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A Study on the Importance of Factors Effecting the Occupational Safety Performance

Cihangir GUMUSTAS[1], Elif HAKTANIR[2*], Gul Tekin TEMUR[1], Ahmet BESKESE[2]

[1]*Department of Management Engineering, Bahcesehir University, 34349, Besiktas, Istanbul, Türkiye*
[2]*Department of Industrial Engineering, Bahcesehir University, 34349, Besiktas, Istanbul, Türkiye*

Highlights

- A generic hierarchical model is proposed for factors affecting occupational safety performance.
- 20 sub-criteria under five main categories are prioritized using IVPF-AHP.
- Organization is found to be the most critical criterion.
- A systematic framework adaptable across industries is presented.

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Abstract

In contemporary workplaces, organizational safety is not just a regulatory obligation but a critical determinant of sustainable success. With the evolving technological advancements in industries, understanding the factors that influence occupational safety becomes paramount. This study examines the multifaceted structure of occupational safety criteria, recognizing its importance in ensuring not only the physical well-being of workers but also the organizational resilience. Utilizing the Interval-Valued Picture Fuzzy Analytic Hierarchy Process (IVPF-AHP) method, this research aims to prioritize the most crucial factors influencing safety performance. Through a comprehensive analysis of 20 sub-criteria under five main categories — Organization, Safety Climate, Regulatory Characteristics, Workplace Environment, and Individual Characteristics — the study reveals insights into the nuanced interplay of organizational, managerial, and individual factors that shape safety outcomes. The findings underscore the prominence of factors such as Workload Pressure, Management and Supervisor Commitment to Safety, Sanctions and Auditing, Number of Subcontractors, and Equipment Conditions in enhancing safety performance.

1. INTRODUCTION

In the dynamic landscape of contemporary workplaces, organizational safety has evolved beyond its traditional role as a regulatory obligation to become a pivotal factor in achieving sustainable success. As industries evolve, embracing technological innovations and intricate processes, occupational safety has been a major global challenge for high-reliability organizations, and the need to define and understand the factors influencing organizational safety has become increasingly paramount. No longer confined to the periphery of compliance, safety is now recognized as a strategic imperative that directly impacts the resilience and viability of modern enterprises. Many examples can be observed in industries such as construction, mining, and shipyard construction [1, 2].

Occupational accidents are painful and expensive as they can cause significant human-related and economic damage, such as worker injuries or disabilities, lost workforce, and decreased productivity. These accidents can also negatively impact the company's reputation, damage an organization's assets, reduce productivity, and impede efficiency. As a result, many businesses are devoting significant time and material resources to prevent accidents, particularly those that result in worker injuries and deaths [3].

The factors influencing safety can vary across cultures, regions, and industries. For example, occupational accidents are generally more frequent in developing countries, causing material losses and threatening

*Corresponding author, e-mail: elif.haktaniraktas@bau.edu.tr

employees' lives. Specifically, Turkey ranks third in the world for fatal accidents after El Salvador and Algeria, and first in Europe for occupational accidents [4]. The occupational accident rate in Turkey is higher than 20 per 100,000, whereas the EU average is 1.74 [5]. According to Mutlu and Altuntas [6], at least 200,000 occupational accidents happen annually. According to the Ministry of Labor and Social Security, Turkey suffers more than 400,000 occupational accidents annually, killing four people and permanently injuring six people [7]. Acknowledging this diversity and tailoring safety strategies accordingly is crucial for organizations to establish comprehensive and effective safety protocols.

Accordingly, industrial management must ensure that workers have safe working conditions. Effective preventive measures, such as investing in safety equipment, training and educating employees, optimizing process design, and maintaining machinery, can help reduce occupational accidents [8]. To create a positive safety culture, workers' attitudes must be changed by adopting best practices, good housekeeping, and changes in work practices. Therefore, addressing these safety measures and developing a safe and sustainable working environment for workers is essential to reduce the risk of work-related accidents and enhance safety performance [9].

The traditional approach to enhancing safety performance and mitigating further losses involves measuring and analyzing data related to accidents, including the frequency of accidents, the severity of accidents, the number of injuries and illnesses resulting from accidents, the associated costs, and the frequency of near misses. This data illustrates the effectiveness of safety management in the aftermath of accidents. However, this approach has been criticized for being reactive and not helpful in preventing accidents. Specifically, focusing on lagging indicators, such as accident data, does not help to create a sustainable safety culture or improve the quality of an occupational health and safety management system [10- 12]. In recent years, there has been a growing movement towards using leading indicators to evaluate and increase safety performance. Leading indicators are measures that can be used to predict the likelihood of an accident occurring. They include measures such as the number of safety training hours, management's commitment to safety regulations, and the frequency of government audits. Using leading indicators can help organizations prevent accidents by identifying and addressing potential hazards before they cause harm. They can also help organizations develop improvement programs and corrective actions to improve their safety performance. By identifying and tracking leading indicators, organizations can predict future performance and take action to improve it [11, 13]. In other words, preventing accidents requires knowledge about how and where employees are exposed to hazardous situations and how the risks are associated [14].

To understand risk assessment and increase safety performance, prior studies have examined certain variables. For instance, Abu-Khader [15] asserts that individual factors are crucial for enhancing safety performance in chemical plants, making employee behavior a critical aspect that should be considered in risk evaluation. In addition, Anderson [16] argues that while human error is often the immediate cause of accidents, organizational and managerial factors are also involved in incidents in all industries. Defining the multifaceted factors that influence safety is imperative for identifying potential hazards, assessing risks, and instigating preventive measures. This proactive stance not only mitigates the immediate dangers but also fosters a culture of vigilance and responsibility, safeguarding both the workforce and the organization's assets. However, previous studies have only identified and highlighted the importance of those characteristics without clarifying or prioritizing the relationships between them. Review studies have also been performed in this area; however, according to the authors' knowledge, no study has examined the distinct safety performance features.

Beyond the traditional realms of physical safety, the contemporary discourse on organizational safety extends to encompass the human element. Factors such as employee well-being, mental health, and workplace culture have a significant impact on the overall safety paradigm. As the global workforce becomes increasingly attuned to the importance of these human-centric elements, organizations are compelled to redefine their safety paradigms, recognizing the intrinsic link between a secure work environment and sustained success. Considering these factors, this study aims to help industrial management identify the root cause of the problem and focus on areas where improvements are needed. It explores the escalating significance of defining the factors that influence organizational safety in navigating the complexities of modern workplaces, thereby forging a path toward a secure and flourishing future. This

enables management to strengthen or reinforce areas that are lacking, based on the assessment results. To encompass the innate subjectivity, ambiguity, and uncertainty in complex decisions related to occupational safety, offering a deeper insight into the compromises at play, this research utilizes the interval-valued picture fuzzy Analytic Hierarchy Process (IVPF-AHP) method. To the best of the authors' knowledge, this study represents the first application of the IVPF-AHP method within this specific field.

In this context, our study is organized as follows: Section 2 provides a review of the literature on the application of multi-criteria decision-making (MCDM) in occupational safety. Section 3 proposes a hierarchical decision model and explains the criteria that influence occupational safety. Section 4 outlines the detailed steps of the proposed methodology. Section 5 calculates the significance of factors influencing the efficacy of occupational safety. Section 6 presents the findings, and Section 7 draws the conclusions.

2. LITERATURE REVIEW ON MCDM UTILIZATION IN OCCUPATIONAL SAFETY

In recent years, scholars and practitioners have increasingly turned their attention to occupational safety evaluation as a multidisciplinary issue. Numerous studies employing MCDM in the realm of occupational safety have been conducted from various perspectives in the literature over the past few years. The objective of this section is to provide a brief review of the selected studies on occupational safety evaluation, with a focus on presenting methodologies that utilize MCDM.

