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APPLICATION OF INTUITIONISTIC FUZZY SETS IN DETERMINING RESEARCH TOPICS FOR MATHEMATICS EDUCATION STUDENTS THROUGH THE NORMALIZED EUCLIDEAN DISTANCE METHOD

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ABSTRACT

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An intuitionistic fuzzy set (IFS) can be helpful in decision-making as a concept to describe uncertainty. This study proposes the application of IFS in determining research topics for students of the mathematics education study program using the normalized Euclidean distance method. This study also shows the differences in the analysis results using the max-min composition method revised by De et al. (2001) with the normalized Hamming distance method and the normalized Euclidean distance method. The results show that the normalized Euclidean distance method can determine student research topics more accurately than other methods because they are careful in looking at distance differences. The normalized Euclidean distance method provides the best distance measure with a high confidence level in terms of accuracy.

Keywords:

Intuitionistic fuzzy sets; Determination of student research topics; Normalized euclidean distance method

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1. INTRODUCTION

The point of providing students with sufficient information for the right choice of research topics cannot be overemphasized by lecturers. This is very important because many of the problems of student's lack of appropriate research topic guide significantly affect the choice of research topics and their efficiency [1], [2]. Therefore, it is prudent that students be provided with sufficient information about discussing a research topic or promote adequate planning, preparation, and choice among the determinants of research topics, such as academic achievement, interests, and others [2]. The intuitionistic fuzzy set concept can solve these problems containing such uncertainty [3]–[6].

The set concept that is commonly used is the classical set concept. George Cantor and Richard Dedekin, in the 1870s, applied to set theory informally as a collection of clearly defined objects. Based on this, a question arises, what about a collection of objects that are not clearly defined or blurred? Zadeh answered this question by putting forward the idea of fuzzy sets [7]. The fuzzy set concept is a generalization or extension of the classical set concept. If the classical set is assessed based on bivalent conditions, it differs from fuzzy set theory based on assessment using membership functions in real number intervals [0,1].

In 1983, Atanassov contributed to developing the concept of fuzzy theory. Atanassov put forward an intuitionistic fuzzy set (IFS) concept that the elements of a set have not only degrees of membership but also degrees of non-membership [8], [9]. Szmidt and Kacprzyk revealed that intuitionistic fuzzy sets are considered more relevant in deciding problem that involves hesitation about the object being examined [10].

Various methods of solving can be used in the intuitionistic fuzzy set problem, including the max-min composition method and the distance method. Samuel and Balamurugan introduced the max-min composition method based on a study on the Sanchez approach [11], [12], which provides a solution to the composition fuzzy relation equation [13]. Experts have refined versions of the max-min composition method, including De et al., who improved the version of the intuitionistic fuzzy relation [14], and Sundari et al., who introduced the concept of max-min average composition [15].

Meanwhile, the distance method between intuitionistic fuzzy sets is based on the geometric interpretation proposed by Szmidt & Kacprzyk [16]–[18]. Four distances are most widely used for fuzzy sets: the Hamming distance method, the Euclidean distance method, the normalized Hamming distance method, and the normalized Euclidean distance method. Many studies have used this distance method, especially the normalized Euclidean distance method. Szmidt and Kacprzyk apply it to medical diagnosis [10]; Ejegwa et al. and Jothi et al. on career determination [19], [20], Tuğrul et al. on high school determination [21]; and Aggarwal et al. on house purchasing decisions [22]. Furthermore, the normalized Euclidean distance method was chosen because it provides the best distance measure with a high confidence level in terms of accuracy [20].

This article will discuss the application of IFS using normalized Euclidean distances in determining research topics for mathematics education students. This study also shows the differences in the analysis results using the max-min composition method revised by De et al. with the normalized Hamming distance method and the normalized Euclidean distance method [14].

2. RESEARCH METHODS

This is an applied research of intuitionistic fuzzy set concept in mapping research topics for mathematics education study program students. This research involves three sets which are composed using two functions. The first function, Q maps, sets A (students) to set B (course cluster), and the second function, R maps, sets B (course cluster) to set C (research topic).

The sets are as follows: $A = \{A_1, A_2, \ldots, A_{30}\}$ is a set of students, B = {*Mathematics*, *Assessment*, *RME-Ethnomathematics*, *Innovative Learning*, *Learning Media*} is a set of course clusters related to research topics, and C = {*Mathematical Ability*, *Design of Models/Lesson Plan/Curriculum*, *Contextual Problems/RME/Mathematical Literacy*, *Learning Media/ Technology*, *Applied Mathematics*} as a set of research topics.

The respondents of this study were 30 students in the 8th semester of the mathematics education study program at Universitas PGRI Semarang in the 2021/2022 academic year. Respondents were selected randomly with cluster random sampling, and one class was selected.

The data collection technique used is documentation, so the instrument is a checklist of documents needed in the study. The secondary data used in this study were the course scores of 30 students in the mathematics education study program at the Universitas PGRI Semarang from semester 1 to semester 7. This value is considered in determining the degree of membership (μ) and non-membership (v) academic ability of students in each group of subjects. In addition, other data collected is the expert's assessment of the degree of membership (μ) and non-membership (v) of the course cluster on the research topic. This data retrieval uses a Focus Group Discussion between the researcher and the coordinator of the course cluster.

