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A hybrid exploratory factor analysis - Grey Delphi framework for prioritization in occupational health and safety risks in the textile industry

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Abstract
The textile industry plays a vital role in supporting the national economy, but is characterized by complex and hazardous working conditions that pose serious challenges to occupational health and safety (OHS). Workers are frequently exposed to high-speed machinery, harmful chemicals, excessive dust, and physically demanding tasks, making risk identification and prioritization essential for improving workplace safety. This study aims to systematically identify and rank the most critical OHS risk factors by employing a hybrid methodology that integrates Exploratory Factor Analysis (EFA) and the Grey Delphi method. Data were collected from 390 textile workers and subsequently validated through the consensus of 12 experts. The EFA process reduced 57 initial indicators into nine underlying categories, while the Grey Delphi analysis prioritized 25 risks. Among these, the five most critical risks identified are: (1) excessive noise generated by weaving and spinning machines, (2) exposure to cotton dust containing endotoxins, (3) unprotected moving machine parts, (4) long working hours without adequate rest, and (5) improper or inconsistent use of personal protective equipment (PPE). The novelty of this study lies in integrating quantitative factor reduction with expert consensus under uncertainty, producing a replicable hybrid framework for data-driven OHS risk prioritization. This approach advances current literature by bridging statistical analysis with expert judgment, thereby improving methodological rigor. The findings provide measurable contributions for both scholars and practitioners by offering evidence-based guidance for policy formulation, resource allocation, and the design of targeted safety interventions to enhance OHS management in the textile sector.

Keywords:
Exploratory factor analysis;
Grey Delphi;
Occupational health and safety;
Risk factor identification;
Textile industry;

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INTRODUCTION

The textile industry is a strategic manufacturing sector that makes a significant contribution to both the national and global economy [1]. However, it also carries complex occupational health and safety (OHS) risks [2][3]. Various production processes, such as spinning, weaving, dyeing, and finishing, involve high-speed machines, hazardous chemicals, high temperatures, and heavy physical loads, thereby increasing the potential for workplace accidents and work-related illnesses [4]. In Indonesia, the challenges in managing OHS in the textile industry include low compliance with safety procedures, limited training, and a lack of structured risk data [5].

A variety of methodologies ranging from single-method to more complex multi-method designs have been applied in OHS risk analysis [6][7]. In recent years, there has been a clear movement toward hybrid approaches that combine quantitative rigor with qualitative insight [8]. For instance, a hybrid model that integrates the weighted Borda method for selecting risk indicators with a group fuzzy Analytic Hierarchy Process (FAHP) for prioritization in the construction sector [7][8] developed a hybrid OHS assessment framework that merges stratified Bayesian Best–Worst Method (BWM) with TOPSIS, resulting in enhanced precision in identifying critical hazards. Similarly, [11] utilized a combination of FAHP and Fuzzy Inference System (FIS) to address uncertainty in OHS decision-making processes. A comprehensive review by [8] further confirms the growing application of Multi-Criteria Decision-Making (MCDM) techniques such as AHP and TOPSIS in OHS research, while also pointing out that many of these models still fall short in incorporating expert consensus under conditions of uncertainty

To provide a clearer comparative perspective, Table 1 summarizes recent studies, their methodological contributions, limitations, and how the present study advances beyond them.

Recent developments in Occupational Health and Safety (OHS) risk assessment have employed various hybrid multi-criteria decision-making (MCDM) models, such as FAHP–TOPSIS, BWM–VIKOR, and FAHP–FIS, to enhance the accuracy of weighting and ranking procedures. However, these models primarily focus on prioritization and often overlook the preliminary, data-driven reduction of extensive indicator sets. For instance, approaches such as FAHP–TOPSIS and BWM–VIKOR focus heavily on synthesizing expert opinions based on predefined criteria, without exploring latent structures within the data itself. In contrast, the framework introduced in this study adopts a fundamentally different strategy by incorporating Exploratory Factor Analysis (EFA) to empirically extract underlying dimensions of risk before applying the Grey Delphi method to establish expert consensus under uncertain conditions. This methodological integration effectively bridges the gap between statistical factor identification and qualitative expert evaluation, ensuring that only the most critical and context-relevant risks are retained. Moreover, unlike most prior hybrid models, which have predominantly been applied in construction or aviation contexts, the present study specifically adapts the framework to the textile industry, an environment characterized by distinct mechanical, chemical, and biological hazards. Thus, the proposed EFA–Grey Delphi approach offers a more holistic, reproducible, and context-sensitive methodology, representing a significant advancement over existing hybrid risk assessment frameworks.

Despite these methodological advances, several critical gaps remain. Most hybrid models focus on weighting or ranking risk factors but often overlook the systematic reduction of large indicator sets through factor analysis before validation via expert consensus [10][11]. Additionally, many frameworks are not explicitly tailored to the specific vulnerabilities encountered in the textile industry, where workers face acute risks from mechanical noise, cotton dust exposure, and ergonomic burdens [12].

Based on the background above, this study aims to identify and prioritize occupational health and safety risk factors in the textile industry by integrating Exploratory Factor Analysis (EFA) and the Grey Delphi method.

Table 1. Comparative overview of recent studies in OHS risk assessment

Reff.	Methods Applied	Limitations / Gaps	Relevance to This Study
[9]	Weighted Borda + group fuzzy AHP	Narrow focus (construction only); lacks systematic factor reduction before ranking	This study adds EFA for large-scale factor reduction prior to expert consensus.
[10]	Stratified Bayesian BWM + TOPSIS	Focuses on weighting and ranking; does not address latent factor reduction	This study bridges the gap by integrating EFA (factor reduction) with Grey Delphi (expert validation)
[11]	FAHP + Fuzzy Inference System (FIS)	High model complexity; dependent on fuzzy rule accuracy; less emphasis on explicit prioritization	This study offers a more replicable and context-sensitive hybrid framework
[8]	Systematic review of MCDM (AHP, TOPSIS, etc.)	Review only; does not propose a new framework; highlights lack of expert consensus under uncertainty.	This study directly addresses this gap through a hybrid EFA–Grey Delphi framework integrating quantitative analysis with expert consensus.

This study provides a methodological contribution by combining EFA-based dimensionality reduction with expert consensus validation via Grey Delphi, which accommodates the uncertainty inherent in linguistic assessments. The research results are expected to serve as a practical reference for OHS management in the textile industry in designing more measurable and effective risk mitigation strategies, as well as a model approach adaptable to other industrial sectors with similar risk characteristics.

The decision to use Exploratory Factor Analysis (EFA) rather than other dimensionality reduction methods was grounded in robust methodological considerations. While Principal Component Analysis (PCA) is effective at simplifying complex datasets, it primarily serves as a mathematical tool. It lacks the capacity to reveal latent constructs or reflect theoretical relationships among variables. In contrast, Confirmatory Factor Analysis (CFA) requires an a priori model, making it more suitable for testing established theoretical frameworks than for uncovering new ones. Given that this study aimed to explore the underlying structure of OHS risk factors within the textile industry, a domain without a standardized factor model, EFA emerged as the most appropriate analytical approach. EFA facilitates the empirical identification of latent dimensions and is widely endorsed in the early stages of scale development and model formulation, particularly in safety science and behavioral research contexts [13, 14, 15]. Therefore, the application of EFA in this study not only ensures methodological rigor but also strengthens the conceptual foundation prior to the subsequent validation phase using the Grey Delphi technique.

