Research On Market Competitive Advantage Evaluation Of Innovation And Entrepreneurship Solutions Based On Multimodal Uncertainty Quantification

Jun Zheng*

International Business School, Xi'an Fanyi University,Xi'an710105,China

**Corresponding author. E-mail: 13891983646@163.com*

Received: Nov. 19, 2025; Accepted: Mar. 01, 2026

Evaluating market competitive advantage requires the effective integration of multidimensional data such as user behavior, technological evolution, and policy dynamics that are typically dispersed across platforms and characterized by uncertainty. To address these challenges, this study proposes a multimodal uncertainty-based assessment framework for innovation and entrepreneurship solutions. Grounded in a theoretical model of market competitiveness, evaluation indicators are systematically classified and screened based on principles derived from industrial cluster theory and high-tech zone competitiveness theory, enabling a structured and theoretically consistent evaluation system. Using returning migrant worker entrepreneurship as a representative case, the proposed framework evaluates the effectiveness of government support across five dimensions: administration, finance, information, financial services, and support services. To enhance robustness and discrimination among indicators, a hybrid weighting strategy is developed by integrating subjective weights obtained via the G1 method with objective weights derived from maximum deviation optimization, forming a multimodal uncertainty-based combination weighting scheme. These weights are embedded within a fuzzy comprehensive evaluation model to capture ambiguity and heterogeneity in policy effectiveness. Experimental results indicate strong administrative support, with policy documentation achieving a score of 4 ("good"), while other policy-related indicators range from 3.4 to 3.5 ("moderate"), suggesting potential for further improvement. Comparative validation demonstrates that the proposed model achieves a low mean squared error of 0.0005 , outperforming conventional SD- and EVA-based approaches and confirming its superior fitting accuracy and predictive reliability.

Keywords: Innovation and entrepreneurship plan; Competitive advantage assessment; Multimodal uncertainty quantification; G1 method subjective weighting; Maximum deviation method

http://dx.doi.org/10.6180/jase.202610_33.005

1. Introduction

Innovations and entrepreneurial research dealing with competitive advantage suffer from issues because of quick innovation progress across the globe and the digital economy. Traditional frameworks that are static in nature cannot deal with innovation speed, like OpenAI's ChatGPT, which decreases the duration of the competitive advantage. Furthermore, traditional frameworks that have linear assessment frameworks cannot handle the synergy among innovations, as shown in a MIT Sloan case study on "scientist venture capital" portfolios in biomedical sciences that had an increased value of 1.8 x over individual assessments [1, 2]. Objectives include creating an intelligent evaluation system based on spatiotemporal dynamics and a new 4D paradigm involving: balancing the technology life cycle and market window with spatiotemporal dynamics [3–5]; solving the problem of "innovative technologies but poor commercialization" in photovoltaic systems; integrating regional innovative systems and quantifying the impact premium of innovation-network location; incorporating nonmeasurable theory into the "patent pool standard essential patent anti-monopoly regulation" [6–9]; employing adversarial generative networks for decision-making among multiple agents and mitigating cognitive bias in behavioral finance [10–12].

In their research, Giakoumelou et al. [13] developed the SD models for competitive advantages and risks in innovation and entrepreneurship based on technological readiness, market adaptability, and Monte Carlo. However, despite its usefulness, the model is very specialized. In turn, Yang et al. [14] designed the innovation value framework with EVA model which included assets linked to R and D, human resource management, and Monte Carlo analysis. The framework minimizes errors of measurement for rapidly growing businesses but is subject to low-risk assessments as the cost of capital is compared against industry. Lastly, Xu et al. [15] suggested a market-oriented model which implements the concept of GRA and analyzes the business value relative to other enterprises in the industry. Liu [16] developed a novel intelligence-based approach for entrepreneurial ecosystem, relying on causal inference and deep representation learning. However, he did not address such important aspects of entrepreneurial ecosystems as innovation/entrepreneurship strategy evaluation, competitive advantage or uncertainty evaluation. Kellekci et al. [17] proposed an innovative approach to venture capital investments using fuzzy AHP and fuzzy TOPSIS, which combines subjective criteria and ranking process in order to enhance the assessment of early-stage startups in conditions of uncertainty. Puzović et al. [18] considered open innovation partners through MCDM with interval type-2 fuzzy sets, focusing on competitive advantage only. Xu and Zhang [19] adopted circular picture fuzzy waspas analysis for identifying the trends in AI-powered service innovations, disregarding innovation planning and approaches such as G1 and maximum deviation. On the other hand, Wu and Huang [20] presented a Choquet fuzzy integral SVM ensemble approach for assessing market competitiveness in innovation planning, creating a fourdimensional model involving technical obstacles, market capacity, human capital, and resource benefits.

- Main Contributions

This study makes the following primary contributions:

a) Development of a multimodal uncertainty-based evaluation framework that integrates heterogeneous indicators under uncertain and complex entrepreneurial environments.

b) Construction of a theoretically grounded competitiveness model based on regional competitiveness theory, industrial cluster theory, sustainable development theory, and entrepreneurial environment theory.

c) Proposal of a hybrid combination weighting method integrating the G1 subjective weighting method and the maximum deviation objective weighting method to enhance robustness and discrimination capability.

d) Embedding of the combined weights into a fuzzy comprehensive evaluation framework, enabling the model to capture ambiguity and non-linear interactions among policy indicators.

e) Empirical validation and comparative performance analysis demonstrating superior accuracy and lower mean squared error compared with SD and EVA models.

- Organization of the Paper

The structure of the paper is as follows: In section 2, research methodology is elaborated; it consists of theoretical basis, competitiveness assessment model, set of indicators, and the combination weights method under the condition of multimodal uncertainty using G1 criterion and maximal deviation criteria. Empirical analysis will be performed in section 3 through the case study and the comparison of the model with the method of fuzzy comprehensive evaluation.

