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Occupational Hazards Evaluation in Residential Construction Projects: Novel Sorting Methods Based on *q*-Rung Orthopair Fuzzy Choquet Integral

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Abstract: Despite multiple efforts to improve safety in construction, insufficient hazard identification remains a significant concern. Failure to address these hazards can lead to severe safety incidents that harm workers and a firm's reputation. This problem is especially prevalent in construction small and medium enterprises (SMEs) due to their limited resources, reliance on manual labor, and lack of technical expertise regarding safety concerns. Thus, this study addresses the gap by offering a computational framework that provides a comprehensive evaluation of occupational hazards, considering multiple factors, such as severity, frequency of occurrence, and the likelihood of detection, which are risk dimensions of failure mode effect analysis (FMEA). Notwithstanding the FMEA-based evaluation methods for safety evaluation in the construction sector, drawbacks attributed to the interdependencies of the risk dimensions and the handling of judgment uncertainties are evident. In this work, an extension of the FMEA is developed that assigns an occupational hazard to a risk category under a holistic framework that better addresses the current limitations of the FMEA. In particular, the study offers a two-fold contribution: (1) putting forward the proposed Choquet–FMEA–Sort methods under a *q*-rung orthopair fuzzy set (*q*-ROFS) environment and (2) demonstrating an actual case study in the Philippines that comprehensively evaluates occupational hazards in construction SMEs. Results of a demonstrative case of residential construction projects show that out of the 26 identified occupational hazards, 18 pose a high risk to workers, while the remaining eight pose a moderate risk. High-risk occupational hazards require more attention for mitigation efforts, especially in residential construction SMEs facing resource constraints. The computational framework offered in this work aids decision-makers in identifying high-risk occupational hazards in a more systematic approach. The robustness and stability of the proposed methods were tested using layers of sensitivity and comparative analyses.

Keywords: occupational hazards; FMEA; residential construction; *q*-rung orthopair fuzzy sets; Choquet integral

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1. Introduction

In the construction industry, infrastructures are built to support the activities of the various sectors of the economy [1]. The industry is considered one of the service sectors that significantly influence an economy, demonstrating its criticality to development [2]. In Australia, the construction industry is one of the largest industries contributing significantly to its Gross Domestic Product (GDP) and employing over 1.15 million workers. This contribution, however, was reduced by about 8% in 2020 due to the ongoing COVID-19 pandemic [3]. However, amidst the pandemic in the Philippines, the industry contributed 16.6% of the country's GDP, employing 9.6% of the 45.075 million work force in 2021 [4]. The construction industry comprises about 90% small and medium enterprises (SMEs), has a broad scope, and is vastly diversified [2,5]. The various demands in the industry are primarily provided through individual specialization. For instance, specific contractors with specialized focus handle auxiliary services attached to a construction project. However, updates in regulations requiring more specialized skillsets, while necessary in improving standards, may result in the further division of SMEs' scope of work brought about by costly upgrading, training requirements, and accreditation [6]. In general, the construction industry is conservative, less flexible, and less receptive to changes due to the uncertainty and complexity of construction projects [7]. Additionally, the productivity and output of SMEs are highly affected by the availability of limited skilled workers [8]. They are also known to have limited financial resources and market share with tight profit margins, resulting in inadequate investments in state-of-the-art infrastructures and resources necessary for safety measures [5,9,10].

Construction work is loosely regulated and considered one of the most dangerous industries in developing economies [11], with labor-intensive methods and limited attention to health and safety issues [12]. Construction workers depend vastly only on their individual and peers' experiences in identifying construction hazards [11]. In addition, they feel obliged to make quick decisions in dealing with hazards independently. Workers' response to these situations may not be ideally the safest course as they are influenced by construction production pressure, workflow, and coordination with coworkers, technical heads, and managers' attitudes, among others [11]. The Occupational Safety and Health Administration (OSHA) has tracked injury patterns from different construction projects. Reports indicate that falls are the leading cause of fatalities in the industry, accounting for one-third of all construction worker fatalities [13]. These fall incidences include falls from roofs, ladders, scaffoldings, and other surfaces, resulting in 20% of the absences of construction workers from work. Injuries resulting from struck-by incidents, caught-in/between, and electrical incidents are the major causes of fatal injuries [14]. These four hazards represent the fatal-four hazards widely known in the industry. In response, OSHA has produced and offered free training materials on the fatal-four hazards, currently administered by authorized trainers, trade unions, and employers [15].

Due to workers' vulnerability in construction sites, workplace safety has become particularly interesting in existing literature, offering myriad approaches to dealing with it [16]. These studies, including those associated with (1) safety performance measurement [17,18]; (2) safety program and management [11,19]; (3) human factors [20,21]; (4) technologies [22–25], aimed at improving safety in the construction industry, covering various areas of interests. In China, Liu et al. [17] conducted a cloud model-based safety performance evaluation on prefabricated building projects with multiple factors (e.g., human, material, management, and methods and technical). Similarly, Guo et al. [18] developed and tested a model to better understand construction workers' safety behavior regarding climate and individual factors. Others paid more attention to safety programs and management in examining the multilevel safety culture and environment of new safety programs [19] and understanding the causal mechanisms of unsafe behaviors of construction workers [11]. Studies on human factors exploring workplace environment and climate to human error and behavior also become highlights [20,21]. There has recently been an increased application of digital technologies, such as Building Information Modeling

(BIM), in the construction industry to improve overall planning and monitoring initiatives. Studies varied from integrating real-time construction safety monitoring systems for hazardous gas, which integrate wireless sensor networks with BIM [22], sensing systems for construction backover [23], to real-time vulnerability assessment using image processing and artificial intelligence [25], and unmanned aircraft systems application in construction safety inspection [24].

While different approaches were put forward to improve construction safety, poor hazard recognition remains widespread at all levels. Perlman et al. [26] investigated hazard recognition of construction superintendents, and their findings suggest that despite the superintendents' vast work experience and safety training, they could hardly identify all hazards presented via photographs and the virtual environment. Similarly, 280 construction workers in the US performed a hazard recognition assessment in a study reported by Albert et al. [27]. Results showed that workers could identify only 57% and 18% of fatal-four and non-fatal-four hazards, respectively. Jeelani et al. [28] investigated the improvement of hazard recognition of construction workers trained under personalized recognition training programs in response to the gaps in poor hazard recognition. Results highlighted a 35% increase in detection after an intervention. Meanwhile, Jeelani et al. [29] further investigated visual search patterns using eye-tracking technology of workers participating in hazard recognition activity. Additionally, cognitive demands of construction hazard recognition were measured and investigated by Liao et al. [30]. Despite extensive works in the literature, poor hazard recognition remains prevalent. One dominant cause for alarming injury rates is poor hazard recognition resulting in unintentional exposure and injuries [31], accounting for as high as 50% of work-related safety hazards in a US study [29]. These numbers reveal the significance of hazard recognition concerning incident prevention, which unfortunately draws limited attention from the domain literature. Numerous practices, however, are currently in place and are adopted to encourage construction hazard recognition. Training programs focused on safety knowledge transfer have become a norm for effective hazard management and recognition [32]. However, Namian et al. [33] argued the efficiency of designing these programs with adult learners, which comprise most, if not all, of workers in construction projects.

Despite some interventions, poor hazard recognition skill is still largely concerning in the construction industry [34], where construction workers fail to recognize many safety hazards. These unrecognized safety hazards can lead to unintended exposure and tragic safety incidents [35]. They are also likely to remain unmanaged and can cascade into unexpected safety incidents [36]. Unfortunately, traditional hazard recognition interventions (e.g., job hazard analyses and safety training) have been unable to tackle the industry-wide problem of poor hazard recognition levels. Emerging evidence has demonstrated that traditional hazard recognition interventions have been designed without understanding the challenges workers experience during hazard recognition efforts [35]. This dilemma is more pronounced in construction SMEs, given limited resources, high manual labor, and insufficient attention to safety issues brought about by inadequate technical workers (e.g., safety officers). Moreover, current approaches to hazard recognition in the literature fail to capture overarching information about the hazard under investigation. For example, excessive hand and arm vibration from vibrating power tools may not be detected as a hazard during exposure. However, prolonged exposure to such activity may result in muscle spasms, musculoskeletal disorders, and even hand-arm vibration syndrome [37]. Using the current binary detection approach (i.e., hazard, no hazard) that lacks the dynamic element of hazard exposure, such an activity may not be recognized as a hazard. Thus, obtaining thorough information about a potential hazard may augment current hazard detection approaches, contributing to better management and allocation of targeted safety initiatives. Such a resource-efficient approach is deemed more beneficial to construction SMEs.

Thus, this work offers an approach that evaluates the degree of risk of a hazard rather than assessing it from a binary detection perspective, as current practices suggest. In our proposed approach, a hazard is viewed in multiple dimensions, encompassing its severity, frequency of occurrence, and propensity for detection. This view may be more relevant and comprehensive as it captures detailed information about the hazard's breadth and depth of impact. For instance, the excessive hand and arm vibration from vibrating tools may be less severe; however, its occurrence is high, especially in construction SMEs, but detection is low, which may impact the design of necessary response mechanisms to address the hazard. This approach provides a complete overview of the hazard instead of focusing only on its severity. For this view, the inherent concepts offered by failure mode and effect analysis (FMEA), a tool popular in manufacturing industries [38], help manage such an approach. FMEA is a systematic and structured method of identifying and preventing system, product, and process problems before they occur, assessing their impact and planning corrective actions. Generally, it concentrates on avoiding safety-related incidents, enhancing safety, and increasing overall stakeholder satisfaction. In recent decades, the application of FMEA has been extended to include risk management assessment, even in the construction industry [39,40].

Given the importance of identifying and assessing occupational hazards in the construction industry [41], scholars advocate integrating several methods in statistical modeling, multicriteria decision-making, and expert systems, among others, into the conceptual framework of the FMEA [41]. In the FMEA, failure modes (or hazards in our case) are assessed for severity, occurrence, and detection. A metric known as the "risk priority number" (RPN) is determined via aggregating these factors to obtain a holistic overview of the degree to which the failure modes impact a system (e.g., project). Following the criticality of that single-valued metric, several literature reviews have been reported to investigate, review, and evaluate the primary applications of FMEA and its various extensions to handle as much information in the computational process, especially in detecting and assessing construction hazards. Some FMEA applications in the construction industry include evaluating the construction quality of apartments [42], occupational risks [41,43], factors affecting cost increases [44], delay factors [45], and construction method [46], among others, with the majority of works focusing on project risks [47–52]. Consequently, the recent extensions of FMEA applications intend to address the gaps in the degree of uncertainty and complexity relative to evaluating the factors (i.e., severity, occurrence, and detection) in various construction industry applications. These include the use of the fuzzy analytic hierarchy process (AHP) [47,48], big data [42], mathematical programming [50], Markov chains [53], Pythagorean fuzzy multi-objective optimization based on ratio analysis (MOORA) [43], fuzzy Stepwise Weight Assessment Ratio Analysis (SWARA) and Weighted Aggregated Sum Product Assessment (WASPAS) [52], and hesitant fuzzy sets [51], among others.

Our proposed approach advances the previous FMEA applications in the construction sector in the following ways. First, conceptually, we advance the application of Mete [43] and Dahooie et al. [41] in breadth and width to comprehensively evaluate all relevant hazards, especially in construction SMEs. Secondly, we argue that the use of SWARA or AHP in assigning weights to the FMEA factors may be ill-founded due to the inherent interrelationships of the factors. For instance, excessive hand and arm vibration from vibrating tools may have low severity at the outset. However, such severity likely increases with multiple occurrences over a sustained period. Thus, from a holistic point of view, it is relevant to address the interdependencies of these factors to capture the overarching nature of the impact of such hazards. Along with this view, we adopted the Choquet integral as an effective tool to encompass the relative magnitude of the factors and the magnitude of interactions and dependencies between them. Choquet integral's non-linearity and aggregation strength encompass other ordinary aggregation operations, and it has now become a popular tool for aggregating information. Choquet integral applications include classification [54,55], multi-attribute decision-making (MADM) under a fuzzy environment [56,57], and data modeling [58,59].

