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A novel dam safety risk assessment approach incorporating the human factors system and the incentive-variable weight method

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Highlights

- Human factors and an indicator system are introduced into dam risk assessment.
- A combined assignment method about human factor weights is proposed.
- An incentive-based variable weighting approach is provided.
- The consequences of dam failure are combined into the evaluation framework.

Abstract

An improved calculation method for dam failure probability that considers human factors was developed to incorporate human error parameters into engineering risk analysis in this study. Firstly, the human factors indicator system with human, technology, organization, and environment as guideline layers was constructed. The assignment of indicators was accomplished using game theory to simultaneously reflect the experts' subjective opinions and the objective information in historical data. A key innovation was the incorporation of the incentive-variable weighting method, which enabled dynamic assignment of top-level indicators and accounted for the influence of weak factors on the failure probability, as well as dynamic calculation across multiple combinations of failing causes. Finally, a new human-driven variable-weighted dam risk dynamic assessment methodology was developed by combining the consequences of dam failure to reflect risk. The novel method has been applied to dam group examples, intuitively reflecting the risk order of different small dams.

Keywords

dam safety, human factor reliability, variable weighting method, AHP, improved CRITIC, risk assessment

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1. Introduction

By the end of 2024, there were 94,608 dams of various sizes in China, providing comprehensive disaster prevention and mitigation benefits while serving multiple functions, including water supply, irrigation, power generation, navigation, and ecology. At the same time, under multiple hazard factors, the risk of danger or even collapse remains, seriously threatening the lives and property safety of people downstream [1,2]. The frequent occurrence of extreme weather and the aging of dams, or even overdue service, have increased the failure probability.

At the same time, rapid social development and significant

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urbanization have exacerbated the failure losses. Therefore, the state and society have set higher requirements for dam safety. In order to guarantee the safe operation of dams throughout their life cycle, it is important to integrate the design, construction and management within a systematic risk management framework that includes aspects of sustainability, resilience and public participation [3].

Due to the enormous economic and social consequences of dam breakage, dam safety management has become an indispensable and important component of all dam projects

worldwide, and the application of quantitative risk analysis has received widespread attention. Risk analysis techniques originated in the United States and were initially used in the military industry. In 1974, the U.S. Atomic Energy Commission published a report on the risk evaluation of commercial nuclear power plants, which attracted worldwide attention, and since then risk analysis technology has been used in various fields. After a series of articles on the principles, methods, and examples of dam risk analysis were published in the United States in the early 1980s, the technique flourished with results in the USA, Canada, Australia, and Western Europe.

The reliability analysis of reservoir dams has been developed for a long time, mainly by using engineering means to reduce the probability of failure. In the past half century, the research on dam engineering mainly focused on the numerical simulation of dam structures, including the finite difference method [4,5], the finite element method [6–8], the discrete element method [9,10], the mesh-free method [11,12], and so on. Software is commonly used to develop finite element models of dams [4,5] and their yielding environments, considering the coupled system mechanics between the dam body, water storage and bedrock. With the rise and development of machine learning, related techniques have been utilized to develop agent models for dam risk assessment [6–8]. Scholars [9] hold that the step-by-step transformation from deterministic method to probabilistic method and then to possibilistic method can achieve more correct reliability evaluation under the condition that the initial data is highly uncertain. The International Commission on Large Dams (ICOLD) added risk, reliability and vulnerability to the discussion in 2011, 2013 and 2015 [10], suggesting that the risk-based approach is a useful tool for dams' systematic risk analysis, encompassing downstream consequence assessment and structural modelling uncertainty. However, despite the continuous development of dam risk analysis methods and integration with digitized advanced technologies, operator reliability has not been taken into account, and human factors have not been combined with engineering factors to form a systematic and comprehensive assessment methodology.

With technology advances and improved emergency management, the proportion of dam failure accidents under high water conditions during flood seasons has gradually declined,

and non-flood accidents have risen. The successive failures of the Lianfeng Dam in Xinjiang, the Xinghuo Dam in Heilongjiang and the Quting Dam in Shanxi owing to violations of regulations and improper operation have shown that there are still obvious weaknesses in the dam management with respect to patrols and inspections, monitoring and warning, operation and scheduling, emergency plans and personnel training. The contribution of human risk to the total risk is relatively higher, and may even become the dominant factor, mainly manifested in a backward management system and imperfect non-engineering measures. Changes in digital and production technologies, such as artificial intelligence for future materials and devices [11–13], and big data analytics have altered the role of the human operator and the nature of industry. The complexity and importance of human-machine systems have increased, and operators have become an important part of industrial systems [14–16]. The 2016 American Dam Safety Annual Conference suggested that all dam accidents and failures can be attributed to human causes. The current risk analysis of dam failure mainly focuses on engineering factors. However, the human factor should not be neglected during dam management.

Human factors are the factors associated with people. Human Reliability Analysis (HRA) is an emerging discipline to evaluate and analyze the reliability of human factors, taking predictive analysis and reducing the human error probability as research core, based on the technology of behavioral cognitive science and information processing [17–19]. Human Error (HE) refers to human performance errors that may adversely affect system safety, performance, and human health [20]. Human error plays a key role in almost every industry in a social system, especially safety-critical industries that are highly dependent on humans and are essential to safety [21]. HRA has been widely used in the fields of nuclear power, aviation and navigation [22–24], but it has been rarely applied in dam risk analysis. There is some research on human-environment systems in water resources management [25,26], but it does not include human factors as a component of risk. Neither coupled engineering risk, nor an independent study of human factors failure probability. Huiwen Wang [27] had introduced human reliability analysis into the field of dam risk evaluation, analyzed the root causes of human error, and proposed a dam failure model and calculation

method based on the Bayesian network. The model utilized expert judgment to complete the conditional probability distribution table, which did not fully take advantage of the historical dam failure data and was inherently subjective.

Dam risk management is a multi-indicator information set problem, making it a challenge to assess the management level of the dam scientifically. The weight method is now introduced in many fields to assess and rank indicators [28,29], achieving the importance expression of different indicators in order to improve the quality of risk assessment and provide guidance for decision-making. However, in risk assessments involving human error, a systematic index system that accounts for weights has not yet been developed. At the same time, a constant-weight approach is often used to combine the risk of dam failure under different causes in dam risk assessment. The constant-weight synthesis method can reflect the summed superiority of the judgement object to a certain extent based on each indicator, and the weights can reflect the relative importance of different indicators in decision-making. However, this method is unreasonable in some practical problems and cannot correctly reflect the actual superiority of different programs according to dynamic changes. In this paper, a human-driven variable-weight dam risk evaluation method was proposed to realize the risk sequence calculation of dam complexes considering human factors, engineering failure and accident consequences, which provides a reliable basis for management decisions.

This paper is structured as follows. Section 2 describes the research methodology, mainly: (1) The historical dam failure accident database was analyzed to obtain a multilayered system of human factors indicators. (2) The subjective and objective weights were determined using the AHP and improved CRITIC

methods, and were assigned in combination using the game theory method. (3) The variable weight method is introduced to dynamically select the weights of the dam-breaking paths, amplify the weak paths, and realize the dynamic calculation of risks under multiple combinations of damage causes. (4) The human error probability is set as the amplification parameter of dam collapse, and the risk calculation formula considering the anthropogenic factors is obtained by combining the human reliability analysis with the engineering risk analysis. (5) A human-driven approach for dam risk assessment in conjunction with the failure consequences is constructed. Section 3 is the example application, which starts with the indicator system weight calculation using the combination assignment method introduced in the previous section. The proposed method was then applied to a dam cluster in a county to perform risk evaluation and risk ranking to verify the applicability and accuracy of the method.

2. Methodology

Dam failure refers to the complete destruction of the entire dam's main and ancillary structures, including the structural damage caused by the spillway being overtopped due to poor design, or by the large amount of water released from the dam due to an error in the design flood calculation. As can be seen from the dam failure data records in China, the proportion with the main cause being mismanagement is relatively small, the shadow of human error is also found in the accidents caused by other causes, such as quality problems caused by failing to follow the specifications strictly, overtopping caused by failing to make timely pre-drainage before rainstorms, and leakage problems not detected for a long time due to insufficient technical skills or poor sense of responsibility.

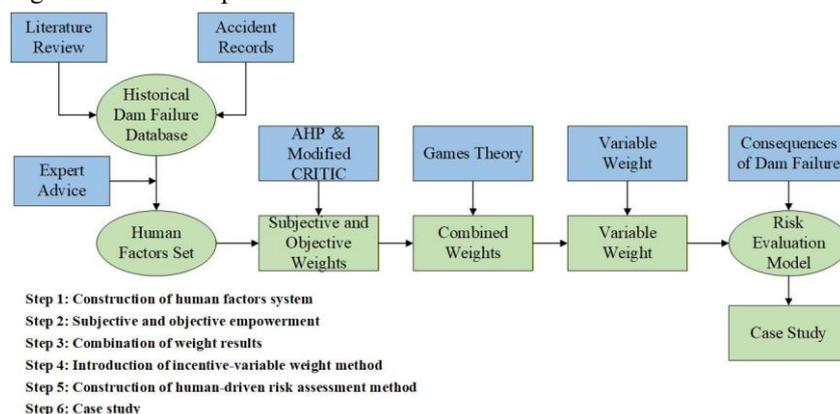


Figure 1. Research framework of this study.

The goal of this paper is to construct a method for dam risk assessment that accounts for human factors. Firstly, the anthropogenic indicator system is built by studying a large amount of human factors literature on dam safety management as well as other fields, excavating the historical failure information, and combining with experts' opinions. The weights of the influencing factors were obtained using a combined assignment method based on AHP and improved CRITIC. The dam failure probability under different failure modes is adjusted on the basis of a variable weighting method to amplify the weak failure paths. The human reliability is introduced into the risk calculation, and a human-driven failure probability method is constructed which is combined with the damage consequences in order to make dam risk discriminations. Finally, a typical dam cluster is selected for the engineering application example. Figure 1 shows the research framework of this study.

2.1. Human factors indicator system

2.1.1. Human factors indicator system construction

With economic development and urbanization, dam safety management is facing new situations and requirements. Modern technology has changed how operators are managed, making it essential to consider the impact of human factors to improve dam management. Factors that may affect human performance in human reliability analysis are referred to as performance shaping factors (PSFs), which are also called performance influencing factors (PIFs), influencing factors (IFs), performance affecting factors (PAFs), error producing conditions (EPCs), and common performance conditions (CPCs) [30]. PSFs are the basis for qualitatively and quantitatively evaluating the reliability of human factors, by determining the positive or negative effects of various factors within the scenario on human performance, in order to obtain qualitative insights into the scenario and predict the probability of human error [31,32].

