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Topic-Based Evaluation of Occupational Safety Knowledge Levels of Manufacturing Sector Employees Using Multi-Criteria Decision-Making Methods

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Abstract

Occupational safety training plays a significant role in protecting employees from accidents and occupational diseases. The effectiveness and content of training also influence the outcomes. In this regard, determining the training topics that employees need is important. In this study, the knowledge levels of manufacturing sector employees were measured using a 30-question test to determine the topics needed in occupational safety training. The data obtained were analyzed using multi-criteria decision-making methods. The aim of the study is to identify the topics in which manufacturing sector employees have knowledge gaps in terms of occupational safety. The results showed that manufacturing sector employees had the most knowledge gaps regarding personal protective equipment. This was followed by labor regulations, safety culture, working at heights, lifting equipment, emergencies, and occupational safety and health warning signs.

Keywords: Occupational Health and Safety Training, Multi Criteria Decision Making, Knowledge Gap Analysis

Öz

İş güvenliği eğitimleri çalışanların kazalardan ve mesleki hastalıklardan korunmasında önemli bir yere sahiptir. eğitimlerin etkinliği ve içeriği de neticeleri etkilemektedir. Bu bakımdan çalışanların ihtiyaç duydukları eğitim konularının belirlenmesi önem arz etmektedir. Bu çalışmada iş güvenliği eğitimlerinde ihtiyaç duyulan konuların belirlenebilmesi için imalat sektörü çalışanlarının bilgi düzeyleri otuz sorudan oluşan bir test kullanılarak ölçülmüştür. Elde edilen veriler çok kriterli karar verme metodları ile analiz edilmiştir. Çalışmanın amacı imalat sektörü çalışanlarının iş güvenliği açısından bilgi eksikliği bulunan konuları saptamaktır. Sonuçlar imalat sektörü çalışanlarının; en çok kişisel koruyucu donanımlar konusunda bilgi eksikliği olduğunu göstermiştir. Ardından çalışma mevzuatı, güvenlik kültürü, yüksekte çalışma, kaldırma ekipmanları, acil durumlar ve isg uyarı işaretleri gelmektedir.

Anahtar Kelimeler: İş Sağlığı ve Güvenliği Eğitimi, Çok Kriterli Karar Verme, Bilgi Açığı Analizi

I.   INTRODUCTION

Occupational health and safety (OHS) has become one of the indispensable elements of modern working life. The importance of this field is increasing day by day, especially as industrialization increases, production processes diversify and the economic and social effects of occupational accidents become more visible. In Turkey, thousands of occupational accidents occur every year and hundreds of workers lose their lives or face permanent disabilities. This picture brings with it not only individual but also corporate and social responsibilities.

Occupational health and safety (OHS) training is critical for employees to recognize the risks they may face at work and to take precautions against these risks. Trainings increase employees' level of knowledge, encourage safe behaviors and contribute to the prevention of occupational accidents.

"Occupational health and safety training is the work of raising awareness and knowledge in this field, which is carried out at regular intervals in order to minimize the risks that workers face in the workplace due to work" [1]. The content of these trainings is clearly defined in the Regulation on the Procedures and Principles of Occupational Health and Safety Training of Employees by the Turkish Ministry of Labor and Social Security (MoLSS) [2]. It is not only a legal obligation but also a fundamental human right for employees to receive occupational health and safety training.

Occupational health and safety(OHS) training plays a crucial role in combating workplace accidents and occupational diseases. OHS training not only informs employees about potential risks they may encounter but also enhances safety culture.

Therefore, it is crucial that training is tailored to specific needs. Training content that is not tailored to employee needs may end up being nothing more than a mere procedure. To address this problem, the training topics required must be examined on a sectoral basis.

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The aim of this study is to identify the OHS topics required by employees in the manufacturing sector. This will ensure that topics are prioritized when creating training content.

In many international studies in the field of occupational health and safety (OHS), multi-criteria decision-making (MCDM) methods are utilized especially for risk analysis and determination of preventive strategies. Gül [3] examined the application of methods such as AHP, TOPSIS, VIKOR to OHS risk assessments in various sectors; however, this study aimed to prioritize risks instead of direct employee knowledge level.Similarly, Jasiulewicz-Kaczmarek et al. [4] integrated ISM, MICMAC, and fuzzy TOPSIS methods to evaluate safety culture factors within the Polish automotive industry. Their study primarily focuses on organizational safety culture.

Demir et al. [5] integrated the F-WENSLO and F-ARTASI methods to prioritize occupational safety risks and determine appropriate intervention strategies, using the Libyan Steel Company (LISCO) in Libya as a case study.

Cerev and Yıldırım [6] investigated the educational attainment of individuals who had experienced occupational accidents. They revealed an inverse relationship between increased education levels and the probability of experiencing an occupational accident. In this context, occupational health and safety training plays a critical role in protecting employees against both occupational accidents and occupational diseases.

A systematic review conducted by Robson et al. [7] indicated that OHS training positively impacts employees' safety behaviors, yet its effects on health outcomes appear limited. Similarly, Burke et al. [8] demonstrated that interactive and hands-on training methods are more effective in knowledge acquisition and the adoption of safe behaviors.

The Ministry of Labor and Social Security of Turkey outlines four main categories for occupational health and safety training: general, health, technical, and job-specific topics [2]. These categories encompass a wide range of sub-topics, from employees' legal rights and responsibilities to chemical risk factors, first aid, and the use of personal protective equipment.

However, in practice, some of these topics may not be directly relevant to employees' daily work, which can hinder their understanding of the training content. Additionally, because training is often delivered with the same standardized content to all employees, sectoral and task-based knowledge gaps can be overlooked.

While the impact of occupational health and safety training on accidents has been frequently examined in the literature, findings regarding employees' topic-specific knowledge levels and areas of deficiency are quite limited. This study aims to identify employees' knowledge gaps regarding the content of occupational health and safety training on a topic-by-topic basis and to determine the priority order of these deficient areas.

This study contributes to the literature by integrating the aforementioned methodological framework with knowledge test-based item analyses. The obtained measurements are then weighted using the SWARA method and subsequently analyzed with the ARAS, TOPSIS, and PSI methods to rank OHS topics requiring training priority. In this regard, the current research stands as one of the first applications in the literature, with few existing examples, to evaluate employee knowledge levels on a topic-by-topic basis by integrating item analysis results with multi-criteria decision-making methods.

II.   MATERIAL AND METHODS

This study adopted a cross-sectional research design to determine the topic-specific occupational safety knowledge levels of manufacturing sector employees and to prioritize deficient areas using multi-criteria decision-making (MCDM) methods. According to the 2023 report published by the Turkish Employment Agency (İŞKUR), the number of employees in the manufacturing sector in Ankara province is 181,308, which constitutes the population of the study [9]. Simple random sampling was used as the sampling method for the study. During the sampling process, each individual in the population was assumed to have an equal probability of being selected. This aimed to increase the representativeness of the findings for the population.

