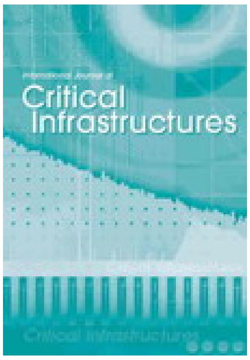


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# Safety risk perception of high-rise building construction process based on digital twin technology

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# Safety risk perception of high-rise building construction process based on digital twin technology


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**Abstract:** A safety risk perception method of high-rise building construction process based on digital twin technology is proposed to address the problems of low recall rate, low perception accuracy, and long perception time in traditional risk perception. Firstly, the improved grey relational analysis method is used to screen the factors affecting construction safety. Secondly, the dimension of the influencing factor data is reduced through local linear embedding method. Finally, a security risk perception architecture based on digital twin technology is constructed, establishing a bidirectional mapping between physical construction space and virtual information space, defining construction risk index, and introducing coupling influence terms between factors to achieve security risk perception. The experimental results show that the recall rate of the influencing factors of the proposed method ranges from 96.57% to 99.06%, the accuracy remains stable between 96.76% and 97.89%, and the perception time ranges from 0.62 s to 0.87 s.

**Keywords:** digital twin technology; high-rise building; construction safety; risk perception; grey relational analysis; dimension.

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## 1 Introduction

As the core carrier of modern urban intensive development, high-rise buildings exhibit notable characteristics during construction, such as great structural height, three-dimensional intersection of workfaces, long construction periods, numerous stakeholders, and a complex external environment with strong coupling effects (Shaikhjan and Jha, 2026). With the breakthrough of building height towards exceeding limits and the widespread adoption of technologies and equipment such as deep excavations, large volume concrete, climbing formwork, and heavy tower cranes, the risk factors that induce safety accidents during the construction process are highly dynamically correlated in time and space dimensions. The degree of energy and hazardous material accumulation far exceeds that of general construction projects. Once the risk evolves into an accident, it often leads to mass deaths, injuries, and significant economic losses (Sodangi, 2024; Zhang et al., 2025). Therefore, conducting systematic research on the real-time status, evolution laws, and coupling mechanisms of risk sources throughout the entire process of high-rise building construction is a theoretical prerequisite for accurately identifying hidden dangers, achieving early warning intervention, and dynamic prevention and control. It has important engineering practice value and disciplinary forefront significance for improving the intrinsic safety level of construction sites, ensuring the life and health of workers, and promoting the transformation of building safety management from experience driven to data risk dual wheel driven (Lianhua et al., 2024).

Wang et al. (2025b) proposed a safety risk perception method for the entire construction process based on dual attention. By cross applying spatial window attention mechanism and channel grouping attention strategy, an effective balance is achieved between computational resource consumption and feature representation capability. On the basis of obtaining geographic feature data and constructing a risk dataset based on it, a correlation mapping relationship between high-dimensional scene information and construction risks is established based on three spatial types: point, line, and area, in order to achieve intelligent perception of safety risks throughout the construction process. However, the dual-attention mechanism used in this method mainly focuses on prominent spatial and channel features, but lacks the capability to capture unconventional risk factors that are sporadically distributed, highly variable, and easily overlooked on construction sites. Therefore, its recall rate of influencing factors is not high. Lei (2026) proposed a safety risk perception method for the entire process of deep excavation construction based on BIM+GIS. A safety risk intelligent perception system integrating BIM and GIS technology has been constructed for the entire process of deep foundation pit construction. This system achieves the integration of high-precision 3D scene modelling and multi-source heterogeneous data by establishing a complete technical architecture covering software and hardware support layer, perception layer, data layer, service layer, application layer, and presentation layer. On this basis, combined with a fine-grained risk discrimination rule library and high-performance analysis algorithms, precise identification and rapid warning response of construction risks have been achieved. However, the multi-level architecture of BIM+GIS relies heavily on the integration of heterogeneous data from multiple sources. In actual construction environments, data collection errors and model update delays can easily lead to deviations between 3D scenes and real working conditions. At the same time, the fine-grained risk discrimination rule library does not fully cover the risk types in complex dynamic scenes, and some unconventional or coupled risks are difficult to accurately identify, resulting in high false alarms or omissions and reducing the overall perception accuracy. Fan proposed a safety risk perception method for the entire construction process based on the multi class Adaboost algorithm (Fan, 2025). The K-means clustering algorithm is used to pre classify the original construction data to determine the feature indicators for safety risk perception. Subsequently, the Adaboost ensemble learning strategy was integrated with the BP neural network to construct a multi class Adaboost algorithm. This algorithm trains multiple BP neural networks in parallel as base classifiers and combines them into multiple strong classifiers. Through comprehensive judgement and decision-making, it achieves quantitative output of objective risk levels in construction scenarios. On this basis, further correlation analysis is conducted between the subjective risk perception utility of construction personnel and the objective situational risk degree, in order to comprehensively determine the type of construction safety risk and complete a comprehensive perception of construction site safety risk. However, the multi class Adaboost algorithm requires parallel training of multiple BP neural networks as base classifiers, which are combined into multiple strong classifiers for comprehensive judgement and decision-making. Although this ensemble mechanism improves classification accuracy, it significantly increases computational complexity. At the same time, the introduction of the correlation analysis of construction personnel's subjective risk perception utility requires additional collection and processing of subjective evaluation data, further extending the entire processing time from data input to risk type determination.

In order to solve the various problems existing in the above methods, a new safety risk perception method of high-rise building construction process based on digital twin technology is proposed, which effectively reduces the accident rate, ensures the safety of construction personnel and the stability of engineering structures, and promotes the intelligent transformation of construction safety management from post disposal to proactive prevention and control in advance. The overall technical route includes three core steps.

In the first step, the grey relational analysis method with dynamic resolution coefficient and TOPSIS method are used to systematically screen the influencing factors of construction safety. The feasibility of this step is based on the adaptability of grey relational analysis to incomplete information system, and the dynamic resolution coefficient is adaptively adjusted by information entropy function, which can effectively solve the problem of insufficient resolution caused by the fixed resolution coefficient of 0.5 in traditional methods. The introduction of positive and negative ideal solutions of TOPSIS method makes the results of factor ranking more objective and interpretable. Related algorithms have been mature in the field of construction safety, and can quickly screen dozens of influencing factors involved in high-rise building construction.

In the second step, the dimension of the filtered influencing factor data is reduced by local linear embedding method. The feasibility of this step lies in that the locally linear embedding method can preserve the local linear structure among samples and ensure the equivalence of risk representation capability between the reduced low-dimensional feature space and the original high-dimensional space. The calculation process only needs to solve the eigenvalue problem of sparse matrix. When the dimension of input data is controlled within a reasonable range, the calculation efficiency can meet the requirements of engineering application, and this method does not involve iterative optimisation process, thus avoiding the uncertainty caused by parameter optimisation in traditional nonlinear dimension reduction methods.

The third step is to build a security risk perception framework based on digital twinning technology, establish a two-way mapping between physical construction space and virtual information space, and define a comprehensive construction risk index containing coupling influence items among factors, so as to realise dynamic risk perception and hierarchical early warning. The feasibility of this step depends on the mature integration scheme of the building information model and the field sensor network. The mapping function from the physical measurement value to the twin state quantity has a clear mathematical form. The introduction of the coupling influence term does not change the basic calculation framework of the twin model, and the judgement logic of the multi-level early warning threshold can be directly embedded in the existing monitoring and management platform on the construction site, so the technical realisation path is clear.

