buildings

Article

Predicting the Effectiveness of Resilient Safety in the Building Construction Sector of Rwanda Using the ANN Model

Esperance Umuhoza and Sung-Hoon An *

Department of Architecture Engineering, Daegu University, Gyeongsan 38453, Republic of Korea; umuespe01@yahoo.fr
* Correspondence: shan@daegu.ac.kr; Tel.: +82-53-850-6518

Abstract: Most construction projects encounter safety issues that may affect project effectiveness and the lives of workers. Although various studies have investigated these factors, in some countries, such as Rwanda, there is still little empirical evidence regarding the important aspects that contribute to safety effectiveness. Therefore, this study was carried out to predict the resilient safety effectiveness in the Rwandan building construction sector via the artificial neural network (ANN) model. Through a literature review, resilient safety variables that may be relevant in the Rwandan construction sector were identified. Data were collected through questionnaires. Moreover, the levels of importance of resilient-safety-effectiveness-related factors were pinpointed and assessed using the analytical hierarchy process (AHP). Consecutively, an ANN model that could predict the effectiveness of resilient safety was developed. This study contributes to the awareness of key factors that may affect the effectiveness of resilient safety, and it helps to forecast the effectiveness of resilient safety not only in Rwanda, but also in other low- and middle-income countries with different conditions by stressing the importance of reducing safety-related risks in building construction projects.

Keywords: safety effectiveness; resilient safety culture; artificial neural network; Rwanda

Academic Editors: Antonio Caggiano and Osama Abudayyeh

Received: 9 December 2024
Revised: 10 January 2025
Accepted: 12 January 2025
Published: 15 January 2025

Citation: Umuhoza, E.; An, S.-H. Predicting the Effectiveness of Resilient Safety in the Building Construction Sector of Rwanda Using the ANN Model. *Buildings* **2025**, *15*, 237. https://doi.org/10.3390/buildings15020237

1. Introduction

Construction projects are prone to safety issues due to the complexity, elevated level of change, and ambiguity of construction projects [1]. Safety incidents that may be present during construction are considered as intrinsic factors affecting the construction industry, as the average safety incident rates are higher within the construction sector than in all other sectors worldwide [2–4]. The number of accidents in the Norwegian construction industry is much higher than that in other industries [5]. In the UK, around one-third of all occupational deaths occur in the construction industry [6], and in Australia and Korea, the fatality rate among construction workers is higher than that in other industries [7,8]. Therefore, evaluation techniques are required to enhance the safety effectiveness within construction sites.

Traditional safety evaluation methods and approaches to management based on established rules, procedures, processes, and goals for safety have been found to be incapable of evaluating new and unanticipated safety hazards. Indeed, they seem to depend on only preventing known risks from reoccurring. Since the construction industry is evolving regarding technology, tasks at work, and organization systems, the current systems have become obsolete, because they cannot adapt to the inevitable natural changes occurring in the industry over time. Therefore, there is a need for an approach that is readily and easily adaptable to effectively manage potential safety risks and unforeseen disasters that may expose construction practitioners to various unmitigated or unrecognized hazards in this dynamic and complex environment.

The evaluation of the effectiveness of safety practices is founded on the principles of resiliency engineering, known as a robust culture of safety, which is a promising approach to improve the effectiveness of safety practices, as it can easily establish potential new forms of safety risks [9]. Resilient safety culture is defined as an organizational culture that reinforces safe practices for cost-effective safety management to foster resilience engineering, continuous improvement, and organizational learning [10]. Different scholars have examined different indicators of resilient safety culture to correct safety management inefficiency. Indeed, most identified indicators have been recognized as general and summarized as the following three primary measures of organizational resilience: psychological, behavioral, and contextual [11]. The first measure is psychological, which describes how well project workers can interpret, analyze, and respond to both regular and irregular safety risks on site; the second measure is behavioral resilience, which describes how well workers recognize, comprehend, anticipate, and respond to dangerous situations; and the final measure is contextual, which describes how well contractors plan for responses to safety issues that have been identified and are evolving [12]. Therefore, the effectiveness of resilient safety culture was measured in this study using psychological, behavioral, and contextual measures.

Safety incidents in the construction industry in low-, middle-, and high-income countries include hazards encountered during construction [5–8]. However, safety incidents become more severe in low- and middle-income countries due to a lack of safety management skills. Rwanda has the same problem as other low- and middle-income countries in construction [13]. Rwanda, a country located in eastern Africa, experienced a peak compound annual growth rate of 9% in 2021, and the construction industry was recognized as one of the sectors contributing to this growth, as reported in the Rwandan annual report [14]. Despite this, Rwanda is facing the same problems as other low- and middle-income countries in the construction sector [15]. Rwanda is also affected by different risks related to safety practices' effectiveness. Therefore, without close monitoring and management strategies, their effects, including health- and project-related issues, might continue to occur.

Although there have been several studies on the impacts of safety practices' effectiveness in the construction sector, these studies focused on case studies from specific countries, typically high-income countries or middle-income countries, and excluded the lowest-income countries. Thus, due to differences in the construction industries between countries, it is not possible to generalize the results of these studies to all countries; therefore, there is still a lack of empirical evidence on the important aspects contributing to the effectiveness of safety practices, particularly in low-income countries such as Rwanda.

Therefore, the purpose of this study was to predict the effectiveness of establishing a resilient safety culture in the Rwandan building construction sector using an ANN model. To this end, the key factors that contribute significantly to the effectiveness of resilient safety culture were derived using the AHP method, and an ANN model was constructed using these factors as input variables. This research contributes to awareness of the alternatives that must be closely monitored to help managers pinpoint the areas in which effort must be made to ensure the sustained effectiveness of resilient safety culture practices and reduce other safety risks. Moreover, the model is useful for predicting the effectiveness of resilient safety culture, specifically in the building sectors of low-income countries such as Rwanda, which may support the establishment of pre-mitigation measures for preventing current and future safety issues.

