



# Big Data Analytics for Mental Health Education: A New Framework for University-Level Evaluation under Linguistic Confidence Interval Neutrosophic Numbers

Hong Zhu\*

Huainan Union University, Huainan, Anhui, 232001, China

\*Corresponding author, E-mail: zhuhong@hnuu.edu.cn

**Abstract:** In the contemporary educational ecosystem, mental health has emerged as a pivotal aspect of holistic student development. The integration of big data analytics offers a transformative path for evaluating the effectiveness of mental health education at universities. This study proposes a comprehensive framework that merges data-driven tools with pedagogical strategies to assess key indicators of mental health support efficacy. Ten criteria—including accessibility, awareness, analytics integration, and data ethics—are used to evaluate a diverse set of intervention alternatives ranging from AI-based detection systems to immersive VR training. By applying a structured multi-criteria decision-making (MCDM) approach, this research identifies optimal strategies that ensure privacy, responsiveness, and personalized support. The findings not only guide administrators in refining their mental health initiatives but also contribute to academic research by introducing a scalable evaluation model that can adapt across institutional contexts. We use the Linguistic Confidence Interval Neutrosophic Numbers (LCINN) to overcome uncertainty and vague information. We use the EDAS method to rank the alternatives and select the best strategies.

**Keywords:** Linguistic Confidence Interval Neutrosophic Numbers; Big Data Analytics; Mental Health Education.

---

## 1. Introduction

As universities witness rising concern over student mental health, the need for scalable, data-informed evaluation mechanisms has become urgent. Traditional qualitative assessments, while insightful, lack the robustness and precision to navigate the complexity of emotional well-being in academic environments[1], [2]. The era of big data brings forth unprecedented opportunities

for educators and administrators to track, analyze, and respond to mental health indicators in real time. With vast digital footprints left through academic platforms, social media, and behavioral analytics, it is now possible to detect patterns that signal distress or disengagement[3], [4].

However, the incorporation of big data analytics into mental health education requires a careful balance between effectiveness and ethical responsibility. Criteria such as data privacy, early warning accuracy, and student receptivity must be evaluated in harmony to avoid unintended consequences[5], [6]. This study aims to construct a dynamic evaluation framework that not only gauges the effectiveness of current interventions but also ranks them against criteria drawn from technological, pedagogical, and psychological domains. The application of MCDM methods enables the prioritization of alternatives based on both quantitative metrics and stakeholder preferences[7], [8]. From app-based trackers to AI-driven sentiment analysis and virtual simulations, modern educational environments are testing a wide spectrum of tools. Each of these carries unique advantages and potential risks, making comparative evaluation critical for decision-making.

Our proposed model highlights the importance of integrating student feedback, behavior patterns, and academic stress markers into institutional decision pipelines. Real-time monitoring tools enhance institutional responsiveness and facilitate early intervention. In doing so, the paper contributes to the evolution of university mental health systems from reactive to predictive paradigms, offering a roadmap for continuous improvement through evidence-based evaluation and technological innovation[9], [10].

A significant area of study in decision theory and methodology is linguistic decision making (LDM). Since linguistic data is ideally matched to human thought patterns and expressions in intricate decision-making situations, LDM has drawn the interest of several academics and applications. Hesitant fuzzy linguistic sets (HFLSs) were developed and used in multiple criteria (group) decision-making (MCDM) to represent various linguistic word values in a hesitant scenario[11], [12].

Then, reluctant fuzzy LDM issues were tackled using a variety of techniques, including an outranking approach. Hesitant intuitionistic fuzzy linguistic sets (HIFLSs), which are based on an extension of HFLSs, were applied to MCGDM problems. Additionally, several scholars suggested HFLS with fuzzy confidence and hesitant intuitionistic fuzzy linguistic aggregation operators for solving MCDM issues[13], [14].

The HFLS and HIFLS cannot be represented separately by true, false, and indeterminate linguistic variables because of their hesitant feature, which only contains distinct linguistic values rather than identical linguistic values. Ye et al. [15] recently proposed a linguistic neutrosophic multivalued set/element (LNMS/LNME) that may have true, false, and indeterminate linguistic term sequences (LTSs) with the same or distinct linguistic values. In the meanwhile, they established the correlation coefficients of CLNSs for the assessment of mine safety and suggested

a transformation strategy from LNMS to the consistency linguistic neutrosophic set (CLNS) to carry out the operation problem of various LTS duration in LNMS[16].

## 2. Linguistic confidence interval neutrosophic number (LCINN)

This section shows definitions of the LCINN to solve the uncertainty and vague information[17]. The score function of the LCINN is defined as:

$$S(\eta_{a(i)}) = \frac{(4r + \eta_{a_i^-} + \eta_{a_i^+} - \eta_{b_i^-} + \eta_{b_i^+} - \eta_{c_i^-} - \eta_{c_i^+})}{8r}; S(\eta_{a(i)}) \in [0,1] \quad (1)$$

$$D(\eta_{a(i)}) = \frac{(\eta_{a_i^-} + \eta_{a_i^+} - \eta_{c_i^-} - \eta_{c_i^+})}{2r}, D(\eta_{a(i)}) \in [-1,1] \quad (2)$$

$$\eta_{a(1)} > \eta_{a(2)} \text{ for } S(\eta_{a(1)}) > S(\eta_{a(2)}) \quad (3)$$

$$\eta_{a(1)} > \eta_{a(2)} \text{ for } S(\eta_{a(1)}) = S(\eta_{a(2)}) \text{ and } D(\eta_{a(1)}) > D(\eta_{a(2)}) \quad (4)$$

$$\eta_{a(1)} = \eta_{a(2)} \text{ for } S(\eta_{a(1)}) = S(\eta_{a(2)}) \text{ and } D(\eta_{a(1)}) = D(\eta_{a(2)}) \quad (5)$$

