



## OPEN A safety risk assessment method for TBM tunnel construction based on attribute interval identification theory

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Based on the identification and analysis of safety risks in TBM tunnel construction, we construct a comprehensive safety risk dynamic evaluation index system tailored to this context. To account for the dynamic nature of safety risks during TBM tunnel construction, variable weight theory is incorporated, allowing for a more accurate reflection of the time-varying importance of risk indicators. Building on the theoretical framework of attribute interval recognition theory, we establish a TBM tunnel construction safety risk evaluation model grounded in attribute interval theory. This model effectively addresses the various uncertainties inherent in the risk evaluation process for TBM tunnel construction. It determines the evaluation level and attribute intervals for each individual indicator, and subsequently calculates the interval values for both the individual indicators and the composite attribute. Finally, a case study demonstrates the model's effectiveness and practical applicability.

**Keywords** TBM, Variable weight theory, Attribute interval recognition, Risk assessment

The Tunnel Boring Machine (TBM) is a large-scale, specialized piece of equipment that integrates mechanical, electrical, hydraulic, guidance, sensing, and information technologies. Widely used in the tunnel construction industry since the 1950s, the TBM offers significant advantages over traditional drilling and blasting methods, including higher efficiency, speed, quality, and safety<sup>1</sup>. However, due to the complex and variable geological conditions encountered in inter-basin water transfer projects, as well as the technical limitations of TBM construction in China, safety risks associated with TBM tunnel construction remain a significant concern<sup>2</sup>. Therefore, conducting a comprehensive safety risk assessment for TBM tunnel construction is of crucial theoretical and practical importance.

Currently, numerous scholars both domestically and internationally have conducted research on TBM construction risks. Benardos et al.<sup>3</sup> assessed TBM construction risks by introducing a vulnerability index, while Clarke et al.<sup>4</sup> subsequently developed a comprehensive risk assessment method for predicting and analyzing damage and vulnerability indicators. Kim<sup>5</sup> and Hamidi<sup>6</sup>, utilizing Bayesian network technology combined with geological prediction and construction decision models, provide predictive guidance to decision-makers prior to tunnel construction. Zhao Yanxi et al.<sup>7</sup>, focusing on the randomness and fuzziness of TBM construction risks, established a risk evaluation index system and proposed a two-level fuzzy comprehensive evaluation model. Zhan Jinwu et al.<sup>8</sup> integrated hierarchical analysis with fuzzy evaluation to develop an intelligent evaluation model and decision support system, providing theoretical and technical support for TBM selection in complex geological conditions. Zong Qiulei<sup>9</sup> applied the C-OWA operator index weighting method to determine evaluation indicator weights and employed ladder fuzzy number operations to assess risk indicator levels. Song Zhanping et al.<sup>10</sup> introduced nonlinear operators to develop an improved FAHP model, enabling a more accurate and reliable quantitative evaluation of TBM construction risks, as validated by practical engineering cases. Fu Tao et al.<sup>11</sup> quantified the risk factors during TBM construction using the material element extension model and applied variable weight theory to determine the comprehensive weights for assessing the risk level. Chen Hongyu et al.<sup>12</sup> performed forward predictive reasoning, event sensitivity analysis, and reverse risk diagnosis

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through an improved cloud Bayesian network, which, combined with appropriate risk management and control measures, enabled dynamic safety perception and control of buildings near karst shield construction.

Traditional comprehensive risk assessment methods for TBM construction include the Bayesian network method<sup>12–14</sup>, analytic hierarchy process<sup>15–17</sup>, fuzzy comprehensive evaluation method<sup>18,19</sup>, cloud model method<sup>20,21</sup>, and Topsis method<sup>22</sup>, among others. In 1994, Professor Cheng Gansheng from Peking University's School of Mathematical Sciences proposed the theory of attribute mathematics, which primarily addresses multi-attribute decision-making issues through attribute sets and attribute space measures. Zhang Chuanfang<sup>23</sup>, Ruan Wanqing<sup>24</sup>, and Ren Zheng<sup>25</sup> have applied attribute interval recognition theory to fields such as natural disaster classification, groundwater exploitation safety evaluation, and sustainable water resource management, verifying the theory's scientific validity and practical utility. Further, Yang Fuqiang<sup>26</sup> and Zou Qiang<sup>27</sup> explored novel applications of entropy principles by combining information entropy theory and the maximum entropy principle with attribute interval recognition. Based on attribute mathematics, Li Shucan<sup>28</sup> proposed an attribute interval evaluation theory emphasizing the range of risk index values, while Zhou Zongqing<sup>29</sup> developed an improved attribute interval recognition method tailored to the complexities and uncertainties of tunnel and underground engineering, detailing multi-index attribute measurement and recognition analysis methods. Gongli<sup>30</sup> constructed an attribute interval identification model for the rockburst propensity class, which belongs to a typical multi-attribute ordered partition class problem, and classified the rockburst propensity class into four classes for prediction. Jiang He<sup>31</sup> establishes an attribute recognition theory-based risk assessment model for the surge water in Hong yashan Tunnel, and realises the risk assessment of the surge water in Hong yashan Tunnel by carrying out single-indicator attribute measurement analysis, multiple-indicator attribute measurement analysis and attribute recognition. Zhao<sup>32</sup> employed single-indicator measurement functions and multi-indicator measurement matrices to classify and assess water level spike risk indicators based on confidence criteria.

Though attribute interval recognition theory has been applied across multiple domains, especially tunnel engineering, it has not yet been directly applied to safety risk assessments in TBM construction. Therefore, this paper applies attribute interval recognition theory to TBM construction safety risk assessment, proposing targeted risk control strategies to support safe TBM tunnel construction practices.

### TBM tunnel construction safety risk evaluation index system

The geological environment of TBM tunnel construction is complicated, the construction team is numerous and the construction technology is complex, which leads to many factors of various risk accidents. Based on data collection, expert investigation and field investigation, combined with the accident cause and hazard identification theory, the initial safety risk factors were identified by the WBS-RBS method, which was divided into six categories: natural risk, geological risk, technical risk, equipment risk, accident risk and management risk, with a total of 44 indicators. The knowledge reduction technology in rough set theory is applied to screen out redundant factors, and finally determine the natural risk, geological risk, technical risk, equipment risk, accident risk and management risk, with a total of 23 indicators. The TBM tunnel construction safety risk evaluation system is obtained, as shown in Fig. 1 below.

