CivilEng

Article

Incident Analysis and Prediction of Safety Performance on Construction Sites

Ibukun Awolusi [1,*], Eric Marks [2], Alexander Hainen [3] and Ammar Alzarrad [4]

1 School of Civil & Environmental Engineering, and Construction Management, The University of Texas at San Antonio, San Antonio, TX 78207, USA
2 School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA 30313, USA; eric.marks@ce.gatech.edu
3 Department of Civil, Construction and Environmental Engineering, University of Alabama, Tuscaloosa, AL 35487, USA; ahainen@eng.ua.edu
4 Department of Civil Engineering, Marshall University, Huntington, WV 25755, USA; alzarrad@marshall.edu
* Correspondence: ibukun.awolusi@utsa.edu

Abstract: The hazardous nature of the construction environment and current incident statistics indicate a pressing need for safety performance improvement. One potential approach is the strategic analysis of leading indicators for measuring safety performance as opposed to using only lagging indicators, which has protractedly been the norm. This study presents a systematic safety performance measurement framework and statistical modeling processes for analyzing safety incident data for accident prediction and prevention on construction sites. Using safety incident data obtained from a construction corporation that implements proactive safety management programs, statistical modeling processes are utilized to identify variables with high correlations of events and incidents that pose dangers to the safety and health of workers on construction sites. The findings of the study generated insights into the different types and impacts of incident causal factors and precursors on injuries and accidents on construction sites. One of the key contributions of this study is the promotion of proactive methods for improving safety performance on construction sites. The framework and statistical models developed in this study can be used to collect and analyze safety data to provide trends in safety performance, set improvement targets, and provide continuous feedback to enhance safety performance on construction sites.

Keywords: analysis; construction safety performance; leading and lagging indicators; prediction; safety incident data; statistical models

check for updates

Citation: Awolusi, I.; Marks, E.; Hainen, A.; Alzarrad, A. Incident Analysis and Prediction of Safety Performance on Construction Sites. *CivilEng* **2022**, *3*, 669–686. https://doi.org/10.3390/civileng3030039

Academic Editors: Giuseppe Piccardo and Angelo Luongo

Received: 25 May 2022
Accepted: 8 July 2022
Published: 21 July 2022

1. Introduction

The construction industry is one of the most hazardous industries worldwide in which the highest rates of occupational injuries, illnesses, and fatalities are recorded when compared with other industries [1–6]. Construction sites are characterized by rugged environments, multiple resources, complex activities, and harsh working conditions that endanger the safety and health of workers [3,7,8]. The safety and health of construction workers is a complex phenomenon because of the risky nature of construction, which involves outdoor operations, work at heights, and complicated on-site equipment operations coupled with workers' attitudes and behaviors towards safety [9]. The high levels of injuries, illnesses, and fatalities being experienced continuously in the construction industry indicate poor safety performance and that a lot more is still required to reduce the prevalence of these unwanted events. Poor safety performance on construction sites physically and psychologically affects workers and impacts the project financially by increasing direct and indirect costs [1]. Incident reports in the construction industry suggest that there is an urgent need to reduce the pervasiveness of fatal and non-fatal injuries in construction [10] and thus a need for continuous monitoring and measurement of construction safety performance regularly updated through discovering leading indicators.

Understanding and addressing the causal factors that lead to accidents could be found to be very useful in developing effective accident prevention strategies [11]. Studies have also expressed that the likelihood of injuries, illnesses, or accidents can be described as a combined outcome of hazardous conditions and at-risk behaviors (such as near misses, unsafe conditions, unsafe actions, etc.), and chance variations as theorized by Heinrich's safety pyramid [12,13]. In a recent study, a prioritized list of potential predictors of serious injury and fatality events was generated [14]. Although it may not be generalized, investigations conducted in these studies demonstrated that one major injury could be preceded by a multitude of minor incidents or leading indicators (such as hazardous conditions and at-risk behaviors), which can be collected, analyzed, and used to predict safety performance and potentially prevent major injuries, illnesses, or fatalities on construction sites.

The proactive measurement of safety performance requires the adoption of a safety approach that is not anchored on the monitoring of injuries or accidents after they occur. This approach has its foundation in resilience engineering, which establishes some essential requirements that are reflected in four abilities that must be properly managed to achieve resilient construction safety performance [15,16]. The essential abilities include (a) responding (i.e., knowing what to do); (b) monitoring (knowing what to look for); (c) learning (knowing what has happened), and (d) anticipating (knowing what to expect) [17]. Safety-related practices can be actively measured during the construction phase to trigger positive responses before an injury or accident occurs [18–20]. The primary goal of measuring safety performance is to create and implement intervention strategies for the potential avoidance of future accidents [21]. To achieve zero incidents, proactive and active methods of safety management should also occur during the construction phase [18]. Current safety performance and potential risks in the operation of the facility can be predicted in advance, and one can take proactive actions to avoid the occurrence of an accident [22]. There is, therefore, a need for continuous monitoring of safety performance indicators to reduce illnesses, injuries, and fatalities on construction sites and enhance safety performance.

The purpose of this study is to present statistical models for analyzing safety incident data and predicting safety performance in construction. A framework for monitoring and measuring safety performance on construction sites is presented. Using safety incident data obtained from a company that implements proactive safety management programs, statistical modeling processes are utilized to identify specific variables that have high correlations of events and incidents that pose dangers to the safety and health of workers on construction sites.

2. Measuring Safety Performance in Construction

Safety performance in construction has historically been measured by "after-the-loss" types of measurements and metrics (or lagging indicators) such as the Occupational Safety and Health Administration (OSHA) recordable injury rate (RIR); days away, restricted work, or transfer (DART) injury rate; or the experience modification rating (EMR) associated with workers' compensation insurance, such as accident and injury rates, incidents, and costs [21,23]. However, most of these methods are reactive or subjective approaches because accident statistics only show the performance of safety management in the past [24,25] and are reactionary. In addition, these traditional safety metrics are out of date given the current ability to collect, analyze, and share safety data [26]. An alternative form of safety metric is the leading indicator. These proactive metrics assess safety performance by gauging processes, activities, and conditions, defining safety performance by their adherence to goals and future outcomes rather than relying on the past [19]. The measurement of safety performance can be used to provide feedback for proactive safety management and continuous improvement.

Indicators are observable measures that provide insights into a concept that is difficult to measure directly, and a safety performance indicator is a means for measuring the changes over time in the level of safety as the result of actions taken [27]. An indicator is a measurable and operational variable that can be used to describe the condition of a broader phenomenon or aspect of reality. An indicator can be considered any measure (quantitative or qualitative) that seeks to produce information on an issue of interest [28]. Safety indicators can play a key role in providing information on organizational performance, motivating people to work on safety, and increasing the organizational potential for safety. Safety performance indicators can be considered as filters through which reality is perceived, experienced, and understood.

The fundamental goal of measuring safety performance is to intervene in an attempt to mitigate unsafe behaviors and conditions that can lead to accidents on construction sites. Performance measurements can either be reactive monitoring or active monitoring [29]. The former means identifying and reporting on incidents, and learning from mistakes, whereas the latter means providing feedback on performance before an accident or incident occurs. Safety performance metrics can be divided into lagging indicators (which are linked to the outcome of an injury or accident) and leading indicators (which are measurements linked to preventive actions) [18,30]. These two categories of safety indicators are described as follows.

2.1. Lagging Indicators

Lagging indicators are reactive monitoring that show when the desired safety outcome has failed, or when it has not been achieved [31]. The use of lagging indicators involves identifying and reporting incidents to check that controls in place are adequate, identifying weaknesses or gaps in control systems, and learning from mistakes [29]. Common examples of these indicators or metrics are accident rate, lost workday injuries, medical aid cases, first aid cases, and Experience Modification Rate (EMR). These metrics are termed "lagging indicators" because the measurement and analysis occur after an accident occurs. Lagging indicators are unable to reflect if a hazard has been mitigated, the severity of an event, or the event's causation [32]. When a lagging indicator of safety is used, the information is, by definition, historical in nature. If the number of injuries is unacceptable, a response is generated that will hopefully prevent or reduce the number of future occurrences. Despite such efforts, they are implemented only after injuries have already occurred [33]. Lagging indicators do not provide further insights into the existing safety conditions once an accident has occurred.