Third, the integration of Pythagorean fuzzy sets in Mete [43] and hesitant fuzzy sets in previous works [41,51] is highly motivated by the notion of better capturing the uncertainties inherent in the judgment elicitation process. However, despite these extensions, decision-makers have limited space to elicit ambiguity and imprecision, which are highly relevant in most applications. Thus, in this work, the integration of q-rung orthopair fuzzy sets (q-ROFS) within the computational framework of the FMEA to handle hazard evaluation in the construction sector is proposed. The notion of q-ROFS introduced by Yager [60] augments the limitation of previously adopted tools (e.g., fuzzy set theory, intuitionistic fuzzy sets, Pythagorean fuzzy sets, Fermatean fuzzy sets) in handling judgment uncertainties brought about by incomplete information, lack of understanding of the domain problem, and the idiosyncrasies at which decisions are made. Finally, due to the comprehensive list of occupational hazards this work attempts to assess, a multicriteria sorting (MCS) approach is deemed more relevant. An MCS problem assigns the hazards to pre-determined categories, a process more suitable for engaging in identifying a subset of these hazards that requires more attention. Thus, this work offers two significant contributions to the literature: (1) a comprehensive evaluation of occupational hazards prominent in construction SMEs and (2) the proposed Choquet–FMEA–Sort under a q-ROFS environment. An actual case study on residential construction projects is carried out to demonstrate our contributions. The insights of the case study and the proposed method provide inputs to designing targeted initiatives for effective safety management and improved hazard recognition.

The remainder of the article is arranged as follows. Section 2 reviews the domain literature on construction hazards. Section 3 presents some relevant preliminary concepts of q-ROFS, q-ROF entropy, and the Choquet integral. Section 4 outlines the case environment and demonstrates the application of the proposed methodologies in sorting various occupational hazards in residential construction workplaces. Sensitivity and comparative analyses are offered in Section 5 to evaluate the variations of the findings given some changes in parameters and to compare how the proposed approach augments similar tools. The findings and their insights are discussed in Section 6. It ends with concluding remarks and identifying future works in Section 7.

2. Literature Review

Construction projects are implemented in a complex and dynamic environment, often exposed to vast uncertainties [61]. One of the effects of such complexity is the presence of construction hazards. Succinctly, construction hazards are situations in construction sites that may threaten life, health, property, and the environment. An extant study in the literature highlighted several methodologies for risk mitigation and prevention of such hazards. One of the most prominent methods with a robust framework for evaluating failure modes is the FMEA approach [49]. In its application in the construction industry, the "failure modes" are identified as construction hazards. Thus, identifying the "failure modes" with the highest priority offers crucial elimination in eliminating the hazard and its associated consequences (i.e., accidents).

Working on a scaffold/stair and working at a height above two meters are activity-based hazards that may result in falling incidents. According to OSHA, these fall incidences constitute 20% of the absences of construction workers from work. In an empirical work by Kaskutas et al. [62], they found that fall prevention and safety communication training for supervisors will positively impact the safety of all workers on the construction site. Most prominent among construction SMEs, labor-intensive activities include handling manual non-electric tools (e.g., hammer, saw, chisel, pliers, shovel), using hydraulic and power tools (e.g., cutter, drill, grinder), utilizing vibrating power tools (e.g., jackhammers, compactors, hand drills), and prolonged and repeated lifting and carrying of objects heavier than 20 kg. These tasks significantly expose workers to injury due to repetitive motion, applying significant physical effort, assuming uncomfortable body positions, constant contact with vibrations, and encountering force [61]. Hence, several methods have been utilized to investigate the severity of these activities and ergonomic solutions to mitigate the impact. Zhu et al. [63] mapped out existing exoskeletal technologies to aid manual handling tasks in construction. Dale et al. [64] pointed out that the implementation of participatory ergonomic intervention in construction SMEs is hindered by their lack of resources or organizational structure to support such a program. They emphasized the importance of the inclusion of both the upper management and construction workers in the intervention program to produce significant results.

On the other hand, electricity, machinery, and equipment are popular physical hazards usually involved in construction works. Specifically, these hazards include carrying out electrical wiring installation and troubleshooting, conducting mechanical/electrical maintenance and driving vehicles on the construction site. Anderson et al. [65] identified 2454 construction incidents related to electrical safety. They also categorized these incidents wherein a large number documented as general physical injury involving laceration, abrasion, strain or stress, and collision by an object. Meanwhile, the second largest cause of incidents is attributed to near-miss electrical incidents, which are linked to the following causes: (a) documentation/procedure error, (b) lockout/tagout incidents, (c) accidentally cut conduit, and (d) voltage found after lockout/tagout. For a more comprehensive discussion, the reader is advised to direct to Anderson et al. [65]. Meanwhile, Floyd [66] provided a guide on applying the hierarchy of electricity hazard control measures.

Construction works are inherently involved with harmful dust, gases, and fumes [67]. They come from various activities, such as operating hydraulic and power tools (e.g., cutter, drill, grinder), applying lacquer/paint thinner, using airborne fibers and materials (e.g., asbestos, roofing insulation, fiberglass) in roof works, and handling cement, sand, gravel, and other concrete aggregates. Calvert et al. [67] reported that the construction industry has a relatively high prevalence rate of workers exposed to skin contact with chemicals, secondhand smoke and vapors, gas, dust, and fumes in comparison to other industries. On a large scale, dust pollution due to construction activities does not only adversely impact workers' health but also the environment. Wu et al. [68] emphasized this environmental concern in their investigation of the current dust prevention strategies of construction firms in China. Aside from those hazardous working conditions, welding/hot work and manual excavation should receive special attention. The US fire department responded to an estimated 4580 structure fires involving hot work per year from 2014–2018 [69]. Following its prevalence and criticality, OSHA provides proactive safety guidelines for such activities [13].

Antwi-Afari et al. [70] examined the variability of a worker's gait pattern in hazardous and non-hazardous conditions. The study proposes a novel, non-intrusive hazard identification method involving a wearable insole pressure system to formulate proactive incident-prevention intervention programs. Hazardous workplace conditions involve working on uneven surfaces, working in the workplace with cables, dangling wires, cut wood, and scrap metals scattered around, working on ground/lower floors with possible flying and falling objects, working in a workplace with protruding objects (e.g., nails), exposure to the extreme noise level in the workplace, and working within a danger zone (e.g., a possible collision with equipment). Notably, workplace injury results from the interaction between the workers and a set of elements in the workplace (e.g., uneven surface, material at height, wind) [71]. Hence, it is important to consider every workplace element in designing safety standards. BIM is a widely utilized efficient tool that accurately designs a digital model of a project's physical structure that captures every element in the setting. Thus, aside from digitizing the structure of a construction project, it has also been used to monitor and mitigate workplace hazards, where Hallowell et al. [72] integrated the attribute-based safety risk data into the BIM.

Construction activities often occur in an unprotected environment, where the workers are exposed to the sun's extreme heat [73] or are vulnerable to animal and insect bites. Other hazards in an unprotected environment include clearing or cutting poisonous plants and working with structural lumber. Statistical data for fatal injuries from insect bites and animal attacks in the construction and extraction industry were reported in 951 cases in 2011–2021 [74]. On the other hand, documented data identified 986 cases wherein workers were fatally injured due to exposure to environmental heat stress in 2011–2021 [74]. Strategies to mitigate the physical and mental health impact of exposure to extreme weather conditions have been provided by the National Institute for Occupational Safety and Health [75]. The implementation of such strategies has been expanded by Karthick et al. [73].

3. Preliminaries

This section details the preliminary concepts of q-ROFS, q-ROF entropy, and the Choquet integral.

3.1. The q-Rung Orthopair Fuzzy Sets

The q-ROFS was proposed by Yager [60] as a computational approach that handles uncertainty inherent in the decision-making process. Furthermore, Yager [60] emphasized that q-ROFS is more precise and flexible in handling vague judgments of decision-makers compared to prior tools. The definition, basic operations, score and accuracy function, and distance measure of q-ROFS are defined as follows.

Definition 1 ([60])**.** *Let X be a non-empty universe of discourse. The q-ROFS $\mathcal{Q}$ is presented as*

$$\mathcal{Q} = \{\langle x, \mu_{\mathcal{Q}}(x), \nu_{\mathcal{Q}}(x)\rangle : x \in X\} \quad (1)$$

where the functions $\mu_{\mathcal{Q}}(x) : X \longrightarrow [0,1]$ and $\nu_{\mathcal{Q}}(x) : X \longrightarrow [0,1]$ refer to the degree of membership and degree of non-membership of $x \in X$ in $\mathcal{Q}$, respectively, such that $0 \leq (\mu_{\mathcal{Q}}(x))^q + (\nu_{\mathcal{Q}}(x))^q \leq 1$ for some finite $q \geq 1$, $\forall x \in X$. The degree of indeterminacy $\pi_{\mathcal{Q}}$ is defined as follows:

$$\pi_{\mathcal{Q}}(x) = \left(1 - (\mu_{\mathcal{Q}}(x))^q - (\nu_{\mathcal{Q}}(x))^q\right)^{\frac{1}{q}} \quad (2)$$

For convenience, $\langle \mu_{\mathcal{Q}}(x), \nu_{\mathcal{Q}}(x)\rangle$ is referred to as a q-rung orthopair fuzzy number (q-ROFN) on $\mathbb{R}$, and is written as $\mathcal{Q} = (\mu_{\mathcal{Q}}, \nu_{\mathcal{Q}})$.

Some interesting results were put forward by Yager [60]. For instance,

Theorem 1 ([60])**.** *If $(\mu_{\mathcal{Q}}, \nu_{\mathcal{Q}})$ is a valid q_1-rung orthopair membership grade, then it is a valid q_2-rung orthopair membership grade for $q_2 > q_1$.*

Proof. Since $(\mu_{\mathcal{Q}})^{q_1} + (\nu_{\mathcal{Q}})^{q_1} \leq 1$, then $(\mu_{\mathcal{Q}})^{q_2} + (\nu_{\mathcal{Q}})^{q_2} \leq 1$ for $q_2 > q_1$. Thus, $(\mu_{\mathcal{Q}}, \nu_{\mathcal{Q}})$ is a q_2-rung orthopair membership grade. □

Theorem 1 implies an important Corollary, as shown below.

Corollary 1. *For $q_2 > q_1$, all q_1-rung orthopair fuzzy sets are q_2-rung orthopair fuzzy sets.*

To illustrate, suppose $\mu_{\mathcal{Q}} = 0.85$ and $\nu_{\mathcal{Q}} = 0.25$. For $q = 2$, the condition $0.85^2 + 0.25^2 \leq 1$ is satisfied; therefore, $(0.85, 0.25)$ is a valid orthopair membership grade. The same is valid for $q = 3$, since $0.85^3 + 0.25^3 \leq 1$. Thus, $(0.85, 0.25)$ is also a 3-rung orthopair membership grade.

The following presents certain operations of q-ROFS.

Definition 2 ([76,77])**.** *Let $\ddot{q}_1 = (\mu_1, v_1)$ and $\ddot{q}_2 = (\mu_2, v_2)$ be two q-ROFNs and $\lambda > 0$, then corresponding operations are defined as follows:*

$$\ddot{q}_1^{\,c} = (v_1, \mu_1) \quad (3)$$

$$\ddot{q}_1 \cup \ddot{q}_2 = (\mu_1 \vee \mu_2, v_1 \wedge v_2) \quad (4)$$

$$\ddot{q}_1 \cap \ddot{q}_2 = (\mu_1 \wedge \mu_2, v_1 \wedge v_2) \quad (5)$$

$$\ddot{q}_1 \bigoplus \ddot{q}_2 = \left(\sqrt[q]{\mu_1^q + \mu_2^q - \mu_1^q \mu_2^q}, v_1 v_2 \right) \quad (6)$$

$$\ddot{q}_1 \otimes \ddot{q}_2 = \left(\mu_1 \mu_2, \sqrt[q]{v_1^q + v_2^q - v_1^q v_2^q} \right) \quad (7)$$

$$\lambda \ddot{q}_1 = \left(\sqrt[q]{1 - \left(1 - \mu_1^q\right)^{\lambda}}, v_1^{\lambda} \right) \quad (8)$$

$$\ddot{q}_1{}^{\lambda} = \left(\mu_1^{\lambda}, \sqrt[q]{1 - \left(1 - \mu_1^q\right)^{\lambda}} \right) \quad (9)$$

$$\ddot{q}_1 \ominus \ddot{q}_2 = \left(\mu_1 v_2, \sqrt[q]{v_1^q + \mu_2^q - v_1^q \mu_2^q} \right) \quad (10)$$

$$\ddot{q}_1 \oslash \ddot{q}_2 = \left(\sqrt[q]{\mu_1^q + v_2^q - \mu_1^q v_2^q}, v_1 \mu_2 \right) \quad (11)$$

where $\ddot{q}_1^c$ is the complement of $\ddot{q}_1$.

