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*Retraction*

# Retracted: Model and Simulation of Engineering Safety Risk Control Based on Artificial Intelligence Algorithm

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] Z. Liu, X. Zhao, J. Tan, and H. Tian, "Model and Simulation of Engineering Safety Risk Control Based on Artificial Intelligence Algorithm," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 3204317, 12 pages, 2022.

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*Research Article*

# Model and Simulation of Engineering Safety Risk Control Based on Artificial Intelligence Algorithm

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The implementation of engineering projects has a profound impact on the national economy and people's livelihood. The current engineering projects are in full swing with the vigorous development of the economy. However, due to the high complexity of the engineering project environment, a large number of participants, the high technical standards, and the high labor intensity, it is easy to induce engineering safety risk accidents. Therefore, the demand for research on safety risks in engineering construction is becoming more and more urgent. However, the traditional construction safety risk management lacks systematicness and standardization, and it has limitations in engineering safety risk early warning and control. In order to solve this problem, this paper applies artificial intelligence algorithms to engineering construction safety risk management and establishes an engineering safety risk early warning control model. The Bayesian formula, information entropy theory, and other algorithms provide the theoretical basis and feasibility analysis for the model. Four engineering safety risk factors, including human factors, physical factors, management factors, and environmental factors, are analyzed through simulation experiments. The results show that the probability of injury to construction personnel has been reduced by 51.3%, the qualified rate of production materials in construction projects has increased by 6.5%, the risk factors of management have been reduced by 7%, and the environmental risk factors have been reduced by 7.7%; the final risk early warning control effect has increased by 7.45%.



## 1. Introduction

The safety of engineering projects not only affects the efficiency of project implementation but also closely affects the life, health, and safety of construction workers. Although relevant researchers attach great importance to engineering safety issues and have conducted a series of theoretical studies on engineering safety, the results of precontrol of engineering safety risk events are not satisfactory. In this paper, the artificial intelligence algorithm is used to apply the risk early warning control model of engineering safety to the actual construction of the project. It not only can transform the concept of passive risk prevention in the past construction but also can systematically and comprehensively analyze the risk factors related to construction safety with advanced artificial intelligence algorithms. It can predict and control engineering safety risks to the greatest extent and ensure the safety and construction efficiency of engineering projects.

A mature engineering safety risk early warning mechanism plays an important role in preventing safety risk events. Many scholars have participated in research in the field of engineering safety risk early warning and control. Huang et al. proposed an intelligent risk perception system combining wireless sensor network (WSN) field visualization technology and elastic repair strategy based. And they monitored the changes in the engineering structure through the microelectromechanical system (MEMS) and uses the LED lights to indicate the safety level of the engineering site, which reduces the risk and accident rate of the site engineering [1]. ASF used the HFACS analysis method to point out eight factors related to construction personnel. Among them, they cited worker skills and training, worker experience, use of safety equipment, and risk perception as important factors. The purpose is to reduce engineering safety risks by studying personal safety risk factors [2]. Jin et al. provided an innovative PtD tool primarily responsible for assessing construction risks during the design and planning stages of engineering projects. It includes engineering risk quantification, 4D model integration of safety risk values, risk assessment, and design alternatives [3]. Zaini analyzed 21 risk drivers using SPSS23 software. He believed that the highest risk driver is insufficient safety management measures and at the same time used exploratory factor analysis (EFT) to further analyze the six key risk drivers, which promotes engineering safety risk management research [4]. Басараб and Basarab developed a safety risk early warning program that uses dynamic programming to reduce the risk of personal injury, which can minimize the risk of accidents during construction, which has important practical significance for reducing personal safety risks [5]. Liu et al. used an approach that combines the USGS hazard model with a modern general normative vulnerability curve. The risk prediction of structural and nonstructural collapse events of engineering buildings not only increases the security of the engineering itself but also reduces the safety risks of the external environment to the engineering project [6]. Benny and Jaishree conducted in-depth research on the safety management procedures of engineering construction by means of on-the-spot investigation, literature search, and collection of safety standards including OSHA (Occupational Safety and Health Administration) in a certain place. They put forward a series of suggestions to improve the occupational safety environment on construction sites [7]. Although the research of the above scholars can reduce the security risk, in theory, the risk control results in the actual implementation process are relatively limited. And, with the continuous change and development of the times, some new problems and new technologies regarding engineering safety risks have emerged. How to combine new technologies and new theories to further control security risks is a new topic that needs to be solved in today's era.

An artificial intelligence algorithm is the application of computer science, mathematics, biology, psychology, and philosophy to simulate information on human consciousness and thinking. Based on data and computing power, a strategic mechanism for solving problems is described in a systematic way. As an emerging advanced technology, artificial intelligence algorithms have been applied to various fields by many researchers. Wang S proposed an online monitoring system embedded with machine learning analysis using artificial intelligence algorithms. Compared with the existing power monitoring and protection devices, it has an obvious effect in detecting high impedance fault (HIF), which properly solves the power safety problems caused by overhead line failures [8]. Deng and Fu established the classification model of surrounding rock stability of coal roadway based on back-propagation artificial neural network (BP-ANN) using MATLAB software. The experimental results show that even under the influence of various factors, the model still has a high recognition accuracy for the classification of the stability of the surrounding rock of the coal roadway [9]. Wang used an artificial intelligence algorithm to establish a model for the English distance education classroom management system. And he can use this model to locate the students and analyze the students' status, which can timely and effectively grasp the students' status [10]. Huang et al. established the optimal logistics distribution path model based on the artificial intelligence ant colony algorithm and found the optimal solution of the logistics distribution path by analyzing the time cost and material cost of reaching each distribution target location, which significantly increases the distribution efficiency and promotes the development of logistics and e-commerce [11]. Chen built an artificial intelligence algorithm innovation and entrepreneurship system based on a neural network algorithm and bat algorithm, which has important practical value for cultivating innovative and entrepreneurial talents in colleges and universities [12]. Liu et al. discussed the effective value of artificial intelligence algorithms for improving the quality of coronary images in low-dose scans of large patients [13]. Aydin used artificial intelligence algorithms to optimize nonlinear network planning problems, creating a "hybrid AI optimization technology," which greatly optimizes the radio frequency identification technology used in the manufacturing industry [14]. The research of the above scholars has proved that the artificial intelligence algorithm has high value and a wide application range. It can play an important role in different fields, but it is not deep enough in the research field of engineering safety risk early warning and control.

