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A novel approach to fuzzy *N*-soft sets and its application for identifying and sanctioning cyber harassment on social media platforms

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Abstract

This study proposes a novel approach to fuzzy *N*-soft sets for handling cases where membership degree and grade are not related. In the standard model of fuzzy *N*-soft sets, membership degree and grade are assumed to be directly proportional. This assumption may not hold true in real-world situations, so a more flexible and nuanced approach is necessary. The proposed approach includes two novel algorithms for decision-making problems involving fuzzy *N*-soft sets. As a result, it is able to be adaptable and sensitive when addressing uncertainties in real-world scenarios, with a particular focus on identifying and sanctioning cyber harassment on social media platforms. Additionally, an innovative perspective and approach to decision-making problems involving fuzzy *N*-soft sets is introduced by extending an established selection process that prioritizes the dominant parameter, resulting in more precise and dependable outcomes. Our study offers an effective tool for decision-making in various fields, including e-commerce, social media, and product reviews.

Keywords Fuzzy *N*-soft set · Weighted fuzzy *N*-soft set · Decision-making · Cyber harassment

1 Introduction

A number of mathematical tools have been developed to face challenges involving uncertainty and vagueness, from fuzzy set theory to rough set theory to vague set theory to soft set theory. These theoretical frameworks have application across a diverse spectrum of domains and disciplines (Sivaprakasam and Angamuthu 2023; Khan et al. 2023; Panchal 2023; Dinçer et al. 2023; Nezhad et al. 2023). Soft sets (Molodtsov 1999) are a mathematical framework for modeling uncertainty and imprecision in sets and their elements. They provide a more flexible and intuitive approach to dealing with incomplete, inconsistent, and uncertain information. Based on the most recent studies (Ma et al. 2017, 2018; Zhan and Zhu 2015), it is apparent that the majority of researchers have focused on developing hybrid models of soft sets using either binary evaluations or real numbers within the range of [0, 1] as the degree of membership. Even so, non-binary evaluations are frequently

Extended author information available on the last page of the article encountered in everyday life, such as in evaluations or rankings. Consider a movie review system where users rate films on a scale of 1 to 5 stars. In this scenario, the user has five options for rating the film, providing a more nuanced evaluation than a binary yes or no vote. This type of ranking or rating system is commonly used in various fields, such as product reviews, restaurant ratings, and music or book ratings. It allows people to indicate their level of satisfaction with a particular item. Herawan and Deris (2009) constructed a novel binary-valued information system using soft sets, which assigns distinct rankings to each parameter. This stands in contrast to the rating orders previously presented by Chen et al. (2013). Meanwhile, Ali et al. (2015) explored a different approach by utilizing a rating system to assess the various elements of soft set parameters.

Fatimah et al. (2018) proposed the theory of N-soft sets to address inadequacies in the current soft set model and provide a finer granularity in handling uncertainties in real-world situations, as motivated by these kinds of examples. Using the decision-making procedure presented by Maji et al. (2002), they presented two procedures that rank alternatives based on their extended choice and extended weight choice values. Alcantud et al. (2019) delved deeper into N-soft sets by incorporating rough structures and approximations. They derived Pawlak's rough set, tolerance rough sets, and multigranular rough set from N-soft sets, and conversely, they showed how N-soft sets can be derived from these rough set models. Since the development of N-soft sets, numerous researchers have dedicated their efforts to exploring this influential concept (Riaz et al. 2019; Alcantud et al. 2022).

Maji et al. (2001) defined fuzzy soft sets as a hybrid model that extends the concept of fuzzy sets by allowing for multiple levels of uncertainty or vagueness in both the membership of elements in a set and the attributes associated with those elements. Akram et al. (2018) introduced a new hybrid model called fuzzy N-soft sets that combines fuzzy set theory with N-soft sets to handle uncertainties in attribute-based grading of objects. There are numerous studies in the literature exploring fuzzy N-soft sets from various perspectives Das and Granados (2022); Akram et al. (2019, 2023).

When faced with vague and uncertain data, fuzzy N-soft sets provide information on how grades are assigned to each member of the universe. As a result, membership degree and grade are directly proportional. Akram et al. (2018) presented three different algorithms to solve these types of decision-making problems. In the first approach, they found the maximum grade for each object by summing them. As for the second, they established a threshold value R based on the grade, and calculated the R-choice value by considering only the membership degrees of those exceeding this threshold and summing these values. Finally, they calculated the score value by exclusively using membership degrees and implementing the algorithm of Roy and Maji (2007). The results from the three methods are consistent because membership degrees and grades are directly proportional. Thus, it is enough to add up the grades to get the right answer.

While membership degree and grade are often assumed to be directly proportional, this assumption may not always hold true in practical scenarios. There can be cases in which the severity of a condition described by a parameter is high, while its frequency of occurrence is relatively low. In such cases, the direct proportionality between membership degree and grade breaks down, and existing approaches may struggle to provide accurate insights.

Consider a healthcare system in which patients are assessed for eligibility for specific medical treatments or surgeries. The system aims to implement a decision-making process that evaluates patients' eligibility degrees based on various criteria. This process involves considering both symptom severity, reflected in the membership degree, and frequency of occurrence of the symptom, which may not necessarily align directly with severity. Imagine a bank that provides loans and financial support to individuals and businesses. The bank aims to make lending decisions that are equitable and informed by assessing various parameters, including the credit score fluctuation, significant financial events, investment volatility and exceptional expenses. In this particular decision-making problem, significant financial events, such as substantial windfalls or unexpected expenses, may exhibit a high level of severity but occur relatively infrequently.

As another scenario, consider an e-commerce website where individuals and businesses can sell products and services to customers. The website provides a safe and secure platform for transactions. However, it faces challenges in controlling negative activities such as fraud, spamming, impersonation, price manipulation, and copyright infringement. To maintain the quality of its platform, the website wants to implement a fuzzy decision-making process to determine the membership degrees of each seller with respect to these negative parameters. The process will use various sources of information to evaluate sellers' behavior. For instance, in order to determine the fuzzy membership degree for the parameter "price manipulation" the factors that can be considered include: (i) Evidence of price manipulation, such as multiple accounts being used to artificially increase or decrease prices, complaints from other users regarding price manipulation (ii) the level of competition in the market for the specific product or service (iii) the rate at which prices change for similar products or services (iv) the overall reputation of the seller and their level of trust within the community. Now assume that the frequency of all these inappropriate behaviours is identified by the numbers $\{0, 1, 2, 3\}$ where 0 serves as "never" and 3 serves as "always". While the membership degree for the parameter "price manipulation" may be very high, it may not be very frequent. As a result, an algorithm based solely on grades is ineffective. It is necessary to create an algorithm that takes both membership degree and grade into account in the evaluation process.

