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FUZZY TOPSIS METHOD OF LEARNING METHODS SELECTION FOR THE DEVELOPMENT OF TIME MANAGEMENT SKILLS AMONG EMPLOYEES OF IT COMPANIES

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Abstract. For IT companies, one of the most important competitive advantages is a highly skilled workforce, so their learning and development, which can provide and stimulate this to a large extent, becomes one of the main priorities. In order to ensure its effectiveness, it is very important to select the most appropriate learning methods for the development of a specific set of skills. Therefore, the *object* of the article is the process of selecting the optimal method of learning of the employees of IT companies for the development of time management skills, which are important for each employee of the IT company, especially in the conditions of remote work. The goal is to improve the tools used to make such a choice. Fuzzy TOPSIS is the *methodological basis* of the article. The paper suggests a list of twelve criteria for achieving the research goal, which are divided into four groups: organisational aspects; resource components; quality criteria; and learning effectiveness criteria. The main choice was made from among six alternatives, including webinars, workshops, MOOCs, case studies, role-playing and shadowing. Because these learning methods are well suited to the development of time management skills. A total of three experts took part in this research. All of them work for IT companies and are qualified to carry out this type of analysis. The experts' linguistic ratings were converted into fuzzy triangular numbers on the basis of a seven-level linguistic scale. As a *result*, it was concluded that the best solution would be to use workshops to develop the time management skills of the company's employees. To check the reliability of the analysis, a sensitivity analysis was carried out, in which twelve different scenarios were analysed. In 75% of the cases, the result remained unchanged, which indicates a satisfactory level of quality of the calculations carried out. Thus, this approach makes it possible to significantly improve the effectiveness of employee learning and development through a well-founded selection of the most appropriate methods for developing a defined set of skills. It is also quite flexible and easily adaptable to other learning and development tasks.

Key words: learning methods, fuzzy set theory, Fuzzy TOPSIS, time management, sensitivity analysis.

JEL Classification: J24, C38, M12, M15, M53

1. Introduction

The growing instability of the external environment, rapid technological change and the increasing availability of information lead to an accelerated obsolescence of knowledge, skills and abilities, which in turn creates a need for timely and high-quality learning and development of personnel. This is particularly true in knowledge-intensive fields such as IT, where a highly skilled workforce is a key competitive advantage. IT companies use a wide range of different methods and techniques for staff learning. It is worth noting that rapid technological development and changes in the nature of work processes contribute to their constant updating and the emergence of new advanced ways of dealing with learning problems. However, the most popular methods are not always the most effective for developing a specific set of skills. Therefore, the task of selecting the most appropriate and useful method or combination of methods is becoming increasingly critical. In particular, it is important to achieve the planned efficiency indicators in the best possible way.

The use of fuzzy methods of multi-criteria analysis and their combinations can be useful in solving this

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type of task. Researchers note that their main goal is to determine the general advantages among options according to a number of different and meaningful criteria. That is, to provide a basis for comparing alternatives, sorting and ranking them depending on the specifics of the decision problem (Kelemenis and Askounis, 2010).

Fuzzy methods of multi-criteria analysis use "linguistic" variables instead of numerical ones. This makes it possible to properly evaluate options even in conditions of limited information and lack of clear quantitative values. That is why such an approach can greatly facilitate the solution of HR problems, especially such as the selection of a specific learning method for the development of a defined set of skills of IT specialists. In most cases, it is very difficult to collect appropriate numerical data for such tasks, and experts have to work mostly with qualitative data.

Taking into account the peculiarities of IT companies, it was decided to carry out an analysis for the selection of learning methods for the formation of time management skills, which are necessary for all specialists, regardless of their position. They have become even more relevant with the increase in remote working, which leads to greater responsibility on the part of employees for the organisation and effective use of their working time. According to Bernard Marr, time management is one of the top ten skills that will be most in demand over the next 10 years (Marr, 2022).

2. Literature Review

Fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), proposed by C. L. Hwang and K. Yun in 1981, is one of the most common methods of multi-criteria analysis. It uses the concepts of ideal positive and ideal negative solutions. The best alternative should have the shortest distance to the former and the longest distance to the latter (Hwang and Yoon, 1981).

In traditional TOPSIS, the weights of the criteria and the scores of the alternatives are well known and can be represented by unambiguous numerical data. However, under many conditions they are not sufficient to model real decision problems, and they are difficult or sometimes impossible to obtain (Kelemenis and Askounis, 2010). This is why Fuzzy TOPSIS, which allows working with fuzzy expert estimates, has gained popularity.