Compared with the traditional methods, the outstanding advantages of this method are embodied in three dimensions: in the aspect of recall, by improving the comprehensive screening of influencing factors by grey relational analysis, the perception model is capable of covering major risk types, such as falls, struck-by objects, collapses, mechanical injuries, and electric shocks, and the systematic risk blind area caused by the omission of key factors is avoided; In terms of accuracy, by introducing the coupling influence term between factors, the risk assessment is upgraded from single-factor independent judgement to multi-factor collaborative comprehensive judgement, which effectively reduces the probability of false positives and false negatives in complex construction scenarios; In the aspect of perception time, the dimension of feature space is reduced by local linear embedding, and the direct state mapping mechanism of twin model is combined to avoid the extra time overhead such as multi-classifier parallel training and subjective evaluation data collection, and realise near-real-time risk perception response. Subsequent chapters will elaborate the specific construction process of influencing factor screening, data dimension reduction and twin risk perception model in turn, and verify the effectiveness and superiority of the proposed method through experiments.

# 2 Safety risk perception method for the entire construction process of high-rise buildings

## *2.1 Selection of safety influencing factors throughout the construction process based on grey relational analysis*

The selection of safety influencing factors throughout the construction process of high-rise buildings directly determines whether the data dimensions and feature space relied upon by the risk perception system are complete. Reasonable and comprehensive selection of influencing factors can ensure that the perception model covers the main risk types such as high-altitude falling, object impact, collapse, mechanical injury, and electric shock, avoiding systematic risk blind spots caused by the omission of key factors, thereby improving the recall and accuracy of risk identification. If the selection of influencing factors is improper or there are deviations, even if the subsequent algorithms are advanced, the perception system will be difficult to make reliable judgements on the real safety situation of the construction site, thereby weakening the timeliness and effectiveness of risk warning, and ultimately affecting the decision-making quality and accident prevention and control ability of construction safety management (Yan and Ma, 2023).

Using grey relational analysis to screen influencing factors can be divided into five steps:

1 Determine the analysis matrix

Setting the safety impact factors of the entire construction process of high-rise buildings as a comparison sequence, and using the evaluation value of operational level as the reference sequence for the optimal standard (Zhang, 2025), the analysis matrix $B$ can be obtained, and its calculation formula is as follows:

$$B = \begin{bmatrix} b_0(1) & b_1(1) & \cdots & b_n(1) \\ b_0(2) & b_1(2) & \cdots & b_n(2) \\ \vdots & \vdots & b_i(j) & \vdots \\ b_0(m) & b_1(m) & \cdots & b_n(m) \end{bmatrix} \tag{1}$$

In the above formula, $b_0$ represents a reference sequence composed of safety assessment values for the entire construction process of high-rise buildings; $b_1 \sim b_n$ represents a comparative sequence consisting of safety influencing factors throughout the entire construction process of high-rise buildings; $b_i(j)$ and $b_n(m)$ respectively represent the $j^{\text{th}}$ data of the $i^{\text{th}}$ influencing factor and contain $n$ influencing factors in the $m$ dimensional analysis matrix.

2 Dimensionalisation of data processing

Due to the different dimensions, units, and scales of safety factors affecting the entire construction process of high-rise buildings, it is necessary to eliminate the influence of varying magnitudes among factors on the evaluation results before performing the correlation analysis. The calculation formula is as follows:

$$b_i''(j) = \frac{b_i(j)}{\bar{b}_i} \tag{2}$$

In order to eliminate the inconsistency between the changing trends of influencing factors and operational level evaluation indicators, these influencing factors are normalised and the reciprocal is taken to make their changing trends consistent with the safety level evaluation indicators of the entire construction process of high-rise buildings. This can avoid the situation where the correlation results are too small and obtain a more accurate analysis matrix $B'$ (Xue et al., 2025; Xiao et al., 2025). The calculation formula is as follows:

$$B' = \begin{bmatrix} b_0'(1) & b_1'(1) & \dots & b_n'(1) \\ b_0'(2) & b_1'(2) & \dots & b_n'(2) \\ \vdots & \vdots & b_i'(j) & \vdots \\ b_0'(m) & b_1'(m) & \dots & b_n'(m) \end{bmatrix} \tag{3}$$

In the above formula, $b_i'(j)$ represents the normalised value of $b_i(j)$.

3 Determine the correlation coefficient

According to the dimensionless analysis matrix $B'$, the difference sequence $C_i(j)$ is calculated by taking the absolute difference between the comparison sequence and the reference sequence, and then forming the difference matrix $C$ from the difference sequence. The calculation formula is as follows:

$$\begin{cases} C = \begin{bmatrix} c_1(1) & c_2(1) & \dots & c_n(1) \\ c_1(2) & c_2(2) & \dots & c_n(2) \\ \vdots & \vdots & c_i(j) & \vdots \\ c_1(m) & c_2(m) & \dots & c_n(m) \end{bmatrix} \\ C_i(j) = \left| b_0'(j) - b_i'(j) \right| \end{cases} \tag{4}$$

Calculate the correlation coefficient $g_i(j)$ based on the data in the difference matrix, and the specific calculation formula is as follows:

$$g_i(j) = \frac{C_{\min} + \varepsilon C_{\max}}{C_i(j) + \varepsilon C_{\max}} \tag{5}$$

In the above formula, $\varepsilon$ represents the resolution coefficient; $C_{\max}$ and $C_{\min}$ respectively represent the maximum and minimum elements in the difference matrix.

4 Calculate the correlation between various influencing factors

The calculation formula for the correlation coefficient of safety factors affecting the entire construction process of high-rise buildings is as follows:

$$\varphi_i = \frac{1}{n} \sum_{i=1}^{m} g_i(j) \tag{6}$$

In the above formula, $\varphi_i$ represents the degree of correlation of the $i^{\text{th}}$ influencing factor.

The degree of correlation represents the degree of influence of each influencing factor on the reference sequence, that is, the degree of influence on the safety of the entire construction process of high-rise buildings. Sort the correlation degree of safety influencing factors throughout the entire construction process of high-rise buildings, and based on the sorting results, determine the ranking of the impact degree of each influencing factor on the safety of the entire construction process of high-rise buildings (Wang et al., 2025a).

In order to improve the applicability of the grey relational analysis method in practical problems, dynamic resolution coefficients are introduced to enhance the differences between data and compensate for the shortcomings of traditional grey relational analysis methods, which are caused by insufficient discrimination and reduced effectiveness of the correlation coefficient due to the conventional value of 0.5.

