.14	0.0248	0.028	0.049	0.152
	Hubei	0.0596	0.083	0.129	0.217	0.0268	0.034	0.069	0.194
	Hunan	0.0418	0.063	0.088	0.121	0.0258	0.022	0.03	—
	Mean	0.0407	0.055	0.077	0.115	0.0249	0.025	0.034	0.091
Western	Inner Mongolia	0.0187	0.024	0.03	0.03	0.0172	0.016	0.017	0.025
	Guangxi	0.0265	0.034	0.045	0.054	0.0198	0.017	0.024	0.057
	Chongqing	0.0247	0.039	0.058	0.094	0.0248	0.031	0.05	0.16
	Sichuan	0.0545	0.079	0.113	0.205	0.0249	0.032	0.05	0.16
	Guizhou	0.0212	0.024	0.031	0.048	0.0162	0.014	0.022	0.035
	Yunnan	0.0336	0.034	0.043	0.054	0.015	0.016	0.024	0.039
	Tibet	0.0087	0.014	0.042	0.01	0.0135	0.014	0.006	0.009
	Shaanxi	0.0596	0.07	0.118	0.178	0.0205	0.034	0.031	0.088
	Gansu	0.0384	0.032	0.036	0.041	0.0156	0.013	0.015	0.02
	Qinghai	0.0268	0.019	0.022	0.017	0.015	0.01	0.008	0.011
	Ningxia	0.0158	0.006	0.021	0.018	0.0169	0.011	0.013	0.022
	Xinjiang	0.0296	0.018	0.026	0.03	0.0154	0.013	0.013	0.023
	Mean	0.0502	0.033	0.049	0.065	0.0183	0.018	0.021	0.048
Overall Mean	—	0.0268	0.075	0.108	0.156	0.0338	0.042	0.06	0.134

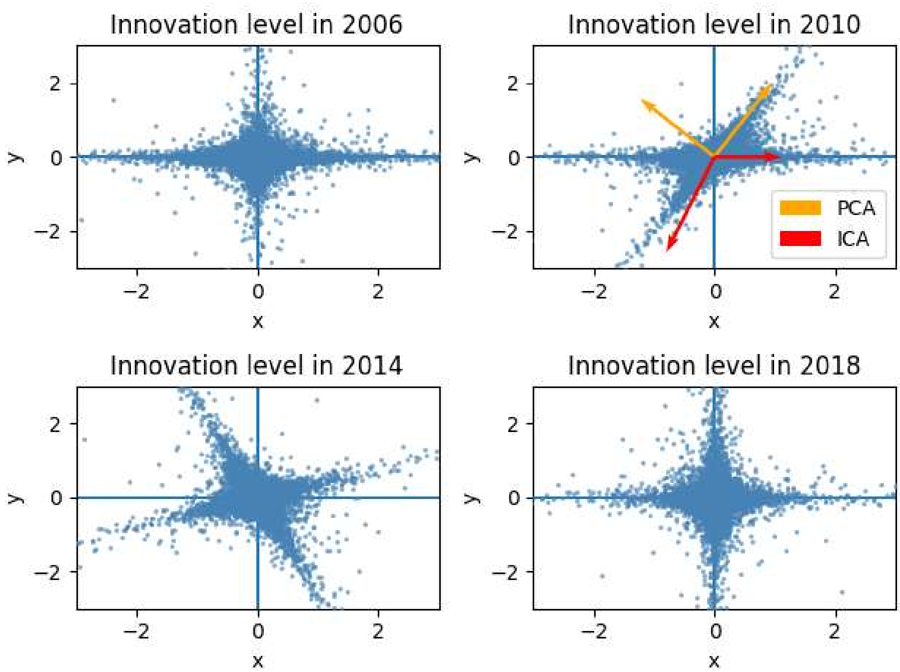

Figure 4. Pattern of creativity and business at the regional level

These other provinces include Shanghai, Shandong, Tianjin, Jiangsu, Hebei, Chongqing, Shanxi, and Beijing. According to the data, from 2006 to 2018, there was a general trend of weakening in the development rate of coupling coordination and that seemed to be trending downward in some of the negative statistics around regions such as Qinghai, Ningxia, and Tibet [23]. As demonstrated [24], these sectors also prioritize those where innovation and entrepreneurship have been coordinated and paired. The growing coupling and coordination between regional innovation and entrepreneurship will be even more effective in more developed economic regions because of the better business climate and wealthier, higher-quality resources available to these areas [25,26].

