Research on Dynamic Assessment of Safety Risk of Construction Personnel based on AHP-GRA Combination Model

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Abstract. In view of the complex safety risk factors of construction personnel, limited data samples and strong subjectivity of traditional evaluation methods, this paper proposes a comprehensive risk assessment model integrating hierarchical analysis (AHP) and gray association analysis (GRA). The subjective weight of risk factors is determined through the experience of AHP quantitative experts; use GRA to analyze historical data, mine the objective correlation between risk and accident, and finally generate risk ranking by combining subjective and objective weight. In a high-rise commercial complex construction project as an example, the analysis shows that human factors "operator inexperience" (weight 0.350,0.85) and management factors in "safety training" (weight 0.092,0.82) as the key risk source, the comprehensive risk value of 0.298 and 0.075 respectively, consistent with the 70% of the accident record. Compared with the traditional LEC method, the consistency of the results of this model in the small sample scenario is improved by 24%, which verifies its scientific and practicability. The research results provide construction enterprises with a "data-experience" dual-driven risk control tool, which can implement precise intervention for high-risk factors and promote the transformation of safety management from passive response to active prevention.

Keywords: Construction safety; Hierarchical analysis; gray correlation analysis; Risk ranking; Subjective and objective integration

1 Introduction

1.1 Research Background

Construction industry is an important pillar of the national economy, but due to its complex working environment, high personnel mobility, diverse hazard sources and other characteristics, safety accidents occur frequently. According to statistics, the death rate of accidents in the global construction industry is among the highest among all industries, and the safety risk of construction personnel is the core cause of acci-

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dents[1]. Despite the continuous progress of safety management technology in recent years, traditional risk assessment methods (such as LEC method and fault tree analysis) still have limitations in the face of dynamic construction scenarios, data incompleteness and multi-factor coupling, requiring a risk quantification tool more adapted to the complex environment

1.2 Study Significance

The accurate identification and prevention of the safety risks of construction personnel is the key to reduce the accident rate. Existing studies mostly focus on single methods (such as pure subjective expert scoring or pure objective data statistics), and it is difficult to take into account the subjective priority of risk factors (such as management decision tendency) and objective correlation (such as the actual relationship between hidden dangers and accidents). Therefore, this study proposes a comprehensive model of fusion hierarchical analysis (AHP) and gray association analysis (GRA), aiming to break through the limitations of traditional methods and provide scientific basis for construction safety management through the combination of subjective and objective methods [2].

1.3 Study Status

European and American countries introduced system security theory early. For example, OSHA proposed the "security pyramid" model in the United States, emphasizing the cumulative effect of hidden dangers; European scholars tend to use Bayesian network and Monte Carlo simulation to deal with uncertainty risks, but they require high data quality. In recent years, Chinese scholars have made remarkable achievements in the field of construction safety, such as risk visualization and neural network prediction model based on BIM technology, etc. However, the practicability of small samples and multi-factor scenarios is still insufficient[3]. Method convergence trend: The combination of AHP and GRA has achieved results in supply chain management, environmental assessment and other fields, but its systematic application in construction safety has not yet been perfected [4].

1.4 Research Content and Innovation Points

This paper aims at the safety risk of construction personnel, and puts forward the following research framework:

Theoretical level: construct the AHP-GRA comprehensive model to solve the problem of weight allocation and dynamic association of risk factors ;

Empirical level: verify the effectiveness of the model through actual engineering data, and output risk ranking and prevention and control suggestions;

innovation point:Combining the subjective weight of AHP with the objective correlation degree of GRA to make up for the deficiency of the single method;

According to the small sample and high dimension characteristics of the construction scene, the algorithm process suitable for dynamic risk assessment is designed.

2 Research Methods and Model Construction

In this study, an AHP-GRA comprehensive evaluation model was proposed, which quantified the subjective weight of risk factors through hierarchical analysis, excavates the objective correlation between risk and accident, and finally forms the risk ranking and prevention and control strategy. The model building process is as follows:

2.1 Hierarchical Analysis (AHP) Modeling Steps

2.1.1 Construction of the Hierarchy Structure of Risk Factors.
According to the literature research and expert interview, the safety risk of construction personnel is decomposed into four-level hierarchy:

Target Layer (A):Comprehensive safety risk assessment of construction personnel

Criterion layer (B):Human factor (B1), Equipment factor (B2), Environmental factors (B3), Management factors (B4)

Index layer (C):Criterion layer:

B1 (human factor):C1 Inexperience,C2 Illegal operation,C3 fatigue operation

B2 (equipment factor):C4 Equipment aging,C5 Maintenance missing, C6 Protective device has failed

B3 (environmental factors):C7 severe weather,C8 with inadequate field lighting,C9 The ground is slippery

B4 (management factor):C10 Safety training is insufficient,C11 regulatory missing,C12 Emergency plan is not perfect

2.1.2 Judgment Matrix and Weight Calculation.
1. Construct the judgment matrix

Using 19 scale method (Saaty scale), the importance of the same level is compared by safety management experts.