Cyber harassment is a widespread issue in contemporary society, extensively studied by researchers Badi and Elghoul (2023), Rosa et al. (2018), Sintaha and Mostakim (2018). To address this challenge, decision-makers may consider applying sanctions, such as warnings, temporary suspensions, or severe penalties, tailored to the individual circumstances of each offender's behavior. These sanctions should factor in both the severity and frequency of the misconduct. While the existing literature has not extensively explored this specific topic, the development of a robust algorithm that integrates factors such as membership degree, grade, and sanctions has the potential to make significant contributions beyond addressing cyber harassment. It can enhance the broader fields of decision-making, user behavior analysis, and the governance of online communities.

In all these discussions, the study's main objectives are summarized as follows:

1. To propose two novel algorithms for decision-making problems that involve fuzzy *N*-soft sets, where membership degree and grade are not directly proportional.
2. To provide practical applications of the proposed algorithms to validate their effectiveness. A decision-making problem was solved using the first algorithm, where the user determined the optimal choice based on the frequency of a given behavior. In an effort to apply the second algorithm, the issue of identifying and properly sanctioning users who exhibit abusive or harassing behavior on a social media platform is examined.
3. To develop new algorithms that build on an existing approach that extends the emphasis on the dominant parameter in the selection process and effectively addresses the problem of unexpected results that can arise when membership degrees are close to each other.

4. To define the concept of weighted fuzzy N-soft set and demonstrate its practical application.

In order to achieve these objectives, the paper is organized as follows: Sect. 2 provides an overview of the fundamental concepts related to N-soft, fuzzy soft, and fuzzy N-soft sets. Section 3 presents innovative algorithms for decision-making procedures that incorporate weighted fuzzy N-soft sets as the central results of this paper. This section also includes practical applications of the algorithms to verify their effectiveness. Section 4 presents a summary and outlook on future work.

2 Preliminaries

This section introduces the key concepts and results used in the subsequent sections. To fully understand N-soft sets and fuzzy N-soft sets, it is important to revisit the theory of fuzzy soft sets first. Suppose that U consists of all the objects under consideration, E is the set of parameters and $A \subseteq E$.

Definition 2.1 (Maji et al. 2001) Suppose $\mathcal{F}(X)$ represents the family of all fuzzy subsets of U and $A \subseteq E$. Then, (F, A) is called a fuzzy soft set over U, where F is a mapping defined by $F : A \to \mathcal{F}(X)$.

Definition 2.2 (Fatimah et al. 2018) Let $G = \{0, 1, \ldots \mathrm{N}{-}1\}$ represent the set of ordered grades where $N \in \mathbb{N}$ and $N \geq 2$. Assume that $F : A \to \mathcal{P}(U \times G)$ is a function such that for each $e \in A$ and $u \in U$ there is a unique $(e, g_e) \in U \times G$ with $(e, g_e) \in F(e)$ and $g_e \in G$. In this case, (F, A, N) is called an N-soft set on U.

Example 2.1 Suppose the owners of a small restaurant want to introduce a new dish to their menu. There are four different recipes $\{u_1, u_2, u_3, u_4\}$. They are having trouble deciding which one to choose and decide to conduct a taste test with a group of regular customers $A = \{e_1, e_2, e_3\}$ to help them make a decision. To conduct the taste test, they need to assign a ranking to each dish, and decide to use a ranking system from 0 to 4, with 0 being the lowest rank and 4 being the highest rank. They ask customers to taste both dishes and give them a score from 0 to 4 based on their taste, appearance, and overall appeal. Thus, a 5-soft set $(F, A, 5)$ can be defined as follows:

$$
\begin{aligned}
F(e_1) =&\{(u_1, 1), (u_2, 3), (u_3, 2), (u_4, 2)\},\\
F(e_2) =&\{(u_1, 3), (u_2, 2), (u_3, 4), (u_4, 3)\},\\
F(e_3) =&\{(u_1, 2), (u_2, 4), (u_3, 3), (u_4, 4)\}.
\end{aligned}
$$

The tabular representation of $(F, A, 5)$ is shown in Table 1.

Definition 2.3 (Akram et al. 2018) Let $K = (F, A, N)$ be an N-soft set on U, and $\mathcal{F}(X)$ be the set of all fuzzy sets on a set X. Assume that μ is a function from E to $\bigcup_{e\in A} \mathcal{F}(F(e))$. In this case, (μ, K) is called a fuzzy N-soft set.

Table 1 Tabular representation of $(F, A, 5)$ in Example 2.1

	e_1	e_2	e_3
u_1	1	3	2
u_2	3	2	4
u_3	2	4	3
u_4	2	3	4

Example 2.2 Suppose a university admissions department is trying to decide which applicants to admit to its computer science program. There are three candidates, namely u_1, u_2 and u_3. The university has collected data on each applicant based on four criteria: e_1: academic performance, e_2: programming skills, e_3: work experience, and e_4: extracurricular activities. The Admissions Department evaluates applicants' qualities based on the following criteria:

$$\begin{aligned} 0 \leq \mu(e,u) &\leq 0.1 \text{ if } g_e = 0\\ 0.1 < \mu(e,u) &\leq 0.3 \text{ if } g_e = 1\\ 0.3 < \mu(e,u) &\leq 0.6 \text{ if } g_e = 2\\ 0.6 < \mu(e,u) &\leq 1 \text{ if } g_e = 3 \end{aligned}$$

Thus we can define a fuzzy 4-soft set as follows:

$$\begin{aligned} \mu_{e_1} &= \{< (u_1, 1), 0.12 >, < (u_2, 3), 0.87 >, < (u_3, 2), 0.45 >\},\\ \mu_{e_2} &= \{< (u_1, 0), 0.09 >, < (u_2, 2), 0.54 >, < (u_3, 2), 0.29 >\},\\ \mu_{e_3} &= \{< (u_1, 3), 0.75 >, < (u_2, 2), 0.32 >, < (u_3, 1), 0.24 >\},\\ \mu_{e_4} &= \{< (u_1, 1), 0.16 >, < (u_2, 1), 0.27 >, < (u_3, 3), 0.73 >\}. \end{aligned}$$

The tabular representation of the fuzzy 4-soft set is given in Table 2.

