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Quantitative Assessment of Air Pollutants and Construction Accidents: Developing Risk-Based Concentration Groups

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Abstract

The construction sector is predominantly characterized by outdoor work, where workers are continuously exposed to environmental factors such as air pollution. Air pollutants, including particulate matter (PM_{10}) and sulfur dioxide (SO_2), are well known for their health impacts, but their potential influence on workplace safety has been underexplored. According to the World Health Organization, air pollutants kill 7 million people annually worldwide. This study investigates the association between air pollutant concentrations and construction site accidents, focusing on whether higher pollution levels are linked with greater accident risk, and proposes new concentration groups considering the probability of accidents. This study was carried out in four phases: (i) collection of data; (ii) classification of data; (iii) probabilistic analysis of air pollutant concentration and accidents; and (iv) clustering of air pollutant concentration groups. As a result, it was identified that the probability of accident occurrence increased with the increase in SO_2 and PM_{10} concentration. Thus, SO_2 and PM_{10} significantly impact construction accidents based on their concentration changes. The new groups of SO_2 and PM_{10} have been developed based on accident probability, and these groups can be utilized to assess the accident risk level of construction sites based on air pollutant concentration.

Keywords: air pollutants; construction accidents; relative probability; hierarchical clustering; K-means clustering; construction safety management

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1. Introduction

Unlike the indoor nature of manufacturing, construction is primarily carried out outdoors, exposing workers to environmental factors such as climate and air pollution [1–5]. Air pollutants, including particulate matter (PM_{10}), ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO), adversely affect human health, causing respiratory, cardiovascular, and neurological conditions [6–8]. PM_{10} possesses small particles and is easily absorbed into the respiratory tract, thereby adversely affecting the human body [9,10]. The consequences of PM_{10} on the human body can affect the airways, lungs, cardiovascular system, and brain, causing asthma, respiratory and cardiovascular diseases. In addition, the World Health Organization (WHO) reported that 7 million people died earlier than life expectancy due to fine dust in 2014, and the International Institute of Cancer (IARC) classified fine dust as the first group of carcinogens directly correlated with cancer in October 2013 [11]. O_3 increases the incidence of airway inflammation, hypersensitivity, and lung disease [12,13]. NO_2 is highly toxic; thus, long-term exposure to low concentrations increases the incidence of bronchitis, gastroenteritis, decreased blood sugar, and Parkinson's disease [14–16]. SO_2 stimulates the respiratory tract and increases the incidence of respiratory diseases [17,18]. CO adversely affects the human body in the form of fatigue, angina pectoris, visual impairment, and brain function deterioration and may lead to death in severe cases [19,20]. Beyond health concerns, recent studies have highlighted that air pollution may also impair worker cognition, focus, and physical endurance, factors that are closely tied to accident risk. The UK Health and Safety Executive (HSE), for instance, consistently reports that the construction industry accounts for a high proportion of workplace accidents, with falls from height, being struck by moving objects, and exposure to hazardous substances among the leading causes. In 2024/25, construction recorded 35 fatal injuries, representing nearly one-quarter of all workplace fatalities in Great Britain [21]. These statistics underscore the vulnerability of construction workers to environmental and situational risks, including air quality. Several researchers have begun exploring the link between ambient air quality and workplace safety. For example, Lavy et al., 2022 demonstrated a causal relationship between air pollution and increased accident rates among construction workers [22]. Similarly, Cabral et al. (2024) provided robust evidence that higher concentrations of PM_{10}, NO_2, and other pollutants elevate the risk of occupational injuries, particularly in high-risk sectors like construction [23].

Various studies have separately evaluated the impact of each air pollutant, and there have been studies that integrated air pollutants into a single index for evaluation. Xu et al. (2023) proposed a safety prediction system for outdoor work using multi-layer fuzzy logic to ensure the safety of construction workers [24]. Yet, many of these studies are either simulation-based or do not quantify the probability of actual accidents. While the literature on economics and public health has progressed toward understanding these environmental risk factors, these approaches often lack construction-specific applications or actionable concentration thresholds. Most focus on health impacts or productivity loss rather than direct accident probabilities.

However, there is a relatively small number of studies that have analyzed the correlation between air pollutants and accidents. Furthermore, there has been little research conducted to quantitatively investigate the influence of air pollutants at construction sites on accidents experienced by workers [25,26].

Through a review of the existing literature, it was found that there have been studies analyzing the correlation between PM_{10} and accidents among air pollutants. Wan et al. (2020) suggested that both PM_{10} and $PM_{2.5}$ are associated with an increase in traffic accidents [27]. However, they did not establish the mechanism or causality between traffic accidents and air pollution [27]. Particularly, Vega-Calderón et al. (2021) conducted a significant study revealing that as the concentrations of PM_{10} and NO_2 increase, more accidents tend to occur [28]. Nonetheless, they did not provide quantitative accident probability, posing a limitation in their research.

Previous studies on construction safety and the factors affecting accidents in the construction industry were focused on weather, worker carelessness, neglect of management, inappropriate work methods, and high-risk work. The environmental context, specifically air quality, has been underexplored despite its relevance. However, this study aims to evaluate the quantitative risk only for air pollutants (O_3, SO_2, NO_2, PM_{10}, CO) that have been actively studied from a health perspective.

Therefore, the objective of this study is to quantitatively assess the relationship between air pollutant concentration levels and accident probabilities at construction sites. It further aims to develop new pollutant concentration groupings based on accident risks rather than health-based thresholds. By doing so, this research bridges the gap between public health, environmental economics, and construction safety, offering practical guidelines for accident risk management using environmental data.

2. Literature Review

2.1. Health Impacts of Air Pollution on the General Population

Air pollution is a major public health concern, with numerous studies documenting its adverse effects. Yang et al. (2009) explored the link between air pollutants and oxidative stress, concluding that prolonged exposure contributes to various chronic conditions, including respiratory and cardiovascular diseases [29]. Kampa et al. (2008) reviewed the impacts of various pollutants, such as CO, SO_2, NOx, VOCs, O_3, $PM_{2.5}$, and PM_{10}, on asthma, lung cancer, and cardiovascular morbidity [30]. Kumar et al. (2018) conducted a health risk assessment of air pollutants along transport corridors in Delhi, India, demonstrating elevated mortality and morbidity due to localized exposure [31]. Yu et al. (2016) used satellite data to quantify health risks from multiple pollutants in China [32]. Chen et al. (2017) demonstrated that high temperatures amplify PM_{10}'s impact on mortality [33], while Contiero et al. (2019) confirmed this synergy in cardiovascular-related emergency visits [34]. Gu et al. (2017) explored the combined effects of PM_{10} and NO_2 on mortality, revealing higher risks from co-exposure [35]. Cothern et al. (2023) examined worker exposure to silica dust in construction, highlighting control measures to mitigate health risks [36]. Ghorani-Azam et al. (2016) provided a comprehensive review of pollutant toxicity, sources, and health impacts, with prevention strategies tailored for high-exposure areas [37].