2. Literature Review

In this study, previous studies were reviewed to identify the potential factors affecting the effectiveness of safety practices in the construction sector. However, considering that these factors may differ from country to country due to differences in construction environments, studies targeting specific countries were also pinpointed. In addition, since this study predicts resilient safety effectiveness in the building construction sector using ANN models, the literature review focused on studies using artificial intelligence techniques such as the ANN model in the safety field.

2.1. Factors Affecting Safety Effectiveness in the Construction Sector

Alruqi et al. [16] studied the relationship between the salient attributes of the construction safety climate and safety effectiveness using a meta-analytic review. Common predictors of safety effectiveness were found to include the supervisor's role in safety, engagement in safety management, and regulations about safety. Mohammadi et al. [17] examined and extracted the elements contributing to the safety effectiveness of building projects from 90 papers and previous studies, and their proposed hierarchical framework was validated through interviews. It was proven that interactions among variables and at various hierarchical levels, as well as management actions, influenced safety effectiveness. Moreover, Sapeciay et al. [18] identified strategic resilience alternatives related to construction organizations through a triangulation analysis of five studies, in-depth interviews, and questionnaire surveys. Planning strategies, capability and capacity or internal resources, roles and responsibilities, organization connectivity, leadership, emergency management planning, participation in exercises, responsive decision making, information gathering, and knowledge leveraging by staff were highlighted as key factors for resilient safe construction projects. Moreover, Kalteh et al. [19] used 31 carefully chosen case studies to assess the significance of safety culture and climate for enhancing safety effectiveness. The results showed that safety compliance and reactive criteria were more in line with safety engagement. It was also highlighted that the significance degree of these factors may have impacted incident reduction and enhanced safety effectiveness metrics.

Chen et al. [20] built a model for the climate of robust safety by measuring it using seven dimensions, including the dedication of management, the supervisor's sense of safety, co-workers' sense of safety, gaining knowledge, submitting reports, planning, and consciousness within 68 construction sites in Ontario, Canada. Ahmed [21] presented different linkages for the top direct and indirect causes and effects of safety for Bangladeshi construction sites through survey questionnaires. A total of 77 causes divided into 14 groups were highlighted, and the impacts of 22 accidents were also identified using the Relative Importance Index (RII). Abukhashabah et al. [22] evaluated the factors contributing to 300 workplace accidents in Jeddah, which is located on the Red Sea coast. The results indicated that a lack of occupational safety awareness and a lack of worker experience were the main factors. Moreover, it was found that the most common accidents and injuries were workers falling from heights and electric shocks. Trinh and Feng [1] addressed new and unpredicted safety hazards to achieve a high safety effectiveness by proposing the related impacts of a robust safety culture and project complexity on the safety effectiveness in Vietnam's construction industry through survey questionnaires.

2.2. Artificial Intelligence Models Related to Safety Effectiveness in the Construction Sector

Goh and Chua [23] conducted a neural network analysis using a health management system audit and quantitative occupational accident safety data from the Singapore construction industry. Basahel and Taylan [24] established a method for analyzing the variables that affected the safety of workers on Saudi Arabian construction sites via the fuzzy analytical hierarchy process. Jitwasinkul et al. [25] developed a Bayesian belief network model of attributes of organization factors for updated safe work conduct in the Thai construction industry. According to the model, safe work practices can be implemented through management dedication, strong leadership, involvement, and a sense of control. Goh et al. [26] assessed the relative significance of various cognitive elements within the theory of reasoned action for determining safety behavior through a supervised learning approach.

Poh et al. [27] presented a machine learning technique for developing safety-related leadership attributes reliably classified in accordance with their safety incident levels in the construction industry. A total of 13 input variables were chosen, 6 of which were project-related and 7 of which related to the contractor's checklists for safety inspection. Ayhan and Tokdemir [28] presented a novel safety assessment methodology designed to anticipate potential outcomes and identify preventive measures. To reduce heterogeneity and recover homogenous subgroups from the safety data, which showed significant heterogeneity according to the mean of the latent class clustering analysis, predictive models based on factual information were presented. Gunduz and Khader [29] ranked possible safety hazards in the building industry according to their frequency of occurrence and interconnections, and through a survey questionnaire, 14 linkages and their frequencies were identified based on the frequency-adjusted importance index and the analytical networking process.

Abbasianjahromi et al. [30] presented the factors influencing the safety effectiveness in one country and constructed an integrated model to suggest methods for improving project safety in cases of inaccurate forecasts. It was discovered that workers' safety, training, safety regulation enforcement, and management engagement were required for safety effectiveness prediction. Moreover, Abbasianjahromi and Aghakarimi [31] determined the safety effectiveness criteria for the Iranian building sector and created a model for estimating safety effectiveness. The results revealed that management safety engagement, providing training about safety, safety teams, and financing safety measures were the main criteria for safety effectiveness.

3. Methodology

The research methodology used in this study was designed to predict the resilient safety effectiveness in the Rwandan building construction sector via the ANN model. It comprised three stages, as shown in Figure 1. The first stage, the "Literature review", was used to identify and establish the factors affecting resilient safety effectiveness. The second stage, the "AHP", was used to pinpoint and assess the importance of resilient-safety-effectiveness-related factors by using the AHP. The third stage, the "ANN", was used to develop an ANN model to predict the resilient safety effectiveness, with the key factors determined using the results of the AHP analysis.

