Coupled Risk Assessment of Construction Workers' Unsafe Behaviors in Human-Robot Interactions

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Abstract –

Human-robot interaction (HRI) is expected to play an important role in the construction industry in the coming decades. However, construction workers face new safety challenges that stem from both external environmental risks and individual internal risks in the HRI environment. Therefore, this study aims to identify safety risk factors related to the HRI environment and develop a coupled risk assessment method for construction workers' unsafe behaviors in the HRI environment.

The research methodology involves literature review, questionnaire surveys, hierarchical analysis, and fuzzy evaluation. As a result, this study identified 59 risk factors (37 external and 22 internal) related to the HRI environment and established a three-level coupled degree indicator system. There are 35 experts invited to rate the influence and occurrence possibility of each indicator. Hierarchical analysis was employed to assign weights to the indicators, taking into account the experts' opinions and using the entropy weight method to improve the accuracy. The composite indicators of the second-level and first-level indicators were calculated to evaluate the coupled risk of unsafe behaviors in the HRI environment.

The findings revealed that the interaction between construction equipment and site condition factors has a strong effect on construction workers' unsafe behavior in the HRI environment, indicating a need for strengthened control measures such as developing construction guidelines. The present study provides a scientific basis for evaluating the safety of the HRI environment in building construction and designing safety management systems and measures for intelligent construction.

Keywords –

Human-robot interaction; Unsafe behavior; Coupled risk; Risk assessment; Construction safety

1 Introduction

The construction industry faces challenges due to an aging population, high casualty rate and shortage of workers, which hinder its healthy growth. Collaborative research dedicated towards the effective use of robotics and automation is suggested to solve the challenges in the construction industry [1]. The Human-robot interaction (HRI) environment refers to the workspace where both construction workers and robots are working at the same time, aiming at accomplishing a different or the same task.

Compared to traditional construction equipment, construction robots possess higher levels of automation and intelligence. However, the increased safety level of construction robots may lead to workers' compensatory risk behavior (e.g., overly trusting the intelligent system or unintentionally entering the interaction area), which may result in more unsafe behaviors and eventually accidents [2]. Therefore, understanding causes of workers' unsafe behaviors in the HRI environment is crucial for construction safety.

In the HRI environment, the causes of unsafe behavior include both robot-related risks (e.g., robot malfunction and mishandling) and traditional construction risks (e.g., workers' safety knowledge and experience) [3]. These two types of risks act in tandem with each other, hereafter referred to as HRI-related risks collectively, and lead to the emergence of unsafe behaviors in the HRI environment. Therefore, understanding interaction risks is critical to understanding construction workers' unsafe behaviors in the HRI environment.

This paper aims to analyze the coupled mechanisms of safety risks affecting construction workers' unsafe behaviors in the HRI environment. Drawing on the findings obtained through the questionnaire-based approach, this study designates influences characterized by high coupled effects as high-impact safety risks. The outcomes pertaining to high-impact safety risks, along with the coupled safety risks, were deliberated upon to augment construction safety.

2 Background

2.1 Safety Risks of the HRI Environment in Construction

Previous research has identified various safety risks associated with the HRI environment. For example, Chung et al. [4] identified seven risk categories (i.e., human, control, unauthorized Access or Operational Situation Awareness, mechanical concerns, environmental sources, power systems and improper installation) related to the HRI environment. Physical safety risks, attentional cognitive safety risks, and physiological response safety risks have been identifies as the three main types of safety challenges in Unmanned Aerial Vehicles (UAVs) construction [5]. A variety of factors such as system malfunction, operator error, and worker stress have also been shown in the literature to trigger safety risks during construction workers' interaction with the machine [6]. In addition to this, existing studies have developed assessment tools for risks in the HRI environment, including 8 categories totaling 40 security risks [7]. Meanwhile, to address these safety risks, researchers proposed solutions and evaluated them through the Hierarchy of Control (HoC) method to verify the effectiveness of these solutions [6]. However, existing research has not yet considered the coupled relationship of internal and external risk factors in the HRI environment, which hinders effective support for elucidating safety management in such environments.

2.2 Assessment of Coupled Safety Risks

In the field of safety risk assessment, researchers have increasingly focused on the assessment of coupled safety risks. Various research methods have been employed, including Bayesian networks and N-K model [8]. Zhi et al. [9] analyzed the tunnel construction risk based on N-K and coupling degree models, and calculated the coupling degree of each component of single-factor and two-factor risk coupling models respectively. Wang et al. [10] established a risk network model based on the complex network theory, analyzed the topological characteristics and key risk characteristics of the tower crane safety network, and then revealed the evolution law and coupling relationship of the safety risks in the whole process of the tower crane, and realized the quantification of key risk characteristics.

