Teaching risk assessment index system using neutrosophic AHP: Data Fusion method

Gustavo Alvarez Gómez [1], Corona Gómez Armijos[1], Ariel Romero Fernández[1,*], Asmaa Ahmed[2,3]

[1] Autonomous Regional University of the Andes (UNIANDES), Ecuador
[2] College of Humanities and Sciences, University of Science and Technology of Fujairah, UAE
[3] Faculty of Social Work, Assiut University, Egypt
Emails:rectorado@uniandes.edu.ec; vicerrectorado@uniandes.edu.ec; dir.investigacion@uniandes.edu.ec; asmaa.ahmed@ustf.ac.ae

Abstract
The technology behind data fusion and picture instruction is continuously advancing along with the progression of society, and new applications for these skills are increasingly becoming available in everyday life to accommodate the expansion of scientific and technological knowledge. The term "data fusion technology" relates to a computer processing method that allows the use of a computer to automatically analyze and synthesize several observation data gleaned in time series in accordance with criteria to complete the necessary decision-making and evaluation tasks. But teaching surrounding multiple risks. This paper aims to identify and assess risks in teaching. The assessment risks in teaching are a critical task and contain multiple conflict criteria. We use Multi-Criteria Decision Making (MCDM). In this paper, we use an Analytical Hierarchy Process (AHP) to rank and compute each criterion's weights. We use five main and twenty sub-criteria. These criteria were evaluated under a neutrosophic environment—an example provided to present the outcomes of the proposed model.

Keywords: AHP; Teaching risk; Assessment; Neutrosophic Sets; Data Fusion

1. Introduction

Risk is a critical element in any society and country. So, risks need to identify and assess to gain the most benefit. The risk assessment in education identified more[1]–[6]. So, the risk in the teaching process is a critical task for countries and society. So, these risks need to be evaluated. The risk in teaching threatens from multi-criteria like uncertainty, probability, servility, activity, knowledge, and value. Assessment teaching risk can help teachers, students, countries, and researchers.

Doi: https://doi.org/10.54216/FPA.140216
Received: July 27, 2023 Revised: November 02, 2023 Accepted: January 21, 2024

The assessment of the risks in teaching has many criteria and sub-criteria. We use five main and twenty sub-criteria. So, the concept of Multi-Criteria Decision Making is used in this paper. MCDM method is used in the decision making problem in different fields[7]–[15]. We use the AHP method for computing the weights of criteria and sub-criteria. The AHP method is an MCDM[15]–[17]. It is used in the decision-making process. It is an easy tool and suitable for this problem. It builds a pairwise comparison matrix between main and sub-criteria for comparison and normalization matrix.

The AHP method integrated under neutrosophic environment. We use single Valued Neutrosophic Sets (SVNSs) for dealing with uncurtaining. Due to this problem contains incomplete and uncertain information. SVNSs provided three values truth, indeterminacy, and falsity values. So, the neutrosophic sets are better than the fuzzy system. Fuzzy systems can consider the truth and falsity value only and ignore the indeterminacy value in calculations[18]–[20].This paper's main contribution is that it is the first time to propose a neutrosophic environment for assessment risk teaching and integrated with the AHP method.

This paper is organized as follows: Section 2 presents the AHP Method, Section 3 presents the results and example. Section four presents' conclusions.

2. Literature Review

The latest educational approaches, like smart educational experiences, use technological and situationally technologies to make the learning process easier for students. With this innovative approach to teaching, a massive amount of data about multimodal kids' experiences, drawn from a wide range of diverse sources, may be collected, combined, and analyzed. It presents a one-of-a-kind chance for educators and academics to be able to uncover new information, which will make it easier for them to analyze the student learning and act appropriately, if required. Yet, to integrate a variety of multimodal learning insights from a variety of sources, it is important to use the appropriate data fusion methodologies and procedures. These inputs or modalities in MLA comprise audio, video, electrodermal transaction data, eye-tracking, client logs, and click-stream data. But these inputs or modalities also contain learning artefacts and more basic human signals like gestures, gaze, voice, or writing. Chango et al. [21] presented an introduction to data fusion in the fields of learning analytics (LA) and educational data mining (EDM), as well as discussed how these data fusion approaches have been used in smart learning.

