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Gauging Urban Security Advances: A Fuzzy Hierarchical TOPSIS Model with MOPSO Optimization

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Abstract: In the era of rapid urban digitalization, intelligent analysis systems are pivotal for urban safety management, yet their applicability lacks a robust evaluation framework. This study develops a comprehensive model integrating the Delphi method, Fuzzy Hierarchical TOPSIS, and MOPSO. Through two-round expert consultations, 36 indicators across four dimensions, technical performance, functionality, interaction modes, and cost-effectiveness, are identified. The MOPSO algorithm dynamically optimizes weights in the fuzzy TOPSIS framework, addressing static evaluation limitations and balancing conflicting objectives like reliability and cost-efficiency. Empirical results show a 12% average improvement in the closeness index and enhanced scenario adaptability, such as an 18% reduction in warning latency during emergencies. This hybrid approach bridges qualitative expert insights with quantitative optimization, offering a systematic tool for evaluating system applicability. The research enriches multi-criteria decision-making methodologies and supports evidence-based urban safety governance, facilitating resource allocation and sustainable planning.

Keywords: applicability evaluation; influencing factors; intelligent analysis system; MOPSO; urban safety

1 INTRODUCTION

In the digital age, AI and big data have transformed urban safety management. Intelligent analysis systems are crucial for processing data and identifying security threats. However, their real-world applicability remains a concern due to the lack of a comprehensive evaluation framework. Existing approaches often focus on limited aspects, like technical performance, and struggle to handle evaluation fuzziness and subjectivity. With the increasing complexity of urban risk sources, researchers have begun to change from "after-the-fact recovery" to "pre-resilience", emphasizing adaptability and safety redundancy mechanisms [1, 2].

This study aims to fill this gap by creating a holistic evaluation model. We use the Delphi method to identify influencing factors and conduct two-round expert consultations. Then, we integrate the Fuzzy Hierarchical TOPSIS method, optimized by the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm. This model assesses system applicability from four dimensions: technical performance, main functionality, interaction modes, and cost-effectiveness. The MOPSO algorithm dynamically optimizes the weights in the Fuzzy Hierarchical TOPSIS framework, overcoming the static nature of traditional methods. This allows for better handling of complex urban safety scenarios and conflicting goals, such as high-performance systems with low costs.

The research has significant theoretical and practical implications. Theoretically, it enriches urban safety management research and multi-criteria decision-making methods. Practically, it helps urban administrators allocate resources effectively, improve emergency response, and support sustainable urban planning. Overall, this study provides a robust tool for evaluating intelligent analysis systems in urban safety, promoting more informed decision-making and enhancing urban safety governance.

2 LITERATURE REVIEW

With the increasing complexity of urban governance, scholars have gradually introduced multi-criteria decision-making methods to quantitatively model urban public safety. Camacho-Collados and Liberatore [3] has developed a decision support system for predictive police deployment, effectively enhancing the initiative of urban safety management. Figueiredo and Mota [4] further combined with GIS-MCDA to establish an urban safety level classification model, while Basilio et al. [5] scientifically divided comprehensive safety areas through multi-criteria sorting methods to improve urban risk awareness. Provide the data basis. In the study of urban public safety, the multi-guideline decision-making method (MCDM) is not only widely used in the construction and optimization of intelligent models, but also shows high adaptability in regional planning and management evaluation. Gurgel et al. [6] built a multi-criteria prioritization model that combines the SMARTS method with Monte Carlo simulation to support the differentiated allocation strategy of urban public safety resources. The model can make weight allocation and priority judgments on public security pressure, social attributes and emergency response capabilities in different regions, and provide a data basis and scenario stability analysis for security planning and decision-making. In terms of methodology, Costa and Silva [7] found through a systematic review that AHP and TOPSIS are the most widely used multi-criteria methods in the field of urban security. Especially in high-dimensional, multi-subject security governance models, hybrid MCDM frameworks are increasingly becoming an important path to solve complex problems in reality.

In urban security research, scholars have been actively constructing intelligent analysis models and conducting evaluations to boost urban safety management. Siddiqui et al. [8] proposed security architecture based on smart contracts, which aims to improve the security of collaborative services in municipal smart cities. The architecture combines software-defined network (SDN) and multi-chain block-chain technology to dynamically manage and control the interaction and transactions between heterogeneous Internet of Things networks through smart contracts, thus ensuring the integrity and confidentiality of data. Li et al. [9] proposed an integrated AI-driven urban public security governance and crisis management optimization model. By introducing multi-dimensional intelligent decision-making and early warning mechanisms, the response efficiency and governance accuracy of cities when facing complex security challenges have been significantly improved. Kumar et al. [10] designed an urban violence identification model based on the expert system. The system can automatically analyze surveillance videos and issue early warnings, enhancing the intelligent identification and dynamic prevention and control capabilities in the public security space. This offers new solutions for data security and privacy in urban safety management. Reza et al. [11] have developed an intelligent traffic control system that combines image processing and deep learning, which can realize real-time monitoring and automated management of urban traffic flow, providing strong technical support for reducing road safety accidents and improving the level of traffic emergency response. Nagy and Simon [12] proposed a traffic prediction model (CTPM) based on the congestion transmission model. By analyzing the transmission phenomenon of congestion in urban road networks, the accuracy of traffic prediction is significantly improved, demonstrating the potential of emerging technologies in improving urban traffic safety.

Some research focuses on creating multi-dimensional evaluation systems for urban public safety risks and emergency management capabilities. Li et al. [13] developed a structural equation-based model to assess public space safety risks, identifying key urban risk factors. Chen et al. [14] proposed a multidimensional framework integrating risk analysis and emergency capacity to support urban safety governance. Zhou and Zhai [15] introduced a multi-hazard risk assessment approach for disaster planning, enabling data-driven urban emergency resilience strategies. Sharifi et al. [16] have built a spatial resilience assessment framework that takes into account different stages of disaster management, systematically identified the key factors affecting the resilience of urban structures, and promoted the quantitative analysis of understanding urban safety risks from the structural level. In response to the vulnerability of coastal cities in the context of climate change García et al. [17] proposed a multi-disaster risk assessment framework that integrates local knowledge and the concept of "urban laboratory", which provides an assessment basis for scenario-based and localized security governance. Zhang et al. [18] designed a WebGIS-based urban multi-disaster periodic safety assessment system, integrating inherent risks, residual risks and emergency capability indicators to form a multi-dimensional evaluation model for dynamic urban governance, which effectively supports regional risk mapping and policies.