2.2. Leading Indicators

Leading indicators are a form of active monitoring that determines if risk control systems are operating as intended [34]. Leading indicators are those metrics associated with measurable systems or individual behaviors linked to accident prevention. Leading indicators are measurements of processes, activities, and conditions that define performance and can predict future results [18]. The common leading indicators used in construction are near-miss reporting, worker observation (to determine unsafe conditions and acts), job site audits, stop work authority, housekeeping, safety orientation, training, etc. These indicators focus on maximizing safety performance by measuring, reporting, and managing positive, safe behaviors [30]. Leading indicators of safety performance are used as predictors of safety performance to be realized. They are used as inputs that are essential to achieving the desired safety outcome [31]. Leading indicators provide a means of tracking or monitoring the performance of a process as it is taking place, or they provide a way of showing whether a particular process or processes are being implemented as planned [26]. Leading indicators are directly related to the project that is to be undertaken and are concentrated on the safety management process [33]. Leading indicators give the probability that a safe project will be delivered by providing the opportunity to make changes as soon as there is an indication that the safety program has a weakness. The predictive nature of safety leading indicators is well-established [35] and studies have shown that leading indicators are not just predictors but also very pivotal in the improvement of safety performance.

3. Materials and Methods

The goal of this research is to analyze safety-leading indicator data and develop models that can be used to predict and prevent injuries, illnesses, and fatalities on construction sites. The research method adopted in this study was chosen in an attempt to provide a practical and adaptable framework that could be used to systematically transition safety performance measurement from the traditional to the modern approach. First, a conceptual framework that juxtaposes the traditional and modern methods for identifying, collecting, and analyzing safety indicators for incident prediction and prevention on construction sites is presented and described. Thereafter, a series of statistical modeling processes are utilized to analyze safety incident data and identify variables that can significantly impact the probability of unhealthful and harmful acts, events, or conditions on a construction site. Lagging indicators, including injuries, illnesses, and fatalities on construction sites, can result from a variety of causal factors relating to construction materials, equipment, work processes, and conditions of the sites and environments, which can be utilized to predict the probability of leading indicators (such as unsafe acts and conditions) and, in turn, the lagging indicators. The analysis of safety incident data presented in this study is categorized into the following two stages: (1) the modeling of causal factors responsible for safety leading indicators; (2) the modeling of the safety leading indicators that can be used to predict the probability of lagging indicators.

3.1. Framework for Monitoring and Measuring Safety Performance

This framework is presented as the basic procedure for the identification, collection, and analysis of safety performance indicators for incident prediction and prevention on construction sites. This practical and adaptable framework implements a systematic and statistical data collection and analysis technique and can be a vital component in the data flow within a safety program of any construction company. Part of the important factors considered when setting up a safety monitoring procedure is the size and structure of the organization or company and the operational environment.

The scope of monitoring should encompass operational, technical, and organizational safety management aspects that are rooted in the organization's safety program. In addition, the framework should incorporate safety performance functions that consider the temporal instability of safety performance correlates [36] of different construction projects and companies. The basic steps involved in the proposed framework for monitoring and measuring safety performance in construction are illustrated in Figure 1 and further described in the following sections.

3.1.1. Step 1: Identification of Safety Indicators

This step involves the identification of safety metrics or indicators that need to be captured in order to measure safety performance on a given construction project. These safety indicators will include both leading (proactive) and lagging (reactive) indicators as described previously in this paper and can either be quantitative or qualitative. Information about the types of indicators to be monitored can be obtained from the organization's safety program. The indicators selected are most efficient when they are aligned with the specific safety goals of an organization and the associated work process. The criteria used to select the indicators may involve the organization's present safety performance level, such as the stages of development of their safety program and their safety culture. For example, an organization that is already implementing an auditing process to achieve safety compliance can transition into continuous safety monitoring and measurement to improve its safety program by introducing other leading indicator programs such as near-miss reporting, worker observation process, safety activity analysis, etc. Examples of leading indicators that can be tracked on construction sites are near-misses, unsafe behaviors or acts, unsafe conditions, etc. Common lagging indicators that can be monitored on construction sites are OSHA recordable incidents, lost workday injury or lost time, medical case injury, first aid, property damage, environmental incidents, etc.

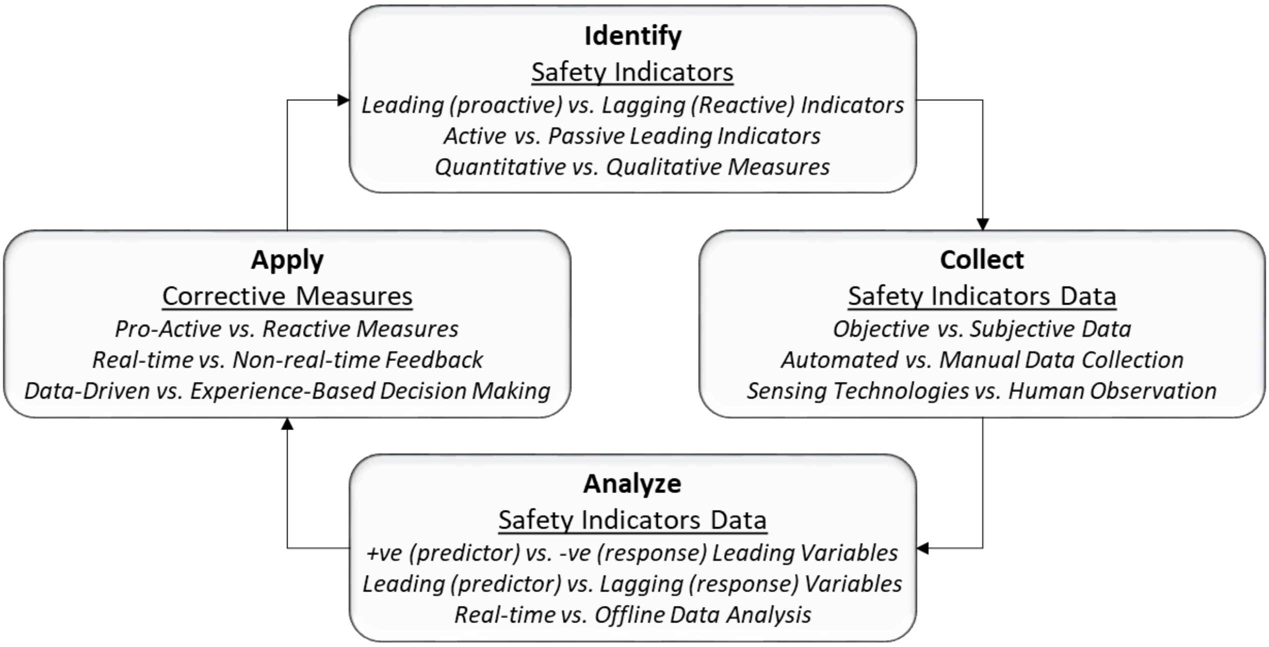

Figure 1. Framework for monitoring and measuring safety performance.

3.1.2. Step 2: Collection of Safety Indicators Data

This involves the collection of safety indicator data through the active tracking or monitoring of the work environment and workers' activities on construction sites. This process can be achieved through an effective safety program involving proactive safety practices such as near-miss reporting, project management team safety process involvement, worker observation process, job site audits, housekeeping programs, stop work authority, safety orientation, training, and more recently, the implementation of cutting-edge sensing technologies. The data obtained from these processes are documented and recorded in a safety management repository for the organization with database capabilities to house the collected data. The collection of data from all safety monitoring activities should be a systematic process to ensure interrelationships are identified. Efforts should be geared toward transitioning the traditional or manual methods of data collection, which are common in the construction industry, to automated methods to increase the accuracy, objectivity, and timeliness of the collected data. For instance, automated data collection using sensing technologies [37,38] and computer vision [39,40] for the monitoring and recognition of construction workers' activities and their work environments can be used to capture different types and categories of safety indicator data.