Due to the fact that the degree of data information resolution of the grey correlation degree sequence is directly affected by the value of the resolution coefficient, quantifying this degree of information resolution is recorded as the entropy function $g(\rho)$ between each data information sequence. The result of normalising the grey correlation degree is denoted as $V = \{v_k \mid \in m\}$. The formula for calculating the entropy value of the data information sequence at this time is as follows:

$$g(\rho) = -\sum_{i=1}^{m} v_k \ln v_k \tag{7}$$

According to the theory of data difference information, the information entropy of a data information sequence is inversely proportional to the degree of resolution of each group of information, that is, the greater the information entropy between sequences, the higher the final resolution, and the more differentiated the data is. When the value of $g(\rho)$ is within the range of 0 and 1, it is more in line with the rising theorem of entropy, and the non-negativity and non-concavity of entropy are more objective at this time. At this point, a series of stable fluctuations in grey correlation degree will cause the entropy value to increase. Based on the above analysis, the static resolution coefficient with a fixed value will be replaced with a dynamic resolution coefficient of $\rho^{(g)}$. To compensate for the shortcomings of static resolution coefficients in calculating correlation. At this point, the calculation formula for the grey correlation coefficient based on the dynamic resolution coefficient is as follows:

$$g_i(j) = \frac{C_{\min} + \rho^{(g)} C_{\max}}{C_i(j) + \rho^{(g)} C_{\max}} \tag{8}$$

Combining the ideas of traditional grey relational analysis and TOPSIS method, set the positive reference sequence as $X_0$ and the negative reference sequence as $X_0^- = [, X_{0.2}^-, ..., X_{0.m}^-]$. At this point, by comparing and analysing the distance between the two influencing factors $X_i$ and $X_j$ relative to $X_0^-$, the relative superiority and inferiority of factors $X_i$ and $X_j$ can be determined. From this, it can be concluded that the grey correlation degree calculation formula between the safety influencing factors of the $i^{\text{th}}$ high-rise building construction process and the negative reference sequence $X_0^-$ is as follows:

$$\varphi_i^- = \frac{1}{n} \sum_{j=1}^{n} g_i^-(j),\ i = 1, 2, ..., m \tag{9}$$

Therefore, the comprehensive grey correlation degree $\psi_i$ is used to measure the degree of impact of various influencing factors on the safety of the entire construction process of high-rise buildings. The calculation of the comprehensive grey correlation degree is as follows:

$$\psi_i = \frac{\varphi_i}{\varphi_i + \varphi_i^-} \tag{10}$$

In the above formula, $\varphi_i^-$ represents the correlation degree of the negative reference sequence; $\varphi_i$ represents the correlation degree of traditional grey correlation method. The size of $\psi_i$ represents the degree of influence of various factors affecting the safety of the entire construction process of high-rise buildings. It can objectively reflect the degree of influence of each factor affecting the safety of the entire construction process of high-rise buildings. By sorting the correlation results, it is possible to more scientifically and effectively analyse each influencing factor.

The selection of the above risk factors follows the principles of comprehensiveness, measurability, independence, and dynamism. The principle of comprehensiveness requires that the preliminary selection factors cover the direct causes of five main types of accidents during the entire construction process of high-rise buildings, including high-altitude falls, object strikes, collapses, mechanical injuries, and electric shocks, including personnel behaviour, equipment status, environmental conditions, and management measures; The principle of measurability requires that each factor can obtain quantitative observations through on-site sensors, wearable devices, or manual inspections, excluding purely qualitative or unquantifiable descriptive indicators; The principle of independence requires that factors should avoid highly linear correlations as much as possible. For combinations of factors with absolute correlation coefficients greater than 0.85, those with higher comprehensive grey correlation should be retained, and redundant factors should be eliminated; The principle of dynamism requires that the selected factors reflect the dynamic characteristics that evolve over time during the construction process, excluding static parameters that are only related to the design phase and do not change with the construction progress. After determining the final set of factors, the weight coefficients of each factor are determined using a combination weighting method. The subjective weight is obtained by constructing a judgement matrix using the nine level scaling method with five experts with more than ten years of experience in high-rise building construction safety management through the analytic hierarchy process. The objective weight is calculated using the entropy weight method based on the information entropy of each factor in historical construction data. The final combination weight is the geometric average of the subjective weight and the objective weight and normalised. This method can reflect the experience and knowledge of domain experts and avoid systematic deviations between subjective judgements and actual data distribution.

## *2.2 Data dimensionality reduction of safety impact factors throughout the entire construction process of high-rise buildings*

Assuming there is a dataset $V = \{x_1, x_2, x_3, \ldots, x_{k-1}, x_k, \ldots, x_{n-1}, x_n\}$ consisting in $n$ of $m$ dimensional samples of safety impact factors during the entire construction process of high-rise buildings, when searching for $k$ nearest neighbour samples to linearly represent a certain data point $x_i$, this process can be regarded as a regression problem. The mean square error is used as the loss function of the regression function. For each data point $x_i$, it is desired to linearly represent it through its $k$ neighbouring points. The goal $J(w)$ of data dimensionality reduction using local linear embedding method is represented as minimising reconstruction error (Jayapal and Annamalai, 2025), and its calculation formula is as follows:

$$\begin{cases} J(w) = \sum_{i=1}^{n} \left\| x_i - \sum_{j \in A(i)}^{k} w_{ij} x_j \right\|_2^2 \\ s.t. \sum_{j \in A(i)}^{k} w_{ij} = 1 \end{cases} \tag{11}$$

In the above formula, $A(i)$ represents the set of $k$ neighbouring samples of data point $x_i$; $w_{ij}$ represents the linear weight between points $x_i$ and $x_j$. Normalise the weight coefficient $w_{ij}$ and matrix target $J(w)$. At this point, formula (11) can be reconstructed as $J(w)$:

$$\begin{cases} J(W) = \sum_{i=1}^{n} \left\| x_i - \sum_{j \in A(i)}^{k} w_{ij} x_j \right\|_2^2 \\ s.t. \sum_{j \in A(i)}^{k} w_{ij} = W_i^T 1_k = 1 \end{cases} \tag{12}$$

In the above formula, $W_i = (w_{i1}, w_{i2}, w_{i3}, \ldots, w_{ik})^T$ represents a vector with $k$ dimensions all equal to 1. By defining the matrix $Z_i = (x_i - x_j)(x_i - x_j)^T$, and by using the Lagrange multiplier method on formula (13), we can obtain:

$$L(W) = \sum_{i=1}^{k} W_i^T Z_i W_i + \lambda\left(W_i^T 1_k - 1\right) \tag{13}$$

In the above formula, $\lambda$ represents the introduced Lagrange multiplier. By taking the derivative of formula (13) and making its value 0, we can obtain:

$$\begin{cases} \dfrac{\partial L(W)}{\partial W} = 2Z_i W_i + \lambda 1_k = 0 \\ W_i = -\dfrac{1}{2}\lambda Z_i^1 1_k \end{cases} \tag{14}$$

Normalise $W_i$ in formula (14) and obtain the calculation formula for weight coefficient $W_i$ as follows (Wang et al., 2024):

$$W_i = \frac{Z_i^{-1} 1_k}{1_k^T Z_i^{-1} 1_k} \tag{15}$$

At this point, it is hoped that the weight coefficients of the corresponding linear relationship remain unchanged after dimensionality reduction. Assuming that the projection in $n$ of $m$ dimensional sample datasets $\{x_1, x_2, x_3, \ldots, x_{k-1}, x_k, \ldots, x_{n-1}, x_n\}$ in the low dimensional space of $d$ dimensions is represented as $J(y)$, the mean squared error loss function $\{y_1, y_2, y_3, \ldots, y_{k-1}, y_k, \ldots, y_{n-1}, y_n\}$ should also satisfy the minimum requirement. Its calculation formula is as follows:

$$\begin{cases} J(y) = \sum_{i=1}^{n} \left\| y_i - \sum_{j \in A(i)}^{k} w_{ij} x_j \right\|_2^2 \\ s.t. \sum_{i=1}^{n} y_i = 0; \frac{1}{n} \sum_{i=1}^{n} y_i y_i^T - I \end{cases} \tag{16}$$