Regarding data security and privacy, Rai et al. [19] studied the integration of IoT and blockchain in energy applications, and their findings can be extended to urban safety management. Abubakar et al. [20] proposed urban planning strategies for Lagos to adapt to climate change, which are relevant for urban safety planning in dealing with environmental risks. Balogun et al. [21] explored AI in construction deconstruction, providing insights for intelligent decision-making in urban safety. Their research on AI technology can also provide insights for intelligent decision-making in urban safety management [22], then combined with neural networks to establish urban safety evaluation systems [23]. Liu et al. [24] proposed a maturity evaluation method for urban safety governance based on big data governance, highlighting data-driven approaches. The application of intelligent analysis technologies has become a key research focus in urban security. Studies not only develop security management and risk assessment models but also integrate emerging technologies with practical needs. For example, Zhang et al. [25] introduced a vision-based human activity recognition system, and Wang et al. [26] created an Intelligent-Led Safety Management model for big data environments. Additionally, AI-powered real-time road sensing and anomaly detection algorithms using the 5G-V2X framework have greatly improved safety prediction and response capabilities [27, 28]. In cybersecurity, scholars have proposed systems that combine data security and intelligent systems, integrating IoT and blockchain for secure evidence preservation [29, 30].

However, the evaluation system for intelligent analysis system applicability in urban safety has significant flaws. There is no unified theoretical framework, and existing research has unclear definitions, scopes, and inconsistent standards. Most studies focus on single scenarios, lacking horizontal comparisons and general evaluation methods. Moreover, research mainly stays at the qualitative stage, lacking empirical data, mathematical models, and comprehensive analysis of influencing factors. This paper aims to address these issues by developing an applicability evaluation system for urban safety intelligent analysis systems. The system focuses on indicator setting, weight distribution, evaluation methods, and practical applications, providing theoretical and practical support for urban safety management.

3 METHODOLOGY

This section presents the empirical foundation of the proposed hybrid evaluation model, combining qualitative indicator identification, fuzzy hierarchical analysis and optimization, the specific flowchart is as follows (Fig. 1). It consolidates both the methodological core and empirical validation process to systematically evaluate the applicability of intelligent analysis systems in urban safety governance.

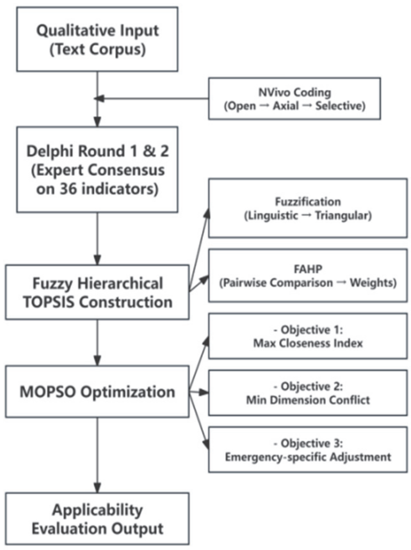

Figure 1 Flowchart of hybrid evaluation

3.1 Evaluation Framework: Fuzzy Hierarchical TOPSIS

In order to effectively deal with the multi-criteria decision-making problem in urban public safety risk assessment, this study adopts the fuzzy hierarchical TOPSIS method to evaluate the applicability of intelligent analysis systems in the field of urban safety, which has been widely used in construction project risk assessment [31] and site safety condition assessment [32] and other fields Its applicability in dealing with uncertainty and multi-factor comprehensive assessment has been verified. This method integrates the fuzzy set theory with a hierarchical structure, enabling effective handling of uncertainties in the evaluation process. In terms of urban resilience evaluation, Xun and Yuan [33] built an evaluation model based on intuitive fuzzy TOPSIS, which was applied to Dalian, China, and verified the effectiveness of the method. In addition, Nguyen et al. [34] used the fuzzy hierarchical TOPSIS method to evaluate the environmental conflict of the titanium industry in the central coastal area of Vietnam, demonstrating the application potential of this method in environmental conflict assessment. In the process of constructing a fuzzy TOPSIS evaluation matrix and calculating the proximity, the proximity index is used to depict the proximity of each scheme relative to the positive ideal solution and the negative ideal solution. Zhang et al.'s study [35] shows that this indicator can still provide a clear basis for multi-program ranking when experts judge that there is ambiguity.

For convenience, the fuzzy number can be denoted using [a, b, c, d; 1], and the membership function (MF) $f_{\tilde{A}}$ of the fuzzy number $\tilde{A}$ = [a, b, c, d; 1], can be expressed as [36]:

$$f_{\tilde{A}} = \begin{cases} f_{\tilde{A}}^{L}(x),\ a \le x \le b \\ 1,\ b \le x \le c \\ f_{\tilde{A}}^{R}(x),\ c \le x \le d \\ 0,\ \text{otherwise} \end{cases} \tag{1}$$

Then,

$$D\left(\tilde{A}, \tilde{B}\right) = \left[\int_0^1 \left(g_{\tilde{A}}^{L} - g_{\tilde{B}}^{L}\right)^2 \mathrm{d}y + \int_0^1 \left(g_{\tilde{A}}^{R} - g_{\tilde{B}}^{R}\right)^2 \mathrm{d}y\right]^{1/2} \tag{2}$$

denotes the distance of $\tilde{A}(x)$ and $\tilde{B}(x)$, and the inverse functions of $f_{\tilde{A}}^{L}$ and $f_{\tilde{A}}^{R}$ are $g_{\tilde{A}}^{L}$ and $g_{\tilde{A}}^{R}$.

Chen and Cheng [37] briefly describe the concept of minimum metric D to calculate the parameter of fuzzy mean x_0 = ($m = x_0$) and fuzzy standard deviation $\sigma(\alpha = \beta = \sigma)$ as follows:

Let $\tilde{A}$ denote a generalized LR fuzzy number and let the inverse functions of $f_{\tilde{A}}^{L}$ and $f_{\tilde{A}}^{R}$ be $g_{\tilde{A}}^{L} = (x_0 - \sigma) + \sigma y$ and $g_{\tilde{A}}^{R} = (x_0 + \sigma) - \sigma y$. The symmetry function $\tilde{A}$'s of $S[x_0, \sigma]$ can be obtained by immunizing this metric D, namely:

$$D\left(\tilde{A}, S[x_0, \sigma]\right) = \int_0^1 \left(g_{\tilde{A}}^{L} - S[x_0, \sigma]^{L}\right)^2 \mathrm{d}y + \int_0^1 \left(g_{\tilde{A}}^{R} - S[x_0, \sigma]^{R}\right)^2 \mathrm{d}y \tag{3}$$

Then, setting $\partial D / \partial x_0 = 0$ and, $\partial D / \partial \sigma = 0$ in Eq. (3), we obtain:

$$\begin{cases} \sigma = \int_0^1 \left(g_{\tilde{A}}^{R} - g_{\tilde{A}}^{L}\right)(1-y)\mathrm{d}y / 2\int_0^1 (1-y)\mathrm{d}y \\ x_0 = 1/2\int_0^1 \left(g_{\tilde{A}}^{R} + g_{\tilde{A}}^{L}\right)\mathrm{d}y \end{cases} \tag{4}$$

A linguistic variable uses words or phrases (e.g., "unsatisfied," "fair," "satisfy") instead of numerical values to describe qualitative concepts [38]. Each term is mapped to numerical values via membership functions. While studies suggest humans can distinguish 7 ± 2 terms [39], this study employs five triangular fuzzy numbers (Tab. 1) to represent unquantified factors. In the context of urban safety intelligent analysis systems, these linguistic variables can effectively capture the subjective evaluations of experts regarding various system attributes, such as the performance of data processing capabilities or the user-friendliness of interaction modes.

