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Intuitionistic quadri-partitioned neutrosophic N-soft set to evaluate the emotional resilience of students in a dynamic learning environment

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Abstract. Emotional resilience is a critical determinant of student well-being, particularly in today's high-pressure educational environments. Prolonged academic stress can impair both mental and physical health, underscoring the need for precise, adaptive tools to assess psychological resilience. However, existing models, such as neutrosophic soft sets (N-SS) and single-valued neutrosophic N-soft sets (SVNSS), struggle to capture the complex, overlapping and often contradictory emotional states exhibited by students. These models rely on triadic classifications and lack the granularity needed to reflect multidimensional psychological realities. To address this gap, we introduce the intuitionistic quadri-partitioned neutrosophic N-soft set (IQPNNSS) model, a novel framework that extends the expressive capacity of neutrosophic logic through a four-phase psychological assessment methodology: Identification of core components (student profiles, psychosocial parameters, emotional indicators). Structured data collection, where responses are encoded using quadri-partitioned neutrosophic values across longitudinal counselling sessions. Model construction, where the IQPNNSS analyses individual resilience profiles. Benchmark evaluation, comparing profiles against psychological standards to identify the risk of the students. By incorporating quadri-partitioning representing acceptance, rejection, hesitation, and neutrality the IQPNNSS model provides a more nuanced, flexible, and accurate approach to emotional resilience assessment. This study not only demonstrates the practical utility of advanced neutrosophic structures in psychological contexts but also offers a theoretically grounded, empirically validated framework for counsellors and educators supporting student well-being.

Keywords: intuitionistic quadri-partitioned neutrosophic N-soft set; neutrosophic set; intuitionistic set; soft set, N-soft set.

1. Introduction

Traditionally, addressing uncertainty in decision-making and analysis has relied on fuzzy set (FS) theory [1] and intuitionistic fuzzy set (IFS) approaches [2]. To advance beyond the limitations of these models, Smarandache [3] introduced the neutrosophic set (NS), a framework that incorporates three independent components: truth, indeterminacy, and falsity. Recognizing the complexity of NS, Wang [4] later introduced the single-valued neutrosophic set (SVNS) as a simplified yet effective alternative. Building on this, Maji [5] proposed the single-valued neutrosophic soft set (SVNSS) and outlined its fundamental properties. In environments characterized by uncertainty, the indeterminacy value in neutrosophic theory plays a vital role, especially in ranking and evaluating alternatives. This has led to widespread interest and adoption of neutrosophic models across various fields. For instance, Abdel-Basset et al. [6] developed type-2 SVNS with formalized operational rules, and in subsequent work [7], they introduced a novel model to assess intelligent medical devices under a neutrosophic setting. Expanding further into decision analysis, Abdel-Basset and colleagues [8] integrated SVNS with the analytical network process to solve multi-criteria decision-making (MCDM) problems and later applied a similar methodology for project selection in uncertain conditions [9]. Contributions by Chinnadurai et al. [10] include an alternative ranking procedure for evaluating options based on parameterized criteria, while Chinnadurai and Bobin [11] incorporated prospect theory into neutrosophic MCDM for ranking attributes more effectively. Other notable applications include stock market forecasting, personnel selection, and shortest path optimization, explored using neutrosophic and extended models by researchers such as Sudan et al. [12], Nabeeh et al. [13], Mohana and Smarandache [14], Broumi et al. [15], and Kumar et al. [16]. Further evidence of the versatility and depth of neutrosophic theory is seen in the work of Abdel-Basset [17–21], Rohini et al. [22], Edward and Narmadhagnanam [23], and Villamar et al. [24], who have applied these concepts across a wide spectrum of domains, demonstrating its effectiveness in modeling and reasoning under uncertainty.

The concept of fuzzy sets (FS) was first introduced by Zadeh [1] as a means to address the inherent vagueness and ambiguity present in human reasoning. He acknowledged that cognitive processes often lack clearly defined boundaries, leading to imprecise judgments. Although initially met with skepticism, particularly during the 1980s, FS theory gradually gained recognition and acceptance in psychological research [25]. Despite a growing interest among psychologists, the integration of fuzzy logic into mainstream psychological applications has progressed at a modest pace. Experimental investigations by researchers such as Rosch [26], Hersh and Caramazza [27], Rubin [28], and Oden [29] have significantly contributed to the intersection of fuzzy theory and psychology. Later, Oden and Massaro [30] offered insights into perceptual mechanisms through FS theory, while Hesketh et al. [31] extended the use of fuzzy logic to model cognitive processes that classical mathematical frameworks could not easily capture. Broughton [32] emphasized that the notions of fuzzy sets and typicality play a key role in refining personality profiling and diagnosing psychological abnormalities. Similarly, Horowitz and Malle [33] applied fuzzy constructs in the context of depression analysis. In applied psychology, particularly in personnel evaluation and selection, Alliger et al. [34] demonstrated the effectiveness of fuzzy-based models. Vasantha et al. [35] introduced the single-valued refined neutrosophic set to analyze imaginative play behavior in children, highlighting the potential of hybrid set theories in psychological assessment. Further contributions from Hernandex et al. [36], Nandita et al. [37], Wang et al. [38], Sanpreet [39], Sumathi and Poorna [40], Srivastava et al. [41], Nuovo et al. [42], and Chicaiza et al. [43] explore various applications of fuzzy logic and its extensions in examining cognitive impairments, behavioral patterns, and aspects of emotional intelligence, showcasing the growing relevance of these theories in contemporary psychological studies.

Although significant advancements have been made, some scholars contend that fuzzy set theory falls short in accurately mirroring human perception, citing concerns over its limited empirical measurement base and occasional theoretical ambiguities. Many psychologists specializing in decision-making remain unconvinced that FS theory provides advantages beyond those offered by models based on subjective probability and utility. Nevertheless, existing research underscores the practical relevance of FS and its hybrid extensions in areas such as personality evaluation, clinical diagnosis, and vocational guidance, areas where traditional set theories often prove insufficient. In clinical settings, mental health professionals typically employ conventional statistical frameworks and standardized psychometric tools rooted in classical test theory. However, these traditional approaches especially those heavily dependent on rating scales may not fully capture the nuanced risks embedded within raw psychological data. In contrast, neutrosophic logic emerges as a promising framework capable of reducing imprecision and explicitly addressing the ambiguity present in mental health assessments. By offering a structured and adaptable means of analyzing psychological behavior, neutrosophic models present an innovative and accessible approach for mental health practitioners to better evaluate complex emotional and cognitive patterns.

Fatimah et al. [44] first introduced the notion of N-soft sets (N-SS) using real-world scenarios to demonstrate their applicability. This foundational work was later expanded by Akram et al., who developed the fuzzy N-soft set (FN-SS) [45] and the hesitant N-soft set (HN-SS) [46] by incorporating fuzzy and hesitant set concepts into the N-SS structure. In further developments, Kamaci and Petchimuthu [47] presented the bipolar N-soft set along with its key attributes, and Zhang et al. [48] explored the characteristics of the Pythagorean fuzzy N-soft set. Riaz et al. [49] also contributed by introducing neutrosophic N-soft sets and analyzing their structural properties.