While existing studies have focused on safety risks in construction, research on coupled safety risks related to unsafe behaviors in the HRI environment is rare. Therefore, this study aims to address this gap by employing coupling evaluation method to construct a coupled risk assessment method for unsafe behaviors in the HRI environment.

3 Research Method

This study conducted a comprehensive literature review to establish a three-level indicator system for assessing the coupled degree. Specifically, four first-level indicators of HRI safety risks, namely, organization, robot, environment and equipment, and workers, were identified based on reference to traditional construction safety classifications. Then, a review of relevant literature was conducted based on the four first-level indicators, which led to the identification of second-level and third-level indicators. This paper constructs a systematic framework by summarizing the factors of three high-quality review papers, then enriches the second-level indicators and third-level indicators based on literature review of empirical studies. To determine the contribution value of each factor in the indicator system, the analytic hierarchy method was employed.. Expert assessment method was chosen because the collection of objective data is challenging. The research methodology is shown in Figure 1

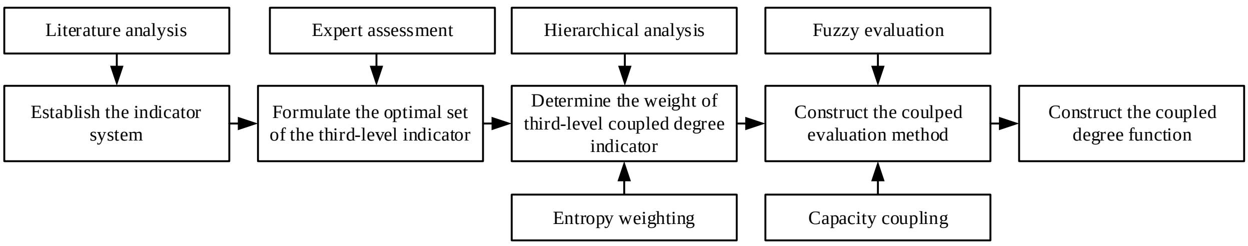

Figure 1. Flow chart of coupled risk assessment for the HRI environment

3.1 Establish the Indicator System

To identify safety risks in the HRI environment, a literature review of publications in databases, including Web of Science and Google Scholar, was conducted. Search keywords include "construct*", "coupling risk OR coupled risk" and "evaluat* OR assess*". The retrieved literature serves as the basis for the indicator system of the risk coupled degree in the HRI environment. The indicator system consists of 4 first-level indicators, 13 second-level indicators and 59 third-level indicators, as shown in Table 1. The three levels of the indicator system were firstly constructed based on three high-quality review studies [4], [7], [11]. Then, the indicators at each level were enriched and refined by reviewing related empirical research, such as those that coosider physiology factors and fatigue levels [7], [13].

Table 1. Indicator system of coupled degree of HRI risk system

First-level indicators	Second-level indicators	Third-level indicators
Organization	Safety management system	Safety leadership, safety supervision, and safety regulation
	Safety climate	Safety education and training, incentives, colleague safety behavior, safety investment and cost, and safety culture
	Construction technical plan	Schedule, project characteristics
	Enterprise organization	Enterprise revenue, enterprise size, enterprise reputation, and financial condition
Robot	Human error	Improper robot control, improper robot assembly and installation, unauthorized access, and inspection and maintenance
	Robot problem	Potential component failures, quality control errors, mechanical failures, and robot aging, wear, and renewal
	Environmental induced robot malfunction	Electromagnetic and radiation interference, electrical failures and overload, and dust
Environment and equipment	Site condition	Vision, auditory, dirt, site layout, overhead load environment, obstructions and congested sites, ground condition, climate conditions, cross operation, blind area, and power system
	Construction equipment	Equipment characteristics-ergonomics, inspection and maintenance of equipment, and aging, wear, and renewal of equipment
Construction workers	Demographic factor	Age, education level, personality, job position, income level, family, occupation type, and qualification
	Work skills	Safety knowledge, working knowledge, working experience, accident experience, and working ability
	Physiology factor	Fatigue level, health, and lifestyle habits
	Psychology factor	Psychological burden, safety awareness, mental state, trust in equipment, and perceived control

Note: Original questionnaire could be provided on request via email.