Table 1 The MF of linguistic variables

Linguistic Variable	Rating
Very unsatisfied (VU)	(1, 1, 3)
Unsatisfied (U)	(1, 3, 5)
Fair (F)	(3, 5, 7)
Satisfy (S)	(5, 7, 9)
Very satisfy (VS)	(7, 9, 9)

Triangular fuzzy number is used to simplify parameterized metric distance. The simplified method can be described as follows:

Let $\tilde{A}$ denote an TFNs, $\tilde{A}(x)$ = (a, b, c), and rewrite Eq. (5) inparameterized form:

$$\tilde{f}_{\tilde{A}} = \begin{cases} (x-a)/(b-a),\ a \le x \le b \\ 1,\ x = b \\ (c-x)/(c-b),\ b \le x \le c \end{cases} \tag{5}$$

Then, the inverse functions of $f_{\tilde{A}}^{L}$ and $f_{\tilde{A}}^{R}$ are

$$g_{\tilde{A}}^{L} = a + (b-a)y,\ g_{\tilde{A}}^{R} = c + (b-c)y \tag{6}$$

let two TFNs be $\tilde{A}(x)$ = (a, b, c), $\tilde{B}(x)$ = (d, e, f), and D($\tilde{A}$, $\tilde{B}$) can be simplified as Eq. (11) via thep-norm metric method:

$$D\left(\tilde{A}, \tilde{B}\right) = \left[\int_0^1 \left[\left(a + (b-a)y\right) - \left(d + (b-d)y\right)\right]^p \mathrm{d}y + \int_0^1 \left[\left(c + (b-c)y\right) - \left(f + (e-f)y\right)\right]^p \mathrm{d}y\right]^{1/p} \tag{7}$$

Fuzzification is a core step in Fuzzy Multi-Criteria Decision Making (FMCDM) methods. It transforms decision-making uncertainty into quantifiable fuzzy numbers, crucial for multi-criteria decision-making like system scheme selection. In this study's initial stage, raw data was fuzzified to form a fuzzy variable matrix. Data points were mapped to fuzzy numbers (a, b, c). Despite being labour-intensive due to large data volume, it is essential for accurate fuzzification. Only a fuzzified data sample is presented here. Post-fuzzification, fuzzy arithmetic operations are applied to the fuzzy numbers, allowing for a comprehensive assessment of different indicators in multi-criteria decision-making.

Subsequently, the original fuzzy matrix is standardized into a fuzzy performance matrix. Each matrix element is a normalized fuzzy number, ready for subsequent calculations. Processed partial matrix is shown in Tab. 2.

Table 2 Standardized fuzzy performance matrix

Average Recovery Time	Data security	Legal and Ethical Compliance
3/7, 5/9, 7/9	1/7, 1/9, 1/3	1, 1, 1
3/7, 5/9, 7/9	1, 1, 1	1, 1, 1

3.2 Optimization Model: MOPSO for Adaptive Weighting

Li et al. [40] pointed out that the integration of PSO and MCDM methods is conducive to achieving effective coordination between weighting and target response in high-complexity scenarios, and improving the overall decision-making quality of the model. To address the limitations of static evaluation and multi-dimensional conflict in traditional Fuzzy Hierarchical TOPSIS, this study introduces the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, which dynamically optimizes evaluation parameters to enhance the adaptability of urban safety intelligent analysis systems. The algorithm has been successfully applied to multi-target optimization problems such as health and safety risk assessment of mining projects [41] and the weight allocation of thermal stress indicators [42]. Traditional TOPSIS relies on fixed weights derived from expert judgments (e.g., FAHP in Section 3.2.2), which may not fully capture the dynamic complexities of urban safety scenarios, such as evolving security threats or resource constraints. In order to further improve the adaptive tuning ability of the model under sudden situations, this study introduces speed adjustment and inertial weighting mechanisms in the dynamic weighting update of parameters to enhance the efficiency of spatial exploration [43]. MOPSO is selected for its superior capability in handling multi-objective optimization problems, where conflicting goals (e.g., high technical performance vs. low operational cost) need to be balanced, and its efficiency in navigating complex solution spaces with both continuous and discrete variables.

The MOPSO algorithm is integrated into the evaluation framework to optimize indicator weights and dimensional adjustment coefficients, working in tandem with the fuzzy hierarchical structure established.

Let the optimization variables be a particle vector $X = [w, \alpha]$, where, $w = [\omega_1, \omega_2, \dots, \omega_{36}]$ denotes the weights of the 36 third-level indicators, satisfying $\omega_j \geq 0$ and $\sum_{j=1}^{36} \omega_j = 1$; $\alpha = [\alpha_A, \alpha_B, \alpha_C, \alpha_D]$ represents the dynamic adjustment coefficients for the four first-level dimensions (Technical Performance A, Main Functionality B, Interaction Modes C, Cost-Effectiveness D), with $\alpha_k \geq 0$ and $\sum_{k=1}^{4} \alpha_k = 1$.

Three interdependent objectives are defined to address the research's core challenges, leveraging the fuzzy TOPSIS framework and urban safety requirements:

Objective 1: Maximizing comprehensive applicability

The Closeness Index (CI) from TOPSIS is used as the primary metric, measuring how close a system is to the FPIS while minimizing distance to the FNIS:

$$\max f_1(x) = \frac{D^-(X)}{D^+(X) + D^-(X)} \tag{8}$$

where $D^+(X)$ and $D^-(X)$ are the Euclidean distances to the FPIS and FNIS, respectively, calculated as:

$$D^{\pm}(X) = \sqrt{\sum_{j=1}^{36} \omega_j \cdot d_{ij}^{\pm}(\tilde{v}_{ij})} \tag{9}$$

where, $\tilde{v}_{ij}$ is the normalized fuzzy performance value of alternative i under indicator j, and $d_{ij}^{\pm}$ are the metric distances to the fuzzy ideal solutions (Section 3.2.1).

Objective 2: Minimizing multi-dimensional conflict

This objective ensures balance across the four first-level dimensions by minimizing the weighted variance of their standardized indicator values:

$$\min f_2(x) = \sum_{k=1}^{4} \alpha_k \cdot Var(X_k) \tag{10}$$

where X_k is the set of standardized values for indicators under dimension k, and $\mathrm{Var}(X_k)$ denotes the within-dimension variance. This prevents over-optimization in isolated dimensions (e.g., excessive technical investment compromising cost-effectiveness).

Objective 3: Scenario-specific optimization goals

For emergency response scenarios, prioritize minimizing warning latency (Indicator B_{33}) and maximizing accident reduction rate (Indicator D_{21}) under cost constraints:

$$\max f_3(x) = \frac{\lambda_1 \cdot B_{34} + \lambda_2 \cdot D_{21}}{\lambda_3 \cdot (D_{11} + D_{12}) + \lambda_4 \cdot B_{33}} \tag{11}$$

where λ_1-$\lambda 4$ are scenario-specific normalization factors, an B_{34} (warning accuracy), D_{11} (operation cost), D_{12} (maintenance cost) are key indicators.