Akram et al. (2018) defined the fuzzy soft set corresponding to a fuzzy N-soft set (F, A, N) and a threshold $R \in (0, N)$ by defining

$$\mu^R(e,u) = \begin{cases} \mu(e)(u, g_e), & \text{if} \quad (u, g_e) \in F(e) \quad \text{and} \quad g_e \geq R\\ 0, & \text{otherwise} \end{cases}$$

Thus, they presented a selection method for finding the R-choice value for a fuzzy soft set corresponding to a fuzzy N-soft set (F, A, N) and a threshold value R, in addition to the method based on finding the maximum grade by summing the membership degrees.

Table 2 Fuzzy 4-soft set given in Example 2.2

	e_1	e_2	e_3	e_4
u_1	$< 1, 0.12 >$	$< 0, 0.09 >$	$< 3, 0.75 >$	$< 1, 0.16 >$
u_2	$< 3, 0.87 >$	$< 2, 0.54 >$	$< 2, 0.32 >$	$< 1, 0.27 >$
u_3	$< 2, 0.45 >$	$< 2, 0.29 >$	$< 1, 0.24 >$	$< 3, 0.73 >$

Table 3 The fuzzy soft set $(\tilde{F}, A, w)$

	$e_1, w_1 = 0.3$	$e_2, w_2 = 0.3$	$e_3, w_3 = 0.3$	$e_4, w_4 = 0.9$
u_1	0.3	0.3	0.3	0.1
u_2	0.29	0.29	0.29	1

Table 4 Weighted table of $(\tilde{F}, A, w)$

	$e_1, w_1 = 0.3$	$e_2, w_2 = 0.3$	$e_2, w_3 = 0.3$	$e_2, w_4 = 0.9$
u_1	0.09	0.09	0.09	0.09
u_2	0.087	0.087	0.087	0.9

A decision-making problem was applied to fuzzy soft sets by Roy and Maji (2007) as discussed in the Introduction section. According to Kong et al. (2009), this algorithm generally does not guarantee optimal choice. In order to show this, they first apply the algorithm given in (Roy and Maji 2007) for finding score values. Following that, they use the algorithm in (Maji et al. 2002) and take the sum of each row to determine the choice value for each object. Each algorithm results in a different choice.

The algorithm of Kong et al. generalized to weighted fuzzy soft sets by Korkmaz et al. (2023). In contrast to other studies that treat weight as a threshold value, this study emphasizes the dominant parameter in the selection process. Additionally, when membership degrees are close together, it solves the problem of encountering unexpected results. The algorithm of Akram et al. (2018) builds upon Roy and Maji's algorithm. Thus, unlike the method in (Akram et al. 2018), we will generalize the algorithm given in (Korkmaz et al. 2023) to fuzzy N-soft sets. Let's provide a brief summary of this algorithm.

Algorithm of Korkmaz et al. (2023)

Step 1: Input a weighted fuzzy soft set (F, A, w).
Step 2: Apply the complement operation to the membership degrees corresponding to the negative attributes (if any) to create the uniform tabular representation of (F, A, w).
Step 3: Create the weighted table with the entries w_{ij}, where $w_{ij} = \mu(e_j, u_i) \times w_j$, where $\mu(e_j, u_i)$ represents the membership degree of u_i for the parameter e_j and w_j is the degree of importance of the parameter e_j
Step 4: Create the comparison table with the entries $(c_{ij})_{n\times n}$, where $c_{ij} = \sum_{k=1}^{m} w_{ik} - w_{jk}$, where n is the number of object and m denotes the number of parameters.
Step 5: Calculate the row sum $r_i = \sum_{j=1}^{m} c_{ij}$.
Step 6: Any u_k that satisfies the condition $r_k = max_{i=1\ldots n} r_i$ is the optimal decision.

Now consider the weighted fuzzy soft set $(\tilde{F}, A, w)$ given in the Table 3.

It can be observed that the values of $\mu(e_j, u_i)$ are relatively similar for $i = 1, 2, 3$. Additionally, the weight of these parameters is much smaller compared to that of e_4. On the other hand, u_2 displays a relatively high value for the dominant parameter e_4. As a result, u_2 appears to be a reasonable option (Tables 4, 5).

Table 5 Comparison table of $(\tilde{F}, A, w)$

	u_1	u_2
u_1	0	− 0.801
u_2	0.801	0

Based on existing literature (Feng et al. 2010), u_1 is the optimal choice. However, we find that $r_1 = -0.801$ and $r_2 = 0.801$, indicating that the optimal choice is u_2, which is in line with our expectations.

In the following section, we will present two innovative algorithms built on Korkmaz et al's algorithm.

3 A novel approach to fuzzy *N*-soft sets and its applications

In this section, the focus is on elucidating the decision-making process employed in models where there is no direct proportionality between membership degree and grade. It is possible to develop an algorithm determining the optimal decision for user-selected grades. Aside from selecting for grades above a specific threshold as in (Akram et al. 2018), users may also desire to find the optimal choice for grades within particular ranges. This will require the following definition.

Definition 3.1 Let $0 \leq R_1 \leq R_2 < N$. The fuzzy soft set corresponding to the fuzzy *N*-soft set (F, A, N) and the interval $[R_1, R_2]$ is defined as follows:

$$\mu_{R_1}^{R_2}(e, u) = \begin{cases} \mu(e)(u, g_e), & \text{if } (u, g_e) \in F(e) \text{ and } R_1 \leq g_e \leq R_2 \\ 0, & \text{otherwise} \end{cases}$$

Example 3.1 Consider the fuzzy 6-soft set given in Table 6. The fuzzy soft sets corresponding to the fuzzy 6-soft set and the intervals [1, 3] and [4, 4] are given by Tables 7 and 8, respectively.

It is worth mentioning that in fuzzy *N*-soft set theory, a weight function can be defined in a similar manner as in fuzzy soft set theory.

Definition 3.2 A weighted fuzzy *N*-soft set is denoted by (F, A, N, w) where $w : A \to [0, 1]$, and $w(e_i)$ represents the degree of importance assigned to the attribute e_i.