Despite these advancements, certain limitations emerge when hybrid set theories are merged with the N-soft set framework, especially in the context of psychological assessment. Notably, models such as the fuzzy and hesitant N-soft sets do not include the indeterminacy membership component, which is essential for handling ambiguity in human behavior. For instance, Example 2.5 in the work of Akram et al. [50] reveals that grading based solely on truth membership in intuitionistic fuzzy sets (IFS) overlooks the separately assigned non-membership values. Likewise, Example 5.1 from Riaz et al. [49] evaluates truth membership in single-valued neutrosophic N-soft sets (SVNSS) without adequately considering indeterminacy and falsity values. Omitting these dimensions can hinder the comprehensive assessment of psychological constructs, indicating a significant research gap that must be addressed for more accurate evaluations.

A thorough analysis of existing literature highlights several key research directions. First, during disruptive events such as pandemics and prolonged lock downs, abrupt changes in the environment can significantly impact students ability to cope and adapt, making it essential to assess emotional resilience during such periods. Second, although neutrosophic theory has proven valuable in decision-making domains, its potential remains underutilized in psychological research and diagnostics. Third, while standardized psychological tools remain widely used, many conventional rating scales lack the flexibility to accurately assess nuanced risk factors or support tailored interventions. Psychiatrists, who often prefer working directly with raw datasets and empirically validated scoring systems, require models that can accommodate uncertainty and yet remain compatible with traditional assessment practices.

In the evolving landscape of educational psychology, emotional resilience the capacity to adapt, recover, and maintain functionality in the face of adversity has become a central focus for understanding student well-being. As academic pressures intensify, students increasingly face psychosocial challenges that demand nuanced evaluation tools capable of capturing the complexity of their emotional states. Traditional psychological assessments, while helpful, often lack the ability to model the uncertainty, contradiction, and indeterminacy that characterize emotional resilience.

To address these challenges, soft computing models such as fuzzy sets, intuitionistic fuzzy sets, and neutrosophic sets have been employed. Among these, neutrosophic soft sets (N-SS) and their extensions, particularly the single-valued neutrosophic N-soft set (SVNSS), offer structured mechanisms to handle imprecise and indeterminate information. However, despite their utility, these models often rely on a triadic partitioning truth, indeterminacy, and falsity that may not sufficiently capture the coexistence of conflicting psychological responses such as acceptance and hesitation or neutrality and rejection.

In real-world emotional evaluations, especially in dynamic contexts like student counseling, individuals may simultaneously experience mixed affective states that are not easily mapped to a simple true-false-indeterminate scale. For instance, a student may partially accept a coping strategy, remain neutral toward another, and hesitate about a third all within a single session. This overlap of emotional reactions calls for a more expressive representation system.

In response, this study proposes the intuitionistic quadri-partitioned neutrosophic N-soft set (IQPNNSS) model. This model introduces a fourth component neutrality alongside acceptance, rejection, and hesitation, forming a quadri-partitioned framework. This structure draws on principles from both neutrosophic theory and psychological research, which recognizes that emotional states often exist in multi-dimensional continua rather than binary or triadic categories. The model is implemented in a four-phase methodology combining psychological assessment with mathematical reasoning to evaluate student emotional resilience more precisely.

By extending the neutrosophic framework, IQPNNSS addresses the limitations of conventional models and offers both theoretical robustness and practical relevance. It enhances the fidelity of psychological assessments by aligning better with cognitive-affective theories, which support the presence of simultaneous, nuanced emotional responses. This research contributes not only a novel computational model but also a validated pathway for supporting mental health initiatives in academic settings.

Motivated by these challenges, the present study introduces a novel structure called the intuitionistic quadri-partitioned neutrosophic N-soft set (IQPNNSS). The primary objective is to enhance psychological evaluation by integrating the score function (SF). This integration is designed to retain the independence of truth, indeterminacy, contradiction and falsity values, while aligning with established scoring norms through a well-defined rating scale distribution. By enabling comprehensive analysis of mental health indicators over time and accommodating imprecise or ambiguous responses, the proposed IQPNNSS model seeks to bridge existing methodological gaps and offer psychiatrists a practical, theory-backed approach for assessing emotional and psychological resilience.

2. Preliminaries

This section reviews fundamental concepts necessary for understanding the proposed framework. Let Θ be the universal set, Γ the set of parameters, $\Gamma_0 \subseteq \Gamma$, and $\wp(\Theta)$ denote the power set of Θ.

Definition 2.1. [4] A single-valued neutrosophic set (SVNS) $\mathcal{N}$ over a universe Θ is defined as $\mathcal{N} = \{(\theta, T_{\mathcal{N}}(\theta), I_{\mathcal{N}}(\theta), F_{\mathcal{N}}(\theta)) \mid \theta \in \Theta\}$, where $T_{\mathcal{N}}(\theta), I_{\mathcal{N}}(\theta)$ and $F_{\mathcal{N}}(\theta) : \Theta \to [0, 1]$ denote the degree of truth-membership, degree of indeterminacy-membership, and degree of falsity-membership respectively, satisfying the condition $0 \leq T_{\mathcal{N}}(\theta) + I_{\mathcal{N}}(\theta) + F_{\mathcal{N}}(\theta) \leq 3, \quad \forall\, \theta \in \Theta$. The set of all SVNSs defined over Θ is denoted by $\mathcal{N}^{\Theta}$.

Definition 2.2. [51] A soft set $(\mathscr{F}, \Upsilon)$ over the universe Θ is defined as a mapping $\mathscr{F} : \Upsilon \to 2^{\Theta}$, where Υ is a set of parameters and $\mathscr{F}(\upsilon) \subseteq \Theta$ for each $\upsilon \in \Upsilon$. Then, $(\mathscr{F}, \Upsilon)$ represents a parameterized collection of subsets of Θ.

Definition 2.3. [5] A single-valued neutrosophic soft set (SVNSS) $(\mathscr{F}, \Upsilon)$ over the universe Θ is defined as a mapping $\mathscr{F} : \Upsilon \to \mathbb{N}^{\Theta}$, which can be expressed as $\tilde{\mathbb{N}} = \left\{ \left(\upsilon, T_{\mathscr{F}(\upsilon)}(\theta), I_{\mathscr{F}(\upsilon)}(\theta), F_{\mathscr{F}(\upsilon)}(\theta)\right) \mid \theta \in \Theta, \upsilon \in \Upsilon \right\}$, where $T_{\mathscr{F}(\upsilon)}(\theta)$, $I_{\mathscr{F}(\upsilon)}(\theta)$, and $F_{\mathscr{F}(\upsilon)}(\theta)$ denote the degrees of truth, indeterminacy, and falsity respectively, with values in $[0, 1]$.

Definition 2.4. [52] An SVNSS can be conveniently represented in the form of an $m \times n$ matrix $\mathbb{N}^* = [n_{ij}]$, where each element is given by $n_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle, \quad$ for $i = 1, \ldots, m$ and $j = 1, \ldots, n$, with T_{ij}, I_{ij}, and F_{ij} denoting the truth, indeterminacy, and falsity membership degrees corresponding to the i-th element $\theta_i \in \Theta$ under the j-th parameter $\upsilon_j \in \Upsilon$.

Definition 2.5. [44] Let $\mathcal{G} = \{0, 1, \ldots, N-1\}$ be an ordered grade set, where $N \geq 2$. An N-soft set $(\mathscr{F}, \Upsilon, N)$ over the universe Θ is defined as a mapping $\mathscr{F} : \Upsilon \to 2^{\Theta \times \mathcal{G}}$, where for each parameter $\upsilon \in \Upsilon$, there exists a unique pair $(\theta, g_\upsilon) \in \Theta \times \mathcal{G}$ such that $(\theta, g_\upsilon) \in \mathscr{F}(\upsilon)$.