In the study, the minimum sample size was calculated based on a 95% confidence level and a 10% margin of error, determining that at least 96 participants were required by using the OpenEpi program. The implementation involved reaching 112 volunteer participants from accessible manufacturing sector employees, thus fulfilling the necessary sample size. Inclusion criteria were being at least 18 years old, residing in Ankara, and currently employed in the manufacturing sector. Exclusion criteria included being under 18, not residing in Ankara, or not working in the manufacturing sector. Data were collected through face to face questionnaires and all participants provided informed consent. Information regarding the participants' demographic characteristics is presented in Table 1.

Table 1. Participant demographic data

Variable		Frequency	Percentage %
Gender	Male	91	81
	Female	21	19
Educational Status	Primary Education	2	2
	High School	44	39
	University	64	57
	Master's Degree	2	2
Seniority Period	0–3 years	71	63
	3–6 years	27	24
	6–10 years	3	3
	10+ years	11	10
Occupation	Technician	56	50
	Engineer	17	15
	Technical Publication Specialist	26	23
	Others	13	12

The survey questions represent 13 distinct occupational safety topics. The questionnaire comprises 30 multiple-choice questions, all derived from the Turkish Ministry of Labor and Social Security's "Regulation on the Procedures and Principles of Occupational Health and Safety Training for Employees." [2] For analysis, correct answers from participants were coded as "1," while incorrect or unanswered questions were coded as "0." The topic-based distribution of these questions is presented in Table 2.

Table 2. Topic distribution of survey questions

Number	Subject	Question number	Frequency
1	Working at Height	Q11, Q13, Q16, Q18, Q19, Q20	6
2	Safety Culture	Q10, Q28, Q30	3
3	Personal Protective Equipment	Q12, Q14, Q15	3
4	Labor legislation	Q1, Q2, Q3	3
5	OHS Signs	Q4, Q9, Q29	3
6	Occupational Accidents	Q23, Q24, Q27	3
7	Hazard and Near Miss Incidents	Q21, Q25	2
8	Emergencies	Q22, Q26	2
9	Working with Display Screen Equipment	Q7	1
10	Electrical Safety	Q8	1
11	Manual Handling and Lifting	Q5	1
12	Fire and Explosion	Q6	1
13	Lifting Equipment	Q17	1

To evaluate the internal consistency of the questionnaire, the Kuder-Richardson 20 (KR-20) reliability coefficient was calculated. The KR-20 method is an appropriate technique for measuring internal consistency in tests scored with dichotomous categories, such as true/false or correct/incorrect. The KR-20 coefficient is based on the assumption that the test items primarily measure a single construct or dimension [10].

The knowledge test employed in this study encompasses 13 distinct topic areas within occupational safety, suggesting that the test could potentially have a multidimensional structure. The calculated KR-20 value is 0.37, which indicates a low level of overall internal consistency for the test. However, considering that the test is composed of numerous different sub-topics, this result is somewhat expected. Therefore, when interpreting the KR-20 value, the multi-topic nature of the test should be taken into account. Furthermore, conducting topic-based analyses will help mitigate the impact of this multidimensionality.

In the study, the prerequisites for Factor Analysis were checked to examine the basic structural validity of the OSH questions; however, the Kaiser-Meyer-Olkin (KMO) Sample Adequacy value was determined to be 0.407. Since this value was below the 0.60 acceptance threshold, it was understood that the questions did not sufficiently represent a latent factor, and it was concluded that the application of Factor Analysis was not statistically appropriate. In light of this situation, the fundamental methodological robustness of the study focused on the integration of three AHP methods (ARAS, TOPSIS, PSI) based on different mathematical assumptions and the validation of these integrated scores using Hierarchical Clustering Analysis.

To gain a more detailed understanding of the performance of the test items, an item analysis was conducted. The following values were calculated for each item.

2.1. Item Difficulty Index (p)
The Item Difficulty Index (p) represents the proportion of all participants who answered a specific item correctly. This value was calculated by dividing the total number of participants who answered the item correctly by the total number of participants who took the test (N=112) [11].

2.2. Item Discrimination Index (D)
The Item Discrimination Index (D) indicates how well an item differentiates between participants who scored high on the overall test and those who scored low. The discrimination index was calculated using the "upper group - lower group" method. Participants were ranked based on their total test scores, and the top and bottom 27% segments (30 individuals each) were designated as the upper and lower groups, respectively. (All participants with equal scores at the upper group's boundary were included in the upper group. The number of individuals in the upper group was equal to that in the lower group.) The discrimination index was calculated by subtracting the number of correct answers in the lower group from the number of correct answers in the upper group, then dividing this difference by the number of individuals in one group [12].

2.3. Item Standard Deviation (si)
The Item Standard Deviation (si) is a measure that expresses how much each data point in a study group deviates from the average. It helps determine how widespread the distribution is. In other words, variance is one of the fundamental measures showing how a studied characteristic or measurement is distributed within a specific population, whether in a narrow or wide range. Standard deviation is another indicator, obtained by taking the square root of the variance, which makes this spread more understandable [13].

2.4. Item-Total Correlation (rit)
The item-total correlation (rit) is a statistic used in psychometrics to evaluate the quality of a test item (question) and its contribution to the test's internal consistency. This correlation indicates the relationship between the score obtained from a single item and the total score obtained from all items on that test (usually corrected by excluding that specific item). Its value ranges from -1 to +1. High positive values suggest that the item effectively discriminates between those who know and those who don't, and that it aligns well with the overall construct measured by the test. Values close to zero or negative indicate that the item is problematic and requires revision [14].

All these item analyses were used to more objectively determine the different difficulty levels of the questions and their power to discriminate among participants with varying knowledge levels. The unique psychometric properties of each item, such as its difficulty and discrimination, suggest that their contributions to representing and measuring overall knowledge levels may differ. Considering these variations, item analyses were conducted to evaluate the performance of the items. Taking these differences into account, item analyses were conducted to evaluate the performance of the items and the statistical results obtained from these analyses were used as data to prioritize the occupational safety issues where there was a lack of information with multi-criteria decision making methods.

Multi-Criteria Decision Making (MCDM) methods were used to prioritize the occupational safety issues where employees lacked the most knowledge. Preliminary analyses and item difficulty indices

revealed that a significant portion of the test items were easy for the participants. Due to the ease of many questions in the design of the test and its potential inadequacy in reflecting differences in knowledge level, it was evaluated that only standardized test scoring or simple item analysis may not be sufficient to determine the importance of knowledge deficiency areas.

Easy items may be limited in accurately reflecting the level of knowledge and may not fully reveal the critical areas in need of training. This necessitated extensive item analysis to understand the measurement ability of each question in more detail and to determine how decisive and effective the questions are in reflecting the level of knowledge.

As a result of the item analysis, decisive statistical features such as difficulty (p), discrimination (D), standard deviation (si) and Item-Total Correlation (rit) of each question were obtained. These features of the items were used to determine the relative importance of the questions using multi-criteria decision-making methods.

