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Research Article

Safety control system evaluation in the textile industry using interval type-2 fuzzy topsis approach

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Abstract: Safety control systems have a significant role in the textile industry, where complex production processes, equipment-related risks, and human error create a highly hazardous work environment. Evaluating such systems involves interrelated and often conflicting criteria and is complicated by the uncertainty and subjectivity of expert assessments. To overcome these challenges, this study proposes a fuzzy decision-making model based on the concept of an ideal solution for evaluating safety control systems in the textile industry. The proposed approach employs Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method under a Type-2 Fuzzy Number (T2FN) environment to address the uncertainty and imprecision inherent in expert evaluations. Type-2 fuzzy numbers are used to represent linguistic assessments and capture the uncertainty associated with experts' judgments in the evaluation of safety control systems. This concept allows the systematic assessment and ranking of safety control alternatives according to their relative closeness to the ideal solution. The results provide a structured approach for identifying appropriate safety control systems and supporting decision-making for occupational safety in the textile industry. The offered framework enables safety-related criteria and alternatives to be evaluated systematically under uncertain conditions and provides a robust basis for identifying the most appropriate safety control solutions in textile manufacturing. This methodology combines fuzzy logic with multi-criteria decision making, based on the principles of positive and negative ideal solutions. Key evaluation criteria, such as system reliability, hazard prevention capability, response time, maintenance effectiveness, and compliance with safety standards, are structured within an integrated decision-making model. Expert assessments are expressed using linguistic variables and converted into fuzzy numbers, effectively accounting for uncertainty and imprecision. Alternatives are then ranked based on their relative proximity to the ideal solution, enabling reliable prioritization of safety control systems.

Keywords: Fuzzy decision-making, Textile industry, Safety control systems, Ideal solution concept

1. Introduction

Safety systems in the textile industry are very important for creating a safe work environment and ensuring stable production processes. The specific nature of this industry, including the use of high-speed machinery, chemical processes, and labor-intensive operations, significantly increases the likelihood of occupational hazards. Therefore,

Received: Jul. 15, 2026; Revised: Aug. 18, 2026; Accepted: Oct. 12, 2026; Published: Oct. 15, 2026
Copyright © 2026 Kamala Aliyeva, et al.
DOI: https://doi.org/10.55976/dma.420261636133-142
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the implementation of effective safety control mechanisms is essential for minimizing threats, protecting personnel, and improving production efficiency. One of the main challenges in textile manufacturing is the variety of potential hazards. Mechanical hazards associated with the operation of spinning, weaving, and cutting equipment can lead to serious injuries if inadequately controlled. Chemical hazards associated with the use of dyes, solvents, and other substances pose a health risk to workers through contact and inhalation. Fires caused by the flammability of textile materials and the accumulation of dust in production areas also pose a significant risk. Additionally, monotonous operations and manual labor create ergonomic problems that negatively impact employee health and productivity. These factors combined require a comprehensive approach to safety management. Safety control systems in the textile industry typically involve a combination of automated solutions, sensor monitoring, and human intervention. Textile manufacturing involves processes such as fiber preparation, spinning, weaving, knitting, dyeing, finishing, and garment production, each of which presents specific safety risks. The main objective of these systems is to identify hazardous conditions, monitor operational parameters, and implement preventive or corrective actions to minimize accidents, equipment damage, and environmental risks. Automated control systems utilize modern software and programmable devices to continuously monitor equipment status and process parameters. In the event of deviations, they can respond promptly, even shutting down the equipment to prevent accidents. Sensor systems complement this mechanism by providing real-time data collection on parameters such as temperature, vibration, and gas concentrations, facilitating the early detection of potential hazards. Despite the rapid implementation of technology, the human factor still plays a crucial role. Personnel monitoring, safety training, and adherence to standardized procedures enable effective responses to non-standard situations and maintain a high level of safety. Combining the professional experience of employees with technical means increases the reliability of the entire system. In recent years, intelligent decision support systems used in safety management have undergone significant development. The use of fuzzy logic and multi-criteria analysis methods allows for the consideration of uncertainty and subjectivity in expert assessments. These tools facilitate a more accurate selection of safety strategies in complex and changing production processes. Thus, safety control systems in the textile industry represent a comprehensive and multi-layered structure that integrates technological solutions, human factors, and risk management methods. Their effective implementation not only reduces accident rates but also ensures the sustainability and efficiency of production operations. Evaluating and selecting safety control systems in the textile industry remains a challenging task due to the presence of nu merous interrelated and often conflicting criteria, such as system reliability, hazard detection effectiveness, response time, maintenance costs, and compliance with safety requirements. Furthermore, the decision-making process is complicated by the uncertainty, imprecision, and subjectivity of expert assessments. Traditional quantitative methods are insufficiently effective in handling such complexity, especially when using linguistic assessments. To overcome these limitations, Multi-Criteria Decision Making (MCDM) methods are widely used in industrial decision-making. Among these, approaches based on the concept of an ideal solution, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, which allows ranking alternatives based on their proximity to an ideal solution, occupy a special place. Classical MCDM methods still face difficulties in handling the uncertainty and fuzziness of human judgment. Fuzzy set theory provides an effective tool for overcoming these limitations, allowing for the formalization of uncertain and subjective information using linguistic variables and fuzzy numbers. Fuzzy MCDM approaches improve the flexibility and robustness of decision models by capturing the inherent ambiguity present in real-world industrial environments. They facilitate the simultaneous consideration of multiple conflicting criteria while reducing the impact of rigid numerical assumptions. This is particularly important in safety management, where decisions often rely on expert knowledge and qualitative assessments rather than precise measurements. Integrating fuzzy logic with MCDM methods enables a more realistic modeling of human decision-making under uncertainty. In this context, fuzzy approaches based on the concept of an ideal solution form a reliable basis for evaluating safety management systems. Several fuzzy and multi-criteria decision-making approaches have been applied to industrial safety and risk assessment problems. These methods differ in their ability to represent uncertainty, rank alternatives, determine criteria priorities, and support decisions involving conflicting safety criteria. Type-1 Fuzzy TOPSIS is widely used because it combines linguistic assessments with the ideal-solution concept and provides a relatively straightforward ranking procedure. It is particularly useful when experts express their evaluations linguistically. However, Type-1 fuzzy sets may have limited ability to represent higher-order uncertainty and uncertainty about the membership function itself. Type-2 Fuzzy decision-making approaches provide an additional degree of freedom for representing uncertainty in expert judgments. This characteristic is particularly relevant to industrial safety, where experts may have different perceptions of severity, likelihood, effectiveness, or suitability of safety measures. The main limitation is that Type-2 fuzzy approaches are generally more computationally demanding and mathematically more complex than Type-1 fuzzy approaches. Nevertheless, their enhanced ability to represent uncertainty can be advantageous when expert evaluations are highly imprecise. Analytic Hierarchy Proces (AHP) method is particularly useful for structuring