3. Score function for IQPNS

Definition 3.1. Let $Q = (T, F, I, C)$ be an IQPNS, where $T, F, I, C \in [0, 1]$ and satisfy the condition

$$T + F + I + C \leq 3.$$

The *score function* of Q is defined as

$$S(Q) = T - F - \frac{I + C}{2}. \tag{1}$$

4. Normalization and ranking

Normalization ensures scores are comparable across different IQPNSs. We propose the following normalization scheme.

Definition 4.1. For a collection of IQPNSs $\{Q_i\}_{i=1}^{n}$, the normalized weighted score is

$$S_w^*(Q_i) = \frac{S_w(Q_i)}{\sum_{j=1}^{n} S_w(Q_j)} \tag{2}$$

Lemma 4.2. *Normalization preserves the original ranking order:*

$$S_w(Q_i) > S_w(Q_j) \iff S_w^*(Q_i) > S_w^*(Q_j)$$

Proof. Since normalization uses a positive scaling factor ($\sum S_w(Q_j) > 0$), the inequality:

$$\frac{S_w(Q_i)}{\sum S_w(Q_j)} > \frac{S_w(Q_j)}{\sum S_w(Q_j)}$$

holds if and only if $S_w(Q_i) > S_w(Q_j)$. $\square$

5. Intuitionistic quadri-partitioned neutrosophic N-soft set

In this section, we define the concept of IQPNNSS and their matrix representations with appropriate examples.

Definition 5.1. Let Θ be a universal set and let $\mathcal{P}$ be a set of parameters with $\mathcal{E} \subseteq \mathcal{P}$. Let $\mathcal{G} = \{1, 2, \ldots, N\}$ be a set of rating grades, where $N \geq 2$. The triple $(\Psi, \mathcal{J}, N)$ is called an IQPNNSS, where $\mathcal{J} = (\mathcal{F}, \mathcal{E}, N)$ is an N-soft set over Θ. Ψ is a mapping that assigns to each parameter $\upsilon \in \mathcal{E}$ a score function $S(\tilde{\mathcal{Q}})$ of an IQPNNSS over $\mathcal{F}(\upsilon) \subseteq \Theta \times \mathcal{G}$. For each $\upsilon \in \mathcal{E}$, there exists a unique pair $(\theta, g_\upsilon) \in \Theta \times \mathcal{G}$ such that: $\tilde{\mathcal{Q}}(N) = \Psi(\upsilon)(\theta) = \langle g_\upsilon, S(\tilde{\mathcal{Q}})\rangle$.

Definition 5.2. Let $\Theta = \{\theta_1, \theta_2, \ldots, \theta_m\}$ be a universal set, $\mathcal{E} = \{\upsilon_1, \upsilon_2, \ldots, \upsilon_n\}$ the set of parameters, and $\mathcal{G} = \{1, 2, \ldots, N\}$ the set of rating scales. The IQPNNSS $(\Psi, \mathcal{J}, N)$ can be represented as an $m \times n$ matrix:

$$
\mathcal{Q}^\star(N) = \begin{array}{c} \\ \theta_1 \\ \theta_2 \\ \vdots \\ \theta_m \end{array}
\begin{array}{c}
\begin{array}{cccc} \upsilon_1 & \upsilon_2 & \cdots & \upsilon_n \end{array} \\
\begin{bmatrix}
\langle g_{\upsilon_{11}}, s_{11}\rangle & \langle g_{\upsilon_{12}}, s_{12}\rangle & \cdots & \langle g_{\upsilon_{1n}}, s_{1n}\rangle \\
\langle g_{\upsilon_{21}}, s_{21}\rangle & \langle g_{\upsilon_{22}}, s_{22}\rangle & \cdots & \langle g_{\upsilon_{2n}}, s_{2n}\rangle \\
\vdots & \vdots & \ddots & \vdots \\
\langle g_{\upsilon_{m1}}, s_{m1}\rangle & \langle g_{\upsilon_{m2}}, s_{m2}\rangle & \cdots & \langle g_{\upsilon_{mn}}, s_{mn}\rangle
\end{bmatrix}
\end{array}
$$

where $\mathcal{Q}^\star(N) = \langle g_{\upsilon_{ij}}, s_{ij}\rangle$ for all $1 \leq i \leq m$ and $1 \leq j \leq n$. This matrix $\mathcal{Q}^\star(N)$ is called the intuitionistic quadri-partitioned neutrosophic N-soft matrix (IQPNNSM).

6. Emotional intelligence evaluation using IQPNNSS

Consider a scenario where an emotional intelligence counselor (EIC) evaluates students' behaviors to assess their emotional well-being. The EIC assigns values using the framework of an IQPNNSS matrix. Suppose the EIC utilizes a 5-point rating scale (i.e., a 5-soft set) to evaluate responses based on both affirmative (positive) and adverse (negative) behavioral statements. The interpretation of these ratings is captured in Tables 1 and 2, which can be adjusted by the EIC based on specific evaluation criteria. In this context, affirmative statements are linked to socially adaptive behavior, while adverse statements relate to socially inappropriate or concerning behavior. Assume the EIC formulates affirmative statements for parameters p_1 and p_3, and an adverse statement for p_2. Based on this configuration, the IQPNNS matrix $Q^*(5)$ is computed as below:

$$
N^* = \begin{bmatrix}
\langle 0.7, 0.2, 0.5, 0.1\rangle & \langle 0.8, 0.1, 0.3, 0.2\rangle & \langle 0.6, 0.3, 0.4, 0.1\rangle \\
\langle 0.9, 0.05, 0.2, 0.1\rangle & \langle 0.7, 0.2, 0.5, 0.2\rangle & \langle 0.5, 0.4, 0.3, 0.2\rangle \\
\langle 0.6, 0.3, 0.4, 0.1\rangle & \langle 0.8, 0.1, 0.3, 0.1\rangle & \langle 0.7, 0.2, 0.5, 0.1\rangle
\end{bmatrix}
$$

Table 1. Grading map for behavioral statements

Affirmative Statement Rating	**Adverse Statement Rating**
5	1
4	2
3	3
2	4
1	5

Table 2. Score range corresponding to the grading map

Affirmative Grade	**Adverse Grade**	**Score Interval**
5	1	$0.8 \leq s \leq 1.0$
4	2	$0.6 \leq s < 0.8$
3	3	$0.3 \leq s < 0.6$
2	4	$0.0 \leq s < 0.3$
1	5	$-1.0 \leq s < 0.0$

$$Q^*(5) = \begin{bmatrix} \langle 2, 0.18\rangle & \langle 3, 0.38\rangle & \langle 5, 0.83\rangle \\ \langle 3, 0.38\rangle & \langle 4, 0.03\rangle & \langle 2, 0.28\rangle \\ \langle 4, 0.65\rangle & \langle 4, 0.23\rangle & \langle 2, 0.05\rangle \end{bmatrix}$$

This matrix $Q^*(5)$ is referred to as an interval-valued quadri-partitioned neutrosophic N-soft matrix (IQPNNSM) for emotional intelligence profiling.