In this paper, an artificial intelligence algorithm is applied to engineering safety early warning control, and a risk early warning control model based on an artificial intelligence algorithm is constructed. Specifically, four algorithms including the Bayesian formula, information entropy theory, decision tree algorithm, and artificial neural network are used. By using the model instead of the actual method to conduct simulation experiments, it is found that the model has a significant effect on the early warning control of engineering safety risks.

## 2. Engineering Safety Risk Early Warning Control Model Based on Artificial Intelligence Algorithm

*2.1. Engineering Safety Risk Factor Model.* This paper summarizes the factors that lead to risk accidents in engineering safety. At the same time, four basic factors are extracted through literature research and legal safety standard research, and through a detailed analysis of these four basic factors, this paper establishes the risk factor system of engineering safety, as shown in Figure 1.

As shown in Figure 1, the engineering risk factor model established in this paper is divided into four parts: human factors, physical factors, management factors, and environmental factors. In terms of human factors, it mainly includes reasons such as low safety awareness, low technical level, and noncompliance with production laws. Common

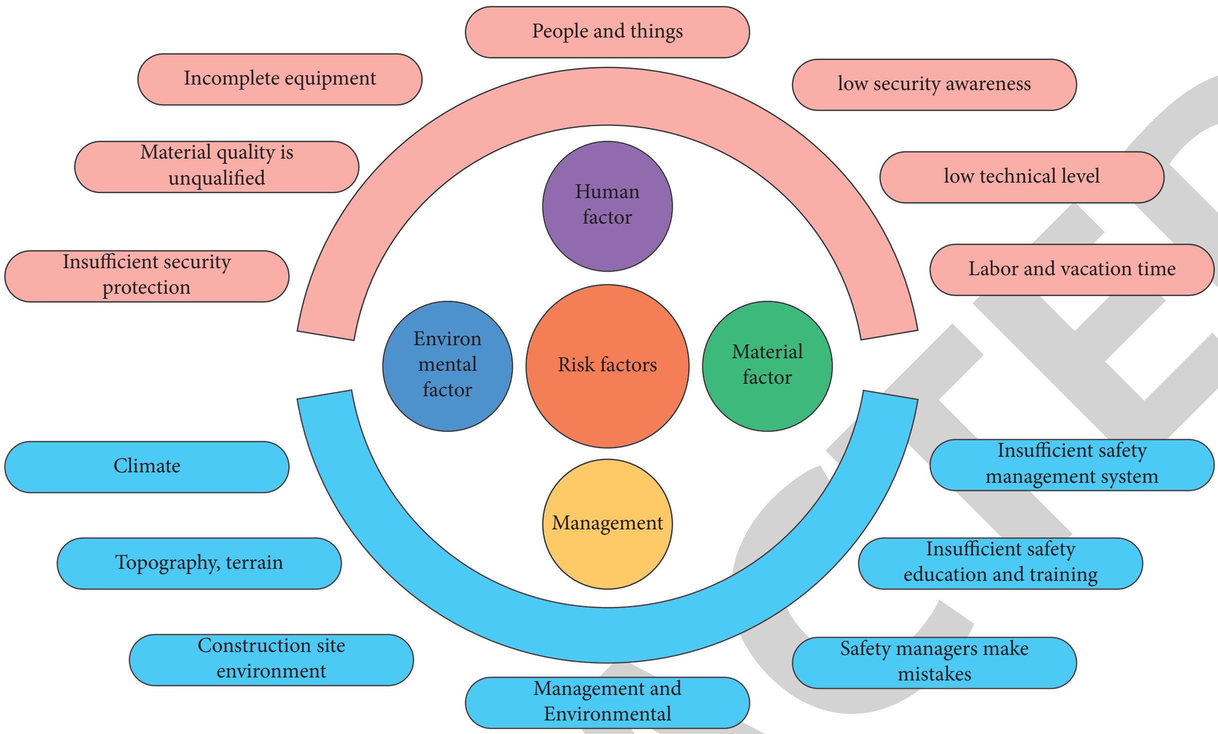


Figure 1: Engineering safety risk factor model.



specific unsafe behaviors include not using professional tools but using hands for labor, not wearing safety protection facilities such as safety helmets, placing items not in accordance with safety regulations, professional construction behaviors not operated by professionals, continuous high-intensity labor, and so on. Physical factors mainly refer to the unsafe state of production tools including machinery and equipment, auxiliary facilities such as scaffolding and ropes, steel bars, cement, and other materials. Management factors include inadequate implementation of management systems, the imperfect organizational configuration of managers, and insufficient preventive measures in safety plans. Environmental factors include harsh climatic conditions, topographical conditions, construction site environment, and so on.

*2.2. Engineering Safety Risk Early Warning Process Based on Artificial Intelligence Algorithm.* The engineering safety risk early warning process based on an artificial intelligence algorithm has four modules, risk identification, risk monitoring, risk assessment, and risk alarm, as shown in Figure 2.

As shown in Figure 2, risk identification is to find the source of danger by judging and analyzing the nature of the risk. Risk identification not only can be judged by experience but also can be judged by scientific statistical data analysis and artificial intelligence algorithms. Risk monitoring is the measures taken by safety managers after risk identification, including monitoring the possibility of risk occurrence, the changing trend, and the strength of risk factors. Risk assessment can determine the magnitude and priority of risks, which can adjust the indicators of risk assessment according to the progress of the project, and risk assessment is directly related to the results of project safety processing. Risk assessment is the use of artificial intelligence algorithms and probability statistics to analyze a large amount of data collected by risk identification. Risk alarm refers to the measures taken by risk indicators in the alarm interval after risk assessment. Through risk alarm, safety management personnel can respond to hidden safety risks more quickly. At the same time, after the risk alarm process is over, a new round of risk identification will include the risk alarm indicators in the key identification scope.

*2.3. Engineering Safety Risk Early Warning Control Model.* The engineering safety risk early warning control model based on an artificial intelligence algorithm is divided into four modules, risk data collection, risk early warning index calculation, early warning information release, and problem rectification management, as shown in Figure 3.

As shown in Figure 3, risk data collection consists of safety management personnel, monitoring system, and system data collection. The index calculation of risk warning relies on the server for data analysis and calculates the corresponding risk index according to the set risk standard. After the calculation result of the risk warning comes out, the warning information will be released according to the corresponding procedure. After the safety risk incident is resolved, the safety risk management personnel will hold a meeting to discuss the problems existing in the engineering safety risk precontrol and record them in the database, which provides reference opinions for new risk data collection, risk standard and scope setting, and risk early warning control.