The research data reflects the case of the intuitionistic fuzzy set. Various methods of solving can be used in the intuitionistic fuzzy set problem, including the max-min composition method and the distance method. Experts have used several refinement versions of the max-min composition method, including De et al., who improved the version of the intuitionistic fuzzy relation **[14]**, and Sundari et al., who introduced the concept of max-min average composition **[15]**. Meanwhile, there are four types of distance methods: the Hamming distance method, the Euclidean distance method, the normalized Hamming distance method, and the normalized Euclidean distance method, described later. This study shows the differences in the analysis results using the max-min composition method revised by De et al. with the normalized Hamming distance method and the normalized Euclidean distance method **[14]**. Several fuzzy set concepts are described as follows.

Definition 1 [7]

Let X be a nonempty set. A fuzzy set A in X is defined as

$$A=\{\langle x,\mu_A(x)\rangle \mid x\in X\} \tag{1}$$

where $\mu_A(x): X \to [0,1]$ is the membership function of the fuzzy set A.

Definition 2 [8], [9]

Let X be a nonempty set. An intuitionistic fuzzy set A in X is an object having the form

$$A=\{\langle x,\mu_A(x),v_A(x)\rangle \mid x\in X\} \tag{2}$$

define respectively, the degree of membership and degree of non-membership of the element $x\in X$, to the set A, which is a subset of X, and for every element $x\in X$,

$$0\le \mu_A(x)+v_A(x)\le 1 \tag{3}$$

According to Fuzzy Set Theory, if the membership degree of an element x is $\mu(x)$ and the non-membership degree of an element x is $v(x)$, then

$$\pi_A(x)=1-\mu_A(x)-v_A(x) \tag{4}$$

called the intuitionistic fuzzy set index or hesitation on the margin of x in A. $\pi_A(x)$ is the degree of indeterminacy of $x\in X$ to the IFS A and $\pi_A(x)\in[0,1]$, i.e.,

$$\pi_A(x): X\to[0,1] \tag{5}$$

for every $x\in X$. $\pi_A(x)$ express the lack of knowledge of whether x belongs to IFS A or not. It is clear that $0\le\pi_A(x)\le 1$, for each $x\in X$.

On the other hand, for each fuzzy set A' in X, we have

$$\pi_{A'}(x)=1-\mu_{A'}(x)-[1-\mu_{A'}(x)]=0 \text{, for each } x\in X \tag{6}$$

Therefore, if you want to describe an intuitionistic fuzzy set fully, you need to use two functions of the triplet: (1) membership function, (2) non-membership function, and (3) hesitation margin. It can be concluded. In other words, using an intuitionistic fuzzy set instead of a fuzzy set means introducing more degrees of freedom in the description of the set (that is, there are v_A or π_A in addition to μ_A).

Definition 3 [14]

Let X be nonempty. Intuitionistic fuzzy sets $A, B, C \in X$. The intuitionistic fuzzy relation Q is assigned from set A to set B. Furthermore, the intuitionistic fuzzy relation R is assigned from set B to set C. The composition T of the intuitionistic fuzzy relationship R and Q has the following membership function:

$$\mu_T(a_i, c_k) = \vee_{b \in B} \left[\mu_Q(a_i, b) \wedge \mu_R(b, c_k) \right] \tag{7}$$

and

$$v_T(a_i, c_k) = \wedge_{b \in B} \left[v_Q(a_i, b) \vee v_R(b, c_k) \right] \tag{8}$$

$\forall a_i \in A,\ b_j \in B$, and $c_k \in C$, where $\vee$ = max and $\wedge$ = min.

The composition $T = R \circ Q$ is obtained from the max-min composition method (**Equation 7-Equation 8**). In the next step, with the same composition T' as composition T but involving the hesitation margin (π) explicitly as well, we obtain an improved version of the intuitionistic fuzzy relation R, or S_R is:

$$S_R = \mu_R - v_R \cdot \pi_R \tag{9}$$

and applies: (1) S_R is the largest, and (2) the $T = R \circ Q$ equation is retained.

This improved version of R (i.e., S_R) will be a more significant intuitionistic fuzzy relation that translates to higher degrees of association, lower degrees of non-association, and lower degrees of hesitation. From the improved version of R (i.e., S_R), one can conclude that paired values one is the degree of association, and the other is the degree of non-association.

Definition 4 [16], [18]

Let X be nonempty. Intuitionistic fuzzy sets $A, B, C \in X$. The distance measure d between intuitionistic fuzzy sets A and B is a mapping $d : X \times X \to [0, 1]$; if $d(A, B)$ satisfies the following axioms:

1. $0 \leq d(A, B) \leq 1$
2. $d(A, B)$ if and only if $A = B$
3. $d(A, B) = d(B, A)$
4. $d(A, C) + d(B, C) \geq d(A, B)$
5. if $A \subseteq B \subseteq C$, then $d(A, C) \geq d(A, B)$ and $d(A, C) \geq d(B, C)$

The distance measure is a term that describes the difference between intuitionistic fuzzy sets and may be considered a twin idea of the similarity measure. Distance measures among intuitionistic fuzzy sets are proposed.