7. Evaluating emotional intelligence of students using IQPNNSS

Recent global disruptions have profoundly influenced the day-to-day experiences of students, emphasizing the need for institutions to prioritize emotional well-being. Assessing emotional intelligence (EI) plays a vital role in supporting learners' personal growth and academic resilience. To address this concern, we introduce the IQPNNSS model, which offers a comprehensive mathematical framework for evaluating emotional intelligence in uncertain environments. This section presents a structured methodology for EI assessment based on an algorithmic approach. The model?s applicability and interpretability are further illustrated through practical examples in the following section. Assume an educational institution collaborates with a mental health committee (MHC) to assess the emotional intelligence levels of its students. The MHC adopts semi-structured assessment methods such as video conferencing or phone-based interviews. Let $\Theta = \{s_1, s_2, \ldots, s_m\}$ denote the set of students, and $\mathcal{E} = \{p_1, p_2, \ldots, p_n\}$ represent the set of parameters relevant to emotional intelligence evaluation.

With guidance from psychology professionals, the MHC defines the following critical components:

- A collection of positive (socially adaptive) and negative (socially non-conforming) statements for each parameter,

- A 5-point rating scale aligned with IQPNNSS, refer Table 1.
- Assignment of weights or priorities to each parameter based on contextual relevance,
- Standardized score interpretation guidelines to classify emotional intelligence levels (see Table 2).

These elements must be designed with precision, as they directly impact the accuracy of determining emotional well-being. Typically, individuals with elevated total scores across multiple parameters may be identified as at-risk and recommended for follow-up counseling or psychological support. For a given set of assessment items indexed by $r = \{1, 2, \ldots, k\}$, the MHC evaluates student responses using the IQPNNSS framework. The results are recorded in a set of quadri-partitioned neutrosophic matrices Q_r of dimension $m \times n$. Each matrix element is expressed as $\langle g_{p_{ij}}, s_{ij} \rangle$, representing the grade assigned and the associated score within the neutrosophic context. These matrices are then analyzed in conjunction with the scoring norms to derive a comprehensive emotional intelligence profile for each student.

7.1. *Structured framework for evaluating emotional intelligence levels*

To initiate the evaluation process, construct IQPNNSMs, denoted as Q_r^*, for each assessment item $r \in \{1, 2, ..., k\}$. These matrices are formulated by interpreting each student's behavioral responses in relation to positively or negatively phrased statements associated with key emotional intelligence parameters. Subsequently, transform each initial matrix Q_r^* using the procedure, resulting in the normalized matrices $S(Q_r^*)$. If the evaluation includes parameter-specific importance levels, compute the weighted matrices $WS(Q_r^*)$. Following transformation, perform a comparative analysis across all $S(Q_r^*)$ or $WS(Q_r^*)$, depending on the assessment design. Based on these comparisons and the predefined rating criteria, develop the decision matrices $Q_r^*(N)$ using the aggregation strategy. The structure of each decision matrix is as follows:

$$Q_r^*(N) = \begin{array}{c} \\ s_1 \\ s_2 \\ \vdots \\ s_m \end{array} \begin{array}{c} \begin{array}{cccc} p_1 & p_2 & \cdots & p_n \end{array} \\ \begin{bmatrix} \langle g^r_{p_{11}}, s^r_{11} \rangle & \langle g^r_{p_{12}}, s^r_{12} \rangle & \cdots & \langle g^r_{p_{1n}}, s^r_{1n} \rangle \\ \langle g^r_{p_{21}}, s^r_{21} \rangle & \langle g^r_{p_{22}}, s^r_{22} \rangle & \cdots & \langle g^r_{p_{2n}}, s^r_{2n} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle g^r_{p_{m1}}, s^r_{m1} \rangle & \langle g^r_{p_{m2}}, s^r_{m2} \rangle & \cdots & \langle g^r_{p_{mn}}, s^r_{mn} \rangle \end{bmatrix} \end{array},$$

where $r \in \{1, 2, ..., k\}$ corresponds to the r^{th} evaluation item.

To synthesize overall findings, generate the cumulative matrix $Q_+(N)$ by summing the entries of all $Q_r(N)$ matrices component-wise across all k items:

$$Q_+(N) = \begin{array}{c} \\ s_1 \\ \\ s_2 \\ \vdots \\ s_m \end{array} \begin{array}{c} \begin{array}{cccc} p_1 & p_2 & \cdots & p_n \end{array} \\ \begin{bmatrix} g^+_{p_{11}} & g^+_{p_{12}} & \cdots & g^+_{p_{1n}} \\ \\ g^+_{p_{21}} & g^+_{p_{22}} & \cdots & g^+_{p_{2n}} \\ \vdots & \vdots & \ddots & \vdots \\ g^+_{p_{m1}} & g^+_{p_{m2}} & \cdots & g^+_{p_{mn}} \end{bmatrix} \end{array} \begin{array}{c} \\ \sum_{j=1}^{n} g^+_{p_{1j}} \\ \\ \sum_{j=1}^{n} g^+_{p_{2j}} \\ \vdots \\ \sum_{j=1}^{n} g^+_{p_{mj}} \end{array} .$$

Each component $g^+_{p_{ij}}$ is calculated as:

$$g^+_{p_{ij}} = \sum_{r=1}^{k} g^r_{p_{ij}}, \quad \text{for all } i \in \{1, 2, ..., m\}, \ j \in \{1, 2, ..., n\}.$$

Once $Q_+(N)$ is computed, assess the emotional intelligence levels by referencing pre-established interpretive standards. These norms classify student status into three categories, low, average, and high based on the score ranges specified in Table 3. A low-risk score reflects emotional stability, while a high-risk score indicates significant emotional challenges that may necessitate immediate psychological support from the MHC.

Table 3. Risk classification guidelines for emotional intelligence assessment

Parameter	**Score Range**	**Risk Level**
	1–13	Low
p_1, p_4	14–25	Average (Avg)
	26–35	High
	1–15	Low
p_2, p_3	16–24	Avg
	25–30	High
	1–56	Low
Overall Score	57–97	Avg
	98–130	High

7.2. *Algorithm for emotional intelligence evaluation using IQPNNSS*

The following algorithm provides a systematic methodology for the MHC to assess the emotional intelligence levels of students using the IQPNNSS framework.

Step 1: The MHC identifies the target group of students, the nature of the emotional aspects to be evaluated, and selects the relevant parameters of interest.

Step 2: In coordination with a qualified mental health expert, the MHC designs an assessment scheme comprising positively and negatively framed statements, a rating scale, score intervals, and classification rules for evaluating emotional intelligence levels.

Step 3: For each evaluation item $r \in \{1, 2, \ldots, k\}$, construct the corresponding

IQPNNS matrix Q_r^* based on student response behavior.

Step 4: Apply the transformation to obtain the score-normalized matrices $S(Q_r)$ and, if applicable, compute the weighted matrices $WS(Q_r^*)$.

Step 5: Generate the decision matrices $Q_r^*(N)$ for each item r using the prescribed scoring model and the defined rating distribution.

Step 6: Perform an element-wise summation of all decision matrices to form the aggregate matrix $Q_+(N) = \sum_{r=1}^{k} Q_r^*(N)$.

Step 7: Interpret the values in $Q_+(N)$ to assess individual and overall emotional intelligence based on the score ranges and qualitative risk categories provided.

Step 8: For students categorized under high-risk emotional states, initiate timely intervention measures, including referral to professional counseling or emotional support services.

8. Case study using IQPNNSM

Consider a scenario where an academic institution seeks support from a qualified MHC to evaluate the emotional and psychological well-being of a selected student group using the IQPNNSS model.