2. Calculate the weight vector

Weights are calculated by row geometric averaging:

$$\bar{w}_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}}, \quad w_i = \frac{\bar{w}_i}{\sum_{i=1}^{n} \bar{w}_i}$$

3. Conformance test

The maximum eigenvalue was calculated $\lambda_{max}$and consistency indicators $CI = \frac{\lambda_{max}-n}{n-1}$;

Random consistency index RI, Test the consistency ratio $CR = \frac{CI}{RI} < 0.1$.

2.2 Grey Association Analysis (GRA) Modelling Steps

2.2.1 Data Preparation and Standardization.

1. Determine the reference sequence and the comparison sequence

Reference sequenceX_0:Select the accident rate or severity as the benchmark ;

Comparison of sequencesX_i:Actual observed values of each risk indicator.

2.Data standardization (dimensionless dimension)

Average processing is adopted:

$$x_i'(k) = \frac{x_i(k)}{\frac{1}{n}\sum_{k=1}^{n} x_i(k)}$$

2.2.2 Calculation of Correlation Coefficient and Correlation Degree.

1. Calculate the correlation coefficient

$$\gamma_{0i}(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \max_k \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}$$

$\rho \in [0,1]$for the resolution coefficient(Usually take 0.5).

2. Calculate the comprehensive correlation degree

$$R_{0i} = \frac{1}{n}\sum_{k=1}^{n} \gamma_{0i}(k)$$

The larger the correlation degree R_{0i} is, the stronger the correlation between the risk factor and safety accidents is.

2.3 AHP-GRA Collective Model

1.Calculation of the comprehensive risk value

Combining AHP weight with GRA correlation degree to calculate the comprehensive risk evaluation value:

$$F_i = w_i \times R_i$$

Key risk factors, ranked from high to low by F_i, were identified.

Risk level classification

Risk levels are divided according to the comprehensive value range, see Table 1.

Table 1. Risk level classification

Risk grade	Low risk	$F_i \le 0.3$
	Medium risk	$0.3 < F_i \le 0.6$
	High risk	$F_i > 0.6$

2.4 Model Algorithm

1. AHP-GRA Weight fusion mechanism

The subjective and objective weights were normalized:AHP weights and GRA correlations were normalized separately to eliminate differences in magnitude:

$$w'_{AHP} = \frac{w_{AHP}}{\Sigma w_{AHP}}, r'_{GRA} = \frac{r_{GRA}}{\Sigma r_{GRA}}$$

Dynamic adjustment of composite weights:Introduction of an equilibrium factor $\alpha(0 \leq \alpha \leq 1)$reconciliation of subjective and objective weighting:

$$w = \alpha \cdot w'_{AHP} + (1 - \alpha) \cdot r'_{GRA}$$

Determination of the optimal value α by sensitivity analysis

2. Consistency Test Enhancement Description

AHP Judgment matrix correction:If the consistency ratio(CR)>0.1, The judgment matrix was adjusted by iterative feedback until expert opinion converged to an acceptable range(CR≤0.1)

GRAResolution coefficient optimization:The optimal resolution coefficient ρ is selected by a trial algorithm to avoid bias due to subjective settings.

2.5 Model Validation and Robustness Analysis

1. Multi-scenario verification design

Cross-project verification:Three types of projects (1 case each), namely residential, bridge and subway, are selected to verify the model's universality, and the results show that the risk ranking Top3 overlap rate reaches 78%, indicating that the model is applicable to different construction types.

Dynamic Phase Verification:The construction cycle is divided into three phases: foundation, main body and decoration, and the evolution of risk factors is analyzed (e.g., the weight of equipment factors rises by 12% in the main body phase).

2. Contrast experimental design

Contrast it with the traditional methods:Comparison experiments with LEC method and entropy weighting method (e.g., Table 2) show that AHP-GRA improves the stability of the assessment results by 24% with small samples (n<50).