The construction of the index system in this study is a multi-stage screening and convergence process, aiming at ensuring its scientificity and integrity. First, through HRA indicators in other fields [33–35], text mining of historical dam failure cases, and comparison with industry safety management norms, an initial indicator pool was established. The historical dam failure data at home and abroad are studied, and 100 typical dam failure

accidents are selected for analysis, including 57 cases in China, which are mainly sourced from the historical dam failure database of the Nanjing Hydraulic Research Institute, and 43 cases in foreign countries, which are mainly sourced from the Association of State Dam Safety Officials, Wikipedia, relevant news reports and dissertation materials. The main selection bases are:

- (1) Consequences of the dam collapse. Analysis is given in preference to contemporaneous events with more serious consequences.
- (2) Age of the dam collapse. The occurrence of dam failures has shown a phased approach.
- (3) Causes of dam collapse. Various causes of dam failure, such as overtopping, infiltration damage, shoulder breakdown, and foundation instability, were included in the selected accidents to gain insights into the major human errors associated with these failure mechanisms.

Subsequently, PSFs were screened using expert opinion and causality analysis. Consider the following principles [36–38]: 1) Factors that have a substantial impact on personnel performance and have a stronger effect should be selected. 2) The selected PSF factors should be able to be transformed into quantitative or semi-quantitative indicators through direct measurement, expert scoring, text mining, and other means. 3) The quantification rules of PSFs should ensure consistency and eliminate subjectivity among experts. 4) The overlap and coupling between factors should be reduced as much as possible during screening.

Table 1. The judgment basis coefficient C_a assignment table.

The judgment basis	Extent of influence on expert judgment		
	Large	Moderate	Small
Theoretical analysis	0.3	0.2	0.1
Practical experience	0.45	0.4	0.3
References	0.15	0.1	0.05
Intuitive feeling	0.1	0.1	0.05
Total	1.0	0.8	0.5

After that, two rounds of expert screening were conducted on the initial index using the weighted Delphi method. Ten experts in hydrology, structure, and safety management were invited to establish an expert weighting system to evaluate their contributions. The weight is determined by the authority coefficient C_r [39] and the background qualification coefficient C_b , in which C_r is obtained by expert self-evaluation, including

the judgment basis C_a and familiarity C_s , $C_r = (C_a + C_s)/2$. The judgment basis coefficient, C_a , is used to evaluate the reliability of expert judgment sources when scoring, and the assignment is shown in Table 1. The familiarity coefficient C_s is set as the expert's self-rated familiarity with each PSF, and the Table 2. The background qualification coefficient C_b .

Indicator	Criteria	Score	Indicator	Criteria	Score	Indicator	Criteria	Score
Working hours (years)	>20	1.0	Title	Professorate Senior Engineer	1.0	Number of papers	Sci>5	1.0
	10-20	0.75		Senior Engineer	0.75		Sci>3	0.75
	5-10	0.5		Engineer	0.5		Sci≥1	0.5
	<5	0.25		Other	0.25		None	0.25

The background seniority coefficient C_b is the average of the three.

The weighted value of the expert score is shown in Equation (1):

$$W_i = \frac{(C_{ri} \times C_{bi})}{\sum_{j=1}^n (C_{rj} \times C_{bj})} \quad (1)$$

Where, W_i is the weight score set of the i -th expert, with a total of n experts.

After each round of consultation, the importance score of each PSF was calculated in combination with the weighting method:

$$\bar{X}_\omega = \sum_{i=1}^n (W_i \times X_i) \quad (2)$$

Where, X_i is the PSFs score set of the i -th expert, and \bar{X}_ω is the weighted PSFs score set.

Then the weighted standard deviation is:

$$\sigma = \sqrt{\sum_{i=1}^n (X_i - \bar{X}_\omega)^2} \quad (3)$$

The traditional Delphi method involves four rounds of feedback and adjustment cycles, and it is considered that two rounds of Delphi are sufficient to achieve the goal [40].

Table 3. The set of human error factors.

The criterion layer	Meaning	The indicator layer
Managerial personnel (A)	The dam site management personnel and equipment operators, the main body of human-computer interaction in the human-computer system, in the form of an individual.	Experience (A1) Sense of responsibility (A2) Psychological quality (A3) Specialized skill (A4)
Technology (B)	The impact of the system on operators, mainly including hardware facilities such as gates, software facilities such as monitoring systems, and emergency planning.	Hardware facilities (B1) Software facilities (B2) Emergency planning (B3)
Organization (C)	The impact of the organization on operators. Many experts consider flaws in organizational management leading to human error and as the root cause of accidents [43].	Internal atmosphere (C1) Supervision effort (C2) Risk awareness (C3) Formal judgment (C4) Routine management (C5)
Environment (D)	The impact of the environment on operators.	Physical environment (D1) Engineering environment (D2)

value is between [0, 1], 0.0 for unfamiliar and 1.0 for very familiar. The background qualification coefficient C_b evaluates the years of experience and professionalism of experts, as shown in Table 2.

Coefficient of variation CV and coefficient of harmonization Kendall's W [41,42] were used to test the agreement of expert group opinions. Convergence is considered to be achieved when there is no significant improvement in W values for two consecutive rounds ($p > 0.05$) and the weighted standard deviation $\sigma < 0.5$.

Finally, the selected indicators are summarized and integrated into four criterion layers to form the final indicator system. As shown in Table 3, the factor set is divided into three parts: the target layer, the criterion layer, and the indicator layer. The target layer is the human factor reliability for dams, the criterion layer is the four classifications, including managerial personnel, technology, organization, and environment, while each of the specific influencing factors in the four categories is the indicator layer, such as experience, sense of responsibility, psychological quality, specialized skill, and so on. For convenience, managers are denoted as A, technologies as B, organizations as C and environments as D. Their sub-factors are denoted as A1, A2,, D1, D2, etc.

The effectiveness of this system is supported by comparison with existing studies. Its criteria (managerial personnel, technology, organization, and environment) are consistent with the classical human reliability analysis (HRA) framework and the kernel of the 'Swiss cheese' model, providing a solid theoretical foundation. Its completeness is tested by the retrospective interpretative power of historical cases. During the construction process, it was found that the selected indicators can effectively cover and explain the key points of human error in the 100 historical cases analyzed, without systematic omissions, indicating that the system has good coverage of engineering scenarios. In the weighted Delphi method, experts evaluated the content validity ratio of the final index set, and the results showed that it fully characterizes human risk.

2.1.2. Human factors indicator system weight calculation

(1) Analytic Hierarchy Process (AHP)

Analytic Hierarchy Process (AHP) was developed initially by Saaty [44,45] and is mainly used for decision-making procedures in management science and operations research. The hierarchical criteria obtained by decomposing the problem are compared with each other, that is, pairwise comparisons are made in order to obtain a ranking between different criteria [46]. This ranking was determined in this research using expert scoring as the subjective assignment component.

Pairwise comparisons in the AHP are made between different indicators at the same level. The factors at the indicator level are first compared, followed by a comparison of each specific influencing element underneath it. A modified nine-point scale [47] was used to assess the comparison weights therein. Consistency tests were performed on the matrices by the following steps to calculate the consistency index CI , and the average random consistency index CR . The eigenvector method is used to compute the weight vector, right-multiply the weight vector W by the weight ratio matrix A , there is:

$$AW = \lambda_{max} W \quad (4)$$

Where, λ_{max} is the largest eigenvalue of the judgement matrix, existing and unique. The components of W are positive. The requested weights are obtained by normalizing the obtained weight vector.

(2) The improved Criteria Importance Through Inter-criteria Correlation (CRITIC) method

The CRITIC method is an objective weighting method proposed by Diakoulaki [48,49] in 1995, which measures the objective weight of indicators by evaluating their comparative strength and conflict. Contrast intensity was expressed as standard deviation and conflictiveness as correlation coefficient. In the use process, scholars have found that the standard deviation is dimensional and the correlation coefficients may be complex. The research uses an improved CRITIC method [50,51], which consists mainly of: replacing the standard deviation with a standard deviation coefficient to eliminate the effect of magnitude; taking the absolute value with the correlation coefficient to eliminate the effect of the plus and minus signs.

Step 1 Firstly, the historical dam failure data were normalized to generate a matrix B containing the standardized column matrices b_j corresponding to the human factor indicator P_j .

Step 2 The human factor indicator coefficient of variation v_j is calculated from the arithmetic mean and standard deviation of the column matrix of the indicator P_j . The human factor indicator independence h_j was calculated from the correlation coefficient of each evaluation index.

Step 3 The indicator composite measure coefficient q_j is the product of the coefficient of variation v_j and the indicator independence h_j .

Step 4 The weight ω_j of indicator j is

$$\omega_j = \frac{q_j}{\sum_{j=1}^n q_j} \quad j = 1, 2, \dots, n \quad (5)$$

(3) Game theory approach to portfolio weighting

Game theory is used to analyze the equilibrium problem of decision making when several decision-makers make joint decisions affecting each other [52,53], and is carried out by all the members to maximize the benefits or minimize the losses. The game parties compromise to pursue the maximization of their common interests. The research uses the Nash equilibrium to find agreement among the different weights obtained by subjective and objective weighting, to consider expert opinions and historical data at the same time.

Before using the combined weighting method, the resulting weights are first checked for consistency. The paper used both subjective and objective methods to determine the weights, which were tested with the Spearman rank correlation coefficient or distance function.

After satisfying the consistency test, the vectors are combined arbitrarily and linearly into the set of possible weights:

$$W = \sum_{k=1}^n \alpha_k w_k^T \quad (\alpha_k > 0) \quad (6)$$

Where, w_k is one possible weight vector of the possible set of weight vectors; α_k is the weight coefficient. The whole of W is the set with all possible combinations of weight vectors.