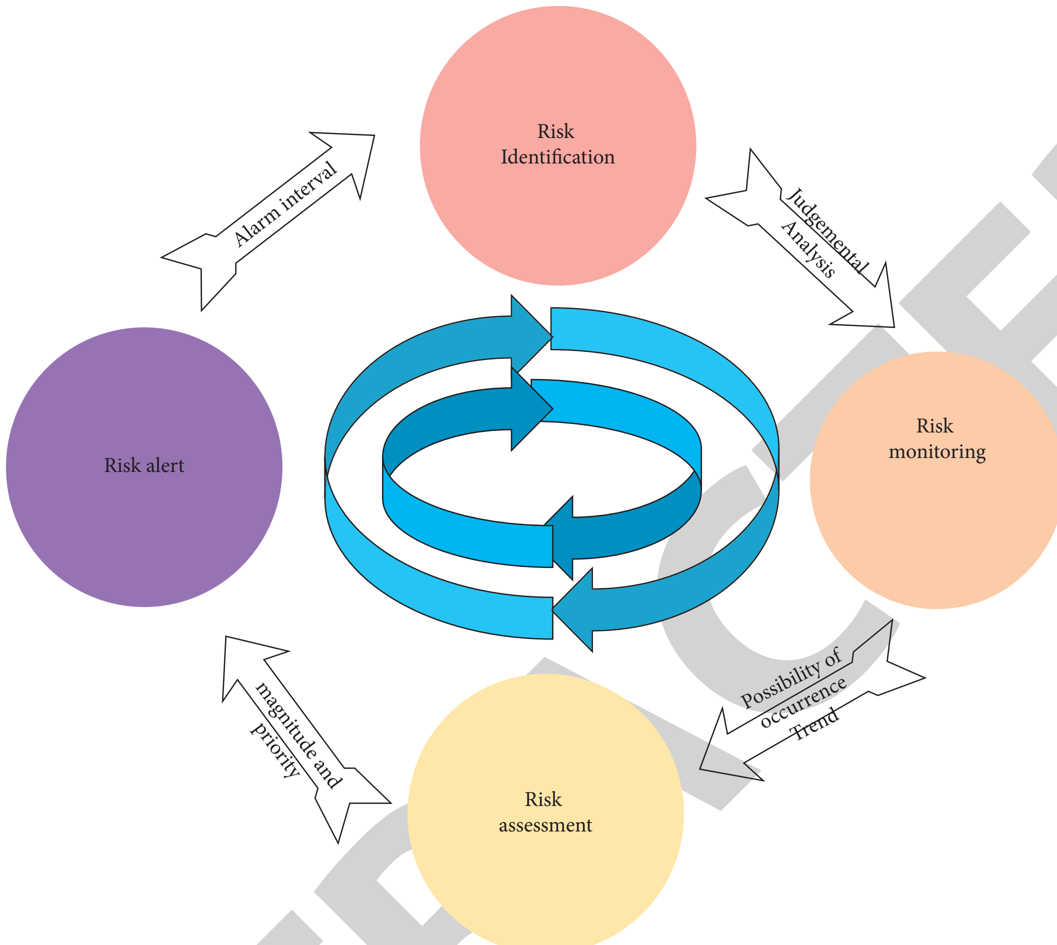


FIGURE 2: Engineering safety risk early warning process.



## 3. Artificial Intelligence Algorithms

Artificial intelligence algorithms are classified based on probability and statistics, including Bayesian principle, information entropy model, logistic regression, maximum expected value, and so on. According to graph theory, there are decision trees, random forests, and so on. If classified as interdisciplinary, there are artificial neural network and genetic algorithm, ant colony algorithm, annealing algorithm, and so on [15].

*3.1. Bayesian Formula.* The Bayesian formula is used to describe the relationship between two conditional probabilities, expressing the probability that event A occurs when event B occurs [16]. But it is worth noting that the probability of event A occurring when event B occurs is different from the probability of event B occurring when event A occurs. The Bayesian formula expressing the probability of random events A and B occurring:

$$P(A_s|B) = \frac{P(B|A_t)P(A_t)}{\sum_s P(B|A_s)P(A_s)}, \tag{1}$$

where $P(A|B)$ represents the possibility that event $A$ occurs when event $B$ occurs and $A_s$ is a complete event.

When there are more than two random events, the Bayesian formula also holds

$$P(A|B,C) = \frac{P(A)P(B|A)P(C|A,B)}{P(B)P(C|B)}. \tag{2}$$

Formula (2) represents the probability that event $A$ occurs when events $B$ and $C$ occur.

Applied to engineering safety risk early warning, event $B$ is set as the probability that construction personnel are not equipped with safety settings to work. Event $C$ is the probability of damage to production equipment, scaffolding, ropes, and other tools, and event $A$ is the probability of personal risk to construction workers. It can be seen from the Bayesian formula that by improving safety awareness and ensuring the safety status of production tools and materials, the probability of safety risk events can be effectively reduced.

*3.2. Information Entropy Theory.* Information entropy refers to the degree of uncertainty of an event. It is not a measure of the amount of information, but a measure of the uncertainty of the event itself [17]. The more effective information is added to the information entropy, the lower the uncertainty of an event and the higher the prediction

