

AI-Driven Neutrosophic Cosine Similarity Framework for Evaluating University Students' Innovation Ability Management

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Abstract: The quick development of artificial intelligence (AI) opens new possibilities for enhancing the assessment and administration of college students' capacity for creativity. The objectivity and comprehensiveness of traditional evaluation methods are limited by their frequent reliance on subjective assessments and disjointed indications. This study integrates data-driven analytics, intelligent decision support, and multi-criteria assessment to present an AI-driven framework for evaluating university students' effectiveness in managing their innovative abilities. Creativity, problem-solving abilities, technology use, collaboration, entrepreneurial spirit, and flexibility are important evaluating factors. This study proposes a neutrosophic methodology to deal with uncertainty information. We compare the proposed results by other functions. Multidimensional student data is gathered, processed, and analyzed using AI techniques including machine learning, data mining, and natural language processing, guaranteeing accuracy and equity in the evaluation procedure. The results show that AI-based evaluation improves transparency, lessens bias, and makes it possible to track students' innovation progress in real time. To create an atmosphere that methodically develops innovative ability in higher education, the framework also helps teachers recognize their strengths, shortcomings, and developmental paths.

Keywords: Cosine Similarity Measures; Neutrosophic Sets; University Students' Innovation; Artificial Intelligence.

1. Introduction and Literature Review

Performance Evaluation of University Students' Innovation Ability Management involves a lot of imprecise, unclear, and inconsistent information, which is crucial knowledge. The relationship between Performance Evaluation of University Students' Innovation Ability Management is characterized by the fact that symptoms typically imply a great deal of unreliable, unclear, and contradictory information. To make the right evaluation decisions, we must deal with the ambiguities and contradictions. Experts base their decisions on how well the unknown sample matches the fundamental patterns.

Each element may have distinct truth-membership, indeterminacy-membership, and falsity-membership functions in certain real-world scenarios. Thus, the idea of a neutrosophic set was first put out by Smarandache [1] from a philosophical perspective. A truth-membership function $TA(x)$, an indeterminacy-membership function $IA(x)$, and a falsity-membership function $FA(x)$ separately characterize a neutrosophic set A in a universal set X .

However, the non-standard unit interval $[-0, 1+]$ is the domain of definition and range of the functions $TA(x)$, $IA(x)$, and $FA(x)$ in a neutrosophic set A . This interval is only utilized in philosophical applications, particularly where a distinction between absolute and relative truth/falsity/indeterminacy is needed [2]. The scope of definition and range of $TA(x)$, $IA(x)$, and $FA(x)$ can be limited to the typical standard real unit interval $[0, 1]$ for convenient usage in technical applications of the neutrosophic set. A simplified neutrosophic set (SNS) is a suitable choice as it is a

simplified version of the neutrosophic set and can readily describe and handle inconsistent, ambiguous, and incomplete information in actual scientific and engineering domains. Interval neutrosophic sets (INSs) and single valued neutrosophic sets (SVNSs) are examples of SNSs [3].

The main contributions of this study are presented as follows:

- This study proposes a decision-making methodology for Performance Evaluation of University Students' Innovation Ability Management Based on Artificial Intelligence.
- This study uses the neutrosophic set to overcome uncertainty information in the decision-making process.
- This study uses the cosine similarity measure to show the final score of each alternative and select the best one.
- This study compares the proposed approach by other functions to show the effectiveness of the proposed approach.

1.1. Literature Review

Investigating artificial intelligence (AI) is essential to improving students' creativity and academic performance as it has emerged as a significant technological advancement impacting both society and education. The model and hypothesis put forward in this study are based on resource-based theory and related research [4]. After pre-research, 561 valid questionnaires were gathered from Chinese higher education institutions (HEIs) that have used AI. AI of HEIs impacts students' learning performance and integrates the current literature to create assessment tools and a formal questionnaire. Then, to analyze the supplied data samples, we built a partial least squares structural equation model (PLS-SEM) using SmartPLS 3.0.