The linear combination weight constraint α_k is adjusted with the goal of minimizing the deviation of w from the individual w_k . According to the differential nature of the matrix, the optimal first-order derivative condition is as follows:

$$\sum_{j=1}^n \alpha_j \times w_j \times w_i^T = w_i \times w_i^T \quad (i = 1, 2, \dots, n) \quad (7)$$

After the linear combination coefficient (α_1, α_2) of subjective and objective weights of human factor indicators is obtained from the above equation, it is normalized to get the combination weights:

$$W^* = \sum_{k=1}^n \alpha_k^* w_k^T \quad (8)$$

2.2. Risk assessment method construction

2.2.1. Human-driven risk assessment method

The risk ranking principle is introduced in conjunction with the concept of dam risk management, that is, the dam risk evaluation that considers the failure consequences. With a high proportion of small dams in China and prominent contradictions in management funding and talent shortages, it is necessary to rank cluster dams using a composite risk index R to ensure that high-risk ones are prioritized for funding support and risk management improvement. The formula is shown below:

$$R = P_f L \quad (9)$$

Where, P_f is the failure probability and L is the comprehensive evaluation function of the failure consequences. It is worth noting that in this research, the 'probability of dam failure' is not the real probability, but a relative one, which is mainly used as a basis for ranking decisions on repair and maintenance, removing and reinforcing, and downgrading and scrapping.

In the calculation of the dam risk probability of traditional analysis, only the engineering factors are considered. By introducing human factors into the risk assessment, a human-driven method for calculating the dam failure probability is proposed. The core idea is that the actual dam failure probability is determined by the inherent project risk, reduced by improvements in personnel reliability and the management

system. The calculation formula is as follows:

$$P_f = \sum_{i=1}^n \frac{P_i \beta}{1 - H_i} = \sum_{i=1}^n \frac{P_i \beta}{1 - \sum_{j=1}^m h_{ij} \omega_{ij}} \quad (10)$$

Where, P_f is the probability of the project's failure after taking into account human error, which includes experiencing multiple causes such as excessive flooding, seepage, pipe surges, and earthquakes. P_i is the inherent failure probability of the project under the i -th dam failure cause (e.g., flood overtopping and seepage failure), calculated using a traditional physical model. H_i is the total human factors failure probability for the i -th cause, which is a combination of human factors and their weights. It represents the failure possibility of the personnel and management system under this risk. h_{ij} is the probability of the j -th human error under the i -th cause of dam failure. ω_{ij} is the weight of the j -th human error factor under the i -th cause. Use $\beta/(1 - H_i)$ as an amplifying factor for the probability of human error to feed back the calculated breakout probability after accounting for human factors. β is the correction coefficient of the engineering inherent probability ($\beta > 0$). Its physical meaning is that it is used to cover systemic risk factors, excluding all human factors such as engineering model and parameter uncertainties. Under the ideal perfect state ($H_i = 0$), the probability of dam failure is $(\beta \cdot P_i)$. Because the inherent, non-human uncertainty of the engineering system itself is not the focus of this paper, β is treated as a constant for simplicity. This means focusing on human error and ignoring other non-human systemic uncertainties in the research. In future studies, more accurate calibration of β is needed. Since H_i is the human error probability of the i -th dam failure risk, and $(1 - H_i)$ represents the "human reliability" of personnel and the management system in successfully performing their duties and avoiding errors when facing the i -th dam failure risk. The denominator part $(1/(1 - H_i))$ shows that the lower the human reliability (the greater H_i), the greater the amplification effect of this coefficient on the engineering failure probability P_i . When H_i tends to 1 (personnel are completely unreliable), the coefficient tends to infinity, and the system will inevitably fail, which aligns with engineering intuition. The amplification factor of human influence is introduced to intuitively reflect the multiplication and deterioration effect of human error on the engineering safety state.

L is calculated as follows:

$$L = \sum_{i=1}^3 S_i F_i = S_1 F_1 + S_2 F_2 + S_3 F_3 \quad (11)$$

Where, S_1, S_2, S_3 are weighting factors for the loss of life, economy, social, and environmental impacts respectively. F_1, F_2, F_3 are severity coefficients for loss of life, economy, social, and environmental impacts, respectively.

2.2.2. Variable weight method

In view of the deficiency of constant weight, scholars have proposed the idea of variable weighting [54,55], which makes the weight of evaluation factors self-adjust with the change of the factor state value, in order to more intuitively reflect the important factors in the specific evaluation. Variable rights are mainly classified as punitive, incentive and hybrid. The penalized variable weighting method is mainly used to balance the variables by reducing sensitivity to the state of low-level factors and increasing retardation to the state of high-level ones. The incentive-type method emphasizes motivation for key factors and is sensitive to increases in single-factor state values at high levels and sluggish to decreases at low levels. The hybrid type, on the other hand, is a combination of both approaches, where one part of the factor is penalized and the other part is incentivized. In dam failure accidents, the destruction risk is mainly controlled by weak indicators, whose impacts have not been sufficiently emphasized in the constant power analysis. Therefore, this paper introduces the variable weighting method into the probability calculation of dam failure, and selects the incentive-type method for the top layer of the dam failure calculation in order to increase the weak indicators' weights.

The incentive variable weights need to satisfy normalization, continuity and incentivization [56,57], that is, weight sums of 1, weight functions that are continuous with respect to each variant, and monotonically increasing with respect to the variant X_j . When the function is an excitation variable weight, the resulting mapping S should be increasing. The variable weight function is constructed based on this principle and the dam failure probability as follows:

$$S_i(x_i) = \begin{cases} \omega_0 & 0 < x_i \leq a \\ \omega_0 + \lambda_1(x_i - a) & a < x_i \leq b \\ S(b) \cdot e^{\lambda_2(x_i - b)} & b < x_i < 1 \end{cases} \quad (12)$$

Where, $S_i(x_i)$ is the state-variant weighting value; x_i is the "equivalent contribution probability" of this path to the overall risk due to the addition of human factors on the i -th path, $x_i = \frac{P_i \beta}{1 - H_i}$; ω_0 is the benchmark weight adjustment coefficient, usually

taken as 1, indicating the invariant weight within the safe interval; λ_1, λ_2 are both excitation coefficients, and $\lambda_2 > \lambda_1 > 0$, which reflects a more substantial amplification effect on higher risks; a and b are zoning thresholds, corresponding to the project risk level. According to the general practice of dam safety management, three risk intervals are defined: normal/low risk zone ($0 < x_i \leq a$) with maintained benchmark values, warning / medium risk zone ($a < x_i \leq b$) with linear incentives, and dangerous/high risk zone ($b < x_i < 1$) with enhanced incentives. In different engineering applications, decision-makers can determine the values of a, b, λ_1 and λ_2 based on the needs of the research object. In this paper, the values are determined by referring to the specifications, historical data inversions, and an expert calibration method. The equation above finds the path with the highest crash probability and amplifies its weight.

To avoid the distortion of evaluation results caused by weight amplification when the proportion of weak indexes is relatively low, the upper limit value of variable weight coefficient $S_{max}=3$ is set. When the calculated value exceeds this upper limit, $S_i(x_i) = S_{max}$ is used to prevent a single index from completely dominating the evaluation result. This is based on the balance between the rationality principle of engineering decision-making and the short-term principle. While considering the short board, it is also necessary to consider the good performance of other aspects.

The variable weight vector $\omega_i(x_i)$ is calculated by using the following equation:

$$\omega_i(x_i) = \omega_i^{(0)} S_i(x) / \sum_{j=1}^m \omega_j^{(0)} S_j(x) \quad (13)$$

Where, $\omega_i^{(0)}$ is the initial constant weights, taken as 1 when each cause of dam failure is of equal priority; $\omega_i(x_i)$ is the calculated variable weights.

The essence of the variable weight incentive method is to amplify the risk response. By identifying which probability calculations of dam failure paths fall into the "warning zone" or "danger zone" and dynamically increasing their weight in the final decision, managers' attention is preferentially focused on the weakest and most dangerous links. The specific calculation steps are as follows:

Step 1: Input and interval determination. Input the failure probability value x_i of each dam break path calculated by considering human factors and the combined weight method.

According to the pre-calibrated thresholds a and b , the risk interval (normal zone, warning zone, or dangerous zone) to which x_i belongs is automatically determined. This step converts continuous probability values into discrete risk levels, enabling the integration of probability calculations with engineering decision-making.

Step 2: Variable weight coefficient calculation. According to the interval to which x_i belongs, the corresponding piecewise function of formula (13) is used to calculate its variable weight coefficient $S_i(x_i)$. In the normal zone, the weight is maintained at the benchmark level, reflecting the safe state's non-intervention. In the warning area, the weight increases linearly with the probability of achieving a smooth warning of risks. In the dangerous zone, exponential incentives are used to achieve a strong focus on high-risk paths. This step is the core of the incentive variable weight method, and its mathematical form directly determines the model's sensitivity and amplification intensity to weak links.

Step 3: Normalization and dynamic weight generation. The variable weight coefficients $S_i(x_i)$ of all paths are multiplied by their corresponding static reference weights $\omega_i^{(0)}$, and then normalized by formula (10). Finally, the dynamic weight $\omega_i(x_i)$ of each path is obtained. Through normalization, the sum of all weights is ensured to be 1, which conforms to the fundamental constraint of probability weights.

Step 4: Output and apply. The output dynamic weight vector $\omega(x) = [\omega_1(x_1), \omega_2(x_2), \dots, \omega_m(x_m)]$ will be used to calculate the total dam break probability $P_{f-all} = \sum_{i=1}^m [\omega_i(x_i) \cdot x_i]$ of the system in combination with the dam break probability obtained in 2.2. 2. In this way, the feedback adjustment from static probability to dynamic weight is completed, so that the final risk estimation not only reflects the initial probability of each path, but also emphasizes the contribution of high-risk paths, and achieves the goal of amplifying weak links.

3. Results and analysis

3.1. Calculation of the indicator system weights

The human factor index influencing factor conversion table shown in Table 4 is used to score and judge each factor in the dam failure history record. The evaluation criteria are divided into five grades, including 'good, relatively good, average, not so good, poor', which vary according to different factors. The

data source is typical historical dam failure data. The value of each factor is comprehensively assessed based on the investigation of the dam break case, the cause of human error, the era, and other factors.

Table 4. The conversion table of human factors.

Qualitative descriptions	Quantitative probabilities	Qualitative descriptions	Quantitative probabilities
Good	1×10^{-5}	Not so good	0.6
Relatively good	0.01	Poor	1.0
Average	0.1		

Among them, the qualitative description of "good, relatively good, average, not so good, and poor" is changed by different factors. For example, for the experience of managerial personnel, it corresponds to "very rich, relatively rich, average, not so rich, and no experience", and for the internal atmosphere of the organization, it corresponds to "full cooperation, relatively full cooperation, average, not sufficient, and no cooperation". The value of each factor is comprehensively judged based on the investigation of a dam failure case, the cause of human error, the era, and other factors. Table 5 takes experience as an example to illustrate the basis of the quantification method.