$$\eta_{a(1)} \oplus \eta_{a(2)} = \left( \begin{array}{c} \left[ \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{a_1^- \pi}{2r} \right) \cos \frac{a_2^- \pi}{2r} \right), \right. \\ \left. \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{a_1^+ \pi}{2r} \right) \cos \frac{a_2^+ \pi}{2r} \right) \right] \\ \left[ \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{b_1^- \pi}{2r} \right) \sin \frac{b_2^- \pi}{2r} \right), \right. \\ \left. \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{b_1^+ \pi}{2r} \right) \sin \frac{b_2^+ \pi}{2r} \right) \right] \\ \left[ \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{c_1^- \pi}{2r} \right) \sin \frac{c_2^- \pi}{2r} \right), \right. \\ \left. \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{c_1^+ \pi}{2r} \right) \sin \frac{c_2^+ \pi}{2r} \right) \right] \end{array} \right) \quad (6)$$

$$\eta_{a(1)} \otimes \eta_{a(2)} = \left( \begin{array}{c} \left[ \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{a_1^- \pi}{2r} \right) \sin \frac{a_2^- \pi}{2r} \right), \right. \\ \left. \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{a_1^+ \pi}{2r} \right) \sin \frac{a_2^+ \pi}{2r} \right) \right] \\ \left[ \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{b_1^- \pi}{2r} \right) \cos \frac{b_2^- \pi}{2r} \right), \right. \\ \left. \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{b_1^+ \pi}{2r} \right) \cos \frac{b_2^+ \pi}{2r} \right) \right] \\ \left[ \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{c_1^- \pi}{2r} \right) \cos \frac{c_2^- \pi}{2r} \right), \right. \\ \left. \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{c_1^+ \pi}{2r} \right) \cos \frac{c_2^+ \pi}{2r} \right) \right] \end{array} \right) \quad (7)$$

$$k\eta_{a(1)} = \begin{pmatrix} \left[ \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{a_1^- \pi}{2r} \right) \right)^k, \right. \\ \left. \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{a_1^+ \pi}{2r} \right) \right)^k \right], \\ \left[ \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{b_1^- \pi}{2r} \right) \right)^k, \right. \\ \left. \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{b_1^+ \pi}{2r} \right) \right)^k \right], \\ \left[ \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{c_1^- \pi}{2r} \right) \right)^k, \right. \\ \left. \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{c_1^+ \pi}{2r} \right) \right)^k \right] \end{pmatrix} \quad (8)$$

$$\eta_{a(1)}^k = \begin{pmatrix} \left[ \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{a_1^- \pi}{2r} \right) \right)^k, \right. \\ \left. \frac{\eta_{2r}}{\pi} \sin^{-1} \left( \sin \left( \frac{a_1^+ \pi}{2r} \right) \right)^k \right], \\ \left[ \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{b_1^- \pi}{2r} \right) \right)^k, \right. \\ \left. \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{b_1^+ \pi}{2r} \right) \right)^k \right], \\ \left[ \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{c_1^- \pi}{2r} \right) \right)^k, \right. \\ \left. \frac{\eta_{2r}}{\pi} \cos^{-1} \left( \cos \left( \frac{c_1^+ \pi}{2r} \right) \right)^k \right] \end{pmatrix} \quad (9)$$

We show the steps of the EDAS method to rank the alternatives. We build the decision matrix using LCINN. The LCINN is converted to crisp values and combined to a single matrix. After that, we obtain the weights of criteria by the average method.

Attain the average solution

$$V_j = \frac{\sum_{i=1}^m x_{ij}}{m}; i = 1, \dots, m; j = 1, \dots, n \quad (10)$$

Attain the distances from the  $V_j$  values for positive and cost criteria.

$$PV_{ij} = \frac{\max(0, (x_{ij} - V_j))}{V_j} \quad (11)$$

$$NV_{ij} = \frac{\max(0, (V_j - x_{ij}))}{V_j} \quad (12)$$

$$PV_{ij} = \frac{\max(0, (V_j - x_{ij}))}{V_j} \quad (13)$$

$$NV_{ij} = \frac{\max(0, (x_{ij} - V_j))}{V_j} \quad (14)$$

Compute the weighted  $PV_{ij}$  and  $NV_{ij}$

$$SPV_{ij} = \sum_{j=1}^n PV_{ij} w_j \quad (15)$$

$$SNV_{ij} = \sum_{j=1}^n NV_{ij} w_j \quad (16)$$

Compute the weighted normalized  $PV_{ij}$  and  $NV_{ij}$

$$NSPV_{ij} = \frac{SPV_{ij}}{\max(SPV_{ij})} \quad (17)$$

$$NSNV_{ij} = \frac{SNV_{ij}}{\max(SNV_{ij})} \quad (18)$$

Compute the appraisal score

$$A_i = \frac{NSNV_{ij} + NSPV_{ij}}{2} \quad (19)$$

Rank the alternatives.

### 3. Results

This section shows the steps of the proposed approach. This study uses ten criteria and eight alternatives. Ten criteria are: Student Awareness of Mental Health, Accessibility of Counseling Services, Integration of Big Data Tools, Early Warning and Prediction Accuracy, Student Satisfaction with Programs, Training Level of Mental Health Educators, Privacy Protection and Data Ethics, Emotional and Behavioral Analytics, Adaptability of Educational Content, Real-time Monitoring and Feedback System. Eight alternatives are: Traditional Lecture-Based Mental Health Programs, Peer-Support and Counseling Integration, App-Based Mental Health Tracking Tools, AI-Driven Early Detection Systems, Social Media Sentiment Analysis Framework, Hybrid Online-Offline Support Platforms, Biometric Data Monitoring for Stress Detection, Virtual Reality-Based Mindfulness Training.

Three experts use LCINN to evaluate the criteria and alternatives as shown in Tables 1-3. We convert the LCINN to crisp values using score function. These values are combined into a single matrix as shown in Fig 1. We obtain the criteria weights as in Fig 2.

Table 1. The first LCINN.

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	C <sub>9</sub>	C <sub>10</sub>
A <sub>1</sub>	<[n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765]>	<[n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920]>	<[n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198]>	<[n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801]>	<[n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920]>	<[n5.0666, n6.5334], [n1.0666, n2.5334], [n1.4666, n2.9334]>	<[n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920]>	<[n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920]>	<[n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765]>	<[n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920]>
A <sub>2</sub>	<[n5.0666, n6.5334], [n1.0666, n2.5334], [n1.4666, n2.9334]>	<[n5.4666, n6.9334], [n1.4080, n2.1920], [n1.1199, n2.0801]>	<[n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765]>	<[n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920]>	<[n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198]>	<[n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801]>	<[n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801]>	<[n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765]>	<[n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920]>	<[n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801]>

[illegible]

Table 2. The second LCINN.