In this analysis, 30 different work safety questions in the test constituted the alternatives to be decided. These statistical data obtained from the item analysis were used as criteria for difficulty (p), discrimination (D), standard deviation (si), and Item-Total Correlation (rit) MCDM methods. The relevant statistical data of each question were processed as data in the created multi-criteria decision-making methods decision matrix. The obtained question-based prioritization results were then interpreted in order to determine the knowledge deficiency degrees and training need priorities of the topics represented by the questions.

The criteria weights to be used in the MCDM analysis were determined by the SWARA (Step-wise Weight Assessment Ratio Analysis) method. SWARA method is known as an expert-oriented method that gives the decision maker the chance to choose priorities[15].

Together with the obtained criteria weights, a decision matrix showing the performance of the subjects according to the determined criteria was created.

Subsequently, the ARAS (Additive Ratio ASsessment), TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), and PSI (Preference Selection Index) methods were applied, utilizing both the established decision matrix and the weights determined by SWARA. These methods aid in decision-making by ranking alternatives (topics) through different approaches. The results obtained from these methods were then compared.
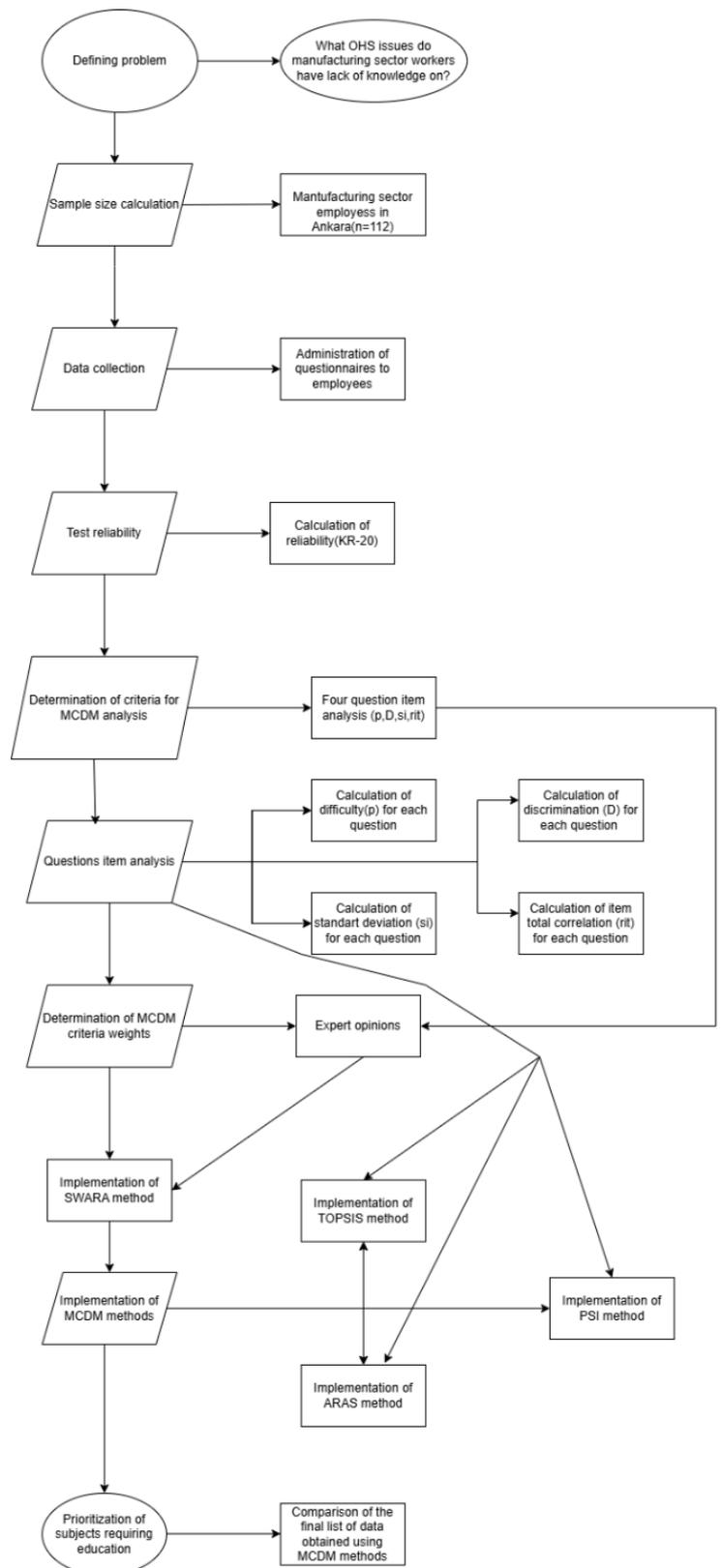
Figure 1. Study Workflow Diagram

The overall methodological flow and data analysis processes followed in this study are schematized in Figure 1. The diagram visually summarizes the key steps and their interrelationships, from the initiation of the study to data collection, examination of the test's psychometric properties, and the identification and prioritization of deficient topics using Multi-Criteria Decision-Making methods.

The item analysis results of the questions are given in Table 3. These data were used as criteria in the Aras, Topsis and PSI methods.

Table 3. Item Analysis Results of Survey Questions

Question number	Item Difficulty Index (p)	Item Discrimination Index (D)	Item Standard Deviation (si)	Item-Total Correlation (rit)
Q1	0,2767	0,2941	0,4474	0,1097
Q2	0,7410	0,3529	0,4380	0,0490
Q3	0,8750	0,2647	0,3307	0,0784
Q4	0,9285	0,1764	0,2575	0,0196
Q5	0,8928	0,2352	0,3092	0,1610
Q6	0,9732	0,1176	0,1614	0,0266
Q7	0,9821	0,1470	0,1324	0,2310
Q8	0,9553	0,2058	0,2065	0,1135
Q9	0,9821	0,0588	0,1324	-0,0965
Q10	0,7142	0,4117	0,4517	0,1641
Q11	0,6607	0,3823	0,4734	0,1730
Q12	0,2053	0,3235	0,4039	0,1714
Q13	0,4107	0,3235	0,4919	0,0268
Q14	0,3482	0,2941	0,4764	0,0624
Q15	0,9017	0,2647	0,2976	0,1459
Q16	0,9910	0,1176	0,0940	0,0979
Q17	0,5803	0,3529	0,4935	0,0966
Q18	0,9464	0,2352	0,2251	0,2019
Q19	0,9821	0,1470	0,1324	0,1705
Q20	0,7857	0,2352	0,4103	-0,0357
Q21	0,4553	0,3235	0,4980	0,0398

Table 3. Item Analysis Results of Survey Questions (cont.)