The optimization problem is subject to both structural and practical constraints:

$$\text{Fitness}(X) = \omega_1 f_1(x) + \omega_2 (1 - f_2(x)) + \omega_3 f_3(x) \tag{12}$$

where ω_1 = 0.5, ω_2 = 0.3 and ω_3 = 0.2 are predefined weights based on expert consensus (via Delphi method), balancing overall applicability, dimensional equity, and scenario-specific efficiency.

3.3 Algorithm Process

The following describes the detailed algorithm process of the Fuzzy Hierarchical TOPSIS combined with MOPSO Optimization:

Step 1. Problem formulation: Identify the evaluation criteria and alternatives and establish a hierarchical structure. Assume K experts analyze a problem involving n criteria and m alternatives.

Step 2. Fuzzy weight elicitation: Perform fuzzy pairwise comparisons of the criteria to quantify their relative importance. Apply the Lambda-Max method to calculate a fuzzy weight for each criterion, check the consistency index (C.I.) of the pairwise comparison matrix, and aggregate the K experts' judgments to obtain a final fuzzy weight vector for the criteria.

Step 3. Normalize and weight performance Matrix: For each alternative i and criterion j, assign the corresponding linguistic term based on expert assessment or measured data, and convert it to a triangular fuzzy number $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. For a benefit criterion $j \in J$, a common approach is $\tilde{r}_{ij} = \dfrac{\tilde{x}_{ij}}{max_i \tilde{x}_{ij}}$; for a cost criterion $j \in J'$, $\tilde{r}_{ij} = \dfrac{min_i \tilde{x}_{ij}}{\tilde{x}_{ij}}$. Then apply criteria weights: multiply each normalized fuzzy rating by the fuzzy weight of that criterion to get $\tilde{r}_{ij}^{w} = \tilde{r}_{ij} \otimes w_j$. Then, weighted normalized fuzzy matrix $\tilde{R} = \left[\tilde{r}_{ij}^{w}\right]_{m \times n}$.

Step 4. Determine fuzzy ideal solutions: Identify the FPIS A^* and FNIS A^- from the weighted performance matrix.

$$\text{FPIS: } A^* = \left\{\tilde{r}_j^* \middle| j \in J;\, \tilde{r}_j^- \middle| j \in J'\right\}$$

$$\text{FPIS: } A^* = \left\{\tilde{r}_j^- \middle| j \in J;\, \tilde{r}_j^* \middle| j \in J'\right\}$$

Step 5. Closeness index calculation: Calculate $h_{ij}^* = d\left(\tilde{r}_{ij}^{w}, \tilde{r}_j^*\right)$, $h_{ij}^- = d\left(\tilde{r}_{ij}^{w}, \tilde{r}_j^-\right)$. For each alternative i, aggregate its criterion-level distances into an overall distance to the FPIS and to the FNIS by using a p-norm. Compute the overall separation measures:

$$D_i^* = \left(\sum_{j=1}^{n}\left(h_{ij}^*\right)^2\right)^{1/2},\quad D_i^- = \left(\sum_{j=1}^{n}\left(h_{ij}^-\right)^2\right)^{1/2}$$

Derive the closeness index CI_I for each alternative as a comprehensive score indicating its relative closeness to the ideal solution.

$$CI_I = \frac{D_i^-}{D_i^* + D_i^-}$$

Step 6. Formulate MOPSO optimization problem**:** Define a particle's position as a vector $X = [\omega, \alpha]$ that encodes the weights of all criteria and the adjustment coefficients for top-level dimensions. The pair (ω, α) thus defines a specific weighting scheme for the hierarchical criteria. Then, design multiple objectives reflecting the goals of the evaluation as Objective 1-3.

Step 7. Particle encoding and swarm initialization: Generate an initial swarm of N particles. Seed the swarm with diverse weight distributions. It is beneficial to include the expert-derived FAHP weight set as one initial particle to incorporate domain knowledge. Assign each particle a random initial velocity $V^{(i)} = \left[v_1^{(i)}, \ldots, v_{n+L}^{(i)}\right]$. For each particle i, evaluate its fitness on all objectives by applying the fuzzy TOPSIS evaluation with the particle's weights.

Set each particle's personal best position $p_{\text{best}} = X^{(i)}$. Determine the initial global best set of solutions. In a strictly single-objective PSO, g_{best} can be chosen as the position with the highest f_1; in MOPSO, maintain an archive of non-dominated solutions and select one representative g_{best} or multiple leaders.

Step 8. Velocity and position update: For each particle in each iteration, compute its current fitness $f(xi)$, update $p_{\text{best},i} = x_i$ if $f(xi)$ is better than $f(p_{best,i})$, and update $g_{\text{best}} = x_i$ if $f(xi)$ outperforms $f(g_{\text{best}})$. Update the velocity and position for each dimension d of particle I using the equations:

$$v_{i,d}^{t} = \omega \cdot v_{i,d}^{t-1} + c_1 r_1\left(p_{best(i,d)} - X_{i,d}^{t-1}\right) + c_2 r_2\left(g_{best,d} - x_{i,d}^{t-1}\right)$$

$$x_{i,d}^{t} = x_{i,d}^{t-1} + v_{i,d}^{t-1}$$

where $r_1, r_2 \sim U(0, 1)$ are random numbers, ω is the inertia weight, and c_1, c_2 are learning factors.

Step 9. Constraint handling: After updating positions, enforce any problem-specific constraints on the particles to ensure they represent valid weight configurations. Project or adjust the particle's components to satisfy $\omega_j \geq 0, \sum_j \omega_j = 1$ and $\alpha_k \geq 0, \sum_k \alpha_k = 1$, if any weight falls outside allowable bounds, it can be clamped or adjusted according to domain rules. Feasible particle positions X_i^t that respect all weighting constraints.

Step 10. Convergence check: Evaluate the chosen criterion - for example, if using maximum iterations, simply check if $t = T_{\max}$ if using fitness improvement, check $\left|CI^*\left(g_{\text{best},\,t}\right) - CI^*\left(g_{\text{best},\,(t-1)}\right)\right| < \in$ and similar for other objectives. A decision to continue the loop (go back to Step 6 for $t = t + 1$ or to terminate if convergence is achieved or iteration limit reached. If multiple Pareto-optimal solutions exist, this set can be provided for decision-maker choice; otherwise g_{best} yields a recommended optimal weighting scheme.

Step 11. Final fuzzy TOPSIS evaluation with optimized weights: Apply the fuzzy hierarchical TOPSIS procedure one more time using the optimized weights ω^*, α^* to obtain the final ranking of alternatives. Repeat Steps 3-5 using ω^*, α^* in place of the original weights. Finally, a set of final closeness indices $\left\{CI_1^*, CI_2^*, \ldots, CI_m^*\right\}$ representing the performance of each alternative given the optimized evaluation parameters. Rank the alternatives in descending order of their closeness index CI_i^*.