Table 6 Fuzzy 6-soft set $(F, A, 6)$ given in Example 3.1

	e_1	e_2	e_3	e_4
u_1	$< 0, 0.09 >$	$< 1, 0.16 >$	$< 3, 0.50 >$	$< 5, 0.86 >$
u_2	$< 1, 0.17 >$	$< 3, 0.56 >$	$< 5, 0.94 >$	$< 4, 0.70 >$
u_3	$< 2, 0.30 >$	$< 5, 0.85 >$	$< 3, 0.42 >$	$< 4, 0.60 >$
u_4	$< 3, 0.50 >$	$< 4, 0.68 >$	$< 1, 0.10 >$	$< 2, 0.20 >$
u_5	$< 2, 0.32 >$	$< 3, 0.56 >$	$< 0, 0.03 >$	$< 1, 0.18 >$

Table 7 Fuzzy soft set corresponding to $(F, A, 6)$ and $[1, 3]$ given in Example 3.1

	e_1	e_2	e_3	e_4
u_1	0	0.16	0.50	0
u_2	0.17	0.56	0	0
u_3	0.30	0	0.42	0
u_4	0.50	0	0.10	0.20
u_5	0.32	0.56	0	0.18

Table 8 Fuzzy soft set corresponding to $(F, A, 6)$ and $[4, 4]$ given in Example 3.1

	e_1	e_2	e_3	e_4
u_1	0	0	0	0
u_2	0	0	0	0.70
u_3	0	0	0	0.60
u_4	0	0.68	0	0
u_5	0	0	0	0

Table 9 Weighted fuzzy 6-soft given in Example 3.2

	$e_1, w_1 = 0.62$	$e_2, w_2 = 0.32$	$e_3, w_3 = 0.23$	$e_4, w_4 = 0.02$
u_1	$< 0, 0.08 >$	$< 1, 0.12 >$	$< 3, 0.55 >$	$< 5, 0.82 >$
u_2	$< 1, 0.15 >$	$< 3, 0.46 >$	$< 5, 0.93 >$	$< 4, 0.67 >$
u_3	$< 2, 0.33 >$	$< 5, 0.92 >$	$< 3, 0.41 >$	$< 4, 0.62 >$

Example 3.2 Table 9 provides an example of a weighted fuzzy 6-soft.

Based on the previous explanations, we can now introduce the first algorithm of this paper.

3.1 Algorithm 1 and its implementation

Within this section, we will initially introduce an algorithm that proves highly beneficial when users need to determine the optimal choice based on the frequency of occurrence of a specific behavior. Subsequently, we will execute a numerical implementation to ensure the accuracy of this algorithm.

3.1.1 Algorithm 1

To address the problem at hand, we propose Algorithm 1, which comprises the following steps:

Step 1: Input a weighted fuzzy N-soft set (F, A, N, w).
Step 2: Choose an interval $[R_1, R_2]$.

Step 3: Find the weighted fuzzy soft sets corresponding to the weighted fuzzy N-soft set (F, A, N, w) and $[R_1, R_2]$.
Step 4: Create the weighted table with the entries w_{ij}, where $w_{ij} = \mu_{R_1}^{R_2}(e_j, u_i) \times w_j$, where $\mu_{R_1}^{R_2}(e_j, u_i)$ denotes the membership degree of u_i for the parameter e_j.
Step 5: Create the comparison table $(c_{ij})_{n \times n}$ with the entries $c_{ij} = \sum_{k=1}^{m} w_{ik} - w_{jk}$, where n is the number of objects and m denotes the number of parameters.
Step 6: Calculate the row sum $r_i = \sum_{j=1}^{m} c_{ij}$.
Step 7: The optimal decision for the interval $[R_1, R_2]$ is u_k such that $r_k = max_{i=1 \ldots n} r_i$.

Algorithm 1 represents a significant breakthrough in decision-making. By offering a new approach that handles decision-making problems where there is no direct relationship between the membership degree and the grade, it fills a critical gap in the existing literature. Another significant contribution of this algorithm is its ability to solve problems containing fuzzy N-soft sets with weighted parameters. This is a powerful tool since it enables us to emphasize parameters with higher weights by multiplying the weight by the membership degree. This allows for more nuanced decision-making in complex situations.

3.1.2 Numerical Example

In this part, we shall examine how Algorithm 1 is employed to address the task of choosing three students for an award, taking into account their favorable conduct and the frequency with which it occurs. This process entails the creation of fuzzy N-soft sets for various types of positive behaviors, which may include but are not limited to, academic performance, creativity, communication skills and leadership. All these parameters can be evaluated based on both degree of quality and frequency.

Determination of the parameters, membership degrees and grades

Imagine that a high school administration must select three students to receive a scholarship. Let $A = \{e_1, e_2, e_3, e_4\}$ be the set of parameters, where "e_1 = academic performance", "e_2 = creativity", "e_3 = leadership", "e_4 = communication skills".

After collecting nominations from the teachers, they select five students who receive multiple nominations and stand out as exceptional candidates for the program. Assume that $U = \{u_1, u_2, u_3, u_4, u_5\}$ is the set of candidates.

Let us now elaborate on the factors to be considered while determining the membership degree and grade for each attribute. This particular example uses grade to describe the frequency of the attribute.

1. Academic performance: Membership degree can be evaluated based on several factors such as the quality and completeness of a student's homework and assignments, the ability to find and analyze information from various sources, and the performance on exams. They can better assess a student's academic performance by considering these factors, and determine the degree of membership.