2.2. Air Pollution Exposure and Health Risks Among Industrial and Construction Workers

Occupational exposure to pollutants poses significant health and safety risks, particularly in construction and industrial settings. Bauleo et al. (2019) evaluated long-term pollutant exposure and mortality among workers in an industrial zone [38]. Cui et al. (2020) measured VOC emissions in asphalt pavement construction and assessed their health implications [39]. Cavallari et al. (2007) observed reduced heart rate variability among boilermaker construction workers exposed to $PM_{2.5}$ [40]. Tovalin et al. (2006) showed a direct link between outdoor occupational exposure to pollutants and DNA damage in workers [41]. Singh et al. (2016) explored the effect of heat and PAH exposure on renal health among kitchen workers [42]. In construction-specific contexts [42], Tong et al. (2018) applied Monte Carlo simulations to assess uncertainty in dust-induced occupational health risks [43], and Sekhavati and Yengejeh (2023) demonstrated that particulate matter at construction sites significantly affects worker health [44]. Sarkar et al. (2023) estimated long-term health burdens from dust exposure on construction sites in India [45]. Maesano et al. (2020) investigated mortality reductions associated with decreased PM_{10} levels due to traffic restrictions in Paris, illustrating how urban policies can mitigate health impacts [46]. Reviews by Cheriyan and Choi (2020) and Khamraev et al. (2021) emphasized the need for industry-specific risk frameworks to manage occupational exposure [47,48].

Beyond health risks, recent economic research has linked air pollution to workplace accidents. Lavy et al. (2022) investigated the causal effect of air pollution on accidents in construction sites in Israel, identifying a statistically significant link between pollutant levels and workplace injuries [22]. Palma et al. (2024) confirmed similar results for Italy, using panel regression models to show that increases in PM and O_3 concentrations raise workplace accident rates [49]. Cabral and Dillender (2024) focused on wildfire smoke and general air pollution in the United States, showing negative effects on both health and worker safety [23].

2.3. Construction Accidents and Environmental Influences

Although traditional construction safety research emphasizes causes such as worker behavior, equipment hazards, and management practices, fewer studies have examined how environmental conditions, particularly air quality, influence accidents. For example, Vega-Calderón et al. (2021) reported that elevated PM_{10} and NO_2 concentrations were associated with increased occupational accidents in Madrid [28]. Similarly, Wan et al. (2020) demonstrated that traffic accidents increased with air pollution exposure, suggesting that impaired cognition and reduced visibility may extend to construction settings [27]. More recently, Lee et al. (2023) applied a relative probability model to quantify the effect of particulate matter on construction accidents, showing that accident probability rises with higher PM levels [26]. These studies highlight an emerging but underdeveloped research area that connects environmental exposures with construction safety outcomes.

2.4. Research Gap and Contribution

While air pollution's health impacts are well documented, limited research has examined how pollutant concentrations influence construction accident risk. Health science studies focus on morbidity and mortality, while recent economic analyses link pollution to macro-level workplace productivity and accident rates. However, these approaches do not provide actionable risk classification models for construction safety management. This study addresses this gap by: (1) Providing a sector-specific quantitative analysis of accident probability in relation to pollutant concentrations. (2) Developing a relative probability-based risk evaluation model tailored to construction environments. (3) Proposing new pollutant concentration groups based on accident data rather than health-based criteria, offering practical thresholds for construction safety management.

3. Materials and Methods

As shown in Figure 1, the study is conducted as follows: (i) Collection of data; (ii) classification of data; (iii) probabilistic analysis of air pollutant concentration and accident; and (iv) clustering of air pollutant concentration groups.

3.1. Collection of Data

A retrospective study was conducted to examine the relationship between air pollutants (PM_{10}, SO_2) and construction accidents in South Korea over 13 years (2007–2019). A total of 214,538 construction accident cases were obtained from the Korea Occupational Safety and Health Agency [50]. Concurrently, air pollutant concentration data (PM_{10}, O_3, NO_2, SO_2, CO) were sourced from the Korea Environment Corporation (K-eco) [51]. All pollutant data were measured by observation equipment installed at fixed monitoring stations distributed across 494 districts in South Korea, and pollutant concentrations were recorded at hourly intervals.

To ensure spatial and temporal accuracy, each accident case was matched to the nearest monitoring station based on administrative district codes. If multiple stations existed in a district, the station with the smallest Euclidean distance to the accident location was selected. Temporally, hourly pollutant data were aligned with the accident timestamp. In cases where hourly data were missing, daily averages from the nearest station were substituted. This ensured that every accident was assigned pollutant concentration values reflective of the actual exposure conditions.

Considering the working hours of construction workers, the analysis focused on accidents occurring between 07:00 and 19:00, accounting for 98% of total cases. This restriction excluded non-occupational exposures such as commuting-related or underlying health issues. Ultimately, this study analyzed 209,833 disaster cases during standard working hours to maintain occupational relevance. The study quantified the effects of air pollutants on construction accidents while controlling for non-occupational exposures. The focus on working hours ensures that concentration data correspond to times when workers were likely present on site, enhancing the validity of the findings. Table S1 (Supplementary

Materials) provides the detailed frequency distribution of accidents by time, confirming the exclusion of cases outside standard working hours.