3.1. Analytic Hierarchy Process (AHP)

The AHP is a multicriteria approach to decision making that was adopted to determine the weight of each safety-related factor by evaluating a pairwise comparison between the factors. The AHP helped us to identify the factors that could influence the target; therefore, pairwise comparison was performed to determine the weight and decision-making priority among the factors for each problem [32]. Therefore, the findings of the AHP enabled decision makers to select the optimal solution by understanding the relationship between each relevant factor through a hierarchical structure based on a logical relationship.

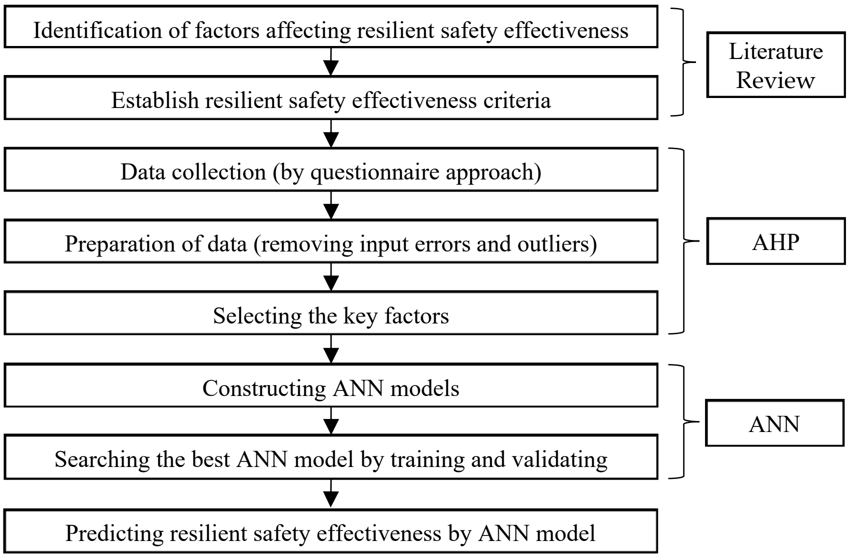

Figure 1. Research methodology process.

The design of any AHP hierarchy involves a problem and a goal to be achieved, alternative ways of reaching the goal, and criteria against which the alternatives are measured. In the AHP, emphasis is placed on consistency calculation, leading to eigenvalue formulation, though the process also prioritizes vectors or weights (w), where the importance level can be checked and then the rank decided. The reliability of the survey results is typically checked by using the consistency index (CI) of a matrix comparison.

3.2. Artificial Neural Network (ANN)

An ANN is recognized as a mathematical means of processing information according to the processes of the human brain; therefore, data are processed in numerous mutually interconnected layers of neurons, and signals are transmitted between neurons that have corresponding weights via linking connections. By altering the weights of the connections between artificial neurons, decision makers can simulate them according to their own judgement. Therefore, this approach was employed to determine if the selected factors that place a high priority on influencing resilient safety effectiveness are the main ones, and if they can reasonably forecast resilient safety effectiveness.

The structure of an ANN is made up of an input layer, a hidden layer, and an output layer. It mainly varies based on the quantity of layers, as some have single layers, whereas other have multiple layers, known as multi-layer perceptrons. Moreover, ANN models use several learning processes, namely feed-forward and back-propagation models. Furthermore, for ascertaining the output signal, every neuron utilizes an activation function or transfer function for the incoming signal, and the applied functions vary between linear, hyperbolic tangent sigmoid, and log sigmoid functions [33]. The input and output of each neuron can be determined mathematically. The input signal from each neuron is expressed by multiplying the weight coefficients with the input signals before the inputs are fed into the hidden-layer neurons and by summing all of them with the bias vector received by the hidden layers. Afterwards, the neurons at the hidden layers produce an output using the activation equation. Then, by repeating this input and output process, the ANN model achieves the optimal value.

4. Selecting the Key Factors Using the AHP

Since the aim of the second stage, the "AHP", was to identify the key factors vital for resilient safety, the AHP was adopted as a technique to logically show the factors that strongly impact resilient safety effectiveness. In this stage, for the AHP analysis, the Likert scale was used through survey questionnaires. The results of this AHP analysis helped us to select the key factors influencing safety effectiveness, and the identified ones were used as the inputs for the ANN model.

4.1. Data Collection

This study was conducted through survey questionnaires, with the aim of determining the main research participants' perspectives on the potential factors contributing to resilient safety effectiveness in the building construction sector of Rwanda. The three indicators of resilient safety effectiveness, namely psychological, behavioral, and contextual resilience, were employed to gauge resilient safety effectiveness. The questionnaire was designed considering the factors affecting resilient safety, which were identified according to earlier studies and based on the opinions of construction experts. From the previous studies, a total of thirty-nine safety attributes categorized into six groups were selected as the potential intrinsic factors that may affect in the construction industry in Rwanda.

A target sample size of 100 participants was formed through purposive sampling. Specifically, research participants with at least five years of experience working in the Rwandan construction industry, such as contractors, consultants, and clients, were selected. From a total of 150 questionnaires sent via e-mail, 100 surveys were returned, implying a response rate of 66.7%.

The survey questionnaire was divided into three sections. The first part consisted of the background data of the respondents, such as the respondents' experience, qualifications, type of employer, position, project experience, knowledge of the frequency of safety issue occurrence, and awareness about resilient safety measures. The second part evaluated the significance levels of the variables affecting resilient safety effectiveness by using a five-point Likert scale (1—very low; 2—low; 3—medium; 4—high; and 5—very high). The third part rated resilient safety effectiveness by evaluating the three key indicators measuring safety, namely psychological, behavioral, and contextual resilience, through a five-item Likert scale (1—very low safety effectiveness; 2—low; 3—medium; 4—high; and 5—very high safety effectiveness).