Question number	Item Difficulty Index (p)	Item Discrimination Index (D)	Item Standard Deviation (si)	Item-Total Correlation (rit)
Q22	0,9553	0,1176	0,2065	-0,0393
Q23	0,9285	0,2058	0,2575	0,0814
Q24	0,9732	0,1764	0,1614	0,2492
Q25	0,9285	0,2352	0,2575	0,1283
Q26	0,7589	0,3235	0,4277	0,0722
Q27	0,9196	0,2647	0,2718	0,1589
Q28	0,9821	0,0882	0,1324	-0,0379
Q29	0,3303	0,3529	0,4703	0,0660
Q30	0,9732	0,1176	0,1614	0,0755

III. RESULTS

In this study, the knowledge levels of the participants regarding occupational health and safety (OHS) training were assessed through the applied multiple-choice test. In line with the obtained data, the item difficulty index, item discrimination index, standard deviation and total item correlations were calculated for each test item and the discrimination of the questions was analyzed. As a result of this analysis, the data were used as criteria in the MCDM methods to determine which subjects the employees had less knowledge on. In this context, SWARA was applied for the criterion weight, and ARAS, TOPSIS and PSI methods were applied to evaluate the performance of the questions, respectively; the steps of each method were followed and the test items were re-ordered according to the knowledge levels of the employees.

The MCDM methods used in this comprehensive methodological process were specifically selected to ensure the scientific reliability and consistency of the analysis. The SWARA technique was chosen for determining the criteria weights due to its ease of application and its proven use in studies requiring weighting. In the evaluation of alternatives, the aim was to confirm the robustness of the results with different algorithms. The ARAS method was initially tested on small data sets and was included in the analysis due to its high performance fidelity. TOPSIS was selected as the reference method because it is one of the most popular and widely used methods in multi-criteria decision-making studies. Finally, the PSI method evaluated the performance values of the alternatives with a balance-oriented approach, adding additional

perspective to the ranking results through an objective preference index. The combined use of these methods provided a methodologically sound basis for the obtained prioritization results.

The application processes of these methods and the findings obtained are presented in detail below.

3.1. SWARA (Step-wise Weight Assessment Ratio Analysis) Method

SWARA (Step-wise Weight Assessment Ratio Analysis) method is an innovative approach used to determine the relative weights of criteria in Multi-Criteria Decision Making (MCDM) problems. This methodology requires decision makers or experts to rank the criteria in order of importance and then step by step evaluate the relative importance of each criterion with respect to the previous (more important) criterion. SWARA provides a more systematic and consistent process compared to direct weighting methods, reducing the influence of subjective judgment while enabling objective derivation of criterion weights, and these weights are used as input for other MCDM methods [16].

Expert opinions were compiled from five individuals in accordance with methodological requirements. Experts were selected from faculty members with at least five years of academic experience in engineering faculties and recognized for their scientific research in the areas of manufacturing systems, risk analysis, or industrial applications that were the focus of the study. During the data collection process, expert assessments were conducted through both in-person and teleconference methods.

The SWARA method was first introduced by Keršuliene, Zavadskas and Turskis.[16] The SWARA steps are as follows:

Step 1: Criteria are ranked in order of importance, starting with the most important [16].

Step 2: Starting from the second criterion, the relative importance of each criterion is determined. For this, criterion j is compared to the preceding criterion (j−1). Keršuliene et al. termed this ratio the "comparative importance of the average value" and denoted it with the symbol sj [16].

Step 3: The coefficient (kj) is determined using Equation 1, as shown below [16].

$$kj = \begin{cases} 1, & j = 1 \\ Sj + 1, & j > 1 \end{cases} \quad (1)$$

Step 4: The significance vector (wj) is calculated using Equation 2, as shown below [16].

$$Wj = \begin{cases} 1, & j = 1 \\ \dfrac{Xj - 1}{kj}, & j > 1 \end{cases} \quad (2)$$

Step 5: The calculation of the criterion weights (qj) is performed using Equation 3, as presented below [16].

$$qj = \frac{Wj}{\sum_{k=1}^{n} Wk} \quad (3)$$

Using the SWARA method, the criterion weights for the item difficulty index (p), item discrimination index (D), standard deviation (si), and item-total correlation (rit) were determined. The criteria were subjectively ranked in order of importance for the questions. The ranking of the criteria is D, p, si, and rit. The calculated weights for these criteria are presented in Table 4.

Table 4. Calculated criterion weights using the SWARA method

Rank no	Kriter	sj	kj	qj	wj
1	Item Discrimination Index (D)		1	1	0,34
2	Item Difficulty Index (p)	0,15	1,15	0,869	0,29
3	Standard Deviation (si)	0,50	1,50	0,579	0,19
4	Item-Total Correlation (rit)	0,10	1,10	0,527	0,18

3.2. ARAS (Additive Ratio Assessment) Method

The ARAS (Additive Ratio Assessment) method is an effective method used to evaluate and rank alternatives in Multi-Criteria Decision Making (MCDM) problems. This method calculates a utility degree by comparing the performance of each alternative with an ideal alternative in line with the determined criteria and their weights. These utility degrees obtained are used to determine the performance level of the alternatives and therefore their priority ranking; a higher utility degree indicates that the alternative is closer to the ideal solution and is more preferable [17].

The ARAS method consists of 4 steps;

Step 1: the decision matrix is created [17].

In the ARAS method, the first step is to create a decision matrix that includes alternatives, criteria, and their scores. However, unlike other multi-criteria decision-making methods, the ARAS method's decision matrix includes a row showing the optimal values for the criteria. The decision matrix, denoted as X, is constructed as follows, as seen in Equation 4, where m represents the number of alternatives and n represents the number of criteria [17].

$$X = \begin{bmatrix} x_{01} & \cdots & x_{0j} & \cdots & x_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{bmatrix}; i = 0,1,\dots,mj = 0,1,\dots,n \quad (4)$$

In the decision matrix X, x_{ij} represents the performance value of alternative i for criterion j, while x_{0j} denotes the optimum value for criterion j. If the optimum value for criterion j is unknown, the optimal value is determined using Equation 5, depending on whether the criterion exhibits a benefit or cost characteristic [17].

$$Xij = max\ Xij$$

$$X0j = min\ X0j \quad (5)$$

Step 2: Normalize the decision matrix.

The normalization of the decision matrix was carried out using the sum normalization including the optimal alternative method, as required by the ARAS methodology, by dividing each element by the sum of its respective column.

The second step in the ARAS method involves normalizing all performance values from the initial decision matrix. For the normalized decision matrix, the X matrix is transformed into the $\bar{x}$ matrix and constructed as Equation 6 [17].

$$\bar{X} = \begin{bmatrix} \bar{x}_{01} & \cdots & \bar{x}_{0j} & \cdots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix}; \quad (6)$$

$$i = 0,1,\dots,mj = 0,1,\dots,n0,1,\dots,n$$

In the $\bar{x}$ matrix, the value x_{0j} is calculated using Equation 7 if a higher performance value for the criterion is preferred [17].

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \quad (7)$$

If a lower performance value for the criterion is preferred, the calculation is performed using Equation 8 [17].

$$x_{ij}^* = \frac{1}{x_{ij}}$$

$$\bar{x}_{ij} = \frac{x_{ij}^*}{\sum_{i=0}^{m} x_{ij}^*} \quad (8)$$

Step 3: Create the weighted normalized decision matrix

The weighted normalized decision matrix (Â) is typically constructed using the w_j criterion weights, which are usually determined through expert evaluations. These criterion weights must satisfy the condition $0<w_j<1$. This calculation is performed as shown in Equation 9 [17].