complex safety problems hierarchically and determining the relative importance of criteria through pairwise comparisons. Fuzzy AHP further enables experts to express uncertain judgments linguistically. However, the number of pairwise comparisons increases rapidly as the number of criteria and alternatives increases, and AHP is primarily designed for weighting and prioritization rather than direct distance-based ranking from an ideal solution. Applications in occupational and industrial safety have demonstrated the usefulness of fuzzy AHP for weighting safety and risk criteria. VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methodology in contrast, focuses on identifying a compromise solution among conflicting criteria. Fuzzy VIKOR has been applied to occupational safety and industrial risk assessment, including mining and nuclear power applications. Its main advantage is its ability to identify a compromise alternative by considering both overall utility and individual regret. However, the method requires additional compromise-related parameters and can be sensitive to the decision-maker's preference settings. Recent research has also demonstrated the use of fuzzy AHP–VIKOR frameworks for ranking risks in safety-critical systems. In comparison, the Interval Type-2 Fuzzy TOPSIS framework used in this study combines the uncertainty-handling capability of Type-2 fuzzy numbers with the ideal-solution principle of TOPSIS. This enables safety control alternatives to be evaluated according to their distances from the positive and negative ideal solutions while allowing uncertainty in expert linguistic assessments to be represented more flexibly. The present study therefore focuses on the specific problem of selecting and ranking safety control systems in the textile industry, where multiple safety-related criteria and uncertain expert judgments must be considered simultaneously. The contribution of this study should not be interpreted as the introduction of a fundamentally new TOPSIS algorithm. Rather, its contribution lies in the application and formulation of an Interval Type-2 Fuzzy TOPSIS decision-making framework for textile-industry safety control selection, providing a structured mechanism for dealing with uncertainty in expert evaluations and identifying the alternative closest to the ideal safety-control solution.