3.1.3. Step 3: Analysis of Safety Indicators Data

In this step, statistical modeling processes are used to analyze the safety indicators data to identify specific variables that have high correlations and effects on events and incidents experienced on the construction sites. The analysis could either be performed non-real-time or in real-time, which is more desirable for rapid decision-making needed in complex and dynamic construction work environments. The safety indicators are analyzed and incidents trends, associated causes, and influencing factors are established. Details from safety incident data will be analyzed to proactively identify predictor variables (e.g., hazardous acts and conditions) of future incidents on construction sites. Since leading indicators of safety performance require meaningful and actionable metrics (which measure actions and conditions that can be controlled), they must be quantifiable and numeric. For instance, a hazardous act (i.e., unsafe act) that is qualitative in nature can be observed and quantified numerically as binary data (which indicates either the absence or presence of the act and is usually represented by 0 and 1) or count data (which indicates the number of occurrences and can take only non-negative integer values). To supply deeper information on qualitative data such as a hazardous act or condition, a Likert scale can be used to express the severity (e.g., low, medium, or high severity). A broad range of statistical and machine learning prediction models or analytical tools (such as the Poisson regression model, binary logistic regression model, decision tree, support vector machine, random forest, etc.) can be implemented to identify correlations of multiple variables derived from the safety incidents data obtained from construction sites [39,41]. These models are selected based on the nature of variables extracted from the safety data. Additionally, various computations are carried out on the collected data to transform the safety indicators data into useful information. In a recent study, machine learning techniques were used to analyze 16 critical accident causal factors and assess the impact of diverse combinations of factors on the performance of predicting the severity of construction accidents [41]. The graphical presentation of the results is also produced to reflect the measurements of safety performance on the construction site.

3.1.4. Step 4: Application of Corrective Measures

This stage involves the correction of hazardous acts or conditions (such as near misses, unsafe behaviors, and conditions) that have the potential for future accidents by training the workers and making necessary changes on the construction site. At this stage, decisions are made by the management of the organization based on the results of the analysis, and recommendations for corrective measures and improvements are provided by the safety management team in the organization. Corrective actions are determined and acted on wherever the monitoring indicates that an element is approaching a point that may affect safety to an intolerable level. Coordination with pertinent units and departments should take place as required. Appropriate plans are made to implement the required corrective measures, which should follow a continuous improvement process. Results are tracked and feedback on performance is provided to the relevant audiences within the organization. A broader audience (including all other site personnel) should be informed of the reported indicator events and corrective actions taken; both steps should be communicated as soon as possible (i.e., the next day's toolbox talks if possible). Safety managers should integrate lessons learned from the reported leading indicators events and data analysis results into existing safety training.

3.2. Analysis of Safety Indicators Data

The analysis of safety incident data in this study is conducted in the following two stages: (1) the modeling of causal factors responsible for safety leading indicators; (2) the modeling of the safety leading indicators that can be used to predict the probability of lagging indicators. In the first analysis, a data set consisting of 2551 observations of safety incident data (collected from an airport construction project site over one year) were used to model the causal factors (independent or predictor variables) that have the most significant influence on safety leading indicators (dependent or response variables) on the construction site. The construction company executes civil infrastructure and commercial construction projects.

The analysis approach adopted in this research considers that each incident of the construction safety leading indicators recorded is either related to a causal factor or not. In the second analysis, 297 records of safety incident data (collected from the same construction site over one year) were used to model the safety leading indicators and other metrics (set as independent variables in this case) that have significant impacts on lagging indicators (dependent variables in this case) on the construction site. The identified variables were critically examined using the abridged model screening guide illustrated in Figure 2 as a sample for the models used in this study as statistical predictive models to better understand how individual safety metrics or indicators can predict incidents on construction sites. This model screening guide was developed through the synthesis of the characteristics of the statistical tools and techniques described and illustrated in [42].

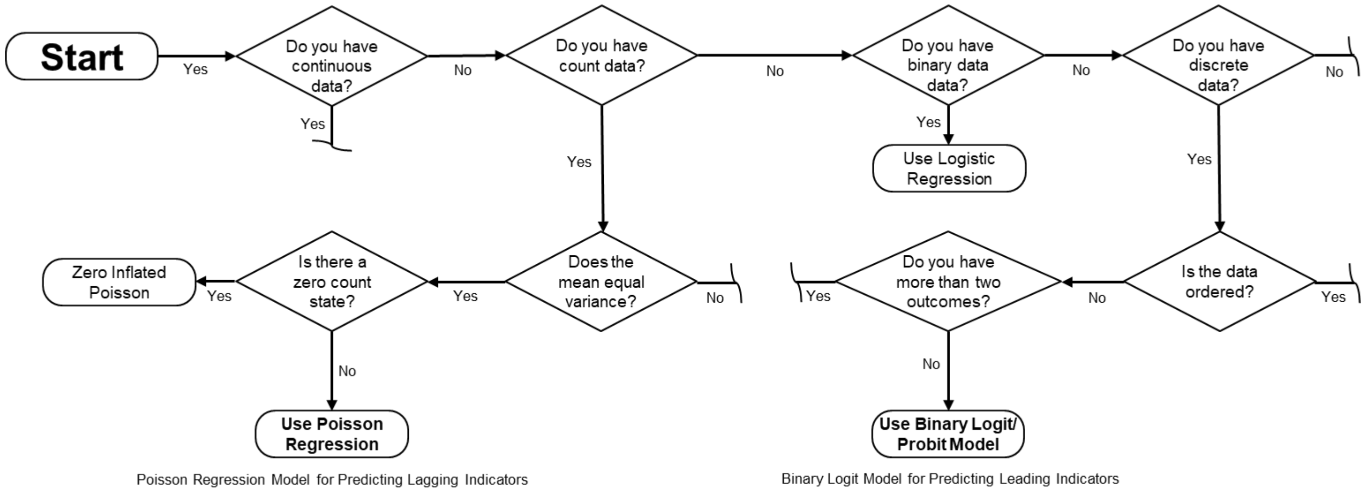

Figure 2. Model screening guide.

A large construction company in the U.S. that specializes in civil infrastructure and commercial construction projects and implements proactive safety programs across their projects provided the researchers access to a safety incident database reported by employees and analyzed by safety managers at the company. Variables retrieved from employee safety incident logs were organized by safety managers into company-specific safety categories. To perform predictive statistical analysis, variable categories were defined as either independent or dependent variables. The variables included all metrics associated with the outcome of a reported incident such as an injury, illness, or fatality as described in Table 1. The frequency of a given indicator category in Table 1 represents the number of times each type of indicator category or event was observed as reported in the safety incident logs. For instance, an unsafe act (a leading indicator) was observed 895 times amounting to 35.08% of the total leading indicator events observed over one year as reported in the safety incident logs. Similarly, events associated with site conditions were observed and reported 625 times amounting to 24.50% of the total injury or accident causal factors reported over one year as documented in the safety incident logs.

3.2.1. Binary Logit Model for Predicting Leading Indicators

Although several efforts have been made to mitigate injuries and accidents on construction sites, predictive models have not been developed to analyze the effects of construction safety indicators. Injuries and fatalities on construction sites can result from a variety of causal factors relating to construction materials, equipment, work processes, and the condition of the construction site and environment. The analysis approach adopted in this research considers that each incident of the construction safety leading indicators recorded is either related to a causal factor or not. This gives a binary outcome that can be coded as one of the recorded incidents is related to the causal factor and zero otherwise. When developing a statistical model of such discrete outcome data, different modeling techniques, including logit, probit, and mixed logit models, can be used [42]. If unobserved factors influencing the probability of alternate discrete outcomes (disturbances) are assumed to be generalized extreme value distributed, the standard multinomial logit formulation is given by the following [43,44]:

$$P_{in} = \frac{EXP[\beta_i X_{in}]}{\sum_{\forall I} EXP[\beta_I X_{In}]} \quad (1)$$

where P_{in} = probability that observation n results in discrete outcome I; X_{in} = vector of characteristics that determine the probability of discrete outcome i for observation n; β_i = vector of estimable parameters; I = set of available discrete outcomes. According to Washington et al. [42], the standard maximum likelihood methods can be used to estimate the model. Thus, P_{in} = probability of a causal factor responsible for the recorded leading indicator n; X_{in} = vector of recorded leading indicator n; β_i = vector of estimable parameters, which includes a coefficient for each leading indicator in X_{in}; I = either 1 if the causal factor is responsible for the recorded leading indicator or 0 if it is not. In this study, the two possible outcomes are either a causal factor is responsible for the leading indicator or not, hence, without loss of generality, $\beta_i X_{in}$ for the not responsible outcome can be set to zero [45]. Using Equation (1), the probability of a leading indicator n being related to a causal factor P_{cn} is then given as follows:

$$P_{cn} = \frac{1}{1 + \mathrm{EXP}(-\beta_c X_{cn})} \tag{2}$$

In order to assess the effect of the vector of estimated parameters β_c, elasticities that measure the magnitude of the impact of specific variables on the outcome probabilities are computed as follows:

$$E_{x_{kcn}}^{P_{cn}} = \frac{\partial P_{cn}}{\partial x_{kcn}} \times \frac{x_{kcn}}{P_{cn}} \tag{3}$$