Since it enables the creation of efficient systems that can improve academic results and prevent damage, student performance prediction is currently one of the most specialized subjects for learning settings, such as colleges and school [5]s. The use of artificial intelligence (AI) in education 4.0 can be crucial in determining new aspects of students' performance, implementing customized learning, responding to common student inquiries, utilizing learning analytics, and predictive modeling. Determining students' results is challenging, and redefining education 4.0 to acknowledge the creative and inventive clever pupils is a new problem. Hybridized Deep Neural Networks (HDNN) are therefore used in this article to forecast student success in Education 4.0.

The index weights are rather subjective, and the indications used in the current evaluation approach are not precise. To estimate the practical innovation ability of both undergraduates and graduate students, Zhang et al. [6] choose evaluation indicators. It then suggests an evaluation algorithm based on deep belief networks (DBN) and an enhanced algorithm based on graduate students' practical innovation ability model. The enhanced algorithm uses the parameter-based transfer learning approach as the evaluation metrics and data distribution of undergraduate and graduate students are quite comparable. As the initial weight of the undergraduate fine-tuning, the weight of the identical undergraduate and graduate student attributes is directly increased by the difference factor.

2. Some Basic Concepts of Simplified Neutrosophic Set

Simplified neutrosophic set is extension of neutrosophic set and is used to overcome uncertainty information in the decision-making process. This section shows some definitions of simplified neutrosophic set (SNS) [7].

Definition 1. SNS is defined as:

$$X = \{T_X(A), I_X(A), F_X(A)\}$$

$$0 \leq T_X(A) + I_X(A) + F_X(A) \leq 3$$

Definition 2. The complement of SNS is defined as:

$$X^c = (F_X(A), I_X(A), T_X(A))$$

Equality is defined as:

$$X = Y \text{ if and only if } X \subseteq Y \text{ and } Y \subseteq X$$

3. Cosine Similarity Measures of SNS

This section shows the cosine similarity measures of SNS.

Definition 3. $S: SNS(A) \times SNS(A) \rightarrow [0,1]$ is called similarity measure on SNS if:

$$\begin{aligned} 0 &\leq S(X, Y) \leq 1 \\ S(X, Y) &= 1 \text{ if and only if } X = Y \\ S(X, Y) &= S(Y, X) \\ \text{if } X &\subseteq Y \subseteq Z, \text{ then } S(X, Z) \leq S(X, Y) \text{ and } S(X, Z) \leq S(Y, Z) \end{aligned}$$

3.1. Cosine Similarity Measures of Single Valued Neutrosophic Set (SVNS)

This part shows the cosine similarity measures of SVNS.

$$M_1(X, Y) = \frac{1}{n} \sum_{j=1}^n \frac{T_X(A)T_Y(A) + I_X(A)I_Y(A) + F_X(A)F_Y(A)}{\sqrt{T_X^2(A_j) + I_X^2(A_j) + F_X^2(A_j)} \sqrt{T_Y^2(A_j) + I_Y^2(A_j) + F_Y^2(A_j)}}$$

3.2. Cosine similarity Measures of Interval Valued Neutrosophic Set (IVNS)

This part shows the cosine similarity measures of IVNS.

$$M_2(X, Y) = \frac{1}{n} \sum_{j=1}^n \frac{\left(\inf T_X(A_j) \inf T_Y(A_j) + \inf I_X(A_j) \inf I_Y(A_j) + \inf F_X(A_j) \inf F_Y(A_j) + \right.}{\sqrt{\left[\inf T_X(A_j) \right]^2 + \left[\inf I_X(A_j) \right]^2 + \left[\inf F_X(A_j) \right]^2 + \left[\sup T_X(A_j) \right]^2 + \left[\sup I_X(A_j) \right]^2 + \left[\sup F_X(A_j) \right]^2} \sqrt{\left[\inf T_Y(A_j) \right]^2 + \left[\inf I_Y(A_j) \right]^2 + \left[\inf F_Y(A_j) \right]^2 + \left[\sup T_Y(A_j) \right]^2 + \left[\sup I_Y(A_j) \right]^2 + \left[\sup F_Y(A_j) \right]^2} \left. \sup T_X(A_j) \sup T_Y(A_j) + \sup I_X(A_j) \sup I_Y(A_j) + \sup F_X(A_j) \sup F_Y(A_j) \right)}$$