2. Materials and methods

2.1. Theoretical Model Construction of Market Competitiveness

The market competitiveness of innovations and entrepreneurship programs refers to the ability to attract clients, create value, and compete with rivals. We consider $X = \{x_1, x_2, \ldots, x_n\}$ as the set of programs and $I = \{i_1, i_2, \ldots, i_m\}$ as the set of competitiveness indices such as technological innovation, industrial clusters, sustainability, and entrepreneurial environment, respectively. The evaluation model takes into account many economic theories; these are regional competitiveness theory, industrial cluster theory, sustainability theory, and entrepreneurial environment theory. By incorporating all these theoretical frameworks, the model assesses the impacts of the presence of local assets, clustering, sustainability, and infrastructure on competitiveness. The collective impact of all these aspects on the competitiveness of x_j can be quantified by the following equation:

$$C\left(x_j\right) = f\left(TIC_j, IC_j, SD_j, EE_j\right), \quad j = 1, 2, \ldots, n \tag{1}$$

where:

- TIC_j represents the technological innovation competitiveness,
- IC_j represents the industrial cluster competitiveness,
- SD_j represents sustainable development competitiveness,
- EE_j represents entrepreneurial environment competitiveness, and
- $f(\cdot)$ denotes a weighted aggregation function reflecting indicator contributions under uncertainty.

Government support is incorporated as a facilitating factor that enhances the above dimensions but does not dominate the evaluation, consistent with the goal of measuring intrinsic program competitiveness within regional clusters. The model provides a structured criterion layer, which guides subsequent selection and weighting of indicators for empirical evaluation.

Derived from the definition of market competitiveness of innovation and entrepreneurship solutions, this study conducts an in-depth analysis of the factors influencing the market competitiveness of entrepreneurship and innovation solutions, and constructs a theoretical model of market competitiveness of innovation and entrepreneurship solutions, as shown in Fig. 1.

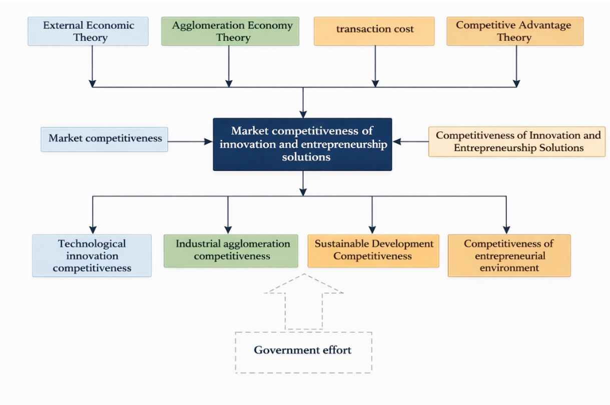

Fig. 1. Market Competitiveness Evaluation Model for Innovation and Entrepreneurship Solutions

In this Fig. 1, one can see the illustration of the support system used by the government in addition to economic theories applied which include regional competitiveness theory, industrial cluster theory, sustainable development theory, and entrepreneurial environment theory.

Market competitiveness of high-tech park is examined from various angles including technological innovation, industrial cluster, sustainable development, and entrepreneurial environment competitiveness which are dependent on the actions of the local government. Technological innovations constitute the foundation of high-tech parks due to the fact that these parks adhere to the innovation-driven strategy implemented in China. Cooperation between enterprises, universities and local government distinguishes high tech parks from industrial parks.

Innovations' competitiveness depends on regional industrial cluster because industrial cluster provides cost and dynamic competitive advantages owing to specialization, technological innovation, and diffusion of knowledge. Sustainable development plays significant role in innovation and entrepreneurship process and it is the indicator of economic development and global significance.

Despite the fact that the government functions as a supporter in Chinese high-tech parks, government involvement in the process of market competitiveness does not play a key role in it. Innovation and entrepreneurship are internal factors and do not need government intervention at all. Moreover, foreign industrial parks arise spontaneously but in China they appear due to the actions of the government.

2.2. Principles for Determining the Evaluation Index System

The selection of indicators was based on the criteria layer of the competitiveness model for innovation and entrepreneurship, which was founded on the following criteria:

1. High Frequency Criterion: The indicators were selected if they had a relatively high frequency in the literature, namely, the percentage of people possessing intermediate and advanced qualifications, R and D investment, and the share of high-technology industrial output to the whole industrial output.
2. Observability Criterion: To improve the reliability of the data, only quantitative indicators were used, which included both absolute and relative indicators.
3. Best Information Criterion: In case multiple indicators were conveying similar information, the most appropriate indicator was selected, namely, the share of local hightechnology firms out of the whole number of firms, and the ratio between R and D expenditure and gross sales.
4. Representativeness and Comprehensive Criterion: The illustrative examples of indicators are value-added by industry, incubator concentration, and industrial value-added per capita.

Table 1. Evaluation System for the Effectiveness of Government Support for Migrant Workers' Hometown Entrepreneurship

Target layer	Criterion layer	Indicator layer
The government's support for migrant workers to return home and start businesses has yielded results (B)	Administrative support effectiveness (B1)	Document issuance (B11) Policy Promotion Method (B12) Policy publicity efforts (B13) Policy support for returning to hometown entrepreneurship (B14) Policy Continuity (B15)
	Financial support effectiveness (B2)	Entrepreneurship activity subsidy (B21) Entrepreneurship Skills Subsidy (B22) Tax incentives (B23)
	Information support effectiveness (B3)	Building an Entrepreneurship Information Platform (B31) Promotion effect of entrepreneurial information (B32) Entrepreneurship Policy Consultation Quality (B33)
	Financial support effectiveness (B4)	Financing support for (B41) Small loan (B42) Provide risk compensation (B43) Entrepreneurship loan channel (B44)
	Service support effectiveness (B5)	Land support (B51) Business Environment (B52) Entrepreneurial Atmosphere (B53) Entrepreneurship Training (B54)

5. Horizontal Comparability Criterion: Examples of indicators are industrial value-added per capita and tax revenues, which were selected because they are horizontally comparable across different high-technology zones, taking into account the variation in the industrial valueadded.