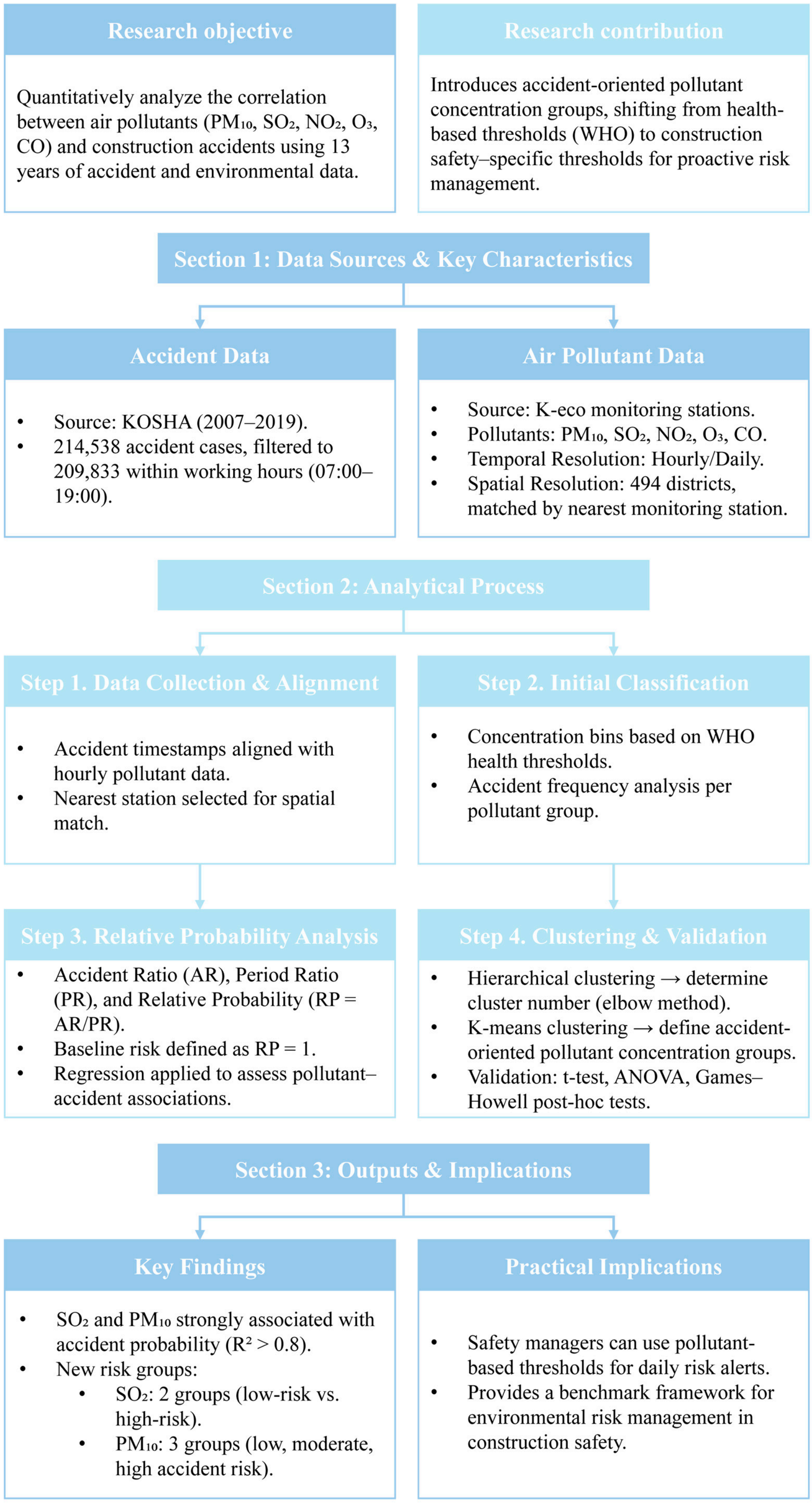

Figure 1. Summary of research process.

3.2. Classification of Data

Currently, WHO manages air pollutants by setting numerical guideline values and interim targets for concentrations of $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2, and CO in relation to health impacts [11]. Importantly, WHO does not classify pollutants into qualitative categories such as "Good," "Moderate," or "Unhealthy." Such descriptive labels originate from Air Quality Index (AQI) systems, including those established by the Korea Environment Corporation (K-eco) [51]. These systems translate numerical pollutant concentrations into qualitative descriptors for public communication (e.g., "Good," "Moderate," "Unhealthy for sensitive groups," "Unhealthy," "Very unhealthy," and "Hazardous").

In this study, we adopted the numerical thresholds from the WHO Global Air Quality Guidelines [11] to define concentration breakpoints, while using AQI-style descriptors solely for interpretability. Table S2 summarizes the concentration intervals applied in this study. Based on these ranges, the distribution of accidents was classified: [11] PM_{10} is "Good" to "Very unhealthy," O_3 is "Good" to "Unhealthy," NO_2 is "Good" to "Unhealthy for sensitive people," and SO_2 and CO were collected in the "Good" group range.

3.3. Probabilistic Analysis of Air Pollutant Concentration and Accident

The exposed period of air pollutant concentration levels per functional unit is varied. And it is hard to evaluate the probability of accident occurrence per concentration level directly. Thus, the relative probability by concentration was calculated using accident data and air pollutant concentration data for 13 years [14]. Previous studies have mentioned that risk should be evaluated considering the frequency and probabilistic aspects. For this reason, this study calculated the relative quantitative thought probability by considering not only the frequency but also the probability aspect through the relative probability calculation [52]. Consequently, in this study, the relative probability was calculated using Equations (1)–(3) [14]. This helps quantitatively calculate the probability of accidents occurring owing to air pollutant concentration in the construction industry.

$$AR = \frac{\sum_{i=1}^{n} A_{air\ pollutants}}{\sum_{i=1}^{n} A} \tag{1}$$

$$PR = \frac{N_{air\ pollutants}}{\sum_{i=1}^{n} X_i} \tag{2}$$

$$RP = \frac{AR}{PR} \tag{3}$$

where AR (Accident Ratio) refers to the proportion of accidents that occurred under a given air pollutant concentration. It is calculated by dividing the number of accidents occurring at a specific concentration level ($A_{air\ pollutants}$) by the total number of accidents across all levels (A). PR (Period Ratio) represents the proportion of time that a specific pollutant concentration level was observed. It is the number of time periods with that pollutant concentration ($N_{air\ pollutants}$) divided by the total number of observation periods (X_i). RP (Relative Probability) is the ratio of the accident occurrence rate (AR) to the period ratio (PR). It measures whether the likelihood of accidents is higher or lower than expected based on how frequently the concentration occurs [14].

In the above way, the baseline probability, defined as numerical number 1, can be set through relative probability analysis. And this baseline means the average probability of accident occurrence at the whole concentration level for each air pollutant. This is because the relative probability is calculated through calculations between ratios rather than conventional frequency analysis. If the relative probability value of the air pollutant concentration is less than 1, the accident probability of the concentration is lower than the average accident probability. Conversely, if the relative probability value of the concentration exceeds 1, it indicates that the accident probability of the concentration is higher than the average accident probability [14].

3.4. Clustering of Air Pollutant Concentration Group

In this study, the relative accident probability associated with air pollutant concentrations was first calculated through the relative probability framework, which normalizes accident counts by the frequency of pollutant exposure. These values were then used to develop a novel concentration group classification focused on construction safety management rather than health-based guidelines.

To operationalize this process, the continuous concentration data for each pollutant were first divided into bins. For PM_{10}, bin intervals were constructed using WHO guideline breakpoints (e.g., 20, 40, 50 $\mu g/m^3$), extended to cover the observed concentration range. For SO_2, equal-interval binning was applied within the observed distribution to ensure sufficient sample size in each bin. For every bin, we computed accident frequency, period ratio, and relative probability, as defined in Equations (1)–(3).

The resulting set of relative probability values was then subjected to a two-step clustering approach:

1. Hierarchical clustering was used to determine the optimal number of accident-risk groups. The elbow method was applied to the sum of squared errors (SSE) curve, identifying the point where additional clusters provided diminishing improvements in model fit.
2. K-means clustering was subsequently performed using this optimal cluster number. This step grouped bins with similar relative probability values into new concentration groups that represent distinct accident-risk levels.

Finally, statistical verification ensured that the derived groups were meaningfully distinct. For SO_2, we applied *t*-tests to compare mean relative probabilities across groups. For PM_{10}, we employed ANOVA with Welch's correction due to unequal variances, followed by Games–Howell post hoc tests to confirm significant differences between groups.

3.4.1. Hierarchical Clustering

This study examined the relationship between air pollutants and accidents that transpire within construction sites and presented a newly modified concentration group that differs from the existing WHO concentration group for air pollutants that have a significant impact on accidents. At this time, the analysis was conducted through K-means clustering. K-average clustering has a limitation in which the user calculates the cluster quantity by individual judgment. However, in this study, the number of clusters was determined using elbow points to calculate the ideal number of clusters through K-means clustering [53].