Definition 5 [16], [18]

Let

$$A = \{ x, \mu_A(x), v_A(x), \pi_A(x) \mid x \in X \} \tag{10}$$

and

$$B = \{ x, \mu_B(x), v_B(x), \pi_B(x) \mid x \in X \} \tag{11}$$

be two intuitionistic fuzzy sets in $X = x_1, x_2, \ldots, x_n$; $i = 1, 2, \ldots, n$. Based on the geometric interpretation of an intuitionistic fuzzy set, Szmidt and Kacprzyk proposed the following four distance measures between A and B [16], [18]:

The Hamming distance:

$$d_H(A, B) = \frac{1}{2} \sum_{i=1}^{n} (|\mu_A(x) - \mu_B(x)| + |v_A(x) - v_B(x)| + |\pi_A(x) - \pi_B(x)|) \tag{12}$$

The Euclidean distance:

$$d_E(A,B)=\sqrt{\frac{1}{2}\sum_{i=1}^{n}[(\mu_A(x)-\mu_B(x))^2+(v_A(x)-v_B(x))^2+(\pi_A(x)-\pi_B(x))^2]} \qquad (13)$$

The Normalized Hamming distance:

$$d_{n-H}(A,B)=\frac{1}{2n}\sum_{i=1}^{n}(|\mu_A(x)-\mu_B(x)|+|v_A(x)-v_B(x)|+|\pi_A(x)-\pi_B(x)|) \qquad (14)$$

The Normalized Euclidean distance:

$$d_{n-E}(A,B)=\sqrt{\frac{1}{2n}\sum_{i=1}^{n}[(\mu_A(x)-\mu_B(x))^2+(v_A(x)-v_B(x))^2+(\pi_A(x)-\pi_B(x))^2]} \qquad (15)$$

3. RESULTS AND DISCUSSION

A data set containing 30 students was considered. For example, $A = \{A_1, A_2, \ldots, A_{30}\}$ is the set of students, B = {*Mathematics*, *Assessment*, *RME-Ethnomathematics*, *Innovative Learning*, *Learning Media*} is the set of course clusters related to the research topic, and C = {*Mathematics Ability*, *Design of Models/Lesson Plan/Curriculum*, *Contextual Problems/RME/ Mathematical Literacy*, *Learning Media/Technology*, *Applied Mathematics*} become a set of research topics. The intuitionistic fuzzy relation $Q(A \to B)$ is given in **Table 1**, and the intuitionistic fuzzy relation $R(B \to C)$ is given in **Table 2**.

Table 1. Student vs Course Cluster

Q	Mathematics	Assessment	RME-Ethnomathe-matics	Innovative Learning	Learning Media
A1	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.8, 0.1)	(0.6, 0.3)
A2	(0.9, 0.0)	(0.6, 0.3)	(0.5, 0.4)	(0.5, 0.3)	(0.8, 0.1)
A3	(0.7, 0.2)	(0.7, 0.1)	(0.6, 0.2)	(0.8, 0.2)	(0.8, 0.1)
A4	(0.5, 0.2)	(0.8, 0.0)	(0.9, 0.0)	(0.5, 0.4)	(0.9, 0.0)
A5	(0.6, 0.3)	(0.7, 0.1)	(0.8, 0.1)	(0.8, 0.1)	(0.8, 0.1)
A6	(0.8, 0.1)	(0.9, 0.0)	(0.5, 0.3)	(0.6, 0.4)	(0.6, 0.2)
A7	(0.9, 0.0)	(0.7, 0.2)	(0.5, 0.5)	(0.5, 0.3)	(0.9, 0.0)
A8	(0.7, 0.1)	(0.7, 0.2)	(0.7, 0.1)	(0.9, 0.1)	(0.6, 0.3)
A9	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.5, 0.4)	(0.5, 0.3)
A10	(0.9, 0.1)	(0.8, 0.1)	(0.7, 0.1)	(0.8, 0.1)	(0.8, 0.2)
A11	(0.8, 0.1)	(0.7, 0.1)	(0.5, 0.4)	(0.5, 0.3)	(0.6, 0.4)
A12	(0.5, 0.3)	(0.7, 0.2)	(0.9, 0.1)	(0.6, 0.3)	(0.8, 0.1)
A13	(0.7, 0.1)	(0.8, 0.0)	(0.7, 0.2)	(0.8, 0.1)	(0.5, 0.4)
A14	(0.9, 0.0)	(0.8, 0.1)	(0.5, 0.4)	(0.6, 0.2)	(0.6, 0.3)
A15	(0.9, 0.1)	(0.8, 0.1)	(0.5, 0.4)	(0.6, 0.3)	(0.6, 0.3)
A16	(0.6, 0.1)	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.8, 0.1)
A17	(0.7, 0.1)	(0.8, 0.1)	(0.9, 0.0)	(0.9, 0.1)	(0.6, 0.2)
A18	(0.6, 0.3)	(0.7, 0.1)	(0.9, 0.1)	(0.5, 0.5)	(0.6, 0.3)
A19	(0.9, 0.0)	(0.8, 0.1)	(0.5, 0.4)	(0.5, 0.2)	(0.6, 0.3)
A20	(0.6, 0.4)	(0.8, 0.1)	(0.8, 0.2)	(0.7, 0.2)	(0.5, 0.4)
A21	(0.5, 0.3)	(0.6, 0.1)	(0.8, 0.1)	(0.6, 0.3)	(0.6, 0.3)
A22	(0.7, 0.2)	(0.8, 0.0)	(0.7, 0.0)	(0.6, 0.2)	(0.7, 0.2)
A23	(0.9, 0.0)	(0.6, 0.3)	(0.5, 0.4)	(0.5, 0.3)	(0.9, 0.0)
A24	(0.7, 0.3)	(0.8, 0.0)	(0.9, 0.0)	(0.8, 0.2)	(0.5, 0.0)
A25	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.0)	(0.8, 0.1)	(0.6, 0.3)
A26	(0.5, 0.2)	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.2)
A27	(0.5, 0.4)	(0.7, 0.2)	(0.7, 0.2)	(0.5, 0.4)	(0.8, 0.1)
A28	(0.9, 0.1)	(0.8, 0.1)	(0.5, 0.4)	(0.5, 0.3)	(0.6, 0.3)
A29	(0.8, 0.1)	(0.7, 0.1)	(0.7, 0.2)	(0.5, 0.4)	(0.6, 0.3)
A30	(0.7, 0.2)	(0.7, 0.1)	(0.7, 0.2)	(0.8, 0.1)	(0.8, 0.1)