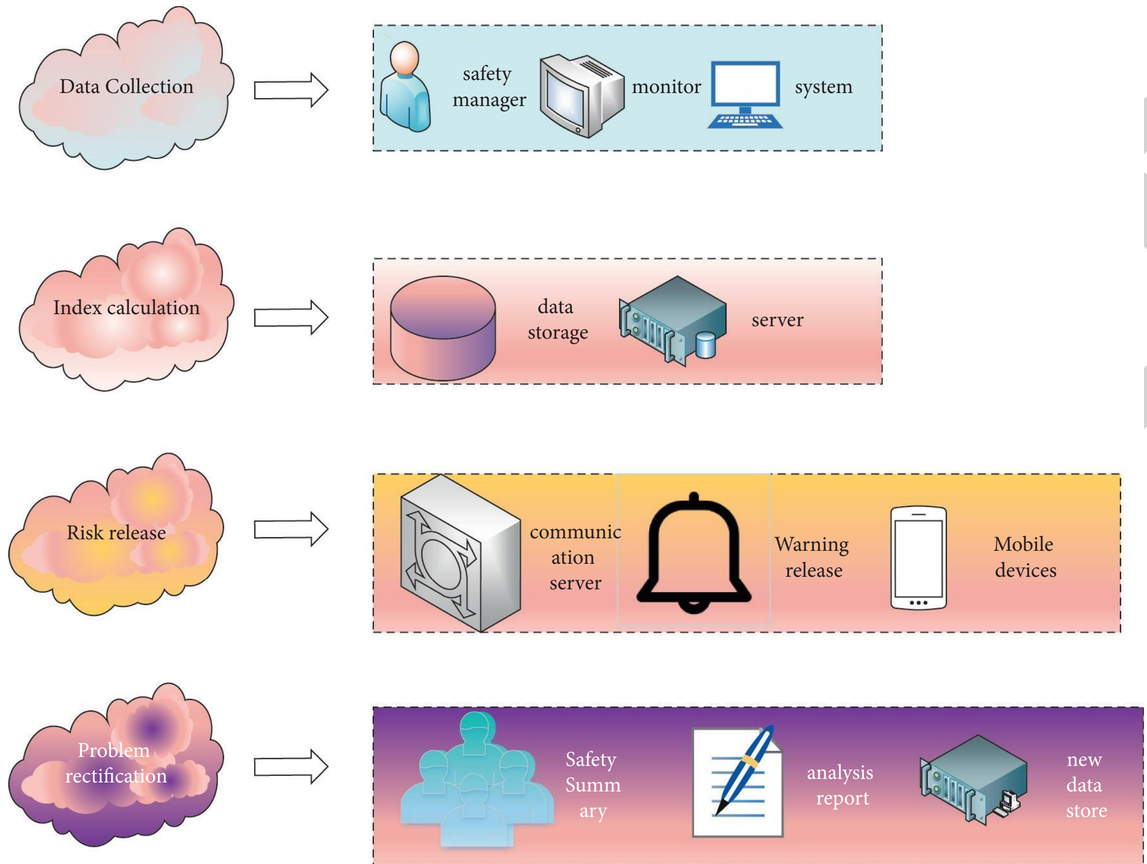


FIGURE 3: Engineering safety risk early warning control model.

accuracy, and vice versa, the lower the prediction accuracy of an event. In engineering safety risk events, the occurrence or not, the time of occurrence and the resulting results are all uncertain.

Define the overall safety risk of a project as $V$; $H$ is the overall uncertainty, and $W$ is the risk loss; there are

$$V = f(H, W). \tag{3}$$

Define $n$ possible risks to take values $x_1, \ldots, x_i \ldots, x_n$, and the probability of their corresponding risks to occur is $p(x_1), \ldots, p(x_i), \ldots p(x_n)$. Information entropy is the average value of the uncertainty of the occurrence of a single risk event:

$$H(X) = -\sum_{x} p(x)\log p(x) = -\sum_{i=1}^{n} p(x_i)\log p(x_i), \tag{4}$$

where $x$ represents a random vector and $p(x)$ represents a probability distribution. The larger the $p(x)$, the larger the entropy value.

The set of engineering safety risk factors is set as $\lambda = \{\lambda_1, \lambda_2, \lambda_3 \ldots \lambda_q\}$, and $p$ is the number of risk factors. $U(\alpha_p, \lambda_{st})$ was set as the influence degree of each risk factor at $\alpha_p$. The formula is as follows:

$$U(\beta_m, \alpha_p, \lambda_{st}) = \frac{U(\alpha_p, \lambda_{st})}{\sum_{n=1}^{i} U(\beta_m, \alpha_p, \lambda_{st})}, \tag{5}$$

where $\lambda_{st}$ represents the weight coefficient of the $n^{\text{th}}$ risk factor in the $s^{\text{th}}$ stage, $\beta_m$ represents the $m^{\text{th}}$ stage, and $\beta = 1,2,3$.

Uncertainty of engineering safety risk is defined as follows:

$$H(\beta_m, \alpha_p) = -\frac{1}{\ln n} \sum_{s}^{t} U(\beta_m, \alpha_p, \lambda_{st}) \ln U(\beta_m, \alpha_p, \lambda_{st}). \tag{6}$$

*3.3. Decision Tree Algorithm.* A decision tree refers to a decision analysis method that uses probability analysis theory to form a tree-like prediction model to measure the mapping relationship between object attributes and object values on the basis of known situations that may occur [18].

Information gain formula is as follows:

$$H(Q) = -\sum_{i=1}^{C} p_i \log_2(p_i), \tag{7}$$

where $H(Q)$ is the uncertainty degree of the information.

If the data in $Q$ is divided into $m$ categories according to attribute $A$, there are

$$H_A(Q) = \sum_{f=1}^{m} \frac{|Q_f|}{|Q|} \times H(Q_f). \tag{8}$$

Let $S$ denote the information generated by dividing $Q$ into $m$ divisions corresponding to the $m$ outputs of A, it is defined as follows:

$$S_A(Q) = -\sum_{f=1}^{m} \frac{|Q_f|}{Q} \times \log_2\left(\frac{|Q_f|}{Q}\right). \tag{9}$$

Definition of information gain rate is as follows:

$$\text{Gain}_{\text{ratio}}(A) = \frac{\text{Gain}(A)}{S(A)}. \tag{10}$$

The CART classification tree algorithm generally uses the Gini coefficient instead of the information gain rate as follows [19]:

$$\text{Gini}(Q) = 1 - \sum_{i=1}^{c} p_i^2. \tag{11}$$

In the field of engineering safety risks, the decision tree algorithm can play a good role in risk classification, and the tree-like classification structure of the decision tree is more conducive to the early warning and prevention and control of risks for engineering safety managers.

*3.4. Artificial Neural Network (ANN).* The artificial neural network (ANN) is one of the artificial intelligence algorithms and is generally used to solve regression and classification problems. ANN can handle more complex nonlinear system models by fitting nonlinear functions with a reasonable network structure [20]. The ANN network model includes an input layer, two hidden layers, and an output layer.

In this paper, the risk factors affecting engineering safety are set as the independent variable $A$, and the change degree of risk warning is set as $B$, we can get

$$\begin{aligned} A &= (a_1, a_2, \ldots, a_m), \\ B &= (b_1, b_2, \ldots, b_n). \end{aligned} \tag{12}$$

Let the control point of the universe be $a_p\,(p = 1, 2, \Lambda, m)$ and $b_q\,(q = 1, 2, \Lambda, n)$.

Let the step size be $\Delta_1 = a_{p+1} - a_p > 0, \Delta_2 = b_{q+1} - b_q > 0$.