4 EMPIRICAL STUDY

Building on the methodology outlined in Section 3, this section demonstrates the operationalization of our proposed hybrid method. It details how the expert-derived indicators, fuzzy evaluation logic, and MOPSO optimization are integrated to form a practical system for evaluating intelligent analysis tools in real-world urban safety scenarios.

4.1 Indicator Identification

Dr Stuart Russell, a leading AI expert, defines that system applicability refers to the extent to which a model can effectively complete tasks and meet user needs in real-world applications. In urban safety management, the applicability of intelligent analysis systems is influenced by multiple interacting factors that together determine their effectiveness. To identify a general model for system applicability, it is essential to clarify these influencing factors.

We began by collecting qualitative data on urban safety and intelligent systems, cleaning and analyzing it using NVivo software. Word frequency analysis (Fig. 2) identified key terms such as "function", "performance", "user", "security", and "system", highlighting the importance of model effectiveness, user needs, and security. Other frequent words like "stability", "data", "time", and "response" reflect the significance of application effectiveness, data quality, and rapid response. Terms such as "economy", "reliability", "effectiveness", and "cost" emphasize the role of economic and system factors. Additionally, words like "processing", "applicable", and "monitoring" point to crucial functions like data processing, system versatility, and real-time monitoring. These findings underscore the multidimensional factors, technology, functionality, user needs, economic costs, and application scenarios, that influence system applicability.

Figure 2 Data quality analysis word cloud map

Based on grounded theory, the original data was preliminarily organized and imported into NVivo software for word frequency analysis. Subsequent research conducted in-depth analysis of the data using the three-stage coding method, followed by open coding, axial coding, and selective coding.

In open coding, the data was broken down, compared, and categorized to identify 134 initial concepts. "Monitoring accuracy", which refers to the degree of conformity between the monitoring results of urban safety-related indicators by the intelligent analysis system and the actual situation, "software, hardware, and network attributes", and "privacy protection" are among these concepts, representing key influencing factors of the system (Fig. 3). These categories were then compared and analyzed to identify main categories. Through axial coding, 48 primary categories were summarized, including technology and maintenance, data and processing, monitoring, warning and response, operational convenience, and operational costs.

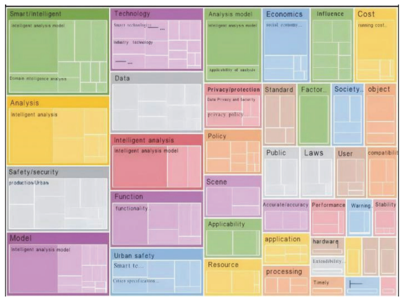

Figure 3 An open encoding hierarchy diagram

Following is the identification of the core categories that best represent the research topic from the spindle code, such as "system reliability", "operation and maintenance costs", "easy to learn", etc., and then integrate the relevant data to demonstrate the possible impact paths of each factor. For example, "main functionality" integrates "system adaptability", "data processing", and "monitoring and warning". Finally, the analysis results were subjected to theoretical saturation testing and compared with existing theories for repeated revisions, forming a framework of the main influencing factors. Based on the analysis results, the key factors and their interrelationships of system applicability are sorted out and divided into four main directions: technical performance, main functionality, user interaction, and cost-effectiveness.

The transformation of qualitative data into quantitative inputs: After identifying the influencing factors through NVivo software analysis, these factors were organized into a questionnaire for the Delphi method. Experts were asked to rate the importance of each factor on a scale of 1-5. For example, a factor considered "very important" might be given a score of 5, while a "less important" factor could be scored 1. These scores are the quantitative inputs for the Delphi method, which are used to calculate indicators such as expert positivity coefficient, opinion concentration, and coordination.

The Delphi method, which achieves consensus through multiple rounds of anonymous feedback and expert consultation, was used to verify the scientific validity of the model developed in this study. The initial factors affecting the applicability of an intelligent analysis system in urban safety were constructed based on qualitative analysis. To ensure the model's rationality, 25 experts were carefully selected for the consultation process.

Expert selection criteria: Our experts had in-depth knowledge in urban safety management, intelligent analysis system technology, and data analysis. They were required to have rich practical experience, like over 5 years in urban safety management projects, and involvement in key aspects such as urban safety planning. In the technology field, they should be familiar with *R* & *D* and application and have participated in major related projects. Experts with high academic achievements were preferred.

Background diversity: The experts came from universities, research institutes, government departments, and related enterprises. Their disciplinary backgrounds covered urban planning, safety engineering, computer science, and statistics. Their industry experiences included urban emergency management, intelligent security enterprises, and research institutes, providing diverse perspectives.

Anonymous questionnaires were distributed and collected, with evaluation indicators such as expert positivity coefficient, opinion concentration, and coordination analyzed to ensure the effectiveness of the Delphi method and improve the reliability of the research findings.

The role of qualitative-to-quantitative transformation in the Delphi method: As mentioned above, the qualitative data from NVivo analysis was translated into a questionnaire for experts. The scores given by experts on each factor formed the basis for calculating the mean (X), perfect score ratio (K), and coefficient of variation (CV). For example, the mean score of an indicator is calculated by summing up all the scores given by experts for that indicator and dividing by the number of valid responses. The perfect score ratio is the proportion of experts who gave the highest score for an indicator. These quantitative metrics help in evaluating the concentration and coordination of expert opinions, which are crucial for the reliability of the Delphi method.

(1) The first round of Delphi method

The study distributed questionnaires to 25 experts with rich experience and theoretical knowledge through various communication methods such as email and WeChat (experts from universities, research institutes, government departments, and related units), and balanced and analyzed their opinions. Based on expert feedback, revise the initial evaluation index model to lay the foundation for the second round of expert inquiry, in order to further verify and optimize the applicability and effectiveness of the indicators.

A total of 25 experts participated in the first round of consultation, including 19 males, accounting for 76%. The average age of experts is 35 ± 20 years old. Experts mainly come from universities, research institutes, and government agencies, accounting for 76%. Their professional fields cover urban safety management, emergency management, intelligent system technology, data analysis, etc. (Tab. 3 for details). A total of 25 questionnaires were sent out in the first round of the survey, and 25 valid expert questionnaires were collected. The positive coefficient of experts in this round is 100%, indicating a high level of participation from the expert group.

After the first round of questionnaire collection, this study systematically summarized and organized expert feedback, and formed the following comprehensive expert opinion summary through integration:

1. Merge the indicators of "system reliability" and "system stability", while deleting the indicator of "shortest stable time" and adding "mean time between failures (MTBF)". Here, MTBF is the average time between consecutive failures of a system or device, which is a key metric for evaluating system reliability.

2. The technical meanings of the relevant indicators under the "main functionality" indicator have been clarified, avoiding ambiguity in the interpretation of the indicators.