Chen et al. [17] addressed the prioritization of occupational risks under uncertainty by integrating the Spherical Fuzzy Set (SFS) with the MABAC and Ordered Weighted Averaging (OWA) methods, focusing on interactive risk factors and ambiguous data. They found that the framework improved the accuracy and reliability of risk prioritization. Aksüt et al. [18] prioritized the wearable technologies in five industries (i.e., construction, mining, agriculture, textile, and chemistry) using AHP and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), considering potential risks causing fatigue, injury, errors, and accidents among employees due to labor-intensive and demanding tasks. Ayvaz et al. [19] integrated the Fermatean fuzzy AHP and WASPAS methods with the Fine-Kinney framework to evaluate occupational hazards in aquaculture, finding that diving was identified as the most severe hazard, followed by heavy lifting, poor posture, repetitive movements, and overexertion. The results of hazard classification provided stakeholders with a guide to implementing effective safety measures. Ayyildiz et al. [20] developed a Pythagorean fuzzy Bayesian network model to assess occupational risks in pharmaceutical warehouses, considering 24 risk factors, and found that the high risk was mainly due to factors such as prioritizing cost reduction over safety when selecting equipment and materials, vulnerabilities in the healthcare supply chain, sudden spikes in demand that impact the warehouse's ability to ensure safety, and employee errors stemming from insufficient training and carelessness. Kursunoglu [21] utilized fuzzy AHP and fuzzy TOPSIS to develop a framework for controlling methane explosions in coal mines, identifying critical sub-risk factors such as ventilation issues. The study found that improving safety technologies and financial investments were the most effective measures to mitigate accidents. Among the 34 sub-risk factors, the "improper ventilation system" ranks the highest, followed by "insufficient air quantity" in second place. Serrato et al. [22] introduced a global probabilistic fuzzy system (GPFSORA) to comprehensively assess occupational risks by combining stochastic and non-stochastic uncertainties. They found that the system provided more reliable and holistic evaluations of risk probabilities and severities. Sherin et al. [23] employed AHP and Fuzzy TOPSIS techniques to analyze risks in surface mining in Pakistan, with a focus on injuries and fatalities. The study found that comprehensive training, the use of safety equipment, and adherence to regulations significantly reduced risks and improved safety. To evaluate health and safety risks, Ahmed et al. [24] weighted environmental, operational, and management-related factors using fuzzy AHP, and the obtained weights were utilized in the second step, which was configured with a fuzzy inference system (FIS). Badida et al. [25] proposed exploring the health risks faced by staff due to various hazards and provided control measures to prevent accidents. The methodology involved a two-stage fuzzy MCDM approach, integrating the fuzzy AHP and fuzzy Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS). The method was applied in a prominent hospital. The top three workplace hazards identified were electrical hazards, faulty medical equipment, and ventilation and air conditioning hazards. Koulinas et al. [26] utilized the AHP method to assess, analyze, and compare the risks associated with road construction sites and their impact

on the health and safety of workers. Additionally, the study examined workplace stress and psychosocial risk factors that could have long-term effects on workers' physical and mental well-being. Küçükarslan et al. [27] aimed to prioritize occupational health and safety (OHS) achievements among ten forest management directorates. Work accident statistics, risk assessment statistics, OHS activities, and training and health control activities were considered as the four main criteria. W. Chen et al. [28] identified the high-risk factors within the excavation system using TOPSIS. In the study, the risk factors were synthesized from various dimensions, including geotechnical conditions, surrounding environment, construction measurements, construction procedures, and management practices. Ye et al. [29] developed a variable-weight fuzzy AHP method to assess the safety of expansive soil slopes continuously. Slope morphology, hydrometeorology, soil properties, and other factors were taken into consideration. In the study of Q.-Y. Chen et al. [28] introduced a novel occupational health and safety risk assessment (OHSRA) model that utilizes Fermatean fuzzy linguistic sets (FFLSs) and a combined compromise solution (CoCoSo) approach to evaluate and prioritize occupational hazards effectively. Ten types of occupational hazards were considered in the study, and the most significant occupational hazard was identified as 'contact with overhead powerlines while working near or under them' in a gas pipeline construction project. Karuppiah et al. [3] aimed to identify, analyze, and assess the faulty behavior risks (FBRs) responsible for triggering occupational accidents and injuries. Through a data triangulation strategy, the study focused on 19 FBR sub-criteria categorized into five main criteria. An integrated approach was proposed, combining the fuzzy Analytic Network Process (ANP) and the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method, to evaluate these FBRs. 'Organizational factors' was found to be the most important main criterion. In contrast, the sub-criterion of absence of continuous monitoring emerged as the most prominent factor contributing to the occurrence of occupational accidents. Marhavilas et al. [30] introduced a hybrid model that integrated AHP, Hazard and Operability (HAZOP), and Decision-Making Risk Analysis (DMRA) techniques to identify critical issues and rank occupational hazard risks within the petrochemical industry. Omidi et al. [31] evaluated the impact of safety climate-related factors on safety performance through an integrated entropy-TOPSIS approach. In this study, safety performance, encompassing compliance, participation, and safety-related outcomes were assessed using data obtained from questionnaires related to safety climate and psychosocial safety climate (PSC). It was observed that PSC has a more significant influence on employee safety performance compared to regular safety climate. Unver and Ergenc [32] evaluated safety risk using AHP, identifying six primary risk criteria and twenty-nine sub-risk criteria for chainsaw operators working in forest logging operations. Among the six main criteria (psychological, physical, technical, organizational, biological, and chemical risks), psychological risks were found to be the most important. The set of variables considered included the use of mobile technology (smartphones), tacit knowledge, explicit knowledge, safety culture (behavioral aspects), safety culture (psychological aspects), attitudes toward safety (psychological aspects), and attitudes toward safety (emotional aspects). In the study by Ferrari et al. [33], the primary objective was to aid and streamline decision-making in health management and occupational safety by identifying and prioritizing relevant occupational health and safety indicators using fuzzy AHP. The findings showed that the 'occupational health and safety management' category was the most important, followed closely by the 'accidents and diseases' and 'risk assessment' categories. The aim of Zytoon [34] was to introduce a prioritization model for regulated safety inspections based on four main criteria (compliance history, complaint history, injury records, and industry characteristics) and 13 sub-criteria. This model employed an integrated approach that combined the Delphi, AHP, and Double-Hierarchical TOPSIS methods. Akbar and Ahsan [35] prioritized the critical challenges for workplace safety compliance using the AHP method. Drawing from the existing literature on social sustainability and the apparel supply chain, they integrated 12 specific challenges categorized under four general challenge categories. These four general categories were factor capacity and capability, cost and financial concerns, cultural issues, and external regulations. 'Cost and financial concerns' was found to be the most important category, and 'cultural issues' was the least important one. Gul et al. [36] proposed an occupational health and safety risk assessment methodology that integrated Pythagorean fuzzy sets, the L-matrix method, and VIseKriterijumsa Optimizacija I Kompromisno Resenje (VIKOR) analysis. They identified a total of 333 distinct hazards affecting stakeholders in a mine company, which were further summarized and categorized under 38 different activity areas. Dağdeviren and Yüksel [37] employed a fuzzy AHP approach to address the challenges associated with measuring the safety of work systems from a behavior-based perspective. They identified the factors underlying the incidents that occurred. Subsequently, a total of 14 factors were identified for assessing FBR within the work systems, which were

categorized into four groups: organizational, personal, job-related, and environmental factors. Ilbahar et al. [38] utilized Pythagorean fuzzy AHP and FIS to assess safety risks. They grouped the criteria affecting safety risks into five categories: environmental factors, staff management, non-secure behaviors, heavy equipment, and construction yard management. Thirty-two sub-criteria were handled, and the results showed that 'not specifying routes of excavation vehicles within the work area' was found to be the most important hazard, and 'landslide due to lack of proper bevel or shoring' was found to be the second. Using the proposed quantitative methodology, Raviv et al. [39] grouped the accident database into five distinct clusters. They evaluated the severity of incidents in each cluster based on their potential to result in accidents of varying severity. Subsequently, in the study by Raviv et al. [40], the total risk potential of each event was computed using the severity level values obtained through AHP. Basahel and Taylan [41] developed a method for identifying and assessing the factors that influence workplace safety conditions at construction sites. Fuzzy AHP was employed to determine the weights of criteria affecting safety, and fuzzy TOPSIS was utilized to rank companies based on their safety performance. Gnoni et al. [42] proposed a method for effectively assessing FBR in the workplace, to support the continuous improvement process mandated by current standards. The proposed approach employed a fuzzy AHP methodology to characterize FBR, considering organizational, personal, job-related, activity, and environmental factors. Organizational factors were found to be the most significant, while personal factors were found to be the least significant. In the study of Enchill and Nyamah [43], AHP was employed to prioritize key safety factors encompassing 'human, organizational, technical, and environmental aspects' that impact safety within an industrial gas manufacturing company. The findings suggested that the primary driver impacting safety within the company was the human factor. The primary objective of Podgórski [44] was to showcase the utilization of an AHP-based approach for prioritizing and selecting leading indicators to measure operational performance in occupational safety and health management systems. Criteria of the SMART approach (Specific, Measurable, Achievable, Relevant, and Time-Bound) were taken into account. Aminbakhsh et al. [45] employed the AHP method to rank the most significant safety risk items. They categorized the criteria into three groups: accident hazards, physical hazards, and chemical hazards. The 'Accident risk' was pinpointed as the most significant, with 'physical hazard' and 'chemical hazard' trailing behind, in sequence. In the study of Zheng et al. [46], fuzzy AHP was employed to assess workplace safety in hot and humid environments. A safety evaluation framework has been developed, comprising three primary factors: work, environment, and workers. Within these factors, ten sub-factors (work nature, work intensity, work duration, temperature, humidity, airflow velocity, heat radiation intensity, seniority structure, safety training, and personal protection) have been identified and incorporated. The 'environment' factor was given precedence, followed by the 'work' factor, and finally, the 'worker' factor. Gürcanli and Müngen [47] suggested using fuzzy sets and AHP to evaluate the risks faced by workers at construction sites, which handles situations characterized by uncertain and insufficient data. Three parameters were derived: accident likelihood, current safety level, and accident severity, which served as input variables for the fuzzy rule-based system. Dağdeviren et al. [48] aimed to determine the FBR, which is significant in work system safety, by using fuzzy ANP. Organizational, personal, and job-related factors, along with thirteen sub-factors, were considered. Organizational factors were identified as the most influential, while personal factors were determined to have the least impact on the work system. Table 1 presents MCDM studies addressing major occupational safety-related issues, along with the specific MCDM methods employed in these studies.