The frequency of the survey responses was displayed according to the three sections mentioned above. The participants' experience was divided into persons with 5 years, 6–10 years, and more than 11 years of experience, and their frequencies were 59%, 24%, and 1.7%, respectively. This ensured that the survey participants provided more useful insights, since they all had over 5 years of experience in the field. The qualifications of the respondents were grouped into undergraduate (74%), master's (23.8%), and PhD (2.2%) degrees. Moreover, to guarantee that the collected data presented numerous views and the questionnaire surveys were fair, the responses received were categorized as being from consultants (31.5%), contractors (43%), and clients (25.5), and the respondents' positions varied, including project directors (23%), architects (27), engineers (25%), quantity surveyors (12%), and owners (13%).

The majority of projects were residential buildings and small-sized projects, with frequency rates of 64.9% and 57%, respectively (including multiple responses). Finally, regarding safety issues and awareness about resilient safety in Rwanda, most respondents (about 90%) indicated that safety issues happen often, and that the majority of construction practitioners are not familiar with applying a resilient safety culture. This demonstrates the necessity of a study on resilient safety culture in the Rwandan construction context.

4.2. Preparation of Data

According to Cheung et al. [34], the accuracy of a model is heavily dependent on information availability and the method used to prepare information. To ensure that the information obtained from the participants was free of errors and outliers according to the logic used, Statistical Package of Social Sciences (SPSS) was first used to detect and remove errors and outliers. Afterwards, the reliability of the data was checked through Cronbach's alpha, which is a common method for measuring test items' internal consistency [35]. The data regarding the significance level of safety-related parameters and the data on safety effectiveness yielded Cronbach's alpha coefficients of 0.97 and 0.93, respectively.

4.3. Selecting the Key Factors

4.3.1. Factors Affecting Resilient Safety Effectiveness According to Importance Levels

This study was conducted to find the importance levels attributed by stakeholders to the potential factors affecting the resilient safety effectiveness in the building construction sector of Rwanda. The overall factors were identified with respect to the aforementioned factors affecting resilient safety, which were found via a literature review and based on the opinions of construction experts. Through this process, 39 safety factors were selected as potential intrinsic factors affecting the construction industry in Rwanda. Then, these 39 selected safety factors were categorized into six groups based on similar characteristics.

Table 1 presents the relative priority weights (PWs) of the factors with a high importance level in affecting the resilient safety effectiveness generated by using the AHP. According to the obtained results, a consistency ratio (CR) below 0.1 was identified for all criteria, which implies that the judgment used when comparing the criteria affecting resilient safety was consistent [32].

Table 1. Priority weights (PWs) of overall factors affecting resilient safety effectiveness.

Category		Description	CR	PW
Management-related factors	F1	Safety management commitment and competence	0.097	0.34
	F2	Making safety plans		0.17
	F3	Updating safety plans		0.03
	F4	Organizational safety response		0.07
	F5	Risk identification and management		0.20
	F6	Site planning and housekeeping		0.05
	F7	Management of unsafe place accessibility		0.10
	F8	Project communication and information management		0.04
Safety-measure-related factors	F9	Following safety instructions and rules	0.095	0.40
	F10	Safety inspection		0.21
	F11	Safety budgets		0.03
	F12	Emergency preparation		0.20
	F13	Hazard analysis and incident control pressure		0.10
	F14	Movement control		0.01
	F15	Safety hazard elimination design		0.05
Teamwork-related factors	F16	Safety personnel support	0.092	0.12
	F17	Project workers' awareness and responses to possible hazards		0.10
	F18	Safety seminars and training for workers		0.03
	F19	Occupational health programs		0.07
	F20	Incentives for workers to use safe work behaviors		0.06
	F21	Site induction for workers		0.11
	F22	Experience and capabilities of project team members		0.14
	F23	Responsive decision making regarding safety		0.22
	F24	Time assigned to workers for safety-related remedial actions		0.15

Table 1. *Cont.*

Category		Description	CR	PW
Resource-related factors	F25	Machinery and equipment maintenance and control regime	0.094	0.27
	F26	Control of hazardous substances and chemical usage		0.30
	F27	Material storage control		0.22
	F28	Availability and accessibility of personal protective materials		0.10
	F29	Providing safety sanitation and welfare facilities		0.09
	F30	Knowledge about permit and signage systems		0.02
Construction-working-condition-related factors	F31	Placing proper barriers, signs, or lights in unsafe working places	0.091	0.32
	F32	Work flow and procedure control		0.36
	F33	Clarity of working methods		0.15
	F34	Project complexity control		0.14
	F35	Compliance with legal and international standards and technology		0.03
External factors	F36	Government safety regulations enforcement	0.096	0.17
	F37	Changes in local weather conditions		0.30
	F38	Changes in the economic environment		0.22
	F39	Conditions on site		0.31

4.3.2. Selecting the Key Factors Affecting Resilient Safety Effectiveness

Table 2 depicts the findings regarding the key factors affecting resilient safety effectiveness in the building construction sector of Rwanda. Out of 39 potential factors affecting safety effectiveness, 12 factors were selected to serve as the ANN model's inputs. In this study, each category's two top factors were selected for ensuring a high chance of prediction ability, as it is worthwhile to concentrate on parameters with peak significance levels instead of using all parameters concurrently for developing a more accurate ability model [36]. Thus, the top 12 factors with high importance levels for influencing the resilient safety effectiveness in the building construction sector of Rwanda are shown in Table 2.

Table 2. Top 12 key factors affecting resilient safety effectiveness.

