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Optimization of Language Learning with TOPSIS

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Abstract

The present study focuses on the application of fuzzy sets in the optimization of language learning with TOPSIS. The appropriate consideration of the candidates' characteristics is an important issue which can affect their language learning. Motivation, learner strategies, perseverance and age are the factors that affect language learning. The hypothesis in this paper was that the difference in the consideration of these factors can affect the individuals' language learning. In this study, for the first time, the analysis of the candidates' characteristics of two age categories was performed for the investigation of their impact on language learning. The purpose of this work was to analyze the candidates' characteristics on the individuals' language learning. The analysis with a decision making algorithm, TOPSIS, revealed the efficiency of this method. One of the advantages of this study was that the effect of different characteristics of the category members on the categories confusion has made the prediction for the optimization of language learning possible. Another advantage was that the modification of the TOPSIS method with the application of fuzzy disjunction has been efficient to provide an automated decision-making tool for this analysis. The results presented in this paper could be used for the development of algorithms and linguistic tools for the optimization of language learning with artificial intelligence.

Keywords:
Automated decision-making
Fuzzy logic
TOPSIS
Optimization
Language learning

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INTRODUCTION

Language learning is a cognitive process that involves memory and requires improved performance and experience. The capacity to manipulate information and relate it to long-term storage plays a crucial role in this process (Demir, 2021). Perception, short-term memory, long-term memory, and working memory, along with a distinguishable construct and higher cognitive function as an interface between these memory types, are essential for information processing. This, in turn, is critical for language learning (Dehn, 2008; Gathercole, 1998; McDougall et al., 1994). Several factors influence language learning, including motivation, learner strategies, perseverance, and age (Hu, 2016; Lin et al., 2021; Matsumoto & Obana, 2001; Ozfidan & Burlbaw, 2019; Teimouri et al., 2020).

Decision-making is a crucial process utilized for prediction and optimization in artificial intelligence. Automated decision-making systems have seen significant development in recent years. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang and Yoon (1981), is a well-known method for identifying optimal solutions from a finite set of alternatives. TOPSIS ranks candidates according to their relative distances from ideal and negative-ideal solutions, taking into account profit and cost criteria (Alkhawlani et al., 2011; Biderci & Canbaz, 2019; Haddad et al., 2021; Jumarni & Zamri, 2018; Sahin et al., 2020).

Fuzzy sets, which categorize members into degrees of membership, are central to fuzzy logic, a non-classical logic with wide-ranging applications in science and engineering (Zadeh, 1965, 1975). Fuzzy logic has been integrated with TOPSIS to address multi-criteria decision-making (MCDM) problems (Alkhawlani et al., 2011; Arif-Uz-Zaman, 2012; Chen, 2000; Jumarni & Zamri, 2018; Yousif & Shaout, 2018). This combination has been used in various fields, including the optimization of material properties and prediction of human traits (Javanbakht, 2022a; Javanbakht & Chakravorty, 2022; Ma et al., 2018; Roghanian et al., 2014; Soufi et al., 2015). Moreover, it has been applied to predict the characteristics of manufactured devices and instruments (Abdel-Basset et al., 2019; Huang & Huang, 2012; Indahingwati et al., 2018; Lata et al., 2021; Motia & Reddy, 2020; Mustapha et al., 2021; Petrillo et al., 2016; Trivedi et al., 2019; Vithalani & Vithalani, 2017).

The analysis of language learning using TOPSIS and fuzzy disjunction has not been explored in the literature. The results of this paper can contribute to the development of linguistic tools and further applications of this method for optimizing language learning.

To investigate the optimization of language learning with the TOPSIS method, the remainder of this paper is structured as follows. Section 2 presents the preliminaries, including key definitions related to fuzzy logic. Section 3 outlines the methods, including a description of the TOPSIS method and its modifications. The analysis results and discussion are presented in Section 4, followed by the conclusion in Section 5, which also highlights potential perspectives for future work.