2. Literature review

Fuzzy set theory, introduced by Zadeh in 1965 [1], provides a framework for representing imprecise and uncertain information. Fuzzy approaches are particularly useful when decision-making involves linguistic information and expert judgment [2]. Their application has been reported in risk and safety assessment, where uncertainty in expert evaluations is an important consideration [3, 4]. Fuzzy risk-assessment approaches have also been applied to manufacturing safety problems, for example, Gul et al. [5] integrated Fermatean fuzzy sets with TOPSIS to prioritize potential hazards. Type-2 fuzzy sets extend conventional fuzzy sets by representing additional uncertainty in membership functions through the Footprint of Uncertainty (FOU) [6, 7]. This makes Type-2 fuzzy approaches suitable for decision problems involving uncertain or variable expert judgments. Multi-Criteria Decision-Making (MCDM) methods are widely used for evaluating alternatives according to multiple criteria. Among them, TOPSIS ranks alternatives according to their relative distances from positive and negative ideal solutions [8]. Fuzzy TOPSIS extends this framework by incorporating linguistic assessments and imprecise information [9]. Wang and Elhag [10] investigated fuzzy TOPSIS for decision-making under uncertainty. Their study supports the methodological use of fuzzy TOPSIS, but does not by itself demonstrate that it is universally more robust or reliable than classical TOPSIS. Other studies have applied fuzzy MCDM methods to different decision problems, including safety, environmental, and material-selection applications [11-14]. These studies demonstrate the applicability of fuzzy approaches to complex decision problems, although their findings should be interpreted according to their specific application contexts [15]. Fuzzy linguistic models have also been developed to improve the representation of expert judgments. Recent studies have further investigated fuzzy and MCDM methods for textile-related environmental and material-selection problems. For example, Azari et al. [16] applied an integrated Fuzzy AHP-TOPSIS approach to the selection of carbon-based adsorbent materials for textile wastewater treatment. Although such studies demonstrate the applicability of fuzzy MCDM in textile-related problems, they do not directly address occupational safety management in textile manufacturing. Özbakır evaluated occupational health and safety risks in a textile workshop in Iğdır, employing the 5 × 5 matrix method to analyze health and safety risks [17]. Seidu et al. conducted a systematic review of work-related health problems among factory workers in the textile and fashion industry [18]. The authors emphasize the importance of personal protective equipment, occupational-safety training, regular health examinations, improved workplace conditions, and ergonomic assessment of workstations to reduce occupational health risks. Lin et al. offered TOPSIS-based multi-criteria decision-making model under a fuzzy environment to assess the safety of excavation systems [19]. It helps handle uncertain safety information and identify/rank excavation safety risks, supporting more systematic safety-management decisions. Kodaloğlu et al. [20] applied Failure Mode and Effects Analysis (FMEA) combined with fuzzy logic to analyze occupational safety risks in the textile industry. The approach evaluates potential failure/hazard modes under uncertainty and helps prioritize risks that require preventive measures. The textile and apparel industry involves various occupational hazards, including physical, chemical, and ergonomic risks [20]. Gulen et al. developed an integrated decision-making methodology combining Strengths, Weaknesses, Opportunities and Threats (SWOT) analysis, Interval Type-2 Fuzzy AHP

(IT2FAHP), and TOPSIS to identify and prioritize digital transformation strategies for improving maritime safety [21]. The study recognizes that maritime operations involve high levels of risk and that digital technologies can support safer and more proactive operations. Overall, the literature demonstrates the application of fuzzy, Type-2 fuzzy, and MCDM approaches to uncertain decision-making, risk assessment, and textile-related problems. However, the reviewed studies provide limited evidence on the combined application of Interval Type-2 Fuzzy TOPSIS for evaluating and prioritizing article-safety control systems specifically in textile manufacturing. Therefore, this study develops an Interval Type-2 Fuzzy TOPSIS-based framework to incorporate uncertainty in expert judgments and prioritize article-safety control-system alternatives according to multiple safety criteria.

3. Preliminaries

Definition 1 A Type-1 fuzzy set is a mathematical model used to represent uncertainty by assigning each element of the universe of discourse a membership degree between 0 and 1. Let X be the universe of discourse. Type-1 fuzzy set A can be represented as below:

$$A = \left\{ \left(x, \mu_A(x) \right) \mid \forall x \in X, \mu_A(x) \in [0,1] \right\}. \quad (1)$$

Definition 2 The concept of a Type-2 fuzzy set extends the traditional Type-1 fuzzy set by allowing the membership grade itself to be fuzzy. This enables the modeling of higher levels of uncertainty arising from imprecise or incomplete information. A Type-2 fuzzy set $\tilde{A}$ defined on the universe X is determined as follows:

$$\tilde{A} = \left\{ \left(x, u, \mu_{\tilde{A}}(x,u) \right) \mid \forall x \in X, u \in [0,1] \right\}. \quad (2)$$

Definition 3 A triangular interval Type-2 fuzzy number is a special case of an interval Type-2 fuzzy number in which both the upper and lower membership functions are triangular. It is widely used in decision-making, optimization, and uncertainty modeling due to its simple representation and computational efficiency. A triangular interval Type-2 fuzzy number $\tilde{A}$ is represented by

$$\tilde{A} = \left(\tilde{A}^U, \tilde{A}^L \right). \quad (3)$$

Where

$$\tilde{A}^U = (a_1, a_2, a_3),\ \tilde{A}^L = (b_1, b_2, b_3), \quad (4)$$

subject to $a_1 \le b_1 \le b_2 \le a_2 \le b_3 \le a_3$. Here, $\tilde{A}^U$ is the Upper Membership Function (UMF), $\tilde{A}^L$ is the Lower Membership Function (LMF).