[illegible]

Table 3. The third LCINN.

	C <sub>1</sub>	C <sub>2</sub>	C <sub>3</sub>	C <sub>4</sub>	C <sub>5</sub>	C <sub>6</sub>	C <sub>7</sub>	C <sub>8</sub>	C <sub>9</sub>	C <sub>10</sub>
<b>A</b>	<[n5.0666, n6.5334]>	<[n5.6160, n7.1840]>	<[n6.4080, n7.1920]>	<[n5.1235, n6.8765]>	<[n5.1235, n6.8765]>	<[n5.8080, n6.5920]>	<[n4.8160, n6.3840]>	<[n4.8160, n6.3840]>	<[n5.8080, n6.5920]>	<[n5.4666, n6.9334]>
<b>1</b>	[n1.0666, n2.5334], [n1.4666, n2.9334]>	[n1.8080, n2.5920], [n1.4080, n2.1920]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>	[n1.3802, n2.6198], [n1.1235, n2.8765]>	[n1.4666, n2.9334], [n1.8080, n2.5920]>	[n1.4666, n2.9334], [n1.8080, n2.5920]>	[n1.3802, n2.6198], [n1.1235, n2.8765]>	[n1.4080, n2.1920], [n1.1199, n2.0801]>
<b>A</b>	<[n5.0666, n6.5334]>	<[n5.1235, n6.8765]>	<[n5.8080, n6.5920]>	<[n5.6160, n7.1840]>	<[n6.4080, n7.1920]>	<[n5.1235, n6.8765]>	<[n5.1235, n6.8765]>	<[n5.8080, n6.5920]>	<[n5.6160, n7.1840]>	<[n5.1235, n6.8765]>
<b>2</b>	[n1.0666, n2.5334], [n1.4666, n2.9334]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>	[n1.3802, n2.6198], [n1.1235, n2.8765]>	[n1.8080, n2.5920], [n1.4080, n2.1920]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>	[n1.3802, n2.6198], [n1.1235, n2.8765]>	[n1.8080, n2.5920], [n1.4080, n2.1920]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>
<b>A</b>	<[n5.4666, n6.9334]>	<[n6.4080, n7.1920]>	<[n6.4080, n7.1920]>	<[n5.1235, n6.8765]>	<[n5.6160, n7.1840]>	<[n6.4080, n7.1920]>	<[n6.4080, n7.1920]>	<[n4.8160, n6.3840]>	<[n6.4080, n7.1920]>	<[n6.4080, n7.1920]>
<b>3</b>	[n1.4080, n2.1920], [n1.1199, n2.0801]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.1199, n2.0801], [n1.9199, n2.8801]>	[n1.8080, n2.5920], [n1.4080, n2.1920]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.4666, n2.9334], [n1.8080, n2.5920]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>	[n1.4666, n2.9334], [n1.3802, n2.6198]>

<b>A</b> 4	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$
<b>A</b> 5	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n5.0666, n6.5334], [n1.0666, n2.5334], [n1.4666, n2.9334] \rangle$	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$
<b>A</b> 6	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$
<b>A</b> 7	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n6.4080, n7.1920], [n1.4666, n2.9334], [n1.3802, n2.6198] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n5.8080, n6.5920], [n1.3802, n2.6198], [n1.1235, n2.8765] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n5.1235, n6.8765], [n1.1199, n2.0801], [n1.9199, n2.8801] \rangle$
<b>A</b> 8	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n5.0666, n6.5334], [n1.0666, n2.5334], [n1.4666, n2.9334] \rangle$	$\langle [n5.0666, n6.5334], [n1.0666, n2.5334], [n1.4666, n2.9334] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n5.6160, n7.1840], [n1.8080, n2.5920], [n1.4080, n2.1920] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$	$\langle [n5.0666, n6.5334], [n1.0666, n2.5334], [n1.4666, n2.9334] \rangle$	$\langle [n4.8160, n6.3840], [n1.4666, n2.9334], [n1.8080, n2.5920] \rangle$

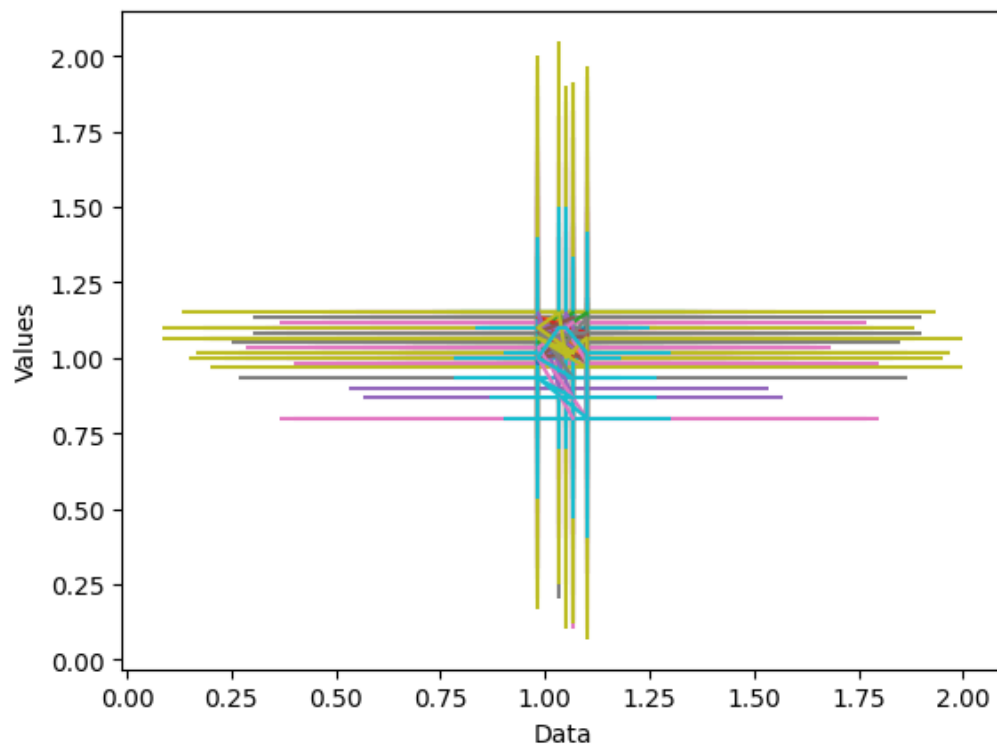


Fig 1. The aggregated decision matrix.