2.3. Construction of the indicator system

This step becomes indispensable in evaluating the power of the market with respect to innovation and entrepreneurship and their impact on the performance measures applied in decision making with reference to more than one criterion. The former technique relies on judgment and hence can be subjective, while the latter might not be applicable in specific cases since it uses the variation in the data. Both these techniques will be used for this research, with the latter being obtained using the Maximum Deviation Method.

These indicators can be classified based on functionality, policy logic, observability, and uniqueness of attribution. Each indicator must fit in one category uniquely. For instance, "Fiscal aid" and "financial assistance" refer to two different categories. The former includes actions by the government such as subsidies and tax concessions, while the latter refers to operations within the financial system like lending and credits. Such a classification provides better coherence, as shown in Table 1.

It should be noted that fiscal support effectiveness (B2) and financial services support effectiveness (B4) are treated as distinct criterion layers. The former focuses on direct government fiscal interventions such as subsidies and tax incentives, while the latter emphasizes market-oriented financial mechanisms, including credit access, loan channels, and risk compensation. This distinction avoids conceptual overlap and enhances the logical rigor and policy interpretability of the evaluation framework.

2.4. Evaluation of Market Competitive Advantage

The assignment of weights plays an important role in assessing the competitive advantages associated with innovation and entrepreneurship, as it determines the validity of indicators used in decision making with the help of multicriteria. On one hand, subjective methods involve the use of experts' opinions, while on the other hand, their findings might be biased. Objective methods, for their part, usually come from the data's distribution; however, their application might often be questioned. In this research, both methods will be simultaneously used in order to calculate the weights [21–23].

2.4.1. *Quantitative determination of multimodal uncertainty combination weights*

- The G1 method determines the weight of indicators
  (1) First, experts determine the sequential importance relationship among the evaluation indicators using the G1 method [24, 25], forming an ordered sequence:

$$x_1 > x_2 > \cdots > x_m \tag{2}$$

(2) Experts provide a rational value of r_i for the ratio of importance between adjacent evaluation indicators x_{i-1} and x_i.

$$r_i = \frac{w_{i-1}}{w_i}, \quad r_i > 1, \quad i = 1,2,3,\ldots,m \tag{3}$$

where w_i denotes the weight of the i-th indicator.

(3) If the expert gives a rational value of r_i, then the G1 method weight of w_i for the i th indicator is:

$$w_i = \left(1 + \sum_{i=2}^{m} \prod r_i\right)^{-1} \tag{4}$$

(4) The weight calculation formula for the $m, m-1, \ldots, 3, 2$-th and 2-th indicators can be obtained from the weight w_i as follows:

$$w_{i-1} = w_i k_i, i = m, m-1, \ldots, 3, 2 \tag{5}$$

Among them, r_i signifies the rational assignment given by experts (or decision-makers); w_{i-1} is the G1 method weight of the $i-1$-th evaluation indicator, and w_k is the G1 method weight of the k-th evaluation indicator [26, 27].

Assuming w_i^Z denotes the vector composed of G1 method weights for the evaluation index, then w_i^Z is:

$$w_i^Z = (w_1, w_2, \ldots, w_m) \tag{6}$$

The fundamental characteristic of the G1 method is that it reflects the relative importance of indicators through expert ranking, assigning higher weights to more important indicators while avoiding the construction of a full pairwise comparison matrix [28, 29], thereby improving computational efficiency and consistency [30].

- Determining the weights of indicators using the maximum deviation method

The main idea behind the maximum deviation weighting method is that the indicators that show more variation among the evaluated objects should be assigned a higher weight, because they have more power to differentiate the evaluation results [31].

For a certain multi-index evaluation problem, let the standardized index value matrix be $B = \left(b_{ij}\right)_{m\times n}$, where b_{ij} is the j-th evaluation object; Scoring score for each indicator [32]. Let w_i be the weight of the i-th indicator, $w_i \geq 0$, and satisfy the unit constraint condition. For indicator i, use $F_{ij}(w)$ to represent the evaluation object; If the deviation from all other evaluation object indicator values is $(k = 1, 2, \ldots, n)$, then:

$$F_{ij}(w) = \sum_{i=1}^{m} \left|b_{ij} w_i - b_{ik} w_i\right| \tag{7}$$

Therefore, for indicator i, the total deviation between all evaluation objects and other evaluation objects can be stated as:

$$F_i(w) = \sum_{j=1}^{n} F_{ij}(w) = \sum_{j=1}^{n} \sum_{k=1}^{n} \left|b_{ij} - b_{ik}\right| w_i \tag{8}$$

Principle of maximizing deviation [33, 34], constructing an optimization model:

$$\max F(w) = \sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{n} \left|b_{ij} - b_{ik}\right| w_i \tag{9}$$

$$\text{s.t.} \left\{ \sum_{i=1}^{w_i} w_i^2 = 1 \right. \tag{10}$$

By solving this optimization model and normalizing it, the formula for maximizing the weight of deviation can be obtained:

$$w_i = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} \left|b_{ij} - b_{ik}\right|}{\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{n} \left|b_{ij} - b_{ik}\right|} \tag{11}$$

The numerator $\sum_{j=1}^{n} \sum_{k=1}^{n} \left|b_{ij} - b_{ik}\right|$ of Eq.8 represents the deviation obtained by subtracting the absolute values of the scores of the i-rd indicator from each of the n evaluated objects and then summing them up, denoted as F_i; The denominator $\sum_{i=1}^{m} \sum_{j=1}^{n} \sum_{k=1}^{n} \mid b_{ij} - b_{ik} \mid$ represents the sum of the deviations F_i of all m indicators.