Definition 3 ([76]). *Suppose that $\ddot{q} = (\mu, \nu)$ is a q-ROFN, then a score function $\mathbb{S}(\ddot{q})$ is defined as*

$$\mathbb{S}(\ddot{q}) = \mu^q - \nu^q \quad (12)$$

Definition 4 ([76]). *Suppose that $\ddot{q} = (\mu, \nu)$ is a q-ROFN, then an accuracy function $\mathbb{H}(\ddot{q})$ is defined as*

$$\mathbb{H}(\ddot{q}) = \mu^q + \nu^q \quad (13)$$

Theorem 2 ([76]). *For any two q-ROFNs $\ddot{q}_1 = (\mu_1, v_1)$, and $\ddot{q}_2 = (\mu_2, v_2)$, a comparison method using the score function $\mathbb{S}$ and $\mathbb{H}$ is defined as follows:*

(1) If $\mathbb{S}(\ddot{q}_1) > \mathbb{S}(\ddot{q}_2)$, then $\ddot{q}_1 > \ddot{q}_2$;
(2) If $\mathbb{S}(\ddot{q}_1) < \mathbb{S}(\ddot{q}_2)$, then $\ddot{q}_1 < \ddot{q}_2$;
(3) If $\mathbb{S}(\ddot{q}_1) = \mathbb{S}(\ddot{q}_2)$, then If $\mathbb{H}(\ddot{q}_1) > \mathbb{H}(\ddot{q}_2)$, then $\ddot{q}_1 > \ddot{q}_2$; If $\mathbb{H}(\ddot{q}_1) = \mathbb{H}(\ddot{q}_2)$, then $\ddot{q}_1 = \ddot{q}_2$.

Theorem 2 allows for the ordering of q-ROFNs, which has a vital role in various areas of applications, especially in MADM. However, some limitations exist for the score and accuracy functions of Liu and Wang [76], prompting others in the literature to offer another formulation. Listed in Table 1 are the existing score function formulations. Note that the list is not comprehensive.

Table 1. Selected existing score functions.

Proponents	Score Functions
Peng et al. [78]	$\mathbb{S}(\ddot{q}) = \frac{1}{2}\left(\mu^2 + \left(\sqrt[q]{1 - v^q}\right)^2\right)$
Jana et al. [79] and Wei et al. [80]	$\mathbb{S}_{JW}(\ddot{q}) = \frac{\mu^q - v^q + 1}{2}$
Banerjee et al. [81]	$\mathbb{S}_b(\ddot{q}) = \frac{1 - v^q}{2 - \mu^q - v^q}$
Farhadinia and Liao [82]	$\mathbb{S}_{fl}(\ddot{q}) = \mu^q + \lambda \pi^q$
Rani and Mishra [83]	$\mathbb{S}_{rm}(\ddot{q}) = \mu^q(1 + \pi)$

In addition to the basic operations of the q-ROFNs introduced by Liu and Wang [76], they also proposed the aggregation operator, namely q-rung orthopair fuzzy weighted averaging operator (q-ROFWA), which is defined as follows.

Theorem 3. *Suppose that $\ddot{q}_k = \left(\mu_{\ddot{q}_k}, \nu_{\ddot{q}_k}\right)(k = 1, 2, \ldots, n)$ is a collection of q-ROFNs, then the q-ROFWA is obtained by*

$$q\text{-ROFWA}(\ddot{q}_1, \ddot{q}_2, \ldots, \ddot{q}_n) = \left(\sqrt[q]{\left(1 - \prod_{k=1}^{n}\left(1 - \mu_{\ddot{q}_k}^{q}\right)^{\omega_k}\right)}, \prod_{k=1}^{n} \nu_{\ddot{q}_k}^{\omega_k}\right) \tag{14}$$

where $\omega_k > 0$ $(\forall k)$ and $\sum_{k=1}^{n} \omega_k = 1$. Here, ω_k denotes the weight assigned to $\ddot{q}_k$.

Aside from the basic operations and aggregation operator for q-ROF, distance measures that handle q-ROFS have also been introduced in the literature. One of these measures is the Euclidean distance. The Euclidean distance measure is based on the idea that every instance in the dataset can be represented as a point in a dimensional space known as a 'Euclidean space.' It measures the actual straight-line distance between two points in a Euclidean space.

The Euclidean distance measure $d_{qROF}(\alpha_1, \alpha_2)$ between any two q-ROFS α_1 and α_2 can be defined as follows.

Definition 5 ([84])**.** *Let $\alpha_i = (\mu_{\alpha_i}, \nu_{\alpha_i})$ and $\beta_i = (\mu_{\beta_i}, \nu_{\beta_i})$ be two sets of q-ROFS in X where $i = 1, \ldots, n$. Then, the Euclidean distance measure $d_{qROF}(\alpha_i, \beta_i)$ is defined as*

$$d_{qROF}(\alpha_i, \beta_i) = \left(\frac{1}{2n}\sum_{i \in X}\left(\left|\mu_{\alpha_i}^{q} - \mu_{\beta_i}^{q}\right|^2 + \left|\nu_{\alpha_i}^{q} - \nu_{\beta_i}^{q}\right|^2\right)\right)^{\frac{1}{2}} \tag{15}$$

Suppose that ω_i is the weight of $i \in X$ and $\sum_{i=1}^{n} \omega_i = 1 (0 \le \omega_i \le 1)$, we can define the weighted Euclidean distance measure $d_{wqROF}(\alpha_i, \beta_i)$ between two q-ROFS α_i and β_i as follows:

$$d_{wqROF}(\alpha_i, \beta_i) = \left(\frac{1}{2}\sum_{i \in X}\omega_i\left(\left|\mu_{\alpha_i}{}^{q} - \mu_{\beta_i}{}^{q}\right|^2 + \left|\nu_{\alpha_i}{}^{q} - \nu_{\beta_i}{}^{q}\right|^2\right)\right)^{\frac{1}{2}} \tag{16}$$

Theorem 4. *Suppose that α_i and β_i $(i = 1, \ldots, n)$ are two sets of q-ROFS in X, such that $\alpha_i = (\mu_{\alpha_i}, \nu_{\alpha_i})$ and $\beta_i = (\mu_{\beta_i}, \nu_{\beta_i})$. Then, the weighted Euclidean distance measure $d_{wqROF}(\alpha_i, \beta_i)$ satisfies the following properties:*

(1) $0 \le d_{wqROF}(\alpha_i, \beta_i) \le 1$,
(2) $d_{wqROF}(\alpha_i, \beta_i) = d_{wqROF}(\beta_i, \alpha_i)$,
(3) $d_{wqROF}(\alpha_i, \beta_i) = 0$, *if an only if* $\alpha_i = \beta_i$, *i.e.*, $\mu_{\alpha_i} = \mu_{\beta_i}$ *and* $\nu_{\alpha_i} = \nu_{\beta_i}$.

3.2. q-ROF Entropy and Cross-Entropy

The entropy method, derived from the concept of Shannon entropy, assesses the content of the information of a given evaluation [85]. In a MADM problem, entropy can be utilized to evaluate the criterion [86] by measuring the diversity of information. Information entropy associated with a given criterion j denotes the degree of discriminability of the alternatives on that criterion. Hence, more considerable weight is assigned to the criterion with higher criterion data [87]. Liang et al. [88] introduced the entropy and cross-entropy measure for q-ROFS.

Definition 6 ([88]). *Let $\ddot{q} = \left(\mu_{\ddot{q}}, \nu_{\ddot{q}}\right)$ be a q-ROFS, then the entropy of $\ddot{q}$, denoted as $E(\ddot{q})$ is defined as,*

$$E(\ddot{q}) = \frac{1}{\sqrt{2}-1}\left(\sin\left(\frac{\pi}{4}\left(1+\mu_{\ddot{q}}^{q}-\nu_{\ddot{q}}^{q}\right)\right)+\sin\left(\frac{\pi}{4}\left(1-\mu_{\ddot{q}}^{q}+\nu_{\ddot{q}}^{q}\right)\right)-1\right) \tag{17}$$

where $E : \ddot{q} \longrightarrow [0,1]$.

Definition 7 ([88]). *Suppose that $\ddot{q}_1 = \left(\mu_{\ddot{q}_1}, v_{\ddot{q}_1}\right)$, and $\ddot{q}_2 = \left(\mu_{\ddot{q}_2}, v_{\ddot{q}_2}\right)$ are two q-ROFS. Then, the cross entropy of $\ddot{q}_1$ and $\ddot{q}_2$ denoted as $CE(\ddot{q}_1, \ddot{q}_2)$ where $1 < p \leq 2$ is,*

$$CE(\ddot{q}_1,\ddot{q}_2) = \frac{1}{1-2^{1-p}}\left(\frac{\mu_{\ddot{q}_1}^{pq}+\mu_{\ddot{q}_2}^{pq}}{2}-\left(\frac{\mu_{\ddot{q}_1}^{pq}+\mu_{\ddot{q}_2}^{pq}}{2}\right)^{p}+\frac{\nu_{\ddot{q}_1}^{pq}+\nu_{\ddot{q}_2}^{pq}}{2}-\left(\frac{\nu_{\ddot{q}_1}^{q}+\nu_{\ddot{q}_2}^{q}}{2}\right)^{p}+\frac{\pi_{\ddot{q}_1}^{pq}+\pi_{\ddot{q}_2}^{pq}}{2}-\left(\frac{\pi_{\ddot{q}_1}^{q}+\pi_{\ddot{q}_2}^{q}}{2}\right)^{p}\right) \tag{18}$$

In MADM, the criterion that provides more information is considered more important. Hence, the average combination entropy of a criterion is defined as follows.

Definition 8 ([88]). *Suppose $A = \{a_1, a_2, \ldots, a_m\}$ be the set of alternatives and $C = \{c_1, c_2, \ldots, c_n\}$ be the set of criteria. The evaluation of alternative a_i with respect to the criterion c_j is represented by a q-ROSF $\ddot{q}_{ij} = \left(\mu_{\ddot{q}_{ij}}, \nu_{\ddot{q}_{ij}}\right)$. Then, the average combination entropy of a criterion denoted as $I(c_j)$ can be calculated as,*

$$I(c_j) = \frac{1}{2m}\sum_{i=1}^{m}\left(\left(1-E\left(\ddot{q}_{ij}\right)\right)+\frac{1}{m-1}\sum_{\theta=1,\theta\neq 1}^{m} CE\left(\ddot{q}_{ij},\ddot{q}_{\theta j}\right)\right) \tag{19}$$

3.3. Fuzzy Measures and q-ROF Choquet Integral

The Choquet integral operator of Murofushi and Sugeno [89] is widely considered an aggregation operator that captures the inherent interdependencies and interactions among the elements through fuzzy measures [90,91]. For brevity, only the overview of fuzzy measures and Choquet integral concepts are described in this section.