   The frequency of academic performance can be evaluated based on several factors, such as such as the number of assignments completed, the number of questions answered correctly, and the consistency of grades over time.
2. Creativity: Membership degree can be evaluated based on several factors, such as originality, usefulness, and aesthetics. For example, a student who comes up with original

and useful ideas that are visually appealing and well-executed could be considered to have a high membership degree for creativity.
The frequency of creativity can be evaluated based on several factors such as the number of ideas generated, the number of creative projects completed, and the consistency of creative output over time. For example, a student who consistently generates creative and innovative ideas, and completes creative projects on a regular basis could be considered to have a high frequency of creativity.
3. Leadership: Membership degree can be evaluated based on several factors such as vision, decision-making, and ability to motivate and inspire others. For example, a student who demonstrates a clear and compelling vision, makes informed and effective decisions, and motivates and inspires others to achieve their goals could be considered to have a high degree of leadership quality.
The frequency of the attribute leadership can be evaluated based on several factors such as the number of opportunities taken to lead, the variety of contexts in which leadership is demonstrated, and the consistency of effective leadership over time. For example, a student who consistently seeks out opportunities to lead, demonstrates leadership in a variety of contexts (e.g. group projects, extracurricular activities, etc.), and consistently shows effective leadership behaviors could be considered to have a high frequency of leadership.
4. Communication skills: Membership degree can be evaluated based on several factors such as clarity, relevance, and effectiveness. Communication skills are considered to be high when students communicate their ideas clearly, concisely, and in a relevant manner to their audience.
The frequency of communication skills can be evaluated based on several factors such as the number of opportunities taken to communicate, the variety of audiences addressed and the consistency of effective communication over time. For example, a student who consistently seeks out opportunities to interact and consistently communicates effectively could be considered to have a high frequency of communication skills.

It is possible to determine the frequency of each attribute using a numerical rating system from 0 to 4. Assume that

- 0 indicates “never”,
- 1 indicates “rarely”,
- 2 indicates “sometimes”,
- 3 indicates “often”,
- 4 indicates “consistently ”.

Determination of the weights

In order to determine the weights of the four parameters in the fuzzy soft set using AHP, we follow these steps:

1. The pairwise comparison matrix is given in the Table 10. To assign values to pairwise comparisons, we use a scale of 1 to 9 to indicate the relative importance of each criterion. 1 indicates equal importance for both criteria, while 9 indicates significant importance for one criterion over the other. Each entry a_{ij} signifies the extent to which the ith

Table 10 Pairwise comparison matrix

	e_1	e_2	e_3	e_4
e_1	1	4	6	5
e_2	1/4	1	4	3
e_3	1/6	1/4	1	1/3
e_4	1/5	1/3	3	1

criterion is preferred over the jth criterion. The particular values are determined based on the assessments and evaluations made by the decision makers who are involved in the process.

2. Table 11 presents the normalized matrix obtained by dividing each element of the pairwise comparison matrix by the sum of its columns.

Then $w_1 = (0.6186 + 0.7164 + 0.4286 + 0.5357)/4 = 0.5748$;$w_2 = (0.1546 + 0.1791 + 0.2857 + 0.3214)/4 = 0.2352$; $w_3 = (0.1033 + 0.0448 + 0.0714 + 0.0357)/4 = 0.0638$; $w_4 = (0.1237 + 0.0596 + 0.2143 + 0.1071)/4 = 0.1262$.

If we round the resulting values to 2 decimal places, we obtain the weights for each parameter as follows:

$w_1 = 0.57, w_2 = 0, 24, w_3 = 0.06, w_4 = 0.13$.

Note that we have $\lambda_{\max} = 4.2094$ and the size of pairwise comparison matrix is $n = 4$. Thus, the Consistency Index (CI) is

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} = \frac{4.2094 - 4}{4 - 1} = 0.0698.$$

According to Saaty (1980), the Random Consistency Index for a 4×4 matrix is 0.9. Therefore, with a Consistency Ratio of $\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} = 0.08$ in our case, we can conclude that our comparison matrix is consistent since $\mathrm{CR} < 0.10$.

Application of Algorithm 1 The high school administration wants to select three students who consistently demonstrate high degrees of quality in the identified behaviours.

Step 1: Input weighted fuzzy 5-soft set (F, A, N, w) as reported in Table 12.
Step 2: Choose the interval [3, 4].
Step 3: Find the weighted fuzzy soft set corresponding to the weighted fuzzy 5-soft set $(F, A, 5, w)$ and [3, 4] as given in Table 13.

Table 11 Normalized matrix

	e_1	e_2	e_3	e_4
e_1	0.6186	0.7164	0.4286	0.5357
e_2	0.1546	0.1791	0.2857	0.3214
e_3	0.1031	0.0448	0.0714	0.0357
e_4	0.1237	0.0597	0.2143	0.1071

Table 12 Weighted fuzzy 5-soft set $(F, A, 5, w)$

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_1	$< 4, 0.7 >$	$< 1, 0.2 >$	$< 3, 0.4 >$	$< 1, 0.3 >$
u_2	$< 1, 0.6 >$	$< 2, 0.6 >$	$< 3, 0.8 >$	$< 4, 0.4 >$
u_3	$< 4, 0.4 >$	$< 3, 0.3 >$	$< 3, 0.9 >$	$< 3, 0.6 >$
u_4	$< 3, 0.5 >$	$< 4, 0.8 >$	$< 1, 0.7 >$	$< 2, 0.2 >$
u_5	$< 2, 0.6 >$	$< 3, 0.9 >$	$< 3, 0.6 >$	$< 1, 0.4 >$

Table 13 Weighted fuzzy soft set corresponding to $(F, A, 5, w)$ and [3, 4]

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_1	0.7	0	0.4	0
u_2	0	0	0.8	0.4
u_3	0.4	0.3	0.9	0.6
u_4	0.5	0.8	0	0
u_5	0	0.9	0.6	0

Table 14 Weighted table of fuzzy soft set corresponding to $(F, A, 5, w)$ and [3, 4]

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_1	0.399	0	0.024	0
u_2	0	0	0.048	0.052
u_3	0.228	0.072	0.054	0.078
u_4	0.285	0.192	0	0
u_5	0	0.216	0.036	0

Table 15 Comparison table of fuzzy soft set corresponding to $(F, A, 5, w)$ and [3, 4]

	u_1	u_2	u_3	u_4	u_5
u_1	0	0.323	− 0.009	− 0.054	0.171
u_2	− 0.323	0	− 0.332	− 0.377	− 0.152
u_3	0.009	0.332	0	− 0.045	0.180
u_4	0.054	0.377	0.045	0	0.225
u_5	− 0.171	0.152	− 0.180	− 0.225	0

Step 4: Create the weighted table of fuzzy soft set corresponding to $(F, A, 5, w)$ and [3, 4] as given in Table 14.

Step 5: Create the comparison table of fuzzy soft set corresponding to $(F, A, 5, w)$ and [3, 4] as presented in Table 15.