	Description	PW
F1	Safety management commitment and competence	0.34
F5	Risk identification and management	0.20
F9	Following the safety instructions and rules	0.40
F10	Safety inspection	0.21
F23	Responsive decision making regarding safety	0.22
F24	Time assigned to workers for safety-related remedial actions	0.15
F25	Machinery and equipment maintenance and control regime	0.27
F26	Control of hazardous substances and chemical usage	0.30
F31	Placing proper barriers, signs, or lights in unsafe working places	0.32
F32	Work flow and procedure control	0.36
F37	Changes in local weather conditions	0.30
F39	Conditions on site	0.31

4.4. Discussion of the Factors Affecting Resilient Safety Effectiveness in the Rwandan Construction Sector

The factors affecting the resilient safety effectiveness of the Rwandan construction sector, as shown in Table 2, are discussed in descending order of PW.

'Following the safety instructions and rules (F9)' was given the highest importance level (PW = 0.40) among the 12 factors. This is because following safety rules can reduce human errors that lead to unsafe behavior [37]. 'Work flow and procedure control (F32)' was ranked second in importance (PW = 0.36). Since construction workers are usually day laborers, sometimes, a changed work flow is not provided to workers even though the work order is changed, and some workers may perform dangerous work without proper instructions on how to protect themselves, which may lead to accidents [38]. The reason why these two factors were considered as the most important is because low-income countries such as Rwanda often have an atmosphere in which regulations are ignored and work is performed arbitrarily [15].

From a project management perspective, 'safety management commitment and competence (F1)' was identified as an important factor that needed to be monitored more than other factors to ensure a safe construction industry in Rwanda (PW = 0.34). A significant number of safety issues are related to construction organization and management systems [39], which may be because safety management plans are often not systematically established before project execution in low-income countries such as Rwanda. 'Placing proper barriers, signs, or lights to unsafe working places (F31)' was given a high importance (PW = 0.32) by Rwandan construction experts because, in general, construction sites in low-income countries such as Rwanda do not place adequate safety equipment such as barriers, signs, or lights, causing accidents, because of cost issues [13].

In addition, 'conditions on site (F39)' was a factor with high importance (PW = 0.31), but it is difficult to control; similarly, 'changes in local weather conditions (F37)' is also a factor that cannot be controlled in construction projects. These two factors can affect the behavior of workers and cause some safety problems, so they should be accounted for, and appropriate alternatives should be presented. Although these factors are common problems that generally occur in all construction sites around the world [39], they should be anticipated, to some extent, in advance, so that construction activities can be properly protected when serious conditions occur.

'Control of the use of hazardous substances and chemicals (F26)' and 'maintenance and control systems for machinery and equipment (F25)' are related to equipment, materials, or substances that can cause some accidents. Maintaining and controlling these factors on-site incur additional costs, which some contractors in low-income countries such as Rwanda try to minimize [13].

'Responsive decision making regarding safety (F23)' and 'risk identification and management (F5)' were also identified as key factors, which may be because most safety issues are not anticipated in advance before project execution to identify and manage risks. Appropriate measures should be assigned to each safety issue before safety risks occur. Compliance with safety rules through 'safety inspection (F10)' can help to mitigate the causes of safety problems before they occur. 'Time assigned to workers for safety (F24)' is related due to the complexity of projects, as it often takes significant time to set up and plan safety mitigation measures. The reason why these four factors (F23, F5, F10, and F24) were included in the twelve key factors affecting the resilient safety effectiveness in the building construction sector of Rwanda was, as explained above, related to the social atmosphere, which does not encourage strong adherence to government regulations, and the minimization of additional costs.

Therefore, it is very important to monitor the 12 key factors listed in Table 2, as this can reduce the safety risks associated with construction projects in Rwanda.

5. The ANN Model for Predicting Resilient Safety Effectiveness

This section describes the process and results of developing a model that contributes to predicting resilient safety effectiveness by integrating the AHP and the ANN. The intrinsic factors that indicated a high priority in affecting the resilient safety effectiveness were highlighted using the AHP. The AHP priority weights (PWs) were preferred to show the significance level of each factor for affecting safety effectiveness, because they could calculate the relative priorities of variables by comparing the importance levels with respect to a particular criterion, and the ratings of each factor were determined according to the weights' values. In addition, the three indicators of resilient safety effectiveness (psychological, behavioral, and contextual resilience) were considered as the outputs when designing a predictive model. In this chapter, the ANN model is constructed, tested, and validated to ensure that the selected key factors can also predict the resilient safety effectiveness in the Rwandan building construction sector.

5.1. Constructing ANN Model

A multi-layered perceptron model with 12 inputs (input layer) and 3 outputs (output layer) was adopted, because this model type consists of more than one layer. The 12 key factors with peak importance levels were employed as inputs, and the output was resilient safety effectiveness expressed in the form of psychological, behavioral, and contextual resilience. The ANN model was used to determine the best configuration of the model, such as the number of layers and neurons. A feed-forward neural network based on back propagation was built to train the ANN. A back-propagation learning algorithm was employed because it is a supervised process most suitable for prediction [40]. Afterwards, model training was performed as a learning process that could modify connection strength with the goal of reducing the error by changing the network's weights and biases [33].

The learning algorithm function used was the scaled conjugate gradient algorithm, and the activation function for the hidden and output layers was SoftMax, as SoftMax has been used as an activation function in recent ANN-related studies on construction [41]. The data were split for testing, training, and validation using the hold-out technique, as this is indicated for use when the data are sufficient [42]. Therefore, the data were split into three sets. Out of the 100 data sets, 75 were utilized for training, 15 for testing, and 10 for validation. The data were allocated as follows: about 70–75% for training and about 25–30% for validation and testing (10% is suitable for validating data); the authors knew from experience that this proportion is appropriate [43].