Xie et al.[22] used the technique of scenario to analyze the similar tech. They provided examples of a virtual exploratory teaching system, an intelligent auxiliary teacher factors, and a virtual traditional classroom system. They then applied the investigation technique and the methodological approach to evaluate the system they suggested in their study and organize students' opinions in a systematic attitude. According to the findings of an experiment and a poll, 78 students feel that the virtual math school system is best suited for mimicking the experience of operating a business and comprehending its underlying concepts.

Chuanqi Ma [23]created a variety of human styles using sensor network figures to accurately measure body movement through into the Internet of Things (IoT). This was done to design personalized curriculum design and practice for the purpose of increasing the popularity of inventive aerobics curriculum. He began by

Doi: https://doi.org/10.54216/FPA.140216
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introducing the technique and the data fusion process before moving on to replicate the aerobics innovative curriculum design.

The technology behind data fusion and picture instruction is continuously advancing along with the progression of society, and new applications for these skills are increasingly becoming available in everyday life to accommodate the expansion of scientific and technological knowledge. The term "data fusion technology" refers to a computer processing technology that makes use of a computer to automatically analyze and synthesize several observation data gleaned in time series in accordance with criteria to complete the necessary decision-making and evaluation tasks. The impact of the traditional method of instruction on students' learning and other elements of help isn't particularly clear, whereas the impact of the video teaching method on students' learning and other aspects of help is very significant. The video teaching approach can not only enhance students' enthusiasm for learning but also assist their learning[24].

Chango et al.[25] employed data fusion methodologies in to forecast the ultimate academic achievement of university students by integrating various, multimodal data from mixed-learning settings. Blended learning environments combine several types of instruction. They gathered information on first-year college students from a variety of sources, including theoretical lectures, practical sessions, online Moodle meetings, and a final examination, and then preprocessed that information. Their goal is to figure out which method of data fusion yields the most beneficial outcomes when applied to our information.

