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Risk Assessment of Inter-State Conflict with Cloud Model and Modified Evidence Theory

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Abstract

The assessment of inter-state conflict risk involves complex multi-domain interactions and dynamic evolutionary characteristics, presenting substantial challenges to conventional risk evaluation methodologies. This study proposes an innovative risk assessment framework for inter-state conflict by integrating the cloud model and quantum entanglement-weighted evidence synthesis. Based on the national security system perspective, an evaluation system consisting of 18 indicators across five dimensions (politics, military, economy, society, and technology) is constructed. The cloud model is employed to generate indicator membership matrices, while tensor network theory is introduced to characterize high-order semantic relationships between evidence and focal elements. Tensor contraction operations are further used to calibrate belief assignments in conflicting evidence. This approach constructs a systematic evidence synthesis paradigm of cloud model measurement, tensor correction, and quantum weighting. The proposed methodology is validated through application to the 2023 inter-state conflict risk assessment between China and ASEAN nations. Experimental results demonstrate the framework's superior performance in processing efficiency for high-dimensional evidence, capability for conflict resolution, and rationality of assessment outcomes. This study provides an interpretable quantitative analytical framework for risk evaluation in complex international security scenarios.

Keywords

Inter-State Conflict, Risk Assessment, Cloud Model, Modified Evidence Theory

1. Introduction

Inter-state conflict risk refers to the probability of confrontations between nations arising from diverging interests, ideological opposition, resource competition, territorial disputes, political standoffs, economic sanctions and military clashes. In recent years, inter-state conflicts have occurred frequently, such as the China-US trade conflict, Russia-Ukraine conflict, and India-Pakistan conflict. These conflicts typically feature strong antagonism, high transmissibility, and far-reaching global impacts. The emergence and evolution of such conflicts are determined not only by direct disputes between involved parties but also by multiple interdependent variables, such as international power structures, economic interdependence, and historical-cultural factors.

Current research oninter-state conflict risk mainly focuses on three aspects: risk identification, risk measurement, and the impacts of such conflicts. The first aspect concerns the analysis of influencing factors. Studies typically employ various methodologies based on different data sources (Bondarenko et al., 2024), including obstacle degree models (Hu et al., 2023), Fourier domain analysis based on transfer entropy spectrum (Dhifaoui et al., 2023), and spatial Durbin models (Hu & Li, 2023), to identify the determinants of inter-state conflict risk. These factors encompass military, economic, climate change and natural resources. The second aspect involves the measurement ofinter-state conflict risk from both temporal and spatial perspectives. Du et al. analyzed the spatiotemporal characteristics of conflict risk distribution in Southeast Asian countries based on event data (Du et al., 2024), while Yao et al. (2024) applied Bayesian networks for risk prediction. The third aspect examines the consequences of inter-state conflicts, including adverse effects on investment behavior (Gao & Du, 2024; He, 2023; Caldara & Iacoviello, 2022), energy transition (Wang et al., 2024; Almeida et al., 2025), and bank loan costs (Nguyen et al., 2025). Such conflicts may also indirectly influence oil prices through economic volatility (Jiao et al., 2023; Mignon & Saadaoui, 2024). Beyond traditional inter-state conflict risks, growing attention has been paid to non-traditional security risks, such as those arising from artificial intelligence (Liu, 2025) and digital platforms (Lu & Zheng, 2024). Preventinginter-state conflict risk is not only a strategic imperative for individual nations, but also a continuing challenge requiring global cooperation. Systemic governance through multilateral collaboration, crisis early warning systems, and inter-civilizational dialogue is essential. However, inter-state conflict risk involves numerous unstructured and ambiguous indicators that are difficult to quantify using conventional models. The cloud model addresses this limitation by transforming fuzzy concepts into computable numerical distributions through membership functions while preserving their inherent randomness and fuzziness, thereby better capturing experts' subjective risk assessment logic. Geopolitical analysis must contend with cognitive uncertainties, including incomplete intelligence data and varying source reliability. Evidence theory supports the recursive fusion of multi-level, multi-dimensional evidence, enabling hierarchical evidence accumulation to minimize misjudgments caused by data fragmentation.

The cloud model is a crucial tool for handling uncertainty. Liu et al. (2004) proposed a normal cloud model, which provides a theoretical basis for qualitative and quantitative conversion. Concurrently, the cloud model has been widely applied in risk assessment research. Wang et al. (2016) enhanced the model into a two-dimensional cloud model incorporating spatial geometric characteristics, demonstrating its advantages in fuzzy information representation. To address qualitative evaluation challenges in multidimensional indicators, Sun et al. (2024) developed a multidimensional cloud generator model, resolving traditional membership functions' excessive reliance on prior distributions. Guo et al. (2024) integrated variable weight theory with the cloud model by considering dynamic changes in indicator weights, effectively addressing randomness and fuzziness in risk assessment while proposing novel approaches for time-varying risk evaluation. The cloud model provides a more realistic uncertainty characterization tool for conflict risk analysis through fuzzy quantification, dynamic modeling and multi-source fusion. It proves particularly suitable for geopolitical scenarios featuring limited data, complex relationships, and the need to incorporate subjective judgments.

The core of evidence theory lies in quantifying uncertainty through basic probability assignment and combination rules, while characterizing the credibility range of propositions using belief and plausibility functions. Its primary advantage resides in effectively processing uncertain information, though limitations persist in handling highly conflicting evidence, thus spawning numerous improvement studies. Modifications to evidence theory are mainly divided into evidence source modification and combination rule improvement. Regarding evidence source modification, approaches addressing multi-source data fusion include: utilizing data deviation degrees (Jiang et al., 2021), calculating information source weights (Deng & Jiang, 2024; Xi et al., 2024; Wang & Xiao, 2024; Torous et al., 2018), integrating composite discount factors with game theory to reflect evidence falsity and credibility (Liu et al., 2023), and excluding unreliable evidence (Zhao et al., 2016). Concerning combination rule improvements, aiming at the problems of general conflict, one-vote veto, robustness and failure of synthesis rules in evidence theory, the improvement is made from the perspective of combination rules to avoid the deviation of evidence synthesis results from facts or the inability to synthesize, reduce false reasoning results and improve the reliability of fusion results. Zhao et al. (2024) proposed a generalized weighted evidence fusion algorithm based on quantum modeling, incorporating quantum interference effects to mitigate quantum evidence conflicts. Gauch Jr. (1973) comprehensively considered evidence similarity, evidence distance, and information content by integrating Bray-Curtis dissimilarity with belief entropy, achieving faster convergence while enhancing combination accuracy and reliability. Thus, evidence theory provides a flexible framework for handling incomplete and uncertain information, representing a significant extension of traditional probability theory.

Based on the aforementioned analysis, current research on inter-state conflict risk assessment under multi-source evidence still faces the following challenges: 1) When directly utilizing cloud model output membership degrees as basic probability assignments (BPAs) in evidence theory, the uncertainty information carried by the cloud model's entropy and hyper-entropy is often neglected. This oversight prevents evidence theory from fully inheriting the original data's fuzziness characteristics during the fusion stage. 2) Inter-state risk involves multi-domain data spanning political, economic, military, and social dimensions. Existing studies predominantly employ simple weighted averages or linear regression for fusion, lacking the capability to model nonlinear correlations and high-dimensional interactions. 3) In inter-state risk evaluation, different information sources may generate conflicting evidence due to divergent perspectives. Conventional methods struggle to effectively distinguish genuine conflicts from data noise. The Dempster combination rule exhibits heightened sensitivity to highly conflicting evidence, potentially yielding counterintuitive synthesis results.

To address the aforementioned challenges, this study proposes an inter-state conflict risk assessment method based on cloud model and enhanced evidence theory. The cloud model is used to model the uncertainty of indicators, converting raw data into fuzzy-grade probability distributions and transforming the output membership matrix into structured basic probability assignment (BPA) functions. Subsequently, tensor networks process high-dimensional correlations and evidence calibration, calculating the game-theoretic combination weights (incorporating both subjective and objective factors) for evidence. Quantum entanglement weighting is then applied to realize dynamic fusion and conflict resolution. Finally, case analysis demonstrates the reliability and accuracy of the proposed methodology.

2. Preparatory Knowledge

2.1. Basic Theory of Cloud Model

The cloud model is a mathematical tool for addressing uncertainty problems, initially proposed by Chinese Scholar Li Deyi in 1995. It organically integrates fuzziness and randomness through bidirectional transformations between quantitative numerical values and qualitative concepts, enabling the representation, reasoning, and decision-making of uncertain knowledge (Liu et al., 2004).

Definition 1 (Liu et al., 2004; Li, 2000): Suppose U is a given universe of discourse representing the quantitative value range corresponding to qualitative concept C in the cloud model. For any element x in U, the membership degree $\mu(x) \in [0, 1]$ reflects its belonging intensity to C, constituting a random number with stable tendency. A cloud drop represents a concrete numerical instantiation of the qualitative concept within the universe, where each drop's positional value x reflects quantitative characteristics while $\mu(x)$ indicates qualitative membership strength. The distribution of $\mu(x)$ over universe U is termed a cloud, with each constituent cloud drop denoted as $(x, \mu(x))$.