METHODS

Research Design

To provide a more systematic overview of the research design, a research process is presented (Figure 1). This flowchart was created to visualize the main research steps in a structured, easy-to-understand manner. The presentation of the research workflow aims to ensure transparency of the methods used and to help readers follow the integration of Exploratory Factor Analysis (EFA) and Grey Delphi methods in identifying occupational health and safety (OHS) risk factors in the textile industry.

This research process comprises several structured, interconnected stages. The first stage begins with a literature review to identify relevant risk factors in the textile industry.

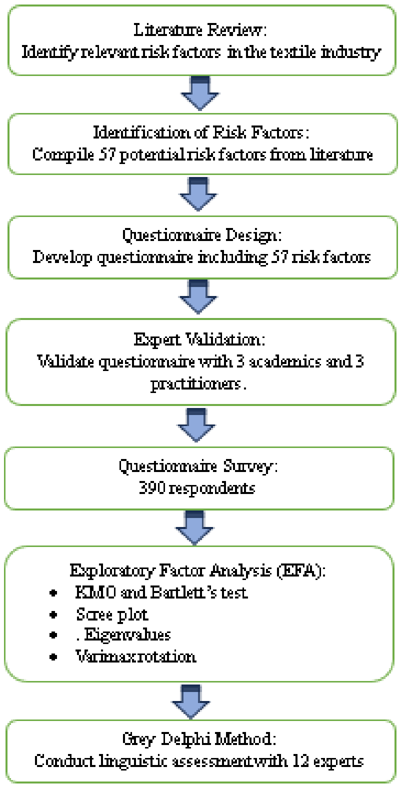

Figure 1. Research Design

The results of the literature review serve as the basis for designing a questionnaire that includes 57 potential risk factors. The questionnaire is then validated by a panel of 3 academics and 3 practitioners to ensure clarity and suitability of content. Before distributing the questionnaire, both face and content validity were assessed by six experts: three HSE managers from different textile companies (each with over ten years of professional experience) and three academics holding doctoral degrees in Industrial Engineering. In instrument development research, involving 5 to 10 experts is a standard and widely accepted practice, especially for content validation using the CVI (Content Validity Index) method [16][17]. Therefore, the number and qualifications of the experts involved at this stage were appropriate and methodologically justified. After validation, the questionnaire is distributed to 390 textile industry respondents to collect primary data. A total of 390 textile workers participated in the survey. The adequacy of this sample size is justified by the widely accepted 10:1 ratio rule in EFA, which recommends at least 10 respondents for every observed variable [8]. With 39 initial items, the sample size exceeded the minimum requirement, ensuring statistical robustness. Survey data are then analyzed using Exploratory

Factor Analysis (EFA). The KMO and Bartlett's test are used to assess data adequacy, and the Scree plot and eigenvalues are used to determine the optimal number of factors, with Varimax rotation applied to facilitate interpretation [13, 14, 15].

The next step is to apply the Grey Delphi method. In the Grey Delphi phase, 12 experts participated: 7 HSE managers with more than 10 years of practical experience and 5 academics with PhDs in Industrial Engineering and Occupational Health and Safety (OHS) research. Delphi-based studies typically recommend involving 10 to 20 experts when the panel is homogeneous and focused on a single domain. Therefore, the inclusion of 12 experts in this study is consistent with established methodological standards for obtaining reliable expert consensus [18, 19, 20]. Therefore, the inclusion of 12 experts in this study is consistent with established methodological standards for obtaining reliable expert consensus [20]. They are involved in providing linguistic assessments for the 57 risk factors. The procedural steps for the Grey Delphi method are outlined as follows [18, 19, 20]:

Step 1: Identification of Occupational Health and Safety Risk Factors

This process involves an extensive literature review to identify and categorize all constraints relevant to the research.

Step 2: Expert Selection. To ensure consistency in expert evaluation, a linguistic scale is used to convert qualitative judgments into grey numbers. The scale used in this study is presented in Table 2.

Step 3: Detailed evaluation using grey numbers. Table 1 shows how the responses were converted into their corresponding grey numbers. The input from the experts is combined using these grey numbers. Let us use the example of a panel of k experts. The assessment of the factor ⊗ Gi is explained full in (1)

$$\otimes\, G_i = \frac{(\otimes G_i^1 + \otimes G_i^2 \ldots\ldots + \otimes G_i^h + \cdots\ldots + \otimes G_i^k)}{K} \qquad (1)$$

where G_i is the overall evaluation of importance barrier, and $\otimes G_i^h$ denotes the hth expert's evaluation of the hth expert on the construction of the toll road.

Table 2. Linguistic scale and its associated grey number

Linguistic Scale	Grey Number
Very Low Important	[0,1]
Low Important	[1,2]
Medium Important	[2,3]
High Important	[3,4]
Very High Important	[4,5]

Intuition: This equation averages the assessments of all experts. Each expert's evaluation is an uncertain "grey" value, and by combining them, the method extracts a consensus that reflects the collective judgment rather than relying on individual opinions.

Step 4: Grey number adjustment. After being initially specified inside the range (Gi = [G1, G] = [G' ∊ G|G < G' ≤ G]), the grey number is whitened using its corresponding whitening value, e, equation (6), which was described in the preliminary section, is used to whiten grey numbers.

Intuition: Grey numbers capture uncertainty by allowing a range of possible values. Whitening can be thought of as "choosing a representative point" within that range, providing a single interpretable score for each factor while still respecting the underlying uncertainty.

Step 5: Choosing the main barriers and establishing the threshold limit. The Grey Delphi method's final step includes choosing and eliminating Important Barriers. Each barrier's relevance is determined by calculating an overall score and comparing it to a predetermined threshold number (λ). The factor is considered important and chosen if the computed value of ⊗ > λ; if not, it is rejected.

Intuition: This step works like a passing grade in an examination. If a factor's overall score exceeds the threshold, it is recognized as critical and retained; otherwise, it is excluded. This ensures that only the most relevant and collectively validated risks are prioritized for further consideration.

Data Collection

To obtain up-to-date, relevant literature on occupational health and safety (OHS) risk factors in the textile industry, this study uses the Scopus database as its primary source. The document selection process is carried out systematically through several filtering stages, as illustrated in Figure 2.