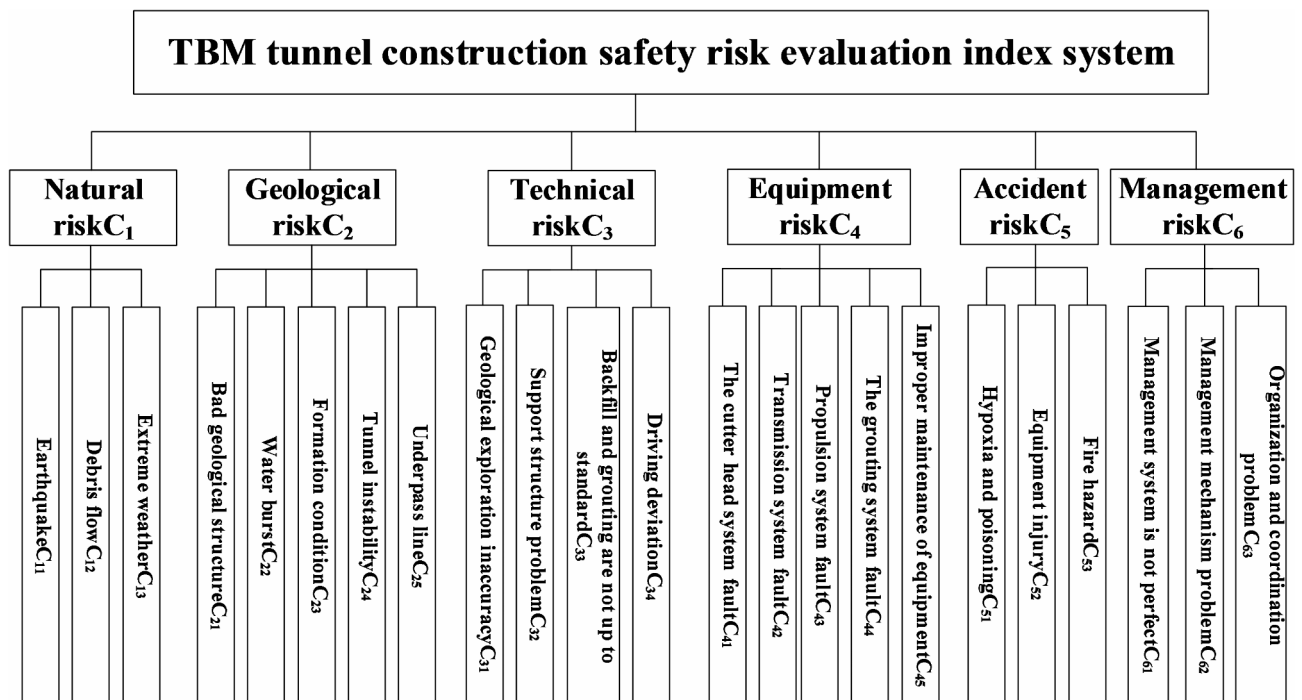


Fig. 1. TBM tunnel construction safety risk evaluation index system.

## Determination of construction safety risk index weight of TBM tunnel

The traditional risk assessment method can not accurately reflect the dynamic change of risk caused by geological conditions or environmental changes in the construction process by using a fixed evaluation index system and weight allocation for one-time risk analysis. Therefore, aiming at the dynamic demand of risk assessment during TBM tunnel construction, this study introduced a dynamic risk assessment model based on variable weight theory and realized real-time and accuracy of risk assessment through dynamic adjustment of weights.

### Normal weight calculation

This section utilizes the Best-Worst Method (BWM) to determine the subjective weights and the entropy weight method to calculate the objective weights. A game theory-based combination method is then employed to better balance subjective and objective factors, providing more comprehensive and accurate results for the dynamic risk evaluation of TBM construction and ensuring the scientific validity of the weight determination process.

*BWM (Best worst Method) is used to determine the subjective weight*

The steps of BWM method to determine subjective weight are as follows:

**Step 1:** Construct a set of evaluation criteria.

The influencing factors of the decision problem are determined by the expert team through discussion and analysis, forming a set containing all the important criteria  $C = \{C_1, C_2, \dots, C_n\}$ .

**Step 2:** Select the best and worst criteria.

Based on the experience of experts and the analysis of the actual situation, the most important criterion (the optimal criterion  $C_B$ ) and the least important criterion (the worst criterion  $C_W$ ) are identified from the criterion set, in which the optimal criterion has a decisive impact on the decision result, while the worst criterion has a relatively minimal impact.

**Step 3:** Comparative evaluation of optimal criteria.

By comparing the optimal criterion with all other criteria in the set, the relative preference degree of the optimal criterion is assessed, and the scoring system of 1 to 9 is used to form a comparison vector based on the optimal criterion  $A_B = [a_{B1}, a_{B2}, \dots, a_{Bn}]$ . Here each  $a_{Bj}$  represents the preference score between the optimal criterion and the JTH criterion, with a self-score of  $a_{BB} = 1$ .

**Step 4:** Comparative evaluation of the worst criteria.

Evaluate the degree of preference of each criterion in the set relative to the worst criterion, again using a rating system of 1 to 9, and construct a comparison vector based on the worst criterion  $A_W = [a_{1W}, a_{2W}, \dots, a_{nW}]^T$ . Here, each  $a_{jW}$  represents the preference score of the JTH criterion compared to the worst criterion, self-scoring  $a_{WW} = 1$ .

**Step 5:** Calculate the subjective weights.

The optimal weight vector is obtained by constructing the following model, where  $w^* = [w_1^*, w_2^*, \dots, w_n^*]$ , where  $w_j^*$  represents the optimal weight of criterion  $C_j$ .

Make  $\xi = \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}$ , the following equation is obtained:

$$\begin{aligned} & \min \xi \\ & s.t. \begin{cases} \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi \quad (j = 1, 2, \dots, n) \\ \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi \quad (j = 1, 2, \dots, n) \\ \sum_{j=1}^n w_j = 1, w_j \geq 0 \quad (j = 1, 2, \dots, n) \end{cases} \end{aligned} \quad (1)$$

After solving Eq. (1), the preferred weight  $w_1^*, w_2^*, \dots, w_n^*$ , and the minimum deviation  $\xi^*$  of the criterion are obtained.

*EWM (Entropy weight Method) is used to determine the objective weight*

**Step 1:** Construct the original matrix.

With  $m$  objects to be evaluated and  $n$  indexes of evaluation indicators, the original data matrix constructed is  $X = (x_{ij})_{m \times n}$ , which can be expressed as:

$$X = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (2)$$

**Step 2:** Standardize treatment.

In order to eliminate the dimensionality difference of construction safety risk index of different TBM, the matrix  $X$  is standardized. For the index that the greater the risk index parameter value, the lower the construction risk, the standardized formula is as follows:

$$b_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad (3)$$

For the index that the smaller the risk index parameter value, the lower the construction risk, the standardized formula is as follows:

$$b_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{4}$$

**Step 3:** Construct a standardized judgment matrix.

$$\tilde{B} = [b_{ij}]_{m \times n} = \begin{bmatrix} b_{11} & b_{21} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \dots & b_{mn} \end{bmatrix} \tag{5}$$

**Step 4:** Calculate the objective weights.

The entropy  $E_j$  of risk index  $X_j$  is calculated by Eq. (6):

$$r_{ij} = (1 + b_{ij}) / \sum_{i=1}^m (1 + b_{ij})$$

$$E_j = -(\ln m)^{-1} \sum_{i=1}^m r_{ij} \ln r_{ij} \tag{6}$$

Then the objective weight  $E_j$  of risk indicator  $X_j$  is:

$$w_j = \frac{1 - E_j}{\sum_{j=1}^n (1 - E_j)} \tag{7}$$

*Game theory combinatorial weighting method*

**Step 1:** Set the comprehensive weight vector  $W_z = \sum_{k=1}^L \alpha_k \cdot W_k^T$ .

Where:  $\alpha_k$  is the combination coefficient and  $W_k = (w_{ki}), k = 1, 2, \dots, L, i = 1, 2, \dots, n$  is the weight value calculated by each weighting method.

**Step 2:** Optimize the combination coefficient.

The obtained game model is shown in Eq. (8), and the conditions for its transformation into the optimal first derivative are shown in Eq. (9):

$$\min \left\| \sum_{k=1}^L \alpha_k \cdot W_k^T - W_t^T \right\|_2 \quad (k = 1, 2, \dots, L) \tag{8}$$

$$\begin{bmatrix} W_1 \cdot W_1^T & W_1 \cdot W_2^T & \dots & W_1 \cdot W_L^T \\ W_2 \cdot W_1^T & W_2 \cdot W_2^T & \dots & W_2 \cdot W_L^T \\ \vdots & \vdots & \ddots & \vdots \\ W_L \cdot W_1^T & W_L \cdot W_2^T & \dots & W_L \cdot W_L^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_L \end{bmatrix} = \begin{bmatrix} W_1 \cdot W_L^T \\ W_2 \cdot W_2^T \\ \vdots \\ W_L \cdot W_L^T \end{bmatrix} \tag{9}$$

**Step 3:** Normalization process.

$$\alpha'_k = \frac{|\alpha_k|}{\sum_{k=1}^L |\alpha_k|} \tag{10}$$

**Step 4:** Solve the comprehensive weight.

$$W'_z = \sum_{K=1}^L \alpha'_k W_k^T \tag{11}$$

**Variable weight evaluation model**

Variable weight theory, proposed by Wang Peizhuang et al., is the key to realizing dynamic risk assessment. Its core is to construct a variable weight vector to realize dynamic weight adjustment. Variable weight vector is based on the synthesis of the constant weight vector and state variable vector, and the state variable reflects the real-time state of the evaluation object. When the state changes, the state variable is recalculated to change the weight vector, thus adjusting the weight to respond to the dynamic change in risk.