At this point, the objective function $J(y)$ can be matrixised to obtain $J(Y)$, and its calculation formula is as follows:

$$\begin{cases} J(Y) = tr\left(Y(I-W)(I-W)^T Y^T\right) \\ s.t.\ YY^T = nI \end{cases} \tag{17}$$

In the above formula, *tr*() represents the trace of the matrix, let $N = (I - W)(I - W)^T$, and for objective function $J(Y)$, the Lagrange multiplier method can be used to rewrite formula (17) as (Ghojogh et al., 2024):

$$L(Y) = tr\left(YNY^T + \lambda\left(YY^T - nI\right)\right) \tag{18}$$

At this point, taking the derivative of formula (18) and making its value 0, we can obtain:

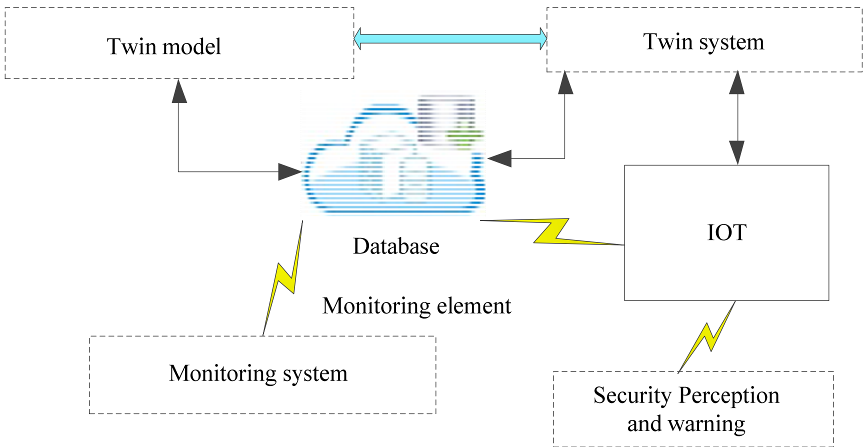
$$\begin{cases} \frac{\partial L(Y)}{\partial Y} = 2NY^T + 2\lambda Y^T = 0 \\ \qquad NY^T = -\lambda Y^T \end{cases} \tag{19}$$

At this point, formula (19) shows that to obtain the $d$ dimensional dataset $V$ of the safety impact factors during the entire construction process of high-rise buildings in a low dimensional space, it is only necessary to obtain matrix $Y = (y_1, y_2, y_3, \ldots, y_d)^T$ composed of the eigenvectors corresponding to the minimum $d$ eigenvalues of matrix $N$. However, since the minimum eigenvalue of matrix $N$, which is 0, cannot reflect the characteristics of the data, it is necessary to remove the eigenvectors corresponding to the eigenvalue of 0. Therefore, it is considered to select eigenvector $Y' = (y_2, y_3, y_4, \ldots, y_{d+1})^T$ corresponding to the second to $d + 1^{\text{th}}$ minimum eigenvalue of $N$ to obtain the final $Y$, which can reduce the dataset from $m$ dimensions to $d$ dimensions.

### 2.3 *Safety risk perception throughout the construction process based on digital twin technology*

Digital twin technology, as a mature data-driven framework, has been widely researched and applied in the field of construction safety. Its core value lies in achieving bidirectional mapping and real-time interaction between physical and virtual spaces. The original contribution of this study lies not in the digital twin technology itself, but in three aspects: firstly, the introduction of dynamic resolution coefficient and the integration of TOPSIS method in the screening of influencing factors, which solves the problem of insufficient discrimination caused by fixed resolution coefficient in traditional grey relational analysis method; The second is to introduce the coupling effect term between factors in the calculation of risk index, which realises the quantitative characterisation of the synergistic effect of multiple risk factors; Thirdly, a unified mapping framework for three types of heterogeneous data covering structural response, environmental loads, and personnel physiological data has been constructed, enhancing the comprehensive representation ability of the twin model for the safety status of the entire construction process. The safety risk perception architecture for the entire construction process of high-rise buildings based on digital twin technology is shown in Figure 1.

**Figure 1** Safety risk perception architecture for the entire construction process of high-rise buildings based on digital twin technology (see online version for colours)

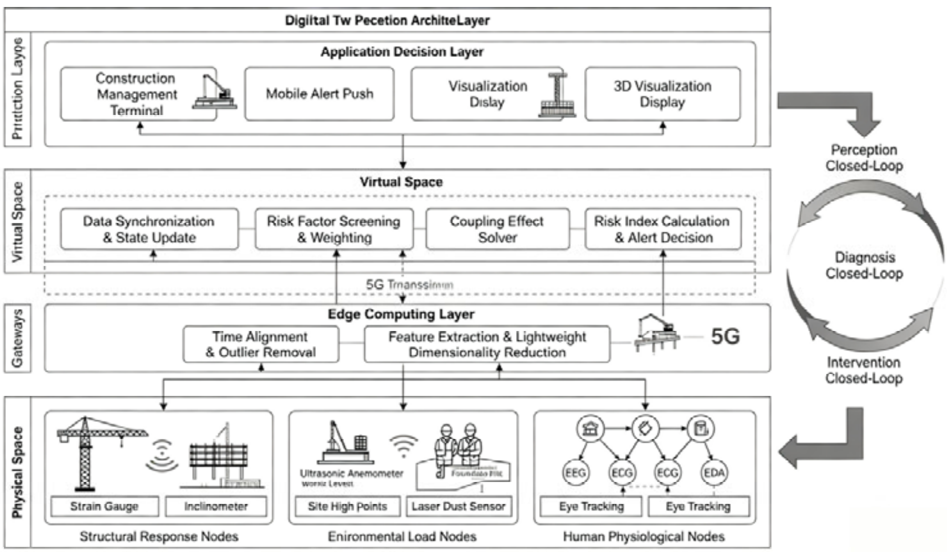



Based on the screening and dimensionality reduction of safety factors throughout the entire construction process of high-rise buildings, a risk perception implementation framework based on digital twins is constructed. Digital twin technology achieves dynamic perception of construction safety status by establishing bidirectional mapping and real-time interaction between physical construction space and virtual information space, mapping key risk characteristic parameters retained after dimensionality reduction to the twin model.