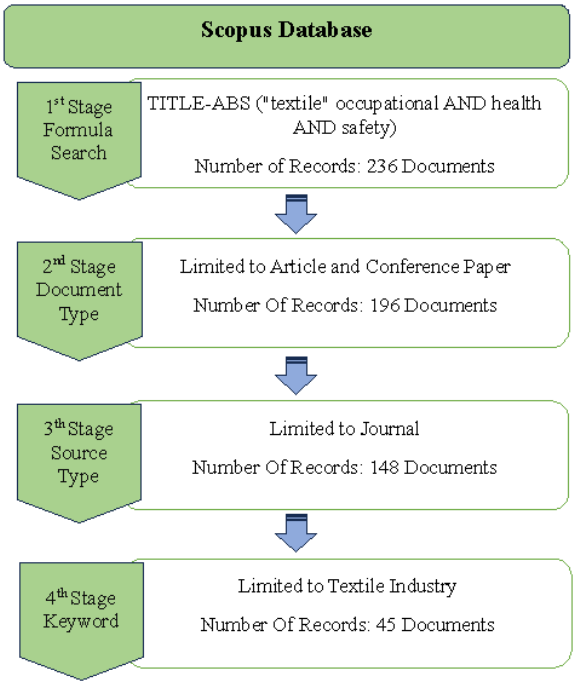

Figure 2. Manuscripts Filtering Stages in the Scopus database (Data Access on January 24, 2025)

The literature identification process was carried out through four filtering stages in the Scopus database:

Stage 1: Formula search

The initial search was conducted using keywords in TITLE-ABS with the formula: "textile" AND occupational AND health AND safety. This resulted in 236 documents that cover the general theme of occupational health and safety in the textile industry.

Stage 2: Document Type

The next filtering step limited the document type to scientific articles, reducing the total to 196. This document type selection was made to ensure the inclusion of formally published scientific content.

Stage 3: Source Type

To improve academic quality, the filtering was further refined to include only journal publications. With this criterion, the number of relevant documents decreased to 148.

Stage 4: Keyword Filtering

The topic was narrowed to keywords specifically associated with the textile sector during the last filtering phase. After applying this filter, 45 documents specifically discussed occupational safety and health in the textile sector.

The Scopus database search identified 54 occupational health and safety (OHS) risk factors in the textile industry. Subsequently, validation was carried out by experts (3 academics and 3 practitioners), and the expert validation resulted in the addition of 3 more risk factors, bringing the total to 57 factors. Additional OHS risk factors provided by experts are as follows:

1. Mold growth in textile materials stored in damp conditions
2. Cross-contamination between textile products and food/beverages in the canteen area
3. Inadequate sanitation facilities.

The identified occupational health and safety (OHS) risk factors are categorized into several hazard groups. A complete list of the 57 initial risk factors is presented in Table 3.

Table 3. List of 57 initial Occupational Health and Safety (OHS) risk factors identified in the textile industry, categorized across physical, chemical, electrical, mechanical, ergonomic, psychosocial, fire and explosion, human error, and biological hazards

No	Safety Risk Factor	No	Safety Risk Factor	No	Safety Risk Factor
1	Excessive noise from weaving/spinning machines [3][21]	20	Use of bleaching agents like hydrogen peroxide [22][23]	39	Strict production targets [22]
2	Vibration from high-speed machines [3][21]	21	Excessive use of optical brightening agents (OBA) [23]	40	Lack of social support in the workplace [24]
3	Inadequate lighting [3][22]	22	Use of hazardous chemicals containing ammonia [23]	41	Long working hours without adequate breaks [2][22]
4	Exposure to heat radiation during the fabric drying process [4][24]	23	Storage of chemicals without clear labeling [22, 25, 26]	42	Unknown roles and responsibilities [27]
5	Air heating in the production area [2][22]	24	Uncontrolled chemical reactions due to mixing incompatible materials [22]	43	Job insecurity or uncertain employment contracts [27]
6	Air humidity control in the production area [22]	25	Exposure to cotton dust containing endotoxins [2][3]	44	Storage of flammable chemicals without proper safety measures [21][26]
7	Insufficient ventilation [2][3]	26	Exposure to fumes from burning or heating chemicals [2][3]	45	Accumulation of flammable fabric fibers [22][26]
8	High humidity during the fabric washing process [2, 22, 28]	27	Cross-contamination between hazardous chemicals and finished products [23]	46	Use of electrical equipment that does not meet safety standards [25][26]

No	Safety Risk Factor	No	Safety Risk Factor	No	Safety Risk Factor
9	Wet or slippery floors due to chemicals [22, 26, 29]	28	Unprotected moving machine parts [2][3]	47	Lack of effective fire detection and suppression systems [21, 22, 25, 26, 29]
10	Unsafe storage rack heights [22]	29	Use of cutting tools without safety guards [2][3]	48	Untrained or untrained emergency evacuation procedures [22, 25, 26]
11	Exposed or damaged electrical cables [22]	30	Poorly maintained machinery [2][21]	49	Employees not understanding Standard Operating Procedures (SOPs) [22][27]
12	Electrical equipment without proper grounding [22]	31	Lack of machine operator training [3, 22, 28]	50	Improper or non-use of personal protective equipment (PPE) [2, 3, 22]
13	Overload in electrical panels [25]	32	Cramped working areas [2][22]	51	Incorrect measurements leading to dangerous reactions [2]
14	Use of electrical equipment in wet areas [5]	33	Poor ergonomic work postures [2][22]	52	No safety instructions in the production area [30]
15	Lack of training on the use of electrical equipment [5]	34	Repetitive tasks without sufficient breaks [2][22]	53	Errors in work instructions/SOPs [28]
16	Exposure to synthetic dyes during the fabric dyeing process [24][26]	35	Lifting heavy loads without assistive devices [2][22]	54	Exposure to microorganisms from natural textile materials [25]
17	Use of organic solvents such as toluene and benzene [22, 23, 25]	36	Improper workplace design [2][12]	55	Mold growth in textile materials stored in damp conditions (Source: Expert)
18	Exposure to formaldehyde in the finishing process [25][26]	37	Use of tools that are not suited to the worker's body size [2][12]	56	Cross-contamination between textile products and food/beverages in the canteen area (Source: Expert)
19	Exposure to heavy metals such as chromium/lead [25][26]	38	High work pressure [2][22]	57	Inadequate sanitation facilities (Source: Expert)

RESULTS AND DISCUSSION

Exploratory Factor Analysis (EFA)

Instrument reliability was assessed using Cronbach's alpha prior to EFA. The overall alpha value was 0.89, exceeding the recommended minimum of 0.70, confirming high internal consistency of the measurement items. Before conducting a factor analysis, the dataset's suitability must be evaluated using statistical tests. The results of the KMO and Bartlett's test are presented in Table 4.

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.959, and Bartlett's test of sphericity was statistically significant ($p < 0.05$). In general, a KMO value above 0.80 is considered very good, while a value exceeding 0.90 indicates excellent suitability for factor analysis. Therefore, the obtained KMO value of 0.959 confirms that the dataset has excellent sampling adequacy and is highly suitable for conducting Exploratory Factor Analysis (EFA) [13, 14, 15].

A high KMO score confirms sufficient sample adequacy and indicates strong shared variance among variables, suggesting that meaningful and reliable latent factors are likely to emerge from the analysis. Thus, the result supports the potential for producing valid and interpretable factor structures in subsequent extraction.

Screen plot and Eigenvalue

The Scree Plot is used to determine the optimal number of factors by visualizing the distribution of eigenvalues across components. The results of this analysis are presented in Figure 3. The first factor, which accounts for the majority of the variance, has a relatively large eigenvalue of 22.76 (see Figure 3).