2. The proposed Teaching Assessment method using Neutrosophic AHP data Fusion Model

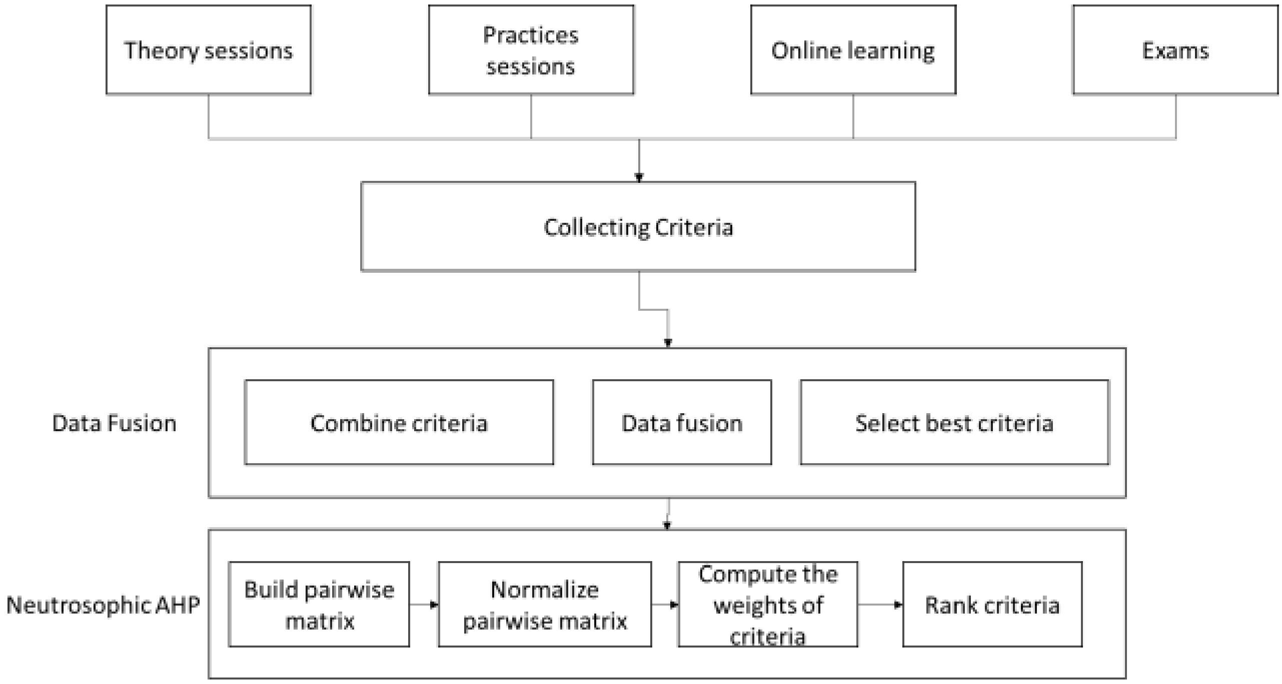

Figure 1: The framework of data fusion and Neutrosophic

It does this by collecting information from several different sources, including theoretical lectures, practical sessions, online sessions via Moodle, and the final exam for the course. In addition to this, various pre-

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processing operations are carried out to generate datasets in two distinct forms, namely numerical and categorical.

It utilizes a variety of data fusion techniques, as well as the selection of the most useful qualities and the neutrosophic AHP method. The Neutrosophic AHP used to compute the weights of criteria.

The AHP method is a MCDM method used for computing the weights of criteria. In this paper used for assessment risks in teaching. The following AHP steps[26]:

Step 1: Collect criteria and sub criteria

Step 2: Collect group of decision makers.

Step 3: Let experts to build a pairwise comparison matrix between criteria then cub criteria.

$$pairwise\ matrix = \begin{bmatrix} <\left[{T_{11}^{U}}^{(1)},{T_{11}^{L}}^{(1)}\right],\left[{I_{11}^{U}}^{(1)},{I_{11}^{L}}^{(1)}\right],\left[{F_{11}^{U}}^{(1)},{F_{11}^{L}}^{(1)}\right]> & \cdots & <\left[{T_{1m}^{U}}^{(1)},{T_{1m}^{L}}^{(1)}\right],\left[{I_{1m}^{U}}^{(1)},{I_{1m}^{L}}^{(1)}\right],\left[{F_{1m}^{U}}^{(1)},{F_{1m}^{L}}^{(1)}\right]> \\ \vdots & \ddots & \vdots \\ <\left[{T_{m1}^{U}}^{(1)},{T_{m1}^{L}}^{(1)}\right],\left[{I_{m1}^{U}}^{(1)},{I_{m1}^{L}}^{(1)}\right],\left[{F_{m1}^{U}}^{(1)},{F_{m1}^{L}}^{(1)}\right]> & \cdots & <\left[{T_{mm}^{U}}^{(1)},{T_{mm}^{L}}^{(1)}\right],\left[{I_{mm}^{U}}^{(1)},{I_{mm}^{L}}^{(1)}\right],\left[{F_{mm}^{U}}^{(1)},{F_{mm}^{L}}^{(1)}\right]> \end{bmatrix}$$

Step 4: Combined pairwise comparison matrix into a one matrix by a mean value.