State variable vector  $S_x$  is weighted by (normalized) Hardarmard product with state vector  $X$ , which can be expressed as:

$$\begin{aligned} X| \rightarrow S_x(X) &= S_x \cdot X = (S_1(X), S_2(X), \dots, S_m(X)) \cdot (x_1, x_2, \dots, x_m) \\ &= (S_1(X) \cdot x_1, S_2(X) \cdot x_2, \dots, S_m(X) \cdot x_m) \end{aligned} \quad (12)$$

Therefore, the variable weight vector  $W_j(X)$  is essentially the normalized product of the constant weight vector  $W$  and the state variable vector  $S_x$ , which can be expressed as follows:

$$W_j(X) = \frac{(w_1 S_1(X), w_2 S_2(X), \dots, w_m S_m(X))}{\sum_{j=1}^m (w_j S_j(X))} = \frac{W \cdot S_x}{\sum_{j=1}^m (w_j S_j(X))} \quad (13)$$

$$S_j(X) = \frac{\partial B(x_1, x_2, \dots, x_m)}{x_j} \quad (14)$$

It can be derived from formula (13) and Eq. (14)

$$W_j(X) = \frac{W \cdot \frac{\partial B(x_1, x_2, \dots, x_m)}{x_j}}{\sum_{j=1}^m (w_j \frac{\partial B(x_1, x_2, \dots, x_m)}{x_j})} \quad (15)$$

Wherein, function  $B(x_1, x_2, \dots, x_m)$  is the equilibrium function of state variables, which is divided into sum type ( $\Sigma$ type) equilibrium function and product type ( $\prod$ type) equilibrium function. In construction risk assessment, variable weight comprehensive model based on sum type state equilibrium function is commonly used, and its expressions are as follows:

$$B(x_1, x_2, \dots, x_m) = \prod_{j=1}^m x_j^\alpha (\alpha > 0) \quad (16)$$

On this basis, the state weight formula of safety risk in each section of TBM tunnel construction is derived as follows:

$$W_j(X) = \frac{w_j x_j^{\alpha-1}}{\sum_{j=1}^m w_j x_j^{\alpha-1}} (0 < \alpha < 1) \quad (17)$$

Formula (17) synthesizes the conventional weights in static risk assessment and the dynamic changes of each risk assessment index in the TBM tunnel construction process, which is helpful to understand and master the safety risk state of tunnel construction in real-time. The parameter  $\alpha$  in the formula reflects the attitude of the judge: When  $\alpha < 0.5$ , it indicates that the evaluators are conservative and pay more attention to the balance of risk factors. When  $\alpha > 0.5$ , it indicates that the evaluator is more open-minded and can tolerate the imbalance of risk factors to a certain extent. In practical applications, based on experience and expert advice, the value of  $\alpha$  is usually set at 0.5 as a standard for balanced risk assessment.

## Safety risk assessment of TBM tunnel construction based on improved attribute interval model

### Single index attribute measure interval analysis

Considering the complexity and uncertainty of the TBM construction process, the values of the evaluation indices are expressed as probability intervals. The safety risk evaluation of TBM tunnel construction is then conducted based on three aspects: single-indicator attribute measurement analysis, multi-indicator attribute measurement analysis, and attribute identification analysis<sup>29</sup>.

Considering the complexity and uncertainty of TBM construction projects, the evaluation system is composed of  $m$  evaluation indexes  $I_j (j = 1, 2, \dots, m)$ , which are divided into  $n$  risk levels  $C_k (k = 1, 2, \dots, n)$ . The actual value range corresponding to each evaluation indicator  $I_j$  is defined as an interval  $t_j = [t_{jx}, t_{jy}]$ . To quantitatively analyze the contribution of each index to the evaluation level, the attribute measure function is used

to calculate the attribute measure of a single index, and the result is expressed as an interval  $\mu_{jk} = \left[ \underline{\mu}_{jk}, \bar{\mu}_{jk} \right]$ .

The classification of risk evaluation is based on the construction method of attribute measure function represented by Eqs. (18) and (19), to realize the quantitative evaluation of the risk level of TBM construction engineering.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2k} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{j1} & a_{j2} & \cdots & a_{jk} & \cdots & a_{jn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mk} & \cdots & a_{mn} \end{bmatrix} \tag{18}$$

$$B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1k} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2k} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ b_{j1} & b_{j2} & \cdots & b_{jk} & \cdots & b_{jn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ b_{m1} & b_{m2} & \cdots & b_{mk} & \cdots & b_{mn} \end{bmatrix} \tag{19}$$

Formula:  $a_{jk} < b_{jk}$  and satisfy  $a_{j1} < a_{j2} < \cdots < a_{jn}, b_{j1} < b_{j2} < \cdots < b_{jn}$ ; Or  $a_{jk} \geq b_{jk}$  and satisfy  $a_{j1} > a_{j2} > \cdots > a_{jn}, b_{j1} > b_{j2} > \cdots > b_{jn}$ .

In the calculation of a single index attribute measure, when the conditions  $a_{jk} < b_{jk}$  and  $a_{j1} < a_{j2} < \cdots < a_{jn}, b_{j1} < b_{j2} < \cdots < b_{jn}$  are met, the following method is used for calculation. The calculation process considers the value range of the indicator  $I_j, t_j = [t_{jx}, t_{jy}]$ , that is, the lower limit  $t_{jx}$  and upper limit  $t_{jx}$  of each evaluation indicator are respectively measured to determine the attribute measure value corresponding to the evaluation level  $C_k$ .

When  $t_j \leq a_{j1}$ ,

$$\mu_{-j1} = 1, \mu_{-j2} = \cdots = \mu_{-jn} = 0 \tag{20}$$

When  $t_j \leq b_{j1}$ ,

$$\bar{\mu}_{j1} = 1, \bar{\mu}_{j2} = \cdots = \bar{\mu}_{jn} = 0 \tag{21}$$

When  $t_j \geq a_{jn}$ ,

$$\mu_{-jn} = 1, \mu_{-j1} = \cdots = \mu_{-jn-1} = 0 \tag{22}$$

When  $t_j \geq b_{jn}$ ,

$$\bar{\mu}_{jn} = 1, \bar{\mu}_{j1} = \cdots = \bar{\mu}_{jn-1} = 0 \tag{23}$$

When  $a_{jk} \leq t_j \leq a_{jk+1}$ ,

$$\mu_{-jk} = \frac{|t_j - a_{jk+1}|}{|a_{jk} - a_{jk+1}|}, \mu_{-jk+1} = \frac{|t_j - a_{jk}|}{|a_{jk} - a_{jk-1}|}, \mu_{-jl} = 0 \tag{24}$$

Where:  $l < k$  or  $l > k + 1$ .

When  $b_{jk} \leq t_j \leq b_{jk+1}$ ,

$$\bar{\mu}_{jk} = \frac{|t_j - b_{jk+1}|}{|b_{jk} - b_{jk+1}|}, \bar{\mu}_{jk+1} = \frac{|t_j - b_{jk}|}{|b_{jk} - b_{jk-1}|}, \bar{\mu}_{jl} = 0 \tag{25}$$

Where:  $l < k$  or  $l > k + 1$ .