Table 4. Results Of KMO And Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin measurement of sampling adequacy.		0.959
Bartlett's Test of Sphericity	Aprox. Chi-Square	15842.090
	df	1596
	Sig.	0.000

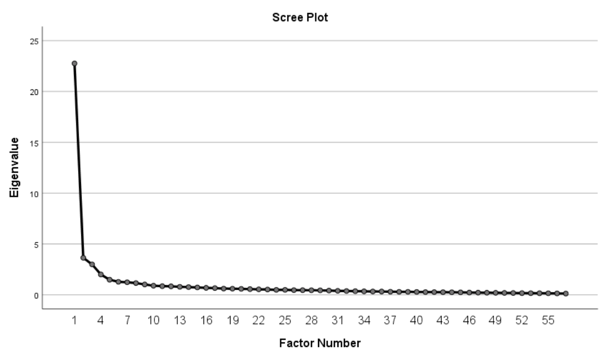

Figure 3. Scree plot showing eigenvalue distribution for OHS risk factors, indicating retention of nine factors above Kaiser's criterion (eigenvalue > 1)

Between the first and second variables, and between the second and third variables, there is a significant drop. The curve flattens out after the tenth factor. Only factors with an eigenvalue larger than 1 are deemed important by Kaiser's criterion [13, 14, 15]. To improve clarity, the Scree Plot was refined by adding exact eigenvalues and labels to each point, making it easier to identify the sharp decline and leveling-off points, which support the decision to retain nine factors.

Determining the Criteria for the Number of Factors (Extraction)

The next step is to determine how many factors need to be removed. The components that most contribute to the data's variance can be identified using the Maximum Likelihood Method in factor extraction.

Based on Total Variance Explained, the 57 risk factors are divided into 9 categories, each category having an eigenvalue greater than 1 [13, 14, 15]. Therefore, the 57 risk factors, divided into 9 categories, were selected for further analysis.

Factor extraction was conducted using the Maximum Likelihood method, as it enables statistical testing and generalization of results. The number of factors retained was based on Kaiser's criterion (eigenvalues > 1) and the Scree Plot, both of which supported retaining nine factors. These nine factors explained over 60% of the total variance, indicating meaningful latent structures supported by both statistical evidence and theoretical relevance.

Eigenvalues indicate how much variance each factor explains. Following Kaiser's criterion, only factors with eigenvalues above 1 were retained, as they account for more variance than a single variable. Thus, the nine resulting categories reflect statistically supported latent structures rather than arbitrary groupings. The nine extracted categories derived from the factor analysis were: Physical Hazards, Chemical Hazards, Electrical Hazards, Mechanical Hazards, Ergonomic Hazards, Psychosocial Hazards, Fire and Explosion Hazards, Human Error Hazards, and Biological Hazards.

Although factors were initially selected based on eigenvalues greater than 1, the final categories were not formed solely based on eigenvalues. After extraction, Varimax rotation was applied to improve clarity and ensure each variable loaded strongly on a single factor. Variables were grouped based on their highest loading values, promoting conceptual consistency within each category. Theoretical insights and OHS domain knowledge were then used to validate and refine each factor. This combined statistical and conceptual process ensured that all categories were homogeneous and meaningful.

Rotated Factor Matrix

The rotation matrix was based on responses from 390 participants who rated 57 OHS risk items using a five-point Likert scale (1 = "Strongly Disagree" to 5 = "Strongly Agree"). These responses generated a correlation matrix, which was analyzed using Exploratory Factor Analysis with Maximum Likelihood extraction. To enhance clarity, Varimax rotation was applied, allowing each item to load strongly on a single factor. The resulting Rotated Factor Matrix shows how strongly each item relates to its underlying construct, facilitating clear categorization.

To improve clarity, the rotation process produces a matrix showing factor loadings, with each item linked to the factor with the highest loading. After applying Varimax rotation, items load strongly on one factor and minimally on others, making it easier to group them into meaningful categories. For example, if an item has a loading of 0.75 on Factor 1 and below 0.30 on others, it is assigned to Factor 1. This matrix visually clarifies how items form distinct latent constructs.

Factor rotation aims to simplify factor interpretation by maximizing the separation between the extracted factors. Varimax rotation is one of the rotation techniques used to produce cleaner, more easily interpretable factors. With 390 respondents, factor loadings are considered significant if they exceed 0.3 [31].

Based on the rotated factor matrix, the 57 OHS risk factors function well, as they have factor loading values greater than 0.3 [31]. Next, all 57 factors will be analyzed to identify the main OHS risk factors in the textile industry using the Grey Delphi method.

Grey Delphi Analysis

Initial Expert Assessment

Following the use of EFA to identify OHS risk factors in the textile industry, experts apply the Grey Delphi technique. Five academic experts and seven industry practitioners are chosen to provide a balanced viewpoint [20]. To gather data, a panel of experts with at least 8 years of experience managing occupational health and safety (OHS) in the textile industry was selected from the technology development and textile sectors. The academic specialists have backgrounds in industrial technology and OHS and are from prestigious universities. Competence and pertinent knowledge in the field of occupational health and safety were the basis for the selection.

To gather data, a structured questionnaire was created using the Grey Delphi method. A copy of the questionnaire was sent to the experts, who were then asked to respond. After that, the specialists assessed the textile industry's identified OHS risk factors and offered their opinions. Following the identification of risk factors, expert judgments were collected using a structured questionnaire. The expert panel's initial linguistic assessments are presented in Table 5.

Table 5. Expert panel's initial linguistic ratings (VH, H, M, L, VL) of 57 OHS risk factors in the textile industry