3.3. Cosine Similarity Measures of SVNS

This part shows the improved cosine similarity measure SVNS.

$$\begin{aligned} M_3(X, Y) &= \frac{1}{n} \sum_{j=1}^n \cos \left[\frac{\pi([T_X(A_j) - T_Y(A_j)]V[I_X(A_j) - I_Y(A_j)]V[F_X(A_j) - F_Y(A_j)])}{2} \right] \\ M_4(X, Y) &= \frac{1}{n} \sum_{j=1}^n \cos \left[\frac{\pi([T_X(A_j) - T_Y(A_j)]V[I_X(A_j) - I_Y(A_j)]V[F_X(A_j) - F_Y(A_j)])}{6} \right] \end{aligned}$$

4. Proposed Methodology

This section shows the proposed methodology steps. Figure 1 shows the steps of the proposed methodology.

- Create the decision matrix between the criteria and alternatives.
- Combine the decision matrix to obtain single matrix.
- Apply the cosine similarity measure to obtain final score of each alternative.
- Rank the alternatives.
- Select the best one.

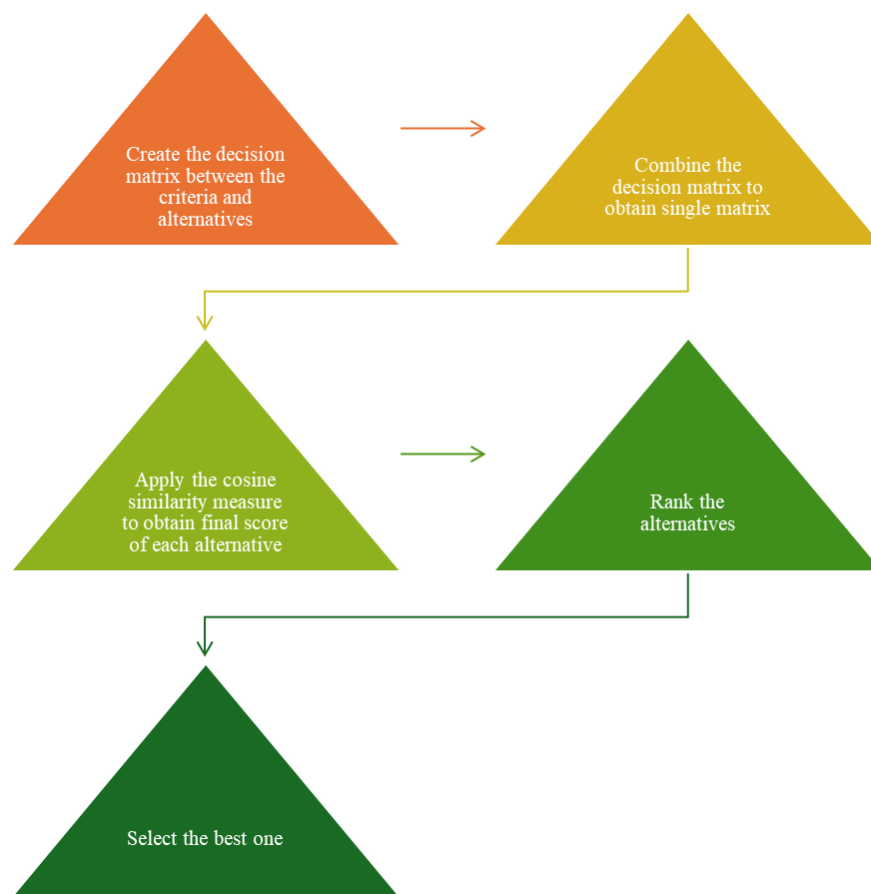


Figure 1. The flowchart.