Using Equations (2) and (3), this is given as follows:

$$E_{x_{kcn}}^{P_{cn}} = [1 - P_{cn}]\beta_{kcn} x_{kcn} \tag{4}$$

where β_{kcn} = estimated parameter associated with the kth variable x_{kcn}. Elasticity values $E_{x_{kcn}}^{P_{cn}}$ can be interpreted as the percent effect that a 1% change in x_{ki} has on the probability of a leading indicator n's being related to a factor P_{cn}. It should, however, be noted that Equation (4) is not applicable for indicator variables (i.e., variables taking on values of 0 or 1). In such a situation, pseudoelasticity can be calculated as follows [42]:

$$E_{x_{kcn}}^{P_{cn}} = \left[\frac{\mathrm{EXP}[\Delta(\beta_c X_{cn})][1 + \mathrm{EXP}(\beta_{kcn} x_{kcn})]}{\mathrm{EXP}[\Delta(\beta_c X_{cn})][\mathrm{EXP}(\beta_{kcn} x_{kcn})] + 1} - 1\right] \times 100 \tag{5}$$

The pseudoelasticity of the variable with respect to a causal factor being responsible for a leading indicator is the percent change in the probability of the causal factor being present when the variable is changed from zero to one.

3.2.2. Poisson Regression Model for Predicting Lagging Indicators

Despite the efforts geared toward mitigating injuries and accidents on construction sites, the benefits of developing predictive models to analyze the effects of construction safety indicators need to be explored. In an attempt to create such a predictive model, a possible mistake would be to simply opt for the traditional regression techniques using linear regression methods. The use of linear regression analysis imposes certain limitations on the model, especially because certain observations may be nonlinear and cannot be modeled as such. The main drawback associated with nonlinear regression is the increase in complexity compared with traditional linear regression. Poisson regression is rarely mentioned as a modeling technique for construction concepts. Poisson regression is a form of regression analysis used to model count data, which assumes that the dependent variable consists of nonnegative integers. For example, the number of first aid cases or injuries that occur on a construction site can be analyzed using a Poisson regression model. The events must be independent in the sense that the occurrence of one will not make another more or less likely, but the probability per unit time of events is understood to be related to covariates.

Table 1. Variables available for model specification.

Category	Description	Frequency	Percentage
Lagging Indicators (dependent variables)			
Property Damage Cases	An incident that results in the destruction of real or personal property.	54	55.67%
First Aid Cases	Any incident that requires stopping work but does not require a trained medical professional for assistance	41	42.27%
Medical Aid Cases	An injury or illness that results in death, days away from work, restricted work, medical treatment beyond first aid, or loss of consciousness	2	2.06%
Leading Indicators (dependent and independent variables)			
Safe Work Observation	Counts of the number of safe actions or conditions in a work area for a given time	223	8.74%
Safety Intervention	An attempt to change how things are performed in order to improve safety	285	11.17%
Unsafe Act	Unaccepted practices that have the potential to contribute to future accidents and injuries	895	35.08%
Unsafe Condition	A situation in which the physical layout of the workplace or work location or the status of tools, equipment, and material violates contemporary safety standards	1069	41.91%
Near Miss	An unplanned event or unsafe condition that has the potential for injury or illness to people, or damage to property, or the environment	79	3.10%
Causal Factors (Independent variables)			
Heavy Equipment	Incidents associated with heavy construction equipment, such as a truck, trailer, and excavator	267	10.47%
Vertical Access Equipment	Incidents associated with vertical access equipment, such as ladders, scaffolds, and stairs	187	7.33%
Site Conditions	Incidents associated with site conditions, such as snow and ice, hole and trench, and roadway	625	24.50%
Non-use of PPE	Incidents associated with failure to use PPE, such as earplugs, hardhats, and safety glasses	733	28.73%
Incident Type	Incident type, such as trip, slip, fall, and electrical	295	11.56%
Construction Materials	Incidents associated with certain construction materials, such as steel/rebar, concrete, nail, and fuel	267	10.47%
Days of the Week	Days of the week on which incidents occur		
Months of the Year	Months of the year in which incidents occur		

Count data are often modeled as a continuous variable instead of a discrete variable, using traditional least squares regression methods [46]. This approach is not strictly correct because regression models yield predicted values that are non-integers and can also predict negative values, both of which are inconsistent with count data. These limitations make standard regression analysis inappropriate for modeling count data without modifying the dependent variable [42]. For this analysis, 297 observations of leading indicators (unsafe conditions, unsafe acts, and near misses), lagging indicators (property damage, first aid, and medical aid), and other metrics for measuring safety performance were collected on a construction site over a one-year duration. The data are non-negative integers with the mean approximately equal to the variance; thus, the data are well suited to the Poisson regression approach. The Poisson model is specified in Equation (6) as follows [42,47]:

$$P(y_i) = \frac{EXP(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{6}$$

where $P(y_i)$ is the probability of a construction site i having y number of lagging indicators (e.g., first aid cases), and λ_i is the Poisson parameter for construction site i. The Poisson parameter is equal to the expected number of lagging indicators (e.g., first aid cases) that occur on the construction site [i.e., $E(y_i)$]. The Poisson parameter is specified as follows [42,47]:

$$\lambda_i = EXP(\beta X_i) \text{ or equivalently } LN(\lambda_i) = \beta X_i \tag{7}$$

where X_i is a vector of explanatory variables and β is a vector of estimable parameters or coefficients. This model can, therefore, be estimated by using standard maximum likelihood methods, with the likelihood function given in Equation (8) [42,47].

$$L(\beta) = \prod_i \frac{EXP[-EXP(\beta X_i)][EXP(\beta X_i)]^{y_i}}{y_i!} \tag{8}$$

The log of the likelihood function is simpler to manipulate and more appropriate for estimation and is given in Equation (9) [42,47].

$$L(\beta) = \sum_{i=1}^{n}[-EXP(\beta X_i) + y_i\beta X_i - LN(y_i!)] \tag{9}$$

4. Results and Discussion

4.1. Analysis of Safety Indicators Data

As indicated in Figure 3, 508 (i.e., 20%) of the observations were positive indicators of safety performance, while the remaining 80% (i.e., 2043 observations) were leading indicators with potential for negative outcomes if not controlled. While a slightly higher percentage of safety interventions was recorded on the site than safe work observations for the positive indicators, unsafe conditions had the highest percentage of observations for the negative indicators, followed by unsafe acts. Near misses had the lowest observation rate. This could be due to the complexities involved in the reporting of near-misses on construction sites. Moreover, the construction company may not have a dedicated near-miss reporting program for appropriately capturing near-miss information on the site.

Figure 4 also shows the periodic distribution of safety leading indicators over one year. The records of each of the safety leading indicators are expressed in terms of percentages, while the total number of leading indicators per period is expressed in terms of frequency of observation. The results indicate that the highest number of leading indicator observations was recorded during the fall season with a total of 861 observations. This large observation could be because of the high volume of construction activities going on during the period. Moreover, the fall season has been touted as the best period of the year for outdoor work due to the mildness of the weather.