Code	Exp. 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9	Exp 10	Exp 11	Exp 12
FR 1	H	M	M	L	M	VH	H	VH	VH	VH	H	VH
FR 2	M	M	M	L	M	VH	H	VH	H	H	M	VH
FR 3	H	H	M	M	H	H	H	H	H	M	H	H
FR 4	M	M	M	L	H	H	M	M	H	H	M	H
FR 5	L	VH	M	M	M	H	M	VH	M	M	M	H
FR 6	M	H	M	L	M	H	M	M	H	M	H	H
FR 7	M	VH	M	M	M	H	M	VH	L	M	H	H
FR 8	L	VH	M	L	M	M	M	VH	H	L	M	M
FR 9	M	VH	H	L	H	H	H	VH	VH	M	VH	H
FR 10	H	VH	H	M	H	H	M	VH	M	M	H	H
FR 11	VH	VH	H	H	VH	VH	VH	VH	VH	VH	VH	VH
FR 12	H	VH	H	H	VH	VH	H	VH	H	VH	H	VH
FR 13	H	VH	VL	M	VH	VH	VH	VH	H	M	VH	VH
FR 14	H	VH	H	L	VH	VH	H	VH	H	VH	H	VH
FR 15	H	H	H	M	H	H	H	H	M	M	H	H
FR 16	H	VH	H	M	M	H	H	VH	M	H	H	H
FR 17	H	VH	VH	M	M	H	H	VH	M	H	H	H
FR 18	H	VH	VH	L	H	H	M	VH	M	H	H	H
FR 19	H	VH	VH	L	H	H	H	VH	H	H	VH	H
FR 20	H	VH	VH	L	L	H	M	VH	VH	M	M	H
FR 21	H	VH	VH	L	L	H	M	VH	M	M	L	H
FR 22	VH	VH	VH	L	M	H	H	VH	H	VH	H	H
FR 23	H	H	VH	M	M	H	H	VH	L	H	VH	H
FR 24	VH	VH	VH	M	L	H	H	VH	VH	VH	VH	VH
FR 25	H	H	VH	M	M	H	H	VH	H	VH	M	H
FR 26	H	H	VH	L	M	H	H	VH	M	H	H	H
FR 27	VH	VH	VH	L	L	H	H	VH	M	H	VH	VH
FR 28	M	VH	H	M	H	H	VH	VH	VH	VH	VH	M
FR 29	H	VH	H	M	H	H	VH	VH	VH	VH	VH	H
FR 30	H	M	H	M	L	H	H	VH	M	H	H	H
FR 31	VH	M	H	M	M	H	H	VH	M	H	H	VH
FR 32	M	M	H	M	L	H	M	M	H	M	L	M
FR 33	M	M	M	M	M	H	H	H	M	M	H	M
FR 34	H	M	M	M	H	H	M	M	H	H	H	H
FR 35	H	H	H	M	M	H	H	VH	H	H	VH	H
FR 36	H	M	M	M	L	H	H	M	H	H	M	H
FR 37	M	M	M	M	M	H	M	M	M	M	M	M
FR 38	H	M	M	M	M	H	H	H	H	H	H	H
FR 39	M	M	M	M	M	H	M	VH	M	M	H	M
FR 40	M	M	M	L	M	H	M	VH	M	M	M	M
FR 41	VH	M	H	M	M	H	H	M	H	H	VH	VH
FR 42	M	M	M	M	L	H	M	H	M	L	M	M
FR 43	M	M	M	M	L	H	M	M	M	L	M	M
FR 44	VH	VH	VH	H	H	H	VH	M	VH	VH	VH	VH
FR 45	M	VH	H	M	H	H	H	VH	H	VH	H	M
FR 46	H	H	H	H	H	H	H	M	H	H	VH	H
FR 47	H	H	VH	VH	H	H	VH	M	H	H	H	H

Code	Exp. 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9	Exp 10	Exp 11	Exp 12
FR 48	VH	H	VH	H	H	H	VH	VH	H	H	H	VH
FR 49	H	H	H	M	H	H	H	VH	H	H	H	H
FR 50	M	H	H	M	H	H	H	VH	VH	H	VH	VH
FR 51	VH	VH	H	M	H	H	H	VH	L	H	VH	VH
FR 52	M	H	M	M	H	H	VH	VH	M	H	H	VH
FR 53	H	H	H	M	H	H	VH	H	M	H	H	VH
FR 54	M	H	M	L	M	H	H	VH	M	VH	M	VH
FR 55	M	H	M	L	L	H	M	VH	H	VH	H	H
FR 56	H	H	H	L	M	H	M	VH	M	VH	H	H
FR 57	H	H	H	M	M	H	H	VH	M	H	H	VH

Based on the expert group's responses, we converted the linguistic values into Grey numbers using Table 1. The linguistic evaluations provided by experts are then converted into grey numbers to capture uncertainty and variability. The results of this conversion process are shown in Table 6.

Table 6. Conversion of expert ratings into grey numbers used as inputs for Grey Delphi analysis of OHS risks.

Code	Exp. 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9	Exp 10	Exp 11	Exp 12
FR 1	[3,4]	[2,3]	[2,3]	[1,2]	[2,3]	[4,5]	[3,4]	[4,5]	[4,5]	[4,5]	[3,4]	[4,5]
FR 2	[2,3]	[2,3]	[2,3]	[1,2]	[2,3]	[4,5]	[3,4]	[4,5]	[3,4]	[3,4]	[2,3]	[4,5]
FR 3	[3,4}	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[2,3]	[3,4]	[3,4]
FR 4	[2,3}	[2,3]	[2,3]	[1,2]	[3,4]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[2,3]	[3,4]
FR 5	[1,2]	[4,5]	[2,3]	[2,3]	[2,3]	[3,4]	[2,3]	[4,5]	[2,3]	[2,3]	[2,3]	[3,4]
FR 6	[2,3]	[3,4]	[2,3]	[1,2]	[2,3]	[3,4]	[2,3]	[2,3]	[3,4]	[2,3]	[3,4]	[3,4]
FR 7	[4,5]	[4,5]	[2,3]	[2,3]	[2,3]	[3,4]	[2,3]	[4,5]	[1,2]	[2,3]	[3,4]	[3,4]
FR 8	[4,5]	[4,5]	[2,3]	[1,2]	[2,3]	[2,3]	[2,3]	[4,5]	[3,4]	[1,2]	[2,3]	[2,3]
FR 9	[4,5]	[4,5]	[3,4]	[1,2]	[3,4]	[3,4]	[3,4]	[4,5]	[4,5]	[2,3]	[4,5]	[3,4]
FR 10	[4,5]	[4,5]	[3,4]	[2,3]	[3,4]	[3,4]	[2,3]	[4,5]	[2,3]	[2,3]	[3,4]	[3,4]
FR 11	[4,5]	[4,5]	[3,4]	[3,4]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]
FR 12	[4,5]	[4,5]	[3,4]	[3,4]	[4,5]	[4,5]	[3,4]	[4,5]	[3,4]	[4,5]	[3,4]	[4,5]
FR 13	[4,5]	[4,5]	[0,1]	[2,3]	[4,5]	[4,5]	[4,5]	[4,5]	[3,4]	[2,3]	[4,5]	[4,5]
FR 14	[4,5]	[4,5]	[3,4]	[1,2]	[4,5]	[4,5]	[3,4]	[4,5]	[3,4]	[4,5]	[3,4]	[4,5]
FR 15	[3,4]	[3,4]	[3,4]	[2,3]	[3,4]	[3,4]	[3,4]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]
FR 16	[3,4]	[4,5]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[3,4]	[3,4]
FR 17	[3,4]	[4,5]	[4,5]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[3,4]	[3,4]
FR 18	[3,4]	[4,5]	[4,5]	[1,2]	[3,4]	[3,4]	[2,3]	[4,5]	[2,3]	[3,4]	[3,4]	[3,4]
FR 19	[3,4]	[4,5]	[4,5]	[1,2]	[3,4]	[3,4]	[3,4]	[4,5]	[3,4]	[3,4]	[4,5]	[3,4]
FR 20	[3,4]	[4,5]	[4,5]	[1,2]	[1,2]	[3,4]	[2,3]	[4,5]	[4,5]	[2,3]	[2,3]	[3,4]
FR 21	[3,4]	[4,5]	[4,5]	[1,2]	[1,2]	[3,4]	[2,3]	[4,5]	[2,3]	[2,3]	[1,2]	[3,4]
FR 22	[4,5]	[4,5]	[4,5]	[1,2]	[2,3]	[3,4]	[3,4]	[4,5]	[3,4]	[4,5]	[3,4]	[3,4]
FR 23	[3,4]	[3,4]	[4,5]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[1,2]	[3,4]	[4,5]	[3,4]
FR 24	[4,5]	[4,5]	[4,5]	[2,3]	[1,2]	[3,4]	[3,4]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]
FR 25	[3,4]	[3,4]	[4,5]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[3,4]	[4,5]	[2,3]	[3,4]
FR 26	[3,4]	[3,4]	[4,5]	[1,2]	[2,3]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[3,4]	[3,4]
FR 27	[4,5]	[4,5]	[4,5]	[1,2]	[1,2]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[4,5]	[4,5]
FR 28	[2,3]	[4,5]	[3,4]	[2,3]	[3,4]	[3,4]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]	[2,3]
FR 29	[3,4]	[4,5]	[3,4]	[2,3]	[3,4]	[3,4]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]	[3,4]
FR 30	[3,4]	[2,3]	[3,4]	[2,3]	[1,2]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[3,4]	[3,4]
FR 31	[4,5]	[2,3]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[3,4]	[4,5]
FR 32	[2,3]	[2,3]	[3,4]	[2,3]	[1,2]	[3,4]	[2,3]	[2,3]	[3,4]	[2,3]	[1,2]	[2,3]
FR 33	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]	[3,4]	[3,4]	[3,4]	[2,3]	[2,3]	[3,4]	[2,3]
FR 34	[3,4]	[2,3]	[2,3]	[2,3]	[3,4]	[3,4]	[2,3]	[2,4]	[3,4]	[3,4]	[3,4]	[3,4]
FR 35	[3,4]	[3,4]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[3,4]	[3,4]	[4,5]	[3,4]
FR 36	[3,4]	[2,3]	[2,3]	[2,3]	[1,2]	[3,4]	[3,4]	[2,3]	[3,4]	[3,4]	[2,3]	[3,4]