- Determination of combined weights

Set the weight set of the indicator combination $w = [w_1, w_2, \ldots, w_m]^T$ and w_i as the i rd indicator weight after combining two weighting methods. Representing w_i as a linear combination of w_i' and w_i'', i.e., w_i is:

$$w_i = \theta w_i' + (1-\theta) w_i'' \tag{12}$$

Among them, w_i' signifies the G1 weight of the i-rd indicator; $(1-\theta)$ denotes the proportion of objective preference coefficients to the combined weight; θ signifies the proportion of subjective preference coefficient weight to the combination weight; w_i'' denotes the maximum deviation weight for the i-th indicator [33, 35, 36].

In order to widen the spread of multi-attribute comprehensive evaluation values among evaluation objects to the greatest extent possible, an objective function $J(W)$ is created for the purpose of maximizing the total sum of squared differences between each evaluation object i and all other evaluation objects.

$$J(W) = \sum_{j=1}^{n} k_j(W) = \sum_{i=1}^{m} \sum_{k=1}^{n} \left[\sum_{j=1}^{n} \left(b_{ij} - b_{ik}\right) w_i \right]^2 \tag{13}$$

Table 2. Expert Information Table

Individual variable	Category	Sample size
Gender	Male	13
	Female	7
Educational level	Undergraduate	15
	Master	2
	Doctor	3
Career	Civil servant	17
	Experts and scholars	3
Position	Leader	8
	Non leadership	12
Years of employment	1-5 years	5
	5-10 years	9
	Over 10 years	6

Here, b_{ij} signifies the score that the j-th evaluation object got on the i-th indicator, while $K_j(W)$ denotes the total of squared differences between the comprehensive evaluation value of the j -th evaluation object and those of all other evaluation objects.

$$\mathbf{B} = \begin{bmatrix} \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{1j}-b_{1k} \\ b_{1j}-b_{1k} \end{pmatrix} & \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{1j}-b_{1k} \\ b_{1j}-b_{1k} \end{pmatrix} & \cdots \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{1j}-b_{1k} \\ b_{1j}-b_{1k} \end{pmatrix} \\ \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{2j}-b_{2k} \\ b_{1j}-b_{1k} \end{pmatrix} & \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{2j}-b_{2k} \\ b_{2j}-b_{2k} \end{pmatrix} & \cdots \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{2j}-b_{2k} \\ b_{nj}-b_{nk} \end{pmatrix} \\ \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{nj}-b_{nk} \\ b_{1j}-b_{1k} \end{pmatrix} & \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{nj}-b_{nk} \\ b_{2j}-b_{2k} \end{pmatrix} & \cdots \sum_{k=1}^{n}\sum_{j=1}^{n} \begin{pmatrix} b_{nj}-b_{nk} \\ b_{nj}-b_{nk} \end{pmatrix} \end{bmatrix} \tag{14}$$

Assuming block matrix $W* = (W', W'')$, according to matrix theory, the normalized eigenvector corresponding to the maximum eigenvalue of symmetric matrix $(W*)^T BW*$ is the optimal solution of Eq.10, which is normalized to a combination weighting coefficient of θ :

$$\theta = \frac{\sqrt{x_{11}x_{12}}}{\sqrt{x_{11}x_{12}} + \sqrt{x_{21}x_{22}}} \tag{15}$$

Here, x_{ij} is used to represent the element located at the intersection of the i th row and the j th column of the matrix $(W*)^T BW*$, which stands for the maximum of the sum of the squared deviations. This method, therefore, will enable a better distribution of multi-attribute assessment criteria, thus making a difference between the indicators. The criterion for maximizing the sum of the squared deviations can be viewed as a good solution to the disadvantages of the two other methods.

2.5. Construction of Market Competitiveness Model

If the final combination weight obtained is the same as the objective and subjective weights, it indicates that the subjective and objective perceptions of the importance of the indicator are the same. If the final combination weight obtained is different from the objective and subjective weights, then the combination weight is the weight obtained by comprehensively considering the subjective and objective information.

Assuming D_j signifies the comprehensive score of the j-th evaluation object, according to the linear weighted comprehensive evaluation formula, the market competitiveness model D_j for innovation and entrepreneurship solutions, the following is constructed:

$$D_j = \sum_{i=1}^{m} b_{ij} w_i \tag{16}$$

Among them, b_{ij} signifies the evaluation index score; w_i denotes the combined weight of the i-th evaluation indicator. Eq.13 is the competitiveness evaluation model for high-tech zones derived from combination weighting [37]. Ranking derived from the score of D_j for the evaluated high-tech zone, the ranking results indicate the strength of the market competitiveness of the evaluated innovation and entrepreneurship solutions.

2.6. Fuzzy Comprehensive Evaluation of Market Competitiveness Model

1. Determination of the Sets of Assessment and Comments: The factor set $U = \{u_1, u_2, \ldots, u_n\}$ is considered to be an indication of the impact on the object of assessment. In this case, there are (n) number of factors. The comment set $V = \{v_1, v_2, \ldots, v_m\}$ is regarded as the level of assessment. There are (m) levels of grades in the set.

2. Determination of the Weight Set: The weight set $W = \{w_1, w_2, \ldots, w_n\}$ is calculated based on the Analytic Hierarchy Process (AHP).

3. Determining the Fuzzy Evaluation Matrix: Using the fuzzy membership theory, the membership degree r

Table 3. Comprehensive weight values of each indicator factor

Criterion layer	Relative Weight	Indicator layer	Relative Weight	Comprehensive Weight
Administrative support effectiveness B1	0.434	Document B11 issued	0.388	0.168
		Policy Promotion Method B12	0.194	0.084
		Policy publicity efforts B13	0.194	0.084
		Policy support for returning to hometown entrepreneurship B14	0.128	0.056
		Policy Continuity B15	0.097	0.042
Financial support effectiveness B2	0.157	Entrepreneurship activity subsidy B21	0.103	0.016
		Entrepreneurship Skills Subsidy B22	0.245	0.038
		Tax incentives B23	0.779	0.122
Information support effectiveness B3	0.157	Building an Entrepreneurship Information Platform B31	0.103	0.016
		Promotion effect of entrepreneurial information B32	0.245	0.038
		Entrepreneurship Policy Consultation Quality B33	0.779	0.122
Financial support effectiveness B4	0.185	Financing support for B41	0.387	0.072
		Small loan B42	0.222	0.041
		Provide risk compensation B43	0.222	0.041
		Entrepreneurship loan channel B44	0.168	0.031
Service support effectiveness B5	0.067	Land support B51	0.448	0.030
		Business Environment B52	0.148	0.010
		Entrepreneurial Atmosphere B53	0.257	0.017
		Entrepreneurship Training B54	0.148	0.010

of the qualitative criteria is established based on the survey results.