For  $t_{jx}$ , two single index attribute measure matrices can be obtained after calculation:

$$\begin{aligned}
 \underline{U}_{jxk} &= \begin{bmatrix} \underline{\mu}_{1x1} & \underline{\mu}_{1x2} & \cdots & \underline{\mu}_{1xk} & \cdots & \underline{\mu}_{1xn} \\ \underline{\mu}_{2x1} & \underline{\mu}_{2x2} & \cdots & \underline{\mu}_{2xk} & \cdots & \underline{\mu}_{2xn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \underline{\mu}_{jx1} & \underline{\mu}_{jx2} & \cdots & \underline{\mu}_{jxk} & \cdots & \underline{\mu}_{jxn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \underline{\mu}_{mx1} & \underline{\mu}_{mx2} & \cdots & \underline{\mu}_{mxk} & \cdots & \underline{\mu}_{m xn} \end{bmatrix} \\
 \bar{U}_{jxk} &= \begin{bmatrix} \bar{\mu}_{1x1} & \bar{\mu}_{1x2} & \cdots & \bar{\mu}_{1xk} & \cdots & \bar{\mu}_{1xn} \\ \bar{\mu}_{2x1} & \bar{\mu}_{2x2} & \cdots & \bar{\mu}_{2xk} & \cdots & \bar{\mu}_{2xn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{\mu}_{jx1} & \bar{\mu}_{jx2} & \cdots & \bar{\mu}_{jxk} & \cdots & \bar{\mu}_{jxn} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \bar{\mu}_{mx1} & \bar{\mu}_{mx2} & \cdots & \bar{\mu}_{mxk} & \cdots & \bar{\mu}_{m xn} \end{bmatrix}
 \end{aligned} \tag{26}$$

According to the analysis of the upper limit of indicator value  $t_{jy}$ , two single indicator attribute measure matrices can be obtained through calculation, whose structure is consistent with the matrix(25) mentioned earlier.

**Multi-index attribute measure interval analysis**

For the single index attribute measure matrix calculated by formula(19)~(24), four comprehensive attribute measures can be obtained correspondingly, and the calculation formula is as follows:

$$\begin{aligned}
 \underline{\mu}_{j'xk} &= \sum_{j=1}^m (\omega_j \underline{\mu}_{jxk}), \bar{\mu}_{j'xk} = \sum_{j=1}^m (\omega_j \bar{\mu}_{jxk}) \\
 \underline{\mu}_{j'yk} &= \sum_{j=1}^m (\omega_j \underline{\mu}_{jyk}), \bar{\mu}_{j'yk} = \sum_{j=1}^m (\omega_j \bar{\mu}_{jyk})
 \end{aligned} \tag{27}$$

Where:  $\omega_j$  is the weight of the JTH evaluation index, satisfied

$$0 \leq \omega_j \leq 1, \sum_{j=1}^m \omega_j = 1 \tag{28}$$

**Improved attribute interval recognition model**

The original attribute interval recognition model has certain limitations. To further improve the accuracy of evaluation results, scholars have optimized and improved the model<sup>[54]</sup>, mainly from the following two aspects:

- (1) Qualitative analysis.

The average value of the comprehensive attribute measure  $\mu_k$  corresponding to the KTH evaluation level is calculated, and the risk level of the evaluation object is judged according to the confidence criterion.

$$\mu_k = \frac{\underline{\mu}_{xk} + \bar{\mu}_{xk} + \underline{\mu}_{yk} + \bar{\mu}_{yk}}{4} \tag{29}$$

- (2) Probability analysis.

Define vectors:

$$\begin{aligned}
 \underline{\mu}_{jxk} &= \left[ \underline{\mu}_{jx1}, \underline{\mu}_{jx2}, \cdots, \underline{\mu}_{jxn} \right], \bar{\mu}_{jxk} = \left[ \bar{\mu}_{jx1}, \bar{\mu}_{jx2}, \cdots, \bar{\mu}_{jxn} \right] \\
 \underline{\mu}_{jyk} &= \left[ \underline{\mu}_{jy1}, \underline{\mu}_{jy2}, \cdots, \underline{\mu}_{jyn} \right], \bar{\mu}_{jyk} = \left[ \bar{\mu}_{jy1}, \bar{\mu}_{jy2}, \cdots, \bar{\mu}_{jyn} \right]
 \end{aligned} \tag{30}$$

In this case, two single index attribute measure matrices can be obtained:

$$U_{jxk} = \begin{bmatrix} \underline{\mu}_{1xk} \\ \underline{\mu}_{2xk} \\ \vdots \\ \underline{\mu}_{jxk} \\ \vdots \\ \underline{\mu}_{mxk} \end{bmatrix}, \bar{U}_{jyk} = \begin{bmatrix} \bar{\mu}_{1xk} \\ \bar{\mu}_{2xk} \\ \vdots \\ \bar{\mu}_{jxk} \\ \vdots \\ \bar{\mu}_{mxk} \end{bmatrix} \tag{31}$$

The single index attribute measure matrix corresponding to the upper limit of measurement  $t_{jy}$  can be expressed as

$$U_{jyk} = \begin{bmatrix} \underline{\mu}_{1yk} \\ \underline{\mu}_{2yk} \\ \vdots \\ \underline{\mu}_{jyk} \\ \vdots \\ \underline{\mu}_{myk} \end{bmatrix}, \bar{U}_{jyk} = \begin{bmatrix} \bar{\mu}_{1yk} \\ \bar{\mu}_{2yk} \\ \vdots \\ \bar{\mu}_{jyk} \\ \vdots \\ \bar{\mu}_{myk} \end{bmatrix} \tag{32}$$

Where: For the JTH evaluation indicator of the evaluation object, the single indicator attribute measures vectors calculated by its measurement values  $t_{jx}$  and  $t_{jy}$  are  $\underline{\mu}_{jxk}$  and  $\bar{\mu}_{jxk}$ , and  $\underline{\mu}_{jyk}$  and  $\bar{\mu}_{jyk}$ , respectively.

By averaging each of these vectors

$$\mu_{jxk} = \frac{\underline{\mu}_{jxk} + \bar{\mu}_{jxk}}{2}, \mu_{jyk} = \frac{\underline{\mu}_{jyk} + \bar{\mu}_{jyk}}{2} \tag{33}$$

Two single index attribute measure matrices are obtained:

$$U_{jxk} = \begin{bmatrix} \mu_{1xk} \\ \mu_{2xk} \\ \vdots \\ \mu_{jxk} \\ \vdots \\ \mu_{mxk} \end{bmatrix}, U_{jyk} = \begin{bmatrix} \mu_{1yk} \\ \mu_{2yk} \\ \vdots \\ \mu_{jyk} \\ \vdots \\ \mu_{myk} \end{bmatrix} \tag{34}$$

Formula:

$$\mu_{jxk} = [\mu_{jx1}, \mu_{jx2}, \dots, \mu_{jxn}], \mu_{jyk} = [\mu_{jy1}, \mu_{jy2}, \dots, \mu_{jyn}] \tag{35}$$

The vectors  $\mu_{jxk}$  and  $\mu_{jyk}$  are arranged successively to form a  $m \times n$  order matrix  $U_{jk}$ , where the single index attribute measure vectors of each index form a row of the matrix. Using this method,  $2^m U_{jk}$  matrix can be constructed, which provides a comprehensive attribute measurement basis for each evaluation index of the evaluation object.

$$U_{jk} = \begin{bmatrix} C_2^1(\mu_{1xk}, \mu_{1yk}) \\ C_2^1(\mu_{2xk}, \mu_{2yk}) \\ \vdots \\ C_2^1(\mu_{jxk}, \mu_{jyk}) \\ \vdots \\ C_2^1(\mu_{mxk}, \mu_{myk}) \end{bmatrix} \tag{36}$$