$$combined\ pairwise\ matrix = \begin{bmatrix} <[T_{11}^{U},T_{11}^{L}],[I_{11}^{U},I_{11}^{L}],[F_{11}^{U},F_{11}^{L}]> & \cdots & <[T_{1m}^{U},T_{1m}^{L}],[I_{1m}^{U},I_{1m}^{L}],[F_{1m}^{U},F_{1m}^{L}]> \\ \vdots & \ddots & \vdots \\ <[T_{1m}^{U},T_{1m}^{L}],[I_{1m}^{U},I_{1m}^{L}],[F_{1m}^{U},F_{1m}^{L}]> & \cdots & <[T_{mm}^{U},T_{mm}^{L}],[I_{mm}^{U},I_{mm}^{L}],[F_{mm}^{U},F_{mm}^{L}]> \end{bmatrix}$$

$$pairwise\ matrix = \begin{bmatrix} a_{11} & \cdots & a_{m1} \\ \vdots & \ddots & \vdots \\ a_{1m} & \cdots & a_{mm} \end{bmatrix}$$

Step 5: Normalize the combined pairwise comparison matrix

$$N = \frac{a_i}{\sum_{i=1}^{m} a_i}$$

Step 6: Compute the weights of criteria by average of row in normalization matrix.

$$W = \frac{n_i}{\sum_{i=1}^{m} n_i}$$

3. Results and Discussion

This section proposes the outcomes of the proposed method. First, we need to assess teaching risk. Three experts were collected to assess the criteria and sub-criteria. The five main criteria and twenty sub-criteria. C1: work related stress, C1.1 lack of student motivations, C1.2: difficulty working with partner, C1.3: increased class size, C1.4: student performance objectives, C1.5: lack of control, C1.6: lack of professional recognition. C2:

Doi: https://doi.org/10.54216/FPA.140216
Received: July 27, 2023 Revised: November 02, 2023 Accepted: January 21, 2024

Risks of the workplace, C2.1: Violence student, C2.2: Violence teacher. C3: legal considerations, C3.1: releasing information requested, C3.2: family provision, C3.3: right of teacher, C3.4: access to educational opportunities, C4.5: risks law designed. C4: technical, C4.1: incomplete activity, C4.2: incomplete value, C4.3: incomplete course, C4.4: incomplete knowledge. C5: economic issue, C5.1: educational aids, C5.2: risk injuries. C5.3: risk of developing carpal tunnel syndrome. Then three experts evaluate the five main criteria to build a pairwise comparison matrix into Table 1-3. Then combined three matrices into one matrix in Table 4. Then normalize the combined pairwise comparison matrix into Table 5. Then compute the weights of criteria in Table 6. Fig 2. Present the weights of primary criteria. C5: economic issues are the highest in teaching risks, and work-related stress is the lowest in teaching assistants.

Table 1: Pairwise comparison matrix for five main criteria by first decision makers.

	C_1	C_2	C_3	C_4	C_5
C_1	0.5	0.9	0.383	0.8167	0.383
C_2	1.111111	0.5	0.8167	0.383	0.283
C_3	2.610966	1.22444	0.5	0.9	0.283
C_4	1.22444	2.610966	1.111111	0.5	0.9
C_5	2.610966	3.533569	3.533569	1.111111	0.5

Table 2: Pairwise comparison matrix for five main criteria by second decision makers.

	C_1	C_2	C_3	C_4	C_5
C_1	0.5	0.8167	0.383	0.8167	0.9
C_2	1.22444	0.5	0.8167	0.383	0.9
C_3	2.610966	1.22444	0.5	0.383	0.8167
C_4	1.22444	2.610966	2.610966	0.5	0.383
C_5	1.111111	1.111111	1.22444	2.610966	0.5

Table 3: Pairwise comparison matrix for five main criteria by third decision makers.

	C_1	C_2	C_3	C_4	C_5
C_1	0.5	0.383	0.9	0.2833	0.8167
C_2	2.610966	0.5	0.8167	0.383	0.383
C_3	1.111111	1.22444	0.5	0.9	0.283
C_4	3.529827	2.610966	1.111111	0.5	0.9
C_5	1.22444	2.610966	3.533569	1.111111	0.5

Table 4: Combined matrix for five main criteria.