Definition 2 (Li & Liu, 2004): The cloud model characterizes the uncertainty of qualitative concepts through three fundamental numerical parameters: expectation E_x, entropy E_n, and hyper-entropy H_e. The expectation E_x represents the central value of the qualitative concept within the universe of discourse, corresponding to the most representative numerical instantiation of the concept, analogous to the peak position in traditional fuzzy sets. The entropy E_n quantifies both the fuzziness and randomness of the qualitative concept, indicating the magnitude of conceptual uncertainty. Greater entropy values correspond to increased conceptual ambiguity and stronger randomness, whereas smaller values indicate clearer concepts approaching traditional precise numerical representations.

Definition 3 (Li & Liu, 2004): The most prevalent variant of the cloud model, referred to as the normal cloud model, is mathematically defined as Equation (1):

$$\mu(x) = e^{-\frac{(x-E_x)^2}{2(E_n')^2}} \tag{1}$$

where E_n' presents a normally distributed random variable that captures the randomness of entropy, thereby ensuring uncertainty in the determination degree of each cloud droplet. The morphology of the normal cloud model is jointly determined by these three parameters, as shown in **Figure 1**.

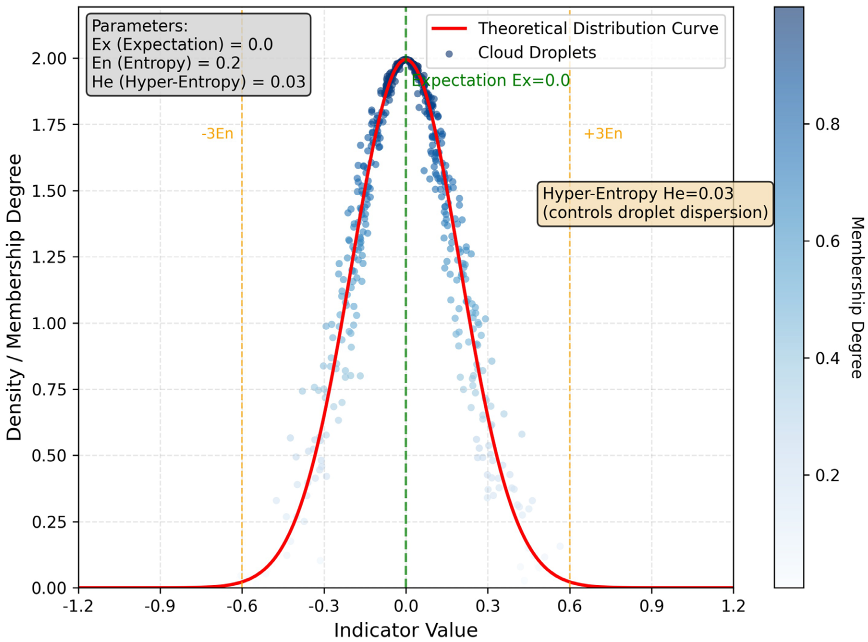

Figure 1. Normal cloud model digital characteristic diagram.

2.2. D-S Evidence Theory

Dempster-Shafer (D-S) theory, initially proposed by Dempster in 1967 (Dempster, 2008) and later expanded by Shafer in 1978 (Shafer, 1976), is a mathematical framework for processing imprecise, uncertain, and partial information. Its fundamental principle involves quantifying propositional support through Basic Probability Assignment, enabling the combination of multi-source evidence with particular efficacy for conflict evidence synthesis. Distinct from conventional probability theory, evidence theory permits more flexible representation of uncertainty by avoiding precise probability assignments when evidence remains insufficient. Instead, it characterizes event confidence through interval-valued belief measures.

Definition 4 (Deng, 2020): Basic Probability Assignment (BPA) Function. Suppose Θ be the frame of discernment, constituting a complete set of mutually exclusive and exhaustive elementary events. The basic probability assignment function $m: 2^{\Theta} \rightarrow [0,1]$ satisfies:

$$\begin{cases} m(\varnothing) = 0 \\ \sum_{A \subseteq \Theta} m(A) = 1 \end{cases} \tag{2}$$

$m(A)$ represents the precise degree of belief in proposition A, quantifying the evidence's support for A.

Dempster's Combination Rule: Suppose $m_1(B)$ and $m_1(C)$ be basic probability assignment functions derived from distinct evidence sources within the same frame of discernment Θ. The combined basic probability assignment function is given by:

$$m(A) = \begin{cases} 0, & A = \varnothing, \\ \dfrac{\sum_{B \cap C = A, \forall B, C \subseteq \Theta} m_1(B) m_2(C)}{1 - K}, & A \neq \varnothing \end{cases} \tag{3}$$

$$K = \sum_{B \cap C = A, \forall B, C \subseteq \Theta} m_1(B) m_2(C) \tag{4}$$

where K denotes the conflict coefficient, quantifying the degree of conflict between m_1 and m_2, with $0 \leq K \leq 1$.

3. Risk Assessment and Decision-Making Methodology with Cloud Model and Modified Evidence Theory

This section establishes a dual-module system integrating cloud model and modified evidence theory. The cloud model module transforms raw data into fuzzy-grade probability distributions, characterizing indicator randomness and fuzziness through expectation, entropy, and hyper-entropy. By converting the output membership matrix into mass functions, it completes uncertainty modeling while overcoming the rigidity of traditional methods in fuzzy concept representation. The evidence theory module addresses inherent conflict-handling limitations through: 1) tensor networks for high-dimensional correlation mining and evidence calibration, 2) game-theoretic weight determination combining subjective and objective factors, 3) quantum entanglement weighting for dynamic evidence fusion and conflict resolution. This integrated approach resolves robustness deficiencies in traditional evidence theory when processing high-dimensional data and synthesizing conflicting evidence, significantly improving reliability and accuracy in complex risk assessment scenarios.

3.1. Indicator Quantification Based on Cloud Modeling

3.1.1. Calculation of Cloud Model Parameters

Assume there are m indicators in the evaluation index system, each with a valid universe of discourse $[x_{\min}, x_{\max}]$. For quantitative indicators, the grade intervals are determined via equidistant partitioning, where the scoring interval for grade k-th is $[a_k, b_k]$. The theoretical cloud parameters can then be calculated using the following formulas:

$$E_x^k = \frac{a_k + b_k}{2} \tag{5}$$

$$E_n^k = \frac{b_k - a_k}{6} \tag{6}$$

$$H_e^k = \lambda \cdot E_n^k \tag{7}$$

where λ denotes the hyper-entropy coefficient, which is typically assigned a value within the range [0.1, 0.3].

3.1.2. Membership Matrix Construction

The membership matrix for each indicator is typically calculated based on the cloud model's certainty function. Consider a system with m indicators and n evaluation grades. For the i-th indicator, the cloud parameters corresponding to the k-th grade are defined as: expectation value $E_{x_{i,k}}$, entropy $E_{n_{i,k}}$, and hyper-entropy $H_{e_{i,k}}$. The membership degree of the i-th indicator with respect to grade k is computed via the normal cloud generator, expressed by the following formula:

$$\mu_{i,k} = \exp\left(-\frac{\left(x_i - E_{x_{i,k}}\right)^2}{2\left(E'_{n_{i,k}}\right)^2}\right) \tag{8}$$

$E'_{n_{i,k}}$ is a normally distributed random variable following $N\left(E_{n_{i,k}}, H_{e_{i,k}}^2\right)$, representing the uncertainty of entropy. For practical computation of the membership matrix, a simplified approach typically assumes $E_{n_{i,k}} = E'_{n_{i,k}}$ (disregarding the randomness of hyper-entropy by using the expectation value of entropy). Under this simplification, the formula reduces to:

$$\mu_{i,k} = \exp\left(-\frac{\left(x_i - E_{x_{i,k}}\right)^2}{2E_{n_{i,k}}^2}\right) \tag{9}$$

The membership degree vector for the i indicator across all n grades is constructed as: $\boldsymbol{\mu}_i = \left[\mu_{i,1}, \mu_{i,2}, \cdots, \mu_{i,n}\right]$, where each element is computed via the Equation (9).