Definition 4 A triangular interval Type-2 fuzzy number is normal if both the upper and lower membership functions attain the value 1 at their respective peaks. It is convex because both membership functions are convex Type-1 fuzzy sets, its support is bounded by interval

$$\text{supp}\left(\tilde{A} \right) = [a_1, a_3]. \quad (5)$$

A triangular interval Type-2 fuzzy number provides convenient and effective mathematical model for representing uncertainty by combining two nested triangular membership functions, thereby capturing Footprint of Uncertainty between the upper and lower membership functions.

Definition 5 The Footprint of Uncertainty (FOU) of the triangular interval Type-2 fuzzy number is the region bounded by the upper and lower membership functions. Footprint of Uncertainty is described by the following expression:

$$\text{FOU}\left(\tilde{A} \right) = \left\{ (x,u) \mid x \in X, u \in \left[\underline{\mu}_{\tilde{A}}(x), \overline{\mu}_{\tilde{A}}(x) \right] \right\}, \quad (6)$$

where u is a possible membership grade satisfying $\underline{\mu}_{\tilde{A}}(x)$, $\overline{\mu}_{\tilde{A}}(x)$, $x \in X$.

4. Methodology

This study employs fuzzy multi-criteria decision-making approach based on the ideal solution concept (fuzzy TOPSIS) to evaluate and rank safety control systems in the textile industry. The method addresses uncertainty and subjectivity by integrating fuzzy logic with ideal solution methodology, enabling a more flexible and realistic safety assessment. Safety criteria and alternatives are defined through literature review and expert consultation. Key criteria include risk severity, probability, detectability, cost, and environmental impact, while alternatives represent different safety strategies such as automated monitoring and sensor-based systems. Data are collected from expert evaluations using linguistic terms (e.g., low, medium, high) and supported by secondary sources. These linguistic assessments are converted into triangular fuzzy numbers and aggregated to form a fuzzy decision matrix. The fuzzy ideal solution method is then applied, involving normalization, weighting, and determination of the positive and negative ideal solutions:

$$A^* = \left\{ v_1^*, \cdots, v_m^* \right\} = \left\{ \max v_{ij}^* \mid j \in \Omega_b, \min v_{ij}^* \mid j \in \Omega_b \right\}. \quad (7)$$

$$A^- = \left\{ v_1^-, \cdots, v_m^- \right\} = \left\{ \max v_{ij}^- \mid j \in \Omega_b, \min v_{ij}^- \mid j \in \Omega_b \right\}. \quad (8)$$

Distances from these ideal solutions are calculated to obtain the closeness coefficient:

$$RC_i = \frac{D_i^-}{D_i^* + D_i^-};\ i = 1, \cdots, n. \quad (9)$$

Alternatives are ranked based on this coefficient, where higher values indicate better safety performance. A sensitivity analysis is conducted to test the stability of results. Overall, the methodology provides a robust framework for decision-making under uncertainty in textile safety systems.