3.2 Formulate the Optimal Set of the Third-Level Indicator

In this research, the coupling degree is calculated based on the coupling degree model, which has the advantages of low sample demand and efficient calculation [14].

3.2.1 Determine the Optimal Indicator Vector

In this paper, an improved grey multi-level theory was employed to calculate the composite indicator of each coupled subsystem of safety risks in the HRI environment. The HRI risk coupled system is divided into three levels, the first-level (organization-C_1, robot-C_2, equipment and conditions-C_3 and workers-C_4),the second-level (F_i, i=1, 2,…, m), and the third- level (F_{ij}, j=1, 2, …, n).

To gather data for the coupled degree indicators, an expert assessment method was adopted. Experts were invited to participate in the study and assess the third-level indicators. The requirement for experts includes a minimum of three years of working experience in the relevant field and a leader of three or more people, or at least a master's degree and publications of peer-reviewed articles in areas such as construction safety, unsafe behavior, or HRI.

The questionnaire administered to the experts is used to assess the degree of influence of each third-level indicator, as well as the likelihood of its occurrence. Both the degree of influence and the likelihood of occurrence are assessed by a 5-point Likert Scale. Thus, the value of each parameter is calculated by the product of the degree of influence and the likelihood of occurrence with a maximum value of 25 points. The average product of influence degree score and possibility score is taken as the importance degree of each third-level indicator. This approach enabled the researchers to quantitatively determine the significance of each indicator within the system.

d_{ij} is the original value of the third-level coupled degree indicator corresponding to the second-level indicator F_{ij}, expressed by the matrix $D_i$as:

$$D_i = (d_{i1},\ d_{i2},\ \ldots,\ d_{ij},\ \ldots,\ d_{in})^T \tag{1}$$

whereD_i represents the initial vector of the ith second-level indicator; d_{ij} represents the original value of the jth third-level indicator under the ith second-level indicator; *n* represents the number of third-level indicators included in second-level indicator.

Subsequently, the matrix D_i was standardized to obtain the standard matrix for each evaluation indicator. Suppose d_{ij}^{max} is the optimal value of the tertiary indicator F_i corresponding to the secondary indicator F_{ij}, then:

$$D_i^{max} = (d_{i1}^{max}, d_{i2}^{max}, \ldots, d_{ij}^{max}, \ldots, d_{in}^{max})^T \tag{2}$$

where D_i^{max} represents the optimal value vector of the second-level coupled degree indicator.

3.2.2 Determine evaluation vector

Take D_i as the vector to be compared and take D_i^{max} as the reference vector, then the correlation degree between the third-level coupled degree indicator and the optimal indicator value can be calculated as:

$$\lambda_{ij} = \frac{min|d_{ik} - d_{ik}^{max}| + \rho * max|d_{ik} - d_{ik}^{max}|}{|d_{ij} - d_{ij}^{max}| + \rho * max|d_{ik} - d_{ik}^{max}|} \tag{3}$$

where λ_{ij} represents the correlation coefficient between the actual value and the optimal value of the third-level coupled degree indicator F_{ij}; k represents the ordinal number of third-level coupled degree indicators, k=1, 2, …, n ; ρ represents resolution coefficient, in general ρ⩽0.5.

Formula 3.3 is used to calculate the correlation degree between the measured value and the optimal value of each indicator. The ρ of 0.5 is used to calculate the correlation degree. Then the evaluation vector of the third-level indicators is:

$$P_i = (\lambda_{i1}, \lambda_{i2}, \ldots, \lambda_{ij}, \ldots, \lambda_{in})^T \tag{4}$$

where P_i represents the coupling evaluation matrix of third-level indicator.

3.2.3 Determine the Weight of Third-level Coupled Degree Indicator

Since this study is reasoning and analyzing about construction workers' unsafe behaviors and risks from a qualitative point of view, and thus obtaining the indicators used for the analysis. Therefore, it was not possible to assign separate weights to each indicator for analysis from a quantitative perspective. For example, the safety risk of equipment, unlike storms with the objective property of risk frequency, is difficult to measure directly. Therefore, hierarchical analysis is used in this study to assign the indicator weight of coupled degree. At the same time, in order to avoid the influence of expert method on the reliability and accuracy of data, entropy weight method was used to modify the analytic hierarchy process, so as to make full use of the available information to improve the accuracy of weight value.