Definition 9. *A fuzzy measure μ on a set X is a set function $\mu : \mathcal{P}(X) \longrightarrow [0,1]$ and satisfies the following:*

(i) *Boundary conditions: $\mu(\varnothing) = 0$ and $\mu(X) = 1$,*
(ii) *Monotonicity: If $A, B \in \mathcal{P}(X)$, and $A \subseteq B$, then $\mu(A) \leq \mu(B)$.*

To calculate the fuzzy measure among the set of elements, λ-fuzzy measure was introduced by Sugeno (1974), wherein

$$\mu(A \cup B) = \mu(A) + \mu(B) + \lambda\mu(A)\mu(B), \lambda \in [-1,\infty), \forall A, B \in \mathcal{P}(X), A \cap B = \varnothing \tag{20}$$

Parameter λ determines the interaction between the elements. If $X = \{x_1, x_2, \ldots, x_n\}$, then λ satisfies Equation (21).

$$\mu(X) = \frac{1}{\lambda}\left(\prod_{i=1}^{n}[1+\lambda\mu(x_i)]-1\right), \lambda \neq 0 \tag{21}$$

The fuzzy density of the subset containing a single element x_i is denoted by $\mu(x_i)$. For every subset $C \in \mathcal{P}(X)$, we have

$$\mu(C) = \begin{cases} \frac{1}{\lambda}\left(\prod\limits_{\S_i \in C}[1+\lambda\mu(x_i)] - 1\right) & \text{if}\lambda \neq 0, \\ \sum\limits_{\S_i \in C} \mu(x_i) & \text{if}\lambda = 0. \end{cases} \tag{22}$$

Thus, λ can be determined from the condition $\mu(X) = 1$, that is,

$$\lambda + 1 = \prod_{i=1}^{n}(1+\lambda\mu(x_i)) \tag{23}$$

Definition 10 ([92])**.** *Let f be a real-valued function and μ be a fuzzy measure on a set $X = \{x_1, x_2, \ldots, x_n\}$, then the discrete Choquet integral of f with respect to μ is defined as follows,*

$$C\mu(f) = \sum_{i=1}^{n}\left[\mu\left(A_{(i)}\right) - \mu\left(A_{(i-1)}\right)\right] f\left(x_{(i)}\right) \tag{24}$$

where (i) represents a permutation on X such that $f\left(x_{(i)}\right) \geq f\left(x_{(i+1)}\right)$, $i = 1,2,\ldots,n-1$ and $A_{(i)} = \left\{x_{(1)}, x_{(2)}, \ldots, x_{(i)}\right\}$, $A_{(0)} = \varnothing$.

To capture the uncertainty and vagueness of eliciting judgment in a decision-making problem, various extensions of the Choquet integral with the different generalizations of fuzzy sets have also been explored in the literature, including intuitionistic fuzzy Choquet integral [93], Pythagorean fuzzy Choquet integral [57], interval-valued intuitionistic hesitant Choquet integral [94], and the fuzzy grey Choquet integral [95]. Among the considered fuzzy sets, q-ROFS offers a broader range of decision space for uncertainty. Hence, to utilize this strength of q-ROFS, Liang et al. [88] introduced the Choquet integral for q-ROFS. The Choquet integral operation is discussed as follows:

Definition 11. *Let α be a q-ROF evaluation on X, and μ be a fuzzy measure on X. Then, the q-ROF Choquet integral (q-ROFCI) of α with respect to μ is defined as*

$$q\text{-ROFCI}\mu(\alpha) = \left(\sqrt[q]{1 - \prod_{i=1}^{n}\left(1 - u\left(x_{(i)}\right)^{q}\right)^{\mu(X_{(i)}) - \mu(X_{(i+1)})}}, \prod_{i=1}^{n} \nu\left(x_{(i)}\right)^{\mu(X_{(i)}) - \mu(X_{(i+1)})}\right) \tag{25}$$

where $\alpha\left(x_{(i)}\right) = \left(u\left(x_{(i)}\right), \nu\left(x_{(i)}\right)\right)$. Furthermore, (i) represents a permutation on X according to a monotonous order that $\alpha\left(x_{(i)}\right) \leq \alpha\left(x_{(n)}\right)$, $i = 1,2,\ldots,n-1$ and $A_{(i)} = \left\{x_{(1)}, x_{(2)}, \ldots, x_{(i)}\right\}$, $A_{(n+1)} = \varnothing$.

4. Methodology

This section presents the proposed methodologies and their application in sorting various occupational hazards in residential construction projects. Figure 1 shows the thematic framework of the study. The construction hazards were assessed and examined with reference to the three risk dimensions: severity, detection, and occurrence. The aggregate scores for each risk dimension would determine its classification, whether a certain construction hazard is of high, medium, or low risk.

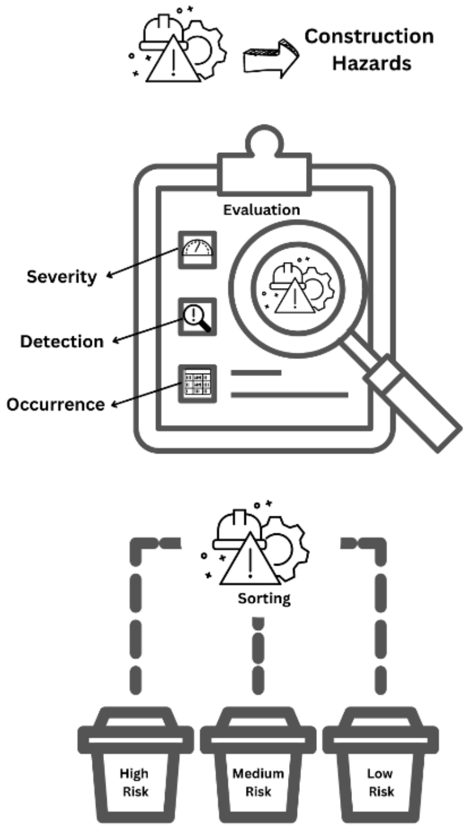

Figure 1. The thematic framework.

4.1. The Proposed Methodologies

In this section, the proposed methodologies are presented, wherein the RPN of the FMEA method was obtained using the q-ROFCI to capture uncertainty in the decision-making process and the interdependencies of the risk dimensions of FMEA. Moreover, two methods of sorting alternatives based on the resulting q-ROF RPN are introduced. As shown in Figure 2, three phases are involved in the proposed methodologies. Phase I calculates the coefficient of each risk dimension of FMEA using q-ROF entropy and cross-entropy, while Phase II obtains the q-ROF RPN. On the other hand, Phase III sorts the alternatives according to their corresponding q-ROF RPN. The steps involved in the proposed methodologies are detailed as follows.

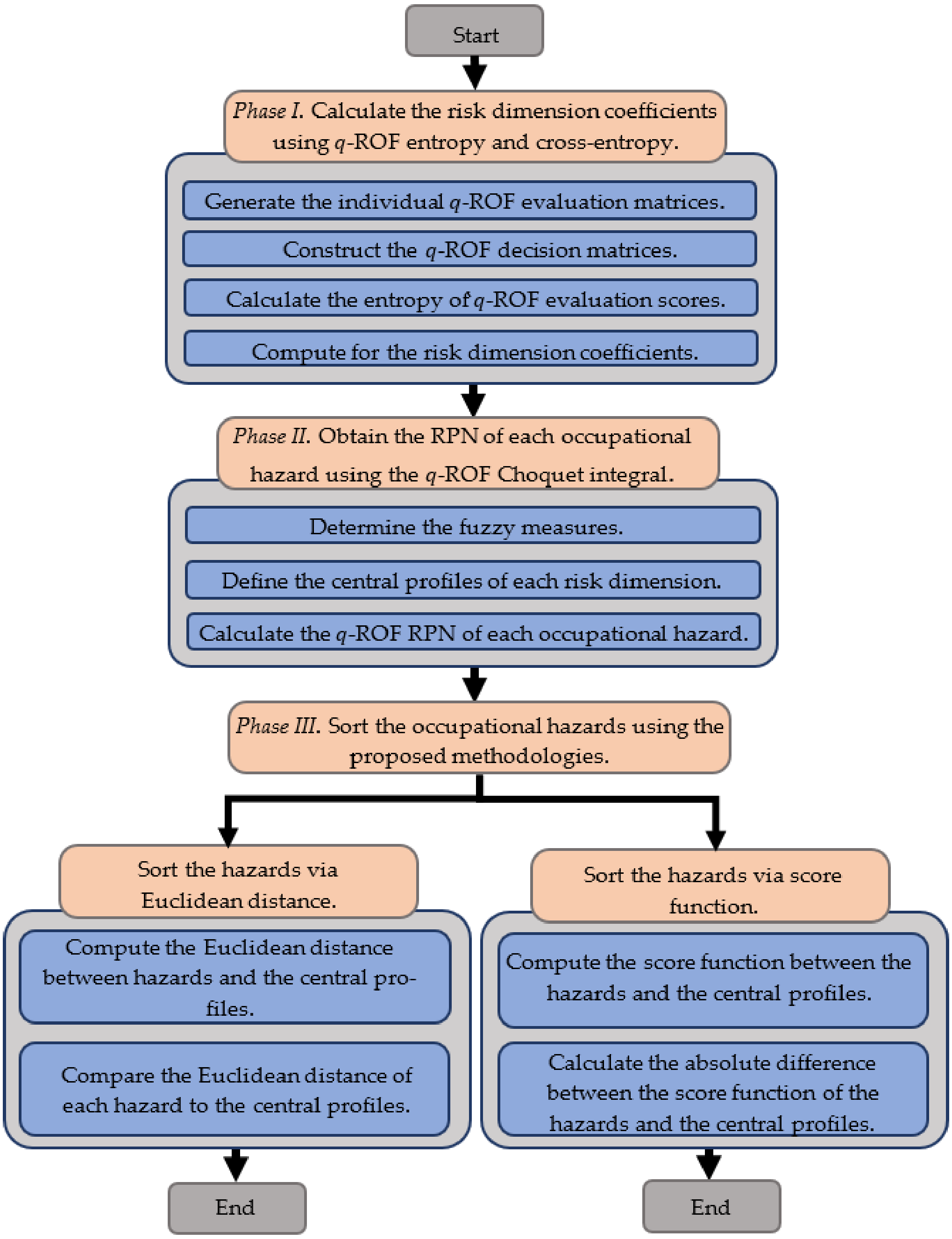

Figure 2. The proposed methodologies.

4.1.1. Phase I—Calculate the Risk Dimension Coefficients Using q-ROF Entropy and Cross-Entropy

Step 1. In FMEA, the set of failure modes is evaluated under the set of risk dimensions (i.e., severity, detection, occurrence). These failure modes (contextually, occupational hazards) are determined through a focus group discussion, literature survey, or a standardized list. An evaluation matrix $X = (x_{ij})_{m \times n}$ is then constructed, wherein x_{ij} is the evaluation of ith failure mode to jth risk dimension.

Step 2. Construct the q-ROF decision matrix. Using a pre-defined linguistic scale, the evaluation matrix X is then transformed into q-ROF $Q = (q_{ij})_{m \times n}$, where $q_{ij} = (u_{ij}, v_{ij})$ and $\pi_{ij} = \left(1 - u_{ij}^q - v_{ij}^q\right)^{\frac{1}{q}}$.

Step 3. Calculate the entropy of the q-ROF evaluation q_{ij}, denoted as $E(q_{ij})$ and the cross-entropy among failure modes denoted as $CE(a_{ij}, a_{\theta j})$, where $\theta \in i, \theta \neq i$. The $E(q_{ij})$ and $CE(a_{ij}, a_{\theta j})$ are obtained using Equation (17) and Equation (18), respectively.

Step 4. Compute the risk dimension coefficient. The average combination entropy, denoted as the coefficient or fuzzy density of jth risk dimension, is calculated using Equation (19).

4.1.2. Phase II—Obtain the RPN of Each Failure Mode Using the q-ROF Choquet Integral

Step 5. Determine the fuzzy measures. The fuzzy measure of each failure mode is obtained using the parameter λ, which is calculated using Equation (23). Then, the fuzzy density of jth risk dimension is determined using Equation (22).

Step 6. Define the central profiles of each risk dimension.

The set of $A = \{a_1, \ldots, a_i, \ldots, a_m\}$ failure modes are to be sorted with respect to the set $C = \{c_1, \ldots, c_j, \ldots, c_n\}$ of risk dimensions, into ordered $\mathscr{K} = \{\hslash_1, \ldots, \hslash_f, \ldots, \hslash_F\}$ categories, where $\hslash_1 \rhd \ldots \rhd \hslash_f \rhd \ldots \rhd \hslash_F$. The categories are characterized by a set of $P = \{p_f : f = 1, \ldots, F\}$ central profiles. The central profiles are used to construct the augmented evaluation matrix $\widetilde{Q} = \left(\widetilde{q}_{ij}\right)_{\widetilde{m} \times n}$, wherein $\widetilde{m} = m + f$.