The raw data required to construct a digital twin risk perception model is divided into three categories based on their sources and physical attributes. The first type is structural response data, sourced from wireless sensor networks deployed on construction sites, including dynamic strain of key stress nodes of tower cranes (collected through resistance strain gauges), rate of change in tower body tilt angle (measured through inclinometers), and template settlement and horizontal displacement in high formwork areas (obtained through laser displacement sensors). The second type is environmental load data, obtained through on-site meteorological and environmental monitoring equipment, including instantaneous wind speed and direction (ultrasonic anemometer), concentration of inhalable particulate matter in the air (laser dust sensor), and on-site image data collected by industrial cameras at a frame rate of 30 fps, used to identify environmental changes and occlusion risks. The third type is personnel physiological and behavioural data, collected through wearable devices during the immersive virtual reality simulation phase, including: power spectral density of frontal lobe EEG signals (theta, alpha, beta, gamma waves), eye tracking parameters (fixation point coordinates, fixation duration, scan amplitude, pupil diameter changes), heart rate and heart rate variability time-frequency domain indicators, skin conductance response and body temperature, used to quantify the risk cognitive load and stress response level of construction personnel. The above multi-source heterogeneous data are uniformly gathered through the 5G edge computing gateway with GPS timestamp, forming a time aligned multi-mode synchronous data set, which serves as the input source for the status update of the twin model.

Based on the digital twin risk perception architecture shown in Figure 1, this article further presents the complete topology structure of the perception model, as shown in Figure 2.

**Figure 2** The complete topology structure of the perception model




The topology consists of four parts: physical space, edge computing layer, virtual space and application decision-making layer. The data flow direction presents a two-way closed-loop feature of gathering from the bottom up and feeding back from the top down. The physical space layer includes three kinds of sensing nodes: structural response nodes are deployed at the key stress points of tower crane, high formwork support system and foundation pit support structure, and the mechanical and geometric states are collected by strain gauges, inclinometers and laser displacement sensors. Environmental load nodes are arranged at the commanding heights of the construction site and the height of the working surface, and meteorological and environmental parameters are collected by ultrasonic anemometer and laser dust sensor. The physiological nodes of personnel are attached to the workers in key positions in the form of wearable devices to collect multi-dimensional physiological signals such as EEG, eye movement, ECG and skin electricity. Each sensing node gathers data to the edge computing gateway distributed in various areas of the construction site through low-power wireless fidelity, and this layer undertakes two core functions: one is the time sequence alignment of the original data and the rejection of outliers, and a reasonable threshold is set according to the nominal accuracy of each sensor, and outliers beyond the range of three standard deviations are marked and interpolated. The second is feature extraction and lightweight dimension reduction, which completes windowing feature calculation at the edge and compresses the high-dimensional original signal into low-dimensional feature vectors, thus reducing the data traffic uploaded to the cloud or server. The feature data after edge processing is transmitted to the virtual space layer through the fifth generation mobile communication network, which includes four functional modules: the data synchronisation and state update module is responsible for receiving the feature vectors pushed by the edge and maintaining the real-time state values of each attribute node in the twin model; The risk factor screening and weight module stores and dynamically updates the correlation ranking and combination weight of each factor to provide parameter support for risk index calculation; The couple effect solving module calculate that coupling influence term among factors in real-time and updates the couple coefficient; The risk index calculation and early warning judgement module performs the aggregation calculation of the comprehensive risk index and compares it with the three-level early warning threshold, and outputs the current risk level. The application decision-making layer includes three sub-modules: construction management terminal, mobile early warning push and three-dimensional visual display, and conveys the risk judgement results of the virtual space layer to the site management personnel in graphical and textual forms. The rationality of this topology design can be demonstrated from two dimensions: data transmission and physical virtual interaction. On the data transmission level, the introduction of edge computing gateway completes the compression and feature extraction of high-dimensional original data that should have been uploaded completely near the data source, and only transmits low-dimensional feature vectors to the virtual space layer. Taking EEG signal as an example, the original sampling rate is 25 6Hz, and the data volume per second is about 4.5 KB, which is reduced to about 120 bytes per second after edge feature extraction, which reduces the communication bandwidth requirement by more than 97% and avoids the impact of data loss caused by network delay or interruption on the continuity of risk perception. The gateway adopts redundant deployment strategy, and when any gateway fails, the neighbouring gateway can take over the sensor nodes in its coverage area to ensure the reliability of data transmission. At the level of physical virtual interaction, the topological structure has established three closed-loop feedback loops: the first is the perception closed loop, and the real-time measured values of physical space are updated by edge processing and feature mapping to ensure that the virtual model and the physical entity are synchronised in time dimension. The second is the diagnosis closed loop, in which the virtual space sorts and feeds back the abnormal attribute nodes identified in the process of risk index calculation and their contribution to the physical space, guiding the site to conduct key review and sensor verification on specific risk parts; The third is the intervention closed loop, which applies the early warning and control instructions issued by the decision-making layer to the construction organisation and protective measures in the physical space after being confirmed by the managers. The effect after the implementation of the measures re-enters the perception cycle through continuous data collection, forming a complete safety control chain from perception to evaluation to intervention to re-perception. The triple closed-loop structure ensures the real-time two-way flow of information between the physical space and the virtual space, so that the risk perception model has adaptive adjustment ability in the dynamically changing construction environment.

Establish a geometric solid model of high-rise buildings based on building information modelling (BIM), and overlay the time-varying attributes of the construction process on this basis to form a four-dimensional construction twin foundation. Define each security impact factor retained after dimensionality reduction as an observable attribute node in the twin model, and establish a mapping relationship between physical space measurement values and twin space state variables. The calculation formula is as follows:

$$S_j(t) = f_j\left(\frac{x_j(t) - \mu_j}{\sigma_j}\right) \tag{20}$$

In the above formula, $x_j(t)$ represents the physical measurement value of the $j^{\text{th}}$ influencing factor at time $t$; $\mu_j$ represents the historical mean of the $j^{\text{th}}$ influencing factor under normal construction conditions; $\sigma_j$ represents the standard deviation of the $j^{\text{th}}$ influencing factor; $f_j(\cdot)$ represents the normalisation and nonlinear correction functions.

In the twin model, the current construction risk index $R(t)$ is defined as a weighted aggregation of the state values of various influencing factors after dimensionality reduction, while considering the coupling effects between factors. Firstly, calculate the deviation risk contribution of each influencing factor using the following formula:

$$d_j(t) = \max\left(0, \left|S_j(t) - S_j^{ref}\right| - \delta_j\right) \tag{21}$$

In the above formula, $S_j^{ref}$ represents the ideal value of the $j^{\text{th}}$ influencing factor under standard construction conditions; $\delta_j$ represents the safety margin bandwidth of $j$ influencing factors.

Secondly, the coupling effect term between factors is introduced to correct the independent risk contribution of a single factor. The calculation formula is as follows:

$$c_{jk}(t) = \lambda_{jk} \cdot S_j(t) \cdot S_k(t) \tag{22}$$

In the above formula, $\lambda_{jk}$ represents the coupling coefficient; $S_j(t)$ $S_k(t)$ represents the twin state values of the $j^{\text{th}}$ and $k^{\text{th}}$ factors respectively.

Finally, the comprehensive construction risk index is obtained through aggregation, and its calculation formula is as follows:

$$R(t) = \sum_{j=1}^{m} w_j d_j(t) + \sum_{j=1}^{m} \sum_{k=j+1}^{m} c_{jk}(t) \tag{23}$$

In the above formula, $m$ represents the total number of security impact factors retained after dimensionality reduction processing; $w_j$ represents the weight coefficient of the $j^{\text{th}}$ influencing factor, satisfying $\sum_{j=1}^{m} w_j = 1$.