Elbow points were identified using hierarchical clustering. Hierarchical cluster analysis is a method of reducing the number of clusters by combining clusters with high similarity or close distance among several clusters. In this case, the elbow point can be identified by examining the point at which the sum of squared errors (SSE) is minimized. The SSE can be computed using Equation (4) provided below [54].

$$SSE = \sum_{i=1}^{n} \sum_{x \in c_i} dist(x,\ c_i)^2 \tag{4}$$

where SSE is the sum of squared error, x is the set of observations, and c_i is the center of each cluster [54].

3.4.2. K-Means Clustering

K-means clustering was performed based on the number of clusters determined using hierarchical clustering and the elbow method. K-means clustering enables the classification of data into k clusters. It is a clustering technique that selects a specific random point to set the center point of the cluster and selects the point closest to the center [55].

This study reclassified the concentration group for air pollutants that affect construction accidents through K-means clustering. The criterion for the new concentration group is the relative probability value calculated to quantitatively evaluate the correlation between air pollutants and accidents in construction.

3.4.3. Statistical Verification

The *t*-test is a parametric statistical method that compares the means between two groups [56]. It is a testing method based on an estimated analysis or standard deviation of a sample representing a population. Its value is obtained by dividing the mean between two groups by the standard error based on the statistical t-value used in the *t*-test [57]. The analysis of variance (ANOVA) is a statistical technique employed to identify significant differences between the means of three or more independent groups. At this time, if there is a difference between the means of the group, a post-test must be conducted to determine how much difference there is between which groups [58]. To perform the ANOVA, it is necessary to determine whether the data to be analyzed are of equal variance based on Levene's test for equivalence of variances. In this case, if data are heterogeneous, the difference in the means between each group should be verified using Welch's test [59].

In the case of post hoc analysis about equal variance, the difference in the mean of each group can be confirmed using the Scheffe and Duncan tests. If heteroscedasticity is confirmed using Levene's test for equality of variances, the distinction in the mean of each group can be verified by employing the Games-Howell statistic [59].

In this study, *t*-test and ANOVA were performed to confirm whether the air pollutants group classified using K-means clustering was a statistically significant group. In the case of the ANOVA, it was confirmed that the variance was heterogeneous by checking the equal variance of the collected data; therefore, Welch's test was used. For post hoc analysis, the difference in the means between each group was confirmed using the Games–Howell test.

Hypotheses of the study:

Hypothesis 1. *Higher concentrations of SO_2 and PM_{10} are associated with a statistically significant increase in construction accident probability.*

Hypothesis 2. *Accident-oriented pollutant concentration groups derived from clustering differ meaningfully from WHO health-based groups and provide more relevant thresholds for construction site safety management.*

4. Results

4.1. Frequency Analysis Between Accidents and Air Pollution Concentration

The frequency of accidents by concentration level for each air pollutant (SO_2, CO, O_3, NO_2, PM_{10}) over a 13-year period was analyzed (Figures 2 and 3, with Figures S1–S3 in the Supplementary Materials). Each figure displays pollutant concentration (*x*-axis), accident count (*y*-axis), and frequency of concentration occurrence as an auxiliary axis. The histogram is the number of accidents according to concentration, and the average number of accidents is presented as a gray horizon. Finally, groups designated by the WHO are indicated by color: "Green" as "Good," "Yellow" as "Moderate," "Orange" as "Unhealthy for sensitive groups," "Red" as "Unhealthy," and "Purple" as "Very unhealthy" group.

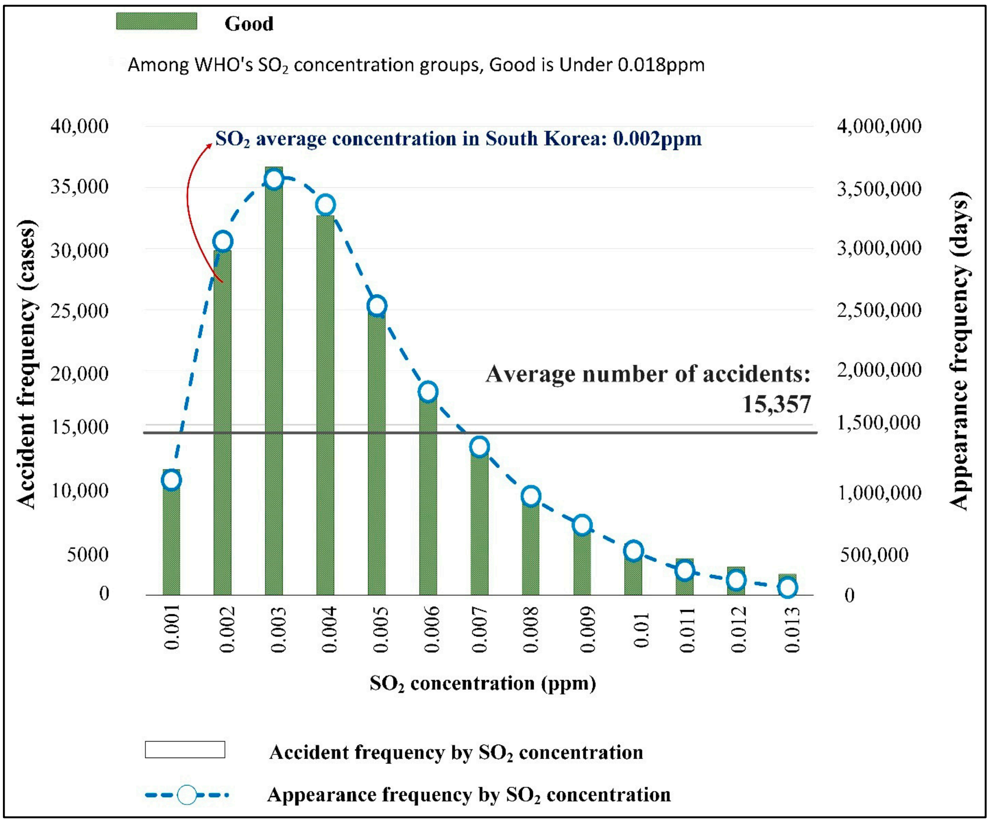

Figure 2. Frequency analysis of accidents to SO_2 concentration and its WHO's classification.