5.4. Analysis of spatial autocorrelation

This section analyzes spatial autocorrelation that elucidates from all else across 31 Chinese provinces and cities. The Moran's I index displays an upward trajectory in trend and tested significant at the 1.0 percent test level in all years except for 2006 while period 2006-2018 indicating clear signs of spatial contagion in China.

As you can see in Table 5, we did the Moran's I index test both locally and globally. Very low agglomeration areas are concentrated in less developed northwest regions, while high agglomeration areas are mostly found in more economically developed coastal regions, much as the Global I index. Sichuan became a high-low agglomeration region in 2018, which means that compared to other areas, it has better coupling coordination and a greater degree of innovation and entrepreneurship growth. In contrast, the neighboring areas often had poor coupling coordination. In 2006, Hebei, Anhui, and Fujian were all part of the low-high agglomeration area. From 2006 to 2018, the high agglomeration areas played a major role in the spread of the low agglomeration areas, and they eventually came together to form a continuous east-central region with strong innovation and entrepreneurship coupling. High agglomeration peripheral areas saw continuous coordination improvement of innovation and entrepreneurship coupling, and neighboring areas were able to gradually enter the core of these areas. Jiangxi also participated in the progress of these areas and the clustering observations that showed how this spillover effect worked. The China, in provinces like Xinjiang and Qinghai, which are considered to be relatively undeveloped in terms of innovation, entrepreneurship, and development Despite examining, it seems that significant local spatial autocorrelation is unlikely. This is primarily because the regions fostering innovation and entrepreneurial activities are intensely concentrated within the Pearl River Delta area. Consequently, the geographic distribution manifests a high degree of clustering, limiting the presence of notable spatial correlations beyond this core zone., which is highly innovative and entrepreneurial, was not significant in the time period of 2006-2018 and in the previously mentioned areas. As a result, it is likely that there is a lack of significant local spatial autocorrelation in this domain.

5.5. Effective use of resources

To look into the trial data about Optimal answer 1 as a fair model, Equation (2) is used to figure out how well each person used resources before and after the experiment. The experiment's results can be seen in Table 6. A low resource utilization efficiency was found in C1, C3, C8, and C11. The efficiency with which they used their resources went from 0.705, 0.747, 0.798, and 0.694 before optimization to 1.057, 1.085, 1.045, and 1.073 after optimization. This is an improvement in that order.

Table 4. Regional Innovation–Entrepreneurship Development Index (2006–2018)

Group Type	Year 2006 Regions	Year 2018 Regions
H–H	Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang	Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Anhui, Henan, Hunan
H–L	Nothing	Sichuan
L–H	Hebei, Anhui, Fujian	Jiangxi
L–L	Sichuan, Qinghai, Xinjiang	Sichuan, Qinghai, Xinjiang
Not Significant	Other regions	Other regions