This method is used to solve a wide range of problems, such as selecting a learning management system (Turker et. al., 2019), selecting suppliers (Junior et. al., 2014), finding the best candidate for a vacant position (Kelemenis and Askounis, 2010), assessing the credit risk of potential strategic partners (Shen et al., 2018), to evaluate a reverse logistics performance (Han and Trimi, 2018), to evaluate an overall company performance (Sun, 2010), to rank solutions to overcome barriers in knowledge management implementation, and so forth (Patil and Kant, 2014). However, such methods are still not very common among HR professionals and are practically not adapted to the problems of employee learning and development.

A very important step in the evaluation process is to establish a list of criteria by which the evaluation will be carried out. They need to be unambiguously perceived by experts in order to avoid distortions and discrepancies in evaluations. Martin et al. proposed to consider criteria such as the level of interaction, cost considerations and time requirements (Martin et al., 2013). However, they are not sufficient for a complete evaluation. Therefore, based on the analysis of literary sources, a list of twelve criteria was formed, conditionally divided into four groups: organisational aspects; resource components; quality criteria; learning effectiveness criteria.

1. Organisational aspects. TC is the cost of training per employee (absolute estimates should be avoided, as the number of employees participating in training can vary significantly between different methods). PT – the period required to prepare for the training (includes the period required, for example, to develop materials, create a course, find a subcontractor, etc.). LD is the duration of learning (the time required for direct training, companies strive to reduce this indicator).

2. Resource components. QL – the level of qualification required to deliver the training (meaning the qualifications of trainers, instructors, coaches, etc.). MTS – compliance of material and technical support with the basic requirements of training (this includes the availability of the necessary equipment for its implementation, premises, etc.). WSE is the number of employees suspended from work for training (not only those who are directly involved in training, but also those specialists involved in its organisation or conduct as mentors, coaches, instructors, etc.).

3. Quality criteria. FI – intensity of feedback during training (as this is a prerequisite for ensuring successful learning). ES – employee satisfaction during/after the training (measuring this indicator and collecting feedback from employees is a prerequisite). PA – successful experience of previous application of the method.

4. Learning effectiveness criteria. ML – the level of learning by the employee (can be measured by the results of testing, scoring of tasks, etc.). BC – positive change in employee behaviour within three months of completing the training (this refers to the use of new techniques, behaviour, improved communication, etc.). SB – breadth of coverage of priority skills (most

training methods lead to the simultaneous development of several skills, so priority is given to those methods that can cover as many of them as possible).

All of the above criteria can be divided into two broad groups: cost criteria (C), which have a monotonically decreasing function, and benefit criteria (B), which have a monotonically increasing function. The first group of criteria is characterised by the fact that the lower their value, the more attractive the alternative is, while the second group, on the contrary, the higher their value, the better the alternative.

3. Framework and Results

Fuzzy TOPSIS involves a number of sequential steps (Figure 1). Starting from identifying the training needs of employees and determining the priority skills for them to the final choice of a training method for their development. Assume that there is a group of k experts (E_1, E_2, …, E_l) with m possible alternatives (A_1, A_2, …, A_m), which should be evaluated according to n criteria (C_1, C_2, …, C_n). Thus, the criteria weights will be denoted by: W_{jk} (j=1,2, …, n; k=1,2, …, l), and the evaluation of alternatives: X_{ijk}=(i=1,2, …, m; k=1,2, …, l; j=1,2, …, n).