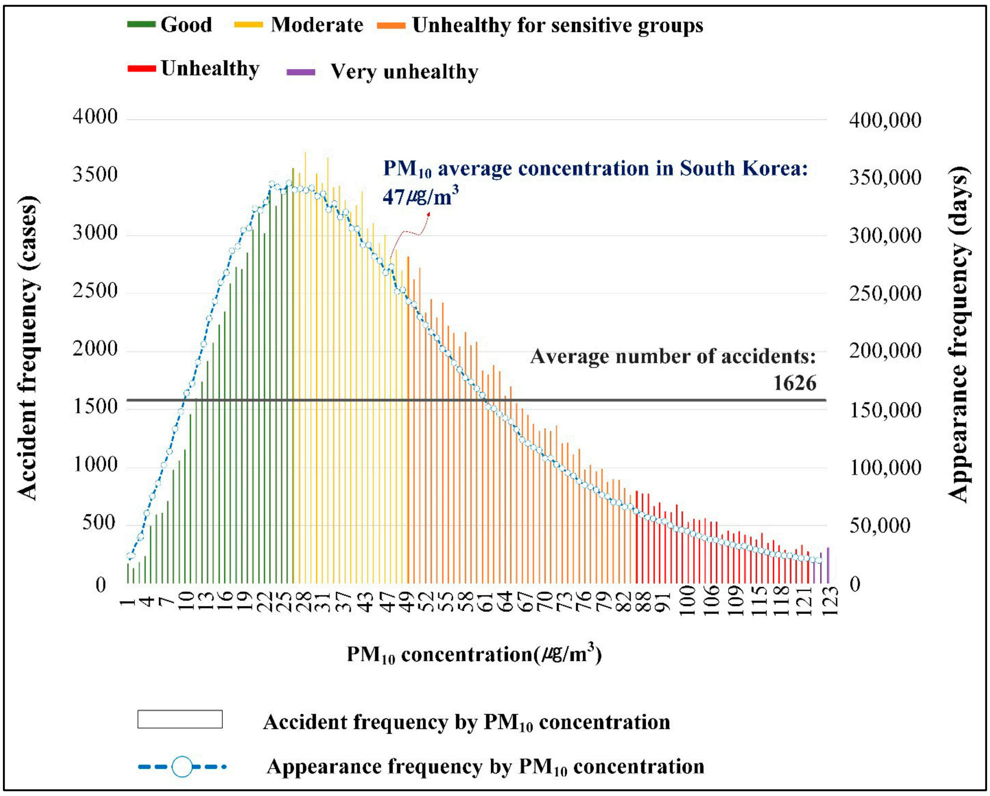

Figure 3. Frequency analysis of accidents to PM_{10} concentration and its WHO's classification.

The frequency analysis results are as follows.

First, in the case of SO_2, all the disasters occurred in the "Good" group of the WHO. The highest accident concentration was 0.003 ppm (35,664 cases), and the average SO_2

concentration in Korea was 0.002 ppm [51]. That is, the highest concentration in the construction industry over the past 13 years was found to be around the average concentration. As a result of analyzing the frequency of appearance for 13 years based on the concentration of SO_2, the value of 0.003 ppm (3,211,180 days) emerged the most, just like the frequency of accidents.

Second, for CO (Figure S1), all accidents also fell within the WHO "Good" range. Most accidents (38,441 cases) occurred at 0.4 ppm, which also had the highest observation frequency (3,428,571 days). This aligns with Korea's average of 0.5 ppm [51].

Third, for O_3 (Figure S2), accidents spanned from "Good" to "Unhealthy" levels. The most frequent and accident-prone concentration was 0.003 ppm (5771 cases), though the national average was higher at 0.023 ppm [51].

Fourth, for NO_2 (Figure S3), accidents occurred between "Good" and "Unhealthy for sensitive groups." Most accidents (8326 cases) were recorded at 0.011 ppm, while 0.010 ppm was the most frequently observed level (604,550 days), both lower than the national average of 0.028 ppm [51].

Finally, based on the analysis of the accidental data of PM_{10}, accidents were distributed from "Good" to "Very unhealthy" groups. The most accidents occurred at 32 μg/m^3 (3721 cases).

4.2. Relative Probability Between Accidents and Air Pollution Concentration

While frequency analysis provides basic trends, it does not quantify accident risk. Thus, this study employed relative probability analysis to normalize accident rates by pollutant exposure frequency. Results for CO, NO_2, and O_3 showed no clear trend and are provided in Supplementary Figures (Figures S4–S6). SO_2 and PM_{10} results are shown in Figures 4 and 5.

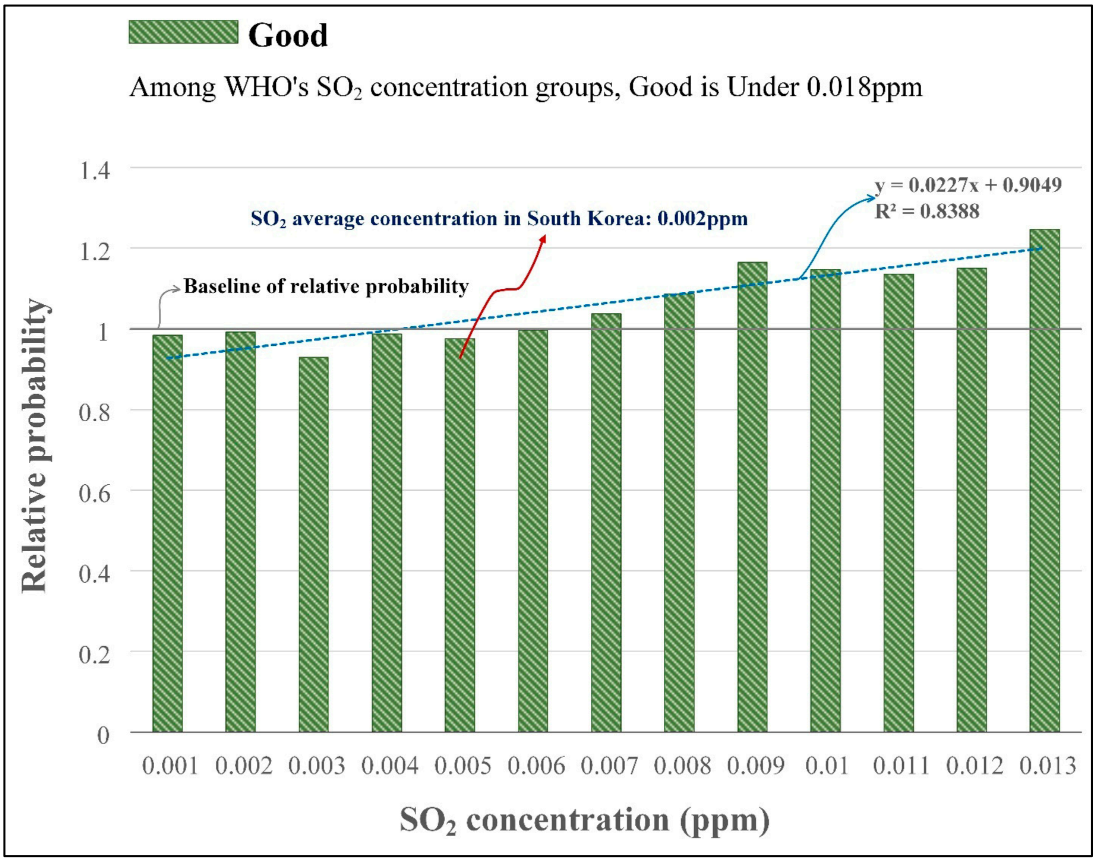

Figure 4. Relative probability analysis of accidents to SO_2 concentration and its WHO's classification.