4.2. Results of Binary Logit Model

The model estimation results and the corresponding variable elasticities for the safety leading indicators are shown in Table 2. All the estimated parameters are statistically significant, and the model coefficients show plausible relationships among the variables. The overall model fit is quite good, with log-likelihood increasing from −1652.963 when $\beta_c = 0$ to −1380.781 when β_c is at its converged value for unsafe acts; from −1734.639 to −1451.982 for unsafe conditions, finally, from −352.273 to −301.606 for near-misses. These result in ρ^2 of 0.165, 0.163, and 0.144 for unsafe acts, unsafe conditions, and near-misses, respectively (computed as one minus the ratio of log-likelihood at convergence to the log-likelihood at zero). These results indicate that the process and relationships described by the model are reflective of the data observed.

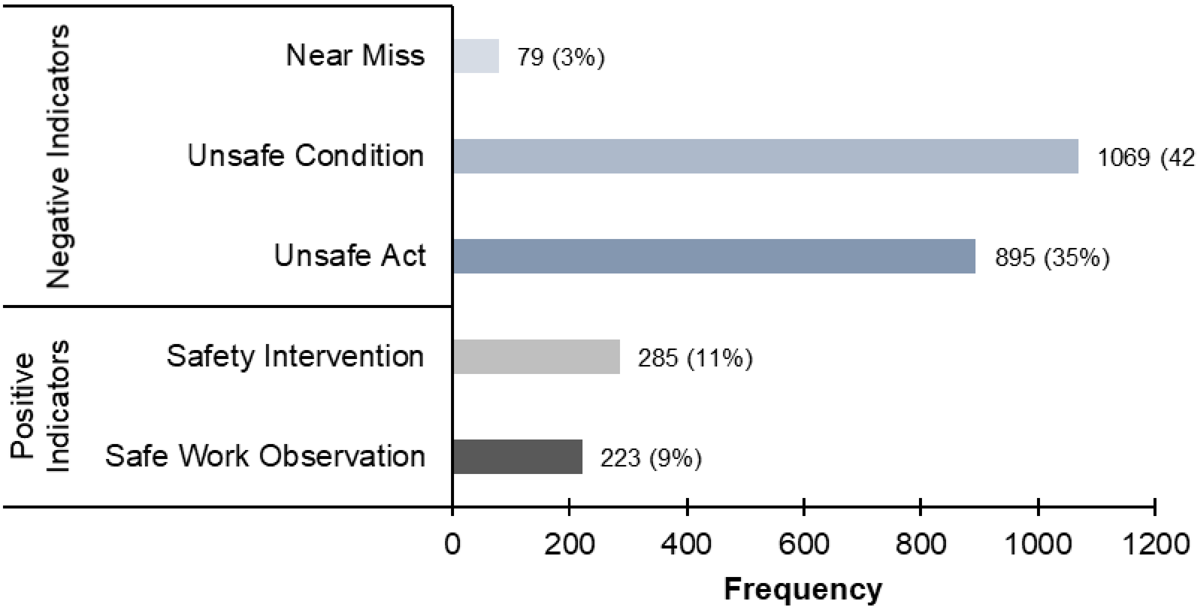

Figure 3. Statistics of safety leading indicators.

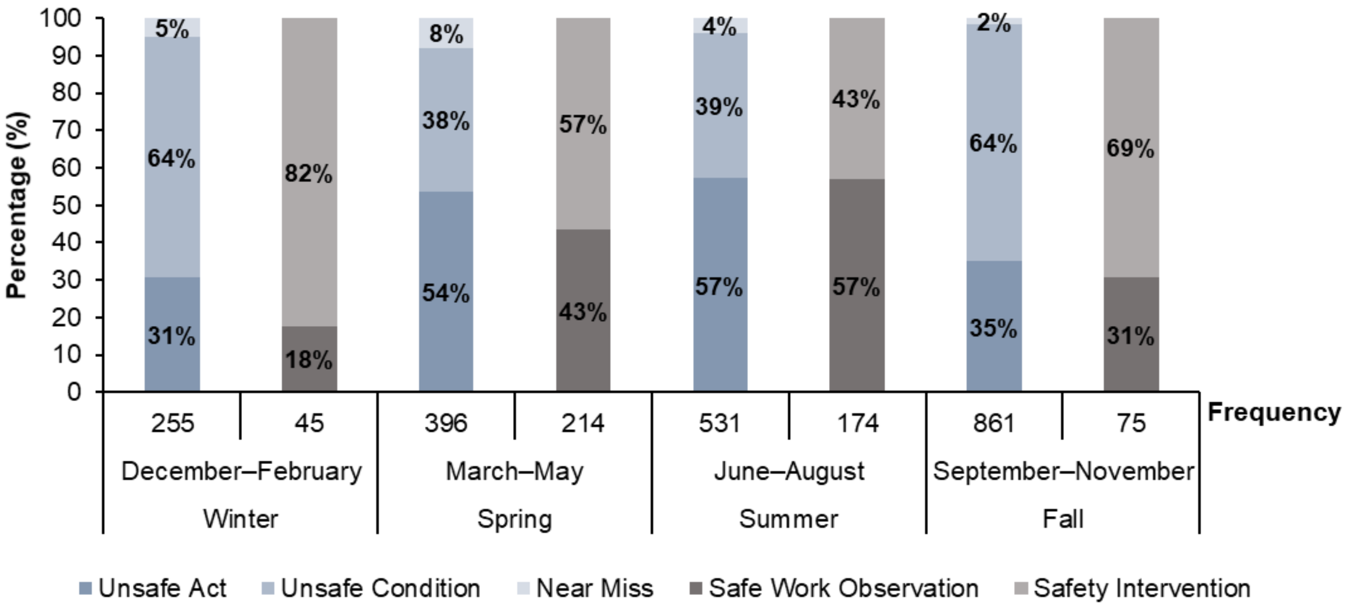

Figure 4. Statistics of safety leading indicators.

The model estimation results and the corresponding average elasticities are presented in Table 2. Out of the variables available for model estimation, a good number of the variables were found to have significant effects on the number of unsafe acts, unsafe conditions, and near-misses recorded on the construction site. The results of the model estimation show that the day of the week had a significant effect on near-miss incidents but not on unsafe acts and conditions. For instance, the results indicate that more near-misses are more likely to be experienced midweek and the value of the average elasticity indicates a probability of 0.017%. These showed that the workload might be different on certain days of the week. For instance, Bryson and Forth [48] stated in their study that people tend to work longer days, on average, in the middle of the week.

Table 2. Model estimation results and elasticity estimates for unsafe act, unsafe conditions, and near miss.

Variables Description	Mean (Std. Dev.)	Unsafe Act			Unsafe Condition			Near Miss		
		Parameter Estimate	t-Statistic	Average Elasticity	Parameter Estimate	t-Statistic	Average Elasticity	Parameter Estimate	t-Statistic	Average Elasticity
Constant		−0.709 ***	−10.150		−1.185 ***	−17.470		−4.160 ***	−18.090	
Midweek Indicator	0.213 (0.409)							0.528 ***	1.990	0.017
First Month of Spring Indicator	0.105 (0.307)	−1.232 ***	−6.560	−0.198	−0.652 ***	−3.930	−0.120	0.853 ***	2.860	0.031
Last Month of Spring Indicator	0.083 (0.277)	0.577 ***	3.630	0.110						
First Month of Summer Indicator	0.118 (0.323)	0.669 ***	4.860	0.128						
Last Month of Fall Indicator	0.297 (0.457)				1.095 ***	10.950	0.229	−1.146 ***	−3.000	−0.025
Incident Related to the Use of Ladder	0.030 (0.170)	0.861 ***	3.420	0.166						
Incident Related to the Use of Scaffold	0.023 (0.150)	−0.667 *	−1.820	−0.113	0.911 ***	2.850	0.184	1.191 *	1.830	0.053
Incident Involving Stairs	0.020 (0.141)	−1.089 *	−1.880	−0.172	0.998 **	2.500	0.201			
Roadway Incident	0.044 (0.205)				0.856 ***	4.040	0.172			
Incident Involving Truck	0.073 (0.259)	0.523 ***	3.080	0.099						
Incident Involving Trailer	0.032 (0.176)	−0.706 **	−2.010	−0.119	1.068 ***	3.680	0.215			
Incident Related to the Use of PPE	0.287 (0.452)	1.086 ***	6.690	0.215				0.757 ***	3.060	0.023
Incident Related to Hearing and Use of Earplugs	0.111 (0.314)	0.559 ***	2.990	0.109						
Incident Related to the Use of Hardhat	0.080 (0.271)	−0.516 **	−2.550	−0.089						
Incident Related to Eye and Use of Glasses	0.044 (0.206)	0.454 *	1.860	0.087						
Incident Related to Snow and Ice	0.177 (0.382)	−1.015 ***	−6.920	−0.172	1.156 ***	9.580	0.239	−1.435 ***	−2.980	−0.027
Trip Incident	0.054 (0.227)	−1.737 ***	−5.390	−0.248	1.453 ***	6.460	0.293	1.146 ***	2.940	0.049
Slip Incident	0.028 (0.165)	−2.789 ***	−4.500	−0.312	1.492 ***	4.460	0.297	1.332 ***	2.910	0.063
Fall Incident	0.046 (0.209)	−0.747 ***	−2.840	−0.125	0.403 *	1.870	0.080	1.762 ***	5.330	0.095
Incident Related to Hole and Trench	0.024 (0.154)	−0.686 **	−2.170	−0.116	0.828 ***	2.970	0.167	1.097 *	1.950	0.047
Electrical Incident	0.046 (0.209)				0.691 ***	3.390	0.138			
Incident Related to the Use of Fuel	0.042 (0.201)							1.252 ***	2.990	0.056
Incident Involving Nails	0.040 (0.196)	−1.628 ***	−4.290	−0.235	2.362 ***	7.970	0.437			
Incident Related to Steel and Rebar	0.033 (0.180)							1.008 **	2.110	0.042
Number of Observations			2551			2551			2551	
Log-likelihood at Zero			−1652.963			−1734.639			−352.273	
Log-likelihood at Convergence			−1380.781			−1451.982			−301.606	