PERILIMINARIES

The definitions for the application of fuzzy sets are reviewed here from Zadeh (1965, 1975), Negi (1989), Buckley (1985), Kaufmann and Gupta (1985), Chen (2000), and Zimmermann (1991). A fuzzy set is characterized by a membership function which has the values in the interval [0,1] in the universe of discourse. The fuzzy set is convex if the condition below is respected:

$$\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)x_2) \geq Min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2))$$

The fuzzy subset in the unverse of disourse is a fuzzy number with an α-cut defined as below:

$$\tilde{n}^{\alpha} = \{x_i : \mu_{\tilde{n}}(x_i) \geq \alpha, x_i \in X\}$$

The α-cut also is in the interval [0.1].

The universe of discourse contains at least a non-empty bounded closed interval with lower and upper bounds that can be written as below:

$$\tilde{n}^{\alpha_1} = [\tilde{n}_l^{\alpha_1}, \tilde{n}_u^{\alpha_1}] \quad , \quad \tilde{n}^{\alpha_2} = [\tilde{n}_l^{\alpha_2}, \tilde{n}_u^{\alpha_2}]$$

A triple (n_1, n_2, n_3) can define the triangular fuzzy number with a membership defined as below:

$$\mu_{\tilde{n}} = \begin{cases} 0 & ; \; x < n_1, \\ \dfrac{x-n_1}{n_2-n_1} & ; \; n_1 \leq x \leq n_2, \\ \dfrac{x-n_3}{n_2-n_3} & ; \; n_2 \leq x \leq n_3, \\ 0 & ; \; x > n_3. \end{cases}$$

The distance between two triangular fuzzy numbers is defined as below:

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1-n_1)^2 + (m_2-n_2)^2 + (m_3-n_3)^2]}$$

If these triangular fuzzy numbers are real numbers with the conditions below:

$$m_1 = m_2 = m_3 = m$$

and

$$n_1 = n_2 = n_3 = n$$

then the distance between them is defined as below:

$$d(\tilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]}$$
$$= \sqrt{\frac{1}{3}[(m - n)^2 + (m - n)^2 + (m - n)^2]}$$
$$= \sqrt{\frac{1}{3}(m_1 - n_1)^2}$$
$$= |m - n|$$

The TOPSIS method that we used is compatible to the fuzzy environment as the definitions above are applicable to the category members and the candidates that are optimized in this method.

METHODS

TOPSIS method

The evaluation matrix of the TOPSIS method includes the entry values for the class of the candidates' characteristics for the study of their languag learning. For each characteristic, triangular fuzzy values of membership degrees and their mean values are attributed according to these terms: low, medium and high. The mean values of fuzzy membership degrees are used in the TOPSIS method. The steps of this method have been described previously by Hwang and Yoon (1981).

Modified TOPSIS

This line was added to the first step of the TOPSIS code as described previously (Hwang and Yoon, 1981):

```
evaluation_matrix[row_size-3][column_size-1] = evaluation_matrix[row_size-3][column_size-1] + 0.8
```

With this modification, only the age as the last criterion of the first candidate would increase with 0.8 and the value 1.0 as its maximum value would appear in the output of TOPSIS. This modification was according to a model from cognitive science called the model of the tree including the Łukasiewicz fuzzy disjunction for creating an automated decision-making process. According to this model, the category members or candidates and their characteristics are considered fuzzy sets with different fuzzy membership degrees (Javanbakht, 2016, 2020). The inappropriate consideration of the crtiteria that would affect the candidates' ranking with TOPSIS were due to the inconsistency in epistemic beliefs, which in turn resulted in the category confusion. Therefore, the application of this model with fuzzy disjunction could help a better understanding of the impact of the epistemic belief inconsistency and category confusion on language learning. The modification with fuzzy disjunction replaced the membership degree for the age of the first young and old candidates with the value 1.0 in the matrices of evaluation as these candidates would understimate the age as a cost criterion and consider it as a profit one. In other words, they would not consider that the increase of their age could reduce their language learning efficiency.