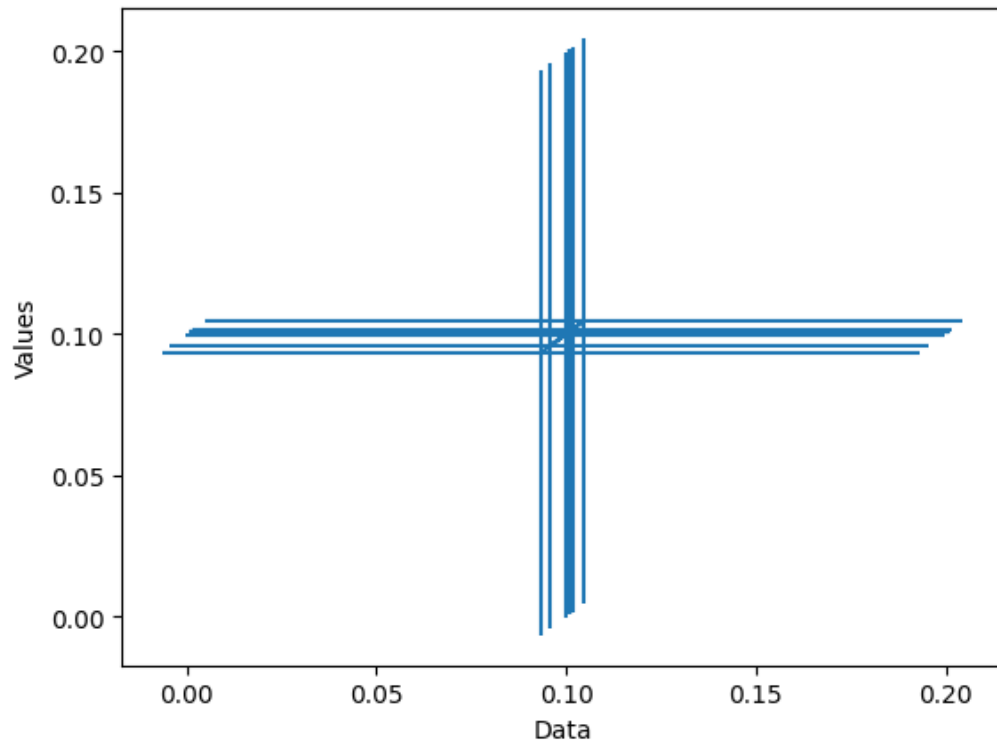


Fig 2. The weights of factors.

Eq. (10) is used to attain the average solution.

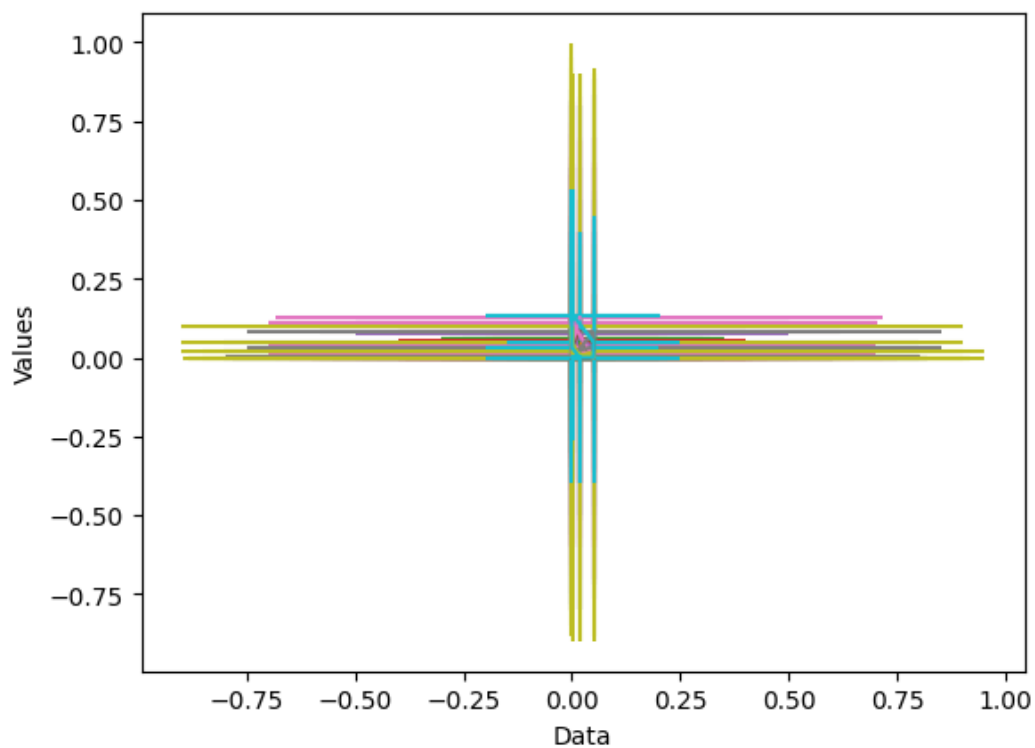
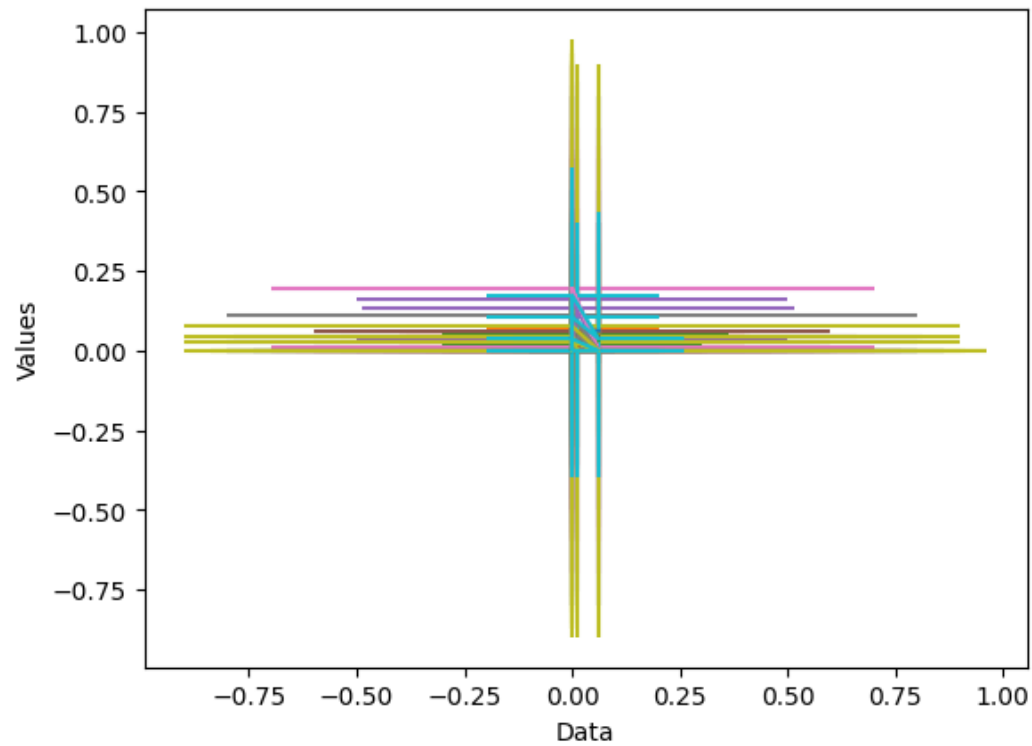
Eqs. (11-14) are used to attain the distances from the  $V_j$  values for positive and cost criteria as shown in Figs 3 and 4