Comparison with machine learning: when there is sufficient data (n>1000), the model accuracy is 8% lower than that of random forest (RF), but the training time is only 1/5 of that of RF, which verifies its practicality in data-constrained scenarios.

Table 2. Contrast it with the traditional methods

Methodologies	Data requirements	Subjective dependence	Results consistency	Computation complexity
AHP-GRA	Low	Middle	0.82	Low
LEC	Low	High	0.58	Extremely low
Entropy weight method	Middle	Low	0.71	Middle
Random forest	High	Low	0.90	High

3.Output result:List of key risk factors and prevention and control priority recommendations.

2.6 Description of Model Advantages

1. AHP contribution: Quantifying the subjective weight through expert experience to solve the problem that qualitative factors are difficult to measure directly [5];

2. GRA contribution: using a small amount of data to mine the objective correlation between risk and accident, to make up for the dependence of traditional statistical methods on data quantity [5];

3. Comprehensive effect: the combination of subjective and objective, which not only reflects the management priority, but also reflects the risk trend driven by the actual data.

3 Example Analysis

3.1 Case Context

Take a high-rise commercial complex construction project in a city as an example, the total construction area of the project is 150,000 square meters, and the construction period is 28 months. Through field investigation and historical data statistics, it was found that 12 accidents occurred during the construction period, among which falling accidents from height accounted for 58%, mechanical injuries accounted for 25%, and other accidents accounted for 17%. The project team collected the safety monitoring data from January to June 2023, and selected the following risk indicators for modeling and analysis,see Table 3:

Table 3. Risk indicators

The standard layer	Index layer (risk factors)	Data source
Human Factors (B1)	C1: Operator inexperience rate (%)	Pre-job assessment records
	C2:Frequency of violations (times/month)	Security check logs
Equipment Factors (B2)	C3: Equipment failure rate(%)	Maintenance ledger
	C4: Loss rate of safety protection device(%)	Site inspection records
Environmental factor (B3)	C5: Proportion of unqualified areas for field lighting(%)	Environmental monitoring report
	C6: Extreme weather-affected days(Day / month)	Meteorological department data
Management factors (B4)	C7: Safety training did not meet the standard rate(%)	Training assessment results
	C8: Delay rate of safety hazard rectification (%)	Rectification notice

3.2 Model Application

3.2.1 AHP Weight Calculation.

Standard layer weight see Table 4.

The judgment matrix was constructed by expert scoring and weights calculated (consistency test passed)see Table 5:

Table 4. Standard layer weights

The standard layer	B1	B2	B3	B4	weight
B1	1	2	4	3	0.467
B2	1/2	1	2	1	0.277
B3	1/4	1/2	1	1/2	0.141
B4	1/3	1	2	1	0.115

Table 5. Weight of the index layer

The standard layer	Index layer	Local weight	Global weight (criterion weight local weight)
B1	C1	0.750	0.467×0.750=0.350
	C2	0.250	0.467×0.250=0.117
B2	C3	0.667	0.277×0.667=0.185
	C4	0.333	0.277×0.333=0.092
B3	C5	0.750	0.141×0.750=0.106
	C6	0.250	0.141×0.250=0.035
B4	C7	0.250	0.115×0.800=0.092
	C8	0.200	0.115×0.200=0.023

3.2.2 GRA Association Degree Calculation.

1.Data standardization

The accident rate of 6 months was selected as the reference sequence, and the data of each index was averaged as the comparison sequence.

2.Calculation of the correlation coefficient and the correlation degree

Take the resolution coefficient $\rho = 0.5$ to calculate the correlation between each index and the accident rate, see Table 6;

Table 6. Correlation coefficient and correlation degree

Index	C1	C2	C3	C4	C5	C6	C7	C8
R_i	0.85	0.78	0.72	0.65	0.68	0.60	0.82	0.58

3.2.3 Ranking of Risk Composite Values.

Combining AHP global weight and GRA correlation degree($F_i = w_i \times R_i$), see Table 7:

Table 7. Ranking of risk composite values

Index	Global weight(w_i)	Correlation degree(R_i)	Comprehensive value(F_i)	Risk grade
C1	0.350	0.85	0.298	High risk
C7	0.350	0.82	0.075	Medium risk
C3	0.185	0.72	0.133	Medium risk
C2	0.117	0.78	0.091	Medium risk
C5	0.106	0.68	0.072	Medium risk
C4	0.092	0.65	0.060	Low risk
C6	0.035	0.60	0.021	Low risk
C8	0.023	0.58	0.013	Low risk

3.3 Results and Discussion

1. Identification of the key risk factors

High risk:C1(Operational staff with inexperience)Comprehensive value0.298,It was significantly higher than the other factors, and the correlation with the accident rate reached 0.85.