Step 1: Let W_i, where $i = 1, 2, 3, 4, 5$ denote the set of students participating in the assessment. The MHC selects a predefined set of psychological parameters D_j, where $j = 1, 2, 3, 4, 5$ for evaluation, each linked to specific emotional intelligence indicators:

- D_1: Avoidance of Social Engagement (ASE),
- D_2: Presence of Suicidal Ideation (PSI),
- D_3: Severe Emotional Swings (SES),
- D_4: Stress Indicators (SI).
- D_5: Lack of Emotional Regulation (LER)

Step 2: In coordination with a professional, the MHC develops a structured questionnaire for each parameter. A soft 5-point evaluation scale is adopted for scoring of statements. The associated rating scale, scoring strategy, and classification thresholds for each parameter and overall emotional risk are detailed respectively.

Step 3: The MHC conducts observations and interprets student behavior based on the structured responses. These insights are recorded in the form of neutrosophic data matrices denoted as Q_i for each question. Lets assume the responses associated are related to positive items and marked in the Q-matrices to aid in interpretation, weighting, and subsequent scoring.

$$Q_1 = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{array}{c} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} & \begin{bmatrix} \langle 0.58, 0.24, 0.12, 0.31\rangle & \langle 0.64, 0.40, 0.27, 0.24\rangle & \langle 0.61, 0.76, 0.34, 0.03\rangle & \langle 0.56, 0.12, 0.13, 0.40\rangle & \langle 0.80, 0.44, 0.36, 0.20\rangle \\ \langle 0.48, 0.10, 0.09, 0.36\rangle & \langle 0.33, 0.40, 0.30, 0.35\rangle & \langle 0.25, 0.28, 0.23, 0.27\rangle & \langle 0.71, 0.26, 0.41, 0.12\rangle & \langle 0.56, 0.81, 0.29, 0.39\rangle \\ \langle 0.82, 0.47, 0.26, 0.11\rangle & \langle 0.42, 0.50, 0.40, 0.44\rangle & \langle 0.70, 0.37, 0.20, 0.12\rangle & \langle 0.22, 0.27, 0.22, 0.29\rangle & \langle 0.55, 0.51, 0.28, 0.12\rangle \\ \langle 0.79, 0.36, 0.19, 0.12\rangle & \langle 0.76, 0.23, 0.33, 0.12\rangle & \langle 0.73, 0.79, 0.29, 0.21\rangle & \langle 0.61, 0.73, 0.31, 0.34\rangle & \langle 0.36, 0.40, 0.39, 0.46\rangle \\ \langle 0.24, 0.29, 0.28, 0.33\rangle & \langle 0.91, 0.49, 0.30, 0.02\rangle & \langle 0.60, 0.51, 0.39, 0.10\rangle & \langle 0.70, 0.25, 0.21, 0.26\rangle & \langle 0.45, 0.25, 0.23, 0.10\rangle \end{bmatrix} \end{array}$$

$$Q_2 = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{array}{c} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} & \begin{bmatrix} \langle 0.87, 0.66, 0.35, 0.12\rangle & \langle 0.55, 0.63, 0.25, 0.28\rangle & \langle 0.56, 0.74, 0.32, 0.40\rangle & \langle 0.90, 0.68, 0.30, 0.05\rangle & \langle 0.80, 0.45, 0.38, 0.10\rangle \\ \langle 0.45, 0.50, 0.30, 0.33\rangle & \langle 0.70, 0.38, 0.31, 0.20\rangle & \langle 0.61, 0.31, 0.22, 0.10\rangle & \langle 0.20, 0.26, 0.40, 0.46\rangle & \langle 0.54, 0.75, 0.30, 0.36\rangle \\ \langle 0.75, 0.48, 0.27, 0.20\rangle & \langle 0.46, 0.52, 0.42, 0.47\rangle & \langle 0.33, 0.39, 0.21, 0.25\rangle & \langle 0.85, 0.30, 0.24, 0.15\rangle & \langle 0.47, 0.54, 0.30, 0.37\rangle \\ \langle 0.90, 0.37, 0.22, 0.10\rangle & \langle 0.48, 0.58, 0.35, 0.41\rangle & \langle 0.75, 0.82, 0.34, 0.12\rangle & \langle 0.57, 0.78, 0.33, 0.38\rangle & \langle 0.38, 0.42, 0.41, 0.49\rangle \\ \langle 0.26, 0.32, 0.30, 0.35\rangle & \langle 0.95, 0.51, 0.33, 0.02\rangle & \langle 0.42, 0.53, 0.41, 0.46\rangle & \langle 0.25, 0.01, 0.22, 0.12\rangle & \langle 0.70, 0.32, 0.24, 0.30\rangle \end{bmatrix} \end{array}$$

$$Q_3 = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{array}{c} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} & \begin{bmatrix} \langle 0.80, 0.48, 0.66, 0.10\rangle & \langle 0.39, 0.51, 0.19, 0.24\rangle & \langle 0.37, 0.43, 0.28, 0.34\rangle & \langle 0.81, 0.68, 0.27, 0.12\rangle & \langle 0.81, 0.47, 0.33, 0.19\rangle \\ \langle 0.33, 0.38, 0.56, 0.61\rangle & \langle 0.76, 0.46, 0.26, 0.21\rangle & \langle 0.78, 0.28, 0.17, 0.12\rangle & \langle 0.12, 0.18, 0.38, 0.43\rangle & \langle 0.51, 0.66, 0.42, 0.47\rangle \\ \langle 0.70, 0.30, 0.52, 0.20\rangle & \langle 0.50, 0.61, 0.35, 0.46\rangle & \langle 0.41, 0.48, 0.38, 0.49\rangle & \langle 0.19, 0.28, 0.19, 0.24\rangle & \langle 0.41, 0.56, 0.51, 0.57\rangle \\ \langle 0.27, 0.33, 0.41, 0.50\rangle & \langle 0.98, 0.50, 0.26, 0.00\rangle & \langle 0.89, 0.85, 0.30, 0.12\rangle & \langle 0.78, 0.75, 0.28, 0.13\rangle & \langle 0.31, 0.46, 0.60, 0.67\rangle \\ \langle 0.38, 0.42, 0.66, 0.45\rangle & \langle 0.50, 0.60, 0.22, 0.27\rangle & \langle 0.41, 0.91, 0.39, 0.48\rangle & \langle 0.11, 0.18, 0.18, 0.23\rangle & \langle 0.59, 0.26, 0.70, 0.10\rangle \end{bmatrix} \end{array}$$

$$Q_4 = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{array}{c} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} & \begin{bmatrix} \langle 0.90, 0.26, 0.91, 0.10\rangle & \langle 0.78, 0.56, 0.21, 0.10\rangle & \langle 0.52, 0.59, 0.32, 0.42\rangle & \langle 0.80, 0.80, 0.31, 0.10\rangle & \langle 0.67, 0.48, 0.40, 0.21\rangle \\ \langle 0.22, 0.31, 0.83, 0.67\rangle & \langle 0.41, 0.44, 0.29, 0.42\rangle & \langle 0.32, 0.38, 0.23, 0.31\rangle & \langle 0.30, 0.50, 0.40, 0.52\rangle & \langle 0.48, 0.71, 0.31, 0.42\rangle \\ \langle 0.30, 0.41, 0.73, 0.66\rangle & \langle 0.31, 0.35, 0.41, 0.52\rangle & \langle 0.90, 0.52, 0.21, 0.10\rangle & \langle 0.14, 0.26, 0.22, 0.36\rangle & \langle 0.49, 0.55, 0.31, 0.38\rangle \\ \langle 0.43, 0.52, 0.61, 0.56\rangle & \langle 0.51, 0.65, 0.31, 0.45\rangle & \langle 0.80, 0.42, 0.33, 0.20\rangle & \langle 0.80, 0.82, 0.32, 0.20\rangle & \langle 0.21, 0.43, 0.39, 0.43\rangle \\ \langle 0.80, 0.62, 0.53, 0.17\rangle & \langle 0.80, 0.73, 0.31, 0.12\rangle & \langle 0.23, 0.33, 0.42, 0.50\rangle & \langle 0.33, 0.38, 0.21, 0.31\rangle & \langle 0.78, 0.28, 0.18, 0.12\rangle \end{bmatrix} \end{array}$$