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

The findings also point out that while the probability of recording a near-miss incident increased in the first month of spring, it decreased for unsafe acts and conditions as indicated by their parameter estimates (−1.232 and −0.652) and average elasticities (−0.198 and −0.120). Moreover, in the last month of spring and the beginning of the summer season, the probability of having an unsafe act increased with a parameter estimate of 0.577 and 0.669 and an average elasticity of 0.110 and 0.128, respectively. While the probability of having an unsafe act in the last month of spring and the first month of summer increased, the last month of fall saw an increase in the probability of an unsafe condition and a decrease in the likelihood of having a near-miss incident.

These findings indicate that changes in season accompanied by variations in weather conditions could impact the safety performance of a construction project, being that construction workers predominantly work outdoors and are constantly exposed to the mercurial and harsh weather elements. The uncertainties caused by weather, such as extreme cold, heat, wind, or precipitation, can adversely affect workers both psychologically and physiologically, thereby influencing the safety performance of the project. Extreme hot weather conditions can increase the health and safety risk to construction workers, the likelihood of workers suffering from heat-related illnesses, workers' absenteeism, and turnover [49]. Strong winds can also make it more dangerous for construction workers to operate at heights [50].

The results also indicate that while the probability of having an unsafe act increased due to incidents related to ladders, trucks, and PPE (including earplugs and glasses), it decreased due to incidents related to scaffolds, stairs, trailers, hardhats, snow and ice, trips, slips, falls, holes and trenches, and nails. Barkhordari et al. [51] have stated that it is essential to identify the factors that influence unsafe acts because unsafe acts and individual factors have been identified as one of the most important causes of accidents in the past. Abdelhamid and Everett [12] cited a few examples of unsafe acts on construction sites and emphasized, in their accident root causes tracing model (ARCTM), the need to investigate why workers act unsafely. The findings of this modeling also show that the probability of unsafe conditions increased due to incidents related to scaffolds, stairs, roadways, trailers, snow and ice, trips, slips, falls, holes and trenches, electricity, and nails. While the likelihood of having a near-miss decreased due to incidents related to snow and ice, it increased with incidents related to scaffolds, PPE, trips, slips, falls, holes and trenches, fuels, steel and rebar.

The model estimation results as presented in Table 3 indicate that in the first month of spring, the probability of having a safe work observation and safety intervention increased. In the first month of summer, the probability of having a safe work observation decreased by 0.038%, as indicated by the value of the average elasticity of 0.038. In the last month of the fall season, the probability of having a safe work observation and safety intervention decreased as indicated by the average elasticities of −0.095 and −0.069. These results also indicate that changes in weather conditions caused by seasonal changes can influence safety performance on construction projects. The probability of having a safe work observation related to the use of ladders and PPE decreased by 0.078 and 0.054%, respectively, while it also decreased expectedly with snow and ice and electrical incidents. On the other hand, the probability of having a safety intervention related to snow and ice increased while the likelihood of having a safety intervention for trip and slip incidents decreased.

4.3. Results of Poisson Regression Model

From the summary statistics, the mean of the number of first aid cases experienced on the construction site was 0.138 while the standard deviation was 0.383 (i.e., the variance of 0.146). Since, the mean, $E(y_i)$ and variance, $var(y_i)$ are very close (i.e., approximately equal), the assumption of a Poisson regression model for the analysis of this distribution holds. The model estimation results and the corresponding average partial (marginal) effects are presented in Table 4. Out of the variables available for model estimation, five variables were found to have significant effects on the number of first aid cases recorded on the construction site. One of the variables was the indicator for midweek which had a parameter estimate of 0.789 and a z-statistic of 2.110. These results indicate that more first aid cases are more likely to be experienced midweek and the partial effects also show that the number of first aid cases recorded is likely to increase by 0.141. Similarly, first aid cases are more likely to be experienced on the fourth day of the workweek as indicated in the parameter estimate (0.569) and the value of the partial effects implies that the number of first aid cases recorded on the construction site is likely to rise by 0.097 on that day. The reasons for these results could be that construction activities on the site might be at their peak midweek and the day after which can correspondingly increase the number of first aid cases. According to Bryson and Forth [48], people work the longest days, on average, in the middle of the week. These days can be taken as the days in the middle of the week and the workers would have been very much submerged in their various tasks on those days of the week. The busier the workers are (i.e., the longer they work), the more likely it is that they experience more incidents due to fatigue and other harsh conditions of the construction environment.

Table 3. Model estimation results and elasticity estimates for safe work observation and safety intervention.

Variable Description	Mean (Std. Dev)	Safe Work Observation			Safety Intervention		
		Parameter Estimate	t-Statistic	Average Elasticity	Parameter Estimate	t-Statistic	Average Elasticity
Constant		−1.869 ***	−17.360		−2.100 ***	−22.280	
First Month of Spring Indicator	0.105 (0.307)	1.282 ***	7.520	0.128	1.044 ***	6.490	0.130
First Month of Summer Indicator	0.118 (0.323)	−0.615 **	−2.290	−0.038			
Last Month of Fall Indicator	0.297 (0.457)	−1.983 ***	−6.450	−0.095	−0.853 ***	−4.550	−0.069
Incident related to the use of Ladder	0.030 (0.170)	−2.186 **	−2.150	−0.078			
Incident related to the use of PPE	0.287 (0.452)	−0.852 ***	−4.610	−0.054	0.357 ***	2.610	0.036
Incident related to Snow and Ice	0.177 (0.382)	−0.450 **	−2.090	−0.029			
Trip Incident	0.054 (0.227)				−1.070 **	−2.300	−0.071
Slip Incident	0.028 (0.165)				−2.425 **	−2.380	−0.103
Electrical Incident	0.046 (0.209)	−1.077 **	−2.280	−0.056			
Number of Observations			2551			2551	
Log-likelihood at Zero			−756.422			−893.101	
Log-likelihood at Convergence			−657.333			−837.514	

Note: ***, ** ==> Significance at 1%, 5% level.

Table 4. Truncated Poisson model and average partial (marginal) effects of first aid cases.