RESULTS AND DISCUSSION

The steps below include the results obtained with the TOPSIS method. First, we determined the mean values of the triangular fuzzy membership degrees of the candidates' characteristics. Table 1 shows the terms, corresponding triangular fuzzy membership degrees of the candidates' characteristics and their mean values, respectively. The information about three candidates in two categories of young and old individuals (C-1, C-2 and C-3) with their characteristics is presented in the table. The first three characteristics, motivation, learner strategies and perseverance, have a positive effect on the output of the candidates' language learning. These are profit criteria. Age as the last characteristic can have positive or negative impact on their language learning. Young people learn languags more easily than old people as they use memory with a function that can be affected with age. However, the first group know that the increasing of age could reduce their language skills, but the second group could neglect this phenomenon. In other words, the young candidates consider the age as a negative criterion, whereas the old ones consider it as a positive criterion. Therefore, for young candidates, age is a negative characteristic and cost criterion and for old candidates, it is a positive characteristic and profit criterion.

Table 1: Terms, corresponding trianguler fuzzy membership degrees of young candidates' characteristics and their mean values

Candidates / Criteria	**Motivation**	**Learner strategies**	**Perseverance**	**Age**
C-1	medium	medium	low	high

C-2	medium	high	low	high
C-3	low	low	high	High
Candidates / Criteria	**Motivation**	**Learner strategies**	**Perseverance**	**Age**
C-1	0.4, 0.5, 0.6	0.4, 0.5, 0.6	0.1, 0.2, 0.3	0.7, 0.8, 0.9
C-2	0.4, 0.5, 0.6	0.7, 0.8, 0.9	0.1, 0.2, 0.3	0.7, 0.8, 0.9
C-3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.7, 0.8, 0.9	0.7, 0.8, 0.9
Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	0.5	0.5	0.2	0.8
C-2	0.5	0.8	0.2	0.8
C-3	0.2	0.2	0.8	0.8

Table 2: Terms, corresponding triangular fuzzy membership degrees of the old candidates' characteristics and their mean values

Candidates / Criteria	**Motivation**	**Learner strategies**	**Perseverance**	**Age**
C-1	medium	medium	low	low
C-2	medium	high	low	low
C-3	low	low	high	Low
Candidates / Criteria	**Motivation**	**Learner strategies**	**Perseverance**	**Age**
C-1	0.4, 0.5, 0.6	0.4, 0.5, 0.6	0.1, 0.2, 0.3	0.7, 0.8, 0.9
C-2	0.4, 0.5, 0.6	0.7, 0.8, 0.9	0.1, 0.2, 0.3	0.1, 0.2, 0.3
C-3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.7, 0.8, 0.9	0.1, 0.2, 0.3
Candidates / Criteria	**Motivation**	**Learner strategies**	**Perseverance**	**Age**
C-1	0.5	0.5	0.2	1.0
C-2	0.5	0.8	0.2	0.2

C-3	0.2	0.2	0.8	0.2

The second steps concerns the determination of the weights of alternatives for each criterion. The weights for each criterion are presented in Table 3.

Table 3: The weights for each criterion

Candidates / Values	Motivation	Learner strategies	Perseverance	Age
C1-C3	0.5	0.5	0.5	0.5

In the next step, the criteria matrices for young and old candidates are determined. Table 4 shows the criteria matrix indicating true for the profit criteria and false for the cost criterion, respectively. Motivation, learner strategies and perseverance are profit criteria, whereas age is the cost criterion for the young candidates. Motivation, learner strategies, perseverance and age are all profit criteria for the old candidates.

Table 4: Criteria matrix for young candidates

Alternatives/ Values	Motivation	Learner strategies	Perseverance	Age
C1-C3	True	True	True	False

The criteria matrix for the old candidates was as follows.