	C_1	C_2	C_3	C_4	C_5
C_1	0.5	0.6999	0.555333	0.6389	0.6999
C_2	1.648839	0.5	0.8167	0.383	0.522
C_3	2.111014	1.22444	0.5	0.727667	0.4609
C_4	1.992902	2.610966	1.611063	0.5	0.727667
C_5	1.648839	2.418549	2.763859	1.611063	0.5

Doi: https://doi.org/10.54216/FPA.140216
Received: July 27, 2023 Revised: November 02, 2023 Accepted: January 21, 2024

Table 5: Normalized combined matrix for five main criteria.

	C_1	C_2	C_3	C_4	C_5
C_1	0.063278	0.093898	0.088897	0.165491	0.240477
C_2	0.208672	0.067079	0.130736	0.099207	0.179353
C_3	0.267163	0.164269	0.080039	0.188484	0.158359
C_4	0.252215	0.350284	0.257896	0.129513	0.250017
C_5	0.208672	0.32447	0.442433	0.417306	0.171794

Table 6: Weights.

	Weights of criteria
C_1	0.130408
C_2	0.137009
C_3	0.171663
C_4	0.247985
C_5	0.312935

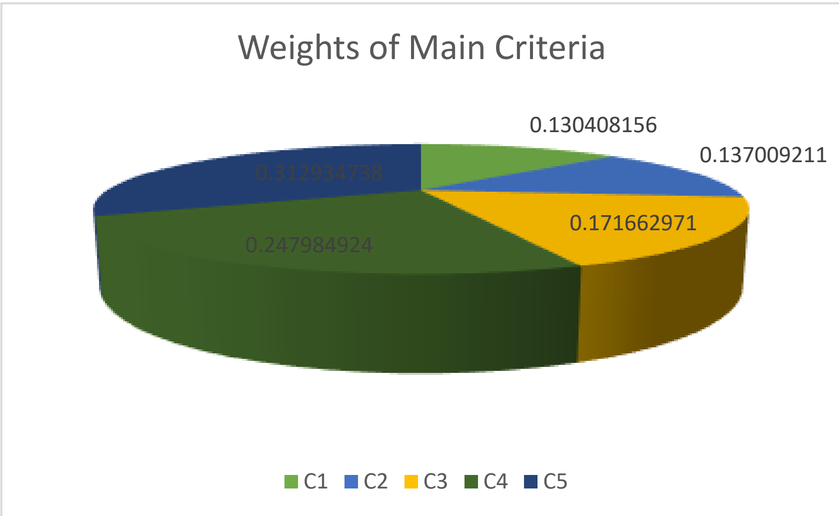

Figure 2: Weights of main criteria.

Then compute weights of sub-criteria C1. Then three experts evaluate the five main criteria to build a pairwise comparison matrix into Table 7-9. Then combined three matrices into one matrix in Table 10. Then normalize the combined pairwise comparison matrix into Table 11. Then compute the weights of criteria in Table 12. Fig 3. Present the weights of Sub criteria. C1: lack of professional recognition is the highest weight in teaching risks, and lack of student motivation is the lowest in teaching assistants.

Table 7: Pairwise comparison matrix for five main criteria by first decision makers.

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$
$C_{1.1}$	0.5	0.8167	0.383	0.283	0.8167	0.9
$C_{1.2}$	1.22444	0.5	0.383	0.9	0.9	0.8167
$C_{1.3}$	2.610966	2.610966	0.5	0.383	0.8167	0.383

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$C_{1.4}$	3.533569	1.111111	2.610966	0.5	0.383	0.283
$C_{1.5}$	1.22444	1.111111	1.22444	2.610966	0.5	0.383
$C_{1.6}$	1.111111	1.22444	2.610966	3.533569	2.610966	0.5

Table 8: Pairwise comparison matrix for five main criteria by second decision makers.