In this study, the effectiveness of model was determined by using the loss function known as the categorical cross-entropy error (CCEE). The reason was that this is generally used for classification models [44] like the model this study, the outputs of which had three classes. The choice of optimal model was made in light of the categorical cross-entropy error generated by every model; therefore, once the minimum error was achieved, training and validation were terminated. In this model, epochs were set at 1,000, the minimum patience was 0.001, and patience range was from 0 to 10. The parameters of the constructed resilient safety ANN model described above are summarized in Table 3.

Table 3. The constructed resilient safety ANN model's parameters.

Inputs	Outputs	Activation Function	Loss Function
Top 12 key factors: F1, F5, F9, F10, F23, F 24, F25, F26, F31, F32, F36, and F39	3 resilient safety measures: psychological, behavioral, and contextual	SoftMax	CCEE

5.2. Searching the Best ANN Model

The choice of optimal model was made in light of the categorical cross-entropy error generated by every model; therefore, once the minimum error was achieved, training and validation were terminated. In the first and second trials, the networks were constructed with respect to the number of hidden layers, as shown in Table 4. The number of hidden layers was limited to two, as a maximum of two hidden layers was adequate for the multiple layer perceptron networks since they could give a better model accuracy and prevent overfitting, especially for nonlinear problems [42].

Table 4. ANN resilient safety effectiveness model according to the number of hidden layers.

Model	Number of Hidden Layers	Validation	
		CCEE	Accuracy (%)
Model 1	1	0.053	96.24
Model 2	2	0.032	98.84

According to this study's findings, the model consisting of two hidden layers offered the best result, with an average categorical cross-entropy error (CCEE) of 0.032 and an accuracy of 98.84% compared with the one-hidden-layer model. Moreover, subsequent attempts were carried out in accordance with the chosen model based on the quantity of the hidden layers. A two-hidden-layer network was then trained again by fluctuating the number of hidden nodes, whereby the nodes were modified to 3, 6, 9, 12, and 15, as shown in Table 5. The best model that showed the lowest error was the model with three hidden nodes, which showed a 0.011 CCEE and a 98.96% accuracy.

Table 5. ANN resilient safety effectiveness model according to the number of hidden nodes.

Model	Number of Hidden Nodes	Validation	
		CCEE	Accuracy (%)
Model 2-3	3	0.011	98.96
Model 2-6	6	0.037	98.27
Model 2-9	9	0.041	97.73
Model 2-12	12	0.058	96.92
Model 2-15	15	0.04	95.35

5.3. Discussion of the ANN Model for Predicting Resilient Safety Effectiveness

This section presents a comparative analysis of the prediction values and target values of the ANN model for the resilience safety effect. According to the validation data in Table 5, the prediction value of the resilience safety effectiveness for the model with 2 hidden layers and 15 hidden nodes (Model 2-15) had an accuracy of 95.35%, which was the lowest accuracy among the five ANN models. On the other hand, among the five ANN models, Model 2-3 (two hidden layers and three hidden nodes) provided the lowest CCEE average of 0.011 and the highest accuracy of 98.96%, which means that this ANN model was the best model. In addition, Table 5 shows that the accuracy of the prediction value gradually decreased as the number of hidden nodes increased.

The reason for this result is that the error also increased as the number of hidden nodes increased in the ANN model. This could be because many connections, which occur with increases in hidden nodes, result in a network that can memorize the input data but reduce the general capacity to supply a good output value [36]. Thus, as the complexity of the network increased, overfitting occurred, which reduced the performance of the ANN model. Therefore, simplifying the ANN model by appropriately limiting the complexity of the network could solve overfitting and improve performance.

Furthermore, these results demonstrate that the ANN model can predict the resilient safety effectiveness in the building construction sector in Rwanda with a very high accuracy. In particular, this model can predict resilient safety effectiveness, especially in terms of psychological, behavioral, and contextual safety resilience.

6. Conclusions

This study examined the key factors affecting the resilient safety effectiveness in the building construction sector in Rwanda. An ANN model for predicting resilient safety effectiveness was developed to check whether the selected key factors could determine the resilient safety effectiveness with a high predictive ability. Psychological, behavioral, and contextual resilience were employed to measure the resilient safety effectiveness. A survey questionnaire was designed and sent to target construction practitioners, such as contractors, consultants, and clients. Thus, information about the importance levels of the safety factors affecting the resilient safety effectiveness and their related resilient safety effectiveness levels could be identified to achieve this study's objective.

The 12 key factors affecting resilient safety effectiveness were determined via AHP analysis. Among these 12 key variables, the top 5 with the highest PWs were as follows: 'Following the safety instructions and rules' means that following safety rules can reduce human errors that lead to unsafe behavior. 'Work flow and procedure control' means that, sometimes, a changed work flow is not provided to workers, and some workers may perform dangerous work without proper instructions on how to protect themselves. 'Safety management commitment and competence' means that safety issues are related to construction organization and management plans, which are often not systematically established in low-income countries such as Rwanda. 'Placing proper barriers, signs, or lights in unsafe working places' means that, in general, some construction sites do not place adequate safety equipment. 'Conditions on site' indicates that their work environment affects the behavior of workers, which may cause accidents.

Regarding the performance of the ANN model, the results of this study showed that the accuracy of the prediction value gradually decreased as the number of hidden nodes increased. This indicates the nature of the relationship between the complexity of the network and the performance of the ANN model. Therefore, by appropriately limiting the network complexity and simplifying the ANN model, overfitting can be solved, and the performance can be improved.

Therefore, these results demonstrate that the ANN model can predict the resilient safety effectiveness in the building construction sector in Rwanda with a very high accuracy. Furthermore, the model can predict resilient safety effectiveness in terms of psychological, behavioral, and contextual safety resilience. In addition, since the key factors that affect the resilient safety effectiveness in the building construction sector are recognized, the model can inform construction practitioners in low- and middle-income countries such as Rwanda about which factors to focus on to safely deliver construction projects. This will help practitioners to predict safety issues that may affect construction projects in advance and design preventive solutions, which will ultimately contribute to reducing accidents in the construction sector.