Step 7. Calculate the q-ROF RPN of each failure mode. The RPN of each failure mode is obtained using the q-ROFCI as defined in Equation (25).

4.1.3. Phase III—Sort the Failure Modes Using the Proposed Methodologies

Method 1—Sorting Using the Euclidean Distance

Step 8. Compute the Euclidean distance between the failure modes and the central profiles. The Euclidean distance denoted is $D\left(a_i, p_f\right)$, as illustrated in Equation (15).

Step 9. Compare the Euclidean distance of each failure mode to the central profiles. Assign failure modes to predetermined categories using the resulting Euclidean distance. The following Algorithm 1 assigns ith alternative to fth category.

Algorithm 1: Sorting failure modes via Euclidean distance

Start
for $i = 1, \ldots, m$
  for $f = 1, \ldots, K$
    if $D\left(a_i, p_f\right) \leq D\left(a_i, p_{f+1}\right) < \ldots < D(a_i, p_K)$
      then $a_i \in \hslash_f$
  end for
end for
End

Method 2—Sorting via Score Function

Step 11. Compute the score function between the failure modes and the central profiles. The score function is denoted as $S(a_i)$, defined by Jana et al. [79].

Step 12. Calculate the absolute difference between the score function of the failure modes and the central profiles, denoted as $T\left(a_i, p_f\right) = \left|S(a_i) - S\left(p_f\right)\right|$. Then Algorithm 2 assigns ith alternative to fth category.

Algorithm 2. Sort alternatives via the score function

Start
for $i = 1, \ldots, m$
  for $f = 1, \ldots, K$
  if $T\left(a_i, p_f\right) \leq T\left(a_i, p_{f+1}\right) < \ldots < T(a_i, p_K)$
    then $a_i \in \hbar_f$
end for
end for
End

4.2. Application of the Proposed Approach in Evaluating the Risk of Occupational Hazards in Residential Construction Projects

In the Philippines, the Philippine Contractors Accreditation Board (PCAB) endorses and issues PCAB licenses to contractors. PCAB licenses signify the company's capability and accountability in implementing projects. The license is mandatory in all government projects but is optional for privately-owned projects subject to the owner's preference. Furthermore, the Department of Labor and Employment (DOLE), the Philippine government arm overseeing labor matters in the private sector, requires construction projects to implement a construction safety and health program in place to ensure the protection and welfare of workers and the general public within and around the vicinity of the construction sites and promote harmonious employer–employee relationships [96]. The construction safety and health program is managed by a committee involved in orienting, instructing, and training workers at the site in view of construction safety and health protocols. In a construction project, the general contractor must have a full-time accredited safety officer and an additional safety officer for every ten-heavy equipment on site. Moreover, one first-aider or safety officer is required for every 50 workers, and a full-time registered nurse for projects with over 50 but not more than 200 workers. Furthermore, while briefings (i.e., toolbox meetings) have shown to be effective at preventing fatalities and resulted in favorable impacts on workers; however, the initiative is not popular in practice [97]. As stipulated in a local department directive, toolbox and gang meetings are required to be a part of a Construction Safety and Health Program [98] of a construction project. In 2017, the DOLE conducted a roadshow with toolbox talks to increase awareness of occupational safety and health practices among young workers. The targeted roadshow, however, was only made available to the country's top five largest construction firms, which are believed to have safety management mechanisms already in place. Similar activities arranged for smaller-sized construction firms have not been reported. Despite this agenda, most construction safety and health programs have ill-designed mechanisms to determine the risk degree of occupational hazards in construction sites. Thus, a rigorous evaluation approach becomes imperative to inform the design of programs targeted at addressing these hazards.

In carrying out the proposed approach, a focus group discussion identifies some occupational hazards from previous studies relevant to residential construction projects mostly implemented by SMEs. As discussed in the literature, construction SMEs are more exposed to these hazards, amplified by resource constraints and the inability to leverage economies of scale. Additionally, as construction SMEs comprise 90% of the industry, highlighting the occupational hazards of their workers is a critical agenda, both for theory and practice. The focus group consists of fifteen (15) experts with more residential project experience of more than a year. This small number of experts comprising a group tasked to elicit judgments is consistent with similar studies in the literature [41,43,52,99]. The group comprises four contractors, five foremen, two supervisors, and four practicing civil engineers with extensive academic backgrounds and practical knowledge of occupational hazards in construction sites. All members have been working in the construction industry for at least ten years; thus, they are capable of eliciting reliable judgments. Consistent with other studies, the results of this kind of analysis draw motivation from the concept of "analytic generalization" by Yin [100]. Unlike statistical generalization, which draws insights from the sample and generalizes the population, analytic generalization intends to support, contest, refine, extend, or elaborate theoretical propositions [100]—in this case—the assignment of occupational hazards to appropriate risk categories. In addition, a small group of experts mimics the scenario of a Delphi group, where an increase in the number of respondents may result in "knowledge redundancy"—any additional member who has the same level of knowledge and expertise as the rest will have a minimal marginal contribution to the group decision.

On the other hand, as residential projects constitute a vast scope of work, not to mention other auxiliary services, the focus group decided only to emphasize those hazards that are inherently present in residential construction sites. Since members of the focus group are operating in the Philippines, the final list that they generate contains idiosyncrasies and is dependent on specific conditions prevalent in the Philippine construction industry, such as predominant manual labor, a small number of skilled works, limited resources to finance appropriate tools and equipment (including personal protective equipment), among others. The group consensus results in the generation of a list of 26 occupational construction hazards found in Table 2. A survey questionnaire was designed to evaluate these hazards in view of the three risk dimensions of the FMEA, which include the degree of severity, frequency of occurrence, and probability of detection using the 7-point scale described in Table 3. The questionnaire was then distributed to the same group of experts, who were given two weeks to return the completed questionnaire. Clarifications regarding any aspect of the questionnaire were dealt with promptly.

Table 2. Occupational hazards in a residential construction workplace.

Codes	Occupational Hazards	Some Accompanying Risks
FM1	Working on a scaffold/stair	Fall, scaffold collapse, struck by scaffold
FM2	Working at a height above two meters	Fall
FM3	Handling manual non-electric tools (e.g., hammer, saw, chisel, pliers, shovel)	Cuts, bruises, struck by, foreign materials into the eyes
FM4	Using hydraulic and power tools (e.g., cutter, drill, grinder)	Cuts, bruises, struck by, foreign materials into the eyes, electrocution, spasm
FM5	Fumes from using hydraulic and power tools (e.g., cutter, drill, grinder)	Nausea, eye irritation, upper respiratory irritation
FM6	Manual excavation works	Soil collapse, fall, struck by
FM7	Uneven surfaces on the site	Trip, fall, slip
FM8	Cables, dangling wires, cut wood, and scrap metals scattered around the workplace	Trip, fall, slip
FM9	Electrical wiring installation and troubleshooting	Electrocution
FM10	Working on ground/lower floors with possible flying and falling objects	Struck by
FM11	Workers stepping on protruding objects (e.g., nails)	Trip, fall, slip
FM12	Vehicular traffic on construction sites	Struck by
FM13	Working within a 'danger zone' (e.g., a possible collision with equipment)	Struck by
FM14	Mechanical/electrical malfunction	Electrocution, burns, cuts
FM15	Exposure to the extreme noise level in the workplace	Hearing disorder, nausea
FM16	Exposure to hazardous substances (e.g., lacquer/paint thinner)	Nausea, eye irritation, upper respiratory irritation, skin irritation, headaches, respiratory problems

Table 2. *Cont.*

Codes	Occupational Hazards	Some Accompanying Risks
FM17	Excessive hand and arm vibrations from vibrating power tools (e.g., jackhammers, compactors, hand drills)	Spasm, blister
FM18	Welding/hot work	Burns, nausea, eye irritation, upper respiratory irritation
FM19	Airborne fibers and materials (e.g., asbestos, roofing insulation, fiberglass)	Nausea, eye irritation, upper respiratory irritation
FM20	Inhalation of fine dust from cement, sand, gravel, and other concrete aggregates	Nausea, eye irritation, upper respiratory irritation
FM21	Sun/extreme weather exposure	Skin burns, dehydration, heat stroke
FM22	Prolonged and repeated lifting and carrying of heavy objects heavier than 20 kg	Muscle pains, back pains, back injury, sprain and strain,
FM23	Snake bites and animal attacks	Poison, fever, cuts and bruises, swelling and inflammation, fatality
FM24	Contact with poisonous plants	Skin irritation, headache
FM25	Insect bites	Skin irritation, headache, swelling and inflammation, fatality
FM26	Molds from structural lumber	Upper respiratory irritation, eye irritation, Skin irritation

Table 3. Linguistic evaluation scale.

Linguistic Terms	Scores	Corresponding q-ROFN
Strongly disagree	1	(0.15,0.9)
Disagree	2	(0.3,0.85)
Somewhat disagree	3	(0.45,0.65)
Neutral	4	(0.5,0.5)
Somewhat agree	5	(0.75,0.4)
Agree	6	(0.8,0.25)
Strongly agree	7	(0.95,0.1)

4.2.1. Phase I—Calculate the Coefficient of Risk Dimensions of FMEA Using q-ROF Entropy and Cross-Entropy

In this study, a set C of risk dimensions of FMEA (i.e., severity, detection, occurrence), while a set $A = \{a_1, \ldots, a_i, \ldots, a_m\}$ of occupational hazards in a residential construction workplace are determined through a focus group discussion. The focus group discussion generated a list of 26 occupational hazards in Table 2. A group of E decision-makers was asked to elicit judgment on the severity, detection, and occurrence of the occupational hazards. The individual evaluation matrix $X^e = \left(x_{ij}^e\right)_{m\times n}$ is then constructed, wherein x_{ij}^e represents the eth $(e = 1, 2, \ldots, E)$ decision-maker evaluation of ith $(i = 1, 2, \ldots, m)$ occupational hazard to jth $(j = 1, 2, \ldots, n)$ risk dimension. A sample of matrix X^e is presented in Appendix A. The X^e matrices are then transformed into q-ROF evaluation matrices $Q^e = \left(q_{ij}^e\right)_{m\times n}$, where $q_{ij}^e = \left(u_{ij}^e, v_{ij}^e\right)$ following the linguistic scale featured in Table 3. The value of $q = 5$ is defined by the decision-makers. A sample of the resulting matrix is shown in Appendix B. The aggregate q-ROF decision matrix denoted as $\ddot{Q} = \left(\ddot{q}_{ij}\right)_{m\times n}$, where $\ddot{q}_{ij} = \left(\ddot{u}_{ij}, \ddot{v}_{ij}\right)_{m\times n}$, is obtained using the q-ROFWA defined in Equation (14), wherein ω_e $\left(\sum_{e=1}^{E} \omega_e = 1\right)$ denotes the weight assigned to eth decision-maker. The weights assigned to the decision-makers are based on the completeness of their responses. The resulting matrix is presented in Table 4. Following Step 3 to Step 5 of Section 4.1, where $p = 1.5$, the entropy of each evaluation $\ddot{q}_{ij}$ (see Appendix C) presents the fuzzy densities of severity, detection, and occurrence are 0.3199, 0.1260, and 0.2504, respectively.

Table 4. Aggregate q-ROF decision matrix.