3.2. Basic Probability Assignment Function Correction Based on Tensor Networks

3.2.1. Evidence-Based Processing of Evaluation Trustworthiness

The transformation of cloud model membership degrees into Basic Probability Assignment functions integrates evidence theory with cloud modeling uncertainty characteristics through the introduction of an uncertainty grade θ as a focal element, constructing an extended frame of discernment: $\Theta = \{C_1, C_2, \cdots, C_n, \theta\}$, where C_k represents definite assessment grades, θ corresponds to unassignable cases. The resulting mass function is defined as:

$$\begin{cases} m_i\left(C_k\right) = \left(1-\theta_i\right)\mu_{i,k} \Big/ \sum_{k=1}^{n} \mu_{i,k} \\ m_i\left(\theta_i\right) = \theta_i \\ \theta_i = 1 - \max\left(\mu_{i1}, \mu_{i2}, \cdots, \mu_{in}\right) \end{cases} \tag{10}$$

3.2.2. Correction of Basic Probability Assignment Functions with Tensor Networks

In evidence theory, mass functions are employed to represent the allocation of uncertainty to propositions. However, traditional approaches face the following challenges when processing high-dimensional data or complex evidential relationships: 1) Dimensional explosion: As the dimensionality of evidence increases, the storage and computational complexity of mass functions grow exponentially; 2) Inadequate modeling of complex dependencies: Conventional methods struggle to capture nonlinear and higher-order dependencies among evidence; 3) Incomplete representation: In high-dimensional scenarios, traditional mass functions may fail to accurately characterize evidential conflicts, redundancies, or hierarchical structures. Tensor networks constitute a mathematical tool for efficiently representing and manipulating high-dimensional tensors. By decomposing high-dimensional tensors into structured products of lower-dimensional tensors, they significantly reduce computational complexity while preserving the tensors' essential geometric and algebraic properties (Verstraete et al., 2008; Orús, 2014). The integration of TN into evidence theory for mass function correction systematically addresses the aforementioned challenges.

Suppose there are m pieces of evidence $E_1, E_2, \cdots, E_m$, where each evidence is associated with a mass function $m_i : 2^{\Theta} \to [0,1]$. To embed these mass functions into tensor space, three key operations are performed:

1) Construction of high-dimensional evidence tensors

Each focal element $B \in \Theta$ is mapped to an n-dimensional binary vector $b = \left(b_1, b_2, \cdots, b_n, \theta\right)$, when $b_k = 1$ if and only if $C_k \in B$.

Construction of Evidence Tensor $M \in \mathbb{R}^{m \times \left(2^n - 1\right)}$: Each evidence E_i constitutes the i-th slice of the tensor, containing mass values for its focal elements. The element at row i and column j corresponds to $m_i\left(B_j\right)$, where B_j denotes the j-th non-empty focal element. For large n, direct storage of the 2^n-dimensional tensor becomes computationally infeasible. Sparse tensor representation and Tensor Decomposition are employed.

2) Tensor decomposition and high-dimensional correlation modeling

The evidence tensor $\mathcal{M}$ is decomposed into a sum of R rank-1 tensors via CP decomposition to capture higher-order correlations among evidence sources:

$$\mathcal{M} \approx \sum_{r=1}^{R} \boldsymbol{u}_r^{(E)} \circ \boldsymbol{u}_r^{(\Theta)} \tag{11}$$

where $\boldsymbol{u}_r^{(E)} \in \mathbb{R}^m$ represents the evidence weight vector in the r-th latent dimension, characterizing inter-evidence correlations in the semantic space, while $\boldsymbol{u}_r^{(\Theta)} \in \mathbb{R}^{2^n - 1}$ denotes the focal element semantic vector in the r-th dimension, capturing high-dimensional semantic features of focal elements. The symbol ∘ indicates the tensor outer product operation.

3) Tensor Network-Based Evidence Similarity Computation

The similarity between evidence E_i and E_j is defined as the cosine similarity of their corresponding tensor slices:

$$s_{ij} = \frac{\boldsymbol{m}_i \cdot \boldsymbol{m}_j}{\|\boldsymbol{m}_i\| \|\boldsymbol{m}_j\|}, \boldsymbol{m}_i, \boldsymbol{m}_j \in \mathbb{R}^{2^n - 1} \tag{12}$$

where $\boldsymbol{m}_i$ denotes the mass vector of evidence E_i.

The collaborative similarity among k pieces of evidence $E_{i_1}, E_{i_2}, \cdots, E_{i_k}$ is defined as the higher-order inner product of their corresponding tensor slices:

$$s_{i_1 i_2 \ldots i_k} = \mathcal{M}(i_1,:) \cdot \mathcal{M}(i_2,:) \cdot \ldots \cdot \mathcal{M}(i_k,:) \tag{13}$$

where the operator "·" denotes tensor contraction along the focal element dimension, with the resulting value quantifying the consistency of support patterns across the *k* pieces of evidence.

4) Tensor network-corrected mass function update

The modified mass function is obtained by using high-dimensional similarity tensor to adjust the credibility of evidence.

Evidence support degree calculation: An hyperparameter $\lambda \geq 0$ is introduced to fuse the *k*-th order support degrees into an aggregated support measure:

$$S_i = S_i^{(2)} + \lambda \sum_{k=3}^{m} \sum_{i_2, \cdots, i_k \neq i} s_{i i_2 \cdots i_k}. \tag{14}$$

In Equation (14), the hyperparameter $\lambda = 0.5$ serves as the neutral value for balancing the second-order similarity (direct evidence correlation) and the higher-order similarity (indirect evidence synergy). Considering that the conflict risk indicators in this study cover multiple dimensions such as politics, military, and economy, direct correlation (such as military expenditure and military force size) and indirect synergy (such as the combined effect of political stability and economic mutual trust) are equally important for risk assessment. With $\lambda = 0.5$, it can avoid model deviation caused by single-dimensional dependence and is suitable for the assessment scenarios of multi-factor coupling.

Mass function correction: Weight the original mass function according to the support degree S_i.

$$m_i'(B) = \frac{S_i}{\sum_{j=1}^{m} S_j} \cdot m_i(B), \forall B \subseteq \Theta \tag{15}$$

The corrected mass function must satisfy the normalization condition $\sum_{B \subseteq \Theta} m_i'(B) = 1$.

3.3. Basic Probability Assignment Function Correction Based on Tensor Networks

3.3.1. Evidence-Based Processing of Evaluation Trustworthiness

Evidence theory is highly sensitive to the rationality of evidence weights, and unreasonable weights may lead to failure in conflict resolution. To address this issue, this paper comprehensively considers subjective and objective weights, and improves evidence theory based on game-theoretic combination weighting. By using combined weights, the influence of highly conflicting evidence is reduced, thereby minimizing its interference in the fusion process.

1) Subjective weights

The G1 method is used to calculate subjective weights. Its core logic involves ranking the indicators by importance and setting the importance ratio coefficients between adjacent indicators, thereby recursively calculating the weights of each indicator. The ordinal relationships and ratio coefficients directly reflect the relative importance among the indicators. Experts compare the importance of adjacent indicators x_{k-1} and x_k, providing the ratio coefficient r_k, which represents the multiple of importance of x_{k-1} relative to x_k.

$$\begin{aligned} & w_{k-1} = r_k \cdot w_k \left(k = 2,3,\cdots,n\right) \\ & w_n = \frac{1}{1+\sum_{k=2}^{n}\prod_{i=2}^{k} r_i} \\ & w_k = \left(\prod_{i=k+1}^{n} r_i\right)\cdot w_n \left(k = 1,2,\cdots,n-1\right) \end{aligned} \tag{16}$$

where w_{k-1} is the weight relationship between adjacent indicators, w_n is the weight of the last indicator and w_k is the weight of other indicators.

Calculate the maximum eigenvalue $\lambda_{\max}$ and the eigenvector $\boldsymbol{w}^s$ of the judgment matrix. After normalization, the subjective weight vector is obtained:

$$\boldsymbol{w}^s = \left[w_1^s, w_2^s, \cdots, w_m^s\right], \sum_{i=1}^{m} w_i^s = 1 \tag{17}$$

2) Objective weights

The similarity coefficient between pieces of evidence is employed to measure their degree of similarity. A higher similarity indicates greater support between indicators. The objective weights w_2 are determined based on the degree to which evidence is supported by other evidence. Cosine similarity is adopted to quantify the evidential similarity between indicators:

$$Sim\left(i, j\right) = \frac{e_i \cdot e_j}{\left\|e_i\right\|\left\|e_j\right\|} \in \left[0,1\right] \tag{18}$$

where e_i and e_j represent the evidence vectors of indicators *i* and *j*, respectively. A higher $Sim\left(i, j\right)$ indicates stronger evidential consistency between indicators *i* and *j*.

The support degree of indicator *i* is the sum of similarity coefficients from all other indicators:

$$Sup\left(i\right) = \sum_{j=1}^{m} Sim\left(i, j\right) \tag{19}$$

The support degree reflects the extent to which indicator *i* is supported by other evidence and the higher the support degree, the greater the objective credibility.

Normalize the support degrees and derive the objective weights.

$$w_i^o = \frac{Sup(i)}{\sum_{k=1}^{m} Sup(k)}, \boldsymbol{w}^o = \left[w_1^o, w_2^o, \cdots, w_m^o\right] \tag{20}$$

3) Game-theoretic combined weights

The Lagrangian function is constructed.

$$L = D\left(\boldsymbol{w}^s, \boldsymbol{w}^o\right) + \mu\left(\sum_{i=1}^{m} w_i - 1\right) + \sum_{k=1}^{K} \nu_k g_k\left(\boldsymbol{w}\right) \tag{21}$$

where μ is the Lagrange multiplier for the normalization constraint, $g_k(\boldsymbol{w})$ is the constraint function for support degree and expert priority, ν_k is the multiplier for the constraint condition.