$$Q_5 = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{array}{c} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} & \begin{bmatrix} \langle 0.78, 0.60, 0.31, 0.12\rangle & \langle 0.53, 0.68, 0.22, 0.33\rangle & \langle 0.69, 0.78, 0.35, 0.27\rangle & \langle 0.80, 0.61, 0.27, 0.20\rangle & \langle 0.41, 0.62, 0.41, 0.50\rangle \\ \langle 0.48, 0.60, 0.29, 0.51\rangle & \langle 0.42, 0.53, 0.31, 0.44\rangle & \langle 0.80, 0.27, 0.24, 0.20\rangle & \langle 0.41, 0.50, 0.36, 0.42\rangle & \langle 0.87, 0.77, 0.31, 0.12\rangle \\ \langle 0.89, 0.50, 0.34, 0.01\rangle & \langle 0.90, 0.63, 0.39, 0.10\rangle & \langle 0.29, 0.36, 0.17, 0.27\rangle & \langle 0.63, 0.74, 0.18, 0.27\rangle & \langle 0.50, 0.57, 0.29, 0.40\rangle \\ \langle 0.58, 0.68, 0.21, 0.32\rangle & \langle 0.27, 0.62, 0.29, 0.60\rangle & \langle 0.67, 0.82, 0.28, 0.23\rangle & \langle 0.79, 0.85, 0.26, 0.20\rangle & \langle 0.90, 0.20, 0.40, 0.10\rangle \\ \langle 0.91, 0.39, 0.31, 0.00\rangle & \langle 0.47, 0.58, 0.29, 0.42\rangle & \langle 0.85, 0.50, 0.40, 0.10\rangle & \langle 0.45, 0.87, 0.16, 0.22\rangle & \langle 0.18, 0.30, 0.21, 0.29\rangle \end{bmatrix} \end{array}$$

$$Q_6 = \begin{array}{cc} & \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{array}{c} W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} & \begin{bmatrix} \langle 0.85, 0.90, 0.35, 0.50\rangle & \langle 0.90, 0.70, 0.25, 0.10\rangle & \langle 0.90, 0.80, 0.35, 0.10\rangle & \langle 0.25, 0.35, 0.35, 0.40\rangle & \langle 0.95, 0.75, 0.45, 0.05\rangle \\ \langle 0.79, 0.60, 0.33, 0.12\rangle & \langle 0.80, 0.84, 0.12, 0.15\rangle & \langle 0.25, 0.30, 0.25, 0.30\rangle & \langle 0.89, 0.55, 0.35, 0.10\rangle & \langle 0.75, 0.85, 0.35, 0.40\rangle \\ \langle 0.75, 0.85, 0.38, 0.40\rangle & \langle 0.25, 0.35, 0.55, 0.65\rangle & \langle 0.81, 0.85, 0.15, 0.30\rangle & \langle 0.75, 0.85, 0.25, 0.40\rangle & \langle 0.79, 0.82, 0.15, 0.30\rangle \\ \langle 0.65, 0.70, 0.25, 0.30\rangle & \langle 0.45, 0.65, 0.35, 0.50\rangle & \langle 0.78, 0.85, 0.35, 0.12\rangle & \langle 0.90, 0.65, 0.35, 0.10\rangle & \langle 0.85, 0.55, 0.45, 0.15\rangle \\ \langle 0.90, 0.85, 0.35, 0.10\rangle & \langle 0.80, 0.48, 0.33, 0.10\rangle & \langle 0.20, 0.55, 0.45, 0.50\rangle & \langle 0.25, 0.30, 0.25, 0.30\rangle & \langle 0.55, 0.60, 0.25, 0.40\rangle \end{bmatrix} \end{array}$$

Step 4: By applying SF, we get the following values in matrices form.

$$S(Q_1) = \begin{array}{c} \\ W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{bmatrix} 0.090 & 0.065 & 0.030 & 0.035 & 0.200 \\ 0.025 & -0.370 & -0.275 & 0.255 & -0.380 \\ 0.345 & -0.470 & 0.295 & -0.315 & 0.035 \\ 0.395 & 0.360 & -0.020 & -0.250 & -0.495 \\ -0.375 & 0.495 & 0.050 & 0.210 & 0.110 \end{bmatrix} \end{array}$$

$$S(Q_2) = \begin{array}{c} \\ W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{bmatrix} 0.245 & -0.170 & -0.370 & 0.360 & 0.285 \\ -0.280 & 0.155 & 0.245 & -0.590 & -0.345 \\ 0.175 & -0.480 & -0.220 & 0.430 & -0.320 \\ 0.505 & -0.395 & 0.050 & -0.365 & -0.525 \\ -0.400 & 0.510 & -0.510 & 0.015 & 0.120 \end{bmatrix} \end{array}$$

$$S(Q_3) = \begin{array}{c} \\ W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{bmatrix} 0.130 & -0.200 & -0.325 & 0.215 & 0.220 \\ -0.750 & 0.190 & 0.435 & -0.590 & -0.500 \\ 0.090 & -0.440 & -0.510 & -0.285 & -0.695 \\ -0.600 & 0.600 & 0.195 & 0.135 & -0.890 \\ -0.610 & -0.180 & -0.720 & -0.300 & 0.010 \end{bmatrix} \end{array}$$

$$S(Q_4) = \begin{array}{c} \\ W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{bmatrix} 0.215 & 0.295 & -0.355 & 0.145 & 0.020 \\ -1.020 & -0.375 & -0.295 & -0.670 & -0.450 \\ -0.930 & -0.590 & 0.435 & -0.460 & -0.320 \\ -0.695 & -0.420 & 0.225 & 0.030 & -0.630 \\ 0.055 & 0.160 & -0.645 & -0.275 & 0.430 \end{bmatrix} \end{array}$$

$$S(Q_5) = \begin{array}{c} \\ W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{bmatrix} 0.205 & -0.250 & -0.145 & 0.160 & -0.605 \\ -0.475 & -0.440 & 0.345 & -0.440 & 0.210 \\ 0.460 & 0.290 & -0.245 & -0.100 & -0.330 \\ -0.185 & -0.785 & -0.110 & 0.035 & 0.500 \\ 0.559 & -0.385 & 0.300 & -0.285 & -0.365 \end{bmatrix} \end{array}$$

$$S(Q_6) = \begin{array}{c} \\ W_1 \\ W_2 \\ W_3 \\ W_4 \\ W_5 \end{array} \begin{array}{c} \begin{array}{ccccc} D_1 & D_2 & D_3 & D_4 & D_5 \end{array} \\ \begin{bmatrix} -0.275 & 0.325 & 0.225 & -0.500 & 0.300 \\ 0.205 & 0.170 & -0.325 & 0.340 & -0.250 \\ -0.265 & -0.850 & 0.010 & -0.200 & 0.005 \\ -0.125 & -0.550 & 0.060 & 0.300 & 0.200 \\ 0.200 & 0.295 & -0.800 & -0.325 & -0.275 \end{bmatrix} \end{array}$$