However, this study has limitations in that it identified the resilient safety effectiveness in the building construction sector in Rwanda. Thus, it is difficult to say whether the results of this study are applicable to other countries with different construction environments, such as high- and middle-income countries. Therefore, further research is needed to develop a resilient safety effectiveness prediction model that can be applied globally.

Author Contributions: Conceptualization, E.U. and S.-H.A.; formal analysis, E.U.; funding acquisition, S.-H.A.; methodology, E.U. and S.-H.A.; supervision, S.-H.A.; validation, E.U. and S.-H.A.; writing—original draft, E.U.; writing—review and editing, E.U. and S.-H.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by a Daegu University Research Grant, 2023.

Data Availability Statement: The datasets in the current study are available from the authors upon reasonable request.

Acknowledgments: The authors would like to thank Daegu University for the contribution made to the realization of this research.

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

References

1. Trinh, M.T.; Feng, Y. Impact of project complexity on construction safety performance: Moderating role of resilient safety culture. *J. Constr. Eng. Manag.* **2020**, *146*, 04020022. [CrossRef]
2. Safe Work Australia. *Guidance on the Principles of Safe Design for Work*; The Australian Safety and Compensation Council, 2006. Available online: https://www.safeworkaustralia.gov.au/system/files/documents/1702/guidanceontheprinciplesofsafedesign_2006_pdf.pdf (accessed on 16 January 2024).
3. Health and Safety Executive (HSE). Workplace Fatalities in Great Britain 2018. *Annual Statistics*. July 2018. Available online: https://www.rsms.co.uk/clientfiles/files/fatalinjuries.pdf (accessed on 20 February 2024).
4. Mučenski, V.; Peško, I.; Trivunić, M.; Ćirović, G.; Dražić, J. Identification of Injury Risk in Building Construction—Education, Experience and Type of Works. *Teh. Vjesn.* **2013**, *20*, 1011–1017.
5. Sandberg, E.; Albrechtsen, E. A study of experience feedback from reported unwanted occurrences in a construction company. *Saf. Sci.* **2018**, *107*, 46–54. [CrossRef]
6. Health and Safety Executive, U.K. Fatal Injuries Arising from Accidents at Work in Great Britain: Headline Results. 2021. Available online: http://www.hse.gov.uk/statistics/fatals.htm (accessed on 10 December 2022).
7. Dodshon, P.; Hassall, M.E. Practitioners' perspectives on incident investigations. *Saf. Sci.* **2017**, *93*, 187–198. [CrossRef]
8. State of industrial disaster at 2023.12 [Internet]. Ministry of Employment and Labor: Sejong, Republic of Korea, 2024. Available online: https://www.moel.go.kr/policy/policydata/view.do?bbs_seq=20240401868 (accessed on 20 December 2024).
9. Pecillo, M. The resilience engineering concept in enterprises with and without occupational safety and health management systems. *Saf. Sci.* **2016**, *82*, 190–198. [CrossRef]
10. Akselsson, R.E.K.; Stewart, S.; Ward, M. Resilience safety culture. In Proceedings of the 17th World Congress on Ergonomics, Beijing, China, 9–14 August 2012. Available online: https://lucris.lub.lu.se/ws/portalfiles/portal/5444743/1608661.pdf (accessed on 10 January 2024).
11. Lengnick-Hall, C.A.; Beck, T.E.; Lengnick-Hall, M.L. Developing a capacity for organizational resilience through strategic human resource management. *Hum. Resour. Manag. Rev.* **2011**, *21*, 243–255. [CrossRef]
12. Trinh, M.T.; Feng, Y.; Sherif, M. Framework for measuring resilient safety culture in Vietnam's construction environment. *J. Constr. Eng. Manag.* **2019**, *145*, 04018127. [CrossRef]
13. Umuhoza, E.; Bitamba, B.F.; An, S.H. Causes and preventive strategies of scope creep for building construction projects in democratic republic of Congo and Rwanda. *Int. J. Constr. Manag.* **2023**, *23*, 1264–1275. [CrossRef]
14. Office of the Auditor General of State Finances, Report of the Auditor of State Finances for the Year Ended 30 June 2017, Rwanda, 2017. Available online: http://www.oag.gov.rw/fileadmin/user-upload/Financialreports/AnnualReport-june-2017-ExecutieSummary.pdf (accessed on 21 May 2023).
15. Boadu, E.F.; Wang, C.C.; Sunindijo, R.Y. Characteristics of the construction industry in developing countries and its implications for health and safety: An exploratory study in Ghana. *Int. J. Environ. Res. Public Health* **2020**, *17*, 4110. [CrossRef]
16. Alruqi, W.M.; Hallowell, M.R.; Techera, U. Safety climate dimensions and their relationship to construction safety performance: A meta-analytic review. *Saf. Sci.* **2018**, *109*, 165–173. [CrossRef]
17. Mohammadi, A.; Tavakolan, M.; Khosravi, Y. Factors influencing safety performance on construction projects: A review. *Saf. Sci.* **2018**, *109*, 382–397. [CrossRef]
18. Sapeciay, Z.; Wilkinson, S.; Costello, S.B.; Adnan, H. Building organisational resilience for the construction industry: Strategic resilience indicators. In *IOP Conference Series: Earth and Environmental Science*; IOP Publishing: Bristol, UK, 2019; Volume 385, p. 012068. [CrossRef]
19. Kalteh, H.O.; Mortazavi, S.B.; Mohammadi, E.; Salesi, M. The relationship between safety culture, safety climate, and safety performance: A systematic review. *Int. J. Occup. Saf. Ergon.* **2021**, *27*, 206–216. [CrossRef] [PubMed]
20. Chen, Y.; McCabe, B.; Hyatt, D. A resilience safety climate model predicting construction safety performance. *Saf. Sci.* **2018**, *109*, 434–445. [CrossRef]
21. Ahmed, S. Causes and effects of accident at construction site: A study for the construction industry in Bangladesh. *Int. J. Sustain. Constr. Eng. Technol.* **2019**, *10*, 18–40.
22. Abukhashabah, E.; Summan, A.; Balkhyour, M. Occupational accidents and injuries in construction industry in Jeddah city. *Saudi J. Biol. Sci.* **2020**, *27*, 1993–1998. [CrossRef]