5. Case Study

According to education 4.0, the most important metric for evaluating university students' performance is their academic achievement. It functions as the fundamental prerequisite for evaluating and selecting university students as well as for grading teaching and learning materials. Due to very competitive educational marketplaces, most institutions nowadays confront formidable obstacles when it comes to hiring new students. As a result, evaluating students' academic performance is crucial to developing the curriculum and raising the bar for education 4.0. However, several factors influence student performance in a complex way, and a student's socioeconomic background and prior academic performance may potentially have an impact on their academic success. Most recent studies only use mathematical techniques to assess and predict students' achievement in a comparatively straightforward formulation of the problem.

This study uses six criteria and eight alternatives as shown in Figure 2.

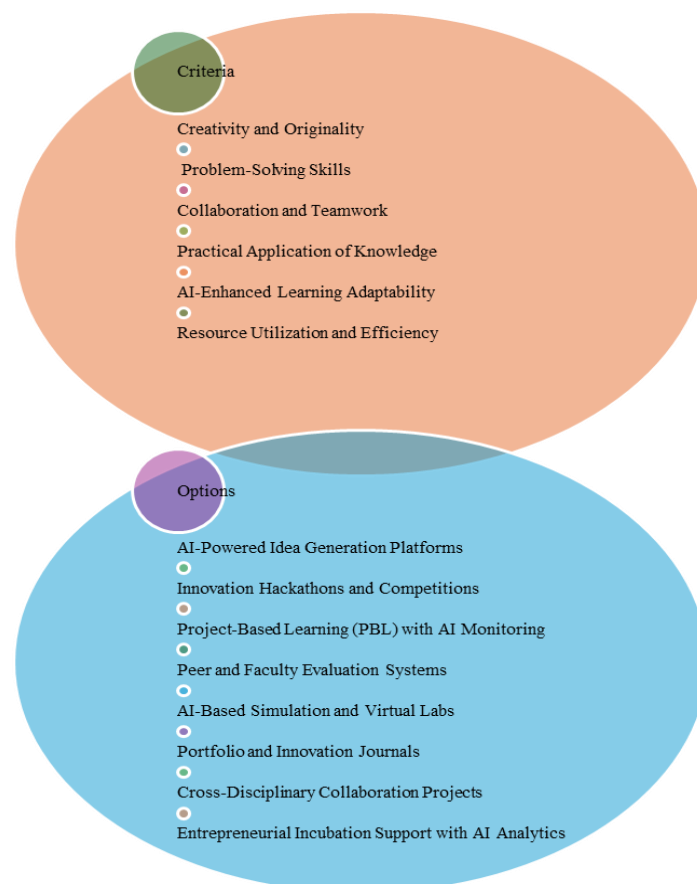


Figure 2. Options.

Create the decision matrix between the criteria and alternatives as shown in Table 1.

Table 1. Decision matrix.