Table 1. *Usage of MCDM methods in occupational safety risk evaluation literature*

Main Problem	**Studies and MCDM Methodologies**
Behavioral Risk Analysis	Fuzzy ANP and DEMATEL [3]; Fuzzy AHP [37, 42]; Fuzzy ANP [48].
General Safety Risk Evaluation	AHP and Fuzzy TOPSIS [23]; Fuzzy AHP [29, 46]; AHP and HAZOP-DMRA [30]; AHP [32]; Pythagorean Fuzzy VIKOR and the L-matrix [36]; Fuzzy Rule-Based System and AHP [47].
Health and Safety Risk Assessment	Fuzzy AHP and FIS [24]; Fuzzy AHP and TOPSIS [25]; AHP [26]; Fuzzy AHP [33].

Occupational Risk Assessment	Spherical Fuzzy Sets with MABAC [17]; Pythagorean Fuzzy Bayesian [20]; Global Probabilistic Fuzzy System [22]; FFLSs and CoCoSo [28].
Performance Evaluation in Occupational Health and Safety	Fuzzy AHP, PROMETHEE [27].
Regulatory and Inspection Prioritization	Delphi, AHP, DH-TOPSIS [34].
Risk Prioritization	Pythagorean Fuzzy AHP and FIS [38]; AHP [39, 45].
Specialized Risk Assessment	AHP and PROMETHEE [18]; Fuzzy AHP, Fuzzy TOPSIS [21].
Workplace Safety Prioritization	Entropy-TOPSIS [31]; AHP [35, 43]; Fuzzy AHP and TOPSIS [41]; AHP [44].

According to the review, it is observed that these papers have real-world applications across various sectors, including manufacturing, healthcare, construction, mining, and forestry. AHP is the most popular weighting method, and most of these studies address problems using integrated methods, which involve combining more than one MCDM method. From an overview of past studies, it is observed that there is a need for a holistic model in occupational safety studies. Additionally, the methods employed fell short in addressing the inherent subjectivity and vagueness that exist in decisions related to occupational safety.

To summarize, based on prior studies in the field of occupational safety, several research gaps have been identified, and the original contributions of this study to fill these gaps can be explained as follows:

- Incorporation of Criteria Weights: The determination of criteria weights is a crucial factor in multi-criteria decision-making processes. However, many previous studies have either neglected this aspect or employed simplistic approaches in prioritizing safety factors. This study introduces a systematic framework that combines expert-based subjective weights to achieve a balanced and comprehensive evaluation.

- Hybrid IVPF-AHP Framework: Traditional AHP methods often struggle to handle uncertainty and indecision in decision-making. This study introduces a hybrid IVPF-AHP framework that incorporates IVPFS to represent expert judgments more effectively. By integrating both qualitative and quantitative criteria, this method allows for a more detailed representation of safety factors, capturing hesitation and subjectivity. The interval-valued approach mitigates the limitations of single-point judgments, offering a more robust framework for situations with high uncertainty.

- Comprehensive Numerical Application: To demonstrate the practical applicability of the proposed methodology, a detailed numerical application is conducted, focusing on occupational safety performance. Additionally, the findings are examined for sectoral differences. The findings provide valuable insights into the prioritization of factors.

3. PROPOSED MODEL

Through a thorough literature review and interviews with three experts from academia and professional life (details about the experts are provided below), a hierarchical model explaining factors effecting occupational safety performance was constructed, as shown in Figure 1. The model comprises five main and 20 sub-criteria, as described below.

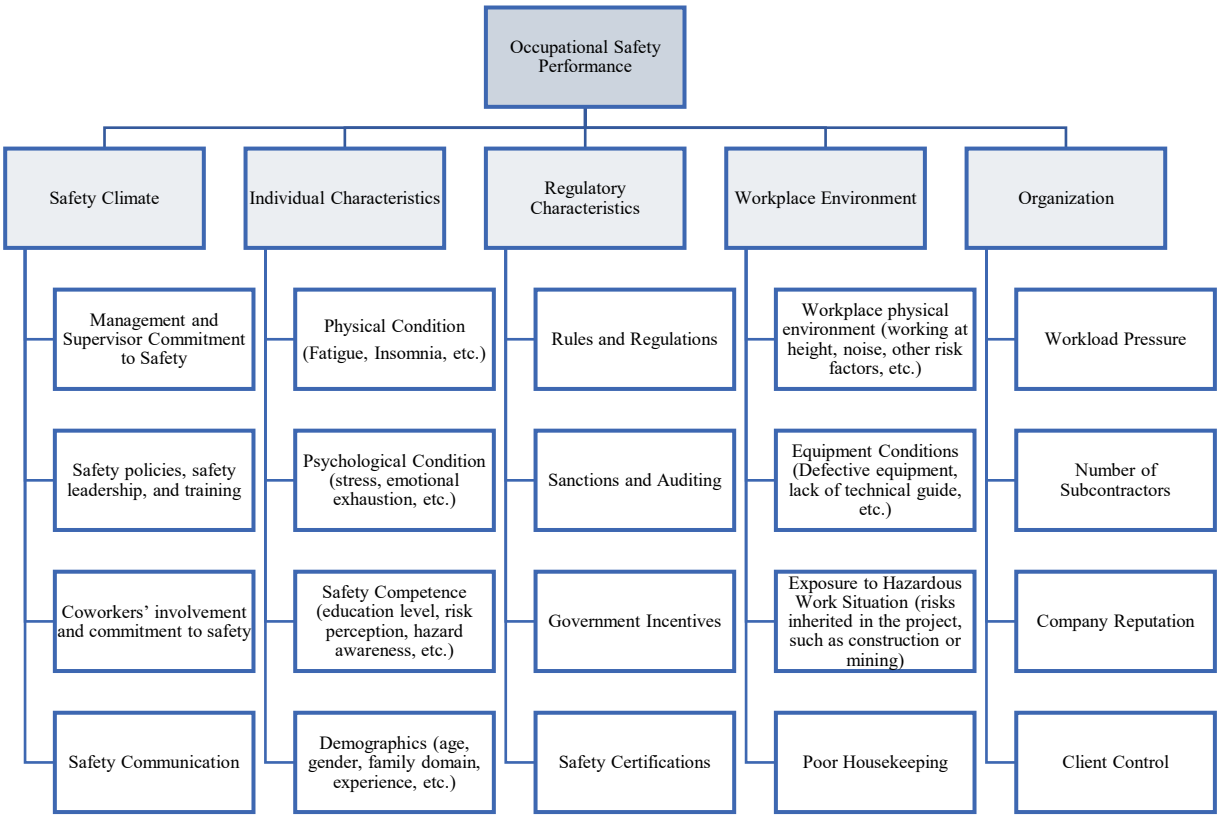


Figure 1. *Proposed model for factors affecting occupational safety performance*

The selection of factors followed a multi-stage process. Firstly, a comprehensive literature review was conducted to identify factors consistently reported in previous research on occupational safety performance. Subsequently, a series of iterative discussions was held with a panel of experts from diverse backgrounds, including academia and the construction sector. These expert consultations provided valuable insights and facilitated the refinement of the factor list, leveraging their practical expertise and contextual knowledge. This iterative approach, integrating rigorous literature review with expert consultation, ensured the identified factors were both theoretically grounded and contextually relevant to the specific research context.

Expert 1 is a faculty member in the Civil Engineering Department at a public university and also serves as a certified Occupational Health and Safety (OHS) specialist. With published academic work in the field, he possesses both theoretical insight and hands-on experience. Expert 2 is an A-level certified OHS professional with over a decade of experience, primarily focused on the construction sector, where he continues to work as an OHS specialist. Similarly, Expert 3 holds an A-level OHS certification and has more than 15 years of industry experience. He currently works as an engineer at a public institution, overseeing waste and garbage incineration operations in the construction context. Considering their academic backgrounds, field experience, and practical involvement in OHS, including areas such as construction and waste management, all three experts are deemed highly competent and well-qualified to contribute to this study.