The scale synthesizes the specific requirements for various tasks from the "Reservoir Dam Safety Management Regulations", "Reservoir Operation Management Regulations", and other industry specifications, as well as data analysis of historical accident investigation reports. The term comprehensively refers to the conversion table issued by the U.S. Bureau of Reclamation in 1999, the Australian risk assessment guidelines, and China's qualitative description and probability conversion suggestion table.

During application, the evaluation team determines the most consistent grade for each indicator based on historical dam failure records, compares the behavior descriptions of each indicator, and assigns a specific probability value with reference to the corresponding probability interval and a detailed discussion to reduce personal subjective bias.

AHP analysis was carried out with expert scoring on a 1-9 scale and the results were calculated using the MATLAB program. The categorization of influencing factors is performed according to the previous section and consists mainly of the guideline layers of managers, technology, organization and environment, with a comparison of the factors under each

guideline layer. The different causes of dam failure are analyzed separately according to overtopping, seepage, and engineering quality problems. The consistency index of the judgment matrix is less than 0.1, which meets the consistency requirements. The

same approach was applied to leakage and engineering quality issues, that is, the experts compared and scored the factors at each level, calculated the weights, and synthesized the subjective values of the indicators as shown in the table 2.

Table 5. Qualitative and quantitative conversion table of experience.

Qualitative descriptions	Basis of judgment	Quantitative probabilities
Good	Engaged in water conservancy work for more than 20 years; Has directly participated in flood control work many times and is very familiar with all links and regulations; Very familiar with dam emergency rescue technology; Has encountered abnormal and dangerous situations in reservoirs and dams many times, and has successfully dealt with them many times.	10 ⁻⁵
Relatively good	Engaged in water conservancy work for more than 15 years; Has directly participated in flood control work and is relatively familiar with all links and regulations; Familiar with dam emergency rescue technology; Has encountered abnormal and dangerous situations in reservoirs and dams, and has successfully dealt with them.	0.01
Average	Engaged in water conservancy work for more than 10 years; Has directly participated in flood control work, but is not very familiar with all links and regulations; Not very familiar with dam emergency rescue technology; Has encountered abnormal and dangerous situations in reservoirs and dams, but did not participate in the disposal as the main personnel.	0.1
Not so good	Engaged in water conservancy work for more than 5 years; Have not directly participated in but studied flood control work, and have a general understanding of flood control work links and regulations; Not familiar with dam emergency rescue technology; Has not encountered any abnormal or dangerous situations in reservoirs or dams.	0.6
Poor	Engaged in water conservancy work for less than 5 years; Not much work experience in the current position; Has not directly participated in or studied flood control work, and is not familiar with flood control work links and regulations; Unclear dam emergency rescue technology.	1.0

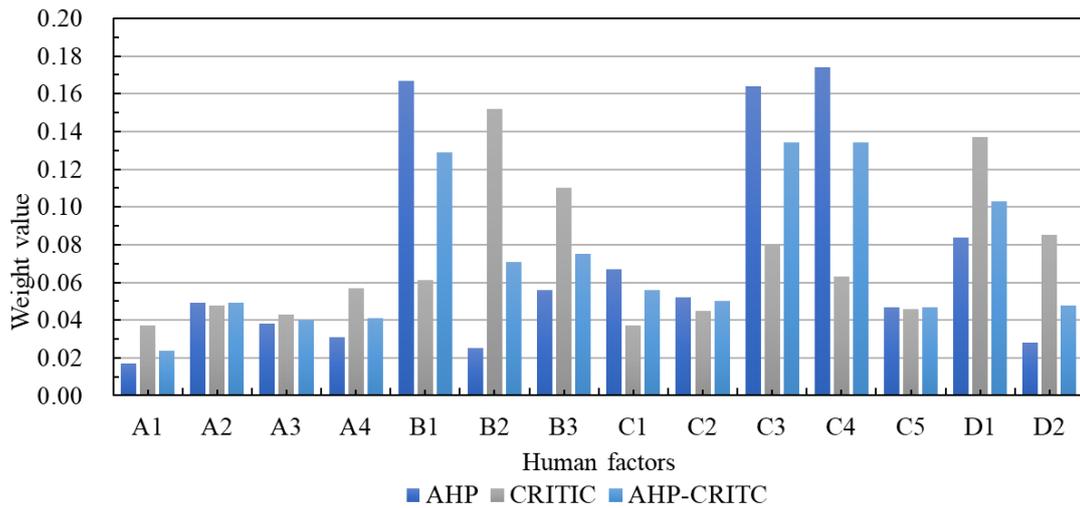
The historical dam failure database constructed in Section 2.1.1 was analyzed for data, and each influencing factor was scored using a qualitative-quantitative conversion method, with the judging criteria selected from Table 1. Among them, the failed dams were categorized according to the breaching causes, including three categories of overtopping, seepage, and engineering quality problems. Overtopping events include 45 cases such as Taum Sauk Dam, Baiguochong Dam, and Pantano De Puentes Dam. Seepage events include a total of 35 cases in the Bayi Dam, Fenghuang Dam, and St. Francis Dam. Dam

failures caused by engineering quality problems include Baogu Dam, Qixian Lake Dam, Patel Dam, and a total of 20 cases. The indicators were normalized and the comprehensive weights were calculated, as shown in Table 2.

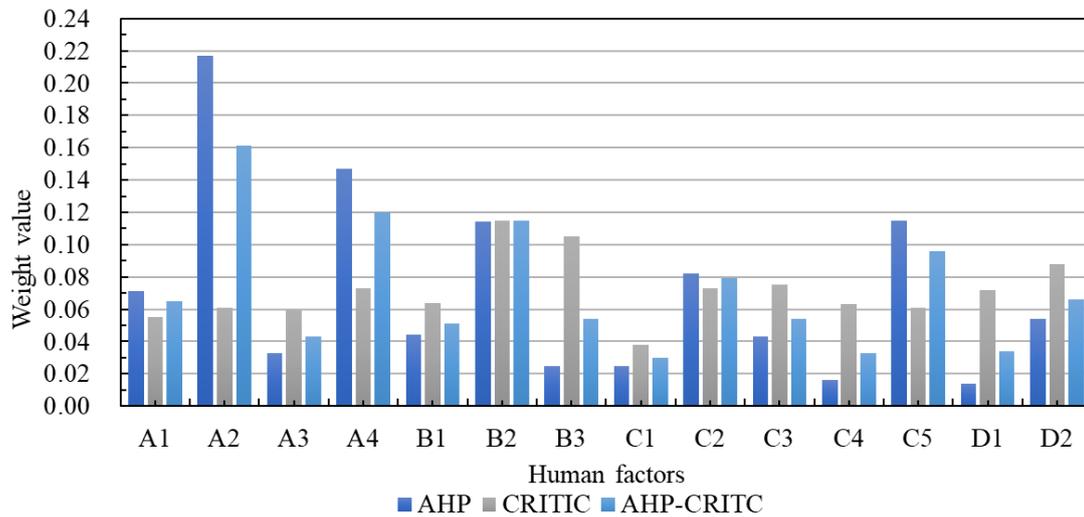
According to the game theory method in Section 2.1.2, the subjective weights obtained from the AHP method, and the objective weights obtained from the improved CRITIC method were coupled to obtain the combined weights under different failure causes, as shown in Table 6 and Figure 2.

Table 6. The combined weight of each influencing factor calculated by AHP, CRITIC, and game theory method.

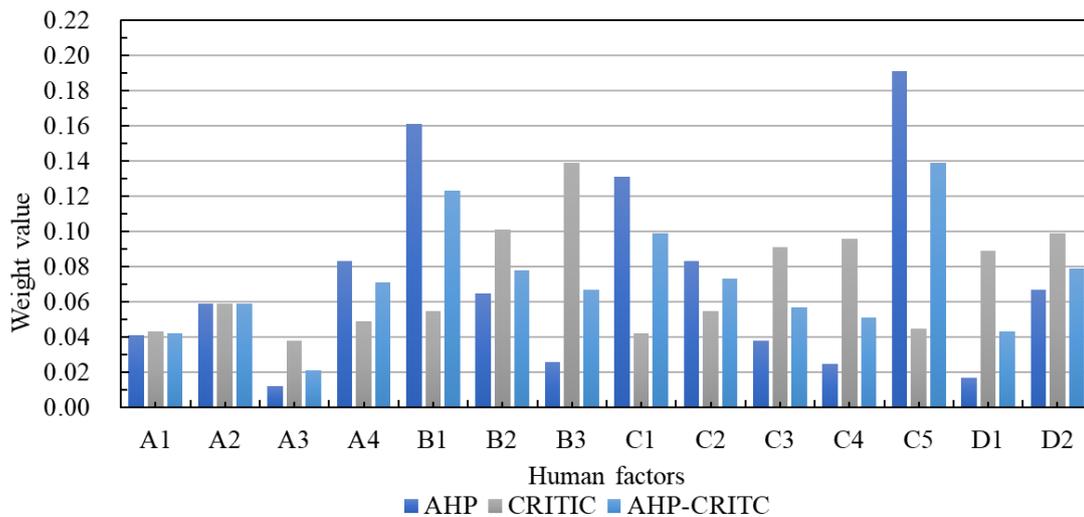
		Overtopping			Seepage			Engineering quality problems		
		AHP	CRITIC	AHP-CRITC	AHP	CRITIC	AHP-CRITC	AHP	CRITIC	AHP-CRITC
A	A1	0.017	0.037	0.024	0.071	0.055	0.065	0.041	0.043	0.042
	A2	0.049	0.048	0.049	0.217	0.061	0.161	0.059	0.059	0.059
	A3	0.038	0.043	0.040	0.033	0.059	0.043	0.012	0.038	0.021
	A4	0.031	0.057	0.041	0.147	0.073	0.120	0.083	0.049	0.071
B	B1	0.167	0.061	0.129	0.044	0.064	0.051	0.161	0.055	0.123
	B2	0.025	0.152	0.071	0.114	0.115	0.115	0.065	0.101	0.078
	B3	0.056	0.110	0.075	0.025	0.105	0.054	0.026	0.139	0.067
C	C1	0.067	0.037	0.056	0.025	0.038	0.030	0.131	0.042	0.099
	C2	0.052	0.045	0.050	0.082	0.073	0.079	0.083	0.055	0.073
	C3	0.164	0.080	0.134	0.043	0.075	0.054	0.038	0.091	0.057
	C4	0.174	0.063	0.134	0.016	0.063	0.033	0.025	0.096	0.051
	C5	0.047	0.046	0.047	0.115	0.061	0.096	0.191	0.045	0.139
D	D1	0.084	0.137	0.103	0.014	0.072	0.034	0.017	0.089	0.043
	D2	0.028	0.085	0.048	0.054	0.088	0.066	0.067	0.099	0.079



(a) Overtopping



(b) Seepage



(c) Engineering quality problems

Figure 2. Combination weight results of each influencing factor.