	SNAC ₁	SNAC ₂	SNAC ₃	SNAC ₄	SNAC ₅	SNAC ₆
SNAA ₁	(0.4,0.6,0.0)	(0.7,0.3,0.0)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.2,0.1,0.7)
SNAA ₂	(0.4,0.6,0.0)	(0.8,0.1,0.1)	(0.2,0.1,0.7)	(0.1,0.1,0.8)	(0.1,0.2,0.7)	(0.3,0.4,0.3)
SNAA ₃	(0.7,0.3,0.0)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.2,0.1,0.7)	(0.7,0.3,0.0)
SNAA ₄	(0.1,0.2,0.7)	(0.3,0.4,0.3)	(0.7,0.3,0.0)	(0.4,0.6,0.0)	(0.8,0.1,0.1)	(0.4,0.6,0.0)
SNAA ₅	(0.1,0.1,0.8)	(0.1,0.2,0.7)	(0.3,0.4,0.3)	(0.7,0.3,0.0)	(0.4,0.6,0.0)	(0.8,0.1,0.1)
SNAA ₆	(0.1,0.1,0.8)	(0.1,0.1,0.8)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.8,0.1,0.1)	(0.2,0.1,0.7)
SNAA ₇	(0.8,0.1,0.1)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.8,0.1,0.1)	(0.4,0.6,0.0)	(0.7,0.3,0.0)
SNAA ₈	(0.4,0.6,0.0)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.2,0.1,0.7)	(0.8,0.1,0.1)	(0.3,0.4,0.3)
	SNAC ₁	SNAC ₂	SNAC ₃	SNAC ₄	SNAC ₅	SNAC ₆
SNAA ₁	(0.1,0.2,0.7)	(0.7,0.3,0.0)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.2,0.1,0.7)
SNAA ₂	(0.3,0.4,0.3)	(0.8,0.1,0.1)	(0.2,0.1,0.7)	(0.1,0.2,0.7)	(0.1,0.2,0.7)	(0.3,0.4,0.3)
SNAA ₃	(0.7,0.3,0.0)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.7,0.3,0.0)
SNAA ₄	(0.4,0.6,0.0)	(0.3,0.4,0.3)	(0.7,0.3,0.0)	(0.7,0.3,0.0)	(0.3,0.4,0.3)	(0.4,0.6,0.0)

SNAA₅	(0.8,0.1,0.1)	(0.1,0.2,0.7)	(0.3,0.4,0.3)	(0.4,0.6,0.0)	(0.7,0.3,0.0)	(0.8,0.1,0.1)
SNAA₆	(0.1,0.2,0.7)	(0.1,0.2,0.7)	(0.1,0.2,0.7)	(0.8,0.1,0.1)	(0.4,0.6,0.0)	(0.2,0.1,0.7)
SNAA₇	(0.8,0.1,0.1)	(0.3,0.4,0.3)	(0.4,0.6,0.0)	(0.1,0.1,0.8)	(0.8,0.1,0.1)	(0.1,0.1,0.8)
SNAA₈	(0.1,0.2,0.7)	(0.1,0.2,0.7)	(0.8,0.1,0.1)	(0.2,0.1,0.7)	(0.4,0.6,0.0)	(0.1,0.2,0.7)
	SNAC ₁	SNAC ₂	SNAC ₃	SNAC ₄	SNAC ₅	SNAC ₆
SNAA₁	(0.4,0.6,0.0)	(0.7,0.3,0.0)	(0.3,0.4,0.3)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.2,0.1,0.7)
SNAA₂	(0.8,0.1,0.1)	(0.8,0.1,0.1)	(0.2,0.1,0.7)	(0.1,0.1,0.8)	(0.1,0.2,0.7)	(0.3,0.4,0.3)
SNAA₃	(0.2,0.1,0.7)	(0.4,0.6,0.0)	(0.1,0.2,0.7)	(0.1,0.1,0.8)	(0.2,0.1,0.7)	(0.7,0.3,0.0)
SNAA₄	(0.1,0.1,0.8)	(0.8,0.1,0.1)	(0.4,0.6,0.0)	(0.4,0.6,0.0)	(0.4,0.6,0.0)	(0.4,0.6,0.0)
SNAA₅	(0.1,0.2,0.7)	(0.2,0.1,0.7)	(0.8,0.1,0.1)	(0.4,0.6,0.0)	(0.8,0.1,0.1)	(0.4,0.6,0.0)
SNAA₆	(0.3,0.4,0.3)	(0.1,0.1,0.8)	(0.2,0.1,0.7)	(0.8,0.1,0.1)	(0.2,0.1,0.7)	(0.8,0.1,0.1)
SNAA₇	(0.8,0.1,0.1)	(0.3,0.4,0.3)	(0.1,0.1,0.8)	(0.8,0.1,0.1)	(0.4,0.6,0.0)	(0.2,0.1,0.7)
SNAA₈	(0.4,0.6,0.0)	(0.1,0.2,0.7)	(0.1,0.2,0.7)	(0.2,0.1,0.7)	(0.7,0.3,0.0)	(0.1,0.1,0.8)

Combine the decision matrix to obtain single matrix as shown in Table 2.