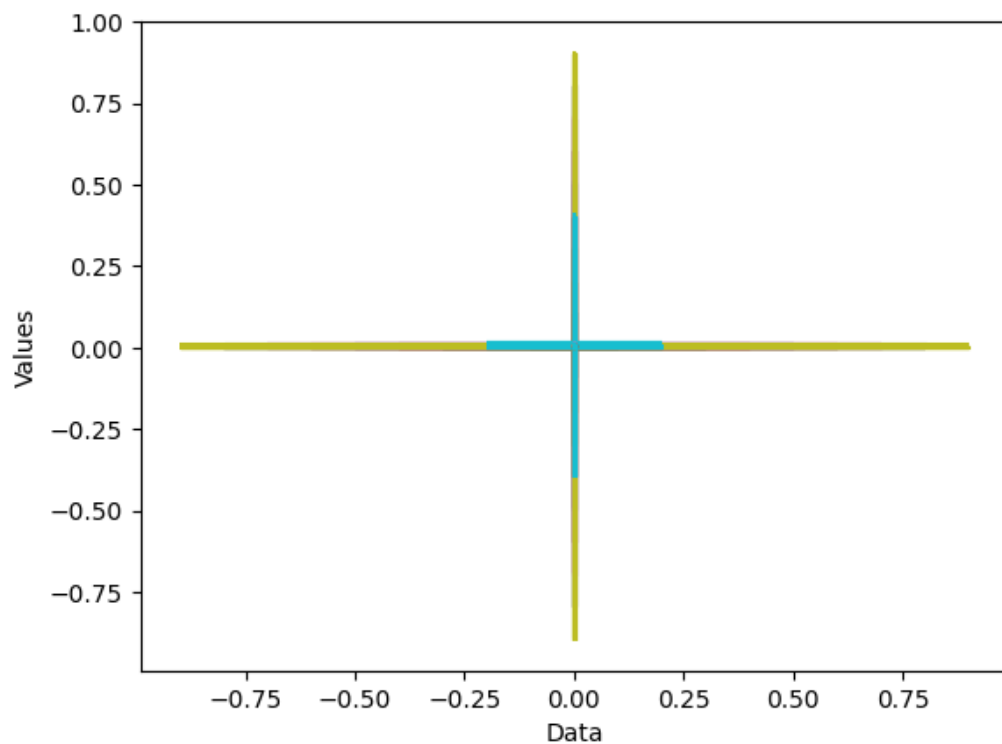
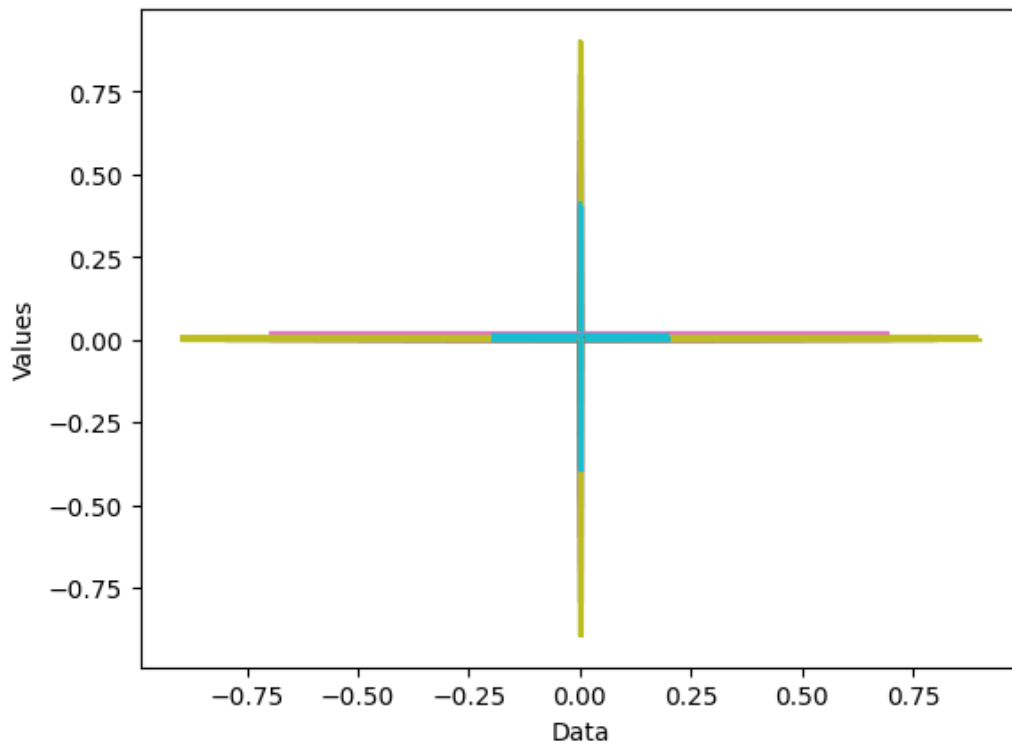
Eqs. (15 and 16) are used to compute the weighted  $PV_{ij}$  and  $NV_{ij}$  as shown in Fig 5 and 6.