In this study, the weights were determined using the SWARA method [17].

$$\sum_{j=1}^{n} Wj = 1 \quad (9)$$

The weighted normalized decision matrix is constructed as shown in Equation 10 [17].

$$\bar{X} = \begin{bmatrix} \bar{x}_{01} & \cdots & \bar{x}_{0j} & \cdots & \bar{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{i1} & \cdots & \bar{x}_{ij} & \cdots & \bar{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{x}_{m1} & \cdots & \bar{x}_{mj} & \cdots & \bar{x}_{mn} \end{bmatrix}; i = 0,1,\dots,mj = 0,1,\dots,n$$

$$(10)$$

According to the Â matrix, the weighted form of all criteria is calculated using Equation 11. [17]

$$\hat{x}_{ij} = \bar{x}_{ij} \cdot w_{ij} \quad (11)$$

In the formula, w_j represents the weight (importance) of criterion j, and x_{ij} denotes its weighted normalized value [17].

Step 4: Calculate the optimality function value.

The optimality function value is calculated using Equation 12 [17].

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}, i = 0,1,\dots,m \quad (12)$$

The S_i value used in the formula represents the optimality function response of alternative i. A higher value indicates that the alternative is better; a lower value indicates that it is weaker. By comparing the S_i value of each alternative with the S_0 value, which represents the best case, the K_i utility is obtained. This ratio is calculated by equation 13 [17].

$$K_i = \frac{S_i}{S_0}, i = 0,1, \dots, m \qquad (13)$$

Ki values are in the range of [0, 1] and are used to determine the relative benefit efficiencies of alternatives. These values are arranged in decreasing order to enable the evaluation and comparison of decision alternatives [17].

The results of the calculations of the ARAS method used in the study are shown in detail in Table 5.

Table 5. ARAS method results

Criteria	Item Difficulty Index (p)	Item-Total Correlation (rit)	Item Discrimination Index (D)	Standard Deviation (si)	Si	Ki
Weight	0,290	0,180	0,340	0,190		
Optimal value	0,0622	0,0652	0,0476	0,0206	0,1956	
Q1	0,0225	0,0072	0,0140	0,0092	0,0529	0,2703
Q2	0,0084	0,0032	0,0168	0,0090	0,0374	0,1913
Q3	0,0071	0,0051	0,0126	0,0068	0,0316	0,1618
Q4	0,0067	0,0013	0,0084	0,0053	0,0217	0,1109
Q5	0,0070	0,0105	0,0112	0,0064	0,0350	0,1791
Q6	0,0064	0,0017	0,0056	0,0033	0,0171	0,0872
Q7	0,0063	0,0151	0,0070	0,0027	0,0311	0,1591
Q8	0,0065	0,0074	0,0098	0,0043	0,0280	0,1430
Q9	0,0063	-0,0063	0,0028	0,0027	0,0056	0,0285
Q10	0,0087	0,0107	0,0196	0,0093	0,0483	0,2470
Q11	0,0094	0,0113	0,0182	0,0098	0,0487	0,2487
Q12	0,0303	0,0112	0,0154	0,0083	0,0652	0,3333
Q13	0,0152	0,0018	0,0154	0,0101	0,0424	0,2170
Q14	0,0179	0,0041	0,0140	0,0098	0,0458	0,2340
Q15	0,0069	0,0095	0,0126	0,0061	0,0351	0,1797
Q16	0,0063	0,0064	0,0056	0,0019	0,0202	0,1033
Q17	0,0107	0,0063	0,0168	0,0102	0,0440	0,2249
Q18	0,0066	0,0132	0,0112	0,0046	0,0356	0,1819
Q19	0,0063	0,0111	0,0070	0,0027	0,0272	0,1389
Q20	0,0079	-0,0023	0,0112	0,0085	0,0253	0,1291
Q21	0,0137	0,0026	0,0154	0,0103	0,0419	0,2144
Q22	0,0065	-0,0026	0,0056	0,0043	0,0138	0,0706
Q23	0,0067	0,0053	0,0098	0,0053	0,0271	0,1386
Q24	0,0064	0,0162	0,0084	0,0033	0,0344	0,1757
Q25	0,0067	0,0084	0,0112	0,0053	0,0316	0,1614
Q26	0,0082	0,0047	0,0154	0,0088	0,0371	0,1898
Q27	0,0068	0,0104	0,0126	0,0056	0,0353	0,1806

Table 5. ARAS method results (cont.)

Criteria	Item Difficulty Index (p)	Item-Total Correlation (rit)	Item Discrimination Index (D)	Standard Deviation (si)	Si	Ki
Q28	0,0063	-0,0025	0,0042	0,0027	0,0108	0,0552
Q29	0,0188	0,0043	0,0168	0,0097	0,0496	0,2538
Q30	0,0064	0,0049	0,0056	0,0033	0,0202	0,1035

An examination of the weighted total performance values obtained using the ARAS method reveals a significant divergence between the questions due to the impact of the criteria weights, with a particularly wide difference in scores between the first items with the highest performance values and the last items with the lowest. This suggests that while some items converge significantly to the optimal value, others deviate significantly from it. According to the ARAS method results, the largest knowledge gaps appear to be regarding personal protective equipment, labor legislation, and OHS signs.

Therefore, the ARAS results clearly demonstrate that employees' knowledge levels are not homogeneous across items, confirming significant weaknesses, particularly in the knowledge areas indicated by the low-performing items.

3.3. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) Method

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is one of the most widely used approaches in Multi-Criteria Decision Making (MCDM) problems. This method is based on the principle that the selected alternative should have both the shortest geometric distance to the "Positive Ideal Solution" (the hypothetical alternative that performs best in all criteria) and the longest distance from the "Negative Ideal Solution" (the hypothetical alternative that performs worst in all criteria). The closeness coefficient to the ideal solution is calculated for each alternative, and the alternative with the highest coefficient is ranked as the most suitable solution according to the specified set of criteria [18].

The TOPSIS method is successfully used in a wide variety of fields thanks to its intuitive logic and applicability. It finds application in a wide range of areas wherever there is a need to select the best alternative or prioritize alternatives by considering multiple criteria. For example, it serves as an effective tool for solving complex decision problems in diverse areas such as supplier selection, project and portfolio evaluation, personnel recruitment, energy policy decisions, logistics center location selection, product design and quality control, environmental impact assessment, and healthcare management. İşci et al. used

the fuzzy version of TOPSIS for risk analysis in their study [19].

The TOPSIS method consists of the following stages [18].

Step 1: Construct the decision matrix.

The decision matrix is formed with the decision points to be ranked in its rows and the evaluation factors to be used in decision-making in its columns. Matrix A is the initial matrix created by the decision-maker. This matrix is constructed according to Equation 14 [18].