Table 2. Single matrix.

	$T_X(A)$	$I_X(A)$	$F_X(A)$	$T_X(A)$	$I_X(A)$	$F_X(A)$
SNAA₁	0.4	0.2	0	0.7	0.3	0
SNAA₂	0.8	0.1	0	0.8	0.1	0.1
SNAA₃	0.7	0.1	0	0.4	0.4	0
SNAA₄	0.4	0.1	0	0.8	0.1	0.1
SNAA₅	0.8	0.1	0.1	0.2	0.1	0.7
SNAA₆	0.3	0.1	0.3	0.1	0.1	0.7
SNAA₇	0.8	0.1	0.1	0.3	0.4	0.3
SNAA₈	0.4	0.2	0	0.1	0.2	0.7
	$T_X(A)$	$I_X(A)$	$F_X(A)$	$T_X(A)$	$I_X(A)$	$F_X(A)$
SNAA₁	0.3	0.4	0.3	0.1	0.2	0.7
SNAA₂	0.2	0.1	0.7	0.1	0.1	0.7
SNAA₃	0.1	0.2	0.7	0.3	0.1	0.3
SNAA₄	0.7	0.3	0	0.7	0.3	0
SNAA₅	0.8	0.1	0.1	0.7	0.3	0
SNAA₆	0.2	0.1	0.7	0.8	0.1	0.1
SNAA₇	0.4	0.1	0	0.8	0.1	0.1
SNAA₈	0.8	0.1	0.1	0.2	0.1	0.7
	$T_X(A)$	$I_X(A)$	$F_X(A)$	$T_X(A)$	$I_X(A)$	$F_X(A)$
SNAA₁	0.1	0.1	0.8	0.2	0.1	0.7
SNAA₂	0.1	0.2	0.7	0.3	0.4	0.3
SNAA₃	0.2	0.1	0.7	0.7	0.3	0
SNAA₄	0.8	0.1	0	0.4	0.6	0
SNAA₅	0.8	0.1	0	0.8	0.1	0
SNAA₆	0.8	0.1	0	0.8	0.1	0.1
SNAA₇	0.8	0.1	0	0.7	0.1	0

SNAAs	0.8	0.1	0	0.3	0.1	0.3
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Apply the cosine similarity measure to obtain final score of each alternative as shown in Figure 3.

Rank the alternatives. Select the best one as shown in Figure 4.