The aforementioned procedure is used to evaluate the competitive advantages of innovative and entrepreneurial activities in the market environment.

3. Results and discussions

3.1. Example

The focus of this study is on the market competitive advantages of innovations and entrepreneurship with regard to the innovation of migrant workers returning to their hometowns to establish businesses. In particular, the research will evaluate the supportive function of the local administration concerning such entrepreneurship regarding *S* district of *K* city. In doing so, the paper will consider five critical support elements, including management support, financial support, information support, financial service support, and general service support. For the survey design, AHP approach was used, involving 20 experts and academics working in the sphere of labor and entrepreneurship support.

Assess the competitive market advantage conferred by innovation and entrepreneurship solutions based on the aforementioned results and data.

3.2. Experimental Result

· **Evaluate Results**

The questionnaires with 20 numbers were administered, and there was a 100 % participation of those who received the questionnaires. The indicators' values were evaluated, and weights for each support level were obtained. The experts involved in the study amounted to twenty, and they participated in the comparison process of the indicators' importance levels in order to develop judgment matrices for criterion and indicator levels. The mean values were calculated to obtain weights for each level. The weight of each factor was established by multiplying criterion and indicator weights together.

The results obtained using the rating evaluation values and corresponding fuzzy matrices are demonstrated in Table 4.

The fuzzy membership matrix of the overall evaluation object is obtained by using the fuzzy matrix of the criteria layer indicators and the weights of the indicators, as follows:

Table 4. Membership and evaluation values of each indicator

Indicator layer	Excellent	Good	General	Poor	Range	Evaluation value
Document B11 issued	0.25	0.5	0.25	0	0	4
Policy Promotion Method B12	0.15	0.45	0.2	0.2	0	3.55
Policy publicity efforts B13	0.1	0.5	0.1	0.3	0	3.4
Policy support for returning to hometown entrepreneurship B14	0.15	0.45	0.15	0.25	0	3.5
Policy Continuity B15	0.1	0.5	0.1	0.3	0	3.4
Entrepreneurship activity subsidy B21	0.2	0.5	0.2	0.1	0	3.8
Entrepreneurship Skills Subsidy B22	0.15	0.45	0.25	0.15	0	3.6
Tax incentives B23	0.1	0.25	0.3	0.2	0.15	2.95
Building an Entrepreneurship Information Platform B31	0.15	0.45	0.2	0.2	0	3.55
Promotion effect of entrepreneurial information B32	0.15	0.4	0.1	0.35	0	3.35
Entrepreneurship Policy Consultation Quality B33	0.1	0.45	0.1	0.3	0.05	3.25
Financing support for B41	0.1	0.45	0.15	0.3	0	3.35
Small loan B42	0.15	0.4	0.2	0.25	0	3.45
Provide risk compensation B43	0.05	0.25	0.1	0.2	0.4	2.35
Entrepreneurship loan channel B44	0.05	0.55	0.25	0.15	0	3.5
Land support B51	0.1	0.25	0.3	0.25	0.1	3
Business Environment B52	0.2	0.5	0.2	0.2	0	4
Entrepreneurial Atmosphere B53	0.05	0.6	0.25	0.1	0	3.6
Entrepreneurship Training B54	0.1	0.55	0.25	0.1	0	3.65

$$
\begin{aligned}
B &= W * R \\
&= \begin{bmatrix} 0.434 \\ 0.157 \\ 0.157 \\ 0.185 \\ 0.067 \end{bmatrix} * \begin{bmatrix} 0.1744 & 0.4844 & 0.1841 & 0.1581 & 0 \\ 0.12255 & 0.32475 & 0.27745 & 0.17745 & 0.0978 \\ 0.1174 & 0.43775 & 0.1103 & 0.30195 & 0.0326 \\ 0.0915 & 0.41085 & 0.16665 & 0.2412 & 0.0888 \\ 0.10205 & 0.4216 & 0.26525 & 0.1673 & 0.0448 \end{bmatrix} \\
&= \begin{bmatrix} 0.1371266 & 0.4319655 & 0.18937815 & 0.199123 & 0.0399024 \end{bmatrix}
\end{aligned} \tag{17}
$$

$$
\begin{aligned}
S &= B * A \\
&= \begin{bmatrix} 0.1744 & 0.4844 & 0.1841 & 0.1581 & 0 \\ 0.12255 & 0.32475 & 0.27745 & 0.17745 & 0.0978 \\ 0.1174 & 0.43775 & 0.1103 & 0.30195 & 0.0326 \\ 0.0915 & 0.41085 & 0.16665 & 0.2412 & 0.0888 \\ 0.10205 & 0.4216 & 0.26525 & 0.1673 & 0.0448 \end{bmatrix} \\
&\quad * \begin{bmatrix} 5 & 4 & 3 & 2 & 1 \end{bmatrix} \\
&= 3.4298
\end{aligned} \tag{18}
$$

The comprehensive calculation yields evaluation results for the market advantages of S district government's support for returning migrant worker entrepreneurship, as presented in Table 5.

As per Table 5, administrative support is described as "good" on a scale of 4, suggesting that there is a high degree of government recognition of the significance of entrepreneurship among returnees. However, the policy promotion, intensity, support, and sustainability are evaluated as being between 3.4 and 3.5, indicating that there is a moderate level of achievement in this regard. Financial support is considered "general," given the rate of achievement of entrepreneurship initiatives at 3.8 and training grants at 3.6.