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$
$C_{1.1}$	0.5	0.383	0.283	0.8167	0.9	0.8167
$C_{1.2}$	2.610966	0.5	0.8167	0.9	0.283	0.9
$C_{1.3}$	3.533569	1.22444	0.5	0.9	0.383	0.283
$C_{1.4}$	1.22444	1.111111	1.111111	0.5	0.9	0.383
$C_{1.5}$	1.111111	3.533569	2.610966	1.111111	0.5	0.8167
$C_{1.6}$	1.22444	1.111111	3.533569	2.610966	1.22444	0.5

Table 9: Pairwise comparison matrix for five main criteria by third decision makers.

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$
$C_{1.1}$	0.5	0.9	0.8167	0.383	0.9	0.283
$C_{1.2}$	1.111111	0.5	0.9	0.283	0.283	0.383
$C_{1.3}$	1.22444	1.111111	0.5	0.8167	0.9	0.283
$C_{1.4}$	2.610966	3.533569	1.22444	0.5	0.8167	0.9
$C_{1.5}$	1.111111	3.533569	1.111111	1.22444	0.5	0.8167
$C_{1.6}$	3.533569	2.610966	3.533569	1.111111	1.22444	0.5

Table 10: Combined matrix for five main criteria.

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$
$C_{1.1}$	0.5	0.6999	0.494233	0.494233	0.872233	0.666567
$C_{1.2}$	1.648839	0.5	0.6999	0.694333	0.488667	0.6999
$C_{1.3}$	2.456325	1.648839	0.5	0.6999	0.6999	0.316333
$C_{1.4}$	2.456325	1.918597	1.648839	0.5	0.6999	0.522
$C_{1.5}$	1.148887	2.726083	1.648839	1.648839	0.5	0.672133
$C_{1.6}$	1.956373	1.648839	3.226035	2.418549	1.686615	0.5

Table 11: Normalized combined matrix for five main criteria.

	$C_{1.1}$	$C_{1.2}$	$C_{1.3}$	$C_{1.4}$	$C_{1.5}$	$C_{1.6}$
$C_{1.1}$	0.04918	0.076557	0.060141	0.076556	0.176304	0.197388
$C_{1.2}$	0.16218	0.054691	0.085168	0.107551	0.098774	0.207259
$C_{1.3}$	0.241604	0.180354	0.060843	0.108413	0.141471	0.093675
$C_{1.4}$	0.241604	0.20986	0.200641	0.077449	0.141471	0.154578
$C_{1.5}$	0.113004	0.298185	0.200641	0.255402	0.101065	0.199037
$C_{1.6}$	0.192429	0.180354	0.392565	0.374629	0.340915	0.148063

Table 12: Weights of sub criteria C1.

	Weights of criteria
$C_{1.1}$	0.106021

Doi: https://doi.org/10.54216/FPA.140216
Received: July 27, 2023 Revised: November 02, 2023 Accepted: January 21, 2024

$C_{1.2}$	0.119271
$C_{1.3}$	0.137727
$C_{1.4}$	0.170934
$C_{1.5}$	0.194556
$C_{1.6}$	0.271492

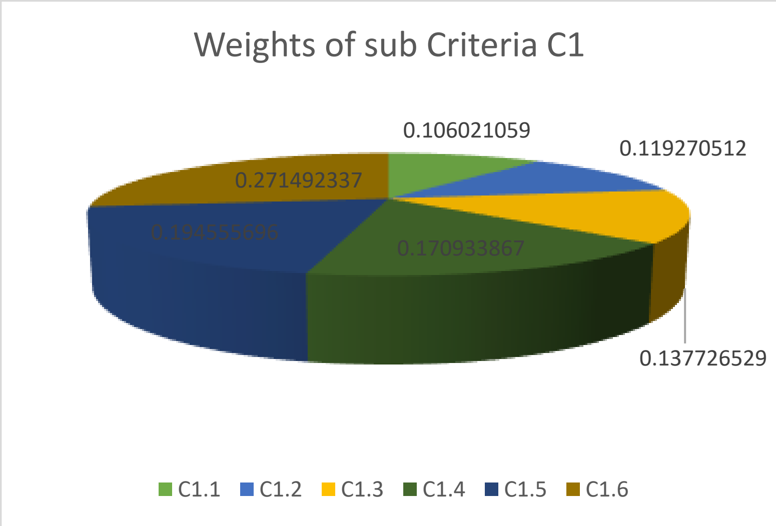

Figure 3: Weights of sub criteria C1.