Safety Climate

Safety climate, introduced by Zohar [49] as employee perceptions of safety policies and practices, is a key predictor of accidents [50]. Improved safety climate can be achieved through strong management commitment [51], but conflicting goals can undermine these efforts. Research shows that safety climate is crucial for safety performance [51]. According to previous studies, several factors are likely to promote a good safety climate within an organization, including managers' and leaders' commitment to safety, safety

policies and their implications, coworkers' involvement in safety practices, and effective safety communication [52].

The view of management and supervisor commitment to safety by employees is a significant aspect of the safety atmosphere that has been emphasized. Specifically, this perception pertains to whether employees acknowledge the importance of safety to management [53]. Management commitment is crucial for safety culture [54]. A favorable safety climate, fostered through worker reporting, involvement, and training [55], is key to preventing accidents [56].

Employee views of the company's safety policies and consequences, such as safety policies, safety leadership, and training, construct another aspect that has been thoroughly studied in the literature on safety atmosphere [57]. A high safety priority motivates employees to take ownership and fosters a favorable safety climate by prioritizing safety over competing demands, such as production [58]. Safety policy outlines clear goals and standards for worker behavior, along with a system to enforce them [59]. Safety leadership goes beyond policy by motivating safe behaviors through rewards, recognition, and worker participation in safety decisions [60]. Such a structure may incorporate fulfilling safety behaviors, appreciating labor's safety behaviors, establishing a safety encouragement system, recording potential incidents and safety suggestions, and encouraging workers' participation in safety decisions [59, 60].

Coworkers' involvement and commitment to safety significantly influence the safety attitude [61]. Their actions establish the standard for acceptable behavior [62], making others more likely to follow their example [63].

Safety communication refers to the extent to which senior managers engage in open communication and frequent interactions with employees, emphasizing the importance of safety [64].

Individual Characteristics

Physical condition (including fatigue, insomnia, etc.) is a significant determinant of safety performance. Demanding work may require high levels of physical exertion, and worker fatigue can impair focus and decision-making, leading to unsafe behaviors [60, 65]. Even factors outside of work, like sleep problems, can contribute to decreased safety [66]. Under physical stress, workers might resort to unsafe shortcuts to finish tasks quickly and alleviate their discomfort [55].

Mental well-being and psychological conditions (such as stress and emotional exhaustion) can also impact safety [67]. Workers can make mistakes when dealing with hazards due to limitations in their information processing capabilities. These limitations can occur at any stage, from recognizing a hazard to determining the appropriate response [55, 68].

Safety competence (education level, risk perception, hazard awareness, etc.) is a key factor in accident prevention. It encompasses a range of factors, including experience, training, hazard awareness, and worker competency [54]. While simply memorizing safety rules can improve task completion, it doesn't guarantee safe work practices [55]. Effective safety training should prioritize fostering a strong safety culture and developing a keen eye for potential hazards [8]. Education and experience equip individuals with the knowledge and skills necessary to work safely, while risk perception and hazard awareness enable them to anticipate and identify potential dangers.

Research across various industries reveals that individuals from diverse demographics (age, gender, family background, experience, etc.) may interpret risks differently, resulting in varying safety performance outcomes. These differences can contribute to human errors, a significant cause of accidents according to Liao et al. [69]. For instance, studies suggest that men and women may have varying risk tolerances, with men being more prone to taking risks and distractions on the job [70]. Additionally, Han et al. [71] found that mid-career employees might be more likely to underestimate risks compared to both new and senior workers. Lastly, family life can influence employee safety at work. Feeling pressure to provide for their

families might lead workers to prioritize speed over safety. Conversely, supportive family norms that emphasize safety can encourage safe work practices.

Regulatory Characteristics

Effective safety management relies heavily on clear rules and regulations [72]. These rules outline specific actions to take or avoid for safe and efficient job completion [73]. Government and industry regulations set the minimum safety standard by requiring investments in basic measures, such as safety equipment [54]. However, research by Swuste et al. [74] suggests that stricter policies, including more frequent inspections, steeper fines for violations, and higher accountability for accident costs, can lead to better implementation of these safety standards at the project level.

Sanctions and audits by regulatory bodies serve as a powerful deterrent against unsafe practices, ultimately enhancing safety performance. The threat of fines, penalties, or even project shutdowns incentivizes companies to prioritize safety measures [70]. Audits, on the other hand, uncover potential hazards and non-compliance with safety regulations. By identifying these issues early on, corrective actions can be taken to prevent accidents and injuries. This combination of enforcement and proactive risk identification creates a strong incentive for companies to maintain high safety standards consistently [59].

Government incentives can be a powerful tool for motivating companies to prioritize safety. These incentives can take various forms, such as tax breaks for companies with strong safety records or reduced insurance premiums for employers with fewer worksite accidents. Ultimately, these incentives encourage companies to invest in safety training, equipment, and protocols, resulting in a safer work environment for employees and a decrease in overall accident rates.

Safety certification (i.e., OHSAS 18001 system) is crucial for many organizations and has become a generalized phenomenon worldwide [75]. Safety certification programs contribute to improved safety performance in a few key ways [76]. Firstly, these programs ensure workers possess the fundamental knowledge and skills to perform their jobs safely. Secondly, the certification process often involves testing hazard identification and risk assessment abilities, making workers more proactive in their safety efforts. Finally, certification programs can instill a sense of professionalism and value for safety within a workforce, further encouraging safe work habits and reducing accidents [77].

Workplace Environment

The factors in the workplace physical environment, such as working at heights, noise, dust, vibration, temperature, light, and sound, can impact how well personnel perform their jobs [78]. Employees often find it more challenging to focus under these circumstances, which can lead to decreased productivity, lower-quality work, or psychological and/or physical stress. The same author contends that unfavorable surroundings hinder colleagues' ability to collaborate to find solutions to tasks. Furthermore, Nahrgang et al. [79] argue that physical demands, complexity, and dangers and hazards serve as roadblocks that reduce employees' likelihood of participating in safety-related activities, adhering to safety protocols, or feeling satisfied.

Ensuring a safe work environment hinges on satisfactory equipment conditions. This includes qualified safety personnel, like certified officers or trainers, to manage safety protocols. Readily available safety gear, proper ventilation, and clear warning signs are all crucial. Research shows a strong correlation between inadequate safety resources and work injuries. For instance, a lack of appropriate Personal Protective Equipment (PPE) can significantly increase the risk of injury. Incidents often occur when employers fail to provide PPE, workers misuse it, or neglect established safety measures. As highlighted by Frazier et al. [80], organizations have a responsibility to invest in proper safety measures and equipment for their employees.

Working in high-risk environments, such as construction or mining, inherently involves exposure to hazardous work situations (e.g., working at heights) and often has poor physical work environments (e.g.,

excessive noise) [81]. Admitting the interconnection of human behavior, work tasks, and workplace conditions, the continuous presence of hazards can lead workers to become insensitive to risk, causing them to neglect safety protocols.

A messy construction site can significantly worsen safety performance [60]. Poor housekeeping may lead to cluttered walkways, scattered debris, and leftover materials, all of which create tripping hazards. Spills and uneven surfaces further increase the risk of slips and falls, which are common causes of injuries on production sites [59].

Organization

Scheduling and workload pressure are closely related. Workers are motivated by management to complete their work within the contracted time frame when progress deviations occur. Safety performance is negatively impacted by the ensuing production pressure (such as having to work more quickly) [82]. Quality deviation-related rework also contributes significantly to schedule pressure, or production pressure, which weakens safety management [83].

The impact of the number of subcontractors on occupational safety cannot be ignored [84]. Many construction projects involve unorganized, small, or medium-sized subcontractors [85]. These factors, combined with weak or nonexistent oversight from health and safety regulators, create significant challenges in both measuring and enforcing safety standards on these projects.

Strong safety performance, as demonstrated by low injury rates and minimal lost production time, enhances the company's reputation [86]. This positive reputation can then translate into increased revenue and profit. Potential clients may be more likely to choose a company with a strong safety record, and employees may be more inclined to work in a safe environment.

Client involvement can be a powerful tool for improving safety on projects, particularly for smaller companies. While some clients of smaller projects may prioritize factors like time and cost over safety [87], their influence shouldn't be underestimated. By exerting client control over the project site, main contractors are pushed to prioritize safety measures. This can include enforcing safety protocols or requiring the selection of subcontractors with strong safety records [88].

4. METHODOLOGY: IVPF-AHP

Büyüközkan and Da Ruan [89] highlighted that MCDM serves as a widely applied method suitable for assessing and prioritizing alternatives in scenarios characterized by numerous, often conflicting, criteria. Furthermore, MCDM techniques enable the simultaneous evaluation of both qualitative and quantitative criteria, allowing for the comparison of alternatives with varying measurement units. In the complex landscape of safety management, organizations face a range of factors that necessitate prioritization and strategic decision-making. MCDM methodologies provide a systematic and comprehensive framework for evaluating diverse safety factors.