Therefore, the compositions $T = R \circ Q$ are given in **Table 3**. But since the max-min composition method is used when searching for the T composition, the "dominant" course cluster is only considered. So, the next step is to use **Equation (9)** to calculate the improved version of R (i.e., S_R). In the calculation of the improved version of R (i.e., S_R), it takes a composition of T (**Table 4**) which is the same as the composition of T (**Table 3**) but explicitly involves the hesitation margin (π) as well, the values of all three parameters are required in this approach. The effects of the proposed improvements by De et al. [14] are presented in **Table 5**.

Table 2. Courses Clusters vs. Research Topics

R	**Mathematics Ability**	**Design of Models/ Lesson Plan/ Curriculum**	**Contextual Problems/RME /Mathematical Literacy**	**Learning Media/ Technology**	**Applied Mathematics**
Mathematics	(0.7, 0.2)	(0.2, 0.7)	(0.4, 0.5)	(0.2, 0.8)	(0.9, 0.0)
Assessment	(0.8, 0.1)	(0.6, 0.3)	(0.3, 0.6)	(0.3, 0.5)	(0.4, 0.5)
RME-Ethnomathematics	(0.2, 0.7)	(0.7, 0.2)	(0.7, 0.2)	(0.5, 0.3)	(0.2, 0.8)
Innovative Learning	(0.3, 0.5)	(0.9, 0.1)	(0.5, 0.3)	(0.6, 0.3)	(0.2, 0.7)
Learning Media	(0.1, 0.8)	(0.1, 0.7)	(0.2, 0.7)	(0.8, 0.1)	(0.5, 0.4)