Step 6: The row sums are found as $r_1 = 0.431$, $r_2 = -1.184$, $r_3 = 0.476$, $r_4 = 0.701$ and $r_5 = -0.424$.

Step 7: When taking into account the favorable attributes, whose weights are determined by the school administration, along with their frequency, it can be concluded that student u_4 is the most successful. It is possible to rank the students as $u_4 > u_3 > u_1 > u_5 > u_2$. Therefore, scholarships are awarded to students u_4, u_3 and u_1.

Algorithm 1 has the potential to benefit in a wide range of scenarios where there is no direct proportion between membership degree and grade. Let us say we are interested in purchasing a smartphone. To aid our decision-making process, we may gather feedback from different channels, such as customer reviews on e-commerce websites like Amazon or Best Buy, and social media platforms such as Twitter or Facebook. By analyzing the complaints, we can create a list of features that customers are dissatisfied with, such as battery life, screen quality, or software performance. It's worth noting that there may not always be a direct proportion between the frequency of complaints and the severity of dissatisfaction. Despite battery life receiving the most complaints, the level of dissatisfaction may not be significant enough to influence our choice.

In order to illustrate the advantages of the proposed model, a pivotal approach is to benchmark it against existing algorithms in the literature. It is worth noting that the weighted fuzzy N-soft sets was not utilized by Akram et al. (2018). Consequently, a direct comparison between the decision-making processes carried out in Algorithm 1 and Algorithm 2 with their methodology is not feasible. In light of this limitation, the only comparison is calculating the choice value by applying the algorithm of Feng et al. (2010) to the weighted fuzzy soft set obtained in Step 3 of Algorithm 1 and Step 4 of Algorithm 2 instead of the algorithm of Korkmaz et al. (2023) According to Feng et al. (2010), the tabular representation $T = (t_{ij})$ of a weighted fuzzy soft set can be constructed by assigning $t_{ij} = 1$ if $\mu(e_j, u_i) \geq w_j$ and $t_{ij} = 0$ otherwise. Further, the weighted choice value c_i corresponding to u_i is calculated by the formula $c_i = \sum_{j=1}^{m} w_j * t_{ij}$, in which m is the number of parameters. Table 16 shows the level soft sets of weighted fuzzy soft set given in Table 13 with weighted choice values ($\overline{c_i}$).

In this case, we have $u_1 > u_3 > u_5 > u_4 > u_2$. This order fails to fully account for the significance of u_4, as it possesses notably high membership values within parameters of greater weight. Moreover, although this specific example yields similar results to our method for other objects, as detailed in the Preliminaries, the algorithm of Feng et al. (2010) may have difficulties making accurate selections when membership values are close to each other.

3.2 Algorithm 2 and its implementation

Unlike the decision-making problem illustrated above, there may be instances where a single $[R_1, R_2]$-choice value does not suffice. For instance, we may encounter situations where we need to select items for each different interval $[R_1, R_2]$, and where multiple items must be chosen for each of these intervals.

Now let us examine the e-commerce website example mentioned in the Introduction to gain insight into how an algorithm capable of solving such problems should operate.

Table 16 Level soft sets of weighted fuzzy soft set given in Table 13 with weighted choice values

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$	$\overline{c_i}$
u_1	1	0	1	0	0.63
u_2	0	0	1	1	0.19
u_3	0	1	1	1	0.43
u_4	0	1	0	0	0.24
u_5	0	1	1	0	0.30

Imagine that the website may take different actions based on each $[R_1, R_2]$-choice value. Assume that

- 0 indicates "never"
- 1 indicates"rarely"
- 2 indicates "often"
- 3 indicates "always"

The algorithm needs to consider the severity and frequency of negative actions taken by sellers and respond appropriately. For instance;

1. Evaluate [2, 3]-choice value and "ban seller"
2. Evaluate [1, 1]-choice value and "warn seller"

Taking inspiration from the e-commerce website problem, let us presume that certain individuals will face varying sanctions for their abusive behavior. To achieve this, a threshold value can be set to determine which users qualify for the sanction. Instead of applying the sanction only to the user with the maximum row sum, the algorithm would apply the same sanction to all users whose row sums exceed the threshold value.

3.2.1 Algorithm 2

To address the problem mentioned above, we need to reorganize Algorithm 1 in a way that enables it to solve the issue. In this part, we will outline the necessary changes to the algorithm.

Step 1: Input a weighted fuzzy N-soft set (F, A, N, w).

Step 2: Determine the actions that will be taken by the algorithm for each $[R_1, R_2]$ and adjust a threshold T for each interval $[R_1, R_2]$ except the last one.

Step 3: Arrange the sanctions in a descending order based on their severity level and start with $[R_1, R_2]$ corresponding to the most severe sanction.

Step 4: Find the weighted fuzzy soft sets corresponding to the weighted fuzzy N-soft set (F, A, N, w) and $[R_1, R_2]$.

Step 5: Create the weighted table with the entries w_{ij}, where $w_{ij} = \mu_{R_1}^{R_2}(e_j, u_i) \times w_j$.

Step 6: Create the comparison table $(c_{ij})_{n \times n}$ with the entries $c_{ij} = \sum_{k=1}^{m} w_{ik} - w_{jk}$, where n is the number of objects and m denotes the number of parameters.

Step 7: Calculate the row sum $r_i = \sum_{j=1}^{m} c_{ij}$.

Step 8: Take the appropriate action for the each u_k such that $r_k \geq T$ and remove these elements from the universe.

Step 9: Iterate the steps 4–8 for each interval $[R_1, R_2]$ in descending order of the severity of sanctions, except for the last interval.

Step 10: Apply the last sanction to all elements of the universe.

Within Algorithm 2, a critical step involves adjusting a threshold T for each interval. There is a practical approach to finding an interval for this threshold. It depends on the weights of parameters and the number of objects under consideration. To establish the upper limit of this interval, we can consider the case where all membership values of one selected object u_k are set to 1, while all values of the others are set to 0. In this case, c_{kk}=0 while c_{kj} will be equal to the sum of the weights for all $j \neq k$. The choice value of this object can then be calculated using the formula "(sum of the weights) $\times$ $(n-1)$". Conversely, for the lower limit of the interval, we can consider the case in which all membership values of one fixed object u_k are set to 0, while the rest are set to 1. In this case, $c_{kk} = 0$ while c_{kj} will be equal to minus the sum of the weights for all $j \neq k$. The choice value of this object can be calculated using the formula "−(sum of the weights) $\times$ $(n-1)$". This method offers a practical means to estimate a threshold range that can be adjusted according to the specific characteristics of each decision-making problem.