Concerning information support assessment, the outcome is stated to be average with entrepreneurial information platforms at 3.55, information promotion at 3.35, and policy consultation quality at 3.25. While the construction of the platform is favorable, other factors are reported to be average, meaning that there have been achievements but much more work should be done. In terms of financial support, the assessment is different as financing support is at 3.35, small loans at 3.45, risk compensation at 2.35, and entrepreneurial loan channels at 3.5.

The assessment of the service support efficiency shows that land support has a rating of 3, while the business environment has a rating of 4. Moreover, there are ratings of 3.6 and 3.65 for entrepreneurship environment and entrepreneurship training, correspondingly. Thus, it can be stated that the degree of support offered is rather high. As for the optimization of the business environment in the S district, considerable success has been achieved despite the problem of land support that cannot be solved owing to the scarcity of land resources.

- Model evaluation performance validation

Market competitive advantage model on innovation and entrepreneurship is evaluated by comparing market competitive advantage model and cross-validation model approach. Fifteen randomly selected data out of twenty sam-

Table 5. Evaluation Results of Market Advantages of S District Government's Support for Migrant Workers to Return to their Hometowns for Entrepreneurship

Target layer	Evaluate	Criterion layer	Evaluate Results	Indicator layer	Evaluate Results
The government of the S district in K city has supported the return of migrant workers to their hometowns for entrepreneurship and achieved remarkable results	3.43	Administrative support effectiveness	3.68	Document issued	4
				Policy Promotion Method	3.55
				Policy publicity efforts	3.4
				Policy support for returning to hometown entrepreneurship	3.5
				Policy Continuity	3.4
		Financial support effectiveness	3.2	Entrepreneurship activity subsidy	3.8
				Entrepreneurship Skills Subsidy	3.6
				Tax incentives	2.95
		Information support effectiveness	3.31	Building an Entrepreneurship Information Platform	3.55
				Promotional effect of entrepreneurial information	3.35
				Entrepreneurship Policy Consultation Quality	3.25
		Financial support effectiveness	3.17	Financing support for	3.35
				Small loan	3.45
				Provide risk compensation	2.35
				Entrepreneurship loan channel	3.5
		Service support effectiveness	3.37	Land support	3
				Business Environment	4
				Entrepreneurial Atmosphere	3.6
				Entrepreneurship Training B	3.65

ple sizes are taken as training sample and testing sample respectively. SD method references [6], EVA model [7] along with their estimated results and corresponding MSE are obtained.

Table 6. SD Model Predicted Values and Mean Squared Error

Project No	Actual value	Estimate	Mean squared error
16	0.15	0.143	0.003
17	0.06	0.042	0.003
18	0.07	0.075	0.003
19	0.28	0.270	0.002
20	0.48	0.472	0.002

In comparison with the conventional models of SD and EVA, the proposed model of multimodal uncertainty provides relatively superior performance owing to its relatively low score of MSE at 0.0005 as compared to 0.0026 for the SD model and 0.0022 for the EVA model. Apart from the superior performance that can be witnessed in terms of calculations through the use of multimodal uncertainty-based model, a relatively better evaluation of various indicators can be seen due to which the gaps in areas of taxation and risk assessment are much better captured.

Table 7. EVA Model Predicted Values and Mean Squared Error

Project No	Actual value	Estimate	Mean squared error
16	0.18	0.173	0.003
17	0.05	0.045	0.002
18	0.08	0.081	0.002
19	0.28	0.281	0.002
20	0.46	0.462	0.002

Table 8. Predicted values and mean square error of the model in this article

Project No	Actual value	Estimate	Mean squared error
16	0.12	0.012	0.001
17	0.03	0.03	0
18	0.02	0.021	0.0005
19	0.18	0.17	0.001
20	0.026	0.026	0

The validation sample consists of 20 cases that have been examined by an expert. When assessing the performance of the model, MSE is far from being the only measure used. Based on the comparative analysis, it was decided that EVA and SD models, based on aggregate data and a linear relationship between their parts, could not take into consideration non-linear relationships and, thus, were insensitive to variations of the main indicators. This proposed model, apart from taking into account an expert's subjective opinion, also assesses the data dispersion.

4. Conclusions

This study proposes a multimodal uncertainty-based evaluation framework to assess the market competitive advantage of innovation and entrepreneurship solutions. By integrating subjective expert judgment through the G1 method and objective data dispersion via the maximum deviation method, a combined weighting scheme is constructed and embedded into a fuzzy comprehensive evaluation model. This approach effectively addresses the limitations of traditional static and single-weight evaluation methods in handling uncertainty, heterogeneity, and non-linear interactions among indicators. Using migrant workers' hometown entrepreneurship in the S District of K City as an empirical case, the proposed framework provides quantitative and structured insights into the effectiveness of government support. The key findings of this study can be summarized as follows:

- The overall competitiveness evaluation score is 3.43 , indicating a moderate level of government support effectiveness.
- Administrative support demonstrates the strongest performance (3.68), with policy documentation achieving a "good" level score of 4.00.
- Service support effectiveness (3.37) and information support effectiveness (3.31) show relatively favorable outcomes but still require structural optimization.
- Financial support effectiveness (3.20) and financial services support effectiveness (3.17) exhibit comparatively weaker performance.
- Tax incentives (2.95) and risk compensation mechanisms (2.35) are identified as the most critical bottlenecks limiting further improvement of the support system.

These findings reveal both the strengths and structural constraints within the current policy framework and provide evidence-based guidance for targeted policy refinement.

From the above analysis, it is evident that the proposed model is superior compared to the traditional models, which have higher mean squared errors of 0.0026 for the SD model and 0.0022 for the EVA model compared to the proposed model (0.0005). This is an indication that the model has superiority in fitting abilities, consistency, and discrimination capabilities, especially with regard to the indicators. With regards to the implementation of the model, it acts as a decision support system for governments and administrative institutions to analyze and improve their innovation and entrepreneurship systems.