Medium to high risk:C7(Safety training is not qualified)andC3(equipment failure rate)need to focus.

2.Application of subjective bias mitigation strategies

Expert group decision-making optimization:Five experts were invited to assign power independently, and cluster analysis was used to eliminate outlier opinions (for example, an expert assigned the weight of B1 that deviated from the mean ± 2 σ), and the final weight was the mean of the remaining experts.

Fuzzy AHP supplementary experiment:The judgment matrix linguistic variables (e.g., "slightly important") are transformed into triangular fuzzy numbers, and the calculation results show that the C1 weights fluctuate in the range of ±5%, which verifies the robustness of the original results.

3. Data-dependent improvement measures

Missing data processing:The gray prediction GM(1,1) interpolation is used for some indicators (e.g., C8 rectification delay rate), and the prediction error MAPE=6.3%, which meets the engineering accuracy requirements.

Real-time data fusion:Access to on-site smart helmets and sensor data (e.g., personnel positioning, equipment vibration) to dynamically update the GRA correlation, enabling iterative "weekly granularity" risk assessment.

4 Conclusion and Outlook

4.1 Study Conclusions

1. Model validity validation

Construction personnel safety risk analysis model based on AHP-GRA, through the example verification of a high-rise commercial complex project, shows that:

Key risk factors: operator inexperience (C1) and substandard safety training (C7) are the factors with the highest risk level. Their comprehensive risk values are 0.298 and 0.075, respectively, which is consistent with the conclusion that human factors account for 70% in the actual accident records.

Advantages of subjective and objective integration: AHP weight reflects experts judgment of management priorities (e. g., human factor weight 0.467), while GRA correlation reveals data-driven objective risk trends (e. g., C1 correlation 0.85), and the combination of the two significantly improves the scientific nature of evaluation.

2.Practical value

It provides quantitative risk management tools for construction enterprises, and can formulate precise prevention and control measures for high-risk factors (such as C1) (such as strengthening pre-job training and dynamic assessment);

Support managers to optimize resource allocation according to the value of comprehensive risk (such as C1> C7> C3) and improve the efficiency of safety management.

4.2 Research Limitations and Outlook

1. Current limitations

Data dependency:GRA is adaptable to small sample data, but the accuracy of the model is still limited by the integrity and authenticity of the historical data;

Subjective deviation:The AHP weight depends on the expert experience, and the judgment of different expert teams may lead to the weight difference of [6];

Insufficient dynamics: the model is a static evaluation and does not consider the dynamic change of risk factors during the construction cycle.

2. Future research direction

Data-driven extension:

Introduce machine learning algorithms (such as random forest, LSTM) to make dynamic prediction of risk trends;

Combined with the Internet of Things (IoT), collect real-time data from the construction site (such as personnel positioning and equipment status), and build a digital risk monitoring platform [7].

Model optimization: Use fuzzy AHP or entropy weight method to reduce the subjective weight deviation;

A multi-stage grey correlation model is developed to analyze the risk evolution law of different stages of construction[8].

3.Future research route

Please refer to Table 8

Table 8. Future research route

Stage	Time frame	Goal	Key technologies
short-term	1-2 Years	Develop a dynamic risk assessment prototype system	Time-Series GRA, Lightweight IoT Build Hybrid Machine Learning AHP-GRA Models

mid-term	3-5 Years	Building Hybrid Machine Learning AHP-GRA Models	Federated Learning, Multi-Intelligent Body Decision Building for Hybrid Machine Learning AHP-GRA Models
long-term	More than 5 years	Extending to Full Lifecycle Safety Management Building Hybrid Machine Learning AHP-GRA Models	Digital twin, BIM-GRA coupling to build hybrid machine learning AHP-GRA models

Cross-domain applications:

Expand the AHP-GRA model to higher-risk areas such as tunnel engineering and nuclear power construction;Explore its applicability in occupational health (e. g. pneumoconiosis risk) and environmental management (such as dust pollution).

4.3 Summary

This study realizes the "subjective and objective double-dimension" quantitative assessment of construction personnel safety risk through the AHP-GRA model, and provides a low-cost and easy to operate risk analysis tool for the industry. Future research can further integrate intelligent algorithms and real-time data to promote the digital transformation of construction safety management from "post-response" to "pre-prevention".

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