Compare the real-time calculated $R(t)$ with the preset multi-level warning threshold ($R_{th1}$, $R_{th2}$, $R_{th3}$ corresponds to yellow, orange, and red warnings). When $R_{th1}$, $R_{th2}$, $R_{th3}$ exceeds the threshold, the twin model highlights the risk area in the virtual space and synchronously pushes the warning information to the on-site management personnel terminal. At the same time, based on the forward deduction ability of the twin model, the risk index for the next moment is corrected, and its calculation formula is as follows:

$$\hat{R}(t + \Delta t) = R(t) + \sum_{j=1}^{m} \alpha_j \cdot \frac{S_j(t + \Delta t \mid t) - S_j(t)}{\Delta t} \tag{24}$$

In the formula: $\Delta t$ represents the prediction step size; $S_j(t + \Delta t \mid t)$ represents the next twin state value estimated based on the current state and trend of change; $\alpha_j$ represents the sensitivity coefficient of the $j^{\text{th}}$ influencing factor state change rate to the overall risk change

When the predicted risk index exceeds the warning threshold, the twin system issues a warning in advance and automatically retrieves the main influencing factors and their contribution rankings that lead to the increase in risk, providing quantitative basis for taking preventive control measures on site, and realising the transformation of safety risks in the entire process of high-rise building construction from passive response to active perception.

# 3 Experimental design

## *3.1 Experimental protocol*

### *3.1.1 Experimental data*

In the safety risk perception experiment of the entire construction process of high-rise buildings, the experimental plan is designed around the framework of human-machine environment multi-source data fusion, and is divided into two implementation stages. In the first stage, typical risk scenarios such as high-altitude falls and tower crane collisions are simulated in an immersive virtual reality environment. The experimenters wear portable EEG devices and collect the power spectral density of frontal lobe EEG signals at a sampling frequency of 256 Hz, including theta waves, alpha waves, beta waves, and gamma waves. At the same time, eye tracking devices are used at a sampling frequency of 120 Hz to record the coordinates of the fixation point, fixation duration, scanning amplitude, changes in pupil diameter, and the time of first arrival at the risk area. In conjunction with smart bracelets, time-domain indicators of heart rate and heart rate variability such as the root mean square of continuous differences, as well as frequency-domain indicators such as the low-frequency to high-frequency power ratio, skin conductance response, and body temperature, are synchronously collected at a frequency of 1Hz to quantify the risk cognitive load and physiological stress response of workers. In the second stage, a wireless sensor network will be deployed at the actual high-rise building construction site. Resistance strain gauges will be pasted at key stress nodes of the tower crane to collect the dynamic change rate of structural stress at the micro strain level. An inclinometer will be installed to measure the change speed of the tower body inclination angle with an accuracy of 0.1 degrees. Laser displacement sensors will be installed in the high formwork area to monitor the settlement and horizontal displacement of the formwork with an accuracy of 0.1 mm. Ultrasonic anemometers will be used to measure instantaneous wind speed and direction with a resolution of 0.1 m/s. The mass concentration of inhalable particles in the air will be obtained in real-time through a laser dust sensor, and on-site images will be collected at a frame rate of 30 fps using an industrial camera. All sensing data are converged uniformly through the fifth generation mobile communication edge computing gateway with the GPS timestamp to form a multi-mode synchronous data set.

### *3.1.2 Experimental indicators*

Selecting method of Wang et al. (2025b), method of Lei (2026), and the proposed method as experimental comparison methods, the application effects of different methods were tested by comparing the full inspection rate of safety risk factors in the entire process of high-rise building construction, the accuracy of safety risk perception in the entire process of high-rise building construction, and the perception time of safety risk in the entire process of high-rise building construction.

The recall of safety risk factors throughout the construction process of high-rise buildings refers to the ratio of the number of correctly identified real risk factors to the total number of actual risk factors present on the construction site in the construction safety risk assessment. This indicator is used to measure the completeness of the coverage of potential risk factors by safety monitoring systems or evaluation methods. A high inspection rate can minimise the omission of risk factors and ensure that construction management personnel have a comprehensive understanding of the distribution of various safety hazards such as high-altitude falls, object strikes, collapses, mechanical injuries, and electric shocks, so as to take targeted preventive measures in the early stages of accidents.

The accuracy of safety risk perception throughout the entire process of high-rise building construction refers to the percentage of risk status samples correctly identified by the safety monitoring system or evaluation model to the total number of tested samples. Correct identification includes accurately identifying hazardous areas with risks and accurately identifying safe areas without risks. High accuracy can ensure that construction management personnel form reliable judgements on the safety conditions on site, avoid ineffective work stoppages and resource waste caused by false alarms, and prevent safety hazards caused by missed reports from not being dealt with in a timely manner. In the context of complex and variable risk factors and serious accident consequences in high-rise building construction, accuracy directly determines the credibility and availability of the perception system in actual engineering.

The perception time of safety risks throughout the entire construction process of high-rise buildings refers to the time delay experienced from the occurrence or sudden change of risk factors on the construction site to the successful identification and output of the risk state. A shorter risk perception time can provide valuable emergency response windows for construction management personnel, enabling timely implementation of safety warnings, personnel evacuation, and protective measures deployment at the early stage of accidents, effectively curbing the occurrence of malignant accidents such as high-altitude falls, tower crane collisions, and foundation pit collapses. It has critical engineering significance for achieving the transformation of construction safety from post disposal to proactive management of pre prevention.

## *3.2 Experimental results*

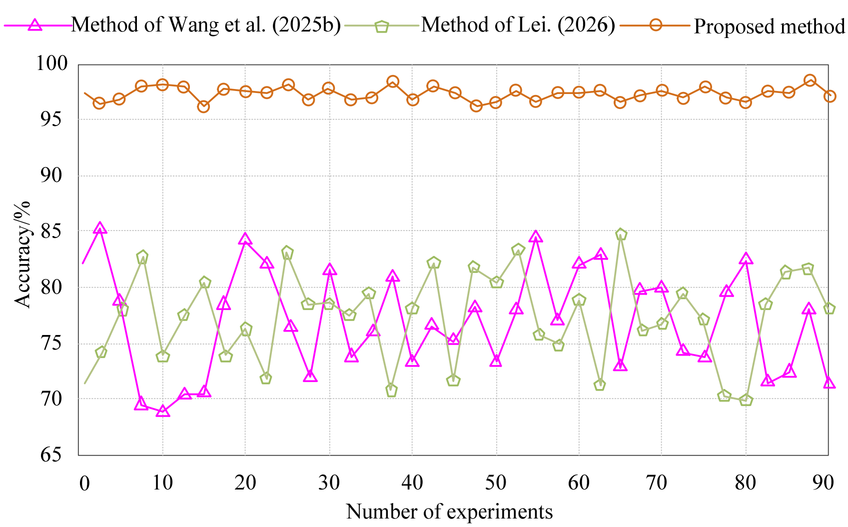
The results of the safety risk factor inspection rate test for the entire construction process of high-rise buildings using three methods are shown in Table 1.