In the realm of MCDM techniques, the AHP has garnered considerable attention in scholarly works [90-92]. AHP structures intricate, complex decision scenarios hierarchically, enabling decision-makers to assess alternatives and criteria through pairwise comparisons, resulting in more thorough, informed, precise, and resilient decision outcomes. Although these comparisons may initially involve inconsistencies, such issues can be addressed through adjustments based on the consistency index.

In the AHP method, having a large group of participants is not essential to achieve reliable results. As noted by Saaty and Özdemir [93], the insights of even a single expert with significant knowledge and experience in the field can provide outcomes that are both valid and robust. However, involving more experts might compromise the evaluation's precision and consistency [93, 94]. Therefore, ensuring that participants possess the necessary expertise and qualifications is vital for preserving the credibility of the assessment

process. Despite its strengths, AHP is often criticized for its limitations in managing uncertain and ambiguous decision-making scenarios [92].

A PFS provides a streamlined mathematical approach to addressing challenges that involve uncertain conditions [95]. The hesitation parameter in PFSs captures the indecision of experts, which is often overlooked in classical AHP and many extensions of fuzzy AHP, such as Pythagorean and intuitionistic fuzzy sets. The interval-valued approach mitigates the subjectivity of exact single-point judgments. It offers a more effective structure than ordinary fuzzy sets when addressing issues involving high uncertainty, as it allows for ranges in criteria weights and preferences [95]. Hence, IVPFSs allow for the expression of membership, non-membership, and hesitation degrees within intervals, which offers a richer framework than traditional binary or single-dimensional approaches [96]. This improves the modelling of complex, uncertain situations where explicit judgments cannot be made. Accommodating diverse opinions and uncertainty levels makes IVPF-AHP well-suited for group decision-making.

In occupational safety, decisions regarding resource allocation, hazard prioritization, and control measures can vary significantly among experts or teams, often involving ambiguity (e.g., assessing the severity of hazards or the likelihood of accidents). Additionally, in an occupational safety evaluation, the costs, feasibility, and worker satisfaction must be balanced. In such circumstances, IVPF-AHP provides a robust mechanism for incorporating multiple conflicting factors, resulting in a more nuanced and realistic analysis. Occupational safety often involves input from multidisciplinary teams (e.g., engineers, safety officers, workers). The method's capacity to integrate conflicting criteria ensures that safety policies are not only practical but also feasible and acceptable to all stakeholders. By capturing hesitation and diverse perspectives, and employing an interval-valued approach, IVPF-AHP ensures that varying opinions are systematically integrated and conflicts among experts are mitigated, fostering trust and cooperation among decision-makers and workers, which is essential for implementing safety measures successfully.

The inherent ambiguity and uncertainty surrounding the evaluations of these criteria highlight the suitability of the interval-valued picture fuzzy set (IVPFS) extension of AHP for such scenarios. Picture fuzzy sets (PFSs) were introduced by Cuong [97]. Khalil et al. [98] presented new operations on IVPFSs. By employing IVPF-AHP, decision-makers benefit from a broader preference domain, facilitating more precise and well-informed decision-making processes. Furthermore, IVPF-AHP considers both qualitative and quantitative aspects of the decision problem, thereby contributing to a more comprehensive evaluation of occupational safety.

IVPF-AHP can be utilized through the steps detailed below.

Step 1. A hierarchical model is constructed, encompassing the main criteria and their corresponding sub-criteria.

Step 2. Domain specialists and experts utilize the linguistic terms provided in Table 2 to perform pairwise comparisons among the criteria and sub-criteria. A linguistic pairwise comparison matrix, denoted as $\left(A_L'^{\,k}\right)$, is created for each assessment conducted by the k^{th} expert, pertaining to a decision involving n criteria, following the procedure outlined in Eq. (1). In this equation, A_{ij}^{k} represents the linguistic pairwise comparison of criterion i with criterion j made by expert k.

Table 2. *Linguistic scale for IVPF-AHP*

Linguistic terms	**IVPFNs**
Absolutely High Importance (AHI)	[0.70, 0.85], [0.05, 0.10], [0.00, 0.05]
Very High Importance (VHI)	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]
High Importance (HI)	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]
Slightly High Importance (SHI)	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]
Equal Importance (EI)	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
Slightly Low Importance (SLI)	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]
Low Importance (LI)	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]

Very Low Importance (VLI)	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]
Absolutely Low Importance (ALI)	[0.00, 0.05], [0.05, 0.10], [0.70, 0.85]

$$A_L'^{k} = \begin{bmatrix} EI & \cdots & A_{1n}^{k} \\ \vdots & \ddots & \vdots \\ A_{n1}^{k} & \cdots & EI \end{bmatrix} \quad (1)$$

Step 3. The linguistic expressions are transformed into IVPFNs denoted as $\tilde{A}$. These IVPFNs are defined over a universe of discourse $X \rightarrow [0,1]$, given by $\tilde{A} = \{[\mu_{\tilde{A}}^{L}(x),\ \mu_{\tilde{A}}^{U}(x)], [\eta_{\tilde{A}}^{L}(x),\ \eta_{\tilde{A}}^{U}(x)], [v_{\tilde{A}}^{L}(x), v_{\tilde{A}}^{U}(x)] | x \in X\}$. Each IVPFN comprises a positive membership degree, a neutral membership degree, and a negative membership degree, denoted with $[\mu_{\tilde{A}}^{L}(x),\ \mu_{\tilde{A}}^{U}(x)]$, $[\eta_{\tilde{A}}^{L}(x),\ \eta_{\tilde{A}}^{U}(x)]$, and $[v_{\tilde{A}}^{L}(x), v_{\tilde{A}}^{U}(x)]$, respectively satisfying $0 \leq \mu_{\tilde{A}}(x) + \eta_{\tilde{A}}(x) + v_{\tilde{A}}(x) \leq 1$, $\forall x \in X$. In this notation, L represents the lower and U represents the upper value of the corresponding membership degree. Subsequently, the IVPF pairwise comparison matrix $\left(\widetilde{A'}^{k}\right)$ is constructed as in Eq. (2). In this equation, $\tilde{A}_{ij}^{k}$ represents the IVPF pairwise comparison of criterion i with criterion j made by expert k

$$\widetilde{A'}^{k} = \begin{bmatrix} [0.30,0.45],[0.05,0.10],[0.30,0.45] & \cdots & \tilde{A}_{1n}^{k} \\ \vdots & \ddots & \vdots \\ \tilde{A}_{n1}^{k} & \cdots & [0.30,0.45],[0.05,0.10],[0.30,0.45] \end{bmatrix} \quad (2)$$

where $\tilde{A}_{ij}^{k} = \left(\left[\mu_{\tilde{A}_{ij}^{k}}^{L}, \mu_{\tilde{A}_{ij}^{k}}^{U}\right], \left[\eta_{\tilde{A}_{ij}^{k}}^{L}, \eta_{\tilde{A}_{ij}^{k}}^{U}\right], \left[v_{\tilde{A}_{ij}^{k}}^{L}, v_{\tilde{A}_{ij}^{k}}^{U}\right]\right)$, and the reciprocal values within the matrix are calculated as $\tilde{A}_{ji}^{k} = \left(\left[v_{\tilde{A}_{ij}^{k}}^{L}, v_{\tilde{A}_{ij}^{k}}^{U}\right], \left[\eta_{\tilde{A}_{ij}^{k}}^{L}, \eta_{\tilde{A}_{ij}^{k}}^{U}\right], \left[\mu_{\tilde{A}_{ij}^{k}}^{L}, \mu_{\tilde{A}_{ij}^{k}}^{U}\right]\right)$.

Step 4. Prior to aggregation, it is necessary to ensure the consistency of each individual pairwise comparison matrix [99]. In the presence of an inconsistent matrix, the evaluations within that matrix should be carefully examined. A matrix is considered consistent if the calculated consistency ratio (CR) is equal to or less than 0.1 [100].

The fuzzy extensions of the AHP commonly employ the method of checking consistency of the defuzzified [101- 103] or crisp conjugate [104- 106] versions of the matrix at hand. In this research, the consistency of an IVPF decision matrix is assessed by referencing the data provided in Table 3, specifically the crisp conjugate version.