Then there are

$$u_{s,t} = \left(1 - \frac{|a - a_s|}{\Delta_1}\right)\left(1 - \frac{|b - b_t|}{\Delta_2}\right). \tag{13}$$

Assuming that risk factor data $(a, b)$ has group $v$, then there is matrix $U$:

$$U = \sum_{k=1}^{v} u_{pq}^{k}, p = 1, 2, \ldots, m; \quad q = 1, 2, \ldots, n. \tag{14}$$

The formula of fuzzy matrix $R$ is

$$R = \frac{U}{v_{pq}}, \quad p = 1, 2, \ldots, m, q = 1, 2, \ldots, n, \tag{15}$$

where $v_{pq} = \max(U)$ and $0 \le R \le 1$.

Let $Y^{(1)}, X^{(1)}$ be a fuzzy subset of the universe of discourse $A, B$; then, we have

$$Y^{(1)} = X^{(1)} * R, \tag{16}$$

where " $*$ " represents the fuzzy relation matrix operation rule.

When $a \le a_1$,

$$X^{(1)} = [1, 0, 0, \Lambda, 0]. \tag{17}$$

When $a > a_m$,

$$X^{(1)} = [0, 0, 0, \Lambda, 1]. \tag{18}$$

When $a_1 < a < a_m$,

$$X^{(1)} = \left[\max\left\{0, 1 - \frac{|a - a_q|}{\Delta_1 -}\right\}\right]. \tag{19}$$

In traditional engineering, there are only two simple criteria: qualified and unqualified, while artificial neural network algorithms can quantify risk factors and adjust the magnitude of risk appropriately. The artificial neural network algorithm guarantees the accuracy and feasibility of the risk model and simulation experiments established in this paper.

## 4. Simulation Experiment Design of Engineering Safety Risk Early Warning Control Model

*4.1. Description of Experimental Design.* In order to ensure the accuracy of the experimental data, this paper collects and organizes the construction data of a large number of engineering projects, including construction personnel, equipment, safety management system, environment, and other factors. The artificial intelligence algorithm and computer technology are used to construct the simulation model of the engineering construction enterprise. The construction companies in groups C and D that used artificial intelligence algorithms were set as the experimental group, and the construction companies in groups E and F that used traditional construction methods were called the control group. Simulation experiments are carried out on four aspects of human factors, physical factors, management factors, and environmental factors.

*4.2. The Purpose of the Experiment.* The risk early warning control model and simulation research established in this paper is to prove that the use of artificial intelligence algorithms has a significant role in engineering safety risk prevention. The use of artificial intelligence algorithms not only can reduce construction safety risks but also can improve construction efficiency. Artificial intelligence algorithms have strong practical value.

## 5. Comparative Results and Simulation Experiments of Risk Early Warning Control Model

*5.1. Comparison of Human Factors.* The comparative experiment of human factors can test the effect of artificial intelligence algorithms in the field of engineering safety risks through the experimental results of safety awareness, technical level, labor, and vacation time. In order to ensure the fairness of the experimental results, this paper eliminates the influence of other factors other than human factors on the construction. The number of construction employees is set to 200; the construction period is uniformly set to 7 months; and index statistics on various factors are carried out at least once a month.

*5.1.1. Safety Awareness.* In terms of human factors, the indicators of safety awareness can be detected from several specific aspects, such as the length of regular safety training, the number of illegal operations without the use of safety protection tools, and the number of injuries; the indicators of security awareness are shown in Figure 4.

The figure above shows that the data of experimental groups C and D are relatively stable in terms of regular safety training duration. And safety training time is increasing. The training time of enterprises E and F in the second month exceeded that of enterprises C and D, reaching 3.5 h and 3 h, respectively. However, the data on the training duration of enterprises E and F are only considerable in the second month. In the seventh month, it is only 3 h and 2 h, while enterprises C and D are only 4 h. Compared with companies C and D, the training time of company F is reduced by 50%. Companies C and D have an average of 24.5% more training time than companies E and F. In terms of the number of illegal operations, the data of the number of illegal operations of companies C and D decreased all the way, from the first 9 times to the last 1 and 2 times, indicating that the scientific artificial intelligence algorithm is applied in the field of security risks and the effect is stable. Enterprise E's figure fell to 1 in the sixth month but rebounded to 8 in the last month. The average number of violations of companies C and D was 45.7% lower than that of companies E and F. In terms of the number of injuries, companies C and D finally reduced the data from 6 to 1 and 2, while the final data of companies E and F were 7 and 6. The average number of injuries of companies C and D was 51.3% lower than that of companies E and F. From the data comparison of safety training duration, the number of illegal operations, and the number of injuries, it can be seen that the risk model based on artificial intelligence algorithm plays an important role in cultivating safety awareness, and the effect is stable.

*5.1.2. Technical Level.* The technical level can be judged by whether there is a professional vocational skills certificate and the reasonable degree to which the specific program design is applied to practice. The results are shown in Table 1.

As shown in Table 1, the monthly average number of technicians that each company needs to recruit is 6. In companies C and D, all 6 technicians were employed with certificates. In companies E and F, the employment rates with certificates were 50% and 83%, respectively. The average number of monthly losses of skilled workers due to design and operation reasons is the least in enterprise C and the most in enterprise E. Compared with enterprise C, the number of losses in enterprise E is twice as high. In terms of the loss amount, the loss amount of enterprise D is 19,000 yuan, and the loss amount of enterprise F is 55,000 yuan; the difference between the two is 36,000 yuan. This experiment proves that the model using artificial intelligence algorithms has a practical role in ensuring technical security. In a sense, it saves costs on the premise of controlling security risks.

*5.1.3. Labor and Vacation Time.* Labor and vacation time include the length of daily continuous labor time, the number of monthly vacation days, and so on, as shown in Figure 5.

Through the comparison of enterprises C and E, this paper finds that the labor hours of enterprise E are generally longer than that of enterprise C. The biggest difference is in the fifth and seventh months. The average daily working hours of enterprise E is 10 h, and the average daily working hours of enterprise C is 8 h, reaching 2 h. The average daily working hours of the enterprise C for 7 months is 8.9 h, and the average daily working hours of the enterprise E for 7 months is 10 h. In terms of vacation, this article does not consider the existence of holidays for the time being. It can be seen from the figure that enterprise D generally has longer monthly vacation days than enterprise F. And, when the difference is the highest for 4 days, the maximum difference between enterprises F and D is 50%. Combining the weight of human factors in security risks, it can be seen that companies C and D have reduced human risk factors by 6.7%. In short, it can be seen from the simulation experiments that the model based on the artificial intelligence algorithm can well guarantee the continuous working time and vacation time of the builder and reduce the safety risk from the level of the builder.