Solve for the optimal weights and take the partial derivative of w_i and set it to 0.

$$\frac{\partial L}{\partial w_i} = 2\left(w_i - w_i^s\right) + 2\left(w_i - w_i^o\right) + \mu = 0 \tag{22}$$

Combined with the normalization condition, the solution is obtained as:

$$w_i = \frac{w_i^s + w_i^o + \frac{\mu}{2}}{2} \tag{23}$$

The parameter μ is iteratively adjusted to satisfy the condition $\sum w_i = 1$.

Evidence support degree calibration. If the support degree of a given indicator *i* is negatively correlated with the combined weight, its weight is forcibly increased:

$$w_i = w_i + \delta \cdot \left(Sup(i) - mean(Sup)\right) \tag{24}$$

δ is the calibration coefficient.

3.3.2. Evidence Fusion Based on Quantum-Entanglement-Weighted Averaging

It should be emphasized that the quantum entanglement utilized in this study refers to a mathematical formalism borrowed from quantum mechanics, rather than physical quantum mechanical phenomena. We employ the mathematical concepts of probability amplitude and interference effect to model the nonlinear correlations and synergistic effects among inter-state conflict risk indicators. The core purpose is to transform the complex interdependencies among multi-dimensional indicators into computable mathematical relationships (i.e., the entanglement coefficient in Equation (25)), rather than implying that the risk assessment process involves physical quantum mechanical mechanisms. This mathematical formalism provides a flexible tool for characterizing the non-independent interactions between indicators, which is consistent with the practical characteristics of inter-state conflict risk factors that are mutually influential and synergistic.

One of the core characteristics of inter-state conflict risk is the interconnectedness of risks across multiple domains, such as the synergistic effects of military deterrence and economic sanctions, or the transmission relationship between political confrontation and social unrest. In traditional evidence theory, the mass functions of indicators are often assumed to be independent events, synthesized merely through simple linear superposition or Dempster's rule, neglecting the strategic interdependencies among indicators. Quantum-entanglement-weighted evidence fusion introduces the concept of "quantum entanglement" to transform the nonlinear correlations among indicators into "entanglement weights," enabling the evidence fusion process to dynamically reflect such strategic interaction effects.

Quantum-entanglement-weighted evidence fusion is grounded in the superposition principle of quantum mechanics, representing experts' perceptions of "uncertain events" as "probability amplitudes" (rather than classical probabilities). Through "entangled superposition," it more accurately conveys risk information that is "possible yet uncertain."

Suppose the modified evidence set be $\{E_1, E_2, \cdots, E_m\}$, which is output through the high-order similarity of the tensor network.

1) Construct the entanglement coefficient matrix $\Gamma \in \mathbb{R}^{m\times m}$, where r_{ij} represents the entanglement strength between evidence E_i and E_j.

$$r_{ij} = \frac{s_{ij} + \lambda \cdot \frac{1}{m-2}\sum_{k\neq i,j} s_{ijk}}{1+\lambda} \tag{25}$$

Pairwise similarity: $s_{ij} = \frac{m_i' \cdot m_j'}{\|m_i'\| \cdot \|m_j'\|}$, normalization of focal element vector dot products.

Third-order similarity: $s_{ijk} = \sum_{B\subseteq\Theta} m_i'(B) \cdot m_j'(B) \cdot m_k'(B)$, Joint support degree of three pieces of evidence for the same focal element

Hyperparameters: λ adopts the setting of λ = 0.5, maintaining consistency with the method in Equation (14). The core logic of this value is the direct and indirect correlations among multiple indicators of the neutral balance, which conforms to the multi-dimensional characteristics of conflict risks between China and ASEAN countries. It ensures that key correlation information is not omitted during the integration process, while avoiding the interference of redundant information.

Symmetry: $\lambda_{ij} = \lambda_{ji}$, Non-directionality of inter-evidence correlations.

2) Calculate the evidence relevance degree to measure the importance of evidence E_i in the correlation network.

$$C_i = \sum_{j=1}^{m} \gamma_{ij} \tag{26}$$

The larger C_i, the stronger the synergistic effect between evidence E_i and other evidence.

3) Derive the entanglement weighting factor by integrating game-theoretic weights and relevance degrees to generate dynamic weighting factors.

$$\alpha_i = \frac{w_i^{com} \cdot C_i}{\sum_{j=1}^{m} w_j^{com} \cdot C_j} \tag{27}$$

4) Quantum-entanglement-weighted averaging: Perform weighted fusion on the modified mass functions.

$$\tilde{m}(B)=\sum_{i=1}^{m}\alpha_i\cdot m_i'(B),\forall B\subseteq\Theta \tag{28}$$

3.4. Risk Assessment and Decision-Making Process Based on Cloud Model and Modified Evidence Theory

Based on the content of the previous two sections, this section will construct a risk assessment and decision-making method using the improved evidence theory as the decision framework. The game-theoretic combined weighting method is employed to determine the weights of indicators during the decision-making process. Meanwhile, the cloud model is utilized to convert continuous data into discrete data. Additionally, the improved evidence theory is applied to address the high uncertainty in multi-source information fusion during decision-making. In summary, this section will develop a novel risk assessment and decision-making method to tackle real-world problems characterized by numerous risk factors and high uncertainty in multi-source information.

In risk assessment and decision-making problems, identifying the research object and subsequently conducting risk assessment are undoubtedly prerequisites and guarantees for making correct decisions. Therefore, risk factor analysis and the construction of a risk criterion system must be performed before decision-making to establish a scientific and comprehensive risk assessment and decision-making process. This section adopts a method integrating the cloud model and improved evidence theory as the decision framework for multi-criteria decision-making (MCDM). The game-theoretic combined weighting method is incorporated into the MCDM process as a tool for determining indicator weights, thereby forming a novel risk assessment and decision-making approach, as illustrated in Figure 2.

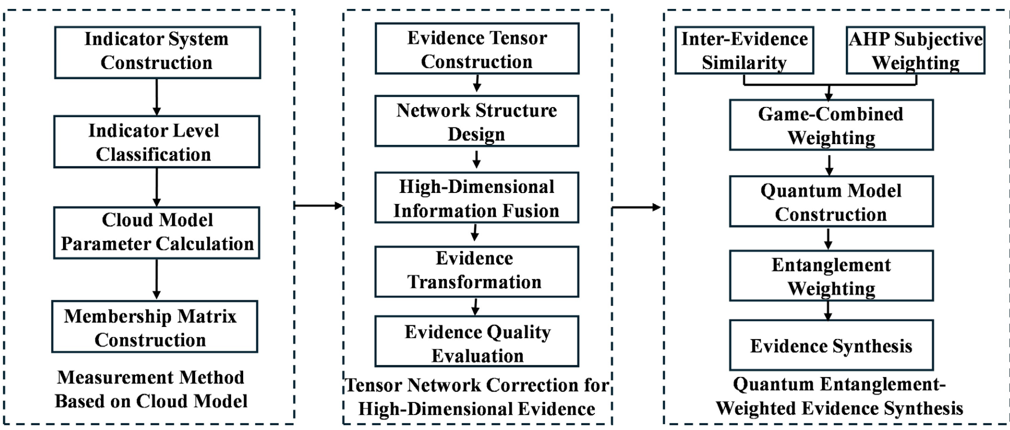

Figure 2. Risk assessment and Decision-Making method based on cloud model and improved evidence theory.

1) Measurement method based on cloud model

The forward cloud generator is employed to determine the numerical characteristics of the cloud model, generating a large number of cloud droplets that conform to the distribution features. By establishing a set of evaluation ratings, the benchmark cloud transformation models for each rating level are obtained. Before the evidence theory yields a comprehensive evaluation result, it is necessary to determine the basic probability assignment (BPA) functions of each evaluation indicator in the scheme, which can be derived from the belief degree functions calculated by the cloud model. After obtaining the numerical characteristics of the cloud model corresponding to each evaluation indicator, the X-conditional forward cloud generator is used to compute the belief degree of each evaluation indicator under the standard cloud. The belief degrees are then normalized to derive the belief degree function of each evaluation indicator across the evaluation ratings.

2) Tensor network correction for high-dimensional evidence

To address the issues of dimensionality explosion and inadequate dependency modeling in traditional evidence theory under high-dimensional scenarios, this study introduces tensor networks for the structured representation and optimization of evidence. The risk belief assignments of each indicator are mapped to multi-dimensional tensors, with structures such as Matrix Product States (MPS) and Tree Tensor Networks (TTN) employed to characterize chain-like, hierarchical, or complex interactive dependencies among indicators. High-dimensional tensors are compressed using canonical multilinear decompositions (CP decomposition), preserving core evidence correlation information while reducing computational complexity. By designing a loss function incorporating regularization terms, the parameters of the tensor network are optimized to correct abnormal belief assignments in conflicting evidence, thereby enhancing the accuracy and completeness of high-dimensional evidence representation. This provides more reliable input for subsequent evidence fusion.