Table 3. *T* Compositions

T	**Mathematics Ability**	**Design of Models/ Lesson Plan/ Curriculum**	**Contextual Problems/RME /Mathematical Literacy**	**Learning Media/ Technology**	**Applied Mathematics**
A1	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.3)	(0.7, 0.2)
A2	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.3)	(0.8, 0.1)	(0.9, 0.0)
A3	(0.7, 0.1)	(0.8, 0.2)	(0.6, 0.2)	(0.8, 0.1)	(0.7, 0.2)
A4	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.8, 0.1)	(0.5, 0.2)
A5	(0.7, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.8, 0.1)	(0.6, 0.3)
A6	(0.8, 0.1)	(0.6, 0.3)	(0.5, 0.3)	(0.6, 0.2)	(0.8, 0.1)
A7	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.3)	(0.8, 0.1)	(0.9, 0.0)
A8	(0.7, 0.2)	(0.9, 0.1)	(0.7, 0.2)	(0.6, 0.3)	(0.7, 0.1)
A9	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.5, 0.3)	(0.8, 0.1)
A10	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.8, 0.2)	(0.9, 0.1)
A11	(0.7, 0.1)	(0.6, 0.3)	(0.5, 0.3)	(0.6, 0.3)	(0.8, 0.1)
A12	(0.7, 0.2)	(0.7, 0.2)	(0.7, 0.2)	(0.8, 0.1)	(0.5, 0.3)
A13	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.3)	(0.7, 0.1)
A14	(0.8, 0.1)	(0.6, 0.2)	(0.5, 0.3)	(0.6, 0.3)	(0.9, 0.0)
A15	(0.8, 0.1)	(0.6, 0.3)	(0.5, 0.3)	(0.6, 0.3)	(0.9, 0.1)
A16	(0.8, 0.1)	(0.8, 0.1)	(0.6, 0.3)	(0.8, 0.1)	(0.6, 0.1)
A17	(0.8, 0.1)	(0.9, 0.1)	(0.7, 0.2)	(0.6, 0.2)	(0.7, 0.1)
A18	(0.7, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.6, 0.3)
A19	(0.8, 0.1)	(0.6, 0.2)	(0.5, 0.3)	(0.6, 0.3)	(0.9, 0.0)
A20	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.6, 0.4)
A21	(0.6, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.3)
A22	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.7, 0.2)	(0.7, 0.2)
A23	(0.7, 0.2)	(0.6, 0.3)	(0.5, 0.3)	(0.8, 0.1)	(0.9, 0.0)
A24	(0.8, 0.1)	(0.8, 0.2)	(0.7, 0.2)	(0.6, 0.1)	(0.7, 0.3)
A25	(0.8, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.6, 0.3)	(0.7, 0.2)
A26	(0.8, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.2)	(0.5, 0.2)
A27	(0.7, 0.2)	(0.7, 0.2)	(0.7, 0.2)	(0.8, 0.1)	(0.5, 0.4)
A28	(0.8, 0.1)	(0.6, 0.3)	(0.5, 0.3)	(0.6, 0.3)	(0.9, 0.1)
A29	(0.7, 0.1)	(0.7, 0.2)	(0.7, 0.2)	(0.6, 0.3)	(0.8, 0.1)
A30	(0.7, 0.1)	(0.8, 0.1)	(0.7, 0.2)	(0.8, 0.1)	(0.7, 0.2)

Table 4. ***T'* Compositions**

T'	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A1	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.7, 0.2, 0.1)
A2	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.8, 0.1, 0.1)	(0.9, 0.0, 0.1)
A3	(0.7, 0.1, 0.2)	(0.8, 0.2, 0.0)	(0.6, 0.2, 0.2)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)
A4	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.2, 0.3)
A5	(0.7, 0.1, 0.2)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)
A6	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.2, 0.2)	(0.8, 0.1, 0.1)
A7	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.8, 0.1, 0.1)	(0.9, 0.0, 0.1)
A8	(0.7, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.7, 0.1, 0.2)
A9	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.5, 0.3, 0.2)	(0.8, 0.1, 0.1)
A10	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.8, 0.2, 0.0)	(0.9, 0.1, 0.0)
A11	(0.7, 0.1, 0.2)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)	(0.8, 0.1, 0.1)
A12	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.3, 0.2)
A13	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.7, 0.1, 0.2)
A14	(0.8, 0.1, 0.1)	(0.6, 0.2, 0.2)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)	(0.9, 0.0, 0.1)
A15	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)	(0.9, 0.1, 0.0)
A16	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.8, 0.1, 0.1)	(0.6, 0.1, 0.3)
A17	(0.8, 0.1, 0.1)	(0.9, 0.1, 0.0)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)	(0.7, 0.1, 0.2)
A18	(0.7, 0.1, 0.2)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.6, 0.3, 0.1)
A19	(0.8, 0.1, 0.1)	(0.6, 0.2, 0.2)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)	(0.9, 0.0, 0.1)
A20	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.6, 0.4, 0.0)
A21	(0.6, 0.1, 0.3)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)
A22	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)
A23	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.8, 0.1, 0.1)	(0.9, 0.0, 0.1)
A24	(0.8, 0.1, 0.1)	(0.8, 0.2, 0.0)	(0.7, 0.2, 0.1)	(0.6, 0.1, 0.3)	(0.7, 0.3, 0.0)
A25	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.7, 0.2, 0.1)
A26	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)	(0.5, 0.2, 0.3)
A27	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)
A28	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)	(0.9, 0.1, 0.0)
A29	(0.7, 0.1, 0.2)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.3, 0.1)	(0.8, 0.1, 0.1)
A30	(0.7, 0.1, 0.2)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)

Table 5. **Improved Version of *R* (i. e. S_R)**

S_R	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A1	**0.79**	**0.79**	0.68	0.57	0.68
A2	0.68	0.57	0.44	0.79	**0.90**
A3	0.68	**0.80**	0.56	0.79	0.68
A4	**0.79**	0.68	0.68	**0.79**	0.44
A5	0.68	**0.79**	0.68	**0.79**	0.57
A6	**0.79**	0.57	0.44	0.56	**0.79**
A7	0.68	0.57	0.44	0.79	**0.90**
A8	0.68	**0.90**	0.68	0.57	0.68
A9	**0.79**	0.68	0.68	0.44	**0.79**
A10	0.79	0.79	0.68	0.80	**0.90**
A11	0.68	0.57	0.44	0.57	**0.79**
A12	0.68	0.68	0.68	**0.79**	0.44
A13	**0.79**	**0.79**	0.68	0.57	0.68
A14	0.79	0.56	0.44	0.57	**0.90**
A15	0.79	0.57	0.44	0.57	**0.90**
A16	**0.79**	**0.79**	0.57	**0.79**	0.57
A17	0.79	**0.90**	0.68	0.56	0.68
A18	**0.68**	**0.68**	**0.68**	0.57	0.57
A19	0.79	0.56	0.44	0.57	**0.90**
A20	**0.79**	0.68	0.68	0.57	0.60
A21	0.57	**0.68**	**0.68**	0.57	0.44
A22	**0.79**	0.68	0.68	0.68	0.68