Future research may expand the sample size, incorporate dynamic time-series data, and integrate intelligent learning algorithms to further enhance the adaptability, scalability, and predictive performance of the evaluation framework.

- Competing of interests: The authors declare no competing of interests.
- Authorship Contribution Statement: Jun Zheng: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.
- Data Availability: On Request
- Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.
- Author Statement: The manuscript has been read and approved by all the authors, the requirements for authorship, as stated earlier in this document, have been met, and each author believes that the manuscript represents honest work.
- Ethical approval: All authors have been personally and actively involved in substantial work leading to the paper, and will take public responsibility for its content.
- Declaration of generative AI: During the preparation of this work the authors used Chat GPT, version 4 in order to language editing and improving readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

References

[1] J. Shi and X. Zhao, (2023) *"Anti-leakage method of network sensitive information data based on homomorphic encryption"* **Journal of Intelligent Systems** ***32***(1): 20220281. DOI: 10.1515/jisys-2022-0281.

[2] S. Kurma, T. A. Lestari, K. Singh, A. Paul, and S. Mumtaz, (2024) *"Active RIS in digital twin-based URLLC IoT networks: Fully-connected versus sub-connected?"* **IEEE Transactions on Wireless Communications** ***23***(9): 12354–12367. DOI: 10.1109/TWC.2024.3391663.

[3] T. J. Silverman, M. G. Deceglie, I. Repins, M. Owen-Bellini, J. J. Berry, J. S. Stein, and L. T. Schelhas, (2025) *"Durability research is pivotal for perovskite photovoltaics"* **Nature Energy** ***10***(8): 934–940. DOI: 10.1038/s41560-025-01786-w.

[4] H. Shi, T. Li, F. Yang, and L. Qiao, (2024) *"Modeling Uncertainties Associated with Single-Valued Neutrosophic Multi-Attribute Decision-Making for Performance Evaluation of Risk Investment in Small and Medium-Sized High-Technology Venture Enterprises"* **Neutrosophic Sets and Systems** ***75***(1): 17.

[5] V. Tatar, (2025) *"Evaluation of Barriers to Digital Transformation in Maritime Logistics Based on A Spherical Fuzzy Multi-Criteria Decision-Making Framework"* **Verimlilik Dergisi** (PRODUCTIVITY FOR LOGISTICS): 29–44. DOI: 10.51551/verimlilik.1526042.

[6] X. Xing, (2025) *"Licensing models for green technology patent pools-should free licences, FRAND licences, or compulsory licences be used?"*:

[7] M. M. Thottoli. "Technology enabled Business Plan for the course entrepreneurship creativity and innovation". In: *International Conference on Environmental, Social, and Governance (ICESG 2024)*. Atlantis Press. 2025, 292–302. DOI: 10.2991/978-2-38476-358-0_22.

[8] L. Ren and Z. Liu, (2025) *"Quality Evaluation Model of Innovation and Entrepreneurship Education Based on Fuzzy"* **International Journal of High Speed Electronics and Systems** ***34***(04): 2540265. DOI: 10.1142/S0129156425402657.

[9] M. K. Akgün and S. Soygüder, (2025) *"A hybrid decision-making framework for evaluating mHealth app quality: integrating fuzzy BWM with the weighted Heronian mean"* **International Journal of Fuzzy Systems**: 1–41. DOI: 10.1007/s40815-025-02093-y.

[10] D. Somaya and J. You, (2024) *"Scalability, venture capital availability, and unicorns: Evidence from the valuation and timing of IPOs"* **Journal of Business Venturing** ***39***(1): 106345. DOI: 10.1016/j.jbusvent.2023.106345.

[11] J. Woehler and C. Ernst, (2023) *"The importance of marketing mix planning and customer orientation for venture capital–financed startups: impacts on valuation, performance, and survival"* **Journal of Research in Marketing and Entrepreneurship** ***25***(1): 1–25. DOI: 10.1108/JRME-08-2021-0098.

[12] N. Sinha and S. Biswas, (2024) *"Social entrepreneurship and philanthropic venture capital financing"* **Business Strategy & Development** ***7***(3): e70011. DOI: 10.1002/bsd2.70011.

[13] A. Giakoumelou, A. Salvi, O. Kvasova, and I. Rizomyliotis, (2025) *"The start-up's roadmap to private equity financing: substituting discounts with a premium in valuation for growth"* **International Journal of Entrepreneurial Behavior & Research** ***31***(2-3): 479–497. DOI: 10.1108/IJEBR-02-2022-0197.

[14] Y. Yang, J.-Q. Yang, R. Bao, D.-C. Zhan, H. Zhu, X.-R. Gao, H. Xiong, and J. Yang, (2021) *"Corporate relative valuation using heterogeneous multi-modal graph neural network"* **IEEE Transactions on Knowledge and Data Engineering** ***35***(1): 211–224. DOI: 10.1109/TKDE.2021.3080293.

[15] Y. Xu, J. F. Yeung, A. P. Chan, D. W. Chan, S. Q. Wang, and Y. Ke, (2010) *"Developing a risk assessment model for PPP projects in China—A fuzzy synthetic evaluation approach"* **Automation in construction** ***19***(7): 929–943. DOI: 10.1016/j.autcon.2010.06.006.

[16] L. Liu, (2025) *"An intelligent assessment method for innovative entrepreneurial ecosystems fusing deep representation learning and causal inference"* **Journal of Computational Methods in Sciences and Engineering**: 14727978251348633. DOI: 10.1177/14727978251348633.

[17] M. Kellekci, U. Cebeci, and O. Dogan, (2025) *"Prioritizing Early-Stage Start-Up Investment Alternatives Under Uncertainty: A Venture Capital Perspective"* **Applied Sciences** ***15***(18): 10060. DOI: 10.3390/app151810060.