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & ... & a_{1n} \\ a_{21} & a_{22} & ... & a_{2n} \\ . & & & . \\ . & & & . \\ . & & & . \\ a_{m1} & a_{m2} & ... & a_{mn} \end{bmatrix} \quad (14)$$

In the Aij matrix, m represents the number of decision points, and n denotes the number of evaluation factors [18].

Step 2: Construct the normalized decision matrix [18].

The normalization of the decision matrix for the TOPSIS methodology was executed using the Vector Normalization method. each element in the original decision matrix was transformed by dividing it by the Euclidean norm of its respective column. This standardized set of values served as the necessary input for calculating the weighted normalized decision matrix and identifying the positive and negative ideal solutions.

The normalized decision matrix (R) is obtained by utilizing the elements of matrix A, as shown in Equation 15 [18].

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & ... & r_{1n} \\ r_{21} & r_{22} & ... & r_{2n} \\ . & & & . \\ . & & & . \\ . & & & . \\ r_{m1} & r_{m2} & ... & r_{mn} \end{bmatrix} \quad (15)$$

Step 3: Construct the weighted decision matrix.

The weighted decision matrix (V) is constructed according to Equation 16. First, the weight values (wi) for the evaluation factors are determined. Then, each element in every column of the R matrix is multiplied by its corresponding wi value to form the V matrix [18].

$$V_{ij} = \begin{bmatrix} w_1r_{11} & w_2r_{12} & ... & w_nr_{1n} \\ w_1r_{21} & w_2r_{22} & ... & w_nr_{2n} \\ . & & & . \\ . & & & . \\ . & & & . \\ w_1r_{m1} & w_2r_{m2} & ... & w_nr_{mn} \end{bmatrix} \quad (16)$$

Step 4: Establish ideal and negative ideal solutions.

The TOPSIS technique is based on the fundamental assumption that evaluation criteria exhibit a monotonic characteristic, either increasing or decreasing. During the method's application, for each column within the normalized and weighted V matrix, ideal reference points are determined based on the optimization direction of the respective criterion (maximization or minimization). In cases of maximization, the highest value in the column is included in the ideal solution set, while for minimization, the lowest value is included. The ideal solution set is calculated according to Equation 17 [18].

$$A^+ = \left\{ \left(\max_i v_{ij} \mid j \in J \right), \left(\min_i v_{ij} \mid j \in J' \right\} \quad (17)$$

For determining the negative ideal solution set, the extreme weighted criterion values (column values) within the V matrix are considered based on the optimization direction. For criteria aimed at minimization, the highest values in the column are selected as negative reference points. Conversely, for criteria targeted for maximization, the lowest values in the column are chosen as negative reference points. The negative ideal solution set is calculated according to Equation 18 [18].

$$A^- = \left\{ \left(\min_i v_{ij} \mid j \in J \right), \left(\max_i v_{ij} \mid j \in J' \right\} \quad (18)$$

Step 5: Calculate distances.

In the TOPSIS method, the performance analysis of alternatives is based on two fundamental distance measurements:

  1. Positive ideal distance (Si+): This signifies the proximity to the ideal solution set.

  2. Negative ideal distance (Si−): This represents the distance from undesirable solutions.

These calculations are performed using the normalized and weighted values of each alternative and the Euclidean distance between the reference points. The Euclidean metric is the most common way to quantitatively evaluate the positions of alternatives in a multidimensional decision space. Small values of S_i+ and large values of S_i^- indicate that the alternative has ideal performance. These two metrics are calculated using the data in the V matrix and form the basis for the final ranking. The positive ideal distance is calculated using Equation 19 and the negative ideal distance is calculated using Equation 20 [18].

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^* \right)^2} \quad (19)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^- \right)^2} \quad (20)$$

Step 6: Calculate the relative closeness to the ideal solution.

In the final stage of the TOPSIS method, the relative proximity value of each alternative to the ideal solution is calculated. Two basic components are used for this calculation: the first is the distance to the ideal solution set, and the second is the distance from the negative ideal solution. The relative proximity value is defined as the ratio of the negative ideal distance to the total distance. This value is a measure between 0 and 1 that shows how close the alternatives are to the ideal solution. A value close to 1 indicates that the alternative is very close to the ideal solution, while a value close to 0 indicates that it is far away. As a result, the alternatives are ranked according to these relative proximity values and the most suitable option is determined. Equation 21 is used in this calculation [18].

$$C_i^+ = \frac{S_i^-}{(S_i^+ + S_i^-)} \quad (21)$$

According to the findings obtained as a result of the analysis carried out with the TOPSIS method, the performance values of the alternatives were determined. The calculated relative closeness coefficients quantitatively express the distance of each alternative to the ideal solution and the distance from the negative ideal solution. The results are given in Table 6.

Table 6. TOPSIS method results

Criteria	S_i^+	S_i^-	C_i^+
Q1	0,0059	0,0140	0,7049
Q2	0,0100	0,0103	0,5056
Q3	0,0135	0,0059	0,3060
Q4	0,0133	0,0069	0,3404
Q5	0,0178	0,0031	0,1496
Q6	0,0151	0,0056	0,2706
Q7	0,0246	0,0004	0,0143
Q8	0,0167	0,0030	0,1531
Q9	0,0146	0,0128	0,4671
Q10	0,0145	0,0081	0,3593
Q11	0,0143	0,0083	0,3683
Q12	0,0078	0,0139	0,6407
Q13	0,0048	0,0157	0,7678
Q14	0,0051	0,0147	0,7436
Q15	0,0169	0,0036	0,1743
Q16	0,0179	0,0025	0,1230
Q17	0,0094	0,0109	0,5368
Q18	0,0210	0,0017	0,0741
Q19	0,0208	0,0010	0,0449
Q20	0,0095	0,0126	0,5692
Q21	0,0058	0,0145	0,7159
Q22	0,0135	0,0094	0,4120
Q23	0,0149	0,0045	0,2306
Q24	0,0253	0,0006	0,0234
Q25	0,0167	0,0033	0,1644
Q26	0,0112	0,0087	0,4367
Q27	0,0178	0,0030	0,1444
Q28	0,0145	0,0089	0,3803
Q29	0,0047	0,0156	0,7688
Q30	0,0166	0,0035	0,1760

The C_i^+ closeness coefficients obtained using the TOPSIS method indicate a significant performance difference between the items. The wide range of scores, particularly between the items with the highest and lowest scores, suggests that employees are significantly challenged in certain knowledge areas. The TOPSIS results reveal a particularly severe lack of knowledge regarding OHS signs, working at height practices, and the use of personal protective equipment.

3.4. PSI (PREFERENCE SELECTİON INDEX) Method

The PSI (Preference Selection Index) method is a relatively new approach used to evaluate and rank alternatives in multi-criteria decision making (MCDM) problems. This method calculates a preference selection index for each alternative based on the deviation of the performance values of each criterion from the mean and the multiplication of these deviations with the criterion weights. The PSI method aims to obtain a more objective and consistent ranking by focusing on reducing inter-criteria dependencies and minimizing the subjective influence of the decision maker. The higher the PSI value calculated for each alternative, the more preferable and prioritized that alternative is [20].