The results obtained by the AHP method have a higher degree of variability, the results obtained by the improved CRITIC method have a lower degree of variability, and the weights obtained by the combined method are in between. At the same time, the results obtained by the AHP and the Improved CRITIC methods are inconsistent, focusing on different factors, while the combined weights obtain results that neutralize the two methods.

3.2. Determination of variable weight parameters

The proposed variable weight method, as shown in equation (12) in Section 2.2.2, contains four critical parameters: threshold values a , b , and excitation coefficients λ_1 , λ_2 . In practical application, they can be changed according to different engineering conditions and decision-making requirements. In this paper, they are determined by referring to specification documents, historical data inversion, and expert calibration.

The thresholds a and b should be set based on "the comprehensive performance corresponding to the engineering probability threshold at the current reliability level of human factors". The engineering probability threshold is the standard for delineating failure probability into normal, warning, and dangerous zones, determined by referring to the norms and studies of many countries. The ALARP (As Low As Reasonably Practicable) guideline for risk areas is considered, as proposed by UK Health and Safety law. It means that unreasonable risks can be rejected, but reasonable risks must be accepted, and risks with significant harm should be reduced as much as possible. Australia, the Netherlands, the United States, Canada, and South Africa have all formulated corresponding "F-N" risk control charts [58], where F represents the failure probability in years and N represents the number of people affected. The socially tolerable risk criterion of images starts with 10^{-3} and 10^{-5} as the horizontal limit values. 10% of the tolerable risk standard is the acceptable risk standard, that is, the acceptable risk standard starts at 10^{-4} and has a horizontal limit of 10^{-6} . Since the total annual dam failure probability of a reservoir is the sum of the failure probabilities along each path. In this paper, the dam failure path is divided into three main paths: overtopping, seepage, and engineering quality problems, and the dam failure probability under each dam failure path is calculated separately, so the engineering probability threshold

is set as 3.33×10^{-6} . At the same time, we refer to the statistical analyses of various international long-term dam-failure data [59–61]. The annual failure probability of earth-rock dams is as high as 10^{-4} , and that of concrete dams is 10^{-5} . After 2000, the annual failure probability of earth-rock dams decreased to 10^{-5} , indicating that the values of a and b are reasonable. This setting ensures that when the risk of a single path increases significantly and begins to have a substantial impact on the overall risk, the variable weight mechanism can be effectively triggered to focus on the real weak links.

In addition to the threshold for engineering failure probability, the corresponding human reliability should also be considered in determining a and b . From Table 4, the average (0.1) and worse (0.3) are used as benchmarks. From Table 4, the average (0.1) and the median of the average and the not-so-good (0.3) are used as benchmarks. The benchmark reliability used to set a represents the desired level of good management, taking $H_i = 0.1$ (human reliability is 0.9). The benchmark reliability used to set b represents the lower management level that needs to be vigilant, taking $H_i = 0.3$ (at this time, the human factor reliability is 0.7). After calculation, $a = 0.25$ and $b = 0.45$.

The physical meaning of the incentive coefficient λ_1 , λ_2 is the willingness to amplify the weight caused by unit risk growth in the warning and danger areas of the model, and its value determines the sensitivity and incentive intensity of the variable weight model. They are determined by the consensus of expert experience and the inversion calibration method used in this paper. Experts are asked to complete the scenario questionnaire to assess "How many times should the importance of a path be magnified when the probability rises from a to b ?". The Delphi method is used to make the opinions consistent, and thus, the values of λ_1 , λ_2 are obtained by back calculation. The specific steps are as follows:

Step 1: Build a calibration scenario. A virtual dam failure scenario including overtopping, seepage and engineering quality problems is designed, and each path is assigned a benchmark probability value x_j near the threshold a . For each path, a dangerous scenario is constructed, that is, x_j is raised to a higher value. For the warning zone scenario, the probability value x_j' near the threshold b is taken, while for the dangerous zone scenario, x_j'' is taken as $(1 + b)/2$.

Step 2: Get expert consensus magnification. The weighted

Delphi method described in Section 2.1.1 is used to organize the expert survey. The core question is "For path j , how many times do you think the relative importance of the path in the final risk assessment should be when its main risk factors deteriorate and its failure probability increases from x_j to x_j', x_j'' ". Through 2-3 rounds of anonymous feedback and statistical analysis, the expert opinions converge, and the consensus values M_1 and M_2 for the weight magnification factor under each path deterioration scenario are obtained.

Step 3: Build and solve the inversion equation. The theoretical value of the weight magnification is determined by the variable weight function, so the values of λ_1 and λ_2 can be inverted from equation (6) according to the obtained M_1 and M_2 . In the warning zone:

$$M_1 = \frac{[\omega_0 + \lambda_1 \times (x_j' - a)]}{\omega_0} \quad (14)$$

In the dangerous zone:

$$M_2 = \exp[\lambda_2 \times (x_j'' - b)] \quad (15)$$

It is worth noting that the magnification factor M_2 refers to the multiple at which the weight of the dam break path probability deteriorates from the upper limit b of the warning zone to a specific target value x_j'' in the dangerous zone.

From this, the preliminary estimates of λ_1 and λ_2 can be obtained by inverse calculation. To improve robustness, the arithmetic mean of the estimates across multiple paths is used as the final calibration value.

Step 4: Consistency check. The calculated final calibration value is substituted back into the equation, and the theoretical magnification in each scenario is obtained, which is compared with the expert consensus value. The average relative error obtained is within 10%, and the results are considered valid. The final calibration results of this paper are as follows: $M_1=1.5$, $M_2=2.0$, $\lambda_1=2.63$, $\lambda_2=13.86$.

3.3. Case study

The sample selected for this paper is based on a number of different dams in a given region, and examines the order of priority in deciding on appropriations and reinforcements, with limited financial amounts. Located north of the Yangtze River and Huaihe River in southern China, the DY county covers an area of 3,000 km² and has a total household population of about one million. Five small dams in DY county were selected for this study, all of which were identified as category II in the last

dam risk evaluation and need upgraded remediation. The location distribution of the five reservoirs in DY County is shown in Figure 3. The risk level assessment method was utilized to calculate the human reliability, failure probability, and consequence coefficient of the five dams, respectively, to obtain the dam risk index and risk order, which was then ranked to provide decision support for subsequent investment and remediation.

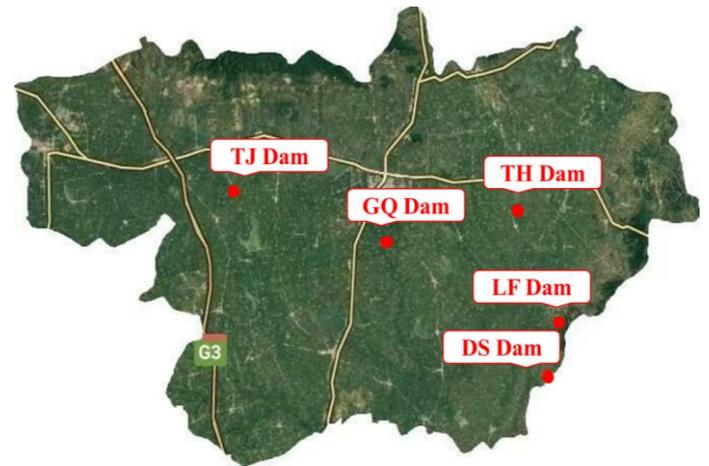


Figure 3. The location distribution of the five reservoirs in DY County.

3.3.1. Risk value calculation

To judge the priority of the compliance remediation of each dam, the DS dam, GQ dam, TH dam, TJ dam, and LF dam in the DY county were evaluated using the assessment methodology. From the dam design information and site research, the human factors of each one were scored using the qualitative-quantitative conversion relationships in Table 1, which were calculated to obtain the influence rating scale with results listed in Table 7. The dam failure consequence analysis was carried out considering the downstream flood protection population, cropland, cities and other factors, with the results listed in Table 8.

In Table 8, the loss of life is calculated proportionally to the downstream population, and the economic loss considers direct and indirect losses. Among them, the average value of fixed assets is RMB 6.6 million/km², and the primary inundation loss is based on 15%, the average value of total industrial and agricultural output is RMB 4.5 million/km², and the loss rate is based on 25%, while the value of household property of urban and rural masses is RMB 3.8 million/km², and the loss rate is

based on 20%.

Based on Tables 7 and 8, the integrated evaluation results considering human reliability of managers and dam failure consequences were calculated and listed in Table 9. The calculated contents include the constant weight dam failure probability without accounting for human factors amplification, Table 7. Scores on human factors for the five dams.

human error probability, constant weight calculations with consideration of the human factor, variable-weight calculations with consideration of the human factor and risk evaluation considering the dam failure consequences. The results and the ordering are shown in Figure 4.

Human factors	Evaluation indicators	DS dam	GQ dam	TH dam	TJ dam	LF dam
Administrator A	A1	0.1000	0.1000	0.2000	0.2000	0.0500
	A2	0.1000	0.1000	0.1000	0.1000	0.0300
	A3	0.1000	0.1000	0.1000	0.1000	0.0500
	A4	0.1000	0.1000	0.2000	0.2000	0.0100
Technology B	B1	0.2000	0.2000	0.1000	0.4000	0.2000
	B2	0.2000	0.3000	0.3000	0.5000	0.5000
	B3	0.1000	0.1000	0.1000	0.2000	0.1000
Organization C	C1	0.1000	0.0500	0.1000	0.1000	0.0200
	C2	0.1000	0.0600	0.0500	0.2000	0.0500
	C3	0.0500	0.0500	0.0500	0.1000	0.0200
	C4	0.1000	0.0500	0.1000	0.1000	0.0500
Environment D	C5	0.0500	0.0500	0.0500	0.1000	0.0100
	D1	0.1000	0.1000	0.1000	0.1000	0.1000
	D2	0.2000	0.2000	0.1000	0.3000	0.3000
Overtopping		0.1158	0.1114	0.1091	0.1957	0.1120
Seepage		0.1157	0.1209	0.1300	0.2062	0.1158
Engineering quality problems		0.1181	0.1155	0.1134	0.2090	0.1144

Table 8. Comprehensive evaluation coefficients for the failure consequences of the five dams.