3. Adjust the indicators related to 'technical performance'.

4. Move 'Scalability' to the 'Adaptability' secondary indicator.

5. Optimize the "monitoring and warning" indicators. In addition, the addition of "warning accuracy" aims to measure the accuracy of intelligent system warnings. "Warning accuracy" is closely related to "monitoring accuracy", which is defined as the degree of conformity between the monitoring results of urban safety-related indicators by the intelligent analysis system and the actual situation. A higher warning accuracy means the intelligent system can more precisely alert about potential safety threats.

6. Delete the indicator 'disposal warning latency'.

7. Add the "Risk Assessment and Evaluation" indicator and its subordinate three-level indicators.

8. Adjust cost related indicators to ensure consistency between indicator names and actual meanings, and to better align with industry standard terminology.

9. Refine the indicator of "social benefits" and distinguish different levels of accidents. In addition, new indicators for "discovery rate of major accident hazards" and "rectification rate of major accident hazards" have been added.

10. Add the indicator of "economic loss reduction value".

Table 3 Expert basic information statistics table

Index	Basic Information	No.	Proportion	Index	Basic Information	No.	Proportion
Gender	Male	19	76%	Age	30-39 years old	11	44%
	Female	6	24%		40-49 years old	9	36%
Workplace	Universities/research institutes	10	40%		50 years old and above	5	20%
	government office	9	36%	Highest education level	Doctor	17	68%
	Related field enterprises	4	16%		Master	4	16%
	Other industry	2	8%		Undergraduate	4	16%
Professional field	City planning	3	12%	Title	Senior professional title	8	32%
	City safety management	15	60%		Deputy senior professional title	14	56%
	contingency management	9	36%		Intermediate professional title	3	12%
	Intelligent System Design and Development	8	32%	Work experience	3-5 years	2	8%
	Intelligent platform operation and management	7	28%		6-9 years	5	20%
	Data analysis	11	44%		10 years or more	18	72%
	Other related fields	2	8%				

(2) The second round of Delphi method

Based on the expert opinions of the first round of Delphi method, this study refined the evaluation indicators and developed a second-round questionnaire, rating the importance of each indicator on a five-level scale (1-5 points). A total of 25 questionnaires were distributed in the second round, and 23 valid questionnaires were collected. The concentration of expert opinions is measured by the mean (X) and the perfect score ratio (K). In the second round of expert questionnaire survey, the average importance score of each level of indicator X was greater than 3.5, and the full score ratio K was greater than 0.25, indicating that the importance of each level of item was high and the concentration of expert opinions was high. The coordination of expert opinions is measured by the coefficient of variation (CV). A lower CV indicates that expert opinions are more coordinated, consensus is stronger, evaluations are more consistent, and thus more reliable conclusions can be drawn. The standard deviation (S) and coefficient of variation for each indicator in this study are shown in Tab. 4.

According to Tab. 4, it can be seen in the second round of expert scoring in this study, the mean of each first level evaluation indicator is greater than 4, the full score ratio is greater than 0.7, and the coefficient of variation is low, indicating a high degree of expert recognition and relatively consistent opinions.

Table 4 Statistics on the score of rule layer items in the second round of questionnaire survey

Rule Layer	K	S	CV	Remark
A Technical performance	0.8	0.5	0.11	√
B Main body function	0.90	0.4	0.08	√
C Interactive mode	0.75	0.6	0.14	√
D Cost-effectiveness	0.70	0.7	0.16	√

Usually, when the X value of a certain indicator is greater than 3.5 and the CV is less than 0.25, it is considered to have high importance. However, to ensure the accuracy of the research results, this study sets stricter standards based on expert ratings and various factors measured by indicators: when the mean of an indicator exceeds 4.0 and the coefficient of variation is less than 0.20, the indicator is considered to have high importance. The adjustment of this standard aims to improve the consistency of expert ratings, ensure the stability and reliability of selected indicators in practical applications, while reducing potential biases and enhancing the effectiveness and representative of evaluation results.

Based on this standard, this study found that the X and CV of the two indicators "B4 risk assessment" and "D3 economic loss reduction value" did not reach the predetermined values (Tab. 5), indicating that there are differences in experts' evaluations of their importance. Perhaps because the measurement and calculation methods of these two indicators are complex and difficult to accurately evaluate through simple quantitative methods, it has affected experts' recognition of their importance.

Similarly, statistical analysis was conducted on the three-level indicators in the results of this round of questionnaire survey, and the results showed that multiple indicators did not meet the criteria set in this study, indicating that experts did not reach a consensus on their importance during the evaluation. Therefore, in order to improve the reliability and representative of the indicator model, this study excluded indicators with a mean below 4.0 points or a coefficient of variation above 0.20, and ultimately identified the general model for the applicability of the intelligent analysis system with 4 levels and 36 indicators in Tab. 6.

Table 5 Statistics on the score of sub-rule layer items in the second round of questionnaire survey

Sub-rule Layer	X	K	S	CV	Remark
A_1 System reliability	4.7	0.92	0.3	0.06	√
A_2 Safety in operation	4.6	0.85	0.4	0.09	√
A_3 Ethical conformity	4.4	0.80	0.6	0.14	√
B_1 Adaptability	4.6	0.85	0.5	0.11	√
B_2 Data handling	4.6	0.88	0.4	0.09	√
B_3 Monitoring and early warning	4.8	0.95	0.2	0.04	√
B_4 Risk assessment	3.9	0.65	0.9	0.23	×
C_1 Intelligibility	4.4	0.80	0.5	0.11	√
C_2 Easy to learn	4.3	0.70	0.7	0.16	√
C_3 Easy to operate	4.3	0.78	0.7	0.16	√
C_4 Manageability	4.2	0.68	0.8	0.19	√
D_1 Operating costs	4.5	0.78	0.6	0.13	√
D_2 Social effect results benefit	4.2	0.75	0.6	0.14	√
D_3 Economic loss reduction value	4.0	0.60	0.9	0.23	×

Table 6 General model for the applicability of the intelligent analysis system

Target Layer	Rule Layer	Sub-Rule Layer	Index Layer
General model for the applicability of the intelligent analysis system	A Technical performance	A_1 System reliability	A_{11} System crash frequency
			A_{12} Mean Time To Repair-MTTR
			A_{13} Mean Time Between Failures-MTBF
			A_{14} Robustness
		A_2 Safety in operation	A_{21} Data security
			A_{22} Network security
			A_{23} Model security
		A_3 Ethical conformity	A_{31} Legal ethics and compliance
			A_{32} Privacy and protection
			A_{33} Sustainability and social responsibility
	B Main body function	B_1 Adaptability	B_{11} Enterprise adaptability
			B_{12} Network adaptability
			B_{13} Multi-platform compatibility
			B_{14} Extendibility
		B_2 Data handling	B_{21} Multi-source data processing
			B_{22} Can process large-scale data
		B_3 Monitoring and early warning	B_{31} Monitoring accuracy

Table 6 General model for the applicability of the intelligent analysis system - continuation