Table 5: Criteria matrix for old candidates

Alternatives/ Values	Motivation	Learner strategies	Perseverance	Age
C1-C3	True	True	True	True

The normalization of fuzzy membership degrees and weights is the next step. The vector normalization of the fuzzy membership degrees of the candidates' characteristics as well as the normalization of their weights are followed by their multiplication, which gives the weighted normalization matrix. The results of the normalized decision matrix and weighted normalized decision matrix are shown in Tables 6 to 9, respectively.

Table 6: The normalized decision matrix for young candidates

Candidates / criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.68041382	0.51847585	0.23570226	0.57735027
C2	0.68041382	0.82956136	0.23570226	0.57735027
C3	0.27216553	0.20739034	0.94280904	0.57735027

Table 7: The normalized decision matrix for old candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.68041382	0.51847585	0.23570226	0.57735027
C2	0.68041382	0.82956136	0.23570226	0.57735027
C3	0.27216553	0.20739034	0.94280904	0.57735027

Table 8: The weighted normalized decision matrix for young candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.17010345	0.12961896	0.05892557	0.14433757
C2	0.17010345	0.20739034	0.05892557	0.14433757
C3	0.06804138	0.05184758	0.23570226	0.14433757

Table 9: The weighted normalized decision matrix for old candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.17010345	0.12961896	0.05892557	0.14433757
C2	0.17010345	0.20739034	0.05892557	0.14433757
C3	0.06804138	0.05184758	0.23570226	0.14433757

In the next step, the best alternative (A^+) and the worst alternative (A^-) are obtained. Tables10 and 11 show the results of these alternatives.

Table 10: The best alternative (A^+) and the worst alternative (A^-) for young candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
A^+	0.17010345	0.20739034	0.23570226	0.14433757
A^-	0.06804138	0.05184758	0.05892557	0.14433757

Table 11: The best alternative (A^+) and the worst alternative (A^-) for the old candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
A^+	0.17010345	0.20739034	0.23570226	0.14433757
A^-	0.06804138	0.05184758	0.05892557	0.14433757

In step 6, the distances from the best alternative (d_i^*) and the worst alternative (d_i^-) are determined. The results of the distances from the best alternative (d_i^*) and the worst alternative (d_i^-) for the candidates are shown in Tables 12 and 13.

Table 12: The distances from the best alternative (d_i^*) and the worst alternative (d_i^-) for young candidates

Candidates	d_i^*	d_i^-
C1	0.1931279	0.12831623
C2	0.1767767	0.18603821
C3	0.18603821	0.1767767

Table 13: The distances from the best alternative (d_i^*) and the worst alternative (d_i^-) for the old candidates

Candidates	d_i^*	d_i^-
C1	0.1931279	0.12831623
C2	0.1767767	0.18603821
C3	0.18603821	0.1767767

The next step was the determination of the similarity coefficients of the young and old candidates according to their worst similarity. Tables 14 and 15 show the similarity coefficients and the rankings of the candidates.

Table 14: The similarity coefficients (CC_i) and the ranking of the young candidates according to the worst similarity

Candidates	CC_i	ranking
C1	0.39918671	2
C2	0.51276341	3
C3	0.48723659	1

Table 15: The similarity coefficients (CC_i) and the ranking of the old candidates according to the worst similarity

Candidates	CC_i	ranking
C1	0.39918671	2
C2	0.51276341	3
C3	0.48723659	1

The distances from the ideal solution and similarity coefficients of the young and old candidates are presented in Fig. 1 and Fig. 2, respectively.