[18] S. Puzović, J. Vesić Vasović, D. D. Milanović, and V. Paunović, (2023) *"A hybrid fuzzy MCDM approach to open innovation partner evaluation"* **Mathematics** ***11***(14): 3168. DOI: 10.3390/math11143168.

[19] Y. Xu and D. Zhang, (2025) *"Identifying AI-driven emerging trends in service innovation and digitalized industries using the circular picture fuzzy WASPAS approach"* **Symmetry** ***17***(9): 1546. DOI: 10.3390/sym17091546.

[20] Z. Wu and N. E. Huang, (2009) *"Ensemble empirical mode decomposition: a noise-assisted data analysis method"* **Advances in adaptive data analysis** ***1***(01): 1–41. DOI: 10.1142/S1793536909000047.

[21] J. H. Yoon, Y. Y. Koo, W. Lee, and D. J. Kim, (2025) *"Fuzzy multinomial logistic regression analysis and its applications to sovereign credit ratings"* **International Journal of Fuzzy Systems**: 1–16. DOI: 10.1007/s40815-025-02013-0.

[22] A. Banal-Estañol, I. Macho-Stadler, J. Nieto-Postigo, and D. Pérez-Castrillo, (2023) *"Early individual stakeholders, first venture capital investment, and exit in the UK startup ecosystem"* **Journal of Corporate Finance** ***80***: 102420. DOI: 10.1016/j.jcorpfin.2023.102420.

[23] M. Valaei and V. Khodakarami, (2024) *"A framework for valuation and portfolio optimization of venture capital deals with contractual terms"* **Mathematical Problems in Engineering** ***2024***(1): 3427721. DOI: 10.1155/2024/3427721.

[24] M. Jin, J. Zhang, S. Cui, M. Kang, Y. Xiao, R. Xiang, and Z. Yan. "Research on comprehensive evaluation of data link based on G1 method and entropy weight method". In: *Journal of Physics: Conference Series*. ***1820***. 1. IOP Publishing. 2021, 012115. DOI: 10.1088/1742-6596/1820/1/012115.

[25] D. Yang and Y. Ma. "Application of combination weighting based on g1-mse in qfd". In: *Journal of Physics: Conference Series*. ***2037***. 1. IOP Publishing. 2021, 012050. DOI: 10.1088/1742-6596/2037/1/012050.

[26] A. Obayemi and K. A. Nguyen. "Uncertainty quantification of multimodal models". In: *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*. Springer. 2025, 272–280. DOI: 10.1007/978-981-96-8889-0_23.

[27] V. A. Knights, M. Prchkovska, L. Krašnjak, and J. G. Kljusurić, (2026) *"Uncertainty-Aware Multimodal Fusion and Bayesian Decision-Making for DSS"* **AppliedMath** ***6***(1): 16. DOI: 10.3390/appliedmath6010016.

[28] Z. Shao, H. Wang, Y. Cai, L. Chen, and Y. Li, (2025) *"UA-Fusion: Uncertainty-aware multimodal data fusion framework for 3D object detection of autonomous vehicles"* **IEEE Transactions on Instrumentation and Measurement**: DOI: 10.1109/TIM.2025.3548184.

[29] Y. Wang, Y. Lei, N. Li, K. Feng, Z. Wang, Y. Tan, and H. Li, (2025) *"Machinery multimodal uncertainty-aware RUL prediction: A stochastic modeling framework for uncertainty quantification and informed fusion"* **IEEE Internet of Things Journal**: DOI: 10.1109/JIOT.2025.3573703.

[30] C. Wang, P. Zheng, F. Zhang, Y. Qian, Y. Zhang, and Y. Zou, (2022) *"Exploring quality evaluation of innovation and entrepreneurship education in higher institutions using deep learning approach and fuzzy fault tree analysis"* **Frontiers in Psychology** ***12***: 767310. DOI: 10.3389/fpsyg.2021.767310.

[31] E. Khajavi, A. R. T. Khanghah, and A. J. Khiavi. "An efficient prediction of punching shear strength in reinforced concrete slabs through boosting methods and metaheuristic algorithms". In: *Structures*. ***74***. Elsevier. 2025, 108519. DOI: 10.1016/j.istruc.2025.108519.

[32] D. Wang, X. An, X. Zhou, and X. Lü, (2019) *"Data cache optimization model based on cyclic genetic ant colony algorithm in edge computing environment"* **International Journal of Distributed Sensor Networks** ***15***(8): 1550147719867864. DOI: 10.1177/1550147719867864.

[33] X. Zhao and X. Wang, (2022) *"The influence of college entrepreneurship education system on the cultivation of applied innovative talents"* **Frontiers in Psychology** ***13***: 844234. DOI: 10.3389/fpsyg.2022.844234.

[34] B. Naeim, A. Javadzade Khiavi, E. Khajavi, A. R. Taghavi Khanghah, A. Asgari, R. Taghipour, and M. Bagheri, (2025) *"Machine learning approaches for fatigue life prediction of steel and feature importance analyses"* **Infrastructures** ***10***(11): 295. DOI: 10.3390/infrastructures10110295.

[35] Z. Yingying, W. Mei, and S. Dewen, (2023) *"Analysis of Innovation and Entrepreneurship Education in Chinese Universities"* **Kuram ve Uygulamada Egitim Bilimleri** ***23***(1): 15–27. DOI: 10.12738/jestp.2023.1.002.

[36] X. Hong and W. Xingqi, (2023) *"The Applicability of Kirkpatrick's Four-Level Evaluation Model in the Evaluation of Innovation and Entrepreneurship Education in Colleges and Universities"* **The Theory and Practice of Innovation and Enntrepreneurship** ***6***(8): 170.

[37] B. Zhang, J. Larsson, and W. Reim, (2025) *"Circular business models for construction companies: a literature review and future research directions"* **Sustainability** ***17***(10): 4688. DOI: 10.3390/su17104688.