Then compute weights of sub-criteria C2. Then three experts evaluate the five main criteria to build a pairwise comparison matrix into Table 13-15. Then combined three matrices into one matrix in Table 16. Then normalize the combined pairwise comparison matrix into Table 17. Then compute the weights of criteria in Table 18. Fig 4. Present the weights of Sub criteria. C2: violence teachers are the highest weight in teaching risks, and violent students are the lowest in teaching assistants.

Table 13: Pairwise comparison matrix for five main criteria by first decision makers.

	$C_{2.1}$	$C_{2.2}$
$C_{2.1}$	0.5	0.8167
$C_{2.2}$	1.22444	0.5

Table 14: Pairwise comparison matrix for five main criteria by second decision makers.

	$C_{2.1}$	$C_{2.2}$
$C_{2.1}$	0.5	0.9
$C_{2.2}$	1.111111	0.5

Table 15: Pairwise comparison matrix for five main criteria by third decision makers.

	$C_{2.1}$	$C_{2.2}$
$C_{2.1}$	0.5	0.283
$C_{2.2}$	3.533569	0.5

Doi: https://doi.org/10.54216/FPA.140216
Received: July 27, 2023 Revised: November 02, 2023 Accepted: January 21, 2024

Table 16: Combined matrix for five main criteria.

	$C_{2.1}$	$C_{2.2}$
$C_{2.1}$	0.5	0.666567
$C_{2.2}$	1.956373	0.5

Table 17: Normalized combined matrix for five main criteria.

	$C_{2.1}$	$C_{2.2}$
$C_{2.1}$	0.203552	0.571392
$C_{2.2}$	0.796448	0.428608

Table 12. Weights of sub criteria C2.

	Weights of criteria
$C_{2.1}$	0.387472
$C_{2.2}$	0.612528

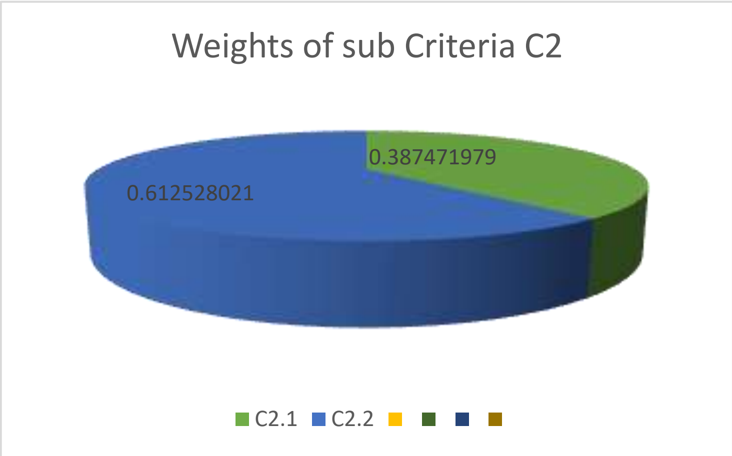

Figure 4: Weights of sub criteria C2.

Fig 5. Present the weights of Sub criteria. C3: risk laws designed are the highest weight in teaching risks, and releasing the information requested is the lowest in teaching assistants. Fig 6. Present the weights of Sub criteria. C4: incomplete knowledge is the highest in teaching risks, and incomplete activity is the lowest in teaching assistants. Fig 7. Present the weights of Sub criteria. C5: The risk of developing carpal tunnel syndrome is the highest in teaching risks, and educational aids are the lowest in teaching assistants.