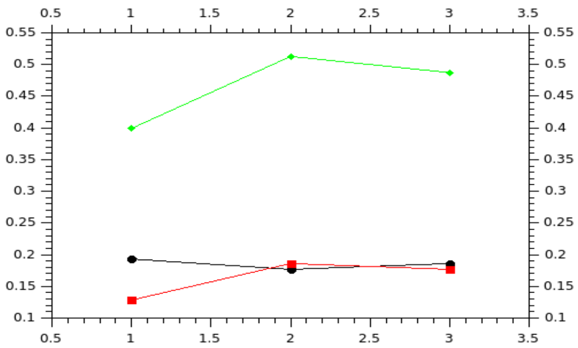

Fig. 1. The distances from the ideal solution and similarity coefficients of the young candidates

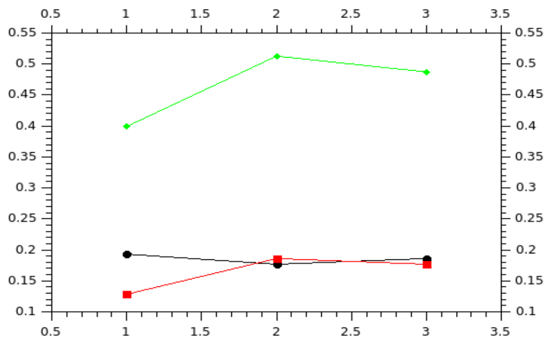

Fig. 2. The distances from the ideal solution and similarity coefficients of the old candidates

The obtained results show that the candidates' distances from the postivie and negative ideal solutions as well as their rankings are the same for young and old candidates and the difference in their consideration of age as a profit or cost criterion does not affect their rankings in both groups.

In another series of experiments, we analyzed the output of the modified TOPSIS for young and old candidates. The obtained results are presented in the tables below.

Table 16: Terms. corresponding triangular fuzzy membership degrees of young candidates' characteristics and their mean values

Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	medium	medium	low	high
C-2	medium	high	low	high
C-3	low	low	high	High
Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	0.4, 0.5, 0.6	0.4, 0.5, 0.6	0.1, 0.2, 0.3	0.7, 0.8, 0.9
C-2	0.4, 0.5, 0.6	0.7, 0.8, 0.9	0.1, 0.2, 0.3	0.7, 0.8, 0.9
C-3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.7, 0.8, 0.9	0.7, 0.8, 0.9
Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	0.5	0.5	0.2	1.0
C-2	0.5	0.8	0.2	0.8

C-3	0.2	0.2	0.8	0.8

Table 17: Terms, corresponding triangular fuzzy membership degrees of the old candidates' characteristics and their mean values

Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	medium	medium	low	high
C-2	medium	high	low	low
C-3	low	low	high	low
Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	0.4, 0.5, 0.6	0.4, 0.5, 0.6	0.1, 0.2, 0.3	0.7, 0.8, 0.9
C-2	0.4, 0.5, 0.6	0.7, 0.8, 0.9	0.1, 0.2, 0.3	0.1, 0.2, 0.3
C-3	0.1, 0.2, 0.3	0.1, 0.2, 0.3	0.7, 0.8, 0.9	0.1, 0.2, 0.3
Candidates / Criteria	**Motivation**	**Learner Strategies**	**Perseverance**	**Age**
C-1	0.5	0.5	0.2	1.0
C-2	0.5	0.8	0.2	0.2
C-3	0.2	0.2	0.8	0.2

The second step concerns the determination of the weights of alternatives for each criterion. The weights for each criterion are presented in Table 18.

Table 18: The weights for each criterion

Candidates / Values	Motivation	Learner Strategies	Perseverance	Age
C1-C3	0.5	0.5	0.5	0.5

In the next step, the criteria matrix was determined. Table 19 shows the criteria matrix indicating true for the profit criteria and false for the cost criterion, respectively. Motivation, learner strategies, perseverance and age are all profit criteria for the young candidates. The first three characteristics are profit criteria, whereas the last one is the cost criterion for the old candidates.

Table 19: Criteria matrix for young candidates

Alternatives/ Values	Motivation	Learner Strategies	Perseverance	Age
C1-C3	True	True	True	True

The criteria matrix for the old candidates is as follows.