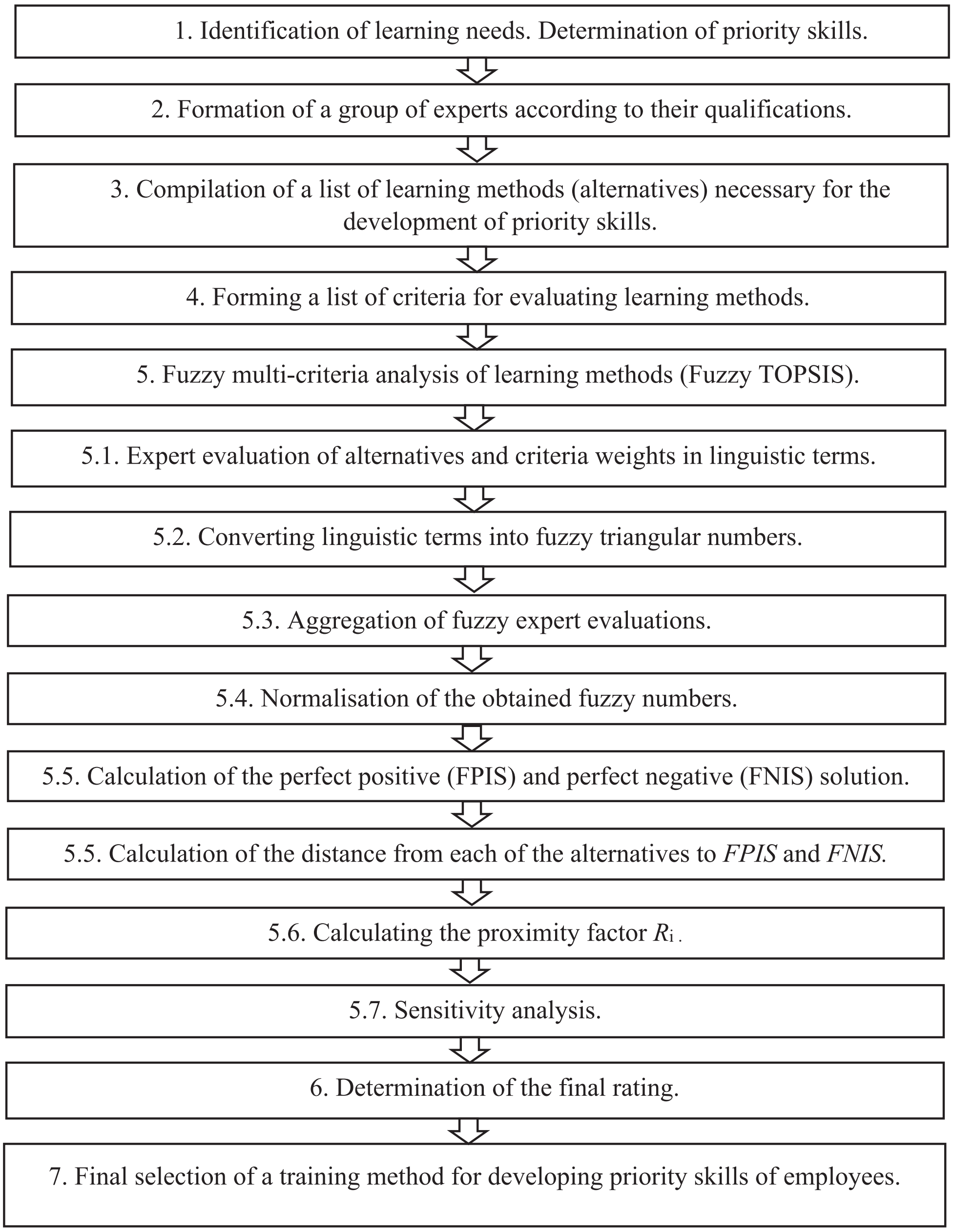

Figure 1. A framework for selecting learning methods based on fuzzy multicriteria analysis

Source: compiled by the authors

Three experts were involved in the evaluation within the study, who are leading specialists from IT companies who have the necessary qualifications and experience to carry out this task. A fuzzy linguistic evaluation scale was proposed, based on a seven-level set of terms, which was used not only to evaluate alternatives but also to evaluate criteria weights. Fuzzy sets are sets where the elements have degrees of membership. Fuzzy sets were introduced into scientific circulation by L. A. Zadeh in 1965 as an extension of the classical concept of a set (Sun, 2010). Therefore, linguistic terms can be transformed into fuzzy triangular numbers (Table 1), which can be represented as follows: (a, b, c). Their membership functions can be illustrated (Figure 2) and described by equation (1):

$$F(x)=\begin{cases}\dfrac{x-a}{b-a}, a\le x\le b\\ \dfrac{c-x}{c-b}, b\le x\le c\\ 0\end{cases} \tag{1}$$

Table 1
Linguistic scale for converting linguistic terms into fuzzy triangular numbers

Linguistic terms	Triangular fuzzy number
Extremely High (EH)	(5;6;6)
Very High (VH)	(4;5;6)
High (H)	(3;4;5)
Medium (M)	(2;3;4)
Low (L)	(1;2;3)
Very Low (VL)	(0;1;2)
Extremely Low (EL)	(0;0;1)

Source: compiled on the basis of data from (Balan, 2021, p. 52)