	DS dam	GQ dam	TH dam	TJ dam	LF dam
Loss of life	10	20	10	5	260
Loss of life severity coefficient F1	0.8513	0.8740	0.8513	0.8214	0.9298
Economic loss / ten thousand yuan	551.1100	689.5500	557.0600	114.6700	517.0500
Economic loss severity coefficient F2	0.8098	0.8187	0.8102	0.7332	0.8072
Social loss	2.5344	3.2670	2.5555	3.1231	3.3880
Social loss severity coefficient F3	0.1010	0.1285	0.1019	0.1236	0.1325
Comprehensive evaluation factor of dam failure consequences L	0.7284	0.7504	0.7286	0.7019	0.7910

Table 9. Dam failure probability of five dams.

Dam failure probability	DS dam	GQ dam	TH dam	TJ dam	LF dam	
Probability of engineering failure	Overtopping	3.46E-06	2.70E-06	4.10E-06	3.08E-06	4.61E-06
	Seepage	3.90E-06	6.30E-06	5.83E-06	5.40E-06	3.65E-06
	Engineering quality problems	3.93E-06	4.28E-06	4.13E-06	3.89E-06	2.70E-06
The constant weight dam failure probability without accounting for human factors amplification	1.13E-05	1.33E-05	1.41E-05	1.24E-05	1.10E-05	
Human error probability	Overtopping	0.1158	0.1114	0.1091	0.1957	0.1120
	Seepage	0.1157	0.1209	0.1300	0.2062	0.1158
	Engineering quality problems	0.1181	0.1155	0.1134	0.2090	0.1144
Total human error probability	0.3496	0.3477	0.3525	0.6108	0.3422	
The constant weight failure probability with human factors amplification	Overtopping	0.2606	0.2026	0.3071	0.2551	0.3459
	Seepage	0.2941	0.4777	0.4469	0.4535	0.2751
	Engineering quality problems	0.2973	0.3222	0.3106	0.3277	0.2032
The constant weight failure probability with human factors amplification	0.8520	1.0025	1.0646	1.0363	0.8242	
The variable weight failure probability with human factors amplification	Overtopping	1.0366	1.0000	1.1590	1.0222	1.2611
	Seepage	1.1248	2.3944	1.5617	1.7109	1.0747
	Engineering quality problems	1.1332	1.1987	1.1682	1.2130	1.0000
The variable weight failure probability with human factors amplification	0.8540	1.1317	1.0929	1.0903	0.8410	
Risk evaluation considering the dam failure consequences	0.6221	0.8493	0.7963	0.7653	0.6652	

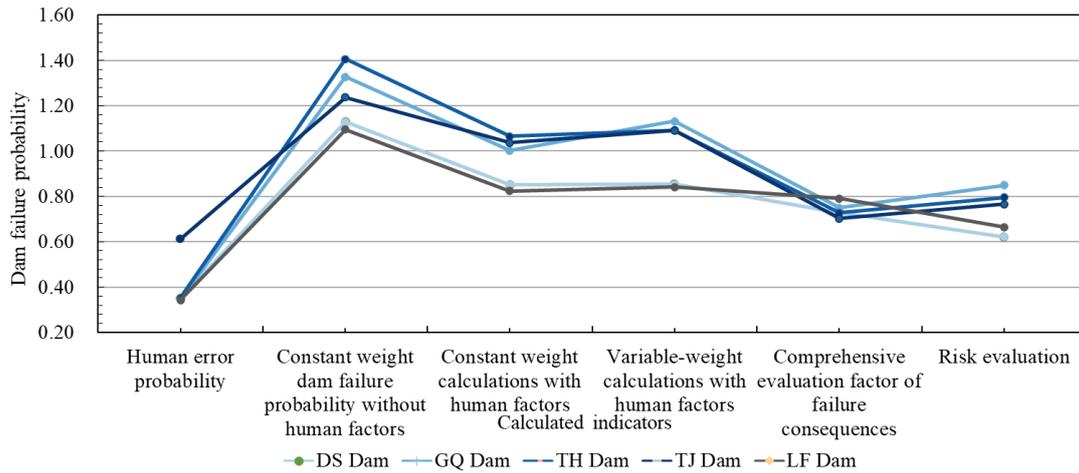


Figure 4. Comprehensive risk evaluation diagram for the five dams.

3.3.2. The analysis of calculation results

The results in Table 9 are ranked. The larger the number, the higher the result, that is, the highest risk. As shown in Table 10, the table clearly shows the changing ranking among reservoirs. Table 10. Comprehensive comparison of failure probability of five reservoirs.

	DS Dam	GQ Dam	TH Dam	TJ Dam	LF Dam
Human error probability	3	2	4	5	1
Constant weight dam failure probability without human factors	2	4	5	3	1
Constant weight calculations with human factors	2	3	5	4	1
Variable-weight calculations with human factors	2	5	4	3	1
Comprehensive evaluation factor of failure consequences	2	4	3	1	5
Risk evaluation	1	5	4	3	2

(1) Comparison with conventional pure engineering methods

When only engineering factors are considered, the risk ranking is TH>GQ>TJ>DS>LF, which is directly obtained from the event tree analysis under the three dam failure modes, reflecting only engineering safety. The failure probability of each node is determined based on the quantitative analysis of engineering conditions. The TH dam has a higher failure probability due to poorer performance of on-site facilities and fewer inspections, with a higher likelihood of pipe surges occurring and a lower probability of timely detection.

The order of GQ dam and TJ dam changed after superimposing the human influences on the engineering factors. After introducing the human coefficients into the engineering failure probability, the breach probability of the GQ dam is

scaled up from 1.33E-05 to 1.0025, and of the TJ dam is scaled up from 1.24E-05 to 1.0363. The TJ dam lacks a specialized management department, and the management system is inadequate. This proves that traditional engineering assessments may seriously underestimate the "hidden risks" posed by organizational defects in management. Dam failures are not only the result of engineering factors, but also the people in the dam site management. The method in this paper addresses this blind spot by coupling human-factor probability, thereby making the risk assessment closer to the essence of "man-machine-ring" interaction in engineering practice.

(2) Comparison with the static human factor coupling (constant weight) method

The risk assessment of five reservoirs is conducted using the variable-weight method, as shown in Figure 5. It can be seen that the dam break probability resulting from variable weight is larger than that with constant weight synthesis. In the constant weight comprehensive assessment, the risk ranking is TH > TJ > GQ > DS > LF. After introducing the incentive variable weight, the ranking becomes GQ > TH > TJ > DS > LF. The key change lies in the rising relative position of GQ reservoir risk. The variable-weight model effectively captures the unusually high probability of GQ dam failure on the "seepage" single-failure path (where engineering and human factors interact), and amplifies the weight of this path through the excitation function. This intuitively reflects the core advantage of the variable weight method of focusing on weak links.

At the same time, it can be observed that the failure probability of LF and DS reservoirs is very close after variable-weight calculation, whereas the probability of LF is clearly

lower under constant-weight calculation. The likelihood of dam failure due to overtopping of the LF reservoir is much higher than in other cases, which is a very prominent weak link. However, the probability of the DS dam is closer in all scenarios. The variable-weight method, used to amplify the weight of the overtopping failure probability of the LF reservoir, can more scientifically characterize the reservoir's dangerous situation.

Although the risk of the TH reservoir is still at a high level, its ranking relative to the GQ reservoir has declined. This just

shows that the variable-weight method not only considers the presence or absence of defects, but also gives greater weight to their severity. The GQ dam has moderate risks on multiple paths, and variable weights more scientifically aggregate this universal weakness into higher overall risks. Compared with static weighting, dynamic variable weighting can more finely reflect the actual impact of different management defects on the overall risk.

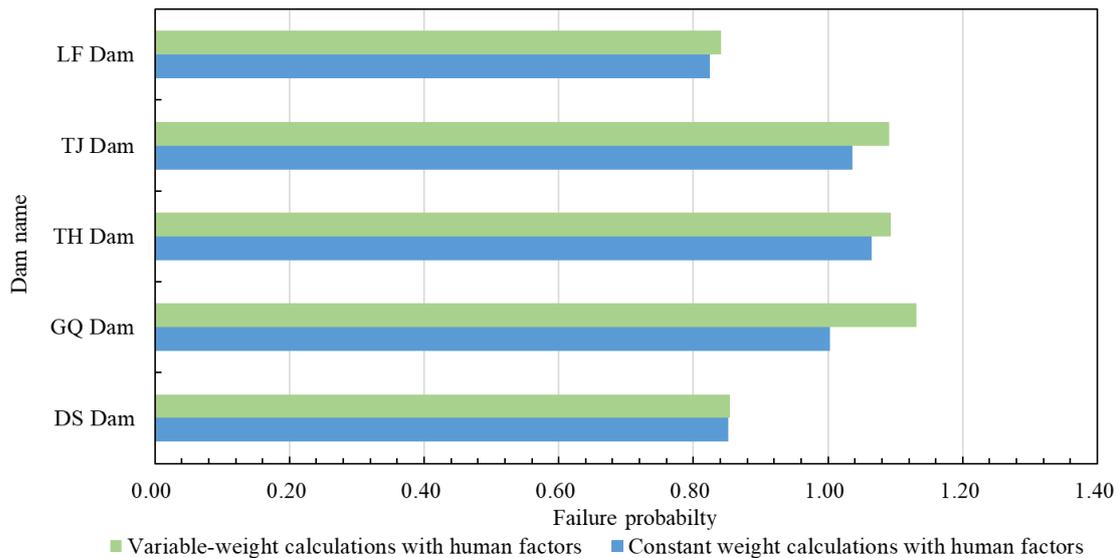


Figure 5. Comparison of calculation results between constant and variable weight.