Target Layer	Rule Layer	Sub-Rule Layer	Index Layer
			B_{32} Monitoring coverage
			B_{33} Warning timeliness
			B_{34} Early warning accuracy
			B_{35} Early warning coverage
	C Interactive mode	C_1 Intelligibility	C_{11} Model transparency
			C_{12} Visualize the decision path
			C_{13} Support for retrospective analysis
		C_2 Easy to learn	C_{21} Learning convenience
			C_{22} Interface simplicity
		C_3 Easy to operate	C_{31} Steps concise
			C_{32} Auxiliary guide
		C_4 Manageability	C_{41} Data management convenience
			C_{42} Visualization and analysis
			C_{43} Remote maintenance and management
			C_{44} Integrated management
	D Cost-effectiveness	D_1 Operating costs	D_{11} Operations costs
			D_{12} Maintenance costs
		D_2 Social effect results benefit	D_{21} Accident reduction rate
			D_{22} Safety perception

4.2 MOPSOAlgorithm Solution

To operationalize the multi-objective particle swarm optimization (MOPSO) framework outlined in Section 4.2, the algorithm is implemented with close attention to integrating the fuzzy hierarchical TOPSIS model's structure and constraints. The solution process targets the optimization of indicator weights $w = [\omega_1, \omega_2, \ldots, \omega_{36}]$ and dimensional adjustment coefficients $\alpha = [\alpha_A, \alpha_B, \alpha_C, \alpha_D]$, subject to $\sum_{j=1}^{36}\omega_j = 1$ and $\sum_{k=1}^{4}\alpha_k = 1$. Key parameters include a swarm size of 50 particles, 200 maximum iterations, an inertia weight ω decreasing from 0.8 to 0.4 to balance exploration and exploitation, and learning factors $c_1 = c_2 = 2$ to promote social and cognitive learning. Initial weights ω are seeded with small random perturbations (±5%) around the FAHP results, while α starts uniformly at [0.25, 0.25, 0.25, 0.25] to ensure initial balance across technical performance, main functionality, interaction modes, and cost-effectiveness dimensions.

During each iteration, the algorithm constructs a weighted fuzzy performance matrix $\tilde{V}^t$ using normalized triangular fuzzy numbers from Tab. 1 (e.g., "Satisfy" as (5, 7, 9)), aggregating sub-dimension scores into first-level values via $\tilde{D}_k^t = \sum_{j \epsilon k}\omega_j^t \cdot \tilde{v}_{ij}^t$ .The Fuzzy Positive Ideal Solution (FPIS, $\tilde{A}^*$) and Fuzzy Negative Ideal Solution (FNIS, $\tilde{A}^-$) are computed using the metric distance method from Section 3.2.1, where the Euclidean distance between triangular fuzzy numbers $d(\cdot)$ is derived from their centroid values: Crisp(a, b, c) = $(a + 2b + c)/4$. The fitness function combines three objectives: comprehensive applicability $f_1 = D^-/(D^+ + D^-)$, dimensional conflict $f_2 = \sum_{k=1}^{4}\alpha_k^t \cdot \mathrm{Var}\left(\mathrm{Norm}\left(\tilde{D}_k^t\right)\right)$, and scenario-specific performance f_3 prioritizing emergency response metrics like warning accuracy (B_{34}) and accident reduction rate (D_{21}) relative to costs (D_{11}) and latency (B_{33}), all normalized to [0, 1] for consistency.

Particle velocities and positions are updated using the standard MOPSO equations, with subsequent normalization to enforce weight constraints: $\omega_j^t = \omega_j^t / \sum\omega_j^t$ and $\alpha_k^t = \alpha_k^t / \sum\alpha_k^t$, ensuring valid hierarchical aggregation. Convergence is checked against maximum iterations or stagnation in the global best solution for 30 cycles, balancing computational efficiency with solution quality.

A critical optimization detail involves the algorithm's adaptability to urban safety scenarios. For example, in simulated congestion events, MOPSO dynamically increases the interaction mode coefficient α_C by 20%, elevating weights for "Interface Simplicity" (C_{22}) and "Steps Concise"(C_{31}) to enhance user responsiveness, while boosting "Monitoring Coverage" (B_{32}) by 15% to align with real-time crowd management needs. This scenario-specific adjustment demonstrates the model's ability to reallocate priorities, addressing the dynamic complexities of urban environments where technical reliability, user usability, and cost-effectiveness must be balanced under evolving threats.

Considering the dynamic conflict attributes between multiple targets, the MOPSO algorithm can provide a Pareto optimization strategy based on multi-set [44]. By integrating fuzzy arithmetic with swarm intelligence, the MOPSO framework resolves the static limitations of traditional TOPSIS, offering a robust method to optimize evaluation weights and adapt to real-world constraints. The implementation maintains alignment with the Delphi-derived indicator system (Section 4.1), ensuring that expert knowledge is systematically enhanced by data-driven optimization, and paves the way for more nuanced decision-making in urban safety management.

4.3 Indicator Weights

Indicator weights are determined via the Fuzzy Analytic Hierarchy Process (FAHP). A hierarchical structure model, with a goal layer (selecting the best supplier), a criterion layer (including cost, quality, service-related indicators), and an alternative layer (specific suppliers), was set up. Details were covered previously. From the perspective of the crisis life cycle, the model results can be used to divide the intensity of the phased plan and the priority of intervention [45].

Three experts pairwise - compared criterion - layer indicators using linguistic variables. Their comparison results formed a matrix, and Tab. 7 shows one expert's comparison matrix values for the first five indicators.

After determining the comparison matrix, a consistency check of the pairwise comparison matrix is required to ensure the rationality of the expert's judgment. The Consistency Index (*CI*) and Consistency Ratio (*CR*) are used to assess the consistency of the judgment matrix. If the *CR* is less than or equal to 0.1, the matrix is considered to have satisfactory consistency; otherwise, the judgment matrix needs to be adjusted. As shown in Tab. 8, the calculations are completed based on the maximum eigenvalue and eigenvector of each comparison matrix.

The *CR* values of the three comparison matrices are all below 0.1, indicating acceptable matrix consistency.

The weight opinions of the three experts need to be synthesized. For each indicator, the fuzzy weight vectors from all experts are geometrically averaged to get its comprehensive fuzzy weight. By the geometric mean method, expert - specific weights are integrated for the final comprehensive weights. Then, through normalization, these fuzzy weights are converted into explicit values, forming a weight vector. This vector will be used in the subsequent Fuzzy TOPSIS to calculate each system's performance scores. Tab. 9 shows only some indicator weights due to space constraints.