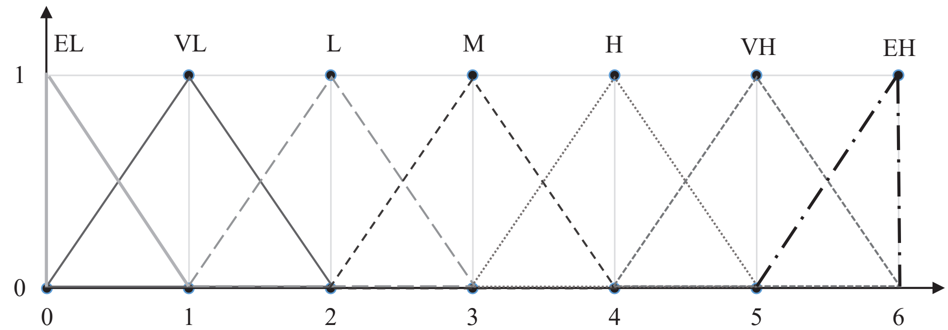

Figure 2. Triangular fuzzy number membership function

Source: compiled by the authors

Table 2
Linguistic expert assessments of alternatives and criteria weights

Methods / Criterion	TC	PT	LD	QL	MTS	WSE	FI	ES	PA	ML	BC	SB	
Webinar	E1	H	M	L	M	L	VH	M	M	H	M	VL	M
	E2	M	M	L	H	H	H	H	H	M	M	M	M
	E3	L	M	L	M	M	EH	L	M	H	H	L	L
Workshop	E1	H	H	M	M	H	H	VH	EH	H	VH	L	M
	E2	M	M	L	H	H	H	H	H	H	H	H	H
	E3	L	M	L	H	M	EH	H	H	H	H	M	M
MOOCs	E1	H	M	M	L	H	H	L	VH	H	VH	L	M
	E2	H	M	M	L	H	H	M	H	H	H	H	H
	E3	L	M	H	M	H	VH	VL	M	M	M	H	VH
Case study	E1	H	M	L	H	M	M	VH	M	H	M	VL	L
	E2	H	M	L	H	H	M	M	H	M	H	M	M
	E3	M	VH	M	H	M	M	H	H	M	VH	L	H
Role-playing	E1	VH	L	L	M	H	M	VH	H	H	H	M	L
	E2	M	M	L	M	H	H	M	L	L	M	M	H
	E3	H	M	M	H	M	L	H	H	H	VH	H	M
Shadowing	E1	M	M	H	VH	M	L	L	H	H	H	H	M
	E2	M	L	M	H	M	M	M	M	M	M	M	H
	E3	L	H	VH	H	M	L	L	H	M	VH	H	H
Criteria weights	E1	EH	H	VH	M	M	VL	VH	EH	H	H	VH	M
	E2	H	M	H	H	H	L	H	H	VH	VH	H	M
	E3	VH	M	VH	H	M	L	H	VH	EH	EH	VH	H

Source: compiled by the authors

To perform calculations, it is important to understand the basic rules for working with fuzzy triangular numbers. Consider that $\widetilde{A}_1 = (a_1, b_1, c_1)$ and $\widetilde{A}_2 = (a_2, b_2, c_2)$ are two fuzzy triangular numbers. In this case, mathematical operations with them will be performed according to the following rules (Han and Trimi, 2018):

$$\widetilde{A}_1 + \widetilde{A}_2 = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \quad (2)$$

$$\widetilde{A}_1 \times \widetilde{A}_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \quad (3)$$

$$k \times \widetilde{A}_1 = (k \times a_1, k \times b_1, k \times c_1) \quad (4)$$

Table 2 shows the linguistic evaluations of the alternatives by the experts according to the proposed criteria. Then, on the basis of the linguistic scale, the experts' ratings were converted into fuzzy triangular numbers.

The next step is to aggregate the fuzzy scores of the alternatives and the weights of the criteria. Given that W_{jk} and X_{ijk} are described with fuzzy triangular numbers (a_k, b_k, c_k) (k=1,2, …, l), the aggregate scores are defined as follows:

$$a = min\{a_k\},\ b = \frac{1}{k}\sum_{k=1}^{l} b_k,\ c = max\{c_k\} \quad (5)$$

Then, based on the calculated aggregated fuzzy scores, the criteria were ranked according to their importance (Table 3).

It is worth noting that several of the criteria have the same ranking, so their weighting will be the same. According to the experts, the most important criteria are the cost of training per employee, employee satisfaction during and after the training, successful experience of previous application of this method and the level of mastery of the material by the employee.