Table 3. *Crisp conjugate values for IVPF-AHP*

Linguistic terms	**IVPFNs**	**Crisp Conjugate Values**
Absolutely High Importance (AHI)	[0.70, 0.85], [0.05, 0.10], [0.00, 0.05]	9
Very High Importance (VHI)	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	7
High Importance (HI)	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	5
Slightly High Importance (SHI)	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	3
Equal Importance (EI)	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	1
Slightly Low Importance (SLI)	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	1/3
Low Importance (LI)	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]	1/5
Very Low Importance (VLI)	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	1/7
Absolutely Low Importance (ALI)	[0.00, 0.05], [0.05, 0.10], [0.70, 0.85]	1/9

To calculate the consistency ratio (CR), as in Eqs. (3-4), several parameters are involved. These include the consistency index (CI), the random index (RI) which can be found in [107] that varies based on the number of criteria (n) considered in a given decision, and the largest eigenvector of the matrix denoted as 'λ_{max}'

$$CR = \frac{CI}{RI} \tag{3}$$

$$CI = \frac{\lambda_{max} - n}{n-1}. \tag{4}$$

Step 5. To aggregate the individual matrices to obtain the aggregated pairwise comparison matrix, $\widetilde{C'}$ (as in Eq. (5)), the Interval-Valued Picture Fuzzy Weighted Arithmetic Mean (IVPFWAM) operator is employed, as shown in Eq. (6) [108]

$$\tilde{C} = \begin{bmatrix} [0.30,0.45],[0.05,0.10],[0.30,0.45] & \cdots & \tilde{c}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{c}_{n1} & \cdots & [0.30,0.45],[0.05,0.10],[0.30,0.45] \end{bmatrix} \tag{5}$$

$$IVPFWAM\left(\tilde{A}_1, \tilde{A}_2, \ldots., \tilde{A}_K\right) = \left[\left(1 - \prod_{i=1}^{K}\left(1 - \mu_{\tilde{A}_i}^{L}\right)^{\lambda_i}\right), \left(1 - \prod_{i=1}^{K}\left(1 - \mu_{\tilde{A}_i}^{U}\right)^{\lambda_i}\right)\right],$$

$$\left[\prod_{i=1}^{K}\left(\eta_{\tilde{A}_i}^{L}\right)^{\lambda_i}, \prod_{i=1}^{K}\left(\eta_{\tilde{A}_i}^{U}\right)^{\lambda_i}\right], \left[\prod_{i=1}^{K}\left(v_{\tilde{A}_i}^{L}\right)^{\lambda_i}, \prod_{i=1}^{K}\left(v_{\tilde{A}_i}^{U}\right)^{\lambda_i}\right]. \tag{6}$$

In Eq. (6), the weight vector $(\lambda_1, \lambda_2, \ldots, \lambda_K)$ is used, where K represents the number of experts and λ_k represents the influence of the k^{th} expert on the decision, such that $\lambda_k \in [0,1]$, and $\sum_{k=1}^{K} \lambda_k = 1$.

Step 6. The IVPFWAM operator in Eq. (6) is utilized to determine the arithmetic average of the IVPFNs in each row of the matrix.

Step 7. The calculated averages in Step 6 are defuzzified using Eq. (7), resulting in the Score Function (SF) for these numbers [109]

$$SF = \frac{\frac{\mu^L + \mu^U}{2} + 1 - \frac{\vartheta^L + \vartheta^U}{2} + 1 - \frac{\eta^L + \eta^U}{2}}{3} \quad . \tag{7}$$

Step 8. To obtain the local weights, the SF values should be normalized. This normalization process ensures that the local weights are in proportion to each other. The global weight of each sub-criterion can then be determined by multiplying its local weight by the weight of its parent criterion. This allows for the calculation of the overall importance of the sub-criteria in relation to the parent criteria.

5. APPLICATION

To define the importance of factors influencing the effectiveness of occupational safety, this study utilizes the IVPF-AHP method, as described below. To simplify the tracking and comprehension process and ensure a smoother, more coherent understanding of the subject matter for readers, the step numbering within the application section aligns consistently with that employed in the methodology. The application of IVPF-AHP is detailed in the steps given below.

Step 1. During the initial model development process, an extensive literature review was conducted. The criteria obtained were reviewed with practitioners from the business world to assess their practical applicability, yielding the hierarchical decision model. Finally, the proposed model was discussed with identified experts and finalized accordingly. The model encompasses five main categories (i.e., Safety Climate (C1), Individual Characteristics (C2), Regulatory Characteristics (C3), Workplace Environment (C4), and Organization (C5)), along with 20 sub-criteria, as illustrated in Figure 1.

Step 2. Three experts from industry and academia with experience in the domain are defined. They utilized linguistic terms provided in Table 2 to perform pairwise comparisons among the criteria and sub-criteria. A linguistic pairwise comparison matrix was created for each assessment conducted by the experts as

defined in Step 2 of the methodology. In Table 4, the linguistic pairwise comparisons of Expert 1 for the main criteria are presented as an example.

Table 4. *Expert 1's linguistic pairwise comparisons for the main criteria*

	C1	C2	C3	C4	C5
C1	EI	VHI	EI	HI	EI
C2		EI	VLI	SLI	LI
C3			EI	HI	EI
C4				EI	SLI
C5					EI

Step 3. The linguistic expressions were transformed into IVPFNs using Table 2. A sample IVPF pairwise comparison matrix for the main criteria representing the evaluations of Expert 1 is given in Table 5.

Table 5. *Expert 1's pairwise comparisons in IVPFNs for the main criteria*

	C1	C2	C3	C4	C5
C1	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
C2	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]
C3	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
C4	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]
C5	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]

Step 4. Conjugate crisp versions of the IVPF comparison matrices were constructed to check whether the original matrices are consistent. Expert 1's conjugate pairwise comparisons for the main criteria are provided in Table 6, as an example.

Table 6. *Expert 1's conjugate crisp pairwise comparisons for the main criteria*

	C1	C2	C3	C4	C5
C1	1.00	7.00	1.00	5.00	1.00
C2	0.14	1.00	0.14	0.33	0.20
C3	1.00	7.00	1.00	5.00	1.00
C4	0.20	3.00	0.20	1.00	0.33
C5	1.00	5.00	1.00	3.00	1.00

CR values were then calculated for each conjugate crisp pairwise comparison matrix. In the event of detecting an inconsistency in one of these matrices, the pairwise comparisons were reviewed until a consistent matrix was obtained.

Step 5. The aggregated pairwise comparison matrices were obtained by using the IVPFWAM operator. For example, Table 7 presents the IVPF pairwise comparison matrices of all three experts for the main criteria, and Table 8 displays the resulting aggregated comparison matrix.

Table 7. *Experts' IVIF pairwise comparison matrices for the main criteria*

		C1	C2	C3	C4	C5
Expert 1	C1	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	**[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]**	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
	C2	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]
	C3	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
	C4	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]
	C5	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
Expert 2	C1	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	**[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]**	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
	C2	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]
	C3	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]
	C4	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]
	C5	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]
Expert 3	C1	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	**[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]**	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]
	C2	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]	[0.05, 0.15], [0.05, 0.10], [0.60, 0.75]
	C3	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.20, 0.35], [0.05, 0.10], [0.40, 0.55]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]
	C4	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.10, 0.25], [0.05, 0.10], [0.50, 0.65]
	C5	[0.40, 0.55], [0.05, 0.10], [0.20, 0.35]	[0.60, 0.75], [0.05, 0.10], [0.05, 0.15]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.50, 0.65], [0.05, 0.10], [0.10, 0.25]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]

Table 8. *Aggregated IVIF pairwise comparison matrix for the main criteria*

	C1	C2	C3	C4	C5
C1	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	**[0.54, 0.70], [0.05, 0.10], [0.08, 0.20]**	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.35, 0.50], [0.05, 0.10], [0.23, 0.40]	[0.27, 0.42], [0.05, 0.10], [0.33, 0.48]

C2	[0.10, 0.22], [0.05, 0.10], [0.52, 0.68]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.10, 0.22], [0.05, 0.10], [0.52, 0.68]	[0.12, 0.25], [0.05, 0.10], [0.49, 0.64]	[0.07, 0.18], [0.05, 0.10], [0.56, 0.72]
C3	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.54, 0.70], [0.05, 0.10], [0.08, 0.20]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.32, 0.47], [0.05, 0.10], [0.25, 0.42]	[0.20, 0.36], [0.05, 0.10], [0.39, 0.54]
C4	[0.28, 0.43], [0.05, 0.10], [0.31, 0.47]	[0.51, 0.66], [0.05, 0.10], [0.10, 0.24]	[0.31, 0.47], [0.05, 0.10], [0.27, 0.43]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]	[0.29, 0.45], [0.05, 0.10], [0.27, 0.45]
C5	[0.34, 0.49], [0.05, 0.10], [0.26, 0.41]	[0.57, 0.72], [0.05, 0.10], [0.06, 0.18]	[0.41, 0.56], [0.05, 0.10], [0.18, 0.34]	[0.35, 0.51], [0.05, 0.10], [0.22, 0.38]	[0.30, 0.45], [0.05, 0.10], [0.30, 0.45]

To illustrate the aggregation process numerically, the operations completed to calculate the value in the cell representing the comparison between two main criteria, 'Safety Climate' and 'Individual Characteristics' (shaded in Tables 7 and 8), are provided below:

$$\left[\left(1-\left[(1-0.60)^{(1/3)}\times(1-0.60)^{(1/3)}\times(1-0.40)^{(1/3)}\right]\right),\left(1-\left[(1-0.75)^{(1/3)}\times(1-0.75)^{(1/3)}\times(1-0.55)^{(1/3)}\right]\right)\right],\left[\left(0.05^{(1/3)}\times0.05^{(1/3)}\times0.05^{(1/3)}\right),\left(0.10^{(1/3)}\times0.10^{(1/3)}\times0.10^{(1/3)}\right)\right],\left[\left(0.05^{(1/3)}\times0.05^{(1/3)}\times0.20^{(1/3)}\right),\left(0.15^{(1/3)}\times0.15^{(1/3)}\times0.35^{(1/3)}\right)\right]=[0.54,0.70],[0.05,0.10],[0.08,0.20].$$

Thus, [0.54, 0.70], [0.05, 0.10], [0.08, 0.20] was reached as shown in the shaded cell in Table 8.