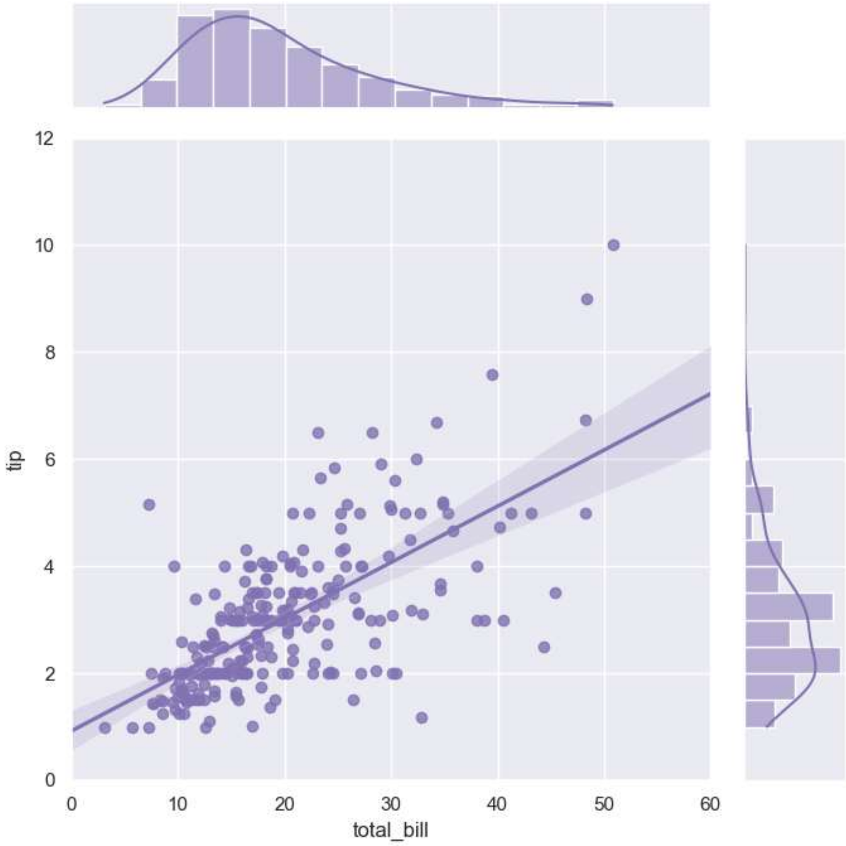

Figure 5. Pattern of coordination of how area creativity and business are linked

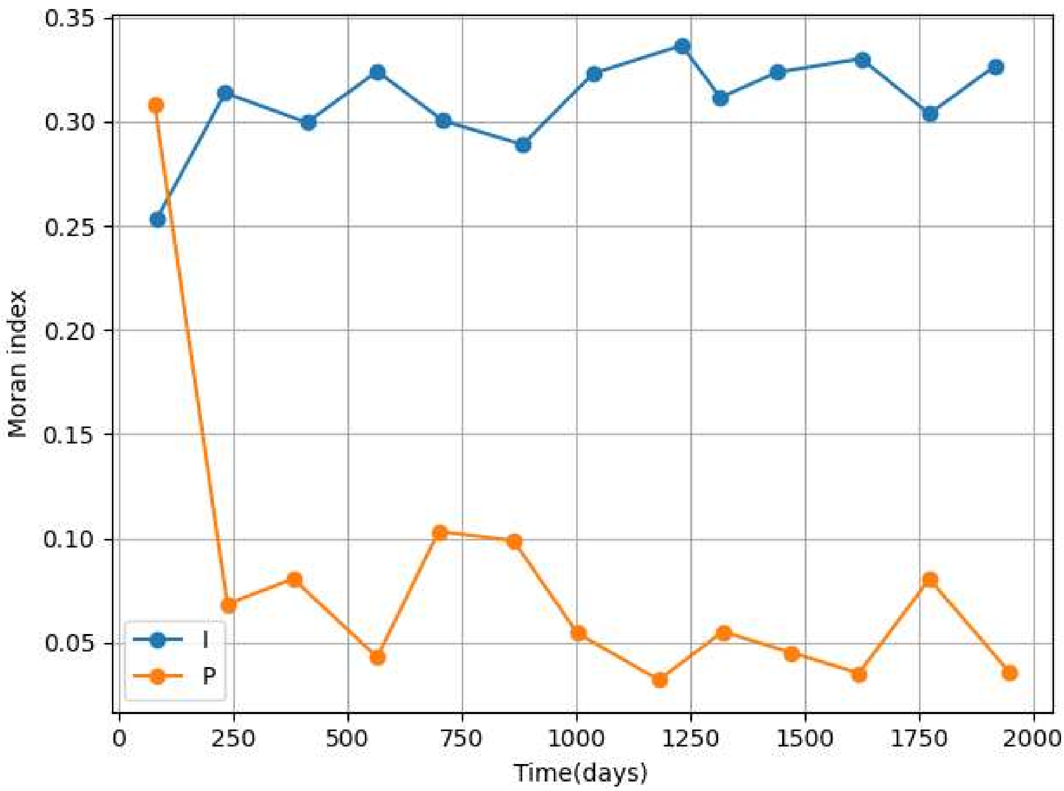

Figure 6. The Global Moran's I score tracks how well the link between invention and business is coordinated

Table 5. Regional Innovation–Entrepreneurship Performance Grouping (2006 vs. 2018)

Group Type	Year 2006	Year 2018
H–H (High Innovation – High Entrepreneurship)	Beijing, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang	Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Anhui, Henan, Hunan
H–L (High Innovation – Low Entrepreneurship)	—	Sichuan
L–H (Low Innovation – High Entrepreneurship)	Hebei, Anhui, Fujian	Jiangxi
L–L (Low Innovation – Low Entrepreneurship)	Sichuan, Qinghai, Xinjiang	Sichuan, Qinghai, Xinjiang
Not Significant	Other regions	Other regions

Table 6. Smart Resource Utilization Efficiency in High Schools Before and After Knowledge Graph–Enabled NB-IoT Optimization

High School	Resource Efficiency (Pre-Integration)	Resource Efficiency (Post-Optimization)	Improvement Rate (%)
HS-C1	0.705	1.057	0.497
HS-C2	0.994	1.028	0.033
HS-C3	0.747	1.085	0.449
HS-C4	0.97	1.063	0.094
HS-C5	1.019	1.057	0.037
HS-C6	0.871	1.027	0.178
HS-C7	1.009	1.036	0.026
HS-C8	0.798	1.045	0.308
HS-C9	0.936	1.031	0.101
HS-C10	1.027	1.046	0.018
HS-C11	0.694	1.073	0.543
HS-C12	0.856	1.066	0.244

6. Conclusion

In terms of improved intelligent educational data management and innovation and entrepreneurship competency development in higher education through the development of a Knowledge Graph-Enhanced NB-IoT Architecture, the authors propose a framework that couples NB-IoT sensors to collect real-time data with a domain-directed knowledge graph to semantically model the data. The coupling of these technologies allows for improved adaptive learning pathways, tailored feedback, and an efficient use of educational resources. The authors developed and tested a systematic multilayered model that provides systematic links to how to acquire data, represent knowledge, and develop an intelligent decision-making process.