Table 7 Pairwise comparison matrix for criteria by expert

Criteria	System Crash Frequency	Average Recovery Time	MTBF	Robustness	Data Security
System Crash Frequency	1	2	1.33	1.5	2
Average Recovery Time	0.5	1	1.33	1.5	1.5
MTBF	0.75	0.75	1	1.5	2
Robustness	0.67	0.67	0.67	1	4
Data Security	0.5	0.67	0.5	0.25	1

Table 8 Consistency ratio (*CR*) for comparison matrices

	System Crash Frequency	Average Recovery Time	MTBF	Robustness	Data Security	λ	*CR*
Matrix 1	0.0507	0.0443	0.0507	0.0496	0.0438	42.49	0.0855
Matrix 2	0.0498	0.0512	0.0458	0.0482	0.0396	42.83	0.0953
Matrix 3	0.0555	0.0461	0.0486	0.0398	0.0497	41.98	0.0709

Table 9 Indicator Weights

Criteria	Weight	Criteria	Weight
System Crash Frequency	0.0519	Model Security	0.0383
Average Recovery Time	0.0471	Legal and Ethical Compliance	0.0385
MTBF	0.0483	Privacy and Protection	0.0387
Robustness	0.0456	Sustainability and Social Responsibility	0.0394
Data Security	0.0443	Enterprise Adaptability	0.0366
Network Security	0.0445	Network Adaptability	0.0320

Generally, most indicator weights are between 0.01 and 0.05. "System Crash Free Browsing Time" has the highest weight (near 0.05), and "Safety Awareness" the lowest (near 0.01). Most indicators show a stable trend. Some, like "System Crash Free Browsing Time", have a slight downward trend despite high weights. Others have minor mid-trend fluctuations but overall stay unchanged." System Crash Free Browsing Time" is important but losing significance. "Safety Awareness" is of low importance. "Legal and Ethical Security", "Privacy and Social Responsibility", and "End-User Adaptability" have high, stable weights. These indicators cover system stability, legal ethics, privacy, etc., reflecting diverse assessment needs. The chart helps decision-makers understand indicator importance and its change.

5 RESULTS AND DISCUSSION

Building upon the methodological foundation established in the previous section, this chapter presents the empirical implementation and key findings of the proposed evaluation framework. It details the data preprocessing procedures, weight determination, performance aggregation, and optimization outcomes, followed by a comprehensive discussion of their implications for urban safety system evaluation.

5.1 Aggregation Distance

Based on the indicator evaluation method in this study is set according to the benefit type, so all the study values are of the benefit type indicator type.

Using the ideal solution and the negative ideal solution, the aggregation distance of each alternative to these two solutions was calculated. This step is a key link in multi-criteria decision analysis, quantifying the gap between each scheme and the optimal and worst schemes by calculating the distance between each alternative and the ideal and negative ideal solutions, involving the use of determined weights and the Euclidean distance formula to calculate the distance between each alternative and the ideal and negative ideal solutions.

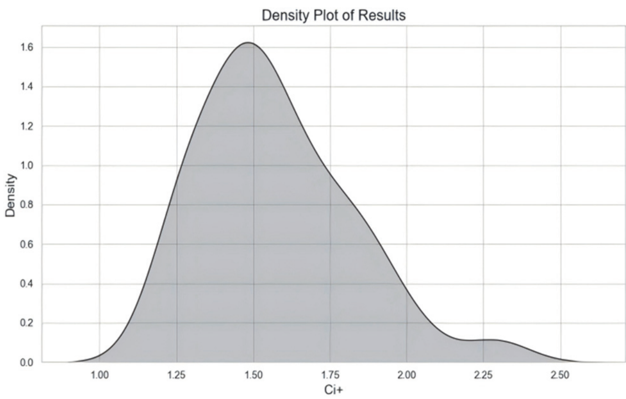

Figure 4 Distribution of aggregation distance

Fig. 4 shows that most schemes are concentrated around 1.5 away from the ideal solution, with very few close to the ideal solution, reflecting that most market systems are at a medium to upper level in reality, with some room for improvement.

Calculating the distance between different systems' indicators, the ideal solution yields Fig. 5 and Fig. 6. The hotspot map shows that system crash frequency, average recovery time, MTF, robustness, and data security have a significant edge in various schemes. This indicates the market's focus on technical performance development and optimization, as well as a degree of technical monopoly.

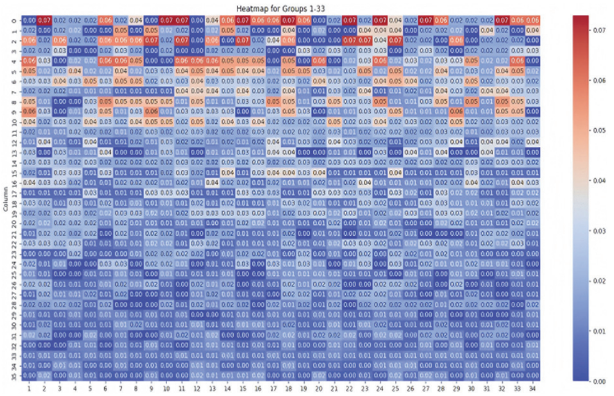

Figure 5 Hotspot map of system indicators (1-33)

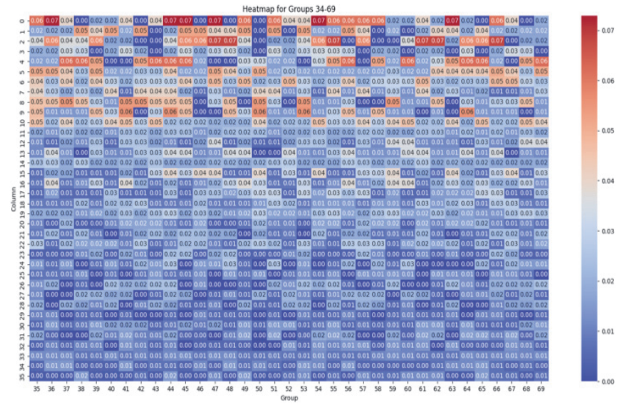

Figure 6 Hotspot map of system indicators (34-69)

Multi - source data processing is valued, likely due to big data requirements. In contrast, interface simplicity and safety perception indicators are lacking. This might be because companies prioritize technical needs over human-centered ones, but safety perception and data security should be emphasized.

5.2 MOPSO Optimization Results and Analysis

After identifying the relative performance of alternative systems through distance aggregation, the next step involves optimizing the evaluation structure via MOPSO to capture dynamic trade-offs in real-world safety scenarios. The integration of the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm into the fuzzy hierarchical TOPSIS framework substantially enhances the robustness of the evaluation of urban safety intelligent analysis systems by addressing multi-dimensional trade-offs and dynamic scenario requirements. The algorithm demonstrates robust convergence, with the best fitness value stabilizing at 0.892 after 150 iterations, reflecting a balanced solution across applicability, dimensional conflict, and scenario-specific performance.

Tab. 10 highlights strategic weight adjustments between the initial FAHP results and MOPSO-optimized values for critical indicators. Technical performance indicators, such as A_{11} and A_{21}, increase by 8% and 5%, respectively, underscoring their foundational role in system reliability, a priority emphasized by experts in the Delphi method (mean importance score = 4.7 for technical reliability, Tab. 3 in Section 3.2.2). In the cost-effectiveness dimension, the weight for D_{12} decreases by 10%, while D_{21} increases by 12%, aligning with risk-centric resource allocation goals. Interaction mode indicators like