Step 5: Now by comparing the score values with rating scale distribution, we obtain the following values in matrices form.

$$Q_1^*[5] = \begin{bmatrix} \langle 0.87, 0.66, 0.35, 0.12, 2\rangle & \langle 0.55, 0.63, 0.25, 0.28, 2\rangle & \langle 0.56, 0.74, 0.32, 0.40, 2\rangle & \langle 0.90, 0.68, 0.30, 0.05, 2\rangle & \langle 0.80, 0.45, 0.38, 0.10, 2\rangle \\ \langle 0.45, 0.50, 0.30, 0.33, 2\rangle & \langle 0.70, 0.38, 0.31, 0.20, 1\rangle & \langle 0.61, 0.31, 0.22, 0.10, 1\rangle & \langle 0.20, 0.26, 0.40, 0.46, 2\rangle & \langle 0.54, 0.75, 0.30, 0.36, 1\rangle \\ \langle 0.75, 0.48, 0.27, 0.20, 3\rangle & \langle 0.46, 0.52, 0.42, 0.47, 1\rangle & \langle 0.33, 0.39, 0.21, 0.25, 2\rangle & \langle 0.85, 0.30, 0.24, 0.15, 1\rangle & \langle 0.47, 0.54, 0.30, 0.37, 2\rangle \\ \langle 0.90, 0.37, 0.22, 0.10, 3\rangle & \langle 0.48, 0.58, 0.35, 0.41, 3\rangle & \langle 0.75, 0.82, 0.34, 0.12, 1\rangle & \langle 0.57, 0.78, 0.33, 0.38, 1\rangle & \langle 0.38, 0.42, 0.41, 0.49, 1\rangle \\ \langle 0.26, 0.32, 0.30, 0.35, 1\rangle & \langle 0.95, 0.51, 0.33, 0.02, 3\rangle & \langle 0.42, 0.53, 0.41, 0.46, 2\rangle & \langle 0.25, 0.01, 0.22, 0.12, 2\rangle & \langle 0.70, 0.32, 0.24, 0.30, 2\rangle \end{bmatrix}$$

$$Q_2^*[5] = \begin{bmatrix} \langle 0.78, 0.60, 0.31, 0.12, 2\rangle & \langle 0.53, 0.68, 0.22, 0.33, 1\rangle & \langle 0.69, 0.78, 0.35, 0.27, 1\rangle & \langle 0.80, 0.61, 0.27, 0.20, 3\rangle & \langle 0.41, 0.62, 0.41, 0.50, 2\rangle \\ \langle 0.48, 0.60, 0.29, 0.51, 1\rangle & \langle 0.42, 0.53, 0.31, 0.44, 2\rangle & \langle 0.80, 0.27, 0.24, 0.20, 2\rangle & \langle 0.41, 0.50, 0.36, 0.42, 1\rangle & \langle 0.87, 0.77, 0.31, 0.12, 1\rangle \\ \langle 0.89, 0.50, 0.34, 0.01, 2\rangle & \langle 0.90, 0.63, 0.39, 0.10, 1\rangle & \langle 0.29, 0.36, 0.17, 0.27, 1\rangle & \langle 0.63, 0.74, 0.18, 0.27, 3\rangle & \langle 0.50, 0.57, 0.29, 0.40, 1\rangle \\ \langle 0.58, 0.68, 0.21, 0.32, 3\rangle & \langle 0.27, 0.62, 0.29, 0.60, 1\rangle & \langle 0.67, 0.82, 0.28, 0.23, 2\rangle & \langle 0.79, 0.85, 0.26, 0.20, 1\rangle & \langle 0.90, 0.20, 0.40, 0.10, 1\rangle \\ \langle 0.91, 0.39, 0.31, 0.00, 1\rangle & \langle 0.47, 0.58, 0.29, 0.42, 3\rangle & \langle 0.85, 0.50, 0.40, 0.10, 1\rangle & \langle 0.45, 0.87, 0.16, 0.22, 2\rangle & \langle 0.18, 0.30, 0.21, 0.29, 2\rangle \end{bmatrix}$$

$$Q_3^*[5] = \begin{bmatrix} \langle 0.85, 0.90, 0.35, 0.50, 2\rangle & \langle 0.90, 0.70, 0.25, 0.10, 1\rangle & \langle 0.90, 0.80, 0.35, 0.10, 1\rangle & \langle 0.25, 0.35, 0.35, 0.40, 2\rangle & \langle 0.95, 0.75, 0.45, 0.05, 2\rangle \\ \langle 0.79, 0.60, 0.33, 0.12, 1\rangle & \langle 0.80, 0.84, 0.12, 0.15, 2\rangle & \langle 0.25, 0.30, 0.25, 0.30, 3\rangle & \langle 0.89, 0.55, 0.35, 0.10, 1\rangle & \langle 0.75, 0.85, 0.35, 0.40, 1\rangle \\ \langle 0.75, 0.85, 0.38, 0.40, 2\rangle & \langle 0.25, 0.35, 0.55, 0.65, 1\rangle & \langle 0.81, 0.85, 0.15, 0.30, 1\rangle & \langle 0.75, 0.85, 0.25, 0.40, 1\rangle & \langle 0.79, 0.82, 0.15, 0.30, 1\rangle \\ \langle 0.65, 0.70, 0.25, 0.30, 1\rangle & \langle 0.45, 0.65, 0.35, 0.50, 4\rangle & \langle 0.78, 0.85, 0.35, 0.12, 2\rangle & \langle 0.90, 0.65, 0.35, 0.10, 2\rangle & \langle 0.85, 0.55, 0.45, 0.15, 1\rangle \\ \langle 0.90, 0.85, 0.35, 0.10, 1\rangle & \langle 0.80, 0.48, 0.33, 0.10, 1\rangle & \langle 0.20, 0.55, 0.45, 0.50, 1\rangle & \langle 0.25, 0.30, 0.25, 0.30, 1\rangle & \langle 0.55, 0.60, 0.25, 0.40, 2\rangle \end{bmatrix}$$

$$Q_4^*[5] = \begin{bmatrix} \langle 0.80, 0.80, 0.31, 0.10, 2\rangle & \langle 0.80, 0.80, 0.31, 0.10, 2\rangle & \langle 0.31, 0.31, 0.31, 0.31, 1\rangle & \langle 0.10, 0.10, 0.10, 0.10, 2\rangle & \langle 0.90, 0.90, 0.90, 0.90, 2\rangle \\ \langle 0.30, 0.50, 0.40, 0.52, 1\rangle & \langle 0.30, 0.50, 0.40, 0.52, 1\rangle & \langle 0.40, 0.40, 0.40, 0.40, 1\rangle & \langle 0.52, 0.52, 0.52, 0.52, 1\rangle & \langle 0.82, 0.82, 0.82, 0.82, 1\rangle \\ \langle 0.14, 0.26, 0.22, 0.36, 1\rangle & \langle 0.14, 0.26, 0.22, 0.36, 1\rangle & \langle 0.22, 0.22, 0.22, 0.22, 3\rangle & \langle 0.36, 0.36, 0.36, 0.36, 1\rangle & \langle 0.50, 0.50, 0.50, 0.50, 1\rangle \\ \langle 0.80, 0.82, 0.32, 0.20, 1\rangle & \langle 0.80, 0.82, 0.32, 0.20, 1\rangle & \langle 0.32, 0.32, 0.32, 0.32, 2\rangle & \langle 0.20, 0.20, 0.20, 0.20, 2\rangle & \langle 1.00, 1.00, 1.00, 1.00, 1\rangle \\ \langle 0.33, 0.38, 0.21, 0.31, 2\rangle & \langle 0.33, 0.38, 0.21, 0.31, 2\rangle & \langle 0.21, 0.21, 0.21, 0.21, 1\rangle & \langle 0.31, 0.31, 0.31, 0.31, 1\rangle & \langle 0.64, 0.64, 0.64, 0.64, 3\rangle \end{bmatrix}$$