In the same way, the calculation of aggregated fuzzy expert opinions for the six selected alternative teaching methods was carried out, the results of which are presented in Table 4. The next step is to normalise the data. If the criterion has a monotonically decreasing function, the normalised value will be calculated as follows:

$$\left(\frac{a_k}{c}, \frac{b_k}{c}, \frac{c_k}{c}\right), c = max\{c_k\} \quad (6)$$

If the criterion has a monotonically increasing function (the company seeks to maximise its value), the normalised value will be calculated using formula (7):

$$\left(\frac{a}{c_k}, \frac{a}{b_k}, \frac{a}{a_k}\right), a = min\{a_k\} \quad (7)$$

In this case, the five criteria relate to costs (C): TC, PT, LD, QL and WSE. Therefore, seven criteria belong to the benefits (B), namely MTS, FI, ES, PA, ML, BC and SB.

The next step is to weight the normalised fuzzy expert opinions (its results are presented in Table 6). This is done by multiplying the normalised expert opinions of the alternatives obtained in the previous step by the weights of the criteria, which were also calculated earlier according to rule (3):

Table 3
Aggregated fuzzy expert estimates of criteria weights and their ranking

Criteria	Expert evaluations	Ranking
TC	(3;5;6)	1
PT	(2;3,33;5)	5
LD	(3;4,67;6)	2
QL	(2;3,67;5)	4
MTS	(2;3,33;5)	5
WSE	(0;1,67;3)	6
FI	(3;4,33;6)	3
ES	(3;5;6)	1
PA	(3;5;6)	1
ML	(3;5;6)	1
BC	(3;4,67;6)	2
SB	(2;3,33;5)	5

Source: compiled by the authors

Table 4
Aggregated fuzzy expert evaluations of learning methods

Methods / Criterion	Webinar	Workshop	MOOCs	Case study	Role-playing	Shadowing
TC	(1;3;5)	(1;3;5)	(1;3,33;5)	(2;3,67;5)	(2;4;6)	(1;2,67;4)
PT	(2;3;4)	(2;3,33;5)	(2;3;4)	(2;3,67;6)	(1;2,67;4)	(1;3;5)
LD	(1;2;3)	(1;2,33;4)	(2;3,33;5)	(1;2,33;4)	(1;2,33;4)	(2;4;6)
QL	(2;2,67;5)	(2;3,67;5)	(1;2,33;4)	(3;4;5)	(2;3,33;5)	(3;4,33;6)
MTS	(1;3;5)	(2;3,67;5)	(3;4;5)	(2;3,33;5)	(2;3,67;5)	(2;3;4)
WSE	(3;5;6)	(3;4,67;6)	(3;4,33;6)	(2;3;4)	(1;3;5)	(1;2,33;4)
FI	(1;3;5)	(3;4,33;6)	(0;2;4)	(2;4;6)	(2;4;6)	(1;2,33;4)
ES	(2;2,67;5)	(3;4,33;6)	(2;4;6)	(2;3,67;5)	(1;3,33;5)	(2;3,67;5)
PA	(2;3,67;5)	(3;4,67;6)	(2;3,67;5)	(2;3,33;5)	(1;3,33;5)	(2;3,33;5)
ML	(2;3,33;5)	(3;4,33;6)	(2;4;6)	(2;4;6)	(2;4;6)	(2;4;6)
BC	(0;2;4)	(1;3;5)	(1;3,33;5)	(0;2;4)	(2;3,33;5)	(2;3,67;5)
SB	(1;2,67;4)	(2;3,33;5)	(2;4;6)	(1;3;5)	(1;3;5)	(2;3,67;5)