Choosing the specific range $[R_1, R_2]$ and the corresponding and threshold values may require some trial and error to determine the optimal values based on our specific data set. For instance, for the most severe sanction, a narrower range could be selected with a higher threshold, ensuring that only the most severe misconduct triggers the sanction. On the other hand, a wider range with a lower threshold could be chosen to identify people exhibiting less severe but still problematic behavior.

3.2.2 Numerical Example

Cyber harassment has become a pervasive issue in today's society, and social media platforms are one of the primary places it occurs. It can take many forms, including bullying, stalking, threatening, or impersonation. Detecting cyber harassment on social media is critical for several reasons. It can help prevent mental health issues for victims, create a safer online environment for everyone, and hold perpetrators accountable for their actions. The issue of cyber harassment on social media has been the subject of numerous research studies. Table 17 lists some of the key research studies on this topic.

In this section, we will analyze the application of Algorithm 2 in examining and taking precautionary measures against abusive or harassing conduct on a social media platform. This process entails the creation of fuzzy *N*-soft sets for various types of abusive or harassing conduct, which may include but are not limited to, threats, insults directed at individuals, mocking or belittling remarks, or hate speech. The sets are constructed by considering the frequency and severity of these behaviors in different categories.

Determination of the parameters, membership degrees and grades

Suppose that $A = \{e_1, e_2, e_3, e_4\}$ is the set of parameters, where "$e_1 =$ threats", "$e_2 =$ insult directed at an individual", "$e_3 =$ mocking or belitting comments", "$e_4 =$ hate speech".

In accordance with the previous example, assume that the weights for each parameter have been set to $w_1 = 0.57, w_2 = 0,24, w_3 = 0.06, w_4 = 0.13$.

Let $U = \{u_1, u_2, u_3, u_4, u_5\}$ be the set of users who exhibit these negative behaviors on a social media platform.

Table 17 Some studies on the detection and analysis of cyberbullying

Researchers	Contribution
Sintaha and Mostakim (2018)	Detecting cyberbullying by machine learning algorithms
Chandra et al. (2018)	Cyberbullying detection using neural networks
Rosa et al. (2018)	Cyberbullying detection with fuzzy fingerprints
Diaz-Garcia et al. (2022)	Cyberbullying analysis based on a fuzzy approach

The membership of a given comment or post by each user can be evaluated based on the following factors:

1. Context: It is important to consider the context in which the comment or post was made. For example, a comment that is humorous in one context may be perceived as abusive in another.
2. Relationship between users:Relationships between users play an important role as well. When comments are made between friends or family, they may be perceived as less abusive than when they are made between strangers.
3. Community guidelines: In order to determine if the comment or post violates any social media platform policies, we should review the platform's guidelines.
4. Timing: Timing is also important when making a comment or posting. It is more likely that comments made in a sensitive or high-stakes situation will be perceived as abusive.
5. Impact on the community: Considering the wider community's impact should also be considered. A divisive or inflammatory comment, for instance, may have a negative impact on the community.

A numerical rating system from 0 to 4 can be used to identify the frequency of detrimental behaviors. Assume that

- 0 indicates "never". The user has not displayed harmful behavior and is in good standing.
- 1 indicates "rarely". The user has engaged in destructive behavior only a few times. This may be caused by a one-time error or judgment lapse, but it does not occur frequently.
- 2 indicates"sometimes". The user sometimes exhibits harmful behavior, but it still does not seem persistent.
- 3 indicates "often". The user frequently exhibits harmful behavior and it has become a persistent pattern.
- 4 indicates "consistently ". The user consistently exhibits extremely harmful behavior.

Determination of the sanctions
There are sanctions that can be applied to users who exhibit abusive or harassing behavior on social media platforms, such as:

1. Warn the user: There may be a warning message that the user's behavior is unacceptable and that further action will be taken if they continue.
2. Remove the offending comment or post: It is a common sanction imposed by social media platforms. Comments and posts that are abusive or harassing may be removed from the platform.
3. Temporary suspension: The user's account may be temporarily suspended for a set period of time, during which they can not access the platform.
4. Account restrictions: Certain features of the user's account may be restricted, such as their ability to post content, send messages, or interact with other users.

Table 18 Weighted fuzzy 5-soft set $(F, A, 5, w)$

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_1	$< 4, 0.7 >$	$< 4, 0.7 >$	$< 3, 0.2 >$	$< 4, 0.5 >$
u_2	$< 4, 0.4 >$	$< 4, 0.8 >$	$< 4, 0.7 >$	$< 1, 0.6 >$
u_3	$< 2, 0.3 >$	$< 2, 0.7 >$	$< 3, 0.1 >$	$< 2, 0.3 >$
u_4	$< 1, 0.7 >$	$< 3, 0.2 >$	$< 2, 0.3 >$	$< 1, 0.6 >$
u_5	$< 3, 0.8 >$	$< 2, 0.9 >$	$< 1, 0.6 >$	$< 2, 0.7 >$

Table 19 Weighted fuzzy soft set corresponding to $(F, A, 5, w)$ and [4, 4]

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_1	0.7	0.7	0	0.5
u_2	0.4	0.8	0.7	0
u_3	0	0	0	0
u_4	0	0	0	0
u_5	0	0	0	0

5. Permanent suspension: If the user's behavior is particularly egregious or repeated, the platform may permanently suspend their account. This would mean that the user could no longer access their account or previously posted content.
6. IP address block: If a user continues to violate the platform's terms of service or community guidelines despite previous sanctions, the platform may block the user's IP address, preventing them from accessing the platform altogether. This would make it harder for the user to create another account and continue their abusive behavior.

Application of Algorithm 2

Step 1: Input a weighted fuzzy 5-soft set $(F, A, 5, w)$ as given in Table 18.
Step 2: Specify the three actions that the algorithm will perform for each interval $[R_1, R_2]$ and adjust a threshold value for each interval as follows:

- Evaluate the [4, 4]-choice value and "permanently suspend the users' account" if their choice value exceeds $T = 2$.
- Evaluate the [3, 4]-choice value and "temporarily suspend the users' account" if their choice value exceeds $T = 0.5$.
- "Warn" all remaining users.