Table 20: Criteria matrix for old candidates

Alternatives/ Values	motivation	learner strategies	perseverance	age

C1-C3	True	True	True	True

he normalization of fuzzy membership degrees and weights is the next step. The vector normalization of the fuzzy membership degrees of the candidates' characteristics as well as the normalization of their weights are followed by their multiplication, which gives the weighted normalization matrix. The results of the normalized decision matrix and weighted normalized decision matrix are shown in Tables 21 to 24, respectively.

Table 21: The normalized decision matrix for young candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.68041382	0.51847585	0.23570226	0.66226618
C2	0.68041382	0.82956136	0.23570226	0.52981294
C3	0.27216553	0.20739034	0.94280904	0.52981294

Table 22: The normalized decision matrix for the old candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.68041382	0.51847585	0.23570226	0.96225045
C2	0.68041382	0.82956136	0.23570226	0.19245009
C3	0.27216553	0.20739034	0.94280904	0.19245009

Table 23: The weighted normalized decision matrix for young candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
C1	0.17010345	0.12961896	0.05892557	0.24056261
C2	0.17010345	0.20739034	0.05892557	0.04811252
C3	0.06804138	0.05184758	0.23570226	0.04811252
C1	0.17010345	0.12961896	0.05892557	0.16556654
C2	0.17010345	0.20739034	0.05892557	0.13245324
C3	0.06804138	0.05184758	0.23570226	0.13245324

Table 24: The weighted normalized decision matrix for old candidates

In the next step, the best alternative (A^+) and the worst alternative (A^-) were obtained. Tables 25 and 26 show the results of these alternatives.

Table 25: The best alternative (A^+) and the worst alternative (A^-) for young candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
A^+	0.17010345	0.20739034	0.23570226	0.16556654
A^-	0.06804138	0.05184758	0.05892557	0.13245324

Table 26: The best alternative (A^+) and the worst alternative (A^-) for old candidates

Candidates / Criteria	Motivation	Learner Strategies	Perseverance	Age
A^+	0.17010345	0.20739034	0.23570226	0.24056261
A^-	0.06804138	0.05184758	0.05892557	0.04811252

In step 6, the distances from the best alternative (d_i^*) and the worst alternative (d_i^-) were determined. The results of the distances from the best alternative (d_i^*) and the worst alternative (d_i^-) for the candidates are shown in Tables 27 and 28.

Table 27: The distances from the best alternative (d_i^*) and the worst alternative (d_i^-) for young candidates

Candidates	d_i^*	d_i^-
C1	0.1931279	0.13251998
C2	0.1798513	0.18603821
C3	0.18896218	0.1767767

Table 28: The distances from the best alternative (d_i^*) and the worst alternative (d_i^-) for old candidates

Candidates	d_i^*	d_i^-
C1	0.1931279	0.23130519
C2	0.26131789	0.18603821
C3	0.26767004	0.1767767

In the next steps, the similarity coefficients of the young and old candidates were determined according to their worst similarity. Tables 29 and 30 show the similarity coefficients and the rankings of the candidates.

Table 29: The similarity coefficients (CC_i) and the ranking of the young candidates according to the worst similarity

Candidates	CC_i	Ranking
C1	0.40694255	2
C2	0.50845461	3
C3	0.48334127	1

Table 30: The similarity coefficients (CC_i) and the ranking of the old candidates according to the worst similarity

Candidates	CC_i	Ranking
C1	0.54497445	1
C2	0.41586157	2
C3	0.39774551	3

The distances from the ideal solution and similarity coefficients of the young and old candidates are presented in Fig. 3 and Fig. 4, respectively.