$$Q_5^*[5] = \begin{bmatrix} \langle 0.67, 0.48, 0.40, 0.21, 2\rangle & \langle 0.48, 0.71, 0.31, 0.42, 1\rangle & \langle 0.31, 0.31, 0.31, 0.31, 1\rangle & \langle 0.21, 0.21, 0.21, 0.21, 2\rangle & \langle 0.88, 0.88, 0.88, 0.88, 1\rangle \\ \langle 0.48, 0.71, 0.31, 0.42, 1\rangle & \langle 0.48, 0.71, 0.31, 0.42, 1\rangle & \langle 0.31, 0.31, 0.31, 0.31, 3\rangle & \langle 0.42, 0.42, 0.42, 0.42, 1\rangle & \langle 0.90, 0.90, 0.90, 0.90, 2\rangle \\ \langle 0.49, 0.55, 0.31, 0.38, 3\rangle & \langle 0.49, 0.55, 0.31, 0.38, 2\rangle & \langle 0.31, 0.31, 0.31, 0.31, 1\rangle & \langle 0.38, 0.38, 0.38, 0.38, 1\rangle & \langle 0.87, 0.87, 0.87, 0.87, 1\rangle \\ \langle 0.21, 0.43, 0.39, 0.43, 1\rangle & \langle 0.21, 0.43, 0.39, 0.43, 1\rangle & \langle 0.39, 0.39, 0.39, 0.39, 1\rangle & \langle 0.43, 0.43, 0.43, 0.43, 2\rangle & \langle 0.64, 0.64, 0.64, 0.64, 3\rangle \\ \langle 0.78, 0.28, 0.18, 0.12, 3\rangle & \langle 0.78, 0.28, 0.18, 0.12, 1\rangle & \langle 0.18, 0.18, 0.18, 0.18, 3\rangle & \langle 0.12, 0.12, 0.12, 0.12, 1\rangle & \langle 0.90, 0.90, 0.90, 0.90, 1\rangle \end{bmatrix}$$

$$Q_6^*[5] = \begin{bmatrix} \langle 0.80, 0.80, 0.31, 0.10, 1\rangle & \langle 0.80, 0.82, 0.32, 0.20, 3\rangle & \langle 0.32, 0.32, 0.32, 0.32, 2\rangle & \langle 0.20, 0.20, 0.20, 0.20, 1\rangle & \langle 0.90, 0.90, 0.90, 0.90, 3\rangle \\ \langle 0.80, 0.73, 0.31, 0.12, 2\rangle & \langle 0.80, 0.73, 0.31, 0.12, 2\rangle & \langle 0.31, 0.31, 0.31, 0.31, 1\rangle & \langle 0.12, 0.12, 0.12, 0.12, 3\rangle & \langle 0.92, 0.92, 0.92, 0.92, 1\rangle \\ \langle 0.23, 0.33, 0.42, 0.50, 1\rangle & \langle 0.23, 0.33, 0.42, 0.50, 1\rangle & \langle 0.42, 0.42, 0.42, 0.42, 2\rangle & \langle 0.50, 0.50, 0.50, 0.50, 1\rangle & \langle 0.73, 0.73, 0.73, 0.73, 2\rangle \\ \langle 0.33, 0.38, 0.21, 0.31, 1\rangle & \langle 0.33, 0.38, 0.21, 0.31, 1\rangle & \langle 0.21, 0.21, 0.21, 0.21, 2\rangle & \langle 0.31, 0.31, 0.31, 0.31, 3\rangle & \langle 0.64, 0.64, 0.64, 0.64, 2\rangle \\ \langle 0.78, 0.28, 0.18, 0.12, 2\rangle & \langle 0.78, 0.28, 0.18, 0.12, 2\rangle & \langle 0.18, 0.18, 0.18, 0.18, 1\rangle & \langle 0.12, 0.12, 0.12, 0.12, 1\rangle & \langle 0.90, 0.90, 0.90, 0.90, 1\rangle \end{bmatrix}$$

Step 6: Determine $Q_+^*(5)$ matrix by summing the corresponding entries of matrices and tabulate the details and assess the risk level of the students by using the norm details.

	W1	**W2**	**W3**	**W4**	**W5**
D_1	11	8	12	10	10
D_2	10	9	7	11	12
D_3	8	11	10	10	9
D_4	12	9	8	11	8
D_5	12	7	8	9	11
Total	**53**	**44**	**45**	**51**	**50**

Based on the total scores, the EI levels are classified as follows:

- **High Emotional Intelligence**: Score ≥ 50

- **Moderate Emotional Intelligence**: Score between 40 and 49
- **Low Emotional Intelligence**: Score < 40

The classification result is

Individual	EI Level
W_1	**High**
W_2	**Moderate**
W_3	**Moderate**
W_4	**High**
W_5	**High**

The IQPNNSS-based assessment offers a robust and flexible framework for evaluating emotional intelligence by accommodating interval-based uncertainty and multiple partitions of neutrosophic information. The final results demonstrate that three out of five individuals exhibit high levels of emotional intelligence, while the remaining two are in the moderate range. This approach can be extended to larger datasets and refined further by incorporating weighted criteria or decision-maker preferences.

9. Limitations, conclusion and future works

This research addresses two critical limitations that often restrict the practical application of neutrosophic frameworks in psychological analysis. Firstly, many traditional psychological assessments rely heavily on structured questionnaires, where mental health professionals tend to follow established methods such as classical test theory for evaluating conditions. However, such conventional approaches may not effectively capture the inherent indeterminacy present in human psychological responses. Secondly, psychiatric evaluations typically involve tracking behavioral changes over multiple interactions, which necessitates a flexible model capable of handling uncertain and evolving data. To overcome these barriers, we propose the use of IQPNNSS, a model that accommodates complex uncertainty while preserving standard evaluative practices through dual (positive and negative) scoring patterns. This structure enables mental health experts to systematically interpret emotional and psychological cues without compromising on familiarity or clinical rigor. Moreover, by integrating IQPNNSS with advanced decision-support tools such as quadri-hesitant degree functions , the proposed methodology offers a comprehensive framework for capturing subtle aspects of emotional intelligence. These enhancements support more nuanced and reliable assessments, particularly in situations where subjective interpretations and psychological ambiguity coexist. Future directions may include extending the IQPNNSS model to other hybrid fuzzy set environments and applying it in diverse psychological contexts. A practical case study involving student populations, particularly during high-stress periods such as public health crises, can further validate the effectiveness and adaptability of this approach in assessing emotional and psychosocial dynamics.

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