In the formula:  $C_2^1(\mu_{jxk}, \mu_{jyk})$  indicates that either  $\mu_{jxk}$  or  $\mu_{jyk}$  is selected.  $U_{jk}$  can be expressed as follows:

$$U_{jk} = [\mu'_{j1}, \mu'_{j2}, \dots, \mu'_{jk}, \dots, \mu'_{jn}] \tag{37}$$

$$\mu'_{jk} = [\mu_{1k}, \mu_{2k}, \dots, \mu_{jk}, \dots, \mu_{mk}]^T$$

Where:  $\mu'_{jk}$  is an  $m$ -dimensional column vector, namely the KTH column of  $U_{jk}$ . Then the comprehensive attribute measure corresponding to  $U_{jk}$  can be calculated by the following formula:

$$\mu_k = \omega_j \mu'_{jk} = [\omega_1, \omega_2, \dots, \omega_m] [\mu_{1k}, \mu_{2k}, \dots, \mu_{jk}, \dots, \mu_{mk}]^T \quad (38)$$

Where:  $\omega_j$  is the weight vector of the evaluation index.

For each calculated single index attribute measure matrix  $U_{jk}$ , the confidence criterion is applied to evaluate its corresponding risk level  $C_{k_0}$ . From this,  $2^m$  risk levels of  $k_0$  can be obtained. Subsequently, for each possible risk level  $1, 2, \dots, n$ , counts the number of occurrences and calculates its proportion among all possibilities.

By constructing different single index attribute measure matrix combinations, the comprehensive measure corresponding to each matrix is calculated, the proportion of occurrence times of each risk level is calculated, and the risk level is analyzed from the perspective of probability. This method provides a probabilistic interpretation of qualitative results and makes the evaluation results more convincing.

## Case analysis

### Project overview

The tunnel is located in Anyang City, with a total length of 13.18 km. Tunnel engineering mainly includes the TBM excavation section, drilling and blasting section, TBM starting point, TBM receiving point and drilling and blasting entrance. For the TBM excavation section with pile number 18 + 896 ~ 30 + 718, the length from the TBM exit section to the TBM starting section is 11,822 m, with a gradient drop of 0.01%. The circular section is adopted, the excavation diameter is 4.33 m, and the design section size is 3.5 m. Double shield TBM is used in excavation construction, the longitudinal design slope is 0.01%, and the plane design turning radius is 1500 m.

### Weight determination

#### The determination of permanent power weight

The BWM method is used to calculate the subjective weight, the entropy weight method to calculate the objective weight, and the game theory method is used to synthesize the weight. The specific weight values are shown in Table 1:

Therefore, the initial weight set of risk assessment indicators is determined as follows:

$$W^0 = \begin{cases} 0.0649 & 0.0542 & 0.0231 & 0.0822 & 0.0518 & 0.0648 & 0.0375 & 0.0290 \\ 0.0524 & 0.0314 & 0.0340 & 0.0518 & 0.0327 & 0.0278 & 0.0969 & 0.0260 \\ 0.0196 & 0.0448 & 0.0475 & 0.0169 & 0.0556 & 0.0311 & 0.0241 \end{cases}$$

#### Determination of variable weight

According to the variable weight theory, the state variable weight vector  $S(X)$  and variable weight vector  $W$  are determined by Eqs. (12)–(16), as shown in Tables 2 and 3.

Through an in-depth analysis of the TBM construction risk weighting vectors presented in Table 3, this study identifies the variations in the importance of several key risk indicators at different construction stages.

Index	BWM	EWM	BWM-EWM
Earthquake	0.0777	0.0509	0.0649
Debris flow	0.0295	0.0811	0.0542
Extreme weather	0.0134	0.0337	0.0231
Bad geological structure	0.1203	0.0407	0.0822
Water burst	0.0668	0.0354	0.0518
Formation condition	0.0668	0.0626	0.0648
Tunnel instability	0.0446	0.0297	0.0375
Underpass line	0.0267	0.0314	0.0290
Geological exploration inaccuracy	0.0758	0.0269	0.0524
Support structure problem	0.0408	0.0212	0.0314
Backfill and grouting are not up to standard	0.0408	0.0266	0.0340
TBM driving deviation	0.0233	0.0828	0.0518
The cutter head system fault	0.0392	0.0256	0.0327
Transmission system fault	0.0261	0.0296	0.0278
Propulsion system fault	0.0749	0.1209	0.0969
The grouting system fault	0.0261	0.0258	0.0260
Improper maintenance of equipment	0.0143	0.0254	0.0196
Hypoxia and poisoning	0.0392	0.0509	0.0448
Equipment injury	0.0211	0.0763	0.0475
Fire hazard	0.0121	0.0221	0.0169
Management system is not perfect	0.0602	0.0506	0.0556
Management mechanism problem	0.0362	0.0256	0.0311
Organization and coordination problem	0.0241	0.0242	0.0241

**Table 1.** The game theory method combines weights.

Index	K <sub>1</sub> <sup>#</sup>	K <sub>2</sub> <sup>#</sup>	K <sub>3</sub> <sup>#</sup>	K <sub>4</sub> <sup>#</sup>	K <sub>5</sub> <sup>#</sup>	K <sub>6</sub> <sup>#</sup>
Earthquake	0.8	0.8	0.85	0.9	0.85	0.9
Debris flow	0.95	0.85	0.95	0.85	0.85	0.9
Extreme weather	0.55	0.6	0.8	0.9	0.9	0.8
Bad geological structure	0.45	0.45	0.25	0.35	0.8	0.4
Water burst	0.98	0.99	0.9767	0.9667	0.98	0.97
Formation condition	0.5	0.35	0.35	0.45	0.8	0.55
Tunnel instability	0.718	0.69	0.65	0.67	0.73	0.71
Underpass line	0.95	0.95	0.95	0.85	0.8	0.75
Geological exploration inaccuracy	0.93	0.91	0.94	0.87	0.92	0.84
Support structure problem	0.75	0.55	0.8	0.85	0.8	0.85
Backfill and grouting are not up to standard	0.85	0.9	0.8	0.85	0.85	0.9
TBM driving deviation	0.85	0.9	0.9	0.95	0.85	0.85
The cutter head system fault	0.65	0.85	0.9	0.9	0.75	0.8
Transmission system fault	0.85	0.85	0.9	0.95	0.8	0.9
Propulsion system fault	0.85	0.9	0.85	0.85	0.9	0.85
The grouting system fault	0.85	0.85	0.9	0.75	0.8	0.85
Improper maintenance of equipment	0.7	0.75	0.75	0.75	0.8	0.75
Hypoxia and poisoning	0.95	0.9	0.95	0.85	0.9	0.85
Equipment injury	0.9	0.95	0.9	0.95	0.9	0.95
Fire hazard	0.75	0.9	0.9	0.9	0.85	0.85
Management system is not perfect	0.8	0.75	0.75	0.85	0.8	0.8
Management mechanism problem	0.75	0.8	0.85	0.8	0.85	0.85
Organization and coordination problem	0.75	0.75	0.65	0.85	0.8	0.8