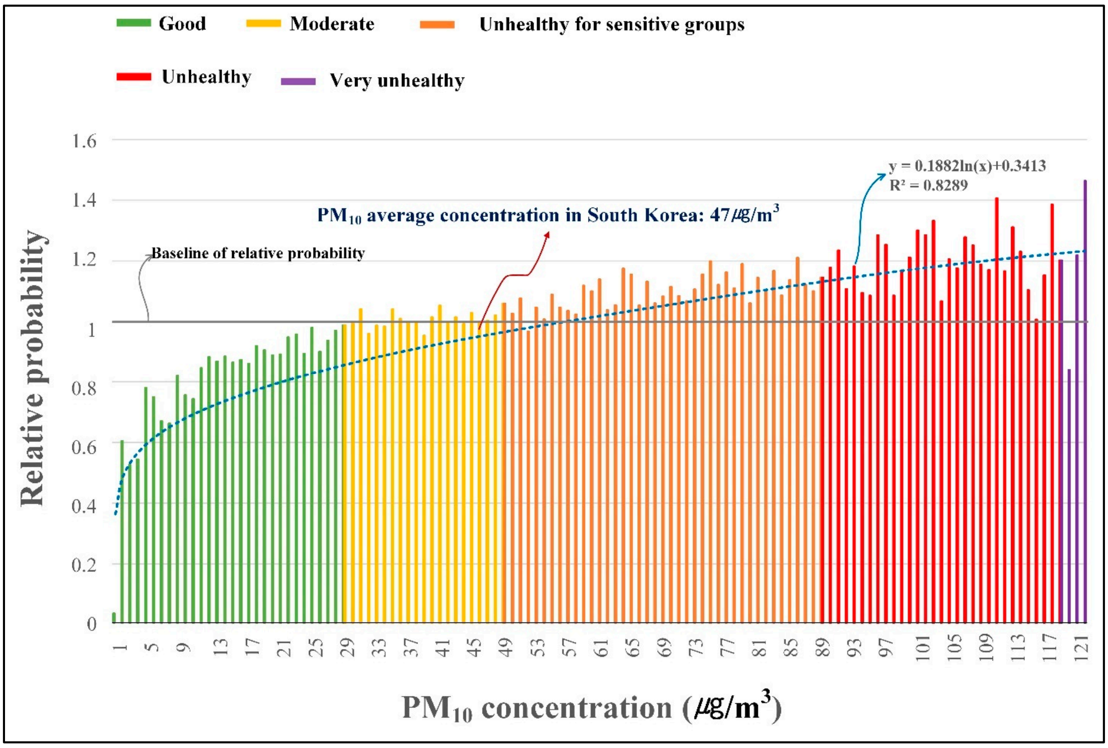

Figure 5. Relative probability analysis of accidents to PM_{10} concentration and its WHO's classification.

For instance, it was identified that the largest number of accidents was found at 0.003 ppm of SO_2 (36,664 cases). However, the analysis revealed that analyzing the relative probability of SO_2, the relative probability value at 0.003 ppm of SO_2 was 0.92 only, which was the lowest in the total concentration range.

As shown in Figure 4 about SO_2, it was verified that the relative probability had been increased according to the concentration level rise. The relative probability value was higher than the baseline probability of 1 from 0.007 ppm and above. Additionally, 0.013 ppm was the highest probability of accidents attributed to SO_2. The R^2 value of the regression analysis was 0.84.

As shown in Figure 5 about PM_{10}, the analysis of the quantitative accident probability through relative probability revealed a positive association between the concentration and the corresponding relative accident probability, either. For instance, the largest number of accidents was found at 32 $\mu g/m^3$, as shown in Figure 3, upon the frequency analysis; however, 123 $\mu g/m^3$ was the highest probability of accidents attributed to PM_{10}, and the relative probability at this concentration level was 1.50. This means that the accident probability is 1.5 times higher than the average level at 123 $\mu g/m^3$ of PM_{10}.

4.3. New Concentration Groups Based on Relative Probability

This study reclassified concentration groups for air pollutants associated with construction accidents. The rationale for creating new groupings is that the World Health Organization (WHO) thresholds are designed for public health protection, focusing on morbidity and mortality outcomes. These health-oriented categories may not capture the probability of acute, short-term workplace accidents. In contrast, our accident-oriented groups are derived from relative probability analysis and clustering, which identify concentration levels most strongly associated with accident risk on construction sites. Thus, the new groups provide site managers with safety-relevant thresholds rather than general health guidelines.

Two clustering methods were used: hierarchical clustering to identify elbow points, and K-means clustering to determine optimal group numbers for SO_2 and PM_{10}, which exhibited high correlation with accident probability (Figures S7 and S8). The elbow point was defined as the point where the reduction in the sum of squared errors (SSE) sharply decreases [54]. Elbow point results for CO and NO_2 are provided in the Supplementary Materials (Figures S9 and S10).

Table S3 lists the number of groups classified by the WHO on the human health aspect and the developed groups on the accident aspect in terms of SO_2 and PM_{10}, respectively. As a result, SO_2 and PM_{10} were presented in two and three groups to classify the accident impact of their concentration level, respectively.

K-means clustering was performed through elbow point analysis to confirm the new concentration group of SO_2 and PM_{10}. Figures 6 and 7 show the newly suggested concentration groups of SO_2 and PM_{10}, respectively.

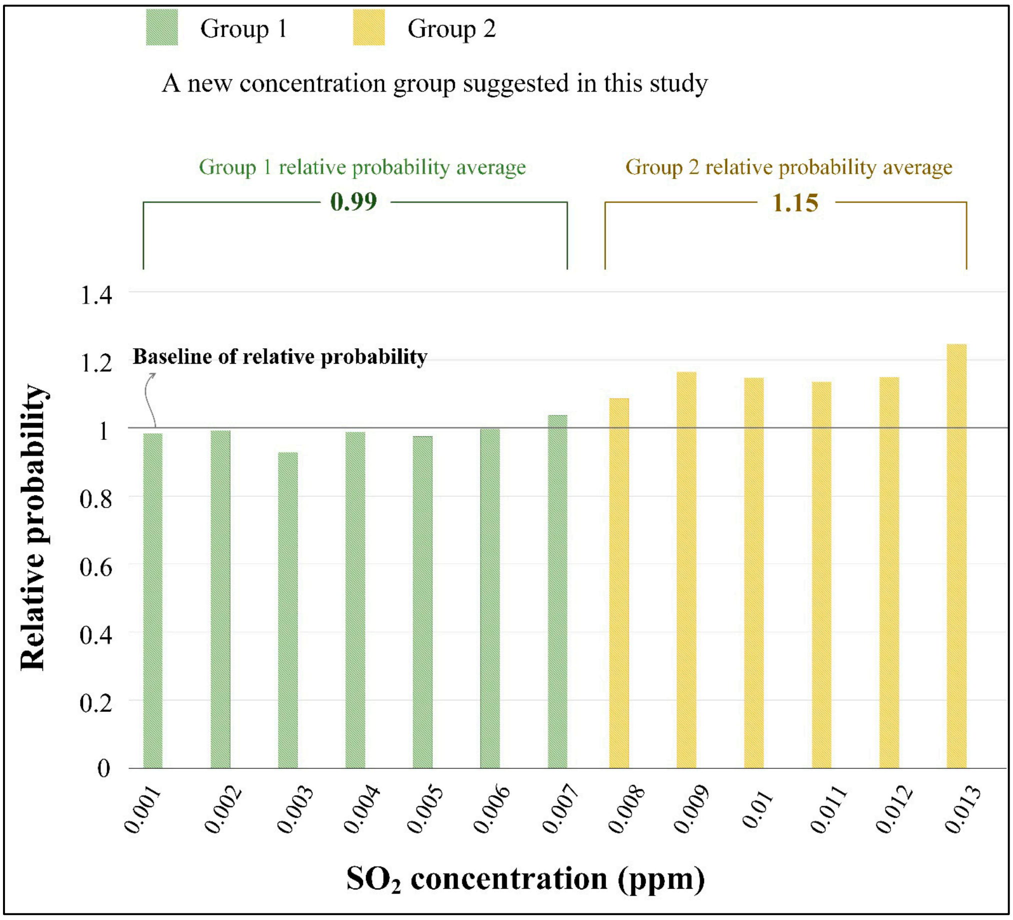

Figure 6. New concentration group of SO_2 using the relative probability of accidents.