Source: compiled by the authors

Table 5
Normalised fuzzy decision matrix

Methods / Criterion	Webinar	Workshop	MOOCs	Case study	Role-playing	Shadowing
TC	(1;0,3;0;2)	(1;0,3;0,2)	(1;0,3;0,2)	(0,5;0,3;0,2)	(0,5;0,3;0,2)	(1;0,4;0,3)
PT	(0,5;0,3;0,3)	(0,5;0,3;0,2)	(0,5;0,3;0,3)	(0,5;0,3;0,2)	(1;0,4;0,3)	(1;0,3;0,2)
LD	(1;0,5;0,3)	(1;0,4;0,3)	(0,5;0,3;0,2)	(1;0,4;0,3)	(1;0,4;0,3)	(0,5;0,3;0,2)
QL	(0,5;0,3;0,2)	(0,5;0,3;0,2)	(1;0,4;0,3)	(0,3;0,3;0,2)	(0,5;0,3;0,2)	(0,3;0,2;0,2)
MTS	(0,2;0,6;1)	(0,2;0,8;1)	(0,6;0,8;1)	(0,4;0,7;1)	(0,4;0,7;1)	(0,4;0,6;0,8)
WSE	(0,3;0,2;0,2)	(0,3;0,2;0,2)	(0,3;0,2;0,2)	(0,5;0,3;0,3)	(1;0,3;0,2)	(1;0,4;0,3)
FI	(0,2;0,5;0,8)	(0,5;0,7;1)	(0;0,3;0,7)	(0,3;0,7;1)	(0,3;0,7;1)	(0,1;0,3;0,7)
ES	(0,3;0,5;0,8)	(0,5;0,7;1)	(0,3;0,7;1)	(0,3;0,6;0,8)	(0,2;0,6;0,8)	(0,3;0,6;0,8)
PA	(0,3;0,5;0,8)	(0,5;0,8;1)	(0,3;0,6;0,8)	(0,3;0,6;0,8)	(0,2;0,6;0,8)	(0,3;0,6;0,8)
ML	(0,3;0,6;0,8)	(0,5;0,7;1)	(0,3;0,7;1)	(0,3;0,7;1)	(0,3;0,7;1)	(0,3;0,7;1)
BC	(0;0,4;0,8)	(0,2;0,6;1)	(0,2;0,7;1)	(0;0,2;0,8)	(0,4;0,7;1)	(0,4;0,7;1)
SB	(0,2;0,5;0,7)	(0,3;0,6;0,8)	(0,3;0,7;1)	(0,2;0,5;0,8)	(0,2;0,5;0,8)	(0,3;0,6;0,8)

Source: compiled by the authors

Table 6
Weighted normalised decision matrix of alternatives

Methods / Criterion	Webinar	Workshop	MOOCs	Case study	Role-playing	Shadowing
TC	(3;1,7;1,2)	(3;1,7;1,2)	(3;1,5;1,2)	(1,5;1,4;1,2)	(1,5;1,3;1)	(3;1,9;1,5)
PT	(1;1,1;1,3)	(1;1;1)	(2;1,1;1,3)	(1;0,9;0,9)	(2;1,2;1,3)	(2;1,1;1)
LD	(3;2,3;2)	(3;2;1,5)	(1,5;1,4;1,2)	(3;2;1,5)	(3;2;1,5)	(1,5;1,2;1)
QL	(1;1,4;1,2)	(1;1;1)	(2;1,6;1,3)	(0,7;0,9;1,2)	(1;1,1;1,2)	(0,7;0,9;0,9)
MTS	(0,4;2;5)	(0,4;2,4;5)	(1,2;2,7;5)	(0,8;2,2;5)	(0,8;2,4;5)	(0,8;2;4)
WSE	(0;0,3;0,5)	(0;0,4;0,5)	(0;0,4;0,5)	(0;0,6;0,8)	(0;0,6;0,6)	(0;0,7;0,8)
FI	(0,5;2,2;5)	(1,5;3,1;6)	(0;1,4;4)	(1;2,9;6)	(1;2,9;6)	(0,5;1,7;4)
ES	(1;2,3;5)	(1,5;3,6;6)	(1;3,4;6)	(1;3,1;5)	(0,5;2,8;5)	(1;3,1;5)
PA	(1;2,3;5)	(1,5;3,9;6)	(1;3,1;5)	(1;2,8;5)	(0,5;2,8;5)	(1;2,8;5)
ML	(1;2,8;5)	(1,5;3,6;6)	(1;3,4;6)	(1;3,4;6)	(1;3,4;6)	(1;3,4;6)
BC	(0;1,9;4,8)	(0,6;2,8;6)	(0,6;3,1;6)	(0;0,9;4,8)	(1,2;3,1;6)	(1,2;3,4;6)
SB	(0,3;1,5;3,4)	(0,7;19;4,2)	(0,7;2,2;5)	(0,3;1,7;4,2)	(0,3;1,7;4,2)	(0,7;2;4,2)

Source: compiled by the authors

$$\widetilde{V_{ijk}} = \widetilde{W_{jk}}^{*} \times \widetilde{X_{ijk}}^{*} \quad (8)$$

It is also possible to proceed to the calculation of the ideal positive solution (FPIS) (9) and the ideal negative solution (FNIS) (10):

$$FPIS = (c_V, c_V, c_V) \text{ де } c_V = max\{c_{V_{ijk}}\} \quad (9)$$

$$FNIS = (a_V, a_V, a_V) \text{ де } a_V = min\{a_{V_{ijk}}\} \quad (10)$$

It is important to note that some of the criteria have a monotonically decreasing function and some have a monotonically increasing function, so the calculation for these two groups will be slightly different (Table 7).