3) Quantum-entanglement-weighted evidence fusion combined with game-theoretic integrated weighting method

This study proposes an integrated fusion framework that combines subjective and objective information while enhancing evidence correlations. First, the G1 method is employed to derive subjective weights reflecting expert knowledge, while objective weights capturing intrinsic data relationships are computed based on inter-evidence similarity. A game-theoretic approach constructs an objective function to balance these weight differences, generating combined weights that integrate both domain expertise and data-driven rationality. Subsequently, the concept of "quantum entanglement" is introduced by constructing an entanglement weighting matrix to simulate nonlinear synergistic effects among evidence. This strengthens the joint support degree of substantively correlated evidence while suppressing interference from independent conflicting evidence. Finally, based on an improved evidence theory fusion method, the weighted evidence undergoes conflict resolution and belief fusion to produce comprehensive assessment results of inter-state conflict risks. This forms a complete closed-loop process from indicator measurement to risk inference, enhancing the scientific rigor and robustness of uncertainty reasoning in complex scenarios.

This section integrates the aforementioned content to propose a risk assessment method based on cloud model and improved evidence theory, with the following steps:

Step 1: Conduct indicator screening and justification to identify key factors influencing inter-state conflict risks. Classify indicator levels to establish a foundation for subsequent cloud model analysis.

Step 2: Based on the cloud model method, use Equations (5)-(7) to calculate the cloud numerical characteristics (expectation Ex, entropy En, hyper-entropy He). Apply Equations (8)-(9) to transform qualitative levels into a quantitative membership degree matrix. Through evidential conversion, employ Equation (10) to convert membership degrees into basic belief assignments (BBAs), achieving the transition from cloud model to evidence theory.

Step 3: Utilize tensor networks for high-dimensional modeling and correction of mass functions in evidence theory, enhancing the accuracy and completeness of evidence representation. Apply Equation (4) to correct the evidence.

Step 4: Adopt the G1 method and Equation (5) to compute subjective weights. Based on evidence similarity, use Equation (6) to derive objective weights. The game-theoretic combined weights integrate subjective and objective weights through game theory principles, with Equation (7) calculating the combined weights to ensure scientific rigor and rationality.

Step 5: Employ the quantum-entanglement-weighted averaging method to weight the evidence, strengthening inter-evidence correlations and holistic consistency. Use Equations (8)-(10) to compute the weighted evidence. Based on improved evidence theory, apply Equation (11) to synthesize and identify conflicting evidence, yielding the final risk assessment results.

4. Case Analysis

4.1. Problem Background

China and ASEAN share geographical proximity, forming a geopolitical and geo-economic complex in the South China Sea. In 2023, bilateral trade between China and ASEAN reached 6.52 trillion RMB, making them each other's largest trading partners. However, the region faces potential risks such as sovereignty disputes in the South China Sea, military security dilemmas, and economic development disparities. Examples include Vietnam's oil and gas exploration activities and the Philippines' joint patrol operations, which may escalate tensions. The ten ASEAN member states are Singapore, Malaysia, Indonesia, Thailand, Vietnam, the Philippines, Myanmar, Cambodia, Laos, and Brunei. Therefore, this study selects China and the ten ASEAN countries as research subjects, utilizing 2023 raw data on geopolitical conflict risk evaluation indicators.

This research systematically constructs a risk assessment indicator system across five dimensions: politics, military, economy, society, and technology. Through bibliometric analysis, core risk factors in the field are identified, supplemented by multiple rounds of expert consultations (involving practitioners and theorists in international relations, security strategy, and regional economics) to form a preliminary indicator pool. Empirical validation and indicator screening are further conducted based on typical geopolitical conflict cases from the past decade (the Russia-Ukraine crisis, U.S.-China technology competition, and South China Sea disputes). Finally, cross-verification from multi-source data and redundancy analysis refine 18 core factors comprehensively reflecting geopolitical conflict risks. This establishes a risk evaluation system (as shown in Figure 3) covering dimensions such as political mutual trust, military deterrence, economic interdependence, social stability, and technological gaps, providing a multidimensional and quantifiable analytical tool for systematic inter-state conflict risk assessment.

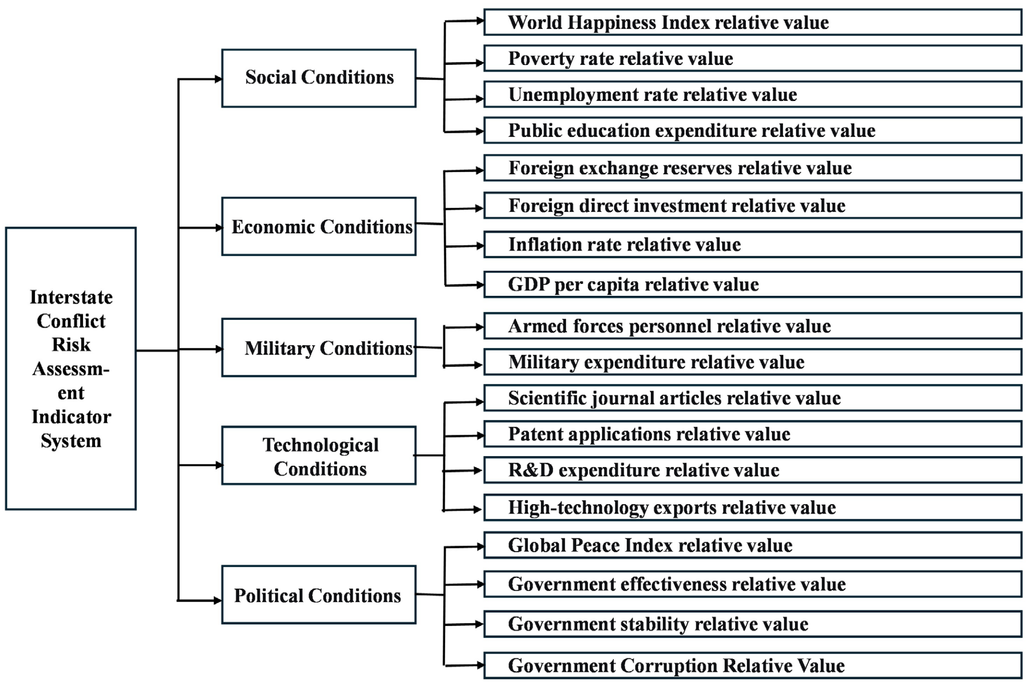

Figure 3. Interstate conflict risk assessment indicator system.

To ensure the reliability and traceability of the research data, the specific sources of the 18 observable indicators under the five latent nodes are clearly specified as follows:

For the social conditions dimension, the World Happiness Index relative value is derived from the World Happiness Report (2023), while the Poverty Headcount Ratio relative value, Unemployment Rate relative value, and Public Education Expenditure relative value are all retrieved from the World Bank Database (2023).

Regarding the economic conditions dimension, the Foreign Exchange Reserves relative value, Foreign Direct Investment relative value, Inflation Rate relative value, and GDP Per Capita relative value are uniformly sourced from the World Bank Database (2023).

For the military conditions dimension, the Armed Forces Personnel relative value and Military Expenditure relative value are obtained from the World Bank Database (2023).

In the technological conditions dimension, the Scientific Journal Articles relative value, Patent Applications relative value, R&D Expenditure relative value, and High-technology Exports relative value are all from the World Bank Database (2023).

For the political conditions dimension, the Global Peace Index relative value is from the Center for Systemic Peace (CSP) Global Peace Index Database (2023), and the Government Effectiveness relative value, Government Stability relative value, and Government Corruption relative value are sourced from the World Bank Worldwide Governance Indicators (WGI) Database (2023).

4.2. Evaluation Procedure

Step 1: Determine evaluation criteria and benchmark clouds.

To facilitate the description of evaluation grade results after the quantitative assessment of geopolitical conflict risks, evaluation benchmarks are constructed as shown in Table 1.

Table 1. Risk evaluation benchmark.