Code	Exp. 1	Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9	Exp 10	Exp 11	Exp 12
FR 37	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]	[3,4]	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]
FR 38	[3,4]	[2,3]	[2,3]	[2,3]	[2,3]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]
FR 39	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]	[3,4]	[2,3]	[2,3]	[2,3]	[2,3]	[3,4]	[2,3]
FR 40	[2,3]	[2,3]	[2,3]	[1,2]	[2,3]	[3,4]	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]	[2,3]
FR 41	[4,5]	[2,3]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[3,4]	[3,4]	[4,5]	[4,5]
FR 42	[2,3]	[2,3]	[2,3]	[2,3]	[1,2]	[3,4]	[2,3]	[2,3]	[2,3]	[1,2]	[2,3]	[2,3]
FR 43	[2,3]	[2,3]	[2,3]	[2,3]	[1,2]	[3,4]	[2,3]	[2,3]	[2,3]	[1,2]	[2,3]	[2,3]
FR 44	[4,5]	[4,5]	[4,5]	[3,4]	[3,4]	[3,4]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]	[4,5]
FR 45	[2.3]	[4,5]	[3,4]	[2,3]	[3,4]	[3,4]	[3,4]	[4,5]	[3,4]	[4,5]	[3,4]	[2,3]
FR 46	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[4,5]	[3,4]	[3,4]	[4,5]	[3,4]
FR 47	[3,4]	[3,4]	[4,5]	[4,5]	[3,4]	[3,4]	[4,5]	[4,5]	[3,4]	[3,4]	[3,4]	[3,4]
FR 48	[4,5]	[3,4]	[4,5]	[3,4]	[3,4]	[3,4]	[4,5]	[4,5]	[3,4]	[3,4]	[3,4]	[4,5]
FR 49	[3,4]	[3,4]	[3,4]	[2,3]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]	[3,4]
FR 50	[2,3]	[3,4]	[3,4]	[2,3]	[3,4]	[3,4]	[3,4]	[4,5]	[4,5]	[3,4]	[4,5]	[4,5]
FR 51	[4,5]	[4,5]	[3,4]	[2,3]	[3,4]	[3,4]	[3,4]	[4,5]	[1,2]	[3,4]	[4,5]	[4,5]
FR 52	[2,3]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[4,5]	[2,3]	[3,4]	[3,4]	[4,5]
FR 53	[3,4]	[3,4]	[3,4]	[2,3]	[3,4]	[3,4]	[4,5]	[4,5]	[2,3]	[3,4]	[3,4]	[4,5]
FR 54	[2,3]	[3,4]	[2,3]	[1,2]	[2,3]	[3,4]	[3,4]	[4,5]	[2,3]	[4,5]	[2,3]	[4,5]
FR 55	[2,3]	[3,4]	[2,3]	[1,2]	[1,2]	[3,4]	[2,3]	[4,5]	[3,4]	[4,5]	[3,4]	[3,4]
FR 56	[3,4]	[3,4]	[3,4]	[1,2]	[2,3]	[3,4]	[2,3]	[4,5]	[2,3]	[4,5]	[3,4]	[3,4]
FR 57	[3,4]	[3,4]	[3,4]	[2,3]	[2,3]	[3,4]	[3,4]	[4,5]	[2,3]	[3,4]	[3,4]	[4,5]

Next, the total Grey weights are likewise determined using Equation (1). The OHS risk factors in the textile industry are then accepted or rejected for additional study based on these figures. According to several studies, including [18]–[20], the precise threshold value (l) is 3.5. Stated differently, OHS risk factors in the textile industry are deemed important if the precise number exceeds 3.5; otherwise, they are eliminated. Although the scale ranges from 1 (Very Low) to 5 (Very High), the Grey Delphi method uses grey intervals and a whitening process instead of simple averages. This captures both importance and expert consensus. Since a score above 3 may still reflect low agreement, a threshold of 3.5 based on prior studies was set to retain only the most critical and widely agreed-upon factors. Although Likert-scale data are ordinal, the Grey Delphi method converts responses into grey intervals to reflect uncertainty. Calculations are then applied to these intervals as continuous data, in accordance with grey system theory. Previous studies support this approach and justify the arithmetic used in Formula 1. Together with the choices made, the overall grey weights and corresponding crisp values are calculated to determine the importance of each risk factor. The final results and decisions are presented in Table 7.

Table 7. Crisp weights and final decisions (accepted/rejected) of 57 OHS risk factors in the textile industry based on the Grey Delphi threshold (λ = 3.50).

Code	Overall GreyWeigh	Crisp Weigh	Decision
FR 1	[3.00,4.00]	3.50	accept
FR 2	[2.67,3.67]	3.17	Reject
FR 3	[2.75,3.75]	3.25	Reject
FR 4	[2.33,3.33}	2.83	Reject
FR 5	[2.42,3.42]	2.92	Reject
FR 6	[2.33,3.33]	2.83	Reject
FR 7	[2.50,3.50]	3.00	Reject
FR 8	[2.17,3.17]	2.67	Reject
FR 9	[3.00,4.00]	3.50	accept
FR 10	[2.83,3.83]	3.33	Reject
FR 11	[3.83,4.83]	4.33	accept
FR 12	[3.50,4.50]	4.00	accept
FR 13	[3.17,4.17]	3.67	accept
FR 14	[3.33,4.33]	3.83	accept
FR 15	[2.75,3.75]	3.25	Reject