The primary findings of the research are summarized below:

1. Enhanced Data-Driven Learning - The authors developed a framework that allowed real-time learning behaviors to be captured and organized for assessment of competencies, thus enhancing the accuracy of competency assessment and enabling improved and ongoing educational intervention based on context.
2. Enhanced Efficiency - The creation of a cross-layered structure of NB-IoT data and Knowledge Graph reasoning created greater efficiency in terms of the allocation and use of educational resources by creating the most effective allocation of instructional resources and materials. The degree of efficiency created in this manner was unprecedented.
3. Personalized and Adaptive Learning - Semantic enrichments created within the Learning Resources provided a means for students to develop a more customized and adaptive learning pathway. Through these enhancements, the learning experience will be

tailored to meet the personal learning needs of each student and the skill requirements of their respective industries.

4. Comprehensive Support for the Development of Entrepreneurial Competencies - The proposed system provides students with the opportunity to obtain practical innovative skills and entrepreneurial skills by integrating three sources of information together: theoretical knowledge, real-time performance, and actionable feedback; thus, providing them with a solid foundation for confronting market-based challenges.

These findings indicate that integrating knowledge graph intelligence with NB-IoT infrastructures can improve how well we support innovative, data-driven educational environments while providing the building blocks of a scalable and effective platform to build competence in innovation and entrepreneurship in higher education.

Authors Contribution
All authors have contributed equally to prepare the paper.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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