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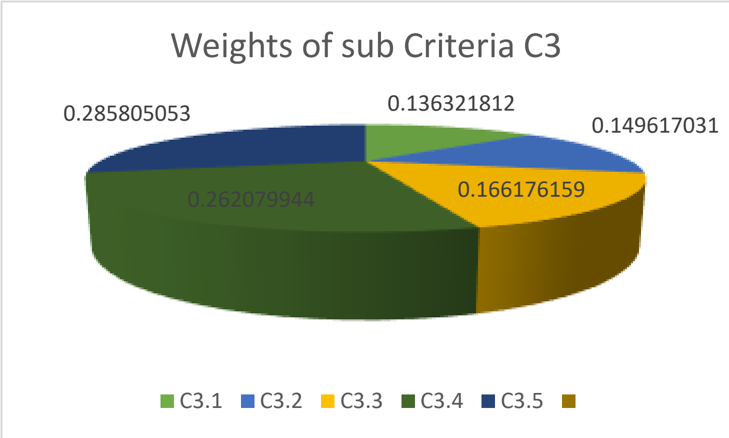
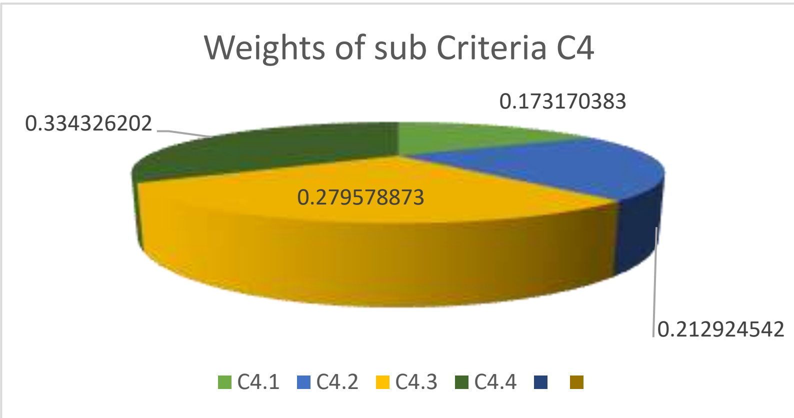


Figure 5: Weights of sub criteria C3.



Figur 6: Weights of sub criteria C4.

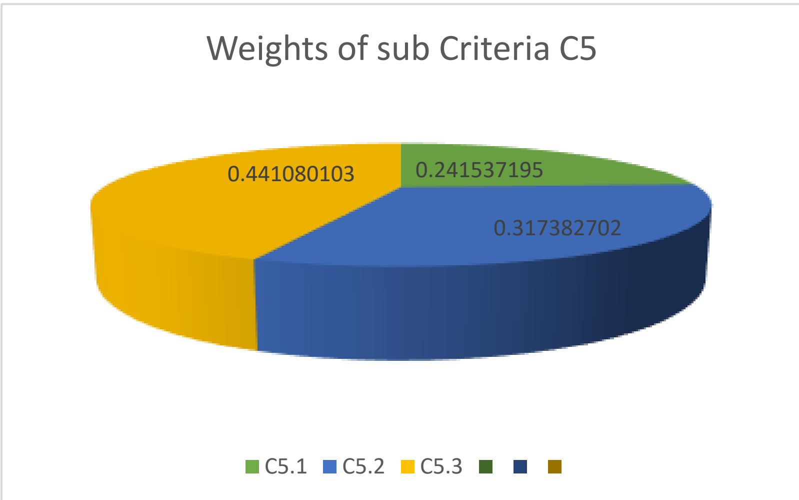


Figure 7: Weights of sub criteria C6.

4. Conclusions

In this paper, we propose the AHP method integrated with the neutrosophic sets to assess teaching assistants' risks. A teaching assistant is a critical task. It contains several criteria and sub-criteria. We used the multi-

Doi: https://doi.org/10.54216/FPA.140216
Received: July 27, 2023 Revised: November 02, 2023 Accepted: January 21, 2024

criteria decision making for dealing with five main criteria and twenty sub-criteria. In the future study, apply other MCDM methods integrated with another scale of neutrosophic for assessment teaching risks.

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