**Table 2.** State variable weight vector.

Index	K <sub>1</sub> <sup>#</sup>	K <sub>2</sub> <sup>#</sup>	K <sub>3</sub> <sup>#</sup>	K <sub>4</sub> <sup>#</sup>	K <sub>5</sub> <sup>#</sup>	K <sub>6</sub> <sup>#</sup>
Earthquake	0.0642	0.0635	0.0604	0.0607	0.0655	0.0612
Debris flow	0.0526	0.0549	0.0510	0.0557	0.0584	0.0546
Extreme weather	0.0294	0.0278	0.0237	0.0231	0.0242	0.0246
Bad geological structure	0.0885	0.0875	0.1152	0.1006	0.0698	0.0948
Water burst	0.0394	0.0388	0.0383	0.0398	0.0414	0.0400
Formation condition	0.0736	0.0869	0.0853	0.0778	0.0612	0.0709
Tunnel instability	0.0342	0.0345	0.0349	0.0355	0.0357	0.0347
Underpass line	0.0244	0.0242	0.0237	0.0259	0.0280	0.0278
Geological exploration inaccuracy	0.0468	0.0468	0.0451	0.0485	0.0495	0.0497
Support structure problem	0.0317	0.0367	0.0298	0.0299	0.0323	0.0301
Backfill and grouting are not up to standard	0.0327	0.0314	0.0327	0.0328	0.0343	0.0321
TBM driving deviation	0.0537	0.0516	0.0506	0.0509	0.0564	0.0542
The cutter head system fault	0.0356	0.0308	0.0294	0.0304	0.0349	0.0324
Transmission system fault	0.0332	0.0329	0.0313	0.0315	0.0360	0.0326
Propulsion system fault	0.0895	0.0860	0.0868	0.0897	0.0914	0.0904
The grouting system fault	0.0253	0.0250	0.0238	0.0270	0.0274	0.0255
Improper maintenance of equipment	0.0244	0.0233	0.0229	0.0236	0.0240	0.0238
Hypoxia and poisoning	0.0421	0.0427	0.0408	0.0446	0.0455	0.0449
Equipment injury	0.0478	0.0460	0.0464	0.0467	0.0503	0.0470
Fire hazard	0.0181	0.0164	0.0161	0.0166	0.0179	0.0172
Management system is not perfect	0.0557	0.0569	0.0558	0.0542	0.0586	0.0563
Management mechanism problem	0.0260	0.0249	0.0237	0.0252	0.0257	0.0247
Organization and coordination problem	0.0310	0.0307	0.0323	0.0292	0.0316	0.0304

**Table 3.** Variable weight vector of the index.

This facilitates the deduction of risk causes and hazards based on typical risk types. Taking the indicators of ‘adverse geological structure’ and ‘stratigraphic conditions’ as examples, their weights differ significantly across construction sections, with these changes reflecting the geological complexity encountered during construction and its impact on project safety. Additionally, although the weight of the ‘propulsion system failure’ indicator remains stable within the range of 0.0860–0.0914 and shows little change, the slight increase observed throughout the construction process emphasizes the ongoing importance of propulsion system reliability, given its influence on construction quality and progress in past projects. The rising weights of the risk indicators ‘oxygen deprivation and poisoning’ and ‘equipment injury’ underscore the critical safety issues associated with the closed construction environment and equipment operation. The graph of variable weights versus constant weights for each segment and the heat map of variable weight vectors are shown in Fig. 2.

### Safety risk evaluation of TBM construction based on improved attribute interval measure

#### Single index attribute measure

According to the quantitative classification standard of TBM tunnel construction safety risk and formula (18)–(26), the attribute measurement function is constructed. Among them,  $I_5$  water burst,  $I_7$  tunnel instability, and  $I_9$  geological exploration inaccuracy are data surveys, and the other indicators are expert scores, as shown in Figs. 3, 4, 5 and 6.

Based on the comprehensive analysis of preliminary geological prospecting and field data collection, the TBM construction safety risks of each section of tunnel K21 + 850 ~ K27 + 850 are evaluated. The value range of evaluation indicators ( $t_{jx}, t_{jy}$ ) are shown in supplementary file.

The attribute measure function is constructed according to Figs. 2, 3, 4 and 5, and the 6-segment single-attribute measure matrix  $\underline{U}_{jxk}, \overline{U}_{jxk}, \underline{U}_{jyk}$  and  $\overline{U}_{jyk}$  for K21 + 850 ~ K27 + 850 are obtained. Due to the excessive length of calculation, this paper only lists the calculation process of the  $K_1^\#$  segment.  $\underline{U}_{jxk}, \overline{U}_{jxk}, \underline{U}_{jyk}$  and  $\overline{U}_{jyk}$  single attribute measure matrix are shown in supplementary file.

#### Multi-index attribute measure

Four synthetic attribute measure matrices are obtained from formula (27), and then formula (29) is used to calculate the  $\mu_k$  attribute measure of  $K_1^\#$  and other tunnel segments.

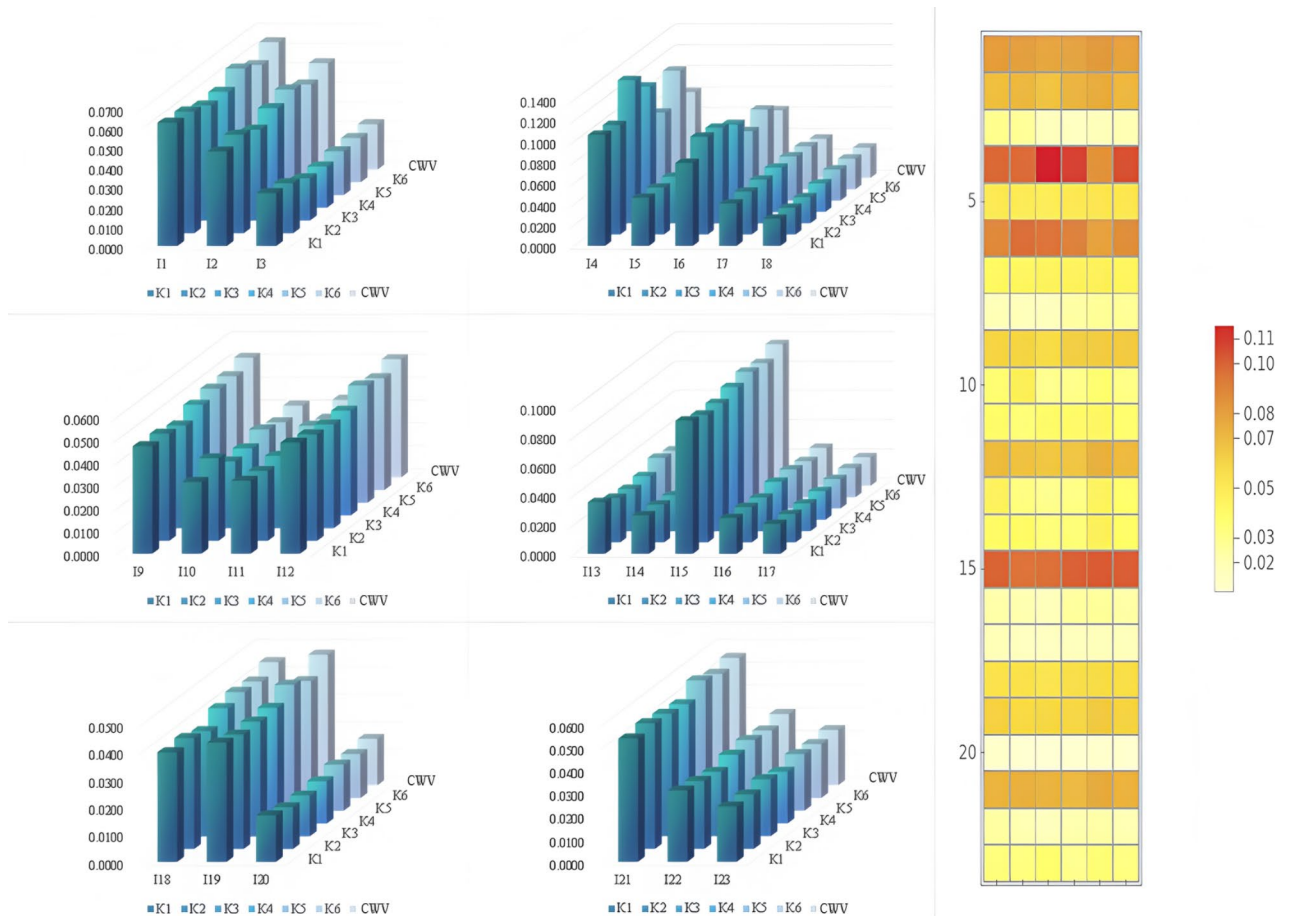


Fig. 2. K1#–K6# variable weight vector comparison diagram and heat map. CWV, constant weight vector.