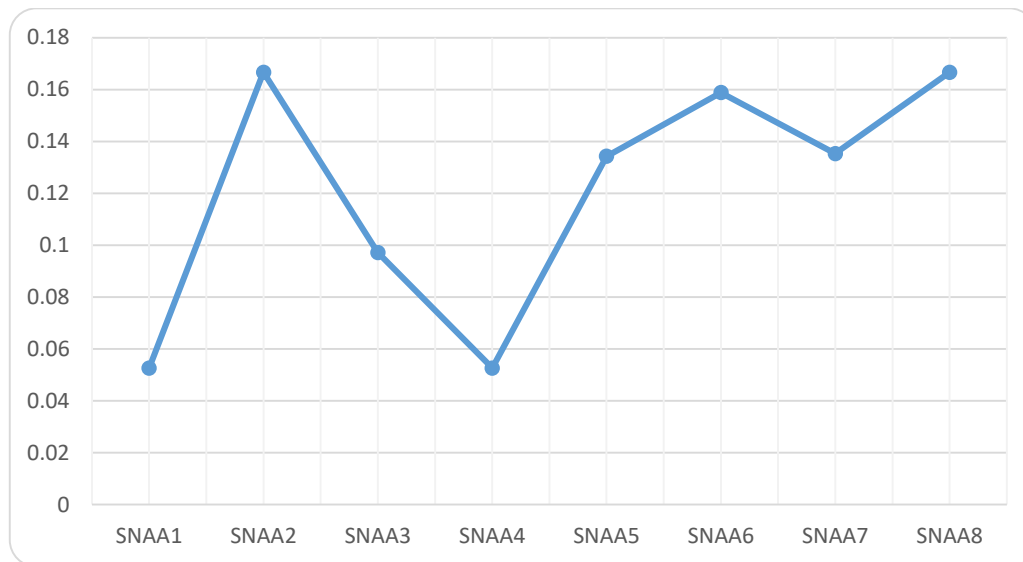


Figure 3. Cosine similarity measure.

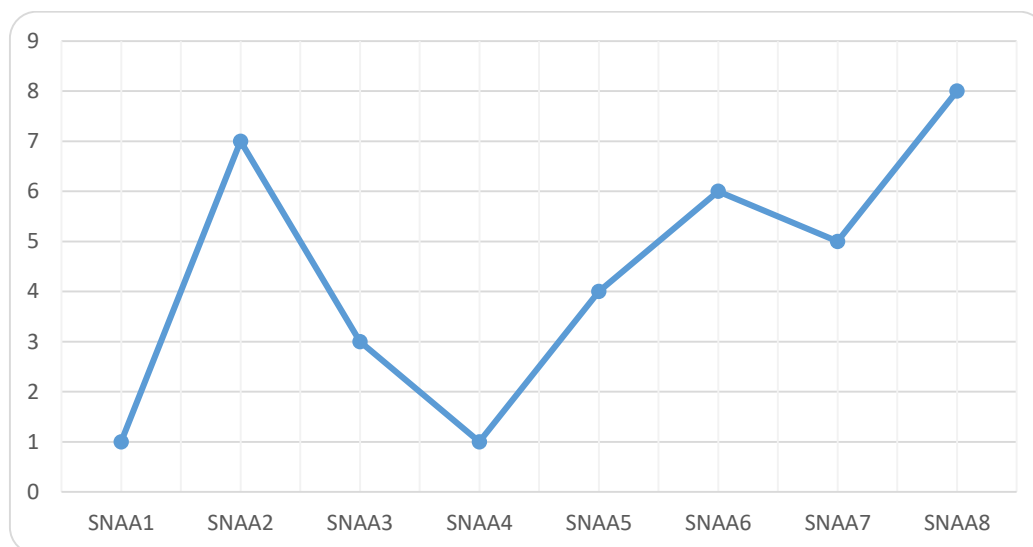


Figure 4. Rank of options.

6. Comparative Analysis

This section shows the comparative analysis between the proposed approach and other methods. This study compares the cosine similarity by the score, accuracy, and certainty function.

Figure 5 shows the results of comparative analysis. The results show the proposed approach is

effective compared to other methods.