For each graph, the *x*-axis denotes the concentration of air pollutants, while the *y*-axis represents the relative probability value. Histogram refers to the relative probability of SO_2 and PM_{10} by concentration. Green, yellow, and primary colors mean group 1, group 2, and group 3 for each. Baseline 1 of relative probability is indicated by a black horizontal line.

First, the newly modified concentration groups of SO_2 presented in this study were identified and two groups were presented. The concentration range of group 1 is 0.001–0.007 ppm, and the concentration range of group 2 is 0.008–0.013 ppm. The average relative probability of SO_2 is 0.99 for group 1 and 1.15 for group 2. In terms of accident probability, the value of group 1 was lower than the baseline score of 1. Therefore, based on the same period, the accident probability was below the average accident probability, and the value of group 2 was greater than 1, indicating a higher probability of an accident.

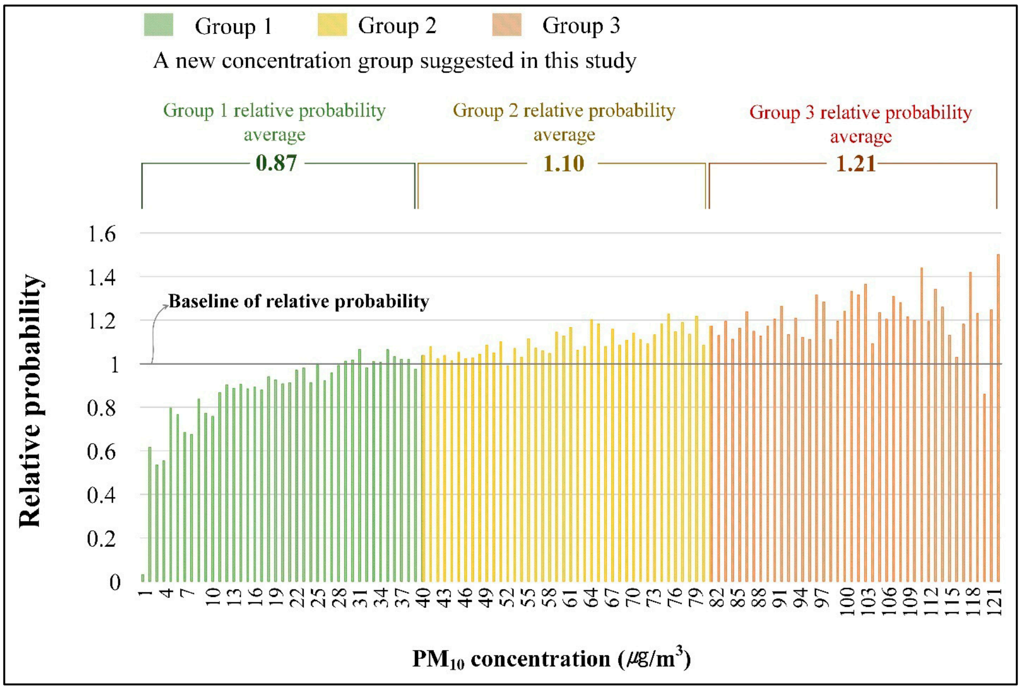

Figure 7. New concentration group of PM_{10} using the relative probability of accidents.

The results of verifying the proposed concentration group by newly modifying it according to the relative probability of PM_{10} are as follows. It was presented in three concentration groups, with each group being assigned a specific concentration range of 1 $\mu g/m^3$ to 40 $\mu g/m^3$ for Group 1, 41 $\mu g/m^3$ to 81 $\mu g/m^3$ for Group 2, and 82 $\mu g/m^3$ to 123 $\mu g/m^3$ for Group 3. The average of the relative probabilities for each group is as follows. Based on the same period, group 1 was 0.87, group 2 was 1.10, and group 3 was 1.21. The group with lower than the average accident probability was 1 and the higher group was 2 and 3.

4.4. Statistical Verification of New Concentration Group

To verify the effectiveness of the newly proposed concentration groups for SO_2 and PM_{10}, statistical tests were conducted. Additional results for CO and NO_2 are available in Tables S4 and S5.

Table 1 presents the *t*-test results for SO_2. The mean relative probability was 0.99 for Group 1 and 1.15 for Group 2, with a statistically significant difference ($p = 0.000$). This confirms that the two SO_2 groups differ meaningfully in terms of accident risk. The results indicate that construction sites operating under SO_2 concentrations in Group 2 (0.008–0.013 ppm) have on average, a 16% higher accident probability compared to sites in Group 1 (0.001–0.007 ppm). This statistically significant difference suggests that the revised grouping captures a meaningful stratification of accident risk based on pollutant levels, which is not reflected in traditional health-oriented classifications.

Table 2 shows the ANOVA results for PM_{10}. The mean relative probabilities were 0.87 (Group 1), 1.10 (Group 2), and 1.21 (Group 3). Levene's and Welch's tests indicate significant variance among the groups ($p < 0.001$). This finding reveals a clear trend where accident risk increases progressively with PM_{10} concentration. The 39% increase in relative accident probability from Group 1 (1–40 $\mu g/m^3$) to Group 3 (82–123 $\mu g/m^3$) highlights the utility of the new classification in identifying elevated risk zones that are not distinguishable through WHO health thresholds.

Table 1. *t*-test results of the new SO_2 concentration group.

Variable	Group	Cases of Samples (n)	Average (Relative Probability)	Standard Deviation	t	p
SO_2	1	7	0.99	0.03	−7.17	0.000
	2	6	1.15	0.05		

Table 2. The results of ANOVA for the new PM_{10} concentration group.

Variable	Group	Cases of Samples (n)	Average (Relative Probability)	Levene's Test	Levene's p	Welch's Test	Welch's p
PM_{10}	1	41	0.87	7.14	0.001	49.21	0.000
	2	42	1.10				
	3	43	1.21				

Table 3 displays the post hoc Games–Howell test, confirming significant differences between all PM_{10} group pairs ($p < 0.001$). These results validate that the newly developed PM_{10} classification effectively distinguishes levels of accident risk. The statistical separation between each group pair further reinforces the robustness of the clustering approach, confirming that each new group represents a unique accident risk profile. Such stratification can serve as a basis for threshold-based interventions on construction sites, such as activity rescheduling or mandatory protective measures when pollutant levels enter higher-risk bands.