Occupational Hazards	Severity	Detection	Occurrence
FM1	(0.8479,0.3374)	(0.4310,0.7700)	(0.7946,0.3670)
FM2	(0.8383,0.2459)	(0.4001,0.8382)	(0.8066,0.3320)
FM3	(0.6993,0.4554)	(0.3819,0.8385)	(0.7346,0.3881)
FM4	(0.8072,0.2737)	(0.5010,0.8230)	(0.7758,0.3560)
FM5	(0.8312,0.2903)	(0.5098,0.7813)	(0.8214,0.3157)
FM6	(0.7079,0.3998)	(0.4186,0.8021)	(0.7155,0.4137)
FM7	(0.8121,0.3195)	(0.4210,0.7948)	(0.8172,0.3007)
FM8	(0.8798,0.2060)	(0.3971,0.8459)	(0.8992,0.1872)
FM9	(0.7706,0.3341)	(0.4001,0.8382)	(0.8115,0.3320)
FM10	(0.8744,0.2125)	(0.4029,0.8306)	(0.7495,0.3758)
FM11	(0.8837,0.1902)	(0.3940,0.8537)	(0.8738,0.2168)
FM12	(0.7194,0.4017)	(0.4713,0.6647)	(0.7015,0.4250)
FM13	(0.9071,0.1722)	(0.4001,0.8382)	(0.7668,0.3626)
FM14	(0.8844,0.1866)	(0.4001,0.8382)	(0.8606,0.2600)
FM15	(0.8772,0.2328)	(0.4468,0.7309)	(0.8111,0.3415)
FM16	(0.7489,0.3901)	(0.4001,0.8382)	(0.8677,0.2509)
FM17	(0.8458,0.2431)	(0.4332,0.7630)	(0.8006,0.3523)
FM18	(0.8438,0.2427)	(0.4029,0.8306)	(0.8203,0.3010)
FM19	(0.9066,0.1730)	(0.4001,0.8382)	(0.8252,0.3132)
FM20	(0.8801,0.2180)	(0.4029,0.8306)	(0.8239,0.3146)
FM21	(0.8835,0.2014)	(0.4001,0.8382)	(0.8132,0.3260)
FM22	(0.8791,0.2069)	(0.4004,0.8373)	(0.8172,0.3234)
FM23	(0.8768,0.2272)	(0.3971,0.8459)	(0.7257,0.4080)
FM24	(0.8763,0.2314)	(0.4162,0.8090)	(0.7229,0.4441)
FM25	(0.7137,0.4699)	(0.4359,0.7623)	(0.7907,0.4099)
FM26	(0.6888,0.4939)	(0.4470,0.7301)	(0.7899,0.4116)

4.2.2. Phase II—Obtain the RPN of Each Occupational Hazard Using the q-ROF Choquet Integral

In this study, three pre-defined categories (i.e., "high risk", "moderate risk", and "low risk") and the central profiles are introduced by the decision-makers. The pre-defined categories and their corresponding central profiles are featured in Table 5. Using Equation (23), $\lambda = 1.7868$, and following Step 5 to Step 7, the fuzzy measures of the risk dimensions and the q-ROF RPN are presented in Tables 6 and 7, respectively.

Table 5. The central profiles.

Central Profiles	Severity	Detection	Occurrence
p_1	(0.8000,0.2500)	(0.8000,0.2500)	(0.8000,0.2500)
p_2	(0.5000,0.5000)	(0.5000,0.5000)	(0.5000,0.5000)
p_3	(0.3000,0.8500)	(0.3000,0.8500)	(0.3000,0.8500)

Table 6. Fuzzy measures of the risk dimensions.

Risk Dimensions	Fuzzy Measures	Risk Dimensions	Fuzzy Measure
Severity	0.3199	Severity, Occurrence	0.7135
Detection	0.1260	Detection, Occurrence	0.4327
Occurrence	0.2504	Severity, Detection, Occurrence	1.0000
Severity, Detection	0.5179		

Table 7. q-ROF RPN values.

Occupational Hazards	q-ROF RPN	Occupational Hazards	q-ROF RPN	Occupational Hazards	q-ROF RPN
FM1	(0.7282,0.5191)	FM11	(0.7947,0.4129)	FM21	(0.7517,0.4837)
FM2	(0.7320,0.4996)	FM12	(0.6375,0.5235)	FM22	(0.7526,0.4836)
FM3	(0.6720,0.5211)	FM13	(0.7373,0.4945)	FM23	(0.7005,0.5386)
FM4	(0.7091,0.5159)	FM14	(0.7848,0.4385)	FM24	(0.6999,0.5463)
FM5	(0.7467,0.4835)	FM15	(0.7498,0.4696)	FM25	(0.7054,0.5216)
FM6	(0.6711,0.4923)	FM16	(0.7619,0.4349)	FM26	(0.6937,0.5278)
FM7	(0.7714,0.4086)	FM17	(0.7316,0.4880)	p_1	(0.8000,0.2500)
FM8	(0.8468,0.3014)	FM18	(0.7433,0.4779)	p_2	(0.5000,0.5000)
FM9	(0.7439,0.4342)	FM19	(0.7691,0.4672)	p_3	(0.3000,0.8500)
FM10	(0.7113,0.5127)	FM20	(0.7575,0.4797)		

4.2.3. Phase III—Sort the Occupational Hazards Using the Proposed Methodologies

Following Method 1 of Section 4.1.3, the assignment of occupational hazards is featured in Figure 3. On the other hand, another assignment of the same hazards based on Method 2 is illustrated in Figure 4.

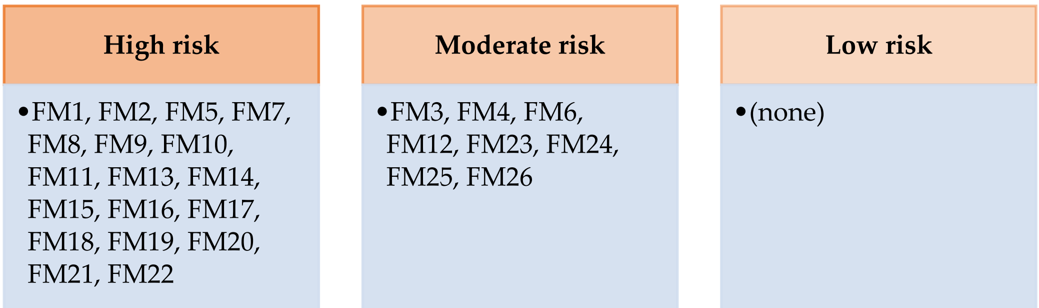

Figure 3. Sorting assignments based on Method 1.

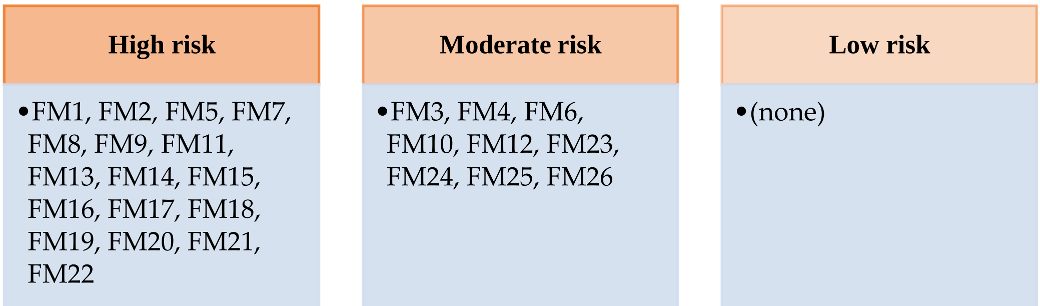

Figure 4. Sorting assignments based on Method 2.

The complete computational process involved in this section is provided in the Supplementary Material.

5. Sensitivity and Comparative Analyses

Sensitivity and comparative analyses are implemented to determine the robustness and efficiency of the proposed methodologies.

5.1. Sensitivity Analysis

In this section, a sensitivity analysis was conducted to assess the robustness of the proposed methods. First, the q parameter was allowed to change, where $q = 2, \ldots, 50$. The percentage that ith occupational hazard is assigned to the fth category is defined as $\rho_{i,f} = \frac{\sum_{q=2}^{50} h_{i,f}^{t}}{49}$, $h_{i,f}^{q} \in \{0, 1\}$, where $h_{i,f}^{q} = 1$ representing that a_i is assigned to f at a parameter value q; otherwise, $h_{i,f}^{q} = 0$. Table 8 presents the percentage of frequency of the assignment of all occupational hazards. It can be observed that for Method 1, 19 occupational hazards (i.e., FM1, FM2, FM4, FM5, FM7, FM8, FM9, FM11, FM14, FM15, FM16, FM17, FM18, FM19, FM20, FM21, FM22, FM25, FM26) are categorized as “high risk” at least 70% of the time and seven hazards (FM3, FM6, FM10, FM12, FM13, FM23, FM24) are categorized as “moderate risk”. At the same time, Method 2, 19 and seven hazards are classified as “high risk” and “moderate risk”, respectively, as illustrated in Table 9. Accordingly, a higher value of q translates to a higher hesitancy degree. Hence, the occupational hazards are likely to be categorized as “high risk” as the value of q increases. At $q = 2, \ldots, 50$, the proposed methods remain stable.

Table 8. Method 1 relative frequency of the assignment of all occupational hazards at different values of q.

Occupational Hazard	High Risk	Moderate Risk	Low Risk	Occupational Hazard	High Risk	Moderate Risk	Low Risk
FM1	1.00	0.00	0.00	FM14	1.00	0.00	0.00
FM2	1.00	0.00	0.00	FM15	1.00	0.00	0.00
FM3	0.00	1.00	0.00	FM16	1.00	0.00	0.00
FM4	0.78	0.22	0.00	FM17	1.00	0.00	0.00
FM5	1.00	0.00	0.00	FM18	1.00	0.00	0.00
FM6	0.00	1.00	0.00	FM19	1.00	0.00	0.00
FM7	1.00	0.00	0.00	FM20	1.00	0.00	0.00
FM8	1.00	0.00	0.00	FM21	1.00	0.00	0.00
FM9	1.00	0.00	0.00	FM22	1.00	0.00	0.00
FM10	0.37	0.63	0.00	FM23	0.37	0.63	0.00
FM11	1.00	0.00	0.00	FM24	0.37	0.63	0.00
FM12	0.29	0.71	0.00	FM25	0.76	0.24	0.00
FM13	0.41	0.59	0.00	FM26	0.73	0.27	0.00

Table 9. Method 2 relative frequency of the assignment of all occupational hazards at different values of q.

Occupational Hazard	High Risk	Moderate Risk	Low Risk	Occupational Hazard	High Risk	Moderate Risk	Low Risk
FM1	0.88	0.12	0.00	FM14	1.00	0.00	0.00
FM2	0.63	0.37	0.00	FM15	1.00	0.00	0.00
FM3	0.00	1.00	0.00	FM16	1.00	0.00	0.00
FM4	0.69	0.31	0.00	FM17	0.88	0.12	0.00
FM5	1.00	0.00	0.00	FM18	0.92	0.08	0.00
FM6	0.00	1.00	0.00	FM19	1.00	0.00	0.00
FM7	1.00	0.00	0.00	FM20	0.98	0.02	0.00
FM8	1.00	0.00	0.00	FM21	0.82	0.18	0.00
FM9	1.00	0.00	0.00	FM22	0.73	0.27	0.00
FM10	0.04	0.96	0.00	FM23	0.02	0.98	0.00
FM11	1.00	0.00	0.00	FM24	0.12	0.88	0.00
FM12	0.29	0.71	0.00	FM25	0.76	0.24	0.00
FM13	0.06	0.94	0.00	FM26	0.73	0.27	0.00

On the other hand, five score functions (see Table 1) and additional distance measures proposed by Peng and Liu [101], as described in Equations (26)–(30), were utilized to evaluate the stability of the proposed methodologies.

$$D_1(M,N) = \frac{1}{2|X|}\sum_{x\in X}\left(\left|u_M^q(x) - u_N^q(x)\right| + \left|v_M^q(x) - v_N^q(x)\right| + \left|\pi_M^q(x) - \pi_N^q(x)\right|\right) \quad (26)$$

$$D_2(M,N) = \frac{1}{2|X|}\sum_{x\in X}\left|u_M^q(x) - u_N^q(x) - v_M^q(x) - v_N^q(x)\right| \quad (27)$$

$$\begin{aligned} D_3(M,N) = \tfrac{1}{4|X|}\Big(\textstyle\sum_{x\in X}\left(\left|u_M^q(x) - u_N^q(x)\right| + \left|v_M^q(x) - v_N^q(x)\right| + \left|\pi_M^q(x) - \pi_N^q(x)\right|\right) + \\ \textstyle\sum_{x\in X}\left|u_M^q(x) - u_N^q(x) - v_M^q(x) - v_N^q(x)\right|\Big) \end{aligned} \quad (28)$$

$$D_4(M,N) = \frac{1}{|X|}\sum_{x\in X}\left(\left|u_M^q(x) - u_N^q(x)\right| \vee \left|v_M^q(x) - v_N^q(x)\right|\right) \quad (29)$$

$$D_4(M,N) = \frac{1}{|X|}\sum_{x\in X}\frac{\left|u_M^q(x) - u_N^q(x)\right| \vee \left|v_M^q(x) - v_N^q(x)\right|}{1 + \left|u_M^q(x) - u_N^q(x)\right| \vee \left|v_M^q(x) - v_N^q(x)\right|} \quad (30)$$

After obtaining the assignment of the occupational hazards, the similarity ratio metric S_r proposed by Keshavarz-Ghorabaee et al. [102] is used to compare the results as illustrated as follows:

$$S_r = \frac{\sum_{i=1}^{m} w_i(x_i, y_i)}{m},\ x_i, y_i \in \{\text{high risk}, \text{moderate risk}, \text{low risk}\} \quad (31)$$

where $w_i(x_i, y_i) = \begin{cases} 1\ if\ x_i = y_i \\ 0\ if\ x_i \neq y_i \end{cases}$ and m is the number of occupational hazards, x_i is the category of ith occupational hazard using a particular method, while y_i is the category of ith occupational hazard using the other method. When $S_r = 1$, then the two methods fully agree on all assignments. Table 10 illustrates the values of S_r among the score functions, while Table 11 features the S_r among the distance measures. As observed, the S_r values among the employed score function are greater than 60%, while the S_r values among the employed distance measure are greater than 96%. This indicates that the proposed sorting methods are stable and feasible when applied to other domain problems.