According to Table 1 analysis, the recall rate of method of Wang et al. (2025b) ranges from 76.29% to 85.98%, method of Lei (2026) ranges from 70.62% to 79.88%, and the proposed method ranges from 96.57% to 99.06%, significantly higher than the two comparison methods in all 90 experiments. These data fully demonstrate the overwhelming advantage of the proposed method in terms of risk factor coverage integrity, which can effectively identify various safety hazards such as high-altitude falls, object strikes, collapses, and mechanical injuries that objectively exist on construction sites. The peak level of its recall rate approaching 99% means that only a very small number of risk factors may be missed. However, the recall rates of method of Wang et al. (2025b) and method of Lei (2026) are significantly low due to limitations in data collection dimensions, feature extraction capabilities, or risk modelling integrity, with about 15% to 30% of risk factors not being identified in a timely manner. From the perspective of data stability, the range of the proposed method is only 2.49%, and the fluctuation amplitude is much smaller than 9.69% in method of Wang et al. (2025b) and 9.26% in method of Lei (2026), proving that the proposed method can maintain stable and excellent risk coverage performance under different experimental conditions. Overall, the proposed method can provide a more comprehensive risk base for the safety management of the entire construction process of high-rise buildings, laying a solid data foundation for subsequent risk warning and intervention decisions, thereby effectively reducing the probability of safety accidents caused by risk omissions.

**Table 1** Test results of completeness rate of influencing factors

| *Number of experiments* | *Recall/%* | | |
|---|---|---|---|
| | *Method of Wang et al. (2025)* | *Method of Lei (2026)* | *Proposed method* |
| 10 | 78.36 | 72.47 | 97.25 |
| 20 | 82.51 | 75.83 | 96.84 |
| 30 | 76.29 | 70.62 | 98.13 |
| 40 | 84.77 | 78.19 | 96.57 |
| 50 | 80.43 | 73.54 | 97.96 |
| 60 | 77.85 | 76.21 | 98.42 |
| 70 | 83.62 | 71.36 | 96.71 |
| 80 | 79.14 | 79.88 | 97.38 |
| 90 | 85.98 | 74.65 | 99.06 |

**Figure 3** Accuracy test results (see online version for colours)



The accuracy test results of safety risk perception throughout the entire construction process of high-rise buildings using three methods are shown in Figure 3.

According to the analysis of Figure 3, the accuracy of method of Wang et al. (2025b) ranges from 68.51% to 85.38%, method of Lei (2026) ranges from 69.71% to 84.82%, while the proposed method remains stable between 96.76% and 97.89%, significantly higher than the two comparison methods in all 90 experiments. These data fully demonstrate the overwhelming advantage of the proposed method in terms of safety risk perception accuracy, which can reliably distinguish whether there are various safety hazards such as high-altitude falls, object strikes, collapses, and mechanical injuries on the construction site. Its accuracy is close to the peak level of 98%, which means that the false positive and false negative rates are extremely low. However, method of Wang et al. (2025b) and method of Lei (2026) have limitations in feature extraction ability, data fusion mechanism, or classifier design, resulting in significantly lower accuracy. From the perspective of data stability, the accuracy of the proposed method consistently remains above 96%, with minimal fluctuations, proving that the method can maintain stable and excellent perceptual performance under different experimental conditions. Overall, the data in the figure verifies that the proposed method can provide high confidence risk state judgement for the safety management of the entire construction process of high-rise buildings, effectively avoiding ineffective work stoppages and resource waste caused by false alarms, and preventing safety hazards caused by missed alarms from being not dealt with in a timely manner, providing reliable technical support for the intelligent transformation of construction safety management.

The results of the safety risk perception time test for the entire construction process of high-rise buildings using three methods are shown in Table 2.

**Table 2** Perception time test results

| *Number of experiments* | *Perceived time/s* | | |
|---|---|---|---|
| | *Method of Wang et al. (2025)* | *Method of Lei (2026)* | *Proposed method* |
| 10 | 2.14 | 1.52 | 0.73 |
| 20 | 2.56 | 1.87 | 0.81 |
| 30 | 1.92 | 1.34 | 0.66 |
| 40 | 2.71 | 1.96 | 0.78 |
| 50 | 2.33 | 1.63 | 0.85 |
| 60 | 1.98 | 1.45 | 0.69 |
| 70 | 2.68 | 2.03 | 0.87 |
| 80 | 2.47 | 1.71 | 0.74 |
| 90 | 2.79 | 1.38 | 0.62 |

According to Table 2 analysis, the perception time distribution of method of Wang et al. (2025b) is between 1.92 seconds and 2.79 seconds, method of Lei (2026) is between 1.34 s and 2.03 s, while the proposed method is between 0.62 s and 0.87 s. In all ninety experiments, it is significantly shorter than the two comparison methods, with an average perception time of about 1/2 to 1/3 of the comparison methods. These data fully demonstrate the significant advantages of the proposed method in real-time safety risk perception, which can complete the full chain processing from risk occurrence to identification output faster, and strive for more sufficient emergency response time for construction management personnel, so as to take timely evacuation and protective measures before sudden risks such as tower crane collisions and foundation pit collapses evolve into malignant accidents. From the perspective of data distribution, the perception time fluctuation range of method of Wang et al. (2025b) and method of Lei (2026) is relatively large, with ranges of 0.87s and 0.69s respectively, while the range of the proposed method is only 0.25 s, proving that the proposed method can maintain stable and efficient perception performance under different experimental conditions. Overall, the data in Table 2 confirms that the proposed method achieves millisecond level rapid response capability while ensuring high recall and accuracy. Its shortest perception time of 0.62 s means that there is almost no perception delay from risk occurrence to warning output, which can meet the engineering requirements of real-time monitoring of dynamic risks in high-rise building construction and provide key technical support for active safety prevention and control.

Based on the experimental results shown in Table 1, Table 2 and Figure 2, the proposed safety risk perception method for the whole process of high-rise building construction based on digital twinning technology shows comprehensive and stable performance advantages in all 90 independent experiments. In terms of recall ratio of influencing factors, the proposed method is between 96.57% and 99.06%, while the method of Wang et al. (2025b) is only between 76.29% and 85.98%, and the method of Lei (2026) is only between 70.62% and 79.88%. The minimum recall rate of 96.57% of the proposed method is still higher than the highest values of 85.98% and 79.88% of the two comparison methods, which means that out of every 100 real risk factors, the proposed method misses at most about 3 to 4, while the comparison method misses about 14 to 24 and 20 to 29 respectively, and the absolute improvement rate of the recall rate reaches 10.59 to 28.44%, which has a significant engineering in the field of construction safety. In terms of risk perception accuracy, the proposed method is stable between 96.76% and 97.89%, the method of Wang et al. (2025b) is between 68.51% and 85.38%, and the method of Lei (2026) is between 69.71% and 84.82%. The lowest accuracy rate of 96.76% of the proposed method is still significantly higher than the highest values of 85.38% and 84.82% of the two comparison methods, and the absolute improvement rate of accuracy reaches 11.38%–12.94%, which means that in every 100 risk judgements, the proposed method has only about 2–3 misjudgements, while the comparison method has about 15–31 misjudgements. The high accuracy rate directly determines the reliability and availability of the sensing system in practical engineering, which can be effectively avoided. In terms of risk perception time, the proposed method ranges from 0.62 s to 0.87 s, the method of Wang et al. (2025b) ranges from 1.92 s to 2.79 s, and the method of Lei (2026) ranges from 1.34 s to 2.03 s. The average perception time of the proposed method is about one-third to one-half of that of the comparative method. The absolute shortening range is 0.72 s to 2.17 s, which seems to be a small time difference. In the high-rise building construction scene with extremely rapid risk evolution, it means that it can win valuable emergency response windows for construction managers, so that safety early warning, personnel evacuation and protective measures deployment can be implemented in time at the embryonic stage of accidents, thus effectively curbing the occurrence of vicious accidents such as falling from high altitude, tower crane collision and foundation pit collapse. From the point of view of performance stability, the extreme range of recall of the proposed method is 2.49%, which is far less than 9.69% of method of Wang et al. (2025b) and 9.26% of method of Lei (2026). The fluctuation range of accuracy is 1.13%, which is far less than the 16.87% and 15.11% of the two comparison methods. The range of perception time is 0.25 s, which is much less than 0.87 s and 0.69 s of the two comparison methods, and the fluctuation range of the three indexes is less than one quarter to one third of that of the comparison method, which proves that the proposed method can maintain stable and excellent perception performance under different experimental conditions and different data batches, and has good engineering adaptability and reproducibility.