Table 3. Results of Games Howell for post-analysis of new PM_{10} concentration group.

Group	1	2	3
1	-	0.000	0.000
2		-	0.000
3			-

5. Discussion

The frequency analysis revealed that most accidents occurred at pollutant concentrations with the highest observation frequency. This suggests that accident frequency may be influenced more by exposure duration than by pollutant intensity. However, such frequency-based interpretation alone cannot capture the true risk associated with different concentration levels.

To address this limitation, this study employed relative probability as a metric to assess accident risk adjusted for the frequency of pollutant exposure. Table 4 summarizes the regression results, clustering, and statistical significance of RP-based analysis for five pollutants: O_3, SO_2, NO_2, PM_{10}, and CO.

This approach is consistent with prior literature that emphasizes the inadequacy of raw frequency data in environmental health and safety analysis. For example, Jeong and Jeong (2022) similarly utilized a relative probability framework to assess fatality risk in construction, highlighting its value in normalizing risk indicators across uneven exposure distributions [52].

SO_2 and PM_{10} demonstrated strong relationships with accident probability, with R^2 values exceeding 0.8. Based on this, two SO_2 groups and three PM_{10} groups were defined using clustering, and their statistical significance was confirmed through *t*-tests and ANOVA. These findings suggest that SO_2 and PM_{10} concentrations are relevant risk indicators for construction site accidents and should be monitored accordingly.

Table 4. The summary of accident impact of air pollutants using relative probability.

Classification	Regression Results	Number of Clustering	Mean Difference Between Groups	Significance	Result
SO_2	0.8388	2	There is a difference	Significant	New Concentration Group Proposal
PM_{10}	0.8289	3	There is a difference	Significant	
CO	0.4354	2	There is a difference	Significant	A new concentration group could not be suggested due to the low R^2 value
NO_2	0.2456	2	There is a difference	Significant	
O_3	0.0832	4	No difference	not significant	There was no correlation with the accident

Our findings align with the results of Cabral and Dillender (2024), who demonstrated that elevated PM concentrations increased occupational injury rates, particularly in high-risk outdoor jobs [23]. Similarly, Lavy et al. (2022) found that increased air pollution levels significantly raised accident incidence among construction workers, attributing this to impaired cognitive function and reduced physical stamina [22]. These studies corroborate our conclusion that PM_{10}, in particular, has a strong link to safety outcomes.

In contrast to health-based studies that often aggregate pollutants into single indices (e.g., AQI), our study provides pollutant-specific insights that are directly linked to safety outcomes. Xu et al. (2023) proposed a fuzzy-logic based system for predicting site safety under outdoor conditions, but it lacked concentration-level thresholds for actionable decision-making [24]. In comparison, our method introduces practical concentration ranges derived from statistical clustering, providing safety practitioners with threshold-based monitoring criteria.

In contrast, CO and NO_2 had lower R^2 values, indicating weak correlations with accident probability. Although clustering and statistical tests showed differences between groups, the explanatory power was insufficient to propose new groupings. The detailed results are provided in the Supplementary Materials (Figures S9–S13). For O_3, no meaningful relationship with accident probability was observed, and no new classification was warranted.

These pollutant-specific disparities highlight the need to move beyond generalized air quality models when assessing occupational risk in construction. For instance, while some studies, such as Wan et al. (2020), linked PM concentrations with increased traffic accidents, they lacked sector-specific applicability and did not address confounding exposure times or industrial contexts [27]. Our RP-based method enhances this by contextualizing the exposure within construction site work hours.

Importantly, the new SO_2 and PM_{10} concentration groups proposed in this study have clear practical applications. Safety managers and environmental health officers can use these risk-based thresholds to implement proactive mitigation strategies. For example, if air pollutant levels reach Group 2 for SO_2 or Group 3 for PM_{10}, site supervisors may opt to delay high-risk tasks, enhance personal protective equipment (PPE) requirements, or increase break frequency to reduce fatigue and exposure. These thresholds can also inform automated alert systems integrated with real-time monitoring equipment on-site, triggering immediate risk notifications or work schedule adjustments. In this way, the proposed groupings serve not only as analytical classifications but as functional decision-making tools for real-time safety risk management.

This study identifies SO_2 and PM_{10} as critical air pollutants influencing construction safety and proposes actionable concentration thresholds based on accident probability, offering a novel perspective for environmental risk management on construction sites.

6. Conclusions

This study introduced a relative probability framework to quantitatively assess how air pollutant concentrations are associated with construction accident risk. While the World Health Organization (WHO) classifies air quality based on health effects, this study proposed a new classification scheme focused on accident probability to enhance construction safety management.

This study was carried out as follows: (i) collection of data; (ii) classification of data; (iii) probabilistic analysis of air pollutant concentration and accident; and (iv) clustering of air pollutant concentration groups.

Key findings are as follows:

First, among the five pollutants analyzed (SO_2, CO, O_3, NO_2, PM_{10}), only SO_2 and PM_{10} showed a strong positive correlation with accident probability, with R^2 values exceeding 0.8. Higher concentrations of SO_2 and PM_{10} were associated with significantly increased accident risk on construction sites.

Second, new concentration groups were proposed based on accident data rather than health thresholds. SO_2 was categorized into two groups and PM_{10} into three, with each showing statistically significant differences in accident probability. These groups were validated using *t*-tests and ANOVA, confirming their effectiveness for practical safety monitoring.

This study contributes to the field by presenting a quantitative method to examine associations between air quality and construction safety. It offers actionable thresholds for risk management and fills a gap between environmental health research and site-level safety planning.

Limitations include the inability to control for potential confounding factors such as weather conditions, seasonal variations, and co-pollutant effects. These factors may influence both pollutant levels and accident risk, and their omission may affect the robustness of the associations observed. Future research should incorporate multivariate approaches or stratified analyses to disentangle these effects and strengthen causal inference. In addition, case studies or field-based validation could provide more detailed insight into how environmental and contextual variables interact with accident risk.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/buildings15183305/s1: Figure S1: Frequency analysis of accidents to CO concentration and its WHO's classification title; Figure S2: Frequency analysis of accidents to O_3 concentration and its WHO's classification; Figure S3: Frequency analysis of accidents to NO_2 concentration and its WHO's classification; Figure S4: Relative probability analysis of accidents to CO concentration and its WHO's classification; Figure S5: Relative probability analysis of accidents to No_2 concentration and its WHO's classification; Figure S6: Relative probability analysis of accidents to O_3 concentration and its WHO's classification; Figure S7: Elbow point analysis about SO_2; Figure S8: Elbow point analysis about PM_{10}; Figure S9: Elbow point analysis about CO; Figure S10: Elbow point analysis about NO_2; Figure S11: New concentration group of CO using relative probability of accident; Figure S12: New concentration group of NO_2 using relative probability of accident; Figure S13: New concentration group of O_3 using relative probability of accident; Table S1: Frequency of accidents by time; Table S2: Air pollutant WHO criteria and concentration ranges were collected for this study; Table S3: Existing WHO groups and newly proposed groups of air pollutants; Table S4: *t*-test results of the new CO concentration group; Table S5: *t*-test results of the new NO_2 concentration group.

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