Variable Description	Estimated Parameter	z-Statistic	Partial Effect	Mean (Std. Dev)
Constant	−1.912 ***	−8.540		
Midweek Indicator	0.789 **	2.110	0.141	0.000 (0.000)
Fourth Day of Workweek Indicator	0.569	1.370	0.097	0.000 (0.000)
Last Month of Autumn Indicator	−1.413	−1.390	−0.112 ***	0.283 (0.452)
Safe Work Observations Indicator	−0.448 *	−1.710	−0.062 *	0.657 (1.521)
Near Misses Indicator	−0.486	−1.260	−0.067	0.259 (0.082)
Number of Observations		297		
Log-likelihood (at Zero)		−124.960		
Log-likelihood at Convergence		−116.858		
Chi-Squared		16.202		

Note: ***, **, * ==> Significance at 1%, 5%, 10% level.

The other variable that significantly affected the number of first aid cases was the last month of the autumn indicator, which had a parameter estimate of −1.413 and z statistics of −1.390. This implies that first aid cases are less likely to be recorded during that month. The result of the partial effects also suggests that the number of first aid cases recorded on the construction site is likely to reduce by 0.112 in the last month of autumn. This could be due to the peculiarities of the construction project, such as the nature of tasks executed in that month of the year. It could also be that a lesser amount of work is undertaken in that month due to weather, which might reduce the number of first aid cases experienced during that period. Another major variable that had a significant influence on the number of first aid cases recorded on the construction site was the number of safe work practices observed on the site. This variable had a parameter estimate of −0.448 and a z statistic of −1.710, which implies that the greater the number of safe work observations, the lower the number of first aid cases recorded on the site. The partial effects also show that the number of first aid cases experienced will be reduced by 0.062 when workers are seen exhibiting safe work practices. This result is very realistic in the sense that workers' exposure to hazards or unforeseen events is reduced if workers engage in safe practices by, for instance, exhibiting safe working behavior, working in a safe condition, and using the correct personal protective equipment.

The last variable that significantly impacted the number of first aid cases experienced on the construction site was the number of near-misses. This variable had a parameter estimate of −0.486 and a z statistic of −1.260. This indicates that the greater the number of near-misses experienced, the less likely it is to experience first aid cases on the construction site. The result of the partial effects also suggests that near-miss reporting is likely to reduce the number of first aid cases by 0.067. The justification for these results could be that the construction workers are using the lessons learned from near-miss reporting to forestall or prevent lagging indicators such as first aid cases. The ρ^2 statistic (or McFadden ρ^2), which gives a measure of the overall model fit, is computed in Equation (10) [42].

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)} = 1 - \frac{-116.858}{-124.960} = 0.065 \tag{10}$$

where LL(β) is the log-likelihood at convergence with parameter or coefficient vector β and LL (0) is the initial log-likelihood (with all parameters or coefficients set to zero).

The perfect model would have a likelihood function equal to one (all selected alternative outcomes would be predicted by the model with probability one, and the product of these across the observations would also be one) and the log-likelihood would be zero, yielding ρ^2 of one. The ρ^2 statistic will be between zero and one, while the closer it is to one, the more variance the estimated model explains. For the model in this study, ρ^2 = 0.065.

5. Conclusions

In this paper, a framework for monitoring and measuring construction safety performance, juxtaposing traditional and modern methods, was presented. Construction safety indicators were analyzed to determine their level of significance and their relative effects on the safety performance of a construction project. One key research finding is the promotion of proactive methods for the improvement of safety performance on construction sites. By identifying hazardous categories before an accident occurs, construction safety managers can eliminate hazardous situations and conditions within the work environment. The novelty and contributions of this study lie in the provision of a systematic safety performance measurement framework and statistical modeling processes for analyzing safety incident data for accident prediction and prevention on construction sites. The practical and adaptable framework presented in this study provides a simplified model that can be easily incorporated into an existing safety program for the active monitoring and measurement of safety performance on construction sites. The framework and statistical models developed in this study can be used to collect and analyze safety data to provide trends in safety performance, set improvement targets, and provide continuous feedback to enhance safety performance on construction sites. This research draws out the benefits of proactive and active monitoring to enhance safety performance on construction sites. The study was limited in scope to the data provided by one company and may not necessarily reflect safety challenges across the industry. To make the results more reliable, it would be worthwhile to conduct this analysis using data obtained from the same company after a certain time or using data from other companies in the construction industry. In addition, future research can include the application of emerging systems and techniques such as automated sensing and computer vision technologies and machine learning to proactively monitor workers' activities and the construction work environment capture and analyze data in real-time to alert construction site personnel of conditions or situations that have previously experienced a high probability of accidents.

Author Contributions: Conceptualization, I.A., E.M. and A.H.; methodology, I.A., E.M. and A.H.; formal analysis, I.A. and A.A.; writing—original draft preparation, I.A.; writing—review and editing, E.M., A.H. and A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available upon reasonable request from the corresponding author. The data are not publicly available due to privacy restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bansal, V.K. Application of geographic information systems in construction safety planning. *Int. J. Proj. Manag.* **2011**, *29*, 66–77. [CrossRef]
2. Yoon, S.J.; Lin, H.K.; Chen, G.; Yi, S.; Choi, J.; Rui, Z. Effect of occupational health and safety management system on work-related accident rate and differences of occupational health and safety management system awareness between managers in South Korea's construction industry. *Saf. Health Work* **2013**, *4*, 201–209. [CrossRef] [PubMed]
3. Poh, C.Q.; Ubeynarayana, C.U.; Goh, Y.M. Safety leading indicators for construction sites: A machine learning approach. *Autom. Constr.* **2018**, *93*, 375–386. [CrossRef]
4. Hong Kong Occupational Safety and Health (HKOSH). Occupational Safety and Health Statistics 2018. Labor Department, The Government of the Hong Kong Special Administrative Region; 2018. Available online: https://www.labour.gov.hk/eng/osh/pdf/archive/statistics/OSH_Statistics_2018_eng.pdf (accessed on 12 May 2022).
5. Health and Safety Executive (HSE). Construction Statistics in Great Britain, 2019. Health and Safety Executive; 2019. Available online: https://www.hse.gov.uk/statistics/industry/construction.pdf (accessed on 12 May 2022).
6. Bureau of Labor Statistics (BLS). Census of Fatal Occupational Injuries (CFOI)-Current and Revised Data. U.S. Department of Labor; 2020. Available online: http://www.bls.gov/iif/oshcfoi1.htm#charts (accessed on 12 May 2022).
7. Awolusi, I.; Marks, E.; Hallowell, M. Physiological data collection and monitoring of construction equipment operators. *Constr. Res. Congr.* **2016**, *2016*, 2946–2956.
8. Anger, W.K.; Kyler-Yano, J.; Vaughn, K.; Wipfli, B.; Olson, R.; Blanco, M. Total Worker Health®intervention for construction workers alters safety, health, well-being measures. *J. Occup. Environ. Med.* **2018**, *60*, 700–709. [CrossRef] [PubMed]
9. Choudhry, R.M.; Fang, D. Why operatives engage in unsafe work behavior: Investigating factors on construction sites. *Saf. Sci.* **2008**, *46*, 566–584. [CrossRef]
10. Seo, J.; Han, S.; Lee, S.; Kim, H. Computer vision techniques for construction safety and health monitoring. *Adv. Eng. Informatics* **2015**, *29*, 239–251. [CrossRef]
11. Mitropoulos, P.; Abdelhamid, T.S.; Howell, G.A. Systems model of construction accident causation. *J. Constr. Eng. Manag.* **2005**, *131*, 816–825. [CrossRef]
12. Abdelhamid, T.S.; Everett, J.G. Identifying root causes of construction accidents. *J. Constr. Eng. Manag.* **2000**, *126*, 52–60. [CrossRef]
13. Marks, E.; Awolusi, I.G.; McKay, B. Near-Hit Reporting: Reducing Construction Industry Injuries. *Prof. Saf.* **2016**, *61*, 56–62.
14. Oguz Erkal, E.D.; Hallowell, M.R.; Bhandari, S. Practical Assessment of Potential Predictors of Serious Injuries and Fatalities in Construction. *J. Constr. Eng. Manag.* **2021**, *147*, 4021129. [CrossRef]
15. Pardo-Ferreira, M.C.; Rubio-Romero, J.C.; Martínez-Rojas, M. Applying Resilience Engineering to improve Safety Management in a Construction Site: Design and Validation of a Questionnaire. *Int. J. Ind. Manuf. Eng.* **2018**, *12*, 1237–1242.
16. Pardo-Ferreira, M.D.; Martínez-Rojas, M.; Salguero-Caparrós, F.; Rubio-Romero, J.C. Evolution of the Functional Resonance Analysis Method (FRAM) through the combination with other methods. *Dir. Organ.* **2019**, *68*, 41–50. [CrossRef]
17. Hollnagel, E.; Woods, D.D.; Leveson, N. (Eds.) *Resilience Engineering: Concepts and Precepts*; Ashgate Publishing, Ltd.: Farnham, UK, 2006.