(3) Comparison with methods without considering the dam failure consequences

After considering the consequences of dam failure, the dam risk ranking is $GQ > TH > TJ > LF > DS$. Changes from the risk evaluation with no consideration of the failure consequences were mainly in the DS and LF dams, caused by the high population under protection in the LF dam, the severe loss of life and economic damage after collapse, and the serious consequences. Therefore, despite being equipped with specialized management institutions, the variable-weight method amplifies its insecurity when there are weak links and exposes it to the risk of dam failure with severe consequences.

(4) Comparison with traditional HRA methods

Different from the classical HRA models, such as THERP and CREAM, which usually give an overall probability of human failure, the method proposed in this paper can not only quantify the influence of human failure and combine it with the probability of engineering failure, but also reversely locate the key sources that lead to increased risk. Compare our proposed

method with the mainstream method (HRA based on a Bayesian network) [36] and substitute it into the human error probability data for the overtopping situation. The Bayesian network is used and calculated to obtain the human error probability of each reservoir as: $P_{DS}=41.5\%$, $P_{GQ}=40.7\%$, $P_{TH}=39.6\%$, $P_{TJ}=34.4\%$, $P_{LF}=41.9\%$. This result is consistent with the ranking of human error probability calculated in this paper, and can reflect the human reliability of different reservoirs. However, this method does not include engineering factors and does not consider changes in human reliability across different failure causes, so the obtained error probability can only be used to compare management levels among different dams.

The classical HRA method and the method in this paper represent two different paradigms of human reliability analysis, probabilistic causal reasoning vs. multi-criteria decision-making and dynamic weight adjustment. Both methods can achieve defect localization. Bayesian networks, through posterior probability calculations and sensitivity analyses, require complex probabilistic reasoning, and interpreting results

requires expertise. The proposed method combines combination weighting and incentive variable weighting, which combines micro PSF weight with macro path risk. Through weight analysis and risk-propagation path tracing to realize two-way positioning, that is, both the top-down incentive-variable-weight method can be used to identify the high-risk dam-failure path, and the bottom-up analysis can be used to analyze the key PSFs and their weights that cause the risk of this path to rise. Instead of generally suggesting that "the reliability of human factors is low", the manager has obtained the risk ranking of the reservoir group and has the relevant rectification direction of each reservoir.

On the other hand, the proposed method lies between the pure engineering method and the complex Bayesian network HRA in terms of computational efficiency. It avoids the huge burden of constructing and calculating a conditional probability table of a Bayesian network, and combines two relatively efficient steps of weighting and piecewise variable weight function through game theory to significantly reduce the computational complexity while maintaining sufficient analysis depth. Under the condition of general data availability, the method in this paper achieves a good balance between accuracy improvement and implementation cost and has strong practical applicability.

Compared with the traditional risk assessment method that does not consider dynamic weight, the advantages of this method are as follows: 1) Incentive variable weight makes risk assessment more sensitive to weak links. 2) The weight can be

Table 11. Impact of single parameter change on risk ranking.

Parameter	Range of change	Sort Change	Conclusion
a	0.15-0.35	Risk ranking has not changed	The results are stable, and the risk ranking is insensitive to a .
b	0.35-0.55	Risk ranking has not changed	Changes in b can affect the identification of high-risk paths, but the ranking has not changed.
λ_1	1.0-4.0	Risk ranking has not changed	The linear incentive coefficient affects the risk value but does not change the ranking.
λ_2	8.0-20.0	Risk ranking has not changed	The weak path weight changes significantly, but does not affect the reservoir risk ranking.
S_{max}	2.0-5.0	Risk ranking has not changed	The upper weight limit prevents distortion in extreme cases.

Table 12. Degree of impact of parameter changes on key outputs.

Parameter	Value	Variable weight change	Amplitude of change	Sensitivity rating
a	0.2-0.25-0.3	1.1353-1.1317-1.1457	1.24%	Low
b	0.35-0.44-0.53	1.3077-1.1317-1.2157	15.55%	Moderate
λ_1	2.1-2.63-3.16	1.1332-1.1317-1.1303	13.25%	Moderate
λ_2	11.09-13.86-16.63	1.1170-1.1317-1.1464	1.30%	Low
S_{max}	2.4-3.0-5.0	1.1034-1.1317-1317	2.50%	Low

dynamically adjusted according to different situational factors, such as extreme weather, and is adaptable. 3) The method can provide decision support, and the result is not only the value of risk, but also the risk composition and changing trend.

The methodology combines dam management levels with engineering risks to increase the focus on human factors and hazardous dam failure pathways. Engineering applications show that the proposed human-driven variable-weight method for dam risk assessment can accurately express the impact of human factors on dam risk, intuitively reflect the danger order of different small dams, and provide a scientific basis for the management decision of dam groups.

3.3.3. Sensitivity analysis

(1) Sensitivity analysis of variable weight parameters

In order to verify the robustness of the proposed variable weight function, this section performs single-factor sensitivity analysis on key parameters, thresholds a , b , excitation coefficients λ_1 , λ_2 , upper weight limit S_{max} . The control variable method is used to test the influence of each parameter on risk ranking and risk value within the reasonable change range. Fix other parameters as reference values, take 5-7 equally spaced points within a reasonable range of parameter values, change each parameter value, and observe the change in risk value and risk ranking. The results are shown in Table 11 and Figure. 6.

Taking the GQ reservoir as an example, the change range is $\pm 20\%$, and the influence of parameter changes on key outputs is shown in Table 12.

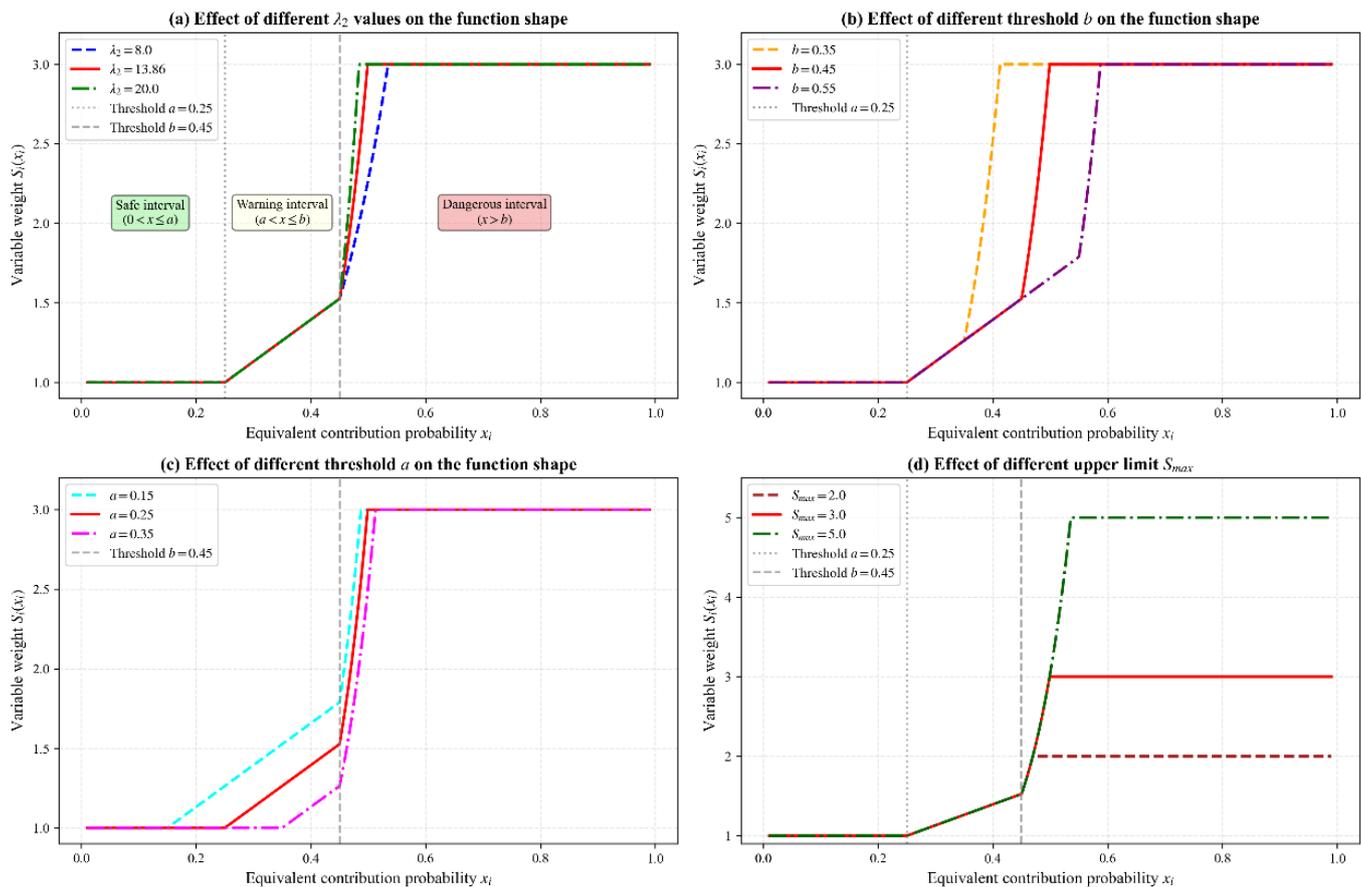


Figure 6. Shape of incentive variable weight function and sensitivity analysis.

From Tables 11 and 12, the risk ranking of each dam remains unchanged across most parameter change scenarios. This shows that the risk ranking method in this paper is robust and that the risk identification results are stable. Within a reasonable range of changes in parameters, management decisions will not change due to small changes in parameters.

The thresholds a and b mainly affect the division of risk intervals, while a has little impact on the comprehensive risk value. b defines the warning and danger interval, and its change will change the risk classification of the path. When b changes, the weight of the high-risk path increases significantly due to the variable-weight function's expansion effect, but it can still remain stable through normalization. The S_{max} setting controls the weight change amplitude to within 2.50%, effectively preventing evaluation distortion. Even if S_{max} is increased to 5, the weight variation is still limited, which proves the validity of the boundary conditions.

The change amplitude of the excitation coefficient λ_2 in Table 12 is less than λ_1 , which is since λ_2 only acts on the dangerous interval. λ_1 acts on the warning interval, which is the main interval of the case, and the linear incentive directly

responds to the increase in risk. In the case of the GQ reservoir, the equivalent contribution probability x_i of each break path does not fully enter the hazard interval and does not fully trigger the exponential excitation part. This verifies that the variable weight function can correctly distinguish between different risk states and apply reinforcement incentives only when necessary. When the risk is low, the parameter sensitivity is minor, and the incentive is mainly aimed at the real high-risk situation.