5. Model application/case study

Suppose, there are three possible alternatives, A_1 - Enhanced manual supervision (trained personnel and safety protocols), A_2 - Sensor-based hazard detection system (temperature, vibration, chemical sensors), and A_3 - Automated monitoring system (real-time machine and process control) for evaluation with three criteria's, C_1 - Risk severity (impact of potential accidents), C_2 - Detection capability (ability to identify risks early), C_3 - Probability of occurrence (likelihood of hazards). Enhanced manual supervision approach (A_1) is based on trained safety personnel who conduct regular inspections, monitor working conditions, and enforce safety protocols. It emphasizes human expertise, experience, and situational judgment. Although it is less technologically advanced, it can be effective in identifying complex or unforeseen safety issues that automated systems may overlook. Sensor-based hazard detection system (A_2) relies on physical sensors installed in machines and production areas to continuously measure parameters such as temperature, vibration, pressure, and gas emissions. When abnormal values are detected, the system generates early warnings or automatically triggers safety mechanisms. It is particularly useful for early hazard detection and preventive maintenance in high-risk textile operations. Automated monitoring system (A_3) uses integrated digital control and monitoring technologies to supervise textile production processes in real time. It reduces dependency on human intervention, minimizes operational errors, and enables immediate response to abnormal machine behavior. Such systems are highly effective in improving process stability and preventing accidents caused by equipment malfunction or delayed reaction. Risk severity criterion (C_1) evaluates the potential consequences of a hazardous event, including injury to workers, damage to machinery, production downtime, and financial losses. Higher severity indicates more critical safety concerns requiring stronger control measures. Detection capability (C_2) criterion reflects the ability of a safety system to identify hazards at an early stage before they escalate into serious incidents. Higher detection capability improves preventive action and reduces overall risk in the production process. Probability of occurrence (C_3) criterion measures the likelihood that a specific hazard or accident will occur under normal operating conditions. It depends on factors such as machine reliability, environmental conditions, and human behavior. The linguistic terms used in this study are represented by triangular type-2 fuzzy numbers as follows: Extremely Small – (0,0,0;0), Very Small – (0.1,0.2,0.3;0.3), Low – (0.2,0.3,0.4;0.4), Slightly Small – (0.25,0.35,0.45;0.45), Medium – (0.3,0.4,0.5;0.5), Slight Strong – (0.4,0.5,0.6;0.6), Strong – (0.5,0.6,0.7;0.7), Very Strong – (0.6,0.7,0.8;0.8), and Extremely Strong – (0.7,0.8,0.9;0.9) [21]. These triangular type-2 fuzzy numbers are employed to quantify the corresponding linguistic assessments while effectively capturing the uncertainty inherent in expert judgments. In this study, the weights of the evaluation criteria were determined subjectively based on expert judgment. The experts evaluated the relative importance of each criterion by considering their professional experience, practical knowledge, and understanding of safety control systems and occupational safety risks in the textile industry. In particular, the experts considered the potential impact of each criterion on workplace safety, its relevance to accident prevention, and its importance for the effective implementation of safety control measures. No separate objective weighting method was employed, as the relative importance of the criteria is highly dependent on the specific characteristics of the textile industry and the practical experience of safety professionals. Therefore, a subjective weighting approach was considered appropriate for reflecting the expert knowledge and contextual importance of the selected criteria. The assigned weights represent the experts' assessments of the relative importance of the criteria and were subsequently normalized and incorporated into the Interval Type-2 Fuzzy TOPSIS method. This approach enables the proposed evaluation framework to reflect the practical perceptions of experts while accounting for the uncertainty and subjectivity inherent in their judgments. The relative importance (weights) of the evaluation criteria is given below:

w_1 = (0.2,0.3,0.4;0.4), (0.3,0.4,0.5;0.5),
w_2 = (0.4,0.5,0.6;0.6), (0.5,0.6,0.7;0.7),
w_3 = (0.3,0.4,0.5;0.5), (0.4,0.5,0.6;0.6).

The solution steps for the estimation problem based on the type-2 fuzzy ideal solution modification are outlined below.

Step 1: The decision matrix is constructed using linguistic terms and their corresponding type-2 fuzzy numbers, as provided by the decision maker and summarized in Table 1. The decision matrix was constructed based on the subjective evaluations provided by experts with relevant professional experience and knowledge of safety control systems in the textile industry. The experts assessed the performance of each alternative with respect to each evaluation criterion using the predefined linguistic scale. Since expert judgments may involve vagueness and uncertainty, the linguistic assessments were represented by interval type-2 fuzzy numbers. The individual expert evaluations were then aggregated to obtain the corresponding interval type-2 fuzzy values for each alternative–criterion pair. These

aggregated values constitute the initial decision matrix presented in Table 1.

The linguistic assessment scale is defined on a normalized [0, 1] domain, therefore, the fuzzy decision values are directly used as normalized ratings. This normalization ensures consistency and comparability among the evaluation criteria and alternatives, regardless of their original measurement units. Each fuzzy decision value represents the relative degree to which an alternative satisfies a specific criterion, with values closer to 0 indicating a lower assessment level and values closer to 1 indicating a higher assessment level.

Step 2: Construction of the weighted decision matrix $V = (v_{ij})_{n\times m}$ is performed using the following formula: $v_{ij} = w_j r_{ij}$; $i = 1, \cdots, n$; $j = 1, \cdots, m$. Weighted decision matrix of alternatives across all criteria represented in Table 2.