In this study, questionnaire data were used as the measured value of the importance degree of each third-level coupled indicator, and the pairwise division was obtained according to the interval division to obtain the importance degree comparison score a_{ij}. The importance degree comparison score is separate from the influence degree score and possibility score above. According to the 5-point system, 1 point represents that the two were equally important, and 5 points represent that the former was extremely important than the latter. In order to avoid numerical errors in the above methods, this study invited 5 experts in related research fields to score the comparison of importance between second-level indicator and third-level indicator as backup data for comparative analysis.

The pair comparison matrix A_{ij} can be obtained by comparison and transformation, each factor in the matrix is not only positive, but also has integer characteristics, that is, the judgment matrix should meet $a_{ij} > 0$, a_{ji}=1/a_{ij}, and when i=j=1, 2, …, m, a_{ij}=1.

$$A_{kl} = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1j} & \cdots & a_{1m} \\ 1/a_{12} & 1 & \cdots & a_{2j} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 1/a_{1j} & 1/a_{2j} & \cdots & 1 & & a_{im} \\ \vdots & \vdots & \cdots & \vdots & 1 & \vdots \\ 1/a_{1m} & 1/a_{2m} & \cdots & 1/a_{im} & \cdots & 1 \end{bmatrix} \tag{5}$$

where A_{kl} represents the paired comparison matrix of the l th second-level indicator of the k th first-level indicator; k represents the number of first-level indicator (k=1, 2, 3, 4); l represents the number of second-level indicator among corresponding first-level indicators; and a_{ij} represents the importance ratio between the ith and jth third-level indicator.

The root method is adopted to solve the weight vector,

$$\omega_i^0 = (\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}} \tag{6}$$

where ω_i^0 represents the root of the judgment matrix. Normalization is then performed,

$$w_i' = \frac{w_i^0}{\Sigma_i w_i^0} \tag{7}$$

where w_i' =$[w_i', w_i', \ldots, w_i']^T$ represents the eigenvector.

By importing the ω_i^0 obtained from the questionnaire into software yaanp and conducting normalization processing, the eigenvector of the judgment matrix W_i' and the maximum eigenvalue of the matrix λ_{max} can be obtained. The consistency test is carried out, and the entropy weight method is used to modify it. Then, the final weight w_i and the desired feature vector $W_i = [w_1, w_2, \ldots, w_n]^T$ can be obtained.

3.2.4 Construct the coupled evaluation method

Calculate the composite indicator of the second-level indicator. The formula for calculating the comprehensive indicator of the second-level indicator is as follows:

$$X_i = W_i^T P_i \tag{8}$$

where X_i represents the composite indicator of the second-level indicator.

Calculate the composite indicator of the first-level indicator. For the comprehensive evaluation of second-level indicators, $X_i = W_i^T P_i$(i=1, 2, …, n), calculate the evaluation value vector of second-level indicators in each subsystem, which can be composed of $R_{C_i} = [X_1, X_2, \ldots, X_n]^T$. Then, the vector composed of the optimal set of corresponding indicators is found out, and the correlation degree is calculated by Formula 3.3 to obtain the evaluation matrix Q_{C_i} of the second-level indicators. Finally, $X_{C_i} = Q_{C_i}^T W_{C_i}$ was used to calculate the composite indicator of each subsystem.

(3) Construction function

Suppose the variable u_i(i=1, 2, …, n) is the ordinal parameter of HRI risk system, and u_{ij} is the jth indicator of the ith order parameter, whose value is X_{ij}(i, j=1, 2, …, n). α_{ij} and β_{ij} respectively represent the upper and lower limits of the jth indicator of the ith order parameter when the system is stable. In this study, the upper and lower limits that can be reached by the evaluation indicator under ideal conditions are adopted for calculation, α_{ij}=1, β_{ij}=0. Then, for the HRI risk system, the efficacy function of the system coupled indicator can be expressed as:

$$u_{ij} = \begin{cases} X_{ij} - \beta_{ij}/\alpha_{ij} - \beta_{ij}, (X_{ij} \text{ has positive effect}) \\ \alpha_{ij} - X_{ij}/\alpha_{ij} - \beta_{ij}, (X_{ij} \text{ has negative effect}) \end{cases} \tag{9}$$

where u_{ij} ∈[0,1] represents the effect of indicators on the order degree of the system, that is, the contribution of indicators to the functional realization of HRI risk system.