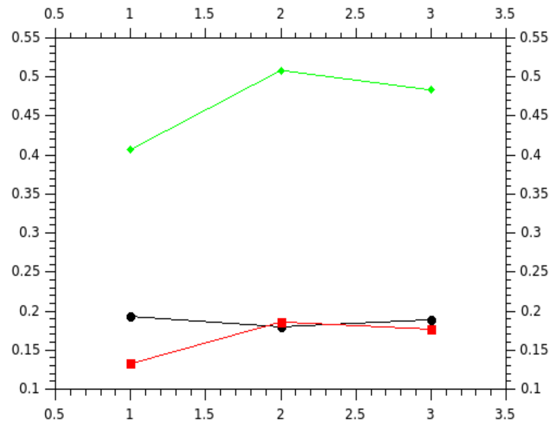

Fig. 3. The distances from the ideal solution and similarity coefficients of the young candidates

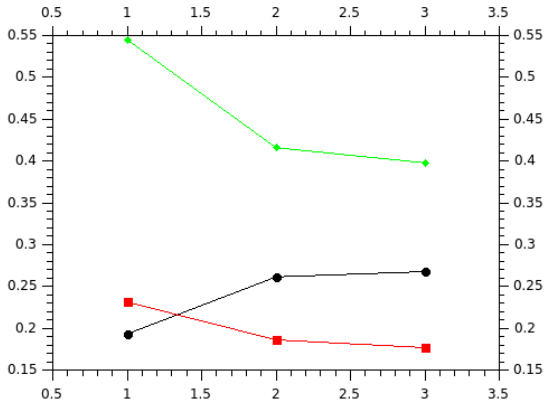

Fig. 4. The distances from the ideal solution and similarity coefficients of the OLD candidates

The obtained results with the modified TOPSIS algorithm show that for young candidates, the same ranking as before was obtained, whereas the ranking of the old candidates changed with the new version of this algorithm. In this last case, the first candidate who was ranked in the third place with the unmodified TOPSIS was ranked in the first place with the modified TOPSIS, whereas the second and third candidates who had the first and second places with the unmodified TOPSIS were ranked in the second and third places, respectively. This shows the efficiency of the modification in the TOPSIS algorithm for the optimization of the candidates' positions in the analysis of their language learning.
TOPSIS is a method for the candidates' classification, and it can be used for the classification of other candidates such as the materials and devices for which the human language has been developed with the applications of new terms in science and engineering (Khan & Hossain, 2022; Javanbakht et al., 2020; Wise et al., 2008; Javanbakht & David, 2020; Javanbakht et al., 2020). In these applications, fuzzy sets as the candidates' characteristics could be analyzed in order to determine in which case an appropriate optimization would be obtainable.
In recent years, the characteristics of materials that are used in the research works for the development of diverse applications have been reported. These materials can be optimized with TOPSIS and be ranked according to the fuzzy membership degrees of their characteristics (Javanbakht et al., 2020; Javanbakht & David, 2020; Javanbakht et al., 2020; Nadar et al., 2022; Dias & Stein, 2002). The investigation of these materials can help improve these applications for further developments.
The investigation of the materials and devices, that are artificial categories and can also be considered as fuzzy sets, has extended the vocabulary and enriched the language and developed its scopes (Dias & Stein, 2002; Martinovich et al., 2018; Loo, 2007; Chalozin-Dovrat, 2019). TOPSIS can also be used for the investigation of these language extensions in order to classify the candidates for the development of their language learning.
More investigation is required to determine the impact of age as an important criterion on the language learning of young and old candidates with the application of the scientific terms in the research works. For this, different time spans can be considered.

CONCLUSION

This paper aimed to present the results of the prediction of language learning with the application of fuzzy sets, fuzzy logic and TOPSIS. The candidates and their characteristics were considered as fuzzy sets. The changes in the fuzzy membership of the candidate's members showed that the profit and cost criteria had impact in this prediction. It can be concluded that the modification in TOPSIS made the application of the fuzzy disjunction possible in the code of this algorithm for the prediction of the categories confusion in language learning. The results demonstrated in this work can be applied in further investigation of the fuzzy sets. In a future work, the modifications of the fuzzy sets will be performed using TOPSIS and fuzzy logic in order to determine their impact in the application of short memory, long memory and working memory in language learning.

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