Code	Overall GreyWeigh	Crisp Weigh	Decision
FR 16	[2.92,3.92]	3.42	Reject
FR 17	[3.00,4.00]	3.50	accept
FR 18	[2.92,3.92]	3.42	Reject
FR 19	[3.17,4.17]	3.67	accept
FR 20	[2.75,3.75]	3.25	Reject
FR 21	[2.50,3.50]	3.00	Reject
FR 22	[3.17,4.17]	3.67	accept
FR 23	[2.95,3.95]	3.42	Reject
FR 24	[3.42,4.42]	3.92	accept
FR 25	[3.00,4.00]	3.50	accept
FR 26	[2.83,3.83]	3.33	Reject
FR 27	[3.08,4.08]	3.58	accept
FR 28	[3.25,4.25]	3.75	accept
FR 29	[3.42,4.42]	3.92	accept
FR 30	[2.67,3.67]	3.17	Reject
FR 31	[2.92,3.92]	3.42	Reject
FR 32	[2.08,3.08]	2.58	Reject
FR 33	[2.33,3.33]	2.83	Reject
FR 34	[2.58,3.58]	3.08	Reject
FR 35	[3.00,4.00]	3.50	accept
FR 36	[2.42,3.42]	2.92	Reject
FR 37	[2.08,3.08]	2.58	Reject
FR 38	[2.67,3.67]	3.17	Reject
FR 39	[2.17,3.17]	2.67	Reject
FR 40	[2.00,3.00]	2.50	Reject
FR 41	[3.08,4.08]	3.58	accept
FR 42	[1.92,2.92]	2.42	Reject
FR 43	[1.92,2.92]	2.42	Reject
FR 44	[3.75,4.75]	4.25	accept
FR 45	[3.00.4.00]	3.50	accept
FR 46	[3.17,4.17]	3.67	accept
FR 47	[3.33,4.33]	3.83	accept
FR 48	[3.42,4.42]	3.92	accept
FR 49	[2.92,3.92]	3.42	accept
FR 50	[3.17,4.17]	3.67	accept
FR 51	[3.17,4.17]	3.67	accept
FR 52	[2.92,3.92]	3.42	Reject
FR 53	[3.08,4.08]	3.58	accept
FR 54	[2.67,3.67]	3.17	Reject
FR 55	[2.58,3.58]	3.08	Reject
FR 56	[2.75,3.75]	3.25	Reject
FR 57	[3.92,3.92]	3.42	Reject

The results of the Grey Delphi indicate twenty-five significant OHS risk factors in the textile industry, as shown in Table 7. These 25 risk factors are important for stakeholders to reduce OHS risk levels effectively. The 25 OHS risk factors in the textile industry are as follows.

1. Excessive noise from weaving/spinning machines
2. Wet or slippery floors due to chemicals
3. Electrical cables exposed or damaged
4. Electrical equipment without proper grounding
5. Overload in Electrical Panels
6. Use of electrical equipment in wet areas
7. Use of organic solvents such as toluene and benzene
8. Exposure to heavy metals such as chromium/lead
9. Use of hazardous chemicals containing ammonia
10. Uncontrolled chemical reactions due to mixing incompatible materials
11. Exposure to cotton dust containing endotoxins
12. Cross-contamination between hazardous chemicals and finished products
13. Unprotected moving machine parts
14. Use of cutting tools without safety guards

15. Lifting heavy loads without assistive devices
16. Long working hours without adequate breaks
17. Storage of flammable chemicals without proper safety measures
18. Accumulation of flammable fabric fibers
19. Use of electrical equipment that does not meet safety standards
20. Lack of effective fire detection and suppression systems
21. Unclear or untrained emergency evacuation procedures
22. Employees do not understand Standard Operating Procedures (SOPs).
23. Improper or nonuse of personal protective equipment (PPE).
24. Incorrect measurements leading to dangerous reactions
25. Mold growth in textile materials stored in damp conditions

Through the Grey Delphi process, 25 priority risk factors were identified, while 32 were excluded for failing to reach the threshold (λ = 3.5). Importantly, the consensus extended beyond traditional hazards to include emerging issues. Excessive noise from weaving and spinning machines and chemical exposures, such as cotton dust and solvents, consistently ranked as the top risks, in line with prior textile industry studies. However, unlike earlier research, our results emphasize mold growth in damp storage areas as a novel emerging risk, underscoring that environmental conditions are increasingly critical for occupational health. Mold growth in damp textile storage areas is considered both a safety risk and a biological hazard because it poses a direct threat to worker health and operational safety. When fabrics remain moist in poorly ventilated spaces, they create ideal conditions for microbial growth. Mold spores and mycotoxins can cause respiratory issues, skin irritation, and allergic reactions, which are health impacts recognized by OSHA and WHO as biological hazards. Moreover, mold can damage materials, reduce product quality, cause cross-contamination, and increase the risk of slips and falls on slippery surfaces. Therefore, identifying mold as an emerging OHS risk is a logical and well-supported decision within the safety framework of this study.

The selected priority risk factors are grouped into categories along with corresponding mitigation strategies. These results are summarized in Table 8.

Table 8. The 25 priority risk factors and solutions are grouped into categories as presented

No	Category	Risk Factor	Solutions
1	Physical Hazards	1. Excessive noise from weaving/spinning machines 2. Wet or slippery floors due to chemicals	1. Engineering Control: Installing noise dampers on machines or providing earplugs for workers. 2. Administrative & Engineering Controls: Installing warning signs, providing anti-slip mats, and ensuring proper drainage systems.
2	Electrical Hazards	1. Electrical cables exposed or damaged 2. Electrical equipment without proper grounding 3. Overload in Electrical Panels 4. Use of electrical equipment in wet areas	1. Engineering & Administrative Controls: Conducting regular inspections, replacing damaged cables, and installing cable protectors. 2. Engineering Control: Installing grounding systems according to standards. 3. Engineering Control: Adjusting electrical panel capacity according to load requirements. 4. Administrative Control & PPE: Prohibiting the use of non-specific electrical equipment in wet areas and requiring anti-electric PPE.
3	Chemical Hazards	1. Use of organic solvents such as toluene and benzene 2. Exposure to heavy metals such as chromium/lead 3. Use of hazardous chemicals containing ammonia 4. Uncontrolled chemical reactions due to mixing incompatible materials 5. Exposure to cotton dust containing endotoxins 6. Cross-contamination between hazardous chemicals and finished products	1–4. Substitution & Engineering Controls: Replacing hazardous chemicals with safer alternatives; if solvents and chemicals must be used, strict PPE use is required. Providing adequate ventilation (local exhaust ventilation) and storing chemicals according to MSDS. 5. Administrative Control & PPE: Implementing job rotation, maintaining workplace hygiene, and providing appropriate respirators. 6. Administrative & Engineering Controls: Implementing strict procedures for chemical storage and handling, and