Step 6. The IVPFWAM operator was utilized to determine the arithmetic average of the IVPFNs in each row of the matrix. Table 9 displays the row averages in the aggregated IVPF pairwise comparison matrix of the main criteria.

Table 9. *Row averages in the aggregated IVPF pairwise comparison matrix of the main criteria*

	Row averages
C1	[0.36, 0.52], [0.05, 0.10], [0.22, 0.38]
C2	[0.14, 0.27], [0.05, 0.10], [0.47, 0.62]
C3	[0.34, 0.50], [0.05, 0.10], [0.23, 0.39]
C4	[0.34, 0.50], [0.05, 0.10], [0.23, 0.39]
C5	[0.40, 0.56], [0.05, 0.10], [0.18, 0.34]

Step 7. The calculated averages in Step 6 were then defuzzified, resulting in the score functions for these numbers. Table 10 provides an example presenting the SF values for the main criteria.

Table 10. *SF values of the main criteria*

C1	**0.69**
C2	0.53
C3	0.68
C4	0.68
C5	0.71

To offer a more lucid comprehension of the mathematical procedure employed, the computation of the SF value for the 'Safety Climate' (highlighted in Table 10) is presented below

$$SF=\frac{\frac{0.36+0.52}{2}+1-\frac{0.05+0.10}{2}+1-\frac{0.22+0.38}{2}}{3}=0.69\ .$$

Step 8. To obtain the local weights, the SF values were normalized. The global weight of each sub-criterion was then determined by multiplying its local weight by the weight of its parent criterion. Weights of the main criteria, and local and global weights of sub-criteria are given altogether in Table 11.

Table 11. *The weights of the main and sub-criteria*

Main Criteria	**Weights of Main Criteria**	**Sub Criteria**	**Local Weights of Sub-Criteria**	**Global Weights of Sub-Criteria**
Safety Climate	0.2092	Management and Supervisor Commitment to Safety	0.2912	0.0609
		Safety policies, safety leadership, and training	0.2559	0.0535
		Coworkers' involvement and commitment to safety	0.2301	0.0481
		Safety Communication	0.2228	0.0466
Individual Characteristics	0.1609	Physical Condition (Fatigue, Insomnia, etc.)	0.2767	0.0445
		Psychological Condition (stress, emotional exhaustion, etc.)	0.2670	0.0430
		Safety Competence (education level, risk perception, hazard awareness, etc.)	0.2453	0.0395
		Demographics (age, gender, family domain, experience, etc.)	0.2110	0.0339
Regulatory Characteristics	0.2062	Rules and Regulations	0.2654	0.0547
		Sanctions and Auditing	0.2875	0.0593
		Government Incentives	0.2430	0.0501
		Safety Certifications	0.2041	0.0421
Workplace Environment	0.2061	Workplace physical environment (working at height, noise, other risk factors, etc.)	0.2691	0.0555
		Equipment Conditions (Defective equipment, lack of technical guide, etc.)	0.2770	0.0571
		Exposure to Hazardous Work Situation (Risks inherited in the project, such as construction or mining)	0.2496	0.0515
		Poor Housekeeping	0.2043	0.0421
Organization	0.2175	Workload Pressure	0.2822	0.0614

		Number of Subcontractors	0.2651	0.0577
		Company Reputation	0.2199	0.0478
		Client Control	0.2328	0.0506

6. DISCUSSION OF FINDINGS

This study aims to assist industrial management in detecting the root cause of the problems and concentrating on the areas in need of improvement by defining the most important factors effecting the occupational safety performance. A data triangulation scheme based on the experts' recommendations was used to examine 20 sub-criteria under five categories to achieve this. The analysis of the main criteria in Table 11 reveals that the factors related to *Organization* (C5 with a weight of 0.2175) are the leading cause of occupational accidents and worker health problems. This is followed by the *Safety Climate* dimension (0.2091), *the Regulatory Characteristics dimension (0.2062), the Workplace Environment dimension (0.2061), and the Individual Characteristics dimension* (0.1609).

In our study, sub-criteria Workload Pressure, Number of Subcontractors, Company Reputation, and Client Control fall within the category of organizational factors (Organization). In particular, Work Pressure and the Number of Subcontractors were found to be the most important sub-criteria within this main criterion, based on their calculated weights. These findings align with the conclusions drawn by Mohammadi et al. [60], who asserted that when work pressure or workload significantly surpasses workers' capacity, the safety of tasks becomes challenging. They also emphasized that an increasing number of subcontractors diminishes communication quality and raises monitoring costs, thereby elevating the risk of accidents.

With its importance weight of 0.2092, the significance of Safety Climate in preventing occupational accidents and injuries cannot be overstated. Fang et al. [55] emphasized the crucial role of maintaining an effective organizational safety climate in avoiding accidents. Various authors have also emphasized the importance of elements such as top management commitment, safety communication, worker involvement, attitudes, competence, and the presence of organizational safety policies as integral components that contribute to a favorable safety climate [56]. The safety climate serves as a standard for guiding and influencing appropriate and adaptable safety behavior [12]. Research on safety climate suggests that the messages conveyed by top management, such as their commitment to safety or the enactment of a safety policy within the organization, shape collective values and norms across different hierarchical levels [110]. This concept has garnered strong support in empirical studies within the construction industry [110, 111].

The Rules and Regulations was identified as the third most important main criterion, having a significant role in accident prevention and control. This criterion consists of legal regulations, sanctions and auditing, government incentives, and safety certifications possessed by organizations. The finding that the rules and regulatory characteristics are essential in preventing occupational accidents is consistent with the literature. For instance, Mohammadi et al. [60] argued that while government and industry regulations establish the baseline for safety investments (e.g., equipment), research by Swuste et al. [74] showed that stricter policies with more frequent checks, harsher penalties for non-compliance, and financial consequences for accidents can lead to more effective implementation of those safety standards. While compliance with regulations is crucial in any occupational safety framework, the pronounced importance of regulations in this study may be attributed to the unique context of Turkey, where government intervention plays a significant role in occupational health and safety. This finding suggests that a strong regulatory framework and effective enforcement mechanisms are critical determinants of successful safety outcomes in the Turkish context. Specifically, Gümüştaş and Küskü [112] argued that government incentives to encourage workplace safety measures can reduce occupational accidents and increase safety performance. The authors also noted that the state should take essential actions to establish a safe working environment, including frequent audits and severe sanctions.

As the fourth most important criterion, with an almost identical importance weight to that of Rules and Regulations, Workplace Environment (C4) is identified as an essential determinant of accident prevention. It has four sub-criteria: Physical Condition of Workers, Equipment Conditions, Risky Work Exposure, and Poor Housekeeping. This result aligns with the findings in the literature. The inherent hazards of industrial work, exemplified by working at heights and exposure to excessive noise, are compounded by construction sites' often poor physical environment [113]. Research suggests that this environment is integral to achieving accident prevention, influencing workers' risk perception and, ultimately, their safety behavior through cognitive and emotional pathways [59, 114, 115]. Therefore, occupational safety emphasizes proactive design for safe work and workplaces from the initial planning phase of construction projects [59]. During the initial planning stage, there has been a longstanding emphasis on incorporating safety measures for work and the workplace in generic occupational safety research, as highlighted by [116]. The previous literature also prioritizes this concern, emphasizing the design of comfortable personal protective equipment, safe working processes for hazardous activities [117], and the creation of a secure workplace to deter workers from engaging in unsafe actions [118].