23. Goh, Y.M.; Chua, D. Neural network analysis of construction safety management systems: A case study in Singapore. *Constr. Manag. Econ.* **2013**, *31*, 460–470. [CrossRef]
24. Basahel, A.; Taylan, O. Using fuzzy AHP and fuzzy TOPSIS approaches for assessing safety conditions at worksites in construction industry. *Int. J. Saf. Secur. Eng.* **2016**, *6*, 728–745. [CrossRef]
25. Jitwasinkul, B.; Hadikusumo, B.H.W.; Memon, A.Q. A Bayesian belief network model of organizational factors for improving safe work behaviors in Thai construction industry. *Saf. Sci.* **2016**, *82*, 264–273. [CrossRef]
26. Goh, Y.M.; Ubeynarayana, C.U.; Wong, K.L.X.; Guo, B.H.W. Factors influencing unsafe behaviors: A supervised learning approach. *Accid. Anal. Prev.* **2018**, *118*, 77–85. [CrossRef]
27. Poh, C.Q.X.; Ubeynarayana, C.U.; Goh, Y.M. Safety leading indicators for construction sites: A machine learning approach. *Autom. Constr.* **2018**, *93*, 375–386. [CrossRef]
28. Ayhan, B.U.; Tokdemir, O.B. Predicting the outcome of construction incidents. *Saf. Sci.* **2019**, *113*, 91–104. [CrossRef]
29. Gunduz, M.; Khader, B.K. Construction project safety performance management using analytic network process (ANP) as a multicriteria decision-making (MCDM) tool. *Comput. Intell. Neurosci.* **2020**, *2020*, 2610306. [CrossRef] [PubMed]
30. Abbasianjahromi, H.; Mohammadi Golafshani, E.; Aghakarimi, M. A prediction model for safety performance of construction sites using a linear artificial bee colony programming approach. *Int. J. Occup. Saf. Ergon.* **2022**, *28*, 1265–1280. [CrossRef] [PubMed]
31. Abbasianjahromi, H.; Aghakarimi, M. Safety performance prediction and modification strategies for construction projects via machine learning techniques. *Eng. Constr. Archit. Manag.* **2023**, *30*, 1146–1164. [CrossRef]
32. Saaty, T.L. *Decision Making for Leaders: The Analytic Hierarchy Process for Decisions in a Complex World*, 3rd ed.; RWS Publications: Pittsburgh, PA, USA, 2013.
33. Ling, F.Y.Y.; Liu, M. Using neural network to predict performance of design-build projects in Singapore. *Build. Environ.* **2004**, *39*, 1263–1274. [CrossRef]
34. Cheung, S.O.; Wong, P.S.P.; Fung, A.S.Y.; Coffey, W.V. Predicting project performance through neural networks. *Int. J. Proj. Manag.* **2006**, *24*, 207–215. [CrossRef]
35. Tavakol, M.; Dennick, R. Making sense of Cronbach's alpha. *Int. J. Med. Educ.* **2011**, *2*, 53–55. [CrossRef]
36. Jha, K.N.; Chockalingam, C.T. Prediction of quality performance using artificial neural networks: Evidence from Indian construction projects. *J. Adv. Manag. Res.* **2009**, *6*, 70–86. [CrossRef]
37. Reece, B.L.; Brandt, R. *Effective Human Relations in Organizations*, 5th ed.; Houghton Mifflin Company: Boston, MA, USA, 1993.
38. Choudhry, R.M.; Fang, D. Why operatives engage in unsafe work behavior: Investigating factors on construction sites. *Saf. Sci.* **2008**, *46*, 566–584. [CrossRef]
39. An, S.-H. Analysis of factors behind human error in fatal construction accidents using the m-SHEL model. *J. Korea Inst. Build. Constr.* **2022**, *22*, 415–423. [CrossRef]
40. Edwards, R.S. Modelling perceptions of building quality—A neural network approach. *Build. Environ.* **2007**, *42*, 2762–2777. [CrossRef]
41. Mitera-Kiełbasa, E.; Zima, K. Automated Classification of Exchange Information Requirements for Construction Projects Using Word2Vec and SVM. *Infrastructures* **2024**, *9*, 194. [CrossRef]
42. Jain, A.K.; Mao, J.; Mohiuddin, K.M. Artificial neural networks: A tutorial. *Computer* **1996**, *29*, 31–44. [CrossRef]
43. Kim, G.-H.; An, S.-H.; Kang, K.-I. Comparison of Construction Cost Estimating Models Based on Regression Analysis, Neural Networks, and Case-Based Reasoning. *Build. Environ.* **2004**, *39*, 1235–1242. [CrossRef]
44. Hui, L.; Belkin, M. Evaluation of neural architectures trained with square loss vs cross-entropy in classification tasks. In Proceedings of the 9th International Conference on Learning Representations (ICLR), Virtual Event, 3–7 May 2021; pp. 1–18.