The above experimental results are rooted in the original contribution of this method at three levels, which are now clarified and expounded one by one as follows. The first original contribution is embodied in the screening mechanism of safety influencing factors. Although the existing methods based on dual attention mechanism can capture significant spatial and channel features, they are insufficient in capturing irregular risk factors that are scattered, changeable and easily overlooked in the construction scene, which is rooted in the lack of effective quantification of the correlation strength between factors in the feature screening process. In this study, the dynamic resolution coefficient is introduced to replace the fixed resolution coefficient in the traditional grey relational analysis, and the value of the resolution coefficient is adjusted adaptively through the information entropy function, which makes up for the problems of insufficient discrimination and reduced effectiveness of the correlation coefficient caused by the fixed resolution coefficient of 0.5 in the traditional method. At the same time, TOPSIS method is integrated, positive reference sequence and negative reference sequence are defined, and comprehensive grey correlation degree is constructed, which realises two-way comprehensive measurement and scientific ranking of the influence degree of each influencing factor. This screening mechanism ensures that the data dimension and feature space on which the perception model depends completely cover the main risk types such as falling, object strike, collapse, mechanical injury and electric shock, and avoids the systematic risk blind area caused by the omission of key factors from the source, which is the fundamental reason why the recall rate can reach the peak of 99.06%. The second original contribution is reflected in the modelling method of risk index. Although the existing methods based on BIM+GIS have realised 3D scene modelling and multi-source data integration, their risk discrimination rule base is insufficient for coupling risk identification in complex dynamic scenes, because its risk assessment model is essentially based on single-factor independent discriminant logic. In the construction of construction risk index, this study not only calculates the independent deviation risk contribution of each influencing factor, but also introduces the coupling influence term between factors, and defines the comprehensive risk index as the aggregation of independent contribution and coupling term. This design makes two factors which are not above the safety threshold in an independent state identify potential risks by the twin model due to their synergistic coupling, thus greatly reducing the probability of false positives and false negatives in complex construction scenes, which is the core reason why the accuracy rate can be stabilised at over 97%. The third original contribution is embodied in the unified mapping and dimensionality reduction strategy of multi-source heterogeneous data. The existing methods based on multi-classification Adaboost need to train multiple BP neural networks in parallel as basic classifiers, and then make comprehensive judgement after combining them into multiple strong classifiers. At the same time, it also needs to collect and process the subjective risk perception evaluation data of construction workers, which leads to a significant increase in the processing time of the whole process. In this study, the dimension of influencing factor data is reduced by local linear embedding method, and the feature space is compressed from high dimension to low dimension on the premise of maintaining the local linear relationship between samples, which greatly reduces the computational complexity of state update of twin model. On this basis, a unified mapping function from physical measurements to twin state variables is established, and three kinds of heterogeneous data, namely structural response, environmental load and human physiology, are included in the same expression framework, which avoids the delay of data integration and model update caused by multi-level architecture, which is the direct reason why the perception time can be shortened to sub-second level. Based on the above three original contributions, this method is significantly superior to the mainstream methods reported in the existing literature in three core indicators: recall, accuracy and perception time, and the performance fluctuation is the smallest, which fully verifies the effectiveness and superiority of this method in the whole process of high-rise building construction safety risk perception. This method can provide reliable technical support for the intelligent transformation of construction safety management from post-disposal to proactive prevention and control in advance, and has important engineering practice value and frontier significance for improving the intrinsic safety level of construction site and ensuring the life and health of workers.

## 4 Conclusions

A safety risk perception method of high-rise building construction process based on digital twin technology is proposed to address the problems of low recall rate, insufficient accuracy, and long perception delay in the entire process of high-rise building construction safety risk perception. Through theoretical analysis and experimental verification, the following conclusions are drawn:

1 In the screening of safety influencing factors, grey correlation analysis with dynamic resolution coefficient and TOPSIS method are adopted to effectively quantify the impact of various factors on construction safety, solving the problem of insufficient discrimination caused by fixed resolution coefficient in traditional methods.

2 By using local linear embedding method to reduce the dimensionality of influencing factor data, the feature space dimension is reduced while maintaining the local linear relationship between samples, providing low dimensional and information preserving feature inputs for the efficient construction of subsequent twin models.

3 The security risk perception architecture based on digital twin technology is constructed, which establishes a mapping relationship between physical measurement values and twin state values, and introduces coupling influence terms between factors to calculate the comprehensive construction risk index, achieving dynamic perception and graded warning of safety risks throughout the construction process.

4 The experimental results show that the proposed method significantly outperforms the comparison methods in terms of recall, accuracy, and perception time across 90 tests. Among them, the highest recall rate reached 99.06%, the highest accuracy rate reached 97.89%, the shortest perception time was 0.62 s, and the fluctuation amplitude of each indicator was smaller than that of the comparison method, showing excellent stability and real-time performance.

In summary, the proposed method can effectively improve the coverage integrity, judgement accuracy, and response timeliness of safety risk perception throughout the entire process of high-rise building construction, providing reliable technical support for the intelligent transformation of construction safety management from passive response to active prevention and control. In addition, the key parameters that constrain the perception accuracy of this model include the entropy function threshold of the dynamic resolution coefficient, the threshold of the cumulative variance contribution rate for dimensionality reduction, and the length of the rolling update window for the coupling coefficient. The threshold of entropy function affects the sensitivity of factor correlation, and grid search can be used to select the optimal value with the goal of maximising the harmonic mean of recall and accuracy. The threshold for cumulative variance contribution rate determines the dimensionality reduction and preservation dimensions. The optimal preservation dimensions for each construction stage can be determined by observing the inflection point of the feature value accumulation curve using the elbow rule. The update window length of the coupling coefficient affects the response speed and stability of the coupling effect. An adaptive window strategy can be used to dynamically adjust the window length based on the time series variance of the risk index. When the risk fluctuates violently, the window is automatically shortened to improve response sensitivity, and when the risk is stable, the window is extended to suppress estimated variance. The above parameter optimisation scheme can be automatically implemented through an online learning mechanism, further improving the prediction accuracy and engineering applicability of the model while maintaining computational efficiency.

## Declarations

All authors declare that they have no conflicts of interest.

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