Node	Number	Parameter Range				
		Grade I (Low Risk)	Grade II (Relatively Low Risk)	Grade III (Moderate Risk)	Grade IV (Relatively High Risk)	Grade V (High Risk)
World happiness index relative value	X1	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Proportion of population in poverty relative value	X2	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Unemployment rate relative value	X3	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Total public expenditure on education relative value	X4	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
Foreign exchange reserves relative value	X5	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
Foreign direct investment relative value	X6	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
Inflation rate relative value	X7	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
GDP per capita relative value	X8	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
Total armed forces personnel relative value	X9	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
Military expenditure (% of GDP) relative value	X10	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Number of scientific journal articles relative value	X11	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
Patent applications relative value	X12	[0, 250]	[250, 500]	[500, 750]	[750, 1000]	[1000, 1250]
R&D expenditure (% of GDP) relative value	X13	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
High-technology exports (% of manufactured exports) relative value	X14	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Global peace index relative value	X15	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Government effectiveness relative value	X16	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Government stability relative value	X17	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]
Government corruption relative value	X18	[0, 0.2]	[0.2, 0.4]	[0.4, 0.6]	[0.6, 0.8]	[0.8, 1.0]

The relative values of indicators in Table 1 are obtained through Min-Max normalization, which maps indicators with different units to the [0, 1] interval while retaining the relative order of raw data. For positive indicators (higher values indicate higher conflict risk), the normalization formula is:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

For negative indicators (higher values indicate lower conflict risk), the normalization formula is:

$$x_i' = \frac{x_{\max} - x_i}{x_{\max} - x_{\min}}$$

where x_i' denotes the normalized relative value, x_i is the raw data of the i-th indicator, and x_{max} / x_{min} are the maximum/minimum values of the i-th indicator among the 10 research objects (China and 10 ASEAN countries) in 2023, respectively.

Step 2: Based on the indicator evaluation criteria in Table 1, we calculated the cloud numerical characteristics using Equations (5)-(7), and generated the standard cloud diagram (Figure 4) for the unemployment rate (X3) corresponding to the five evaluation grades via the cloud generator.

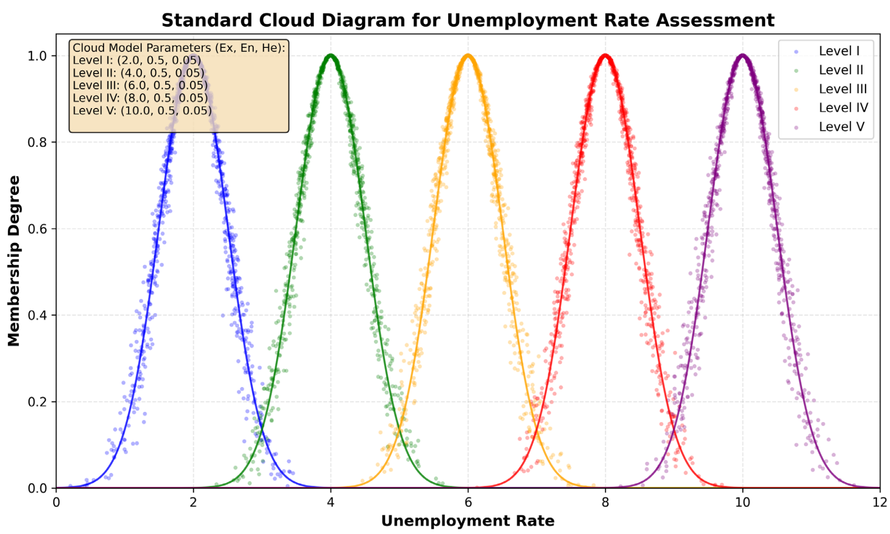

Figure 4. Benchmark cloud model.

Step 3: Transform qualitative grades into quantitative membership degree matrices using Equations (8)-(9), with the results presented in Table 2.

Step 4: Convert membership degrees into basic belief assignments (BBAs) through evidential transformation using Equation (10), with the results presented in Table 3.

Step 5: Based on tensor networks, correct the mass functions in evidence theory using Equations (11)-(16), with the results presented in Table 4.

Step 6: Calculate subjective weights using the G1 method through Equations (16)-(17), with the results presented in Table 5.

Table 2. Quantitative membership degree matrix.

Indicator	Grade I	Grade II	Grade III	Grade IV	Grade V
Inflation Rate Relative Value	0.149164	0.074685	0.099322	1.86E-05	0.042111
Foreign Exchange Reserves (USD 100 Million) Relative Value	0.063104	0.034269	0.033985	0.015114	0.071046
Foreign Direct Investment (USD 100 Million) Relative Value	0.050514	0.091346	0.037552	0.102933	0.140409
GDP Per Capita Relative Value	0.033803	0.027426	0.22592	0.102481	0.07972
Global Peace Index Relative Value	0.044981	1.49E-05	0.414064	0.00261	0.070927
Government Stability Relative Value	0.170874	0.127032	0.090637	0.007169	0.019758
Government Effectiveness Relative Value	0.173228	0.038845	0.108204	0.076354	0.000548
Government Corruption Relative Value	0.045367	0.042311	0.079739	0.068251	0.109491
World Happiness Index Relative Value	0.305914	0.040779	0.026957	0.018816	0.040503
Poverty Headcount Ratio Relative Value	0.289265	0.046437	0.006108	1.61E-05	0.000494
Unemployment Rate Relative Value	0.015082	0.135735	0.078089	0.036072	0.088385
Tertiary Education Attainment Relative Value	0.014705	0.178355	0.016426	0.077122	0.056501
Total Armed Forces Personnel Relative Value	0.000483	0.000284	0.210385	0.000644	0.134314
Military Expenditure Relative Value	0.208631	0.05265	0.065326	0.024464	0.044147
Number of Scientific Journal Articles Relative Value	0.039989	0.029812	0.088477	0.064414	0.070892
Patent Applications Relative Value	0.080543	0.021636	0.049763	0.040105	0.142232
R&D Expenditure Relative Value	0.043786	0.063896	0.000465	0.104695	0.081209
High-Technology Exports Relative Value	0.009257	0.001083	0.082876	0.101903	0.101029

Table 3. Basic belief assignment.

Indicator	Grade I	Grade II	Grade III	Grade IV	Grade V	θ
Inflation Rate Relative Value	0.1492	0.0747	0.0993	0	0.0421	0.6347
Foreign Exchange Reserves (USD 100 Million) Relative Value	0.0631	0.0343	0.034	0.0151	0.071	0.7825
Foreign Direct Investment (USD 100 Million) Relative Value	0.0505	0.0913	0.0376	0.1029	0.1404	0.5772
GDP Per Capita Relative Value	0.0338	0.0274	0.2259	0.1025	0.0797	0.5306
Global Peace Index Relative Value	0.045	0	0.4141	0.0026	0.0709	0.4674
Government Stability Relative Value	0.1709	0.127	0.0906	0.0072	0.0198	0.5845
Government Effectiveness Relative Value	0.1732	0.0388	0.1082	0.0764	0.0005	0.6028
Government Corruption Relative Value	0.0454	0.0423	0.0797	0.0683	0.1095	0.6548
World Happiness Index Relative Value	0.3059	0.0408	0.027	0.0188	0.0405	0.567
Poverty Headcount Ratio Relative Value	0.2893	0.0464	0.0061	0	0.0005	0.6577
Unemployment Rate Relative Value	0.0151	0.1357	0.0781	0.0361	0.0884	0.6466
Tertiary Education Attainment Relative Value	0.0147	0.1784	0.0164	0.0771	0.0565	0.6569
Total Armed Forces Personnel Relative Value	0.0005	0.0003	0.2104	0.0006	0.1343	0.6539
Military Expenditure Relative Value	0.2086	0.0527	0.0653	0.0245	0.0441	0.6048
Number of Scientific Journal Articles Relative Value	0.04	0.0298	0.0885	0.0644	0.0709	0.7064
Patent Applications Relative Value	0.0805	0.0216	0.0498	0.0401	0.1422	0.6657
R&D Expenditure Relative Value	0.0438	0.0639	0.0005	0.1047	0.0812	0.7059
High-Technology Exports Relative Value	0.0093	0.0011	0.0829	0.1019	0.101	0.7039

Table 4. Tensor network-corrected basic probability assignment.

Indicator	Grade I	Grade II	Grade III	Grade IV	Grade V	θ
Inflation Rate Relative Value	0.84	0	0	0	0	0.1600
Foreign Exchange Reserves (USD 100 Million) Relative Value	0.162	0.162	0.162	0.162	0.162	0.1901
Foreign Direct Investment (USD 100 Million) Relative Value	0.1705	0.1705	0.1705	0.1705	0.1705	0.1476
GDP Per Capita Relative Value	0	0.8627	0	0	0	0.1373
Global Peace Index Relative Value	0	0.877	0	0	0	0.1230
Government Stability Relative Value	0.8508	0	0	0	0	0.1492
Government Effectiveness Relative Value	0.8468	0.0001	0	0	0	0.1531
Government Corruption Relative Value	0.1672	0.1672	0.1672	0.1672	0.1672	0.1642
World Happiness Index Relative Value	0.8546	0	0	0	0	0.1454
Poverty Headcount Ratio Relative Value	0.8352	0	0	0	0	0.1648
Unemployment Rate Relative Value	0.1675	0.1675	0.1675	0.1675	0.1675	0.1625
Tertiary Education Attainment Relative Value	0.835	0.0003	0	0	0	0.1646
Total Armed Forces Personnel Relative Value	0.1672	0.1672	0.1672	0.1672	0.1672	0.1640
Military Expenditure Relative Value	0.8464	0	0	0	0	0.1536
Number of Scientific Journal Articles Relative Value	0	0.8251	0	0	0	0.1749
Patent Applications Relative Value	0.1667	0.1667	0.1667	0.1667	0.1667	0.1665
R&D Expenditure Relative Value	0.8252	0.0001	0	0	0	0.1748
High-Technology Exports Relative Value	0	0.8256	0	0	0	0.1744

Table 5. Subjective weights.