(2) Sensitivity analysis of human factors

The human factors sensitivity analysis is conducted using the DS reservoir as an example. As shown in Figure 7, take the influence of factors on the results when they are "fair" and "not very good". With all the remaining factors at 0.1, each factor is taken 0.6 in turn, yielding the results of the constant-weight and variable-weight approaches to check the response of the HRA model to changes in systemic risk.

A one-factor sensitivity quantification study is performed to calculate the absolute impact of worsening the i -th factor on the system's total risk. The effects are added to determine the proportion of the change in risk caused by each factor relative to the sum of the change in risk across all factors, i.e., the

percentage contribution. The results obtained are shown in Table 13.

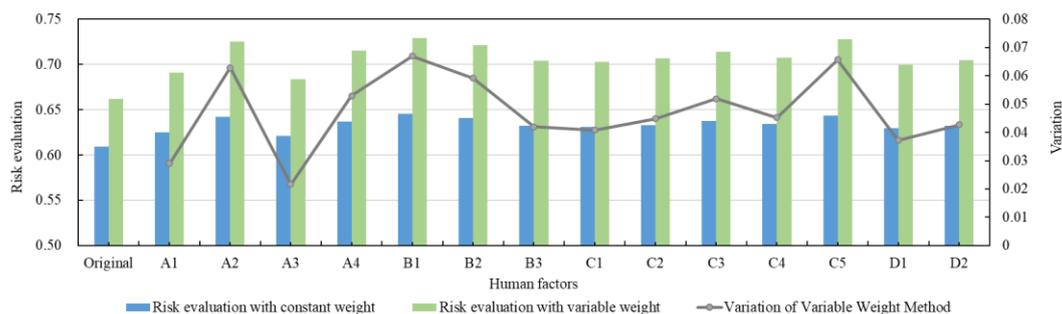


Figure 7. The sensitivity analysis of human factors.

Table 13. Human factor percentage contribution table.

Factor	A1	A2	A3	A4	B1	B2	B3	C1	C2	C3	C4	C5	D1	D2
Variable weight result	0.69	0.72	0.68	0.72	0.73	0.72	0.70	0.70	0.71	0.71	0.71	0.73	0.70	0.70
Risk variation	0.03	0.06	0.02	0.06	0.07	0.06	0.04	0.04	0.05	0.05	0.05	0.07	0.04	0.04
Percentage contribution	4.52	9.42	3.44	7.98	10.01	8.88	6.39	6.22	6.80	7.83	6.87	9.82	5.71	6.50

As shown in Figure 7 and Table 13, on the whole, the influence of various influencing factors on the results is not much different, and the variable weight risk value is higher than that of constant weight risk results. Under the single-factor deterioration scenario, the change range of the total system risk is between [0.01, 0.10], which reflects that the reservoir risk system has certain robustness to a single fault. 'Hardware facilities', 'Routine management' and 'Sense of responsibility' are the three factors that lead to the most significant increase in risk value and can be regarded as key sensitivity factors. In contrast, the individual effects of 'Psychological quality' and 'Experience' are relatively small.

In this case, 'Hardware facilities' is an important part of small reservoir managers' operations, and failure can be directly and quickly transmitted to operators and technical systems with little buffering. This reflects the typical characteristics of safety management in small reservoirs. Small reservoirs often lack redundant systems, and a single point of failure can directly cause monitoring or operational failure. Limited by financial and technical support, the hardware update cycle often exceeds the design life, increasing the probability of failure. Therefore, for small projects like the DS reservoir, a regular evaluation mechanism for the health of hardware facilities should be established to prioritize ensuring the reliability of key

equipment.

'Routine management' is an important link in reservoir safety management. Dam failure accidents in the non-flood season are caused mainly by the lack of daily inspections. Small reservoirs often lack a comprehensive inspection system, a record-keeping system, and a closed-loop mechanism for addressing problems, resulting in hidden dangers that go undetected in time and are not effectively addressed. To solve this problem, it is recommended that the small reservoirs implement standardized, digital, and closed-loop routine management improvement strategies, including formulating standardized operating procedures, deploying mobile inspection systems, and establishing a closed-loop problem tracking system.

'Sense of responsibility' directly affects the seriousness with which operators perform routine management, the acumen with which they detect equipment abnormalities, and the quality of their decision-making in emergencies. In small projects with few staff and relatively weak supervision, the role of responsibility is particularly critical. Improving the sense of responsibility requires systematic cultivation measures, including clarifying job responsibilities, establishing incentive mechanisms, and creating a safety culture.

Through sensitivity analysis of influencing factors, it can be

concluded that in the case of limited funds of DS reservoir, priority should be given to the update and maintenance of hardware facilities, and daily management and patrol inspection should be ensured by front-line operators. It is worth noting that although the deterioration of a single factor will not lead to a significant increase in risk, it is important to be alert to the coupling failure of multiple highly sensitive factors. In this case, the systemic risks will be nonlinear superimposed, and it is easy to enter a high-risk state.

3.3.4. Discussion

The study primarily provides a simple, operational risk-prioritization tool for small reservoirs with limited funds and resources and a relatively weak management system. There are systematic differences between small reservoirs and medium or large reservoirs in management system, technical dependence and risk tolerance. Therefore, it may not be appropriate to directly apply the weight system and variable weight parameters constructed in this study to large reservoirs. However, the core framework of this method (identifying key human factors, combining weighting, and amplifying weak links through context-sensitive variable weight functions) has universal theoretical value. By adjusting the PSF set and calibrating variable-weight parameters, future research can apply this method to reservoirs of different sizes, dam types, and climate zones to verify and expand its wide applicability.

The study holds that human reliability is not a static attribute but changes dynamically with engineering failure modes and emergencies. The induced modes of dam failure are divided into "overtopping", "leakage", and "engineering quality problem", and the human error and engineering failure probability are calculated according to the situation. The weights of human factors indexes under different failure modes are significantly different, reflecting the dynamic changes in human reliability across these modes. Then, the excitation variable weight function is introduced to dynamically amplify the high-risk situation, and the quantitative representation of the dynamic characteristics of human reliability is preliminarily realized.

In this study, there are still limitations in using the subjective and objective weighting methods to couple human error and engineering error with different accident probabilities, and to change the weight of error path probability. Although the

weighted Delphi method was used to determine the indicators, the scores remained dependent on expert experience and may be influenced by cognitive biases. Due to data scarcity, historical human error records are incomplete, and part of the scoring is based on analogical inference. Sensitivity analysis uses static hypothesis inference, with hypothesis factors changing independently, but in practice, human error often results from multi-factor coupling.

Appropriate simplification has been made in the consequence analysis. Monetized simplification of transforming difficult-to-quantify consequences, such as ecological losses and social impacts, into economic losses. For casualty statistics, the fixed population distribution assumption is adopted, and day-night and seasonal changes are not considered. These simplifications are based on engineering practicality considerations for risk assessment. For minor projects, overly complex consequence models may exceed actual management needs. The simplified model effectively identifies key risk sources and improvement directions when compared.

The historical dam-failure database on which this study relies, like most historical engineering data, may be subject to reporting bias. Most dam failure records are accidents caused by obvious external natural factors, such as over-standard floods and leaks, and ignore human factors. Deep human errors, such as long-term improper maintenance and flawed design decisions, may be underestimated or relegated to other categories. This statistical bias can affect the accuracy of the objective weights derived from historical data in this study. To alleviate this problem, this study adopts a combination of subjective and objective weighting methods and compensates for the deficiency of pure data-driven approaches by introducing expert subjective weights. At the same time, the incentive variable weight mechanism can also raise attention to low-frequency and high-risk events.

This study focuses on quantifying the influence of human factors on the overall risk probability of dam failure by coupling the engineering failure probability with a human factors index system, which falls under a macro analysis at the system reliability level. How specific human errors trigger and accelerate specific physical failure processes, such as hydraulics and geotechnical mechanics, has not been deeply developed.

The physical coupling between human error and engineering failure is a multi-level, nonlinear, and complex process. Future research can combine digital twins and mechanism models to explore the corresponding human factor-engineering coupling path. For example, management errors such as illegal water storage will cause the overtopping load to exceed the threshold; Monitoring negligence will delay the identification of abnormal seepage development and miss the golden window of engineering intervention; Maintenance defects will lead to the degradation of material properties and reduce the local shear strength of the dam body.

4. Conclusions

The existing reservoir risk assessment only focuses on engineering factors, and does not consider the important role of human factors in dam safety. This paper focuses on the calculation of dam risk combined with human factors, constructs a human factors index system, and combines subjective and objective methods to empower human factors indexes. A human-driven variable weight dam risk calculation method is put forward, which comprehensively reflects the risk in combination with the consequences of dam failure. The results show that the proposed risk assessment methodology effectively achieves the objectives, with the following main contributions:

- (1) Introducing human factors into dam risk assessment, an indicator system with three layers of human factors, including the target layer, the code layer, and the indicator layer, was proposed. The assignment of human factors indicators is realized using a combined weighting method, and the top failure pattern is varied using an incentive-based variable weighting method to amplify

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the dominant failure pattern, which can more accurately respond to the danger of weak indicators in collapsed dams.

- (2) A formula for calculating dam failure probability driven by human factors is proposed. With the introduction of accident consequences based on the risk management concept, a risk assessment methodology that integrates the human error probability, the dam failure consequences, and the engineering failure probability is proposed to provide methodological support for the risk evaluation of dam complexes considering human causes.
- (3) The method has been applied to the engineering examples. The human-driven risk assessment method can scientifically and intuitively reflect the impact of human management on dam safety, the risk level of dams, and provide a scientific basis for management decisions.
- (4) A sensitivity analysis of human factors was conducted to accurately identify several key factors (Hardware facilities, Routine management) that have the greatest impact on risk. Therefore, an operable single reservoir management promotion path can be obtained, realizing the leap from theoretical model to decision support.

To sum up, the novel variable weight risk assessment method driven by human factors can intuitively reflect the risk sequence of reservoir groups, and determine the investment priority of each factor of a single reservoir, providing an important reference for the decision-making of reservoir groups and single reservoirs. The method is reasonable and accurate, with good applicability. It can increase the attention to personnel management and make up for the shortcomings found in the existing evaluation methods.

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