The next step (Table 8) is to calculate the distance from each alternative to the ideal positive and ideal negative solution using the following formulas:

$$S^{+} = \sqrt{\frac{1}{3}\left[\left(a_{V_{ijk}} - c_V\right)^2 + \left(b_{V_{ijk}} - c_V\right)^2 + \left(c_{V_{ijk}} - c_V\right)^2\right]} \quad (11)$$

$$S^{-} = \sqrt{\frac{1}{3}\left[\left(a_{V_{ijk}} - a_V\right)^2 + \left(b_{V_{ijk}} - c_V\right)^2 + \left(c_{V_{ijk}} - c_V\right)^2\right]} \quad (12)$$

Table 7
Calculated ideal positive and ideal negative solutions

	FPIS	FNIS
TC	(1,5;1,25;1,02)	(3;1,85;1,5)
PT	(1;0,9;0,85)	(2;1,23;1,25)
LD	(1,5;1,17;1,02)	(3;2,34;1,98)
QL	(0,66;0,84;0,85)	(2;1,58;1,25)
MTS	(1,2;2,66;5)	(0,4;2;4)
WSE	(0;0,33;0,51)	(0;0,72;0,75)
FI	(1,5;3,12;6)	(0;1,26;4,02)
ES	(1,5;3,6;6)	(0,51;2,25;4,98)
PA	(1,5;3,9;6)	(0,51;2,25;4,98)
ML	(1,5;3,6;6)	(1;2,8;4,98)
BC	(1,2;3,41;6)	(0;0,93;4,8)
SB	(0,66;2,23;5)	(0,34;1,5;3,35)

Source: compiled by the authors

The last step is to calculate the proximity factor R_i (Table 9):

$$R_i = \frac{\sum_1^n S_{ij}^{-}}{\sum_1^n S_{ij}^{+} + \sum_1^n S_{ij}^{-}}, i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n \quad (13)$$

Table 8
Distance from alternative learning methods to FPIS and FNIS

	S^+						S^-					
	A1	A2	A3	A4	A5	A6	A1	A2	A3	A4	A5	A6
TC	0,90	0,90	0,88	0,12	0,00	0,97	0,21	0,21	0,27	0,93	0,97	0,00
PT	0,26	0,10	0,26	0,00	0,65	0,60	0,58	0,61	0,58	0,65	0,00	0,16
LD	1,23	1,03	0,17	1,03	1,03	0,00	0,00	0,34	1,12	0,34	0,34	1,23
QL	0,37	0,23	0,91	0,10	0,26	0,00	0,61	0,68	0,00	0,87	0,66	0,91
MTS	0,00	0,01	0,03	0,19	0,14	0,26	0,26	0,25	0,24	0,10	0,13	0,00
WSE	0,60	0,48	0,00	0,34	0,27	0,73	0,58	0,63	0,83	0,64	0,67	0,23
FI	0,99	0,00	1,73	0,32	0,32	1,67	0,82	1,79	0,10	1,59	1,59	0,29
ES	1,02	0,00	0,33	0,73	0,94	0,73	0,28	1,13	0,91	0,54	0,32	0,54
PA	1,16	0,00	0,82	0,91	1,04	0,91	0,28	1,26	0,54	0,42	0,32	0,42
ML	0,80	0,00	0,33	0,33	0,33	0,33	0,00	0,80	0,67	0,67	0,67	0,67
BC	1,32	0,49	0,38	1,73	0,16	0,00	0,54	1,33	1,49	0,00	1,60	1,73
SB	1,06	0,53	0,00	0,62	0,62	0,50	0,00	0,54	1,06	0,47	0,47	0,58
Sum	9,71	3,79	5,85	6,42	5,75	6,71	4,15	9,58	7,80	7,22	7,73	6,78

Source: compiled by the authors

In the Fuzzy TOPSIS method, the alternatives are ranked according to the closeness coefficient; the higher the value of this indicator, the more attractive the alternative. According to the evaluation results for this case, the second alternative, a workshop, is the best decision for developing time management skills among employees. This learning method is relatively inexpensive, involves a high degree of interaction and feedback, and allows not only theoretical knowledge to be acquired, but also to be immediately integrated into working routines.