Indicator	Subjective Weights
Inflation Rate Relative Value	0.000213
Foreign Exchange Reserves (USD 100 Million) Relative Value	0.24692
Foreign Direct Investment (USD 100 Million) Relative Value	0.000119
GDP Per Capita Relative Value	3.66E−05
Global Peace Index Relative Value	6.59E−05
Government Stability Relative Value	0.013068
Government Effectiveness Relative Value	0.023522
Government Corruption Relative Value	0.004033
World Happiness Index Relative Value	0.000384
Poverty Headcount Ratio Relative Value	0.001245
Unemployment Rate Relative Value	0.000692
Tertiary Education Attainment Relative Value	0.00726
Total Armed Forces Personnel Relative Value	0.07621
Military Expenditure Relative Value	2.03E−05
Number of Scientific Journal Articles Relative Value	0.444456
Patent Applications Relative Value	0.042339
R&D Expenditure Relative Value	0.137178
High-Technology Exports Relative Value	0.002241

Step 7: Compute objective weights based on evidence similarity using Equations (18)-(20), with the results presented in **Table 6**.

Table 6. Objective weights.

Indicator	Objective Weights
Inflation Rate Relative Value	0.050201
Foreign Exchange Reserves (USD 100 Million) Relative Value	0.059977
Foreign Direct Investment (USD 100 Million) Relative Value	0.059487
GDP Per Capita Relative Value	0.051432
Global Peace Index Relative Value	0.049179
Government Stability Relative Value	0.058841
Government Effectiveness Relative Value	0.062976
Government Corruption Relative Value	0.06217
World Happiness Index Relative Value	0.051103
Poverty Headcount Ratio Relative Value	0.049
Unemployment Rate Relative Value	0.053394
Tertiary Education Attainment Relative Value	0.056988
Total Armed Forces Personnel Relative Value	0.057326
Military Expenditure Relative Value	0.045831
Number of Scientific Journal Articles Relative Value	0.061588
Patent Applications Relative Value	0.058026
R&D Expenditure Relative Value	0.058275
High-Technology Exports Relative Value	0.054206

Step 8: Calculate the game-theoretic combined weights using Equations (21)-(24), with the results presented in **Table 7**.

Step 9: Weight the evidence using the quantum-entanglement-weighted averaging method based on the calculated combined weights to enhance inter-evidence correlations and holistic consistency. Compute Singapore's final risk assessment results through Equations (25)-(28), with the results presented in **Table 8**. Repeat the aforementioned steps to obtain basic probability assignments for other countries, as shown in **Table 10**. The interstate conflict risk zonation map between China and the ten ASEAN nations is presented in **Figure 5**.

4.3. Comparative Analysis

To validate the accuracy and feasibility of the proposed cloud model-improved evidence theory weighted fusion evaluation method, this study compares the results with those obtained from the cloud model-fuzzy comprehensive evaluation method developed by Liu et al. (2018) and the traditional cloud model-evidence theory approach proposed by Zhou et al. (2023). The comparative results are presented in **Table 9**.

Table 7. Game-theoretic combined weights.

Indicator	Game-Theoretic Combined Weights
Inflation Rate Relative Value	0.025207
Foreign Exchange Reserves (USD 100 Million) Relative Value	0.153448
Foreign Direct Investment (USD 100 Million) Relative Value	0.029803
GDP Per Capita Relative Value	0.025734
Global Peace Index Relative Value	0.024623
Government Stability Relative Value	0.035954
Government Effectiveness Relative Value	0.043249
Government Corruption Relative Value	0.033101
World Happiness Index Relative Value	0.025744
Poverty Headcount Ratio Relative Value	0.025123
Unemployment Rate Relative Value	0.027043
Tertiary Education Attainment Relative Value	0.032124
Total Armed Forces Personnel Relative Value	0.066768
Military Expenditure Relative Value	0.022925
Number of Scientific Journal Articles Relative Value	0.253022
Patent Applications Relative Value	0.050182
R&D Expenditure Relative Value	0.097727
High-Technology Exports Relative Value	0.028223

Table 8. Evidence combination results.

Country	Grade I	Grade II	Grade III	Grade IV	Grade V	θ
Brunei	0	0.997	0	0	0	0.0029
Indonesia	0.9997	0	0	0	0	0.0003
Cambodia	0.0003	0.9968	0.0001	0.0003	0.0002	0.0024
Laos	0.4501	0.4333	0.0004	0.0001	0.0002	0.116
Myanmar	0.8042	0.0928	0	0	0	0.103
Malaysia	0.9993	0	0	0	0	0.0007
Philippines	0	0.0001	0.9928	0	0	0.0071
Singapore	0.6492	0.2357	0	0	0	0.115
Thailand	0.9988	0	0	0	0	0.0012
Vietnam	0.1981	0.0368	0.5667	0.035	0.0623	0.1011

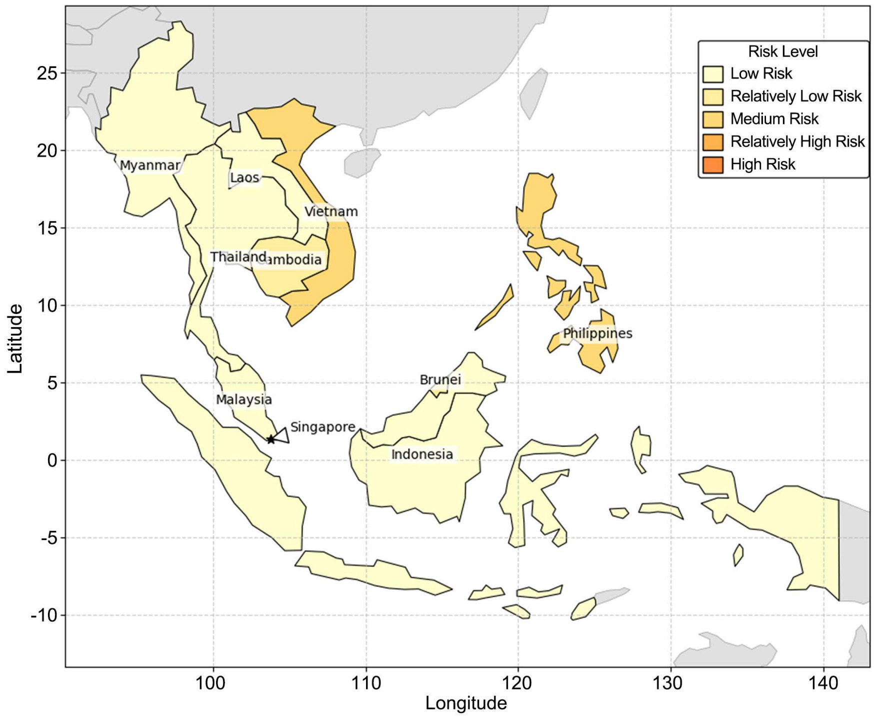

Figure 5. Conflict risk zonation map between China and the ten ASEAN countries.

Table 9. Algorithmic results comparison.

Country	Method	Grade I	Grade II	Grade III	Grade IV	Grade V	θ	Results
Brunei	Liu et al.	0.1968	0.2445	0.2284	0.1426	0.1875		II
	Zhou et al.	0	0.9055	0.0944	0	0	0	II
	This article	0	0.9970	0	0	0	0.0029	II
Indonesia	Liu et al.	0.1693	0.2109	0.2684	0.1246	0.2266		III
	Zhou et al.	0	0.0021	0	0	0.9979	0	V
	This article	0.9997	0	0	0	0	0.0003	I
Cambodia	Liu et al.	0.3721	0.1814	0.1553	0.1793	0.1118		I
	Zhou et al.	1	0	0	0	0	0	I
	This article	0.0003	0.9968	0.0001	0.0003	0.0002	0.0024	II
Laos	Liu et al.	0.2098	0.1274	0.2382	0.1891	0.2353		III
	Zhou et al.	0	0	0.9413	0.0428	0.0158	0	III
	This article	0.4501	0.4333	0.0004	0.0001	0.0002	0.116	I
Myanmar	Liu et al.	0.2033	0.1111	0.2461	0.1728	0.2664		V
	Zhou et al.	0	0	0.9947	0	0.0052	0	II
	This article	0.8042	0.0928	0	0	0	0.103	I
Malaysia	Liu et al.	0.1805	0.1512	0.1956	0.2485	0.2239		IV
	Zhou et al.	0	0	0	0.9991	0.0009	0	IV
	This article	0.9993	0	0	0	0	0.0007	I