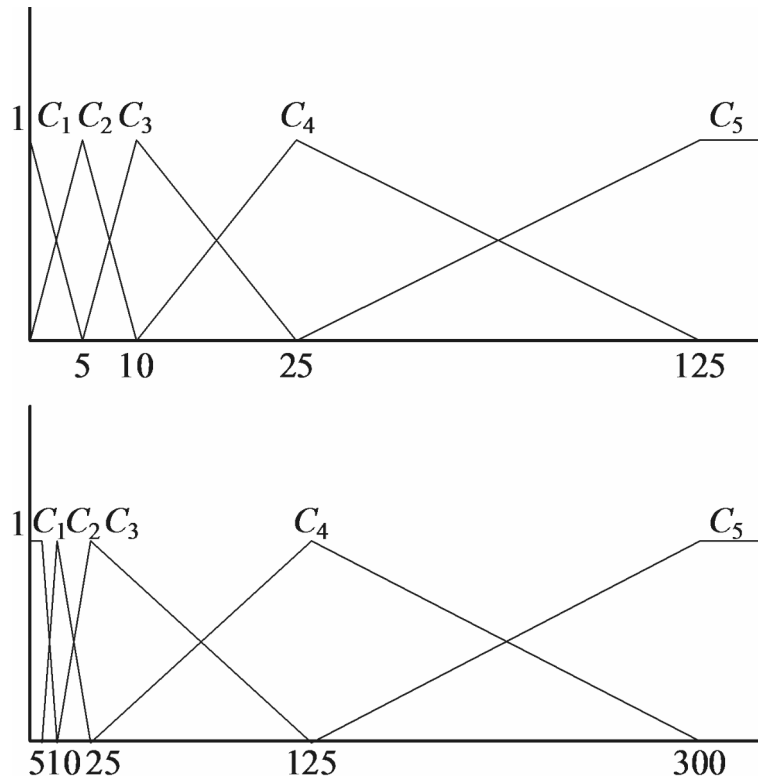


Fig. 3. Water burst index.

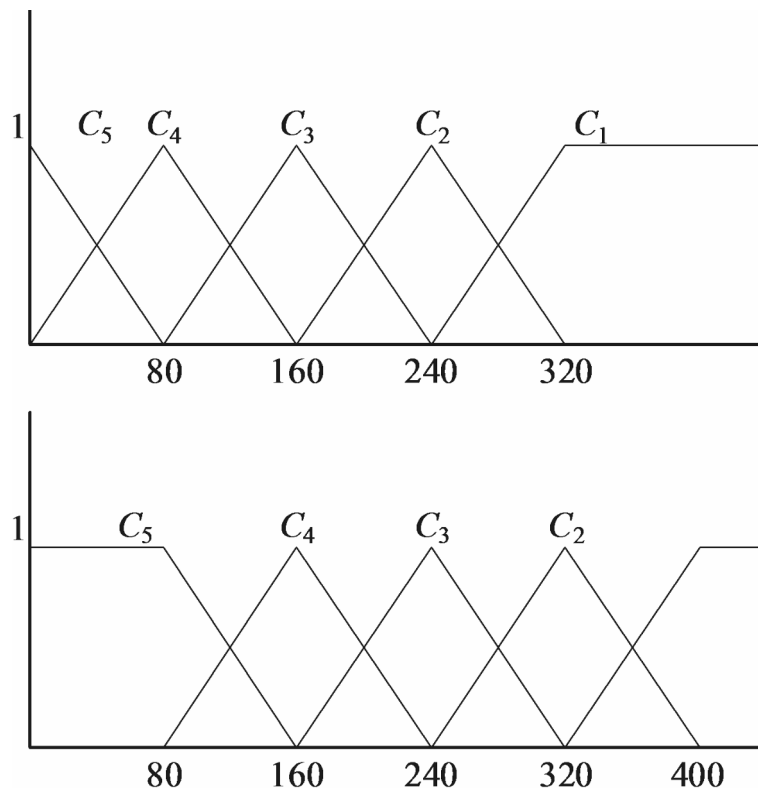


Fig. 4. Tunnel instability index.

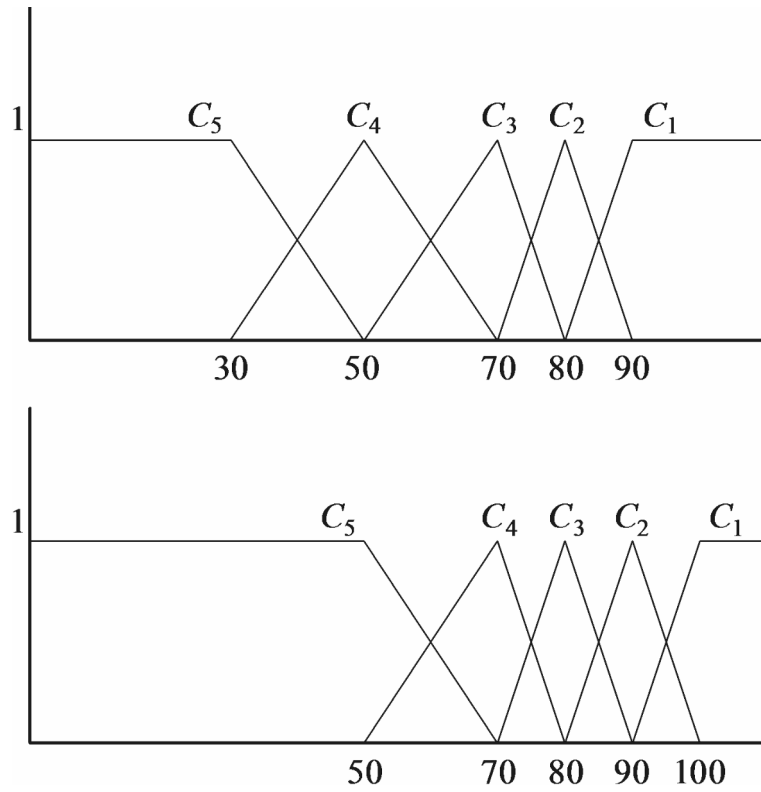


Fig. 5. Geological exploration index.

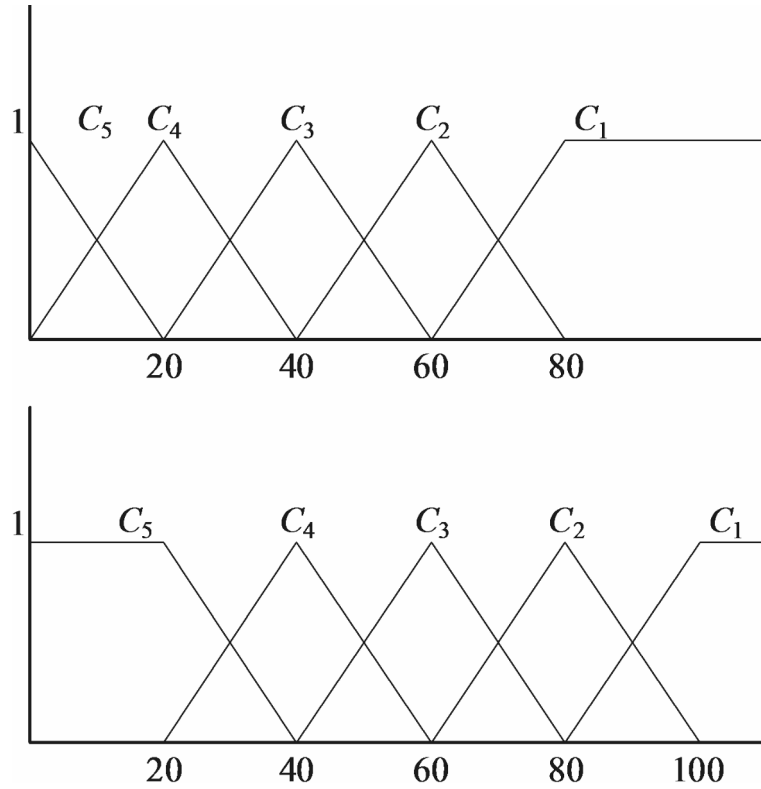


Fig. 6. Remaining indices.