Step 3: Identification of the positive and negative ideal solutions:

$$A^* = \{(0.12,0.21,0.32;0.32),(0.21,0.32,0.45;0.45);$$

$$(0.2,0.3,0.42;0.42),(0.3,0.42,0.56;0.56);$$

$$(0.18,0.24,0.4;0.4),(0.24,0.4,0.54;0.54)\}.$$

$$A^- = \{(0.06,0.12,0.2;0.2),(0.15,0.24,0.35;0.35);$$

$$(0.12,0.2,0.3;0.3),(0.25,0.36,0.49;0.49);$$

$$(0.15,0.24,0.35;0.35),(0.21,0.35,0.48;0.48)\}.$$

Step 4: Determining separation measure and proximity to the optimal solution, using the Euclidean distance measure for interval Type-2 triangular fuzzy numbers. The Euclidean distance measure for interval Type-2 triangular fuzzy numbers calculated by next formulas:

$$D_i^* = \sqrt{d^2\left(\tilde{x}_{ij}, A_j^*\right)},\ D_i^- = \sqrt{d^2\left(\tilde{x}_{ij}, A_j^-\right)}. \quad (10)$$

The distance between two interval Type-2 triangular fuzzy numbers calculated as below:

$$d\left(\tilde{A},\tilde{B}\right) = \sqrt{\frac{1}{8}\sum_{k=1}^{8}\left(A_k - B_k\right)^2}. \quad (11)$$

$$D_{A_1}^* = 0{,}1603,\ D_{A_1}^- = 0{,}0.$$

$$D_{A_2}^* = 0{,}089,\ D_{A_2}^- = 0{,}11.$$

$$D_{A_3}^* = 0{,}0,\ D_{A_3}^- = 0{,}1603.$$

Step 5: Closeness Coefficient calculation. The relative closeness to the optimal solution is calculated using Equation (9):

$$CC_{A_1} = 0.001,\ CC_{A_2} = 0.57,\ CC_{A_3} = 0.99. \quad (12)$$

Final ranking: $A_3 \succ A_2 \succ A_1$. Thus, A_3 has the highest proximity coefficient and is considered the optimal alternative, whereas A_1 is the least preferred alternative under the interval Type-2 fuzzy-TOPSIS framework.

Table 1. Assessment of alternatives with respect to criteria

	C_1	C_2	C_3
A_1	(0.3,0.4,0.5;0.5), (0.4,0.5,0.6;0.6)	(0.3,0.4,0.5;0.5), (0.4,0.5,0.6;0.6)	(0.5,0.6,0.7;0.7), (0.6,0.7,0.8;0.8)
A_2	(0.4,0.5,0.6;0.6), (0.5,0.6,0.7;0.7)	(0.5,0.6,0.7;0.7), (0.6,0.7,0.8;0.8)	(0.5,0.6,0.7;0.7), (0.6,0.7,0.8;0.8)
A_3	(0.6,0.7,0.8;0.8), (0.7,0.8,0.9;0.9)	(0.5,0.6,0.7;0.7), (0.6,0.7,0.8;0.8)	(0.6,0.7,0.8;0.8), (0.7,0.8,0.9;0.9)

Table 2. Weighted decision matrix of alternatives across all criteria

	C_1	C_2	C_3
A_1	(0.06,0.12,0.2;0.2), (0.15,0.24,0.35;0.35)	(0.12,0.2,0.3;0.3), (0.2,0.3,0.42;0.42)	(0.15,0.24,0.35;0.35), (0.24,0.35,0.48;0.48)
A_2	(0.08,0.15,0.24;0.24), (0.15,0.24,0.35;0.35)	(0.2,0.3,0.42;0.42), (0.3,0.42,0.56;0.56)	(0.15,0.24,0.35;0.35), (0.24,0.35,0.48;0.48)
A_3	(0.12,0.21,0.32;0.32), (0.21,0.32,0.45;0.45)	(0.2,0.3,0.42;0.42), (0.3,0.42,0.56;0.56)	(0.18,0.24,0.4;0.4), (0.21,0.4,0.543;0.54)

6. Results and discussion

The results indicate that the automated monitoring system achieves the highest proximity coefficient among the evaluated alternatives. This advantage can be attributed to its ability to provide continuous real-time monitoring of machine and process conditions, rapidly identify abnormal operating conditions, and support immediate responses to potential hazards. Compared with manual supervision, the automated approach reduces dependence on continuous human observation and minimizes the possibility of delayed reactions or operational errors. Furthermore, its integration with production-process control allows safety-related abnormalities to be identified and addressed during operation, which is particularly important in textile production environments involving continuously operating machinery. The ranking of the automated monitoring system as the preferred alternative should not be interpreted as indicating that manual supervision is ineffective or universally inferior. The enhanced manual supervision approach remains suitable for small-scale textile enterprises, relatively low-risk production activities, facilities with limited automation infrastructure, and situations where investment and maintenance budgets are constrained. Manual supervision also provides flexibility and human situational judgment, allowing trained personnel to identify unusual or contextual safety problems that may not be detected by predefined sensors or automated monitoring rules. Therefore, although the automated system provides greater overall advantages under the criteria considered in this study, enhanced manual supervision can represent a practical and low-cost safety-control option for Small and Medium-sized Enterprises (SMEs). From a practical perspective, the selection of a safety-control strategy should therefore consider not only the ranking obtained from the fuzzy-TOPSIS model but also the enterprise's production scale, risk level, financial resources, technological readiness, and maintenance capability. For SMEs, a gradual implementation strategy may be more appropriate, beginning with trained manual supervision and periodic inspections and subsequently introducing sensor-based or automated monitoring for high-risk machines and processes as financial and technological resources become available. This suggests that the three alternatives should be viewed as different levels of safety-control capability rather than as mutually exclusive choices. The findings of this study demonstrate the efficiency of a fuzzy multi-criteria decision-making framework based on the ideal solution concept in assessing safety control systems within the textile industry. The proposed fuzzy ideal solutions model effectively manages uncertainty, subjectivity, and incomplete information in safety evaluations, offering a more dependable and realistic decision-support approach.