*5.2. Comparison of Factors of Matter.* The manifestation of the physical factors can be compared in terms of the inspection times of the mechanical equipment that meets the standard and the qualification rate of the steel bar material, as shown in Figure 6.

Judging from the number of inspections of machinery and equipment that meet the standards, the number of inspections by enterprises C and D is relatively high, and the number of inspections is increasing steadily. It proves that the model constructed by the artificial intelligence algorithm has played a good role in promoting the work of security risk precontrol. Comparing the qualification rate of steel bar materials, the qualification rate of enterprises C and D is higher and is constantly approaching 100%. Enterprise E's pass rate fluctuated significantly, but it ended up being 1% lower than initially. The pass rate of enterprise F in the first three months continued to rise but began to decline continuously in the fourth month and finally fell to 91%. The data of the experimental group fully demonstrate that the risk model established in this paper can reduce the risk factors of substances. From the point of view of the number of equipment inspections and the qualified rate of materials, the risk factors of enterprises C and D related to material were reduced by 6.5%.

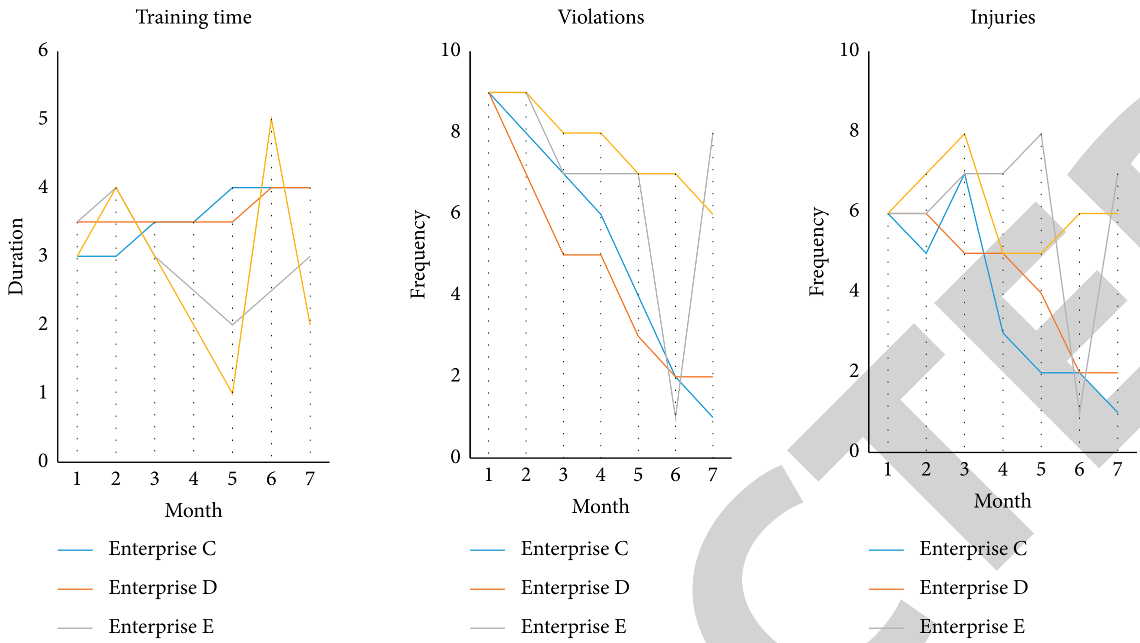


FIGURE 4: Security awareness indicators.

TABLE 1: Technical level.

| | Enterprise C | Enterprise D | Enterprise E | Enterprise F |
|---|---|---|---|---|
| Recruit skilled workers | 6 | 6 | 6 | 6 |
| Recruiting licensed skilled workers | 6 | 6 | 3 | 5 |
| The number of losses | 1 | 1.5 | 2 | 1.8 |
| Amount of loss (10,000 yuan) | 2.6 | 1.9 | 3.7 | 5.5 |

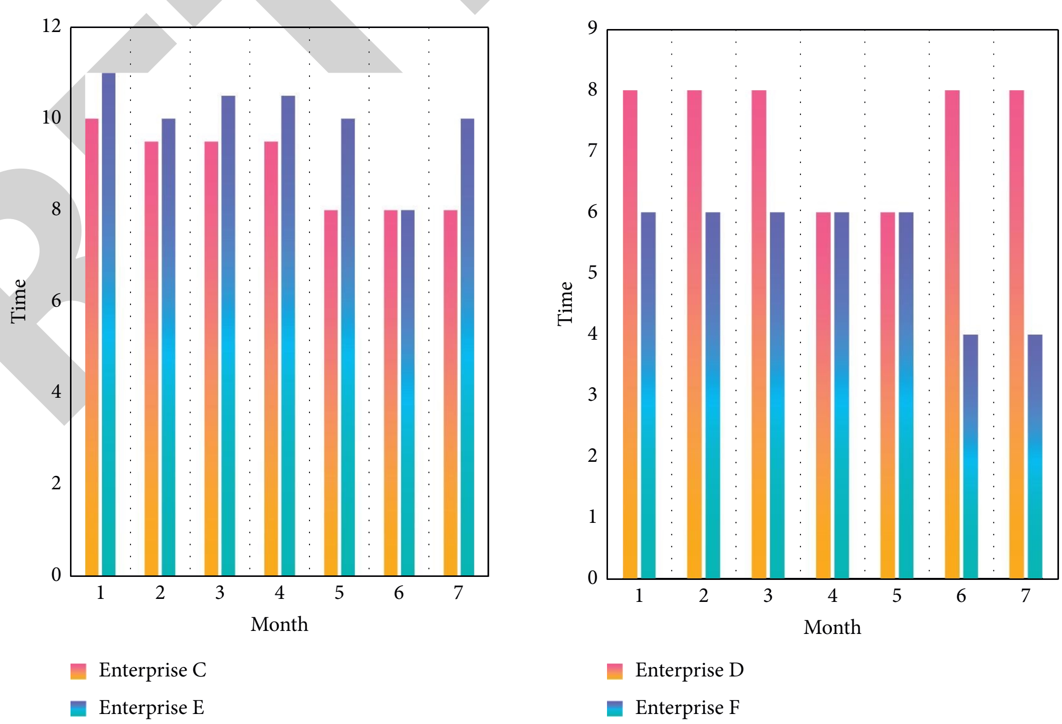


FIGURE 5: Labor and vacation time.