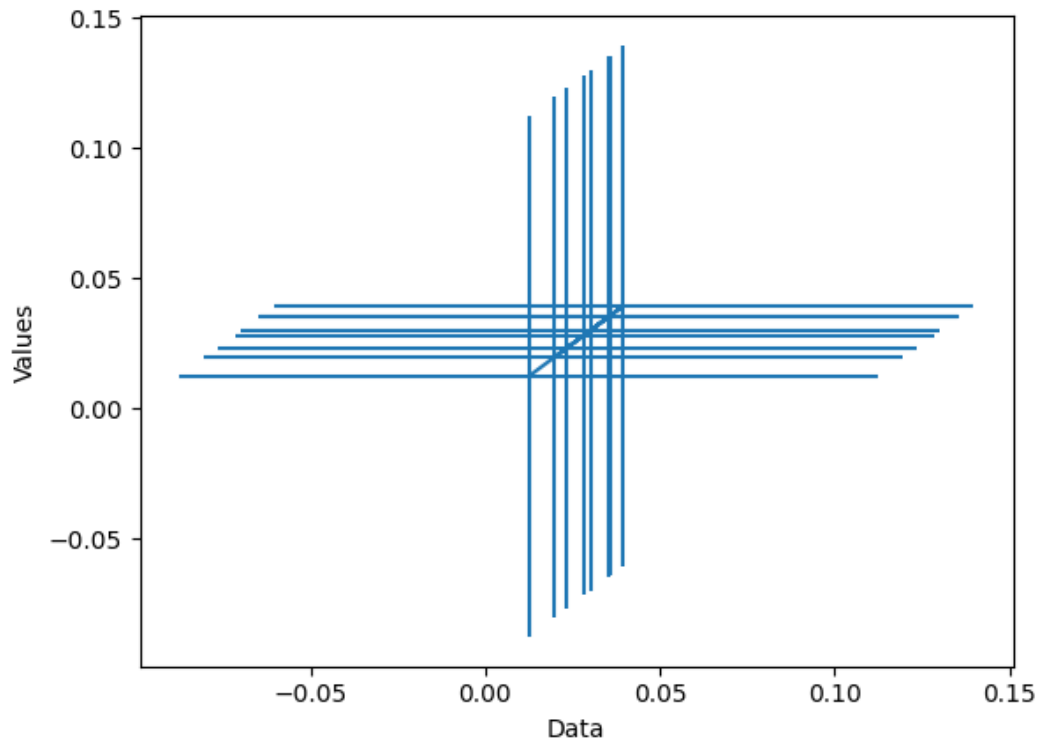
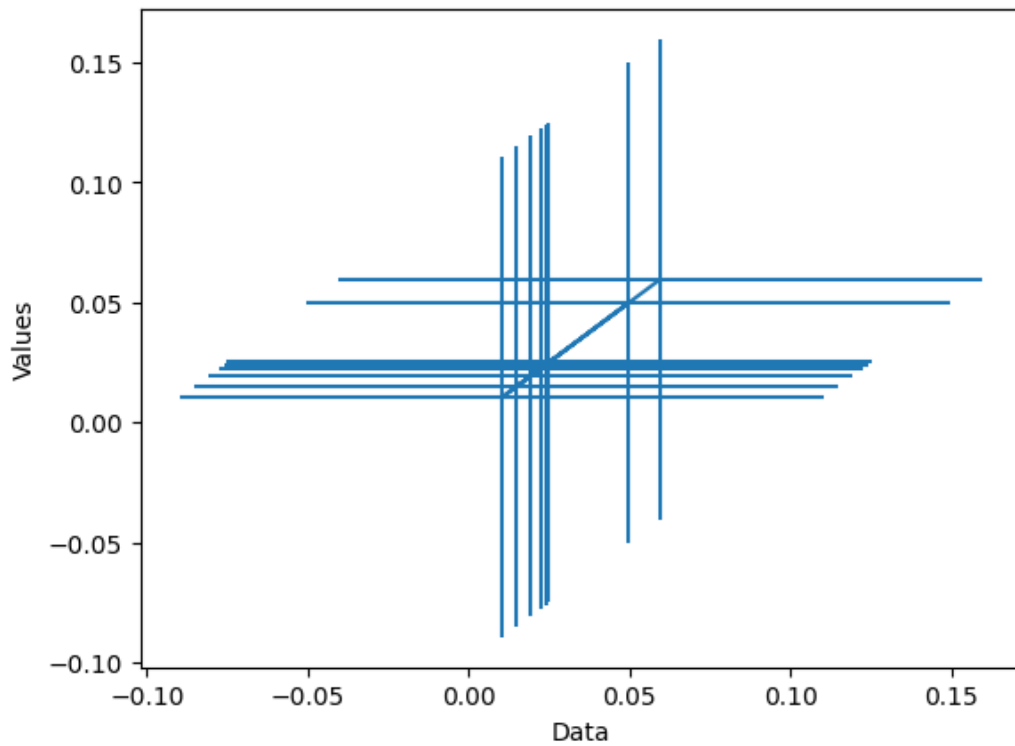
Eqs. (17 and 18) are used to compute the weighted normalized  $PV_{ij}$  and  $NV_{ij}$  as shown in Fig 7 and 8.

Eq. (19) is used to compute the appraisal score as shown in Fig 9.

Rank the alternatives as shown in Fig 10.

Fig 3. The values of  $PV_{ij}$ .Fig 4. The values of  $NV_{ij}$ .

Fig 5. The values of  $SPV_{ij}$ .Fig 6. The values of  $SNV_{ij}$ .