To ensure that the decision taken is correct, it is also worth carrying out a sensitivity analysis by changing the weighting of the criteria. In this case, 12 different scenarios were analysed (Table 10). There was a consistent change in the weighting of one criterion, while the values for other criteria remained the same. For example, for the first scenario, the weight of the TC criterion is (5;6;6) and the weight of all other criteria is (0;1;2). A similar operation was performed for all other criteria.

Based on the results of the sensitivity analysis, it can be concluded that the ranking of alternatives changes for different scenarios. However, a workshop was identified as the best alternative for nine out of 12 scenarios, i.e., 75% of the time.

Therefore, it can be concluded that the results of this method are quite reliable. In certain situations, it is advisable not only to choose one of the teaching methods, but also to consider other alternatives that would complement and strengthen it, in which case the ones that are next in the ranking should be taken into account.

Table 9
Rating of learning methods for developing time management skills among IT employees by Fuzzy TOPSIS method

	Webinar	Workshop	MOOCs	Case study	Role-playing	Shadowing
$\sum_1^n S_{ij}^+$	9,710	3,786	5,847	6,417	5,752	6,709
$\sum_1^n S_{ij}^-$	4,150	9,575	7,795	7,216	7,734	6,777
$\sum_1^n S_{ij}^+ + \sum_1^n S_{ij}^-$	13,86	13,36	13,64	13,63	13,49	13,49
R_i	0,299	0,717	0,571	0,529	0,573	0,503
Ranking	6	1	3	4	2	5

Source: compiled by the authors

Table 10
Scenarios for sensitivity analysis

Scenario	Criteria weights	Ranking
1	TC=(5;6;6), the others=(0;1;2)	A5>A4>A2>A3>A6>A1
2	PT=(5;6;6), the others =(0;1;2)	A2>A3>A4>A1>A5>A6
3	LD=(5;6;6), the others =(0;1;2)	A3>A6>A2>A5>A4>A1
4	QL=(5;6;6), the others =(0;1;2)	A2>A4>A5>A6>A1>A3
5	WSE=(5;6;6), the others =(0;1;2)	A2>A3>A4>A1>A5>A6
6	MTS=(5;6;6), the others =(0;1;2)	A3>A2>A5>A4>A6>A1
7	FI=(5;6;6), the others =(0;1;2)	A2>A5>A4>A3>A6>A1
8	ES=(5;6;6), the others =(0;1;2)	A2>A3>A4>A5>A6>A1
9	PA=(5;6;6), the others =(0;1;2)	A2>A3>A5>A4>A6>A1
10	ML=(5;6;6), the others =(0;1;2)	A2>A3>A5>A4>A6>A1
11	BC=(5;6;6), the others =(0;1;2)	A2>A5>A3>A6>A4>A1
12	SB=(5;6;6), the others =(0;1;2)	A2>A3>A5>A6>A4>A1

Source: calculated by the authors

4. Conclusions

Therefore, the use of methods of fuzzy multicriteria analysis can significantly improve the speed and quality of decision making regarding the selection of methods and forms of learning for the personnel of IT companies for the formation and development of a certain set of skills. In addition, it is possible to use sensitivity analysis to check the reliability of the obtained results. The main advantage of the proposed framework is the possibility to take into account not only quantitative data, but also qualitative data based on expert assessments in linguistic terms. This makes it possible to make informed decisions even under conditions of limited information and increases the effectiveness of learning, thus reducing the percentage of wasted resources. It is worth noting that expert judgements may raise some concerns about their objectivity, but a well-designed strategy for their selection and the use of additional tools to harmonise their opinions can largely eliminate this risk.

In addition, the proposed framework is quite flexible and can be easily adapted to solve other learning and development problems, such as the selection of learning management systems, the selection of learning service providers, and the selection of mentors or coaches among their staff. Depending on the capabilities of the organisation, the number of experts involved in the analysis can be changed to increase the objectivity of the evaluations, the list of criteria can be revised and improved, and additional tools can be used to determine the weights of the criteria, such as Fuzzy AHP. It is also possible to extend the research by using other methods of Fuzzy Multi-Criteria Analysis, such as Fuzzy VIKOR, or a combination of them.

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