Continued

Philippines	Liu et al.	0.1851	0.1571	0.2365	0.1463	0.2749		V
	Zhou et al.	0	0	0.9241	0	0.0758	0	III
	This article	0	0.9928	0	0	0	0.0071	III
Singapore	Liu et al.	0.2206	0.1416	0.2517	0.1536	0.2323		III
	Zhou et al.	0.3472	0	0.6336	0	0.0191	0	III
	This article	0.6492	0.2357	0	0	0	0.115	I
Thailand	Liu et al.	0.1467	0.1608	0.2797	0.1803	0.2323		III
	Zhou et al.	0	0	0.9991	0	0.0008	0	III
	This article	0.9988	0	0	0	0	0.0012	I
Vietnam	Liu et al.	0.1938	0.1742	0.2316	0.1691	0.2311		III
	Zhou et al.	0	0	0.9788	0.0208	0.0003	0	III
	This article	0.1981	0.5667	0.0368	0.035	0.0623	0.1011	III

The evaluation results reveal significant differences between the two methods for Indonesia and Singapore. For Indonesia, the traditional cloud model-evidence theory method exhibits abnormal belief concentration in Grade V (High Risk), with a negative θ value. This indicates logical inconsistency, caused by forced normalization of highly conflicting evidence that leads to misjudgment. In contrast, the proposed method demonstrates belief concentration in Grade I (Low Risk) with θ = 0.0003, strongly supporting low risk assessment that aligns with the stable China-Indonesia relations in reality. This discrepancy occurs because traditional evidence theory fails in high-conflict scenarios, while the improved method corrects errors through correlation modeling. For Singapore, the traditional method produces contradictory belief distributions with θ = 0, failing to reflect uncertainty, whereas the proposed method achieves more reasonable Grade I results with θ = 0.115 by incorporating economic interdependence and capturing synergistic effects through tensor networks, overcoming traditional theory's limitation in handling weakly correlated multi-evidence scenarios.

The two methods yield markedly different results for Myanmar. The fuzzy comprehensive evaluation method shows maximum membership in Grade V (High Risk), while the proposed method concentrates belief in Grade I with θ = 0.103, indicating low risk by effectively suppressing interference from single conflict indicators. This difference arises because fuzzy evaluation is overly sensitive to extreme values, whereas the improved evidence theory mitigates outlier impacts through evidence weighting.

A comprehensive comparison is conducted across five dimensions: evidence fusion mechanisms, weight determination approaches, conflict evidence handling, non-classical uncertainty adaptation, and high-dimensional/correlation processing capabilities, with detailed results presented in **Table 10**.

Table 10. Comparative analysis of algorithmic principles.

	Liu et al.	Zhou et al.	Method of This Article
Evidence Fusion Mechanism	Fuzzy transformation matrix weighted average	Dempster's orthogonal sum direct combination	Quantum-entanglement-weighted evidence fusion
Weight Determination Approach	Subjective weighting	Static weights based on evidence reliability	Game-theoretic combined weighting
Conflict Evidence Handling	No dedicated conflict resolution mechanism	Traditional Dempster's rule may produce paradoxes under high evidence conflict	Quantum entanglement coefficients adjust evidence conflict; tensor decomposition reconstructs
Non-classical Uncertainty Adaptation	Partial (only static fuzzy-random description)	Limited (relies on cloud conversion without direct cognitive uncertainty modeling)	Strong (quantum superposition states characterize cognitive fuzziness; tensors preserve nonlinear features)
High-dimensional/ Correlation Processing Capability	Weak (assumes independent indicators with subjective weights)	Relatively weak (high dimensions cause mass sparsity; relies on independence assumption)	Strong (tensor network compresses high dimensions; quantum entanglement captures nonlinear correlations)

The algorithmic and theoretical comparisons reveal that traditional evidence theory has significant limitations in high-conflict or high-dimensional scenarios, as evidenced by abnormal θ values, making it reliable only for simple cases with highly consistent evidence. While fuzzy evaluation works for independent indicators with complete data, it lacks robust uncertainty characterization, resulting in unstable outcomes. The proposed method systematically addresses these shortcomings through tensor networks and quantum-entanglement weighting, demonstrating superior performance particularly in complex international relations assessments where it effectively resolves conflict handling failures and high-dimensional modeling deficiencies inherent in traditional approaches.

5. Conclusion

This study proposes a method for assessing interstate conflict risks based on cloud models and improved D-S evidence theory, incorporating national security system data to construct a comprehensive risk evaluation model. The results indicate:

1) Overall low conflict risk. The risk assessment outcomes for China and the ten ASEAN countries show most nations maintain relatively low risk levels. The majority demonstrate high membership degrees in Grade I or II—Indonesia, Malaysia, and Thailand exhibit extremely high probabilities (>0.8) in Grade I, while Brunei and the Philippines show strong probabilities in Grade II, indicating generally stable China-ASEAN relations with minimal conflict risks.

2) Complex scenarios in specific cases. Vietnam presents more complicated risk profiles with dominant Grade II membership (0.5667) but notable probabilities across other grades (Grade I: 0.1981, III: 0.0368, IV: 0.035, V: 0.0623), suggesting multifaceted influences on China-Vietnam relations. Laos shows distributed probabilities between Grade I (0.4501) and II (0.4333), reflecting relationship complexity while maintaining moderate overall risk.

3) Indicator impact analysis. Economic indicators (foreign exchange reserves, FDI, GDP per capita) predominantly show high Grade I probabilities (>0.7), confirming robust economic cooperation as a stabilizing factor. Governance indicators (government stability, effectiveness) mainly cluster in Grade II, revealing moderate governance challenges without escalating to high-risk levels. Inflation, corruption, and poverty indicators display evenly distributed membership across grades, indicating their context-dependent, non-linear impacts on conflict risks.

Based on the empirical results and against the backdrop of intensifying global geopolitical risks, this study proposes the following policy recommendations:

1) First, strengthen economic cooperation and exchanges. Given the positive role of economic indicators in mitigating conflict risks, China should continue to deepen economic cooperation with ASEAN countries. Further promote trade liberalization and facilitation, and expand bilateral trade volume. Specific measures include exploring further reductions in tariff barriers, such as for complementary products like China's high-tech goods and ASEAN's specialty agricultural products and resource commodities, through bilateral or multilateral negotiations to gradually reduce or even eliminate tariffs, thereby promoting further trade expansion. In terms of simplifying trade procedures, establish a unified e-trade platform to enable real-time information sharing and one-stop processing, reducing cumbersome approval procedures in trade and improving efficiency. Simultaneously, enhance customs cooperation through information sharing and joint supervision to combat illegal trade activities like smuggling and maintain a fair trade environment.

2) Enhance political communication and trust-building. For countries with relatively more complex conflict risks, such as Vietnam and Laos, strengthening high-level dialogue and political communication mechanisms is crucial. Establish regular high-level intergovernmental dialogue mechanisms, such as annual bilateral leader summits, to facilitate in-depth exchanges and consultations on major bilateral issues and regional/international hot topics. During these summits, parties can frankly exchange views on sensitive issues like the South China Sea and seek effective pathways for peaceful dispute resolution. Meanwhile, coordinate positions on international and regional affairs of mutual concern to enhance political mutual trust. In addition to leader summits, regular foreign minister meetings and departmental consultation mechanisms can be established to promptly communicate and resolve potential issues and disagreements.

3) Focus on specific indicators and risk factors. For indicators like inflation rate, government corruption, and poverty headcount ratio that have complex impacts

on conflict risks, China can share relevant experiences and policy measures with ASEAN countries to jointly explore coping strategies. Regarding inflation control, China can share experiences in monetary policy regulation and price stabilization measures. For instance, China has rich practical experience in adjusting money supply and stabilizing prices through macroeconomic monetary policies, and can conduct exchange and cooperation with ASEAN central banks to help improve their monetary policy formulation and implementation capabilities. In combating government corruption, strengthen experience sharing and technical cooperation to help ASEAN countries improve governance standards. China has established a series of institutions and supervisory mechanisms in clean governance, such as supervisory system reforms, and can share these institutional building experiences with ASEAN countries while cooperating on technical methods like using big data and AI to enhance monitoring and early warning of corrupt activities.

This study possesses the following characteristics:

1) Targeting the features of interstate conflicts, a risk assessment system is constructed by integrating cloud models with D-S evidence theory. This approach simultaneously considers the objectivity of data in interstate conflicts and the fuzziness/uncertainty in risk assessment language conversion, thereby avoiding the strong subjectivity inherent in traditional risk evaluation methods.

2) As demonstrated by the maximum membership principle, Brunei and China's overall risk variation falls within the relatively low-risk category, which aligns with actual international situations. This confirms the rationality and feasibility of our risk assessment model. Compared with traditional evidence theory, the improved D-S evidence theory enhances conflict resolution capability among evidence, significantly improving the precision and accuracy of interstate conflict risk assessments.

3) The multi-source information fusion based on improved D-S evidence theory is applied to interstate conflict risk evaluation, effectively transforming incomplete data into basic probability assignment functions for target recognition decisions. This method efficiently extracts characteristic parameters from data and provides robust solutions to the challenge of determining risk levels when monitoring indicators approach or reach different warning thresholds.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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