Fig 7. The values of  $NSPV_{ij}$ .Fig 8. The values of  $NSNV_{ij}$ .

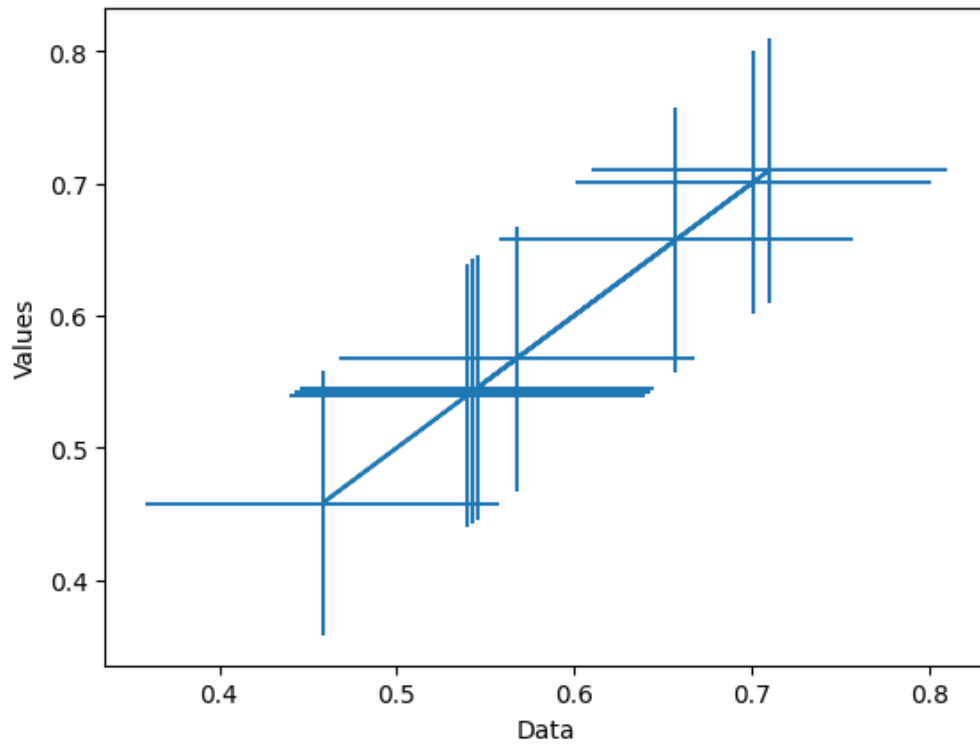
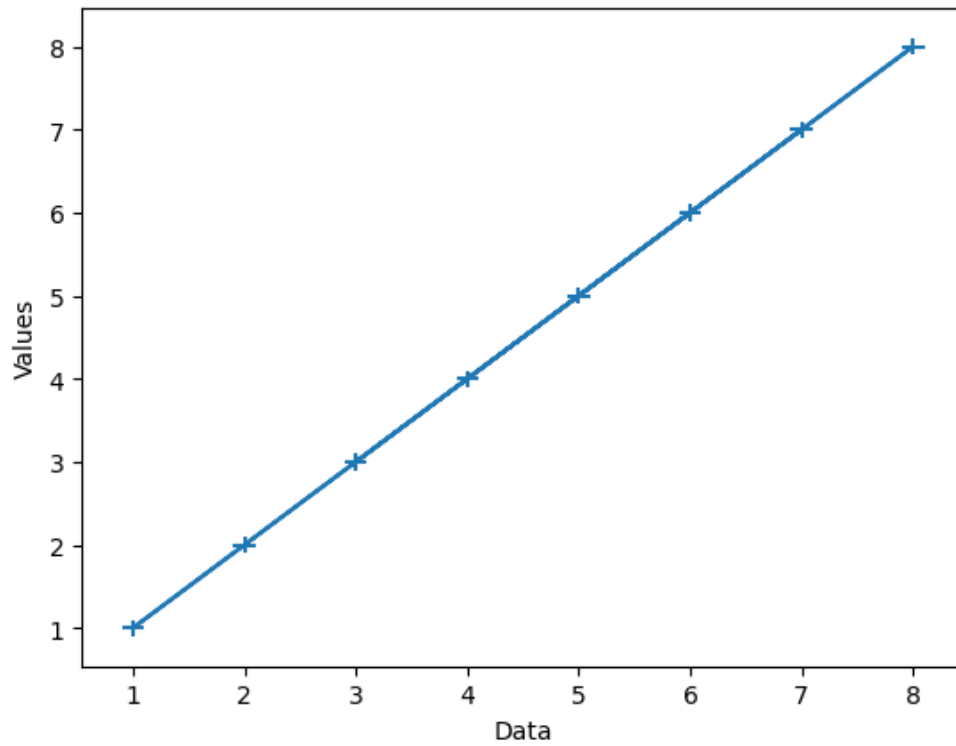
Fig 9. The values of  $A_i$ .

Fig 10. The rank of alternatives.

#### 4. Comparative Analysis

This section shows the comparative study between the proposed approach and other methods such as: RAM Method, TOPSIS Method, VIKOR Method, PROMETHEE Method. Then we use the criteria weights by the proposed approach. Then we show the comparative results as shown in Fig 11. The results show the proposed approach is effective compared to other methods. The proposed approach and other methods show alternative 6 is the best and alternative 5 is the worst