No	Category	Risk Factor	Solutions
			separating production areas for hazardous chemicals and finished products.
4	Mechanical Hazards	1. Unprotected moving machine parts 2. Use of cutting tools without safety guards	Engineering & Administrative Controls: Installing guards on all moving machine parts, ensuring all tools have safety features, and conducting regular inspections.
5	Ergonomic Hazards	1. Lifting heavy loads without assistive devices	Engineering & Administrative Controls: Providing lifting aids (e.g., hoists, forklifts) and training workers in proper lifting techniques.
6	Psychosocial Dangers	1. Long working hours without adequate breaks	Administrative Controls: Setting reasonable working hours, providing clear rest schedules, and implementing flexible work policies where possible.
7	Fire and Explosion Hazards	1. Storage of flammable chemicals without proper safety measures 2. Accumulation of flammable fabric fibers 3. Use of electrical equipment that does not meet safety standards 4. Lack of effective fire detection and suppression systems 5. Unclear or untrained emergency evacuation procedures	1–3. Administrative & Engineering Controls: Storing flammable materials in designated areas, cleaning the workplace regularly, and using certified electrical equipment. 4–5. Administrative & Engineering Controls: Installing fire alarms and sprinklers, providing fire extinguishers, and developing as well as disseminating evacuation procedures through regular training and simulations.
8	Human Error Hazards	1. Employees do not understand Standard Operating Procedures (SOPs). 2. Improper or nonuse of personal protective equipment (PPE). 3. Incorrect measurements leading to dangerous reactions	Administrative Control & PPE: Providing comprehensive training and certification, conducting routine supervision, and applying both sanctions and rewards to ensure compliance with SOPs and proper PPE use
9	Biological Hazards	1. Mold growth in textile materials stored in damp conditions	Administrative & Engineering Controls: Regulating storage conditions to prevent humidity (e.g., using dehumidifiers) and ensuring proper air circulation

In contrast to studies focused on the construction or petrochemical industries, this research highlights biological risks, especially mold growth, as a significant concern in textile manufacturing. Previous studies have largely neglected biological hazards in the textile industry [2][24], with greater emphasis placed on physical and chemical risks. The identification of biological risks in our study may be linked to the specific conditions of textile production, such as high humidity and exposure to organic materials, which promote mold growth. This finding underscores the need to consider industry-specific risk profiles and develop tailored risk management approaches for the textile sector.

DISCUSSION

Theoretical implications

Theoretically, the combination of Exploratory Factor Analysis (EFA) and the Grey Delphi method demonstrate how integrating quantitative and qualitative techniques can overcome the limitations of using a single method. EFA is useful for reducing data complexity and identifying hidden patterns, but it often cannot include expert judgment, especially in uncertain situations. On the other hand, qualitative approaches like the Delphi method are effective for gathering expert opinions but can be biased. By merging both, this hybrid framework offers a balanced approach that combines data-driven analysis with expert insights. This aligns with current trends in OHS research that encourage the use of mixed methods to connect broad statistical findings with real-world, context-specific knowledge [8, 9, 10].

This mixed method combines EFA and Grey Delphi to balance empirical data and expert judgment. EFA identifies risk factors from worker responses, while Grey Delphi validates and prioritizes them using expert insight. This integration ensures both statistical rigor and practical relevance in OHS risk prioritization.

Importantly, the discovery of mold growth as an emerging risk shows that this hybrid method can help identify unusual or overlooked hazards that traditional tools might miss. Although initially suggested by experts, the hybrid method confirmed mold growth as a valid risk. EFA showed it fit the overall factor structure, and Grey Delphi confirmed strong expert agreement. This combination ensured mold growth was recognized as a credible and emerging safety issue. This suggests that such methods not only improve the reliability of detecting common risks (such as noise or chemical exposure) but also increase awareness of new types of threats. These findings support global research that highlights the growing importance of environmental and biological hazards, especially in industries affected by climate change and limited resources [10][11].

Furthermore, while previous studies have largely relied on single-method or conventional multi-criteria decision-making approaches, this study introduces a hybrid EFA–Grey Delphi framework that integrates data-driven factor reduction with expert consensus under uncertainty. This methodological advancement enhances both the robustness and practical applicability of OHS risk prioritization.

Overall, the findings of this study not only confirm existing knowledge but also contribute new insights by identifying emerging risks and proposing a more comprehensive and systematic approach to OHS risk assessment in the textile industry.

Practical implications

In practice, this study provides useful guidance for managers and policymakers in the textile industry by presenting a ranked list of 25 risk factors grouped into 9 main categories. Unlike previous approaches that often generate long lists without a clear sense of priority, this method produces an evidence-based hierarchy that helps decision-makers focus on the most serious risks. In addition, the framework is flexible and can be applied to other sectors that face similar challenges in OHS risk management.

Unlike single-method tools like fuzzy AHP or Bayesian MCDM, which are effective for ranking and group consensus, this study's integration of EFA and Grey Delphi offers added value. EFA identifies data-driven risk categories, while Grey Delphi validates and ranks them with expert input under uncertainty. This combination ensures a risk hierarchy that is both evidence-based and expert-validated.

From a management perspective, prioritizing mechanical and human error hazards underscores the immediate need for stricter enforcement of machine safety measures, regular maintenance schedules, and training programs focused on employee competence. Textile companies should adopt real-time monitoring systems to track chemical exposure and enforce mandatory PPE use, backed by supervisory oversight and behavioral reinforcement. At the policy level, regulators can refer to the 25 identified high-priority risks to update national OHS guidelines tailored to the textile industry, with particular attention to chemical handling, ergonomic limits, and control of biological hazards (such as mold prevention). Incorporating this hybrid framework into workplace risk assessment procedures can also aid government inspections and certification programs, facilitating data-driven decision-making and efficient resource allocation to address high-risk areas.

CONCLUSION

This study proposed and implemented a hybrid framework combining Exploratory Factor Analysis (EFA) with the Grey Delphi method to identify and prioritize occupational health and safety (OHS) risks in the textile industry. Through this integrated approach, the research identified 25 key risk factors, grouped into nine major categories: physical, chemical, electrical, mechanical, ergonomic, psychosocial, fire and explosion, human error, and biological hazards.

The contributions of this study can be outlined across three key areas. First, from a methodological standpoint, the research introduces a structured hybrid model that merges the strengths of quantitative data analysis with the depth of qualitative expert judgment. This model offers a more comprehensive and resilient alternative to single-method approaches, which often fall short in addressing the multidimensional nature of workplace risks. Second, on a theoretical level, the study reinforces the value of using multi-method strategies in advancing the academic discourse on OHS risk management. The hybrid model demonstrated higher sensitivity in identifying emerging risks, such as mold growth in humid textile storage areas, which traditional assessment tools might miss. Third, the study provides practical value by offering a prioritized list of 25 OHS risks. This serves as a clear and actionable reference for industry managers and policymakers to design more effective prevention and control measures in high-risk environments.

However, this study has several limitations. First, its geographic focus is restricted to the textile industry in a single country, which may limit the applicability of the results to other regions. Second, there is the potential for expert bias in the Grey Delphi process, as personal preferences may have influenced expert opinions. Lastly, the data gathered in this study were based on self-reports from workers and experts, which could introduce subjective biases.

Looking ahead, the proposed framework has strong potential for broader application in other high-risk sectors, including construction, mining, and chemical manufacturing. Future studies could extend this hybrid framework to other sectors and conduct cross-country comparisons to assess its relevance and applicability in various industry settings. Furthermore, integrating real-time data from IoT devices or wearable technologies could improve the precision and flexibility of OHS risk assessments in future research. By enabling cross-industry comparisons and benchmarking, this model could support the development of more standardized, transferable OHS risk-prioritization practices. Consequently, while the study directly addresses the needs of the textile industry, it also lays the groundwork for more holistic, adaptable risk assessment models across diverse industrial domains.

Conflict of interest

The authors declare that they have no conflict of interest.

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