Table 10. Similarity ratio among various score functions in sorting occupational hazards.

Score Function	Jana	Banerjee	Farhadinia	Rani	Peng
Jana	1.00	0.96	0.96	0.88	0.73
Banerjee	-	1.00	0.92	0.85	0.69
Farhadinia	-	-	1.00	0.92	0.77
Rani	-	-	-	1.00	0.85
Peng	-	-	-	-	1.00

Table 11. Similarity ratio among various distance methods in sorting occupational hazards.

Distance Method	Euclidean	D1	D2	D3	D4	D5
Euclidean	1.00	0.96	0.96	0.96	1.00	1.00
D1	-	1.00	0.92	0.92	0.96	0.96
D2	-	-	1.00	1.00	0.96	0.96
D3	-	-	-	1.00	0.96	0.96
D4	-	-	-	-	1.00	1.00
D5	-	-	-	-	-	1.00

5.2. Comparative Analysis

A proposed methodological approach to categorize occupational hazards is introduced in this study. Layers of comparative analysis are implemented to assess the approach's effectiveness in practical application compared to prior methods. The first comparable method is the canonical FMEA. An $m(i = 1, .., m)$ number of failure modes of a specific process or product is evaluated using the three dimensions of FMEA, referred to as risk dimensions. The risk dimensions are denoted as $j = 1, \ldots, n$. The evaluation r_{ij} denotes the assessment of the ith failure mode with respect to each $j$the dimension. These evaluations are utilized to determine the risk priority number R_i of each failure mode, wherein $R_i = \prod_{j=1}^{n} r_{ij}$. This FMEA process is applied to the domain problem discussed in Section 4. Here, the failure modes are an occupational hazard in the construction industry. The resulting R_i values are presented in Table 12.

Table 12. Risk priority numbers using the canonical FMEA.

Occupational Hazards	Severity	Detection	Occurrence	R_i
FM1	4.2400	1.9200	4.5200	36.7964
FM2	5.7400	1.6000	5.1200	47.0221
FM3	4.0800	1.7400	4.9400	35.0700
FM4	5.7400	1.6200	5.1800	48.1678
FM5	5.3400	1.9400	5.2000	53.8699
FM6	4.7000	1.7800	4.6600	38.9856
FM7	5.1400	1.9400	5.2600	52.4506
FM8	6.0600	1.4400	6.1000	53.2310
FM9	5.2400	1.6000	5.0400	42.2554
FM10	5.9200	1.7600	5.0000	52.0960
FM11	6.2400	1.2800	5.9400	47.4440
FM12	4.5400	2.7200	4.4800	55.3226
FM13	6.2800	1.6000	5.1600	51.8477
FM14	6.2800	1.6000	5.4800	55.0630
FM15	5.7800	2.2400	4.9600	64.2181
FM16	4.4200	1.6000	5.6400	39.8861
FM17	5.8400	2.0800	4.8200	58.5495
FM18	5.7600	1.7600	5.3200	53.9320
FM19	6.2600	1.6000	5.3200	53.2851
FM20	5.9200	1.7600	5.3000	55.2218
FM21	6.0800	1.6000	5.1400	50.0019
FM22	6.0400	1.6200	5.2600	51.4680
FM23	5.6000	1.4400	4.6600	37.5782
FM24	5.4200	1.7200	4.3400	40.4592
FM25	4.2200	2.0800	4.3000	37.7437
FM26	3.9000	2.2600	4.3000	37.9002

When $R_i \geq \tau$, then ith occupational hazard is considered "high risk." The parameter τ is the 80th percentile of all R_i. Here, $\tau = 53.9320$. This parameter is anchored on the Pareto principle or the 80/20 rule. Consequently, only six occupational hazards are categorized as "high risk", namely, FM12, FM14, FM15, FM17, FM18, and FM20.

The second comparable method is the categorization of occupational hazards through FlowSort. The integration of FMEA in FlowSort is introduced by Lolli et al. [103]. This approach follows the canonical FlowSort method, wherein the three risk dimensions of FMEA are considered the evaluation criteria in the decision matrix. Note that the failure modes (i.e., occupational hazard) are considered alternatives in the matrix. The application of the comparable method is demonstrated using the same problem discussed in Section 4. The ordered category $\hslash_f$ where $\hslash_1 \triangleright \ldots \triangleright \hslash_f \triangleright \ldots \triangleright \hslash_F$ is set by the decision-makers. Here, three categories are defined as $\hslash_1 =$ high risk, $\hslash_2 =$ moderate risk, and $\hslash_3 =$ low risk. These three ordered categories are characterized by the set central profiles where $P = \{2, 4, 6\}$. Meanwhile, the preference function $F(d)$ is determined using the Type 3 criterion wherein,

$$F(d) = \begin{cases} 1 & -d \leq -p_* \\ \frac{-d}{p_*} & -p_* \leq -d < 0 \\ 0 & -d \geq 0 \end{cases} \quad (32)$$

where $p_* \in \{p_{severity}, p_{occurence}, p_{detection}\}$ is determined by the decision-makers. Here, $p_{severity} = 0.7$, $p_{occurence} = 0.3$, and $p_{detection} = 0.3$. Following the methodological steps of the FlowSort, Table 13 shows the categorization of the failure modes.

Table 13. Assignment results using FlowSort.

Occupational Hazards	Category	Occupational Hazards	Category	Occupational Hazards	Category
FM1	moderate risk	FM10	moderate risk	FM19	moderate risk
FM2	moderate risk	FM11	moderate risk	FM20	moderate risk
FM3	low risk	FM12	moderate risk	FM21	moderate risk
FM4	moderate risk	FM13	moderate risk	FM22	moderate risk
FM5	moderate risk	FM14	moderate risk	FM23	moderate risk
FM6	moderate risk	FM15	moderate risk	FM24	moderate risk
FM7	moderate risk	FM16	low risk	FM25	moderate risk
FM8	moderate risk	FM17	moderate risk	FM26	moderate risk
FM9	moderate risk	FM18	moderate risk		

To illustrate the comparison of the results from the proposed method and two comparable methods, Table 14 summarizes the category assignments of the occupational hazards. It is apparent in the results that there is a wide disparity in the categorization of occupational hazards. However, it should be emphasized that five out of six "high risk" occupational hazards from FMEA are also categorized as "high risk" using the proposed method. Meanwhile, the six "high risk" occupational hazards by the canonical FMEA are categorized as "moderate risk" through FlowSort. Hence, it can be noted that the disparity of the FMEA results to FlowSort is more nuanced than the proposed method. This disparity in the results may be due to the different inherent properties of the computational framework of FlowSort and FMEA. Additionally, the high similarity of results of FMEA and the proposed method can be attributed to the retention of the multiplicative property of FMEA in the proposed method, which satisfies some theoretical underpinnings.

Table 14. Assignment results from comparable methods.

Occupational Hazards	Categories via Different Methods		
	Proposed Method	FlowSort	FMEA
FM1	high risk	moderate risk	-
FM2	high risk	moderate risk	-
FM3	moderate risk	low risk	-
FM4	moderate risk	moderate risk	-
FM5	high risk	moderate risk	-
FM6	moderate risk	moderate risk	-
FM7	high risk	moderate risk	-
FM8	high risk	moderate risk	-
FM9	high risk	moderate risk	-
FM10	high risk	moderate risk	-

Table 14. *Cont.*

Occupational Hazards	Categories via Different Methods		
	Proposed Method	FlowSort	FMEA
FM11	high risk	moderate risk	-
FM12	moderate risk	moderate risk	high risk
FM13	high risk	moderate risk	-
FM14	high risk	moderate risk	high risk
FM15	high risk	moderate risk	high risk
FM16	high risk	low risk	-
FM17	high risk	moderate risk	high risk
FM18	high risk	moderate risk	high risk
FM19	high risk	moderate risk	-
FM20	high risk	moderate risk	high risk
FM21	high risk	moderate risk	-
FM22	high risk	moderate risk	-
FM23	mod	moderate risk	-
FM24	mod	moderate risk	-
FM25	mod	moderate risk	-
FM26	mod	moderate risk	-

6. Results and Discussion

Despite being a crucial contributor to national economies, the construction industry is considered one of the most hazardous industries, particularly in developing economies, where SMEs comprise a significant portion of the industry. To assist financially constrained construction SMEs in managing and allocating resources for worksite safety initiatives, this work adopts the notion of the FMEA by considering assessing occupational hazards in terms of their severity, detection probability, and occurrence frequency, rather than simply in a binary detection perspective, as current literature suggests. Furthermore, it enriches previous methodological approaches based on FMEA by offering a computational mechanism that determines risk categories for a set of occupational hazards. With an actual demonstration in residential construction projects, this study helps project managers make informed decisions about the nature of occupational hazards and aids in the design of targeted initiatives that address those hazards. By evaluating hazards based on their severity, detection, and frequency of occurrence, managers could prioritize which hazards demand more attention and critical information to allocate resources effectively. In this section, we analyzed our findings in the previous sections in more detail.

Based on Section 4, crisp scores ranging from 0 to 1 were used to evaluate and rank all the identified occupational hazards according to individual risk dimensions (i.e., severity, detection, and frequency) and presented as heatmaps (Table 15). The presented heatmaps are defined in such a way that the highest value in the dimension is shown in red and signifies a higher degree of risk. Red-Orange represents a high degree of severity (HS), high probability of detection (HD), and high possibility of occurrence (HF) in the heat maps. Furthermore, the integration of the crisp scores of the three dimensions for each hazard was used to sort the hazards according to three categories, namely low (LR), moderate (MR), and high (HR) risk. Of the twenty-six (26) identified hazards, eighteen (18) are categorized as high risk, eight (8) as moderate risk, and zero (0) as low risk.

Table 15. Heat map of the aggregate crisp scores of the risk dimensions.

Occupational Hazards	Severity	Detection	Occurrence
FM1			
FM2			
FM3			
FM4			
FM5			
FM6			
FM7			
FM8			
FM9			
FM10			
FM11			
FM12			
FM13			
FM14			
FM15			
FM16			
FM17			
FM18			
FM19			
FM20			
FM21			
FM22			
FM23			
FM24			
FM25			
FM26			

Low risk index: ; Moderate risk index: ; High risk index: .