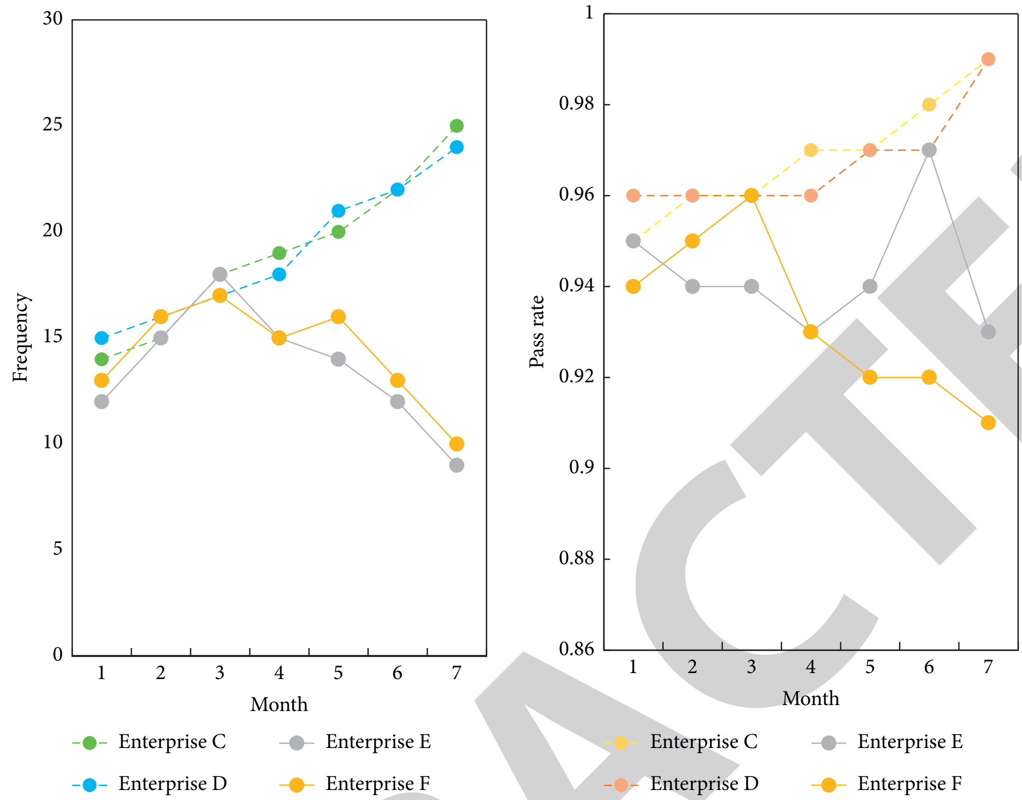


Figure 6: Factor index.



*5.3. Comparison of Management Factors.* The comparative indicators of management factors can be detected from the number of punishments imposed on construction personnel by the management system and the proportion of safety management funds in the total project funds, as shown in Figure 7.

By analyzing the punishment times of construction personnel, it can be found that the punishment times of the four enterprises in the first month are not much different. Enterprises C and D have 7 times, and enterprises E and F have 8 and 9 times, respectively. However, the number of penalties imposed by enterprises C and D is gradually decreasing and has been reduced to one in the seventh month. The proportion of capital investment of enterprises C and D is also gradually increasing. Through simulation research, this paper finds that the experimental group using an artificial intelligence algorithm performs better in risk early warning control than the control group. Combining the weight of management factors in security risks, companies C and D have a reduction of 8.9% in terms of managing risk factors.

*5.4. Comparison of Environmental Factors.* There are several manifestations of environmental factors, such as high temperature, working hours in rainy weather, the placement of safety warning signs on the construction site, and the security and hygiene conditions of the construction site. The monthly working hours in high temperatures and rainy weather are shown in Figure 8. Setting the monthly average warning sign placement, public security, and health indicators out of 10 points, the score results are shown in Table 2.

Figure 8 shows that the working hours of the enterprises in the experimental group did not change much in high temperature and rainy weather, while the working hours of the enterprises in the control group showed an overall increasing trend. The working hours of enterprise F increased from 43 h to 47 h, an increase of 9.3% compared to the first month. The construction of the control group in bad weather is not conducive to the early warning and control of safety risks.

In Table 2, the public security index of enterprise E is 8.6, and the hygiene index of enterprise F is 7.8. Compared with 9.8 of enterprise C and 9.9 of enterprise D, it is much worse, indicating that traditional construction methods and models are difficult to reduce the risk factors caused by the environment. Combining the weight of environmental factors in safety risk, experimental groups C and D have a 7.7% reduction in environmental risk factors.

*5.5. Comparison of Construction Efficiency.* In the 7-month simulation experiment, the construction efficiency of the experimental group and the control group is significantly different, and the results are shown in Figure 9.

From Figure 9, it is clear that the construction efficiency in the first two months was in the growth stage, and in the third month, the efficiency of enterprise E began to decline