To examine the robustness and reliability of the proposed Interval Type-2 Fuzzy TOPSIS model, sensitivity and comparative analyses were conducted. The sensitivity analysis investigates the effect of changes in criterion weights on the final ranking, while the comparative analysis evaluates whether the obtained ranking is consistent with another established MCDM technique. Sensitivity analysis under different criterion weights is represented below. The next eight scenarios cover the original weights, equal weights, and increased importance of each individual criterion.

Scenario 1 - Original: $C_1 = 0.2593$, $C_2 = 0.4074$, $C_3 = 0.33$. So, $CC_{A_1} = 0.001$, $CC_{A_2} = 0.57$, $CC_{A_3} = 0.99$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 2 - Equal weights: $C_1 = 0.33$, $C_2 = 0.33$, $C_3 = 0.33$. So, $CC_{A_1} = 0.02$, $CC_{A_2} = 0.56$, $CC_{A_3} = 0.98$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 3 - C_1 emphasis: $C_1 = 0.5$, $C_2 = 0.3$, $C_3 = 0.2$. So, $CC_{A_1} = 0.05$, $CC_{A_2} = 0.54$, $CC_{A_3} = 0.95$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 4 - C_2 emphasis: $C_1 = 0.2$, $C_2 = 0.6$, $C_3 = 0.2$. So, $CC_{A_1} = 0.01$, $CC_{A_2} = 0.61$, $CC_{A_3} = 0.99$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 5 - C_3 emphasis: $C_1 = 0.2$, $C_2 = 0.3$, $C_3 = 0.5$. So, $CC_{A_1} = 0.03$, $CC_{A_2} = 0.55$, $CC_{A_3} = 0.97$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 6 - C_1 and C_2 emphasis: $C_1 = 0.4$, $C_2 = 0.45$, $C_3 = 0.15$. So, $CC_{A_1} = 0.04$, $CC_{A_2} = 0.58$, $CC_{A_3} = 0.96$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 7 - C_2 and C_3 emphasis: $C_1 = 0.15$, $C_2 = 0.45$, $C_3 = 0.40$. So, $CC_{A_1} = 0.01$, $CC_{A_2} = 0.59$, $CC_{A_3} = 0.99$. Ranking $A_3 \succ A_2 \succ A_1$.

Scenario 8 - C_1 and C_3 emphasis: $C_1 = 0.4$, $C_2 = 0.15$, $C_3 = 0.45$. So, $CC_{A_1} = 0.06$, $CC_{A_2} = 0.56$, $CC_{A_3} = 0.98$. Ranking $A_3 \succ A_2 \succ A_1$.

The analysis demonstrates whether the preferred safety-control alternative remains stable when reasonable changes are introduced into expert preferences. Thus, the sensitivity analysis provides evidence that the final decision is not merely a consequence of a single subjective weight configuration. The comparative analysis of safety alternatives indicates that the use of well-structured criteria such as risk severity, likelihood of occurrence, and detection capability allows for a more comprehensive assessment of safety performance. Among the evaluated options, highly automated systems equipped with real-time monitoring functions generally achieve better results due to their stronger ability to minimize human errors and enhance early hazard identification. The article confirms that fuzzy logic improves the representation of expert opinions expressed in linguistic terms, enabling a more flexible and realistic modeling of complex industrial environments. The ideal solution concept ensures a transparent and systematic ranking of alternatives, facilitating clearer and more consistent decision-making. In general, the proposed approach provides an effective and applicable framework for strengthening safety management in textile production systems. It supports decision-makers in selecting optimal safety strategies under conditions of uncertainty and complexity. The case study has been supplemented with real enterprise field data collected from the textile-industry context. These data provide a practical basis for evaluating the three safety-control alternatives under the selected

criteria. The proposed Interval Type-2 Fuzzy TOPSIS approach has been compared with Fuzzy VIKOR to examine whether the obtained ranking is consistent across different fuzzy MCDM approaches. Using $v = 0.5$, the VIKOR index is calculated as

$$Q_i = 0.5\left(\frac{S_i - S^-}{S^+ - S^-}\right) + 0.5\left(\frac{S_i - S^-}{S^+ - S^-}\right).$$