Results are clustered according to a high level of risk per dimension (1) (HS-HD-MF); (HS-LD-HF); (HS-LD-MF); (HS-LD-LF); (2) (LS-LD-LF); (3) (LS-LD-HF). First, exposure to extreme noise levels in the workplace (FM15) showed HS-HD-MF. This result is consistent with Yang et al. [104], highlighting how noise pollution is a pervasive stressor and a major compromise to the health and well-being of construction workers and off-site residents near the construction site. The negative effect of construction noise lies primarily within the dimensions of safety behavior. It was found in the work of Ning et al. [105] that the degree of severity is high as noise associated with residential construction buildings is related to activities such as electric drills (102 dB noise level), cutting of tiles (90 dB), rebar work (94–96 dB), grinder (97 dB), handheld power tools (94 dB), use of jackhammer (105 dB), hammering nails into timber (131 dB), actuated tools into masonry (147 dB), among others, while permissible noise exposure for an eight hour-work shift is the 80 dB noise level. Long exposure to noise can cause serious health problems (e.g., hearing loss, tinnitus, stress-related disorders) that can be irreversible and permanent. Moreover, hazard FM15 has high detection as noise in the construction site is foreseen not only to cause noise within the vicinity of the worksite but to cause noise disturbance to adjacent structures, which most likely are residential units. Construction noise during extended work shifts often causes disputes between adjacent unit owners and construction site heads. In this case, decision-makers in residential construction SMEs must implement measures and mitigation strategies to minimize noise levels. Such strategies may include installing sound barriers, providing hearing protection for workers, and layout optimization as preparation before the start of construction activities. Meanwhile FM8, FM11, FM13, FM14, and FM22 resulted to HS-LD-HF. Common among these high-severity hazards is the need for immediate medical attention when incidents occur. Moreover, these are associated with HF due to the prolonged presence of these hazards spanning the entire duration of the construction projects. Due to the limited space in most residential construction sites, workers tend to pass the danger zone (FM13).

Similarly, space limitations expose workers to unkept conditions with dangling wires, scrap metals, cut wood (FM8), and protruding objects (FM11). Trip hazards, falling objects, and cuts from sharp objects are common results of poor housekeeping practices [106]. Moreover, it is important to note that the identified hazards have a low probability of detection (LD) brought about by workers' long exposure to these hazards and thus are perceived as a normal site condition, making it critical mitigating them a priority. Thus, construction employers or managers need to allocate resources for housekeeping and consistent equipment maintenance during the whole duration of the project. Employing modeling tools that design and layout a digital, physical structure of a project to monitor and mitigate workplace hazards can be explored as a possible mitigating option. Moreover, strategies such as putting up clear and comprehensive warning signs, regularly reviewing work processes, and providing appropriate footwear can prevent or mitigate the negative impacts of trip hazards.

Moreover, due to limited resources, construction workers in SMEs may not have proper training and orientation and thus resulting in the lack of knowledge of workers of hazards in the worksite, consequently showing low detection of some common worksite hazards. Furthermore, this is intensified by high labor turnover in the construction industry [107], which negatively affects the performance of the construction business. FM19, FM20, and FM21, respectively, are identified as HS-LD-MF. Similar to the above HS hazards, FM19 and FM20 have possible immediate effects that need first aid or medical attention, including skin irritation and respiratory problems, among others. Meanwhile, the excessive heat from sun exposure in tropical countries, such as the Philippines, resulted in FM21 being categorized as HS. Sun exposure is overly present during the start of the construction project because of limited shaded locations. These three hazards are identified as MF because workers' exposure to these hazards does not happen during the project duration. FM21, FM20, and FM19 occur only at the start of construction, during masonry and concrete works, and finishing work, respectively. Lastly, for HS, FM23 and FM24 are identified as HS-LD-LF. Immediate attention to incidents resulting from these hazards becomes imperative. However, they are identified as LD and LF because these hazards most often occur during site clearing at the onset of the project. Most construction workers cannot detect poisonous plants and habitat situations of snakes or other animals, especially those endemic to the locality. Moreover, hiring specialized personalities to deal with these conditions is not a common practice, especially for SMEs with limited capacities.

Secondly, vehicular traffic on construction sites (FM12) resulted in the highest probability of detection. This may be due to, among the listed hazards, vehicular traffic avoidance is normally practiced regardless of the conditions. It may be observed that crisp scores for the probability of detection are relatively lower (highest is 0.45) compared to the degree of severity and frequency of occurrence (highest at 0.81 and 0.79, respectively). This indicates that the level of detection of hazards or hazard recognition remains low, as supported by others in the literature [36]. Lastly, exposure to hazardous substances (e.g., lacquer/paint thinner) (FM16) is categorized as LS-LD-HF. Lengthy day-long exposure to these substances is common, thus resulting in being recognized as HF. However, due to a lack of knowledge of unforeseen health effects that typically occur much later, FM16 is identified as LS and LD. Eighteen (18) of the twenty-six (26) identified hazards are categorized as high risk. The heatmaps show that integrating the three domains with pronounced severity and frequency scores resulted in numerous high-risk hazards. This implies that workers perceive a hazard more based on the frequency of occurrence and degree of severity of the risk associated with the hazard and that detection of hazards remains low.

7. Conclusions and Future Directions

Despite various attempts to enhance construction safety, inadequate identification of hazards remains a significant and prevalent concern in a construction setting. Failure to recognize and mitigate these hazards can result in tragic safety incidents that harm the workers and the construction firm's reputation. The dilemma is more prevalent in construction SMEs, given their limited resources, high dependence on manual labor, and insufficient attention to safety concerns due to the lack of technical workers. To address this concern, this study presents a novel method for assessing the risk level of an occupational hazard, which differs from the traditional binary detection approach commonly used in current methods. Our proposed approach considers multiple dimensions of a hazard, including its severity, frequency of occurrence, and the likelihood of detection—characteristics embedded in FMEA. However, current FMEA extensions and applications in construction safety have some computational shortcomings that form the main departure of this work, particularly in capturing the interdependencies of the risk dimensions and the uncertainty of judgment elicitations of experts. In particular, this study offers a two-fold contribution to the literature: (1) a comprehensive evaluation of occupational hazards prominent in construction SMEs, and (2) the proposed Choquet–FMEA–Sort methods under a q-ROFS environment.

Results reveal that working on a scaffold/stair, working at a height above two meters, fumes from using hydraulic and power tools, uneven surfaces, cables, dangling wires, cut woods, and scrap metals scattered around workplace, electrical wiring installation and troubleshooting, working on ground/lower floors with possible flying and falling objects, workers stepping on protruding objects (e.g., nails), working within a 'danger zone' (e.g., a possible collision with equipment), mechanical/electrical malfunction, exposure to the extreme noise level in the workplace, exposure to hazardous substances (e.g., lacquer/paint thinner), excessive hand and arm vibrations from vibrating power tools, welding/hot work, airborne fibers and materials, inhalation of fine dust from cement, sand, gravel, and other concrete aggregates, sun/extreme weather exposure, and prolonged and repeated lifting and carrying of heavy objects heavier than 20 kg are categorized as "high risk" while the remaining eight occupational hazards are categorized as "moderate risk". With the limited resources that residential construction SMEs have, decision-makers in the industry should focus their efforts and resources on mitigating the occupational hazards categorized as "high risk" since these hazards are more likely to cause severe injuries, difficult to detect, and have a high frequency of occurrence. By mitigating these hazards, construction SMEs can enhance the well-being of their workers, reduce the risk of property damage and financial losses, improve company reputation, increase worker morale and productivity, and foster a workplace safety culture.

However, despite the contributions to the literature, this study has some limitations, like any other work. First, the results of the analysis may be confined to the idiosyncrasies of the case environment. The existing preventive measures, document control protocols, and some cultural orientations present in managing Philippine residential construction projects were considered a priori when expert decision-makers evaluated the occupational hazards. Thus, the resulting categories of occupational hazards may yield differently in other cases, especially those countries with more rigorous workplace safety regulations. For future work, the proposed methods may also be applied to more complex construction projects, such as bridges, buildings, and ports. Second, it may be necessary to conduct a prospective study to obtain more comprehensive insights by analyzing the findings with more decision-makers. Third, an in-depth post-analysis that would result in carefully designed preventive measures grounded on the study results is an interesting future work for practitioners. Moreover, the novel sorting methods introduced in this study can be applied in sorting other FMEA-based problems across various domains (e.g., manufacturing, healthcare, and education). Lastly, an additional comparative analysis may be employed between the proposed methodologies and various sorting methodologies in the literature.

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Appendix A. Raw Evaluation Scores of *e*th Decision-Maker

Occupational Hazard	Severity	Detection	Occurrence
FM1	7	1	6
FM2	6	1	5
FM3	4	1	4
FM4	5	1	5
FM5	4	3	4
FM6	4	1	3
FM7	3	3	3
FM8	7	1	7
FM9	4	2	4
FM10	4	2	4
FM11	7	1	7
FM12	3	3	4
FM13	6	1	5
FM14	7	1	7
FM15	5	1	5
FM16	4	1	7
FM17	6	2	5
FM18	4	2	4
FM19	7	1	5
FM20	5	2	5
FM21	5	1	4
FM22	5	2	5
FM23	2	1	3
FM24	1	1	3
FM25	2	2	2
FM26	3	2	2

Appendix B. q-ROF Evaluation Matrix of eth Decision-Maker

Occupational Hazard	Severity	Detection	Occurrence
FM1	(0.95,0.10)	(0.15,0.90)	(0.80,0.25)
FM2	(0.80,0.25)	(0.15,0.90)	(0.75,0.40)
FM3	(0.50,0.50)	(0.15,0.90)	(0.50,0.50)
FM4	(0.75,0.40)	(0.15,0.90)	(0.75,0.40)
FM5	(0.50,0.50)	(0.45,0.65)	(0.50,0.50)
FM6	(0.50,0.50)	(0.15,0.90)	(0.45,0.65)
FM7	(0.45,0.65)	(0.45,0.65)	(0.45,0.65)
FM8	(0.95,0.10)	(0.15,0.90)	(0.95,0.10)
FM9	(0.50,0.50)	(0.30,0.85)	(0.50,0.50)
FM10	(0.50,0.50)	(0.30,0.85)	(0.50,0.50)
FM11	(0.95,0.10)	(0.15,0.90)	(0.95,0.10)
FM12	(0.45,0.65)	(0.45,0.65)	(0.50,0.50)
FM13	(0.80,0.25)	(0.15,0.90)	(0.75,0.40)
FM14	(0.95,0.10)	(0.15,0.90)	(0.95,0.10)
FM15	(0.75,0.40)	(0.15,0.90)	(0.75,0.40)
FM16	(0.50,0.50)	(0.15,0.90)	(0.95,0.10)
FM17	(0.80,0.25)	(0.30,0.85)	(0.75,0.40)
FM18	(0.50,0.50)	(0.30,0.85)	(0.50,0.50)
FM19	(0.95,0.10)	(0.15,0.90)	(0.75,0.40)
FM20	(0.75,0.40)	(0.30,0.85)	(0.75,0.40)
FM21	(0.75,0.40)	(0.15,0.90)	(0.50,0.50)
FM22	(0.75,0.40)	(0.30,0.85)	(0.75,0.40)
FM23	(0.30,0.85)	(0.15,0.90)	(0.45,0.65)
FM24	(0.15,0.90)	(0.15,0.90)	(0.45,0.65)
FM25	(0.30,0.85)	(0.30,0.85)	(0.30,0.85)
FM26	(0.45,0.65)	(0.30,0.85)	(0.30,0.85)

Appendix C. The Entropy Values

Occupational Hazard	Severity	Detection	Occurrence	Occupational Hazard	Severity	Detection	Occurrence
FM1	0.8037	0.9313	0.8992	FM14	0.6965	0.8299	0.7693
FM2	0.8220	0.8299	0.8809	FM15	0.7204	0.9617	0.8744
FM3	0.9771	0.8277	0.9558	FM16	0.9461	0.8299	0.7495
FM4	0.8781	0.8747	0.9205	FM17	0.8053	0.9378	0.8904
FM5	0.8373	0.9309	0.8562	FM18	0.8098	0.8453	0.8577
FM6	0.9705	0.8933	0.9677	FM19	0.6129	0.8299	0.8493
FM7	0.8718	0.9032	0.8629	FM20	0.7112	0.8453	0.8517
FM8	0.7119	0.8130	0.6427	FM21	0.6996	0.8299	0.8705
FM9	0.9249	0.8299	0.8733	FM22	0.7143	0.8319	0.8638
FM10	0.7291	0.8453	0.9449	FM23	0.7218	0.8130	0.9621
FM11	0.6991	0.7945	0.7307	FM24	0.7233	0.8831	0.9659
FM12	0.9651	0.9881	0.9744	FM25	0.9723	0.9387	0.9073
FM13	0.6106	0.8299	0.9297	FM26	0.9834	0.9622	0.9084

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