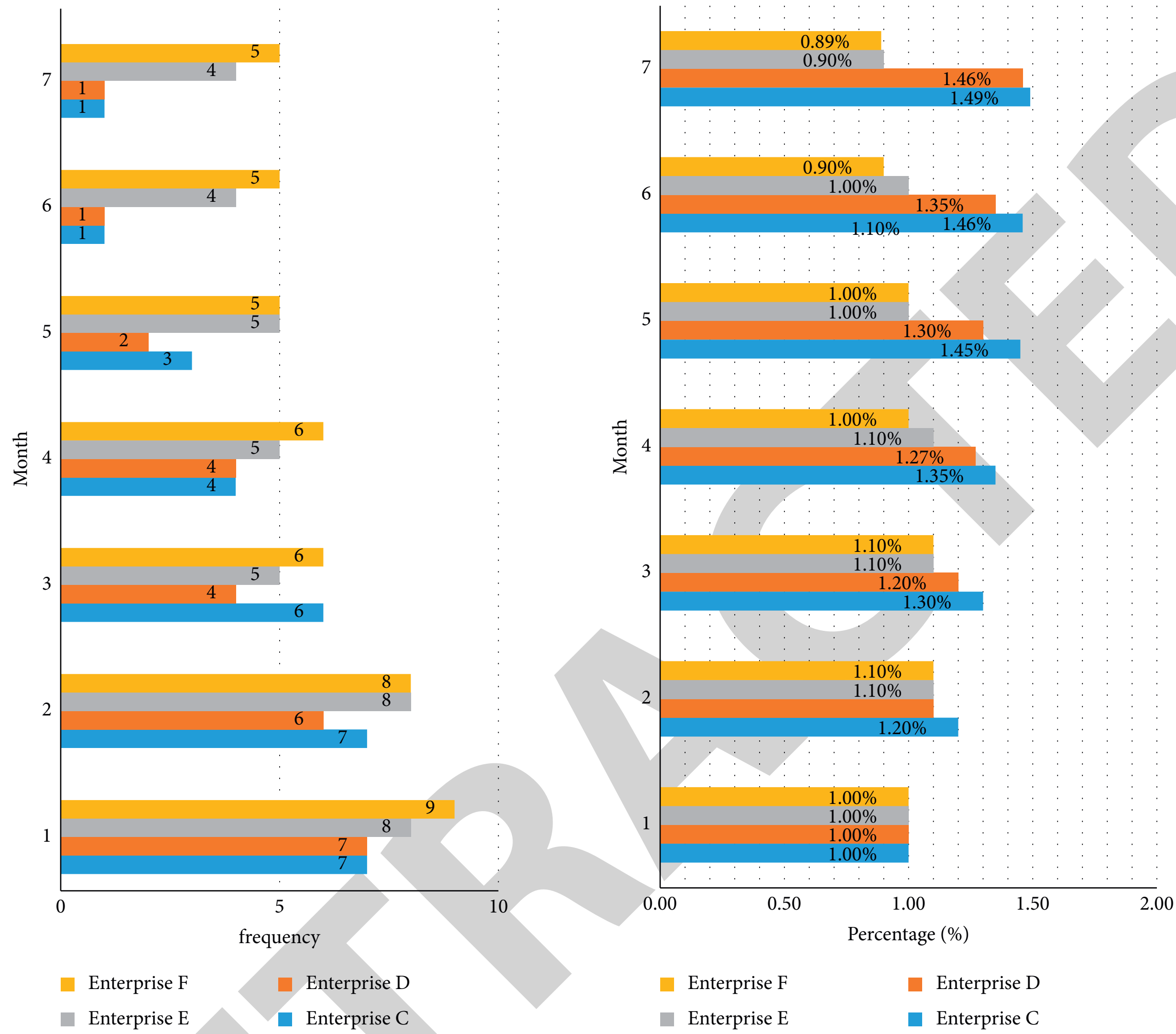


Figure 7: Management factor comparison.

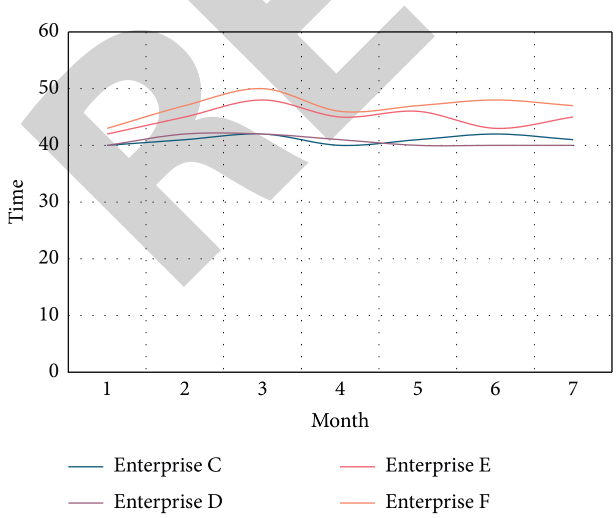


Figure 8: High temperature and rainy weather working hours.

and finally dropped to 1.02. In the last month, the efficiency dropped by 22% compared to the initial one. The construction efficiency of enterprise F in the first three months has been continuously improved, and it has become 1.06 in the seventh month, which is 3.7% lower than the initial efficiency. Looking at the data of enterprises C and D, this paper finds that their construction efficiency is increasing. Enterprise C increased from 1.12 to 1.35, increasing the efficiency by 23%. Firm D increases from 1.2 to 1.32, with a 12% increase in efficiency and a 10% increase.

To sum up, compared with the traditional engineering construction safety risk model, the engineering safety risk early warning control model based on an artificial intelligence algorithm not only can reduce the four factors that lead to safety risks, namely human, physical, management, and environmental factors but also can play a significant role in improving the efficiency of engineering construction.

Table 2: Construction site environment.

| | Enterprise C | Enterprise D | Enterprise E | Enterprise F |
|---|---|---|---|---|
| Placing warning signs | 9.9 | 9.8 | 8.8 | 8.9 |
| On-site construction security | 9.8 | 9.7 | 8.6 | 8.8 |
| Hygiene standard | 9.8 | 9.9 | 8.6 | 7.8 |

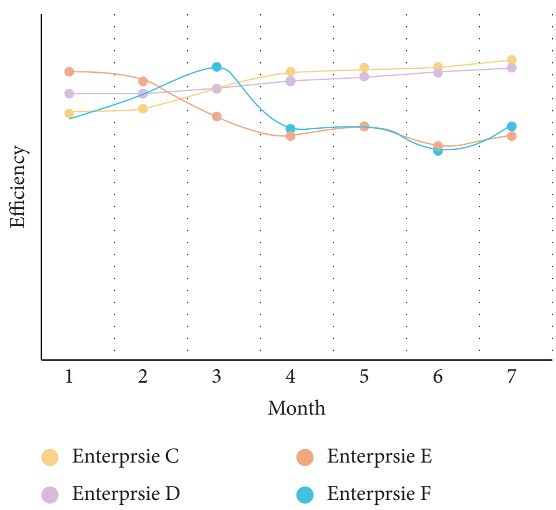


Figure 9: Construction efficiency.

## 6. Conclusion

In order to reduce safety risk accidents in engineering construction, this paper establishes a risk early warning control model for engineering safety and uses artificial intelligence algorithms to conduct simulation research on the model. Through the simulation experiment, the comparative analysis of the four factors of engineering safety risk has been carried out, which proves that the engineering safety risk early warning control model based on an artificial intelligence algorithm has more advantages than the engineering safety risk model using traditional construction methods. This advantage is that it not only can reduce the safety risks of the project but also can improve the construction efficiency under the premise of ensuring the safe and smooth construction of the project and promote the long-term development of the project construction.

## Data Availability

The data that support the findings of this study can be obtained from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare that there are no potential conflicts of interest with respect to the research, authorship, or publication of this article.

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