Tunnel section	1	2	3	4	5	Risk level
$K_1^{\#}$	0.4501	0.3431	0.1514	0.0554	0	3
$K_2^{\#}$	0.4619	0.3069	0.1379	0.0824	0.0109	3
$K_3^{\#}$	0.4646	0.2838	0.0975	0.1003	0.0539	3
$K_4^{\#}$	0.4975	0.2977	0.1107	0.0817	0.0126	3
$K_5^{\#}$	0.5711	0.3854	0.0435	0	0	2
$K_6^{\#}$	0.4786	0.3518	0.1119	0.0518	0.0059	2

**Table 4.** Risk scale.

Tunnel section	1	2	3	4	5	Risk level
$K_1^{\#}$	0	41.724	58.276	0	0	3
$K_2^{\#}$	0	11.133	88.867	0	0	3
$K_3^{\#}$	0	0	75.000	25.000	0	3
$K_4^{\#}$	0	45.312	54.688	0	0	3
$K_5^{\#}$	0	100.000	0	0	0	2
$K_6^{\#}$	0	79.199	20.801	0	0	2

**Table 5.** Risk probability table.

$$\mu_k = \begin{pmatrix} 0.4501 & 0.3431 & 0.1514 & 0.0554 & 0 \\ 0.4619 & 0.3069 & 0.1379 & 0.0824 & 0.0109 \\ 0.4646 & 0.2838 & 0.0975 & 0.1003 & 0.0539 \\ 0.4975 & 0.2977 & 0.1107 & 0.0817 & 0.0126 \\ 0.5711 & 0.3854 & 0.0435 & 0 & 0 \\ 0.4786 & 0.3518 & 0.1119 & 0.0518 & 0.0059 \end{pmatrix}$$

*Attribute recognition analysis*

The improved attribute interval recognition model is used for comprehensive measure analysis, and qualitative and probability analysis are used to analyze the example.

(1) Qualitative analysis.

The  $\mu_k$  attribute measure of 6 tunnels is obtained. A risk assessment was carried out, and the confidence coefficient  $\lambda$  was set at 0.8 to determine the risk levels of each paragraph, as shown in Table 4.

(2) Probability analysis.

According to Eq. (26),  $U_{jxk}$  and  $U_{jyk}$  of each tunnel matrix can be obtained, and  $2^{23}$  combinations can be obtained by combining  $\mu_{jxk}$  and  $\mu_{jyk}$ .

In the description of geological conditions in Table 5, tunnel sections  $K_1^{\#}$  to  $K_6^{\#}$  are affected by different faults, resulting in large differences in rock integrity. The integrity of  $K_1^{\#}$  and  $K_2^{\#}$  is poor due to F-4 and F8-1 faults. However,  $K_3^{\#}$  and  $K_4^{\#}$  segments are affected by F8-2 and F9 fracture, respectively, and show a broken state. On the contrary, the geological condition of  $K_5^{\#}$  is relatively good, not affected by obvious faults, and the integrity of the rock mass is good. However,  $K_6^{\#}$  is affected by F10 fault, and the integrity of the rock mass is also poor.

Combined with the qualitative analysis of risk levels, it is found that  $K_1^{\#}$ ,  $K_2^{\#}$ ,  $K_3^{\#}$  and  $K_4^{\#}$  are all qualitatively classified as C3 levels, indicating that there are high construction safety risks. Specifically, the probability of  $K_1^{\#}$  level 2 is 41.724%, and the probability of level 3 is 58.276%. The probability of  $K_2^{\#}$  Class 2 is 11.133%, and the probability of class 3 is 88.867%. The probability of  $K_3^{\#}$  Grade 3 is 75.000%, and the probability of grade 4 is 25.000%. The probability of  $K_4^{\#}$  Grade 2 is 45.3125%, and the probability of grade 3 is 54.688%. In contrast, section  $K_5^{\#}$  is characterized as Class C2 with a Class 2 probability of 100.000%, indicating a relatively low construction safety risk. On the other hand, the  $K_6^{\#}$  segment is characterized as class C2, but the probability of Class 2 is 79.199%, and the probability of Class 3 is 20.801%, which still needs to be concerned about its higher potential risk.

*Countermeasures and suggestions*

In the process of TBM tunnel construction, faced with the construction risk caused by the difference of geological conditions in different tunnel sections, this study adopts qualitative and probabilistic analysis methods. The analysis results show that the  $K_1^{\#}$  to  $K_4^{\#}$  section is located in the fault zone, the degree of rock fragmentation is high, and there are great construction safety risks. In contrast,  $K_5^{\#}$  section is not affected by a fracture because of the integrity of the rock mass, and the construction risk is low. Although the qualitative risk grade of  $K_6^{\#}$  is low, the probability analysis shows that there is a high-risk probability that cannot be ignored, mainly because of the influence of F10 fracture.

For tunnel sections with different risk levels, the following prevention and control strategies are proposed:

- (1) High-risk segment ( $K_1^{\#}$ – $K_4^{\#}$ ): Strengthen on-site monitoring, adjust TBM operating parameters to reduce rock mass disturbance, build a risk warning system, and take additional dry pipe jacking and temporary support measures to enhance rock mass stability.
- (2) Middle and low risk segment ( $K_5^{\#}$ ): Maintain routine monitoring and standard support measures to ensure continuous construction safety.
- (3) Specific risk segment ( $K_6^{\#}$ ): Pay attention to rock deformation and stress distribution, formulate emergency plans, and adopt advanced support measures to deal with potential risks when necessary.

In addition, other sources of risk, such as mechanical failures and ventilation systems, must be addressed through comprehensive risk management strategies. These targeted measures can effectively reduce the safety risk in the TBM construction process and ensure the smooth progress of the project.

## Conclusion

Based on data analysis and site investigation, this study identifies, optimizes, and analyzes six categories of risk—namely, natural, geological, technical, equipment, accident, and management risks—resulting in a total of 23 indicators tailored to the safety characteristics of TBM tunnel construction. By using a game-theory-based variable weight approach, the model allows risk assessment index weights to adapt in real time to changing risk environments, thereby enhancing both the accuracy of evaluation results and the effectiveness of decision-making processes. Additionally, the improved attribute interval identification method is applied to assess TBM construction safety risks, enabling a quantitative analysis that accounts for the uncertainties associated with various influencing factors in the TBM construction process. Through example analysis, the construction process is divided into six segments. The accuracy and effectiveness of the model are verified by dynamically identifying and analyzing the relevant influencing factors in each construction segment and proposing key risk sources and countermeasures for each segment in a targeted manner.

## Data availability

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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### Author contributions

Bo Wang: Project administration, Methodology, Formal analysis. Qikai Li: Writing – original draft, Validation, Software, Investigation. Zefan Xu: Validation. Shibin Niu: Writing – review & editing, Data curation. Xiangtian Nie: Validation, Supervision, Resources.

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### Competing interests

The authors declare no competing interests.

### Additional information

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