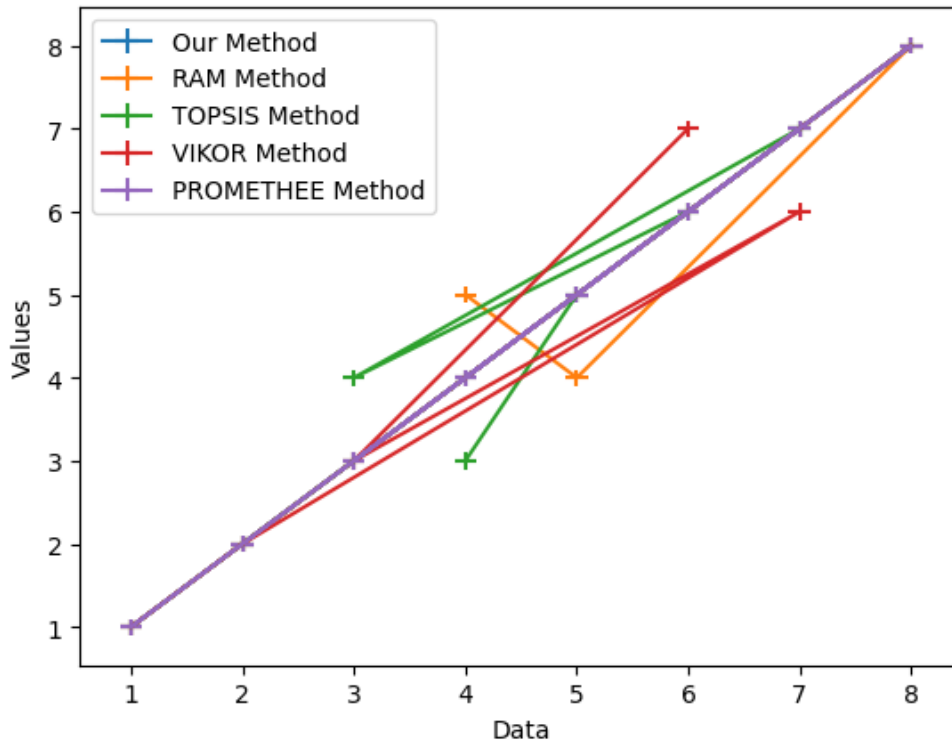


Fig 11. Comparative analysis.

#### 5. Conclusions

This research underscores the significance of leveraging big data analytics to elevate the standard of mental health education in higher institutions. By establishing a robust evaluative structure based on multi-dimensional criteria, universities can better align their support systems with student needs. This study proposed a MCDM methodology for ranking the alternatives and obtaining the weights of criteria. We used the Linguistic Confidence Interval Neutrosophic Numbers to overcome uncertainty and vague information. The EDAS method is used to rank the alternatives.

The outcomes of this study not only assist in choosing the most impactful intervention strategies but also demonstrate that technological advancement, when ethically managed, can bridge the

gap between psychological support and academic success. Future work may extend this model to incorporate cross-cultural dynamics and longitudinal data, further enriching its application across global academic settings.

### Acknowledgment

This work was supported by 2024 Anhui Province Higher Education Institution Scientific Research Project «A Study on the Cultivation of Self-Care Ability in College Students and Its Impact on Mental Health» (2024AH053231).

### References

- [1] A. Rosenfeld *et al.*, "Big data analytics and AI in mental healthcare," *arXiv Prepr. arXiv1903.12071*, 2019.
- [2] X. Ji, "Research on Mental Health Assessment and Intervention Methods for College Students based on Big Data Analysis," *Scalable Comput. Pract. Exp.*, vol. 25, no. 6, pp. 4702–4711, 2024.
- [3] X. Zhang and S. Jia, "The ways of college mental health education based on big data," in *Journal of Physics: Conference Series*, IOP Publishing, 2021, p. 32030.
- [4] A. Rosenfeld *et al.*, "Big Data analytics and artificial intelligence in mental healthcare," in *Applications of big data in healthcare*, Elsevier, 2021, pp. 137–171.
- [5] Y. Jia, "Impact of Music Teaching on Student Mental Health Using IoT, Recurrent Neural Networks, and Big Data Analytics," *Mob. Networks Appl.*, pp. 1–20, 2024.
- [6] J. Heo, H. Lim, S. B. Yun, S. Ju, S. Park, and R. Lee, "Descriptive and predictive modeling of student achievement, satisfaction, and mental health for data-driven smart connected campus life service," in *Proceedings of the 9th international conference on learning analytics & knowledge*, 2019, pp. 531–538.
- [7] Q. Liu and X. Liao, "Research on university mental health education based on computer big data statistical analysis," in *2021 2nd International Conference on Big Data and Informatization Education (ICBDIE)*, IEEE, 2021, pp. 29–34.
- [8] W. Xie, "Big data Analysis on The Management Content of College Students' Mental Health Education," in *2021 13th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA)*, IEEE, 2021, pp. 662–665.
- [9] A. Kamran Ul haq, A. Khattak, N. Jamil, M. A. Naeem, and F. Mirza, "Data analytics in mental healthcare," *Sci. Program.*, vol. 2020, no. 1, p. 2024160, 2020.
- [10] Z. Wei and L. Yan, "Construction of an intelligent evaluation model of mental health based on big data," *J. Sensors*, vol. 2022, no. 1, p. 4378718, 2022.
- [11] A. Al-Quran, H. Hashim, and L. Abdullah, "A hybrid approach of interval neutrosophic vague sets and DEMATEL with new linguistic variable," *Symmetry (Basel)*, vol. 12, no. 2,

- p. 275, 2020.
- [12] S. Zhai, L. Zhao, and D. Hou, "Bonferroni Mean operator of interval linguistic neutrosophic uncertain linguistic number and its application in multi-attribute group decision-making," *HyperSoft Set Methods Eng.*, vol. 1, pp. 119–140, 2024.
  - [13] J. Ye, "Multiple attribute decision-making methods based on the expected value and the similarity measure of hesitant neutrosophic linguistic numbers," *Cognit. Comput.*, vol. 10, pp. 454–463, 2018.
  - [14] J. Ye, "Linguistic neutrosophic cubic numbers and their multiple attribute decision-making method," *Information*, vol. 8, no. 3, p. 110, 2017.
  - [15] J. Ye, S. Du, and R. Yong, "Mine safety evaluation method using correlation coefficients of consistency linguistic neutrosophic sets in a linguistic neutrosophic multivalued environment," *Soft Comput.*, vol. 27, no. 13, pp. 8599–8609, 2023.
  - [16] L. Q. Dat, N. T. Thong, M. Ali, F. Smarandache, M. Abdel-Basset, and H. V. Long, "Linguistic approaches to interval complex neutrosophic sets in decision making," *IEEE access*, vol. 7, pp. 38902–38917, 2019.
  - [17] J. Ye, "Group decision-making strategy based on aggregation operators of linguistic confidence interval neutrosophic numbers in a linguistic neutrosophic multivalued scenario," *Eng. Appl. Artif. Intell.*, vol. 141, p. 109823, 2025.

Received: Nov. 11, 2024. Accepted: April 12, 2025