Step 3: Start iteration by selecting the interval [4, 4].
Step 4/1: Find the weighted fuzzy soft set corresponding to the weighted fuzzy 5-soft set $(F, A, 5, w)$ and [4, 4] as provided in Table 19.
Step 5/1: Create the weighted table of fuzzy soft set corresponding to $(F, A, 5, w)$ and [4, 4] as given in Table 20.

Table 20 Weighted table of fuzzy soft set corresponding to $(F, A, 5, w)$ and $[4, 4]$

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_1	0.399	0.168	0	0.065
u_2	0.228	0.192	0.042	0
u_3	0	0	0	0
u_4	0	0	0	0
u_5	0	0	0	0

Table 21 Comparison table of fuzzy soft set corresponding to $(F, A, 5, w)$ and $[4, 4]$

	u_1	u_2	u_3	u_4	u_5
u_1	0	0.170	0.632	0.632	0.632
u_2	− 0.170	0	0.462	0.462	0.462
u_3	− 0.632	− 0.462	0	0	0
u_4	− 0.632	− 0.462	0	0	0
u_5	− 0.632	− 0.462	0	0	0

Table 22 Weighted fuzzy soft set corresponding to $(F, A, 5, w)$ and $[3, 4]$

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_2	0.4	0.8	0.7	0
u_3	0	0	0.1	0
u_4	0	0.2	0	0
u_5	0.8	0	0	0

Table 23 Weighted table of fuzzy soft set corresponding to $(F, A, 5, w)$ and $[3, 4]$

	$e_1, w_1 = 0.57$	$e_2, w_2 = 0.24$	$e_3, w_3 = 0.06$	$e_4, w_4 = 0.13$
u_2	0.228	0.192	0.042	0
u_3	0	0	0.006	0
u_4	0	0.048	0	0
u_5	0.456	0	0	0

Step 6/1: Create the comparison table of fuzzy soft set corresponding to $(F, A, 5, w)$ and $[4, 4]$ as given in Table 21.

Step 7/1: The row sums are found as $r_1 = 2.066$, $r_2 = 1.216$ and $r_3 = r_4 = r_5 = -1.094$.

Step 8/1: Permanently suspend the account of u_1 and remove u_1 from the universe.

Step 9/1: Iterate the steps 4–8 for the interval $[3, 4]$.

Step 4/2: The weighted fuzzy soft set corresponding to the weighted fuzzy 5-soft set $(F, A, 5, w)$ and $[3, 4]$ is presented in Table 22.

Step 5/2: Create the weighted table of fuzzy soft set corresponding to $(F, A, 5, w)$ and $[3, 4]$ as reported in Table 23.

Step 6/2: Create the comparison table of fuzzy soft set corresponding to $(F, A, 5, w)$ and $[3, 4]$ as given in Table 24.

Step 7/2: The row sums are found as $r_2 = 0.876$, $r_3 = -0.948$, $r_4 = -0.780$ and $r_5 = 0.852$.

Step 8/2: Temporarily suspend the account of u_2 and u_5, and remove them from the universe.

Step 10: Warn users u_3 and u_4.

The algorithm analyzes the behavior of different users on the social media platform and finds that user u_1 engaged in severe cyber harassment, which has a high weight, frequency, and severity. The social media platform identifies this behavior as particularly significant, and u_1's account is permanently suspended. Users u_2 and u_5 also engage in cyber harassment, but their behavior does not exceed a certain threshold value set for the [4,4]-choice value. Their behavior is still more noticeable and serious than that of other users, and their accounts have been temporarily suspended for this reason. Users who engage in some form of cyber harassment, but not as severe as u_1, u_2, and u_5, will be punished with a milder method of punishment, which is a warning.

Considering the effectiveness of the algorithm is important when dealing with a larger user population. It may be necessary to narrow the intervals of the algorithm, which can be accomplished by increasing the number of intervals, in order to achieve optimal results. In doing so, the sanctions can be diversified to improve their impact. By taking these steps, the algorithm can be better adapted to meet the needs of a larger user base and provide more effective results.

4 Conclusion and future works

This study introduces two novel algorithms designed to tackle decision-making problems involving fuzzy *N*-soft sets, where membership degree and grade are not directly proportional. The efficacy of these algorithms has been demonstrated through their application to different decision-making problems. Algorithm 1 enables the concurrent consideration of both the membership degree and grade while evaluating such problems. Algorithm 2 facilitates the selection of different elements from the universe based on varying intervals of grades, and it provides a viable solution for problems that require distinct sanctions following each decision. Our work is particularly potent as it can effectively identify and analyze the underlying factors that contribute to abusive or harassing behavior on a social media platform. Through the adoption of a multifaceted approach that entails taking varying actions for each user, we provide a more nuanced and comprehensive analysis of social media interactions. Furthermore, by extending an established selection process that prioritizes the dominant parameter, we introduce an innovative perspective and approach to

Table 24 Comparison table of fuzzy soft set corresponding to $(F, A, 5, w)$ and [3, 4]

	u_2	u_3	u_4	u_5
u_2	0	0.456	0.414	0.006
u_3	− 0.456	0	− 0.042	− 0.450
u_4	− 0.414	0.042	0	− 0.408
u_5	− 0.006	0.450	0.408	0

decision-making problems involving N-soft sets, resulting in more precise and dependable outcomes.

The proposed algorithms are also versatile and powerful tools for analyzing complex interactions in various fields. It can potentially be applied to any online community or platform where users can engage in interactions with each other, such as forums, chat rooms, messaging apps, and online gaming platforms. It may also be useful for companies or organizations that provide customer support or manage employee behavior, as well as for law enforcement agencies to monitor and address cyber harassment and hate speech.

We acknowledge the potential limitations inherent in our study. A key limitation pertains to the methodology employed for determining the weights of parameters. In our research, we utilized the Analytic Hierarchy Process (AHP), which falls under the category of subjective methods. While AHP offers valuable insights by considering the preferences of decision makers, it introduces subjectivity into the validation process. Therefore, as a future work, we can benefit from objective methods designed to mitigate human-made instabilities and rely on mathematical models without taking into account the preferences of decision makers. Moreover we can extend our algorithm to other practical applications involving fuzzy N-soft sets, and we can continue to investigate its effectiveness in real-world scenarios.

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Declarations

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