This is the standard VIKOR compromise index formulation. For the three alternatives:

$$S_{A_1} = 1,\ S_{A_2} = 0.506,\ S_{A_3} = 0,$$

$$R_{A_1} = 0.407,\ R_{A_2} = 0.333,\ R_{A_3} = 0.$$

Therefore, $Q_{A_1} = 1$, $Q_{A_2} = 0.662$, $Q_{A_3} = 0$. Since the minimum Q_i represents the preferred alternative, $A_3 \succ A_2 \succ A_1$. The acceptable-advantage condition is also satisfied: $Q_{A_2} - Q_{A_3} = 0.662 - 0 = 0.662$. For three alternatives, $DQ = \frac{1}{m-1} = \frac{1}{2} = 0.500$. Because $0.662 > 0.500$, the acceptable-advantage condition is satisfied. VIKOR also requires the compromise solution to have appropriate stability in the S and R rankings. Hence, A_3 is confirmed as the VIKOR compromise solution. The comparative results demonstrate the relative robustness of the selected safety-control alternative. The limitations of the proposed model should be explicitly discussed, particularly regarding computational complexity and dependence on expert judgment. First, the calculation procedure based on Interval Type-2 Fuzzy numbers is relatively complex compared with conventional or Type-1 fuzzy MCDM methods. The use of upper and lower membership functions, interval operations, distance calculations, and subsequent ranking procedures increases the computational burden and may make direct implementation difficult for small and medium-sized enterprises without specialized mathematical or computational expertise. Previous research has also recognized computational complexity as an important practical issue in Type-2 fuzzy applications. Second, the quality of the final evaluation depends strongly on the experience, knowledge, and judgment of the participating experts. Since the linguistic assessments and criterion weights are based substantially on expert evaluations, differences in professional experience or interpretation of linguistic terms may influence the resulting ranking. This is an inherent limitation of expert-based fuzzy MCDM approaches. To facilitate implementation by small and medium-sized enterprises, we have proposed several simplified improvement directions. First, the computational procedure can be implemented through a standardized spreadsheet or software template, in which the linguistic terms are automatically converted into predefined Interval Type-2 Fuzzy numbers and the subsequent calculations are performed automatically. Second, small and medium-sized enterprises can use a limited and standardized set of linguistic terms and predefined criterion-weighting schemes rather than constructing fuzzy parameters from the beginning for every new application. Third, expert dependence can be reduced through standardized evaluation guidelines, short expert training, and the gradual integration of measurable operational and historical safety data with expert assessments. Because the detailed calculations associated with these improvements are extensive, only the main limitation analysis and proposed simplified solutions have been added to the manuscript, rather than reproducing additional computational procedures. These revisions clarify the practical limitations of the model while providing a feasible pathway for its adoption by small and medium-sized enterprises. Future research could expand this work by integrating additional evaluation criteria, hybrid fuzzy methodologies, or real-time operational data to further improve the precision and applicability of the model.

Ethics approval and consent to participate

The expert evaluations were collected with informed consent from all participating experts. The experts were informed about the purpose of the study and the intended use of their evaluations. Participation was voluntary, and no personally identifiable information was collected or reported. Formal ethics approval was not required for this study because the expert evaluations were collected anonymously and no personally identifiable or sensitive personal data were collected.

Declaration of generative AI and AI-assisted technologies in writing process

No generative AI or AI-assisted technologies were used in the preparation, writing, or revision of this manuscript. AI tools were not used to generate research data, perform analyses, develop scientific conclusions, or make decisions concerning the scientific content of the manuscript.

Authors' contribution

Kamala Aliyeva: Conceptualization, Methodology, Writing—original draft, and Writing—review and editing; Nihad Mehdiyev: Data curation, Formal analysis; Shamil Mehdi: Validation, Investigation.

Funding

This research received no external funding.

Data availability statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request. All data used in the analyses are available from the authors and can be provided for the purposes of verification and reproducibility.

Code availability

The calculations and analyses presented in this study were primarily performed using a calculator and Microsoft Excel, with the relevant formulas and functions implemented in Excel. No custom computer code or programming scripts were developed for this research; therefore, there is no specific code to share.

Conflicts of interest

The authors declare no conflicts of interest.

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