In the PSI method, the preference index (Ij) is calculated for each alternative using the general preference value and the alternatives are ranked according to this index value. The method generally consists of the following steps:

Step 1: The decision matrix is created.

As seen in equation 22, the decision matrix (X) is created by determining the alternatives and criteria [20].

$$X = [x_{ij}]_{mxn} = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} i = 1, \ldots, m j = 1, \ldots, n \tag{22}$$

Step 2: Normalize the decision matrix.

The decision matrix for the PSI methodology was standardized using the Linear Max-Min Normalization method.

The decision matrix is normalized. For benefit criteria, Equation 23 is used, and for cost criteria, Equation 24 is applied [20].

$$n_{ij} = \frac{X_{ij}}{max(X_{ij})} \tag{23}$$

$$n_{ij} = \frac{min(X_{ij})}{X_{ij}} \tag{24}$$

Step 3: Calculate the preference variance value.

The preference variance value is calculated according to Equation 25 [20].

$$Pvj = \sum_{i=j}^{N} \left(x\_(ij)^* \cdot \overline{(x)}\_j^* \right)^2 \qquad (25)$$

For the average of the normalized values of alternative j, Equation 26 is used to calculate x∗ [20].

$$\overline{(x)}\_j^* = (1/N) \sum \_(i = 1)^N x\_(ij)^* \qquad (26)$$

Step 4: Calculate the overall preference value (ψj)

To find the deviation in preference value (Φj), Equation 27 is used [20].

$$\Phi j = 1 - PVj \qquad (27)$$

The overall preference value is calculated using Equation 28 [20].

$$\psi j = \frac{\Phi j}{\sum_{J=1}^{n} \Phi j} \qquad (28)$$

The sum of all criterion weights must equal 1. That is, $\sum_{J=1}^{n} \Phi j = 1$.

Step 6: Calculate the preference selection index.

The Preference Selection Index (PSI) is calculated using Equation 29 [20].

$$Ii = \sum_{J=1}^{n} xij * . \psi j \qquad (29)$$

Based on the analysis conducted using the PSI method, the similarity scores of the elements have been calculated. The computed normalized Ψj values quantitatively express each element's relative weight within the total similarity. The results are presented in Table 7.

Table 7. PSI method results

Criteria	Ii
Q1	0,6188
Q2	0,4931
Q3	0,4634
Q4	0,2599
Q5	0,6223
Q6	0,1980
Q7	0,6408
Q8	0,4464
Q9	-0,1109
Q10	0,7750
Q11	0,7979
Q12	0,7424
Q13	0,4693
Q14	0,5296
Q15	0,5921
Q16	0,3149
Q17	0,6320
Q18	0,6623
Q19	0,5076
Q20	0,2494
Q21	0,5009
Q22	0,0793
Q23	0,4060
Q24	0,7085
Q25	0,5194
Q26	0,5280
Q27	0,6055
Q28	0,0283
Q29	0,5544
Q30	0,3056

The results of the PSI method revealed a clear hierarchy in prioritizing the topics where manufacturing workers lack knowledge. According to the analysis, working at height, which received the highest score, was identified as the most critical priority topic in terms of knowledge gaps. This was followed by safety culture and personal protective equipment. This finding suggests that the topics where workers exhibit the greatest knowledge gaps are also the topics supported by statistical criteria such as the highest discrimination power and therefore have the highest potential for training effectiveness.

As a result of the analysis, the output of each method is compared as shown in Table 8. The data shown in the table are ranked from highest to lowest. In other words, the items with the most frequent mistakes on a question basis (the most in need of training) were ranked first in the score rankings. The results of all methods were ranked from highest to lowest and the performances of the questions were compared.

The 15 questions with the highest scores in the 3 methods applied to determine the topics in need of training were listed. Then, each question was selected according to whether or not it was in the 3 methods. In other words, in order to identify the lack of topics, a question must be in the top 15 in all three methods.

The hierarchical clustering method was chosen in this study to identify item based knowledge gaps and to classify items into natural groups. Because this method can create clusters based on the data's inherent structure, it offers an analysis opportunity independent of pure ranking or arbitrary thresholds at the researcher's discretion [21].

The analysis results showed that the data were divided into three main clusters; these clusters were interpreted as high-, medium-, and low-performing items, respectively. The high-performing cluster contained 11 items, the medium-performing cluster contained 11 items, and the low-performing cluster contained 8 items. This distribution clearly demonstrates that employees' knowledge levels were not homogeneous across items, with more gaps in certain topics.

The top 15 question threshold was not determined solely based on the number of items in the high-performing cluster. Instead, a threshold of 15 questions was set to cover approximately 50% of the items within the high- and medium-performing clusters. This approach supports the use of data-driven clustering and information criteria recommended in the literature [22]. It established a logical and methodologically transparent boundary that encompasses both high- and medium-performing items, slightly extending beyond the point where a significant decrease in the natural distribution of performance values is observed. This method facilitates the interpretation of study results and the identification of the most critical areas of information gap.

Table 8. Hierarchical clustering results

Cluster	1	2	3
Size	11	11	8
Explained proportion within-cluster heterogeneity	0.482	0.178	0.339
Within sum of squares	10.80	3.990	7.596

Table 9. Comparison of results

Rank	ARAS	TOPSIS	PSI
1.	Q12	Q29	Q11
2.	Q1	Q13	Q10
3.	Q29	Q14	Q12
4.	Q11	Q21	Q24
5.	Q10	Q1	Q18
6.	Q14	Q12	Q7
7.	Q17	Q20	Q17
8.	Q13	Q17	Q5
9.	Q21	Q2	Q1
10.	Q2	Q9	Q27
11.	Q26	Q26	Q15
12.	Q18	Q22	Q29
13.	Q27	Q28	Q14
14.	Q15	Q11	Q26
15.	Q5	Q10	Q25
16.	Q24	Q4	Q19
17.	Q3	Q3	Q21
18.	Q25	Q6	Q2
19.	Q7	Q23	Q13
20.	Q8	Q30	Q3
21.	Q19	Q15	Q8

Table 9. Comparison of results

Rank	ARAS	TOPSIS	PSI
22.	Q23	Q25	Q23
23.	Q20	Q8	Q16
24.	Q4	Q5	Q30
25.	Q30	Q27	Q4
26.	Q16	Q16	Q20
27.	Q6	Q18	Q6
28.	Q22	Q19	Q22
29.	Q28	Q24	Q28
30.	Q9	Q7	Q9

TOPSIS offers a robust heuristic structure based on its approach of measuring distance to ideal and anti-ideal solutions; however, its sensitivity to the normalization technique of criteria is one of the method's known limitations [23].

The ARAS method, on the other hand, provides a more direct evaluation by considering the absolute benefit values of alternatives. The method's high dependence on weights and the linear assumption of benefit values are among its criticized aspects [17].