S_R	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A23	0.68	0.57	0.44	0.79	**0.90**
A24	0.79	**0.80**	0.68	0.57	0.70
A25	**0.79**	**0.79**	0.68	0.57	0.68
A26	**0.79**	0.68	0.68	0.56	0.44
A27	0.68	0.68	0.68	**0.79**	0.46
A28	0.79	0.57	0.44	0.57	**0.90**
A29	0.68	0.68	0.68	0.57	**0.79**
A30	0.68	**0.79**	0.68	**0.79**	0.68

The maximum value of S_R indicates a suitable research topic for students. According to Szmidt and Kacprzyk [10], this S_R approach has several weaknesses. First, the max-min composition method rule alone does not provide a solution, and De et al. proposed several changes to get a solution [14]. The second is a membership function that describes a weak R relation.

To solve this problem, but without manipulation of the knowledge base on the research topic and taking into account all the characteristics of the course cluster for each student, a new method based on distance calculation is proposed (**Definition 5**, especially in this study, **Equation 14** - **Equation 15** are used).

As in De et al., a knowledge base on the research topic is needed to determine the appropriate research topic C for student A with a given grade from course cluster B [14]. The knowledge base is formulated using an intuitionistic fuzzy set in this case.

The same data are used to compare the approach proposed in this article with De et al.'s revised max-min composition method [14]. The data are given in **Table 6**, and three numbers describe each course cluster: membership μ, non-membership v, and hesitation margin π. The data in **Table 2** and **Table 6** are the same, but by explicitly involving the hesitation margin, the values of the three parameters are required in this approach.

Table 6. ***R'***

R'	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
Mathematics	(0.7, 0.2, 0.1)	(0.2, 0.7, 0.1)	(0.4, 0.5, 0.1)	(0.2, 0.8, 0.0)	(0.9, 0.0, 0.1)
Assessment	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.3, 0.6, 0.1)	(0.3, 0.5, 0.2)	(0.4, 0.5, 0.1)
RME-Ethnomathematics	(0.2, 0.7, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.5, 0.3, 0.2)	(0.2, 0.8, 0.0)
Innovative Learning	(0.3, 0.5, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)	(0.2, 0.7, 0.1)
Learning Media	(0.1, 0.8, 0.1)	(0.1, 0.7, 0.2)	(0.2, 0.7, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)

The set of students considered is $A = \{A_1, A_2, \ldots, A_{30}\}$. The characteristics of the course clusters for students are given in **Table 6**. Three parameters (μ, v, π) are needed to describe each course cluster, but the data are the same as in **Table 1**.

Table 7. ***Q'***

Q'	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A1	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)
A2	(0.9, 0.0, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.4, 0.1)	(0.5, 0.3, 0.2)	(0.8, 0.1, 0.1)
A3	(0.7, 0.2, 0.1)	(0.7, 0.1, 0.2)	(0.6, 0.2, 0.2)	(0.8, 0.2, 0.0)	(0.8, 0.1, 0.1)
A4	(0.5, 0.2, 0.3)	(0.8, 0.0, 0.2)	(0.9, 0.0, 0.1)	(0.5, 0.4, 0.1)	(0.9, 0.0, 0.1)
A5	(0.6, 0.3, 0.1)	(0.7, 0.1, 0.2)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)
A6	(0.8, 0.1, 0.1)	(0.9, 0.0, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.4, 0.0)	(0.6, 0.2, 0.2)
A7	(0.9, 0.0, 0.1)	(0.7, 0.2, 0.1)	(0.5, 0.5, 0.0)	(0.5, 0.3, 0.2)	(0.9, 0.0, 0.1)