3.2.5 Construct the coupled degree function

Using the concept of capacity coupling and the model of coupled coefficient in the field of physics, the coupled degree calculation model of any two or more first-order indicator systems can be determined respectively. The coupled degree formula of any two first-level indicator systems is as follows:

$$C_{ij} = [U_i \cdot U_j/(U_i+U_j)(U_j + U_i)]^{\frac{1}{2}} \tag{10}$$

where C_{ij} represents the coupled degree of the ith first-level indicator system and the jth first-level indicator system.

The coupled degree formula of multiple first-level indicator systems is as follows:

$$C = \sqrt[m]{\frac{U_1 \cdot U_2 \cdot \ldots \cdot U_m}{\prod_{j=1}^{m}[\prod_{i=1, i\neq j}^{m}(U_i+U_j)]}} \tag{11}$$

where C represents the coupled degree of the entire system.

Value range of coupled degree between systems is $C \in [0, 1)$. According to the classification of coupled states in physics, $C \in [0, 0.3)$ represents weak interaction, $C \in [0.3, 0.7)$ represents medium interaction, and when $C \in [0.7, 1)$ represents strong interaction. According to the above classification, the results of coupled degree between systems can be discussed.

4 Data Analysis and Discussion

4.1 Coupled Risk Assessment

In this study, a total of 33 questionnaires were received, out of which 25 were valid and 8 were invalid. The invalid questionnaires were primarily due to identical responses for each question, resulting in low data reliability. The correlation and weight values were calculated based on the valid questionnaire data collected (Table 2). The results indicate that construction workers exhibit the highest correlation and weight values among the first-level indicators, highlighting their high impacts on HRI risk systems. Moreover, the influence of construction workers shows the strongest correlation with the other three influencing factors. Regarding internal organizational factors, the safety management system holds the utmost importance, while the enterprise organization exhibits the strongest correlation with the other three factors. Noteworthy third-level indicators with high correlation and weight values include safety supervision (r (correlation)=0.843; w(weight)= 0.339), project characteristics (r=0.810; w=0.380), robot control system errors (r=0.957; w=0.261), aging wear and update of construction equipment (r =0.966; w=0.348), poor health condition (r=0.836; w=0.340), and so on.

The utility values of the first-level and second-level indicators are shown in Table 3. Among the first-level indicators, construction workers exhibit the highest utility value, consistent with the results of correlation and weights. The results indicate that construction workers are more susceptible to engaging in unsafe behavior in the HRI environment. Concerning the second-level indicators, robot failures resulting from enterprise organization, environmental factors, and construction equipment significantly impact their respective first-level indicators. Due to space limitations, the detailed calculation results for all third-level indicators were not explicitly provided in this article.

The results of this study demonstrate that the coupled degree C of unsafe behavior risk in the HRI environment is 0.230. The results indicate a low level of interaction within the entire system, suggesting the presence of an coupled relationship between various subsystems that influences unsafe behavior in the HRI environment. The coupled degree of the first-level indicators is as follows: Organization (Co) = 0.147, Robot (Cr) = 0.263, Construction equipment and site conditions (Ce) = 0.498, and Construction workers (Cw) = 0.158.

The coupled state (R) of organizations, robots, and construction workers within their respective subsystems is low, implying a weak correlation between the second-level indicators within each subsystem. The coupled degrees between subsystems are as follows: Organizations-Environment (Cor)=0.497, Organizations -Construction equipment (Coe) = 0.499, Organizations-Construction workers (Cow) = 0.494, Robots-Environment (Cre) = 0.499, Robots-Construction workers (Crw) = 0.500, and Environment-Construction equipment (Cew) = 0.498.

The coupled degree between on-site conditions and construction equipment is relatively high, indicating a strong interaction relationship between these factors. The coupled effect resulting from this interaction increases the risk of unsafe behavior, thereby posing a greater danger to the overall system.