The PSI method offers advantages in ranking problems due to its computational simplicity and low level of subjectivity with an alternative scoring approach. Its excessive sensitivity to criterion variance and its tendency to overgeneralize high/low performance values are noted as limitations in the literatüre [24].

Therefore, the comparative discussion of the three methods significantly strengthens the methodological robustness of the findings. The fact that each method has its own mathematical assumptions carries the risk of results in MCDM studies falling into the systematic bias of a single method. Therefore, the diversity in the theoretical assumptions of the TOPSIS, ARAS, and PSI methods offers the potential to balance the weaknesses of these methods with each other.

According to the correlation analysis, the highest correlation was observed between the PSI and ARAS methods ($r = 0.788$). This finding indicates that both methods produced similar ranking structures for the alternatives. In contrast, the TOPSIS method showed low correlation with both PSI ($r = -0.129$) and ARAS ($r = 0.439$). In particular, the PSI–TOPSIS relationship is almost non-existent, revealing that the ranking methodologies of these two methods diverge significantly from each other.

To assess the overall consistency among the rankings of the three methods (ARAS, TOPSIS, PSI), Kendall's W rank correlation coefficient was calculated. This approach is one of the fundamental methods proposed for measuring the consistency between rankings.[25] The obtained $W = 0.577$ value indicates a medium-high level of agreement between the methods. This result shows that the methods do not produce completely different results, but that the TOPSIS method in particular sometimes diverges from the other two methods. Therefore, the method-based sensitivity analysis reveals that the ranking results are to a certain extent method-dependent, but that the general trend is maintained.

IV.　　CONCLUSIONS

Based on the analysis and the data obtained, the ranking of the top 15 questions according to the ARAS method, from the highest to the lowest score, is as follows: Q12, Q1, Q29, Q11, Q10, Q14, Q17, Q13, Q21, Q2, Q26, Q27, Q15, Q18, Q5.

When the results of the TOPSIS method are examined, the ranking of the top 15 questions based on performance is as follows: Q29, Q13, Q14, Q21, Q1, Q12, Q20, Q17, Q2, Q9, Q26, Q22, Q28, Q11, Q10.

According to the results of the PSI method, the top 15 questions are ranked as follows: Q11, Q10, Q12, Q24, Q18, Q7, Q17, Q5, Q1, Q27, Q15, Q29, Q14, Q26, Q25.

When the results of all methods are analyzed, it is noticeable that the results differ from each other. In the ARAS method, the question Q12 showed the highest performance (in other words, the subject that needed the most training). Q5 is in the last row of the first 15 questions specified in the study's method.

Q29 showed the best performance in the TOPSIS method. Q10 ranked last in the first 15 questions.

In the PSI method, the best performing question was Q11, while Q15 was at the bottom of the first 15 questions.

According to the methodology of the study, questions that appear in the top 15 rankings across all three methods are identified, and the topic to which each of these questions belongs is determined. On the other hand, questions that are ranked in the top 15 in only two of the three methods, but not in the third, are not included in the selection.

The questions that ranked in the top 15 across all three methods—ARAS, TOPSIS, and PSI—are Q1, Q10, Q11, Q12, Q14, Q17, Q26, and Q29. Analyzing the topic areas of these questions reveals that two of them (Q12 and Q14) are related to personal protective equipment, indicating that this is the area where training is most needed. The distribution of the

remaining questions suggests deficiencies in occupational safety knowledge and training in the following areas: labor legislation (Q1), safety culture (Q10), working at heights (Q11), lifting equipment (Q17), emergencies (Q26), and occupational health safety signs (Q29).

The findings obtained within the scope of the study show that participants' OSH knowledge levels are concentrated in certain areas, but remain significantly low in areas requiring technical knowledge, particularly personal protective equipment, labor legislation, safety culture, and working at heights. These results are similar to the technical knowledge deficiencies identified by Gul and Guneri[26] in the aluminum industry and are also consistent with the findings of Calixto and Michaloski on the prioritization of accident risks in laboratory environments [27]. This parallelism with similar studies reported in the literature confirms that OSH training should focus on specific technical areas where the lowest performance is demonstrated, rather than on general topics.

The study has some methodological limitations. First, the cross-sectional design of the research does not allow for definitive causal inferences between variables; findings should be interpreted as reflecting the current situation at a specific point in time. The fact that the internal consistency coefficient (KR-20) of the scale is below the expected threshold values stems from the multidimensional structure of the test. Since OSH knowledge measurements cover independent and heterogeneous areas of expertise such as fire safety, ergonomics, and legislation, rather than expecting high correlations between items, this situation is considered to reflect the content validity and structural diversity of the test. On the other hand, the combined use of different AHP methods such as SWARA, PSI, ARAS, and TOPSIS in the study provided a significant advantage. The decision-making mechanism was balanced by incorporating expert opinions with SWARA and data-based objective weights with PSI. The integration of the ARAS and TOPSIS methods enabled the validation of the obtained ranking independently of the mathematical model and led to more robust results.

The findings showed that there were significant knowledge deficiencies in various basic issues related to occupational health and safety, along with the use of personal protective equipment by the employees. This finding is supported by Güner et findings showed that there were significant knowledge deficiencies in basic issues related to occupational health and safety, along with the use of personal protective equipment by the employees. This finding is supported by Güner et al.As emphasized in the study conducted by , on the employees of the casting factory, it shows that the employees have a lack of holistic information in different risk categories. The results obtained are; the occupational health and safety legislation once again

reveals that training in areas such as safety culture, working at heights, lifting equipment, emergency management and proper understanding of occupational health and safety signs should be comprehensive and continuous [28].

The knowledge gaps identified in this study once again highlight the critical impact of the content and methods of occupational health and safety training on employees' learning levels. Indeed, as emphasized in the study by Jozan et al., traditional training models may be insufficient to cover all risk areas, particularly in the manufacturing sector; more systematic, continuous, and digitally supported training models are needed for employees to develop lasting learning and behavioral change. The findings reported in the literature support the need for training to be enhanced with more comprehensive and modern methods, given the widespread knowledge gaps identified in this study across a broad range of areas, including regulatory knowledge, safety culture, working at heights, emergencies, and the correct understanding of signs [29].

Based on this study, occupational health and safety training analyzes can be applied to other sectors. A more reliable questionnaire can be applied by increasing the number of samples and increasing the variety of tests. This study can provide a source for other studies on analyzing trainings using quantitative data.

According to the data obtained, personal protective equipment should be prioritized in occupational safety and health training provided to employees in the manufacturing sector in Ankara province. When determining the duration of training, more time should be allocated to topics where deficiencies are identified. In particular, topics such as labor law, working at heights, and lifting equipment should be included in in-service training beyond legal requirements.

This study is based on a cross-sectional design. Therefore, the findings reflect only the current situation at the time the data collection process took place. This design does not allow for establishing cause and effect relationships and only enables the assessment of relationships between variables at a correlational level. Furthermore, data based on participants' statements may have limitations due to possible recall bias or subjective evaluation differences. In future studies, the preference for longitudinal or experimental approaches will contribute to a more accurate analysis of changes over time and causal relationships.

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