Q'	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A8	(0.7, 0.1, 0.2)	(0.7, 0.2, 0.1)	(0.7, 0.1, 0.2)	(0.9, 0.1, 0.0)	(0.6, 0.3, 0.1)
A9	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.5, 0.4, 0.1)	(0.5, 0.3, 0.2)
A10	(0.9, 0.1, 0.0)	(0.8, 0.1, 0.1)	(0.7, 0.1, 0.2)	(0.8, 0.1, 0.1)	(0.8, 0.2, 0.0)
A11	(0.8, 0.1, 0.1)	(0.7, 0.1, 0.2)	(0.5, 0.4, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.4, 0.0)
A12	(0.5, 0.3, 0.2)	(0.7, 0.2, 0.1)	(0.9, 0.1, 0.0)	(0.6, 0.3, 0.1)	(0.8, 0.1, 0.1)
A13	(0.7, 0.1, 0.2)	(0.8, 0.0, 0.2)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)
A14	(0.9, 0.0, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)	(0.6, 0.2, 0.2)	(0.6, 0.3, 0.1)
A15	(0.9, 0.1, 0.0)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)	(0.6, 0.3, 0.1)	(0.6, 0.3, 0.1)
A16	(0.6, 0.1, 0.3)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)
A17	(0.7, 0.1, 0.2)	(0.8, 0.1, 0.1)	(0.9, 0.0, 0.1)	(0.9, 0.1, 0.0)	(0.6, 0.2, 0.2)
A18	(0.6, 0.3, 0.1)	(0.7, 0.1, 0.2)	(0.9, 0.1, 0.0)	(0.5, 0.5, 0.0)	(0.6, 0.3, 0.1)
A19	(0.9, 0.0, 0.1)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)	(0.5, 0.2, 0.3)	(0.6, 0.3, 0.1)
A20	(0.6, 0.4, 0.0)	(0.8, 0.1, 0.1)	(0.8, 0.2, 0.0)	(0.7, 0.2, 0.1)	(0.5, 0.4, 0.1)
A21	(0.5, 0.3, 0.2)	(0.6, 0.1, 0.3)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)	(0.6, 0.3, 0.1)
A22	(0.7, 0.2, 0.1)	(0.8, 0.0, 0.2)	(0.7, 0.0, 0.3)	(0.6, 0.2, 0.2)	(0.7, 0.2, 0.1)
A23	(0.9, 0.0, 0.1)	(0.6, 0.3, 0.1)	(0.5, 0.4, 0.1)	(0.5, 0.3, 0.2)	(0.9, 0.0, 0.1)
A24	(0.7, 0.3, 0.0)	(0.8, 0.0, 0.2)	(0.9, 0.0, 0.1)	(0.8, 0.2, 0.0)	(0.5, 0.0, 0.5)
A25	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.8, 0.0, 0.2)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)
A26	(0.5, 0.2, 0.3)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)
A27	(0.5, 0.4, 0.1)	(0.7, 0.2, 0.1)	(0.7, 0.2, 0.1)	(0.5, 0.4, 0.1)	(0.8, 0.1, 0.1)
A28	(0.9, 0.1, 0.0)	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)	(0.5, 0.3, 0.2)	(0.6, 0.3, 0.1)
A29	(0.8, 0.1, 0.1)	(0.7, 0.1, 0.2)	(0.7, 0.2, 0.1)	(0.5, 0.4, 0.1)	(0.6, 0.3, 0.1)
A30	(0.7, 0.2, 0.1)	(0.7, 0.1, 0.2)	(0.7, 0.2, 0.1)	(0.8, 0.1, 0.1)	(0.8, 0.1, 0.1)

Our task is to determine the appropriate research topic for each student a_i, $i = 1, ..., 30$. To fulfill this task, we propose to calculate for each student a_i the academic ability distance in his course cluster (**Table 7**) from a set of courses clusters b_j, $j = 1, ..., 5$ characteristics for each research topic c_k, $k = 1, ..., 5$ (**Table 6**). The smallest distance obtained indicates the right research topic.

In Szmidt & Kacprzyk **[16]**, **[18]**, it is proved that the only correct way to calculate the most widely used distance for an intuitionistic fuzzy set is to consider all three parameters: membership function, non-member function, and hesitation margin. To be more precise, the normalized Hamming distance for all course clusters from the *i*-th student of the *k*-th research topic through **Equation (15)** for this case is equal to

$$d_{n-H}(A,C)=\frac{1}{10}\sum_{j=1}^{5}(|\mu_j(a_i)-\mu_j(c_k)|+|v_j(a_i)-v_j(c_k)|+|\pi_j(a_i)-\pi_j(c_k)|) \qquad (16)$$

The distance **Equation (16)** for each student from a series of possible research topics considered is given in **Table 8**. The smallest distance indicates the right research topic: A1 correctly chooses the research topic Design of Models/Lesson Plan/Curriculum, A2 chooses Learning Media/Technology or Applied Mathematics, A3 selects Learning Media/Technology, etc.

Table 8. The Normalized Hamming Distance

$d_{n-H}(A,C)$	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A1	0.32	**0.28**	0.32	0.36	0.40
A2	0.32	0.40	0.32	**0.26**	**0.26**
A3	0.36	0.32	0.36	**0.26**	0.42
A4	0.40	0.44	0.38	**0.34**	0.48
A5	0.40	0.30	0.34	**0.28**	0.46
A6	**0.30**	0.38	0.38	0.32	0.34
A7	0.32	0.46	0.38	0.32	**0.28**
A8	0.38	**0.26**	0.34	0.36	0.40
A9	**0.26**	0.32	0.28	0.36	0.30
A10	0.40	0.36	0.40	**0.34**	0.42