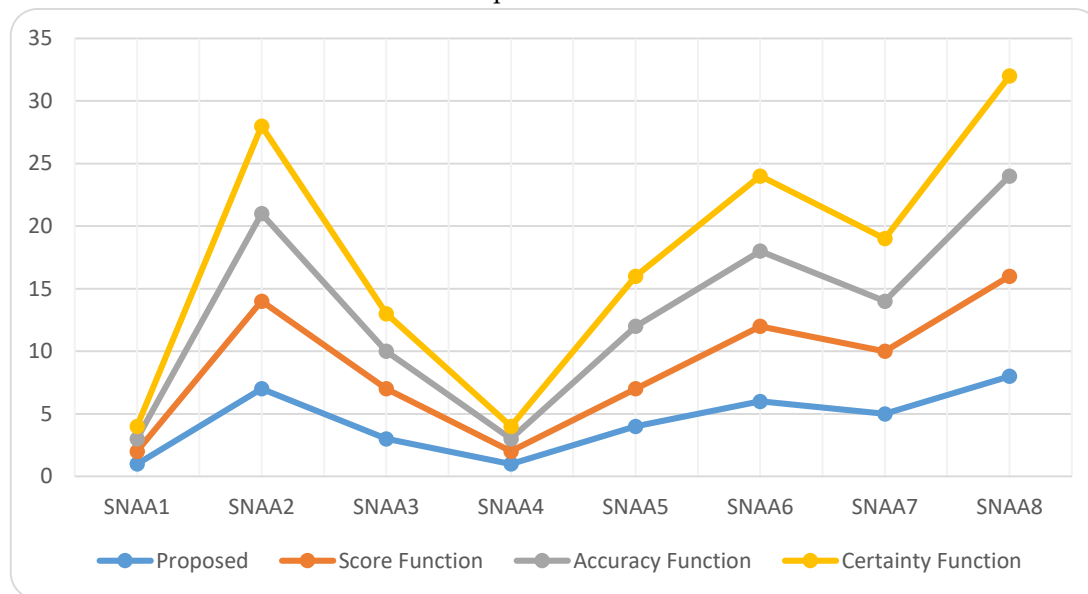


Figure 5. Comparative results.

- SNAA1 (1, 1, 1, 1) SNAA1 consistently ranks the lowest across all functions, showing minimal performance in proposed value, scoring, accuracy, and certainty. It suggests that SNAA1 lacks effectiveness and contributes little to innovation ability management.
- SNAA2 (7, 7, 7, 7) SNAA2 performs strongly and consistently across all metrics. Its uniform high ranking shows reliability, high accuracy, and strong alignment between proposed outcomes and actual results. It is one of the top-performing alternatives.
- SNAA3 (3, 4, 3, 3) SNAA3 shows mid-level performance, slightly better in the accuracy function (4) but still moderate overall. It indicates some potential but not consistent enough to be among the top.
- SNAA4 (1, 1, 1, 1) Similar to SNAA1, SNAA4 ranks at the bottom across all measures. It shows poor innovation support and limited contribution to effective evaluation, making it one of the least desirable alternatives.
- SNAA5 (4, 3, 5, 4) SNAA5 demonstrates moderate performance, with its best ranking in certainty (5). This suggests that while not top-performing, it provides some dependable outcomes, especially in terms of reliability.
- SNAA6 (6, 6, 6, 6) SNAA6 maintains consistently high performance, though not as strong as A2 or A8. It shows balanced results, making it a reliable and stable choice for evaluation and innovation support.
- SNAA7 (5, 5, 4, 5) SNAA7 is moderately strong, slightly weaker in accuracy (4), but generally stable. It indicates fair performance with room for improvement, especially in maintaining precise results.
- SNAA8 (8, 8, 8, 8) SNAA8 stands out as the best performer across all functions. With the highest scores in proposed value, accuracy, and certainty, it represents the most effective and reliable alternative for managing and evaluating innovation ability.

7. Conclusions

This study emphasizes how artificial intelligence might improve the assessment of university students' success in managing their innovative abilities. AI-driven models overcome the drawbacks of conventional methods and make evaluations more precise, transparent, and individualized by

fusing formal evaluation criteria with objective data analytics. This study used the neutrosophic set to overcome uncertainty information. This study used cosine similarity measures to show the final score of each alternative. The results are compared with other functions. The results show the proposed approach is effective compared to other functions.

The findings demonstrate how AI enables educators and educational institutions to track the evolution of creativity in real time, modify their teaching methods, and offer focused assistance to students with a range of innovative potentials. Additionally, the suggested paradigm increases productivity, lessens the bias of evaluators, and develops a scalable solution for innovation education in higher education. All things considered, using AI in this area not only maximizes student innovation management but also advances the long-term objective of fostering innovation

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

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

Competing Interests

The authors declare no competing interests in the research.

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