Table 2. Results of correlation degree and weight

First-level indicators	Correlation	Weight	Second-level indicators	Correlation	Weight
Organization	0.609	0.249	Safety management system	0.439	0.323
			Safety climate	0.615	0.261
			Construction technical plan	0.640	0.258
			Enterprise organization	1.000	0.158
Robot	0.834	0.218	Human error	0.709	0.600
			Robot problem	0.776	0.217
			Environmental induced robot malfunction	1.000	0.183
Construction equipment and site conditions	0.706	0.225	Site condition	0.490	0.583
			Construction equipment	1.000	0.417
Construction Workers	1.000	0.309	Demographic factor	0.748	0.214
			Work skills	0.865	0.337
			Physiology factor	0.766	0.237
			Psychology factor	1.000	0.212

Table 3. Results of utility

First-level indicators	Utility value $\boldsymbol{u_{ij}}$	Second-level indicators	Utility value $\boldsymbol{u_{ij}}$
Organization	0.626	Safety management system	0.864
		Safety climate	0.922
		Construction technical plan	0.928
		Enterprise organization	0.978
Robot	0.777	Human error	0.940
		Robot problem	0.947
		Environmental induced robot malfunction	0.966
Construction equipment and site conditions	0.702	Site condition	0.812
		Construction equipment	0.956
Construction workers	0.845	Demographic factor	0.869
		Work skills	0.895
		Physiology factor	0.873
		Psychology factor	0.918

4.2 Comparison with the Traditional Construction Environment

First, coupled safety risks of unsafe behavior in the traditional environment assessed in the literature [15] are higher than the coupled safety risks of unsafe behavior in the HRI environment assessed in the present study (0.6997>0.230). A possible explanation is that the application of robots reduces the interaction between traditional safety risks and the intelligence of robots improves the level of risk management.

Second, robot-related safety risks have coupled effects on unsafe behavior with traditional safety risks. As (upgraded) substitutes of workers and machines, robots conduct construction tasks with workers or independently. The nature of construction tasks and environment causes coupled safety risks between robots and other safety risks, as validated in the present study. Thus, safety management of the HRI environment should consider the new coupled safety risks found in the present study.

Third, workers are the most important indicator of unsafe behavioral safety risks for the both traditional environment and HRI environment. The cognitive process of workers' unsafe behaviors has become one of the core issues in construction site safety research and many scholars have analyzed workers' unsafe behaviors from a cognitive perspective [16]. Thus, all safety risks may interact with workers and then cause unsafe behavior. Considering the intelligence application of robots in construction industry, training and education of construction workers on robot-related knowledge and skills should be well designed and strengthened for safety.

4.3 Reliability and Validity

Due to time constraints and limited availability of experts, this study employed a relatively small sample size. Two data collection methods were utilized to determine the weights, including direct scoring of importance comparison by 5 experts and 30 experts. The coupled analysis results are shown in Table 4. Although there is a difference in the way the questionnaires were filled out by the 5 experts and 30 experts, the results obtained are similar and therefore the results enhance the reliability and validity of the study's findings. This study was somewhat unaffected by the bias inherent in the expert assessment method, which was eliminated as much as possible by screening the qualifications of the experts, actively collecting future field data, designing standardized research steps, and repeating the means of validation.

Moreover, the design of research steps, selection of research methods and the consistent results among two groups of experts ensure the validity of the methodology of this study.

Table 4. Comparison of coupled results

Indicators	Results of 5 experts	Results of 30 experts
Organization	0.155	0.147
Robot	0.263	0.262
Construction equipment and site conditions	0.498	0.498
Construction workers	0.159	0.158
Total (HRI system)	0.233	0.230

5 Conclusion

This study built a model to quantitatively assess the coupled risk of unsafe behavior among construction workers in the HRI environment. The research findings indicate the presence of coupled safety risks in this environment, particularly the interaction between construction equipment and on-site conditions, as well as a high correlation between construction workers and other factors. Therefore, it is recommended to enhance safety management in the HRI environment through regular inspection and maintenance of construction equipment, as well as by providing efficient safety education for construction workers. Strengthening safety management measures for construction equipment, on-site conditions, and construction workers is crucial.

Although the coupled degree of robot-related factors may not be the highest, it is essential to consider their coupled effects in the design and implementation of safety management measures for robots, as the existing measures are still being explored. This study introduces the concept of coupled effects into the safety risk assessment of the HRI environment for construction operations, presenting a three-level coupled indicator system and evaluation method for analyzing the unsafe behavior of construction workers. This approach expands the knowledge in the field of the HRI environment safety for construction by considering coupled safety risks.

The HRI risk system constructed in this study could provide a theoretical basis for designing construction safety management documents, guiding safety training and inspection, etc.

Due to the limited number of construction projects in the HRI environment, this study used questionnaire-based survey as a method to obtain data. The application and promotion of the proposed method in practice should be studied in the future. Future research could utilize the questionnaire and coupled calculation methodsproposed in this study with larger sample sizes, which will enhance the reliability and validity of the research results.

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