Lastly, the main criterion, Personal Characteristics (C5), was identified as the least important factor among the others existing in the model. However, it still has a considerable importance weight (0.1609) in preventing occupational accidents. Personal Characteristics include Physical Condition, Psychological Well-Being, Safety Competence, and Demographic Factors. The heavy physical demands of construction jobs take a toll on workers' bodies and minds, leading to decreased focus, impaired judgment, and, ultimately, a decline in safety-oriented behavior [60, 65]. This fatigue is further exacerbated by factors outside work hours, like sleep problems, creating a perfect storm for unsafe practices. In some cases, workers may even resort to shortcuts to alleviate physical discomfort, further jeopardizing their safety [59]. Regarding psychological well-being, workers' mental state plays a significant role in shaping their safety behavior. Studies show that emotional exhaustion, negative feelings, and even moderate stress can disrupt attention and decision-making, ultimately leading to unsafe choices around hazards [68, 119, 59]. To ensure a safe work environment, supervisors must be attentive to workers' mental well-being and foster positive relationships that address these concerns.

After calculating global weights, the sub-criterion *Workload Pressure* was found to be the most predominant factor in occupational accidents. This was followed by the factors *Management and Supervisor Commitment to Safety*, *Sanctions and Auditing*, *Number of Subcontractors*, and *Equipment Conditions*.

The Workload Pressure encompasses various elements such as production pressure, work overload, fatigue and burnout, working pace, working time, overtime work, and schedule delay [60]. The presence of multiple pressures on construction sites undermines safety protocols [88]. Construction projects often face significant production pressure due to schedule delays [71, 88]. Under production pressure, management may not prioritize safety [71], leading to production goals taking precedence over safety concerns [88]. Consequently, managers and supervisors may allocate less time and effort to safety measures and may even encourage shortcuts to meet production deadlines, exacerbating existing delays. Moreover, when work pressure surpasses workers' capacities, they struggle to perform tasks safely [71]. Although increasing working pace and hours can temporarily boost productivity and alleviate schedule delays, workers sometimes engage in risky behaviors under pressure to expedite tasks despite being aware of the potential consequences [120]. Instances of work pressure, as described by construction workers, involve supervisors habitually urging them to 'hurry up' [121] or emphasizing the need for swift performance by instructing them to 'rush to complete the work' [122].

After the sub-criterion Workload Pressure, Management and Supervisor Commitment to Safety was found to have the second most important influence on safety performance. It is evident that perceptions of a manager's safety attitude and work behaviors directly influence the behaviors of workers at the managerial level [123, 124]. Hallowell et al. [125] stated that safety performance significantly improves when top management actively participates in safety initiatives. Senior managers should prioritize safety alongside other organizational aspects, such as production, to foster a robust safety culture. Management's dedication

to safety not only sets a positive example for workers but also stands as one of the most crucial factors in promoting safe work behaviors among employees in the construction industry [55, 126].

Sanctions and Auditing appeared as the third most important factor in improving safety performance. This sub-criterion encompasses safety rules, compliance with these rules, sanctions, and audits imposed by regulatory bodies. At a broader level, investments in fundamental safety measures, such as the provision of safety equipment, are dictated by government and industry regulations to uphold the minimum safety standards [54, 127]. Conversely, on a more localized level, Cheng et al. [128] highlighted that a stringent policy, which includes more frequent inspections, increased fines for non-compliance, and higher accident costs, can result in improved adherence to safety standards.

The Number of Subcontractors has the fourth most important impact on safety performance. The pre-qualification process for subcontractors and contractors regarding safety entails evaluating their safety and health performance when selecting them. Once a contract is granted, subcontractors are obligated to adhere to the minimum safety and health standards outlined in the general contractor's program [126]. Additionally, Kang and Ryu [129] observed that workers employed by small enterprises often lack adequate qualifications, leading to a decreased awareness of safety hazards and a higher incidence of occupational accidents. Furthermore, the authors emphasized the challenge of monitoring compliance with safety rules and regulations among an increasing number of subcontractors.

Finally, Equipment Conditions emerged as the fifth most significant sub-criterion, demonstrating a substantial impact on safety outcomes. Consistent monitoring of machinery in industrial settings offers valuable information about its operational status. This proactive approach helps identify faults or malfunctions early, indicating the need for maintenance and thereby preventing potential workplace accidents and injuries. Kang and Ryu [129] emphasized the importance of predictive maintenance in human-machine interaction settings, as it proactively identifies issues before they escalate into accidents. In conclusion, selecting the right equipment, using it correctly, and inspecting it regularly are crucial for achieving optimal efficiency, productivity, and safety.

On the other hand, it is well known that each sector operates with its own unique set of priorities and risk profiles when it comes to occupational safety. Thus, it is essential to evaluate and discuss how findings specific to one sector may be relevant and applicable to others. The findings highlight organizational factors, particularly workload pressure, as the leading contributors to occupational safety performance. This aligns closely with observations by Omidi et al. [31] in the petrochemical industry, where organizational communication and adherence to rules are critical. The importance of a safety climate, encompassing management's commitment, safety communication, and worker involvement, is consistent with Raviv et al. [40] in the construction industry, where a safety climate is vital for mitigating risks in tower crane operations. Omidi et al. [31] also emphasize the role of safety climate in the process industry, noting that top management's dedication significantly improves safety outcomes. Rules and regulations are identified as critical in accident prevention, mirroring findings by Podgórski [44] in occupational health management. The significance of workplace environment factors, such as physical conditions, equipment, and risk exposure, aligns with the study by Zheng et al. [46] in hot and humid environments. The findings underscore the importance of personal characteristics, including workers' physical and psychological well-being. This is in contrast to the article by Unver and Ergenc [32] in the logging sector, where worker morale is a significant risk.

Overall, while management commitment, regulatory compliance, and workplace environment are universally relevant across sectors, this study places significant weight on organizational and workload factors. In contrast, sectors such as healthcare and agriculture emphasize environmental or task-specific risks more.

7. CONCLUSION

This paper aims to define and prioritize the factors that contribute to safety performance. Using the IVPF-AHP methodology, 20 sub-criteria were identified under five main criteria through a literature survey and

recommendations from industrial managers. Using the IVPF-AHP framework, the study identified Workload Pressure, Management and Supervisor Commitment to Safety, Sanctions and Auditing, Number of Subcontractors, and Equipment Conditions as the five most critical factors influencing safety performance. Two of these factors fall under the category of Organization. This result is consistent with the ranking of the main factors, which shows that Organization is the primary factor among others. This result emphasizes the importance of firm-specific features.

Both safety regulations and individual characteristics play significant roles in determining safety performance. When safety rules and procedures are implemented, management can foster employee awareness and comprehension of safety protocols. As organizations evolve, increased employee dedication is likely to establish adherence to rules and procedures as a standard practice rather than something that needs to be enforced. It is the responsibility of the general contractor to ensure that subcontractors adhere to safety protocols and are fully integrated into the project's safety culture. By involving subcontractors as integral participants in the safety management process, communication can be enhanced, and potential misunderstandings can be minimized [126]. According to research findings, it can be anticipated that employees who are engaged and content with their work and perceive safety as a top priority among management, colleagues, and organizations are more likely to exhibit safer behaviors [125]. Therefore, organizations should highlight and convey the message that safety is their top priority.

This study proposes a generic model applicable to various industries, regardless of the company's size. However, occupational safety criteria can vary significantly across different sectors. As a limitation, focusing on one or a few industries may yield more accurate results specific to that domain, although it limits the generalizability of the findings. Additionally, the study's findings may be time-bound and not necessarily applicable to future contexts without regular updates, as occupational safety criteria can evolve due to changes in regulations, technology, or work practices. Moreover, the expertise of the expert panel primarily focused on the construction industry. While this domain-specific knowledge provided valuable insights, it may limit the generalizability of the findings to other sectors. Also, the study was conducted within the Turkish context, characterized by significant government intervention in occupational health and safety. This unique contextual factor may have influenced the findings, particularly the pronounced emphasis on regulations and rules. Additionally, the high prevalence of subcontracting within the Turkish construction industry may have contributed to the specific findings related to this factor. The impact of subcontracting on occupational safety performance may vary considerably across contexts with different subcontracting practices. These limitations should be carefully considered when extrapolating the study's findings to other contexts. Future research should investigate the generalizability of these findings to other industries, countries with varying regulatory frameworks, and contexts with different levels of subcontracting." Finally, the paper might not adequately address cultural or regional variations in occupational safety criteria. What's considered essential in one culture or region may not hold the same weight elsewhere. Thus, the methodology, as numerically illustrated, can be applied to any country to achieve more specific results for each case in focus.

Further studies could explore cross-industry comparisons to identify commonalities and variations in safety criteria, conduct longitudinal analyses to track evolving trends, and incorporate qualitative research methods to gain deeper insights into the underlying factors shaping occupational safety. Moreover, future research could focus on performing criteria weighing on a sectoral basis to understand better how the identified criteria may vary across different sectors. Additionally, examining the impact of emerging technologies, international regulatory frameworks, and psychosocial factors on safety criteria could provide valuable avenues for future research in enhancing workplace safety.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

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