18. Hallowell, M.R.; Hinze, J.W.; Baud, K.C.; Wehle, A. Proactive construction safety control: Measuring, monitoring, and responding to safety leading indicators. *J. Constr. Eng. Manag.* **2013**, *139*, 4013010. [CrossRef]
19. Awolusi, I.G.; Marks, E.D. Safety activity analysis framework to evaluate safety performance in construction. *J. Constr. Eng. Manag.* **2017**, *143*, 5016022. [CrossRef]
20. Akroush, N.S. Leading Safety Indicators in the Construction Industry: The Case of Tennessee. Master's Thesis, The University of Tennessee, Knoxville, TN, USA, 2017.
21. Grabowski, M.; Ayyalasomayajula, P.; Merrick, J.; Harrald, J.R.; Roberts, K. Leading indicators of safety in virtual organizations. *Saf. Sci.* **2007**, *45*, 1013–1043. [CrossRef]
22. Chen, J.R.; Yang, Y.T. A predictive risk Index for safety performance in process industries. *J. Loss Prev. Process Ind.* **2004**, *17*, 233–242. [CrossRef]
23. Hinze, J.; Thurman, S.; Wehle, A. Leading indicators of construction safety performance. *Saf. Sci.* **2013**, *51*, 23–28. [CrossRef]
24. Dağdeviren, M.; Yüksel, İ.; Kurt, M. A fuzzy analytic network process (ANP) model to identify faulty behavior risk (FBR) in work system. *Saf. Sci.* **2008**, *46*, 771–783. [CrossRef]
25. Mahmoudi, S.; Ghasemi, F.; Mohammadfam, I.; Soleimani, E. Framework for continuous assessment and improvement of occupational health and safety issues in construction companies. *Saf. Health Work* **2014**, *5*, 125–130. [CrossRef]
26. Costin, A.; Wehle, A.; Adibfar, A. Leading indicators—A conceptual IoT-based framework to produce active leading indicators for construction safety. *Safety* **2019**, *5*, 86. [CrossRef]
27. Organization for Economic Cooperation and Development (OECD). *Guidance on Safety Performance Indicators*; OECD Environment, Health and Safety Publications, Series on Chemical Accidents; Organization for Economic Cooperation and Development (OECD): Paris, France, 2003; No. 11.
28. Reiman, T.; Pietikäinen, E. Leading indicators of system safety–monitoring and driving the organizational safety potential. *Saf. Sci.* **2012**, *50*, 1993–2000. [CrossRef]
29. Health and Safety Executive (HSE). *Developing Process Safety Indicators: A Step-By-Step Guide for Chemical and Major Hazard Industries*; Health and Safety Executive (HSE): London, UK, 2006.
30. Toellner, J. Improving safety & health performance: Identifying & measuring leading indicators. *Prof. Saf.* **2001**, *46*, 42.
31. Øien, K.; Utne, I.B.; Herrera, I.A. Building safety indicators: Part 1–theoretical foundation. *Saf. Sci.* **2011**, *49*, 148–161. [CrossRef]
32. Flin, R.; Mearns, K.; O'Connor, P.; Bryden, R. Measuring safety climate: Identifying the common features. *Saf. Sci.* **2000**, *34*, 177–192. [CrossRef]
33. Hinze, J. A Paradigm Shift: Leading To Safety. In Proceedings of the 4th Triennial International Conference Rethinking and Revitalizing Construction Safety, Health, Environment and Quality, Gqeberha, South Africa, 17–20 May 2005; pp. 1–11.
34. Fearnley, J.; Nair, S.R. Determining process safety performance indicators for major accident hazards using site process hazard information. *IChemE Symp.* **2009**, *155*, 221–225.
35. Hallowell, M.R.; Bhandari, S.; Alruqi, W. Methods of safety prediction: Analysis and integration of risk assessment, leading indicators, precursor analysis, and safety climate. *Constr. Manag. Econ.* **2020**, *38*, 308–321. [CrossRef]
36. Fu, X.; Liu, J.; Jones, S.; Barnett, T.; Khattak, A.J. From the past to the future: Modeling the temporal instability of safety performance functions. *Accid. Anal. Prev.* **2022**, *167*, 106592. [CrossRef]
37. Awolusi, I.; Marks, E.; Hallowell, M. Wearable technology for personalized construction safety monitoring and trending: Review of applicable devices. *Autom. Constr.* **2018**, *85*, 96–106. [CrossRef]
38. Ahn, C.R.; Lee, S.; Sun, C.; Jebelli, H.; Yang, K.; Choi, B. Wearable sensing technology applications in construction safety and health. *J. Constr. Eng. Manag.* **2019**, *145*, 3119007. [CrossRef]
39. Tang, S.; Golparvar-Fard, M. Machine Learning-Based Risk Analysis for Construction Worker Safety from Ubiquitous Site Photos and Videos. *J. Comput. Civ. Eng.* **2021**, *35*, 4021020. [CrossRef]
40. Ding, L.; Fang, W.; Luo, H.; Love, P.E.; Zhong, B.; Ouyang, X. A deep hybrid learning model to detect unsafe behavior: Integrating convolution neural networks and long short-term memory. *Autom. Constr.* **2018**, *86*, 118–124. [CrossRef]
41. Zhu, R.; Hu, X.; Hou, J.; Li, X. Application of machine learning techniques for predicting the consequences of construction accidents in China. *Process Saf. Environ. Prot.* **2021**, *145*, 293–302. [CrossRef]
42. Washington, S.P.; Karlaftis, M.G.; Mannering, F.L. *Statistical and Econometric Methods for Transportation Data Analysis*; Taylor and Francis Group: Abingdon, UK, 2011.
43. McFadden, D. Econometric Models of Probabilistic Choice. In *Structural Analysis of Discrete Data with Econometric Applications*; Manski, C.F., McFadden, D.L., Eds.; MIT Press: Cambridge, MA, USA, 1981; p. 198272.
44. Hubbard, S.M.; Bullock, D.M.; Mannering, F.L. Right turns on green and pedestrian level of service: Statistical assessment. *J. Transp. Eng.* **2009**, *135*, 153–159. [CrossRef]
45. Winston, C.; Maheshri, V.; Mannering, F. An exploration of the offset hypothesis using disaggregate data: The case of airbags and antilock brakes. *J. Risk Uncertain.* **2006**, *32*, 83–99. [CrossRef]
46. Wallace, B.; Mannering, F.; Rutherford, G.S. Evaluating effects of transportation demand management strategies on trip generation by using Poisson and negative binomial regression. *Transp. Res. Rec.* **1999**, *1682*, 70–77. [CrossRef]
47. Devore, J. *Probability and Statistics*, 9th ed.; Cengage Learning: Boston, MA, USA, 2015; pp. 131–136.

48. Bryson, A.; Forth, J. Are There Day of The Week Productivity Effects? London Manpower Human Resources Lab, London School of Economics and Political Science. Discussion Paper. July 2007. Available online: https://cep.lse.ac.uk/pubs/download/mhrldp0004.pdf (accessed on 24 May 2022).
49. Alshebani, M.N.; Wedawatta, G. Making the construction industry resilient to extreme weather: Lessons from construction in hot weather conditions. *Procedia Econ. Financ.* **2014**, *18*, 635–642. [CrossRef]
50. Jung, M.; Park, M.; Lee, H.S.; Kim, H. Weather-delay simulation model based on vertical weather profile for high-rise building construction. *J. Constr. Eng. Manag.* **2016**, *142*, 4016007. [CrossRef]
51. Barkhordari, A.; Malmir, B.; Malakoutikhah, M. An analysis of individual and social factors affecting occupational accidents. *Saf. Health Work* **2019**, *10*, 205–212. [CrossRef]