$d_{n-H}(A,C)$	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A11	**0.24**	0.38	0.30	0.32	0.28
A12	0.40	0.34	0.30	**0.26**	0.42
A13	0.32	**0.28**	0.32	0.38	0.38
A14	**0.26**	0.38	0.34	0.34	0.28
A15	**0.26**	0.38	0.34	0.30	0.28
A16	0.36	0.34	0.38	**0.30**	0.42
A17	0.40	**0.30**	0.40	0.42	0.46
A18	0.32	0.34	**0.30**	0.34	0.36
A19	**0.26**	0.40	0.34	0.36	0.28
A20	0.32	**0.26**	**0.26**	0.32	0.38
A21	0.36	0.30	**0.26**	0.28	0.40
A22	0.34	0.38	0.34	**0.32**	0.44
A23	0.34	0.42	0.34	**0.28**	**0.28**
A24	0.44	**0.36**	0.42	0.40	0.52
A25	0.34	**0.30**	0.34	0.36	0.42
A26	0.36	**0.30**	0.32	0.34	0.44
A27	0.34	0.30	0.24	**0.22**	0.38
A28	**0.24**	0.40	0.32	0.32	0.28
A29	**0.28**	0.34	**0.28**	0.32	0.30
A30	0.36	0.30	0.34	**0.28**	0.42

We obtained the same and even more accurate results, namely the research topic of the same quality for each student when looking for a solution by applying the normalized Euclidean distance method [16], [18] through Equation (16) for this case is the same as

$$d_{n-E}(A,C)=\sqrt{\frac{1}{10}\sum_{j=1}^{5}((\mu_j(a_i)-\mu_j(c_k))^2+(v_j(a_i)-v_j(c_k))^2+(\pi_j(a_i)-\pi_j(c_k))^2} \quad (17)$$

The results of Equation (17) are given in Table 9, the lowest distance for each student a_i from the possible research topic C indicates a solution. As before, A1 chose the right research topic for the Design of Models/Lesson Plan/Curriculum, A2 chose Applied Mathematics, A3 chose Learning Media/Technology, etc. This method looks more accurate in seeing the difference in distance. Initially, with the normalized Hamming distance method, A2 has two choices of research topics, but with the normalized Euclidean distance method, A2 has one more appropriate research topic. The normalized Euclidean distance method provides the best distance measure with a high confidence level in terms of accuracy [20].

Table 9. The Normalized Euclidean Distance

$d_{n-E}(A,C)$	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A1	0.40	**0.32**	0.34	0.37	0.45
A2	0.37	0.46	0.38	0.36	**0.28**
A3	0.42	0.38	0.38	**0.32**	0.41
A4	0.49	0.45	0.43	**0.37**	0.48
A5	0.46	0.36	0.37	**0.31**	0.47
A6	**0.33**	0.40	0.40	0.39	0.35
A7	0.40	0.50	0.44	0.39	**0.31**
A8	0.41	**0.33**	0.34	0.37	0.44
A9	**0.32**	0.37	0.33	0.39	0.34
A10	0.44	0.42	0.41	**0.40**	0.44
A11	**0.27**	0.38	0.33	0.37	0.29
A12	0.45	0.37	0.34	**0.30**	0.44
A13	0.36	**0.32**	0.35	0.40	0.43
A14	**0.31**	0.41	0.38	0.41	0.32
A15	**0.30**	0.40	0.37	0.39	0.31
A16	0.42	0.39	0.40	**0.35**	0.42

$d_{n-E}(A,C)$	Mathematics Ability	Design of Models/ Lesson Plan/ Curriculum	Contextual Problems/RME /Mathematical Literacy	Learning Media/ Technology	Applied Mathematics
A17	0.47	**0.36**	0.39	0.41	0.49
A18	0.38	0.34	**0.31**	0.33	0.40
A19	**0.30**	0.43	0.38	0.41	0.31
A20	0.35	**0.26**	0.29	0.33	0.42
A21	0.39	0.30	**0.28**	0.29	0.41
A22	0.41	0.38	0.37	**0.36**	0.44
A23	0.41	0.49	0.42	0.37	**0.30**
A24	0.49	**0.37**	0.41	0.40	0.51
A25	0.42	**0.33**	0.35	0.37	0.47
A26	0.41	**0.32**	0.34	0.34	0.44
A27	0.40	0.36	0.33	**0.24**	0.38
A28	**0.29**	0.41	0.36	0.39	0.30
A29	0.33	0.38	**0.33**	0.37	0.33
A30	0.44	0.38	0.38	**0.33**	0.43

4. CONCLUSIONS

An intuitionistic fuzzy set can express hesitation about the object being examined. The method proposed in this article performs a diagnosis based on calculating the distance from the case to all the research topics considered, considering the scores of all students' academic abilities in each course cluster. As a result, our approach makes it possible to include weights for all students' academic abilities in each course cluster. The normalized Euclidean distance method can determine students' research topics more accurately than other methods because they are careful in seeing distance differences. The normalized Euclidean distance method provides the best distance measure with a high confidence level in terms of accuracy. Such an approach is impossible in the method described by De et al. because the rules of the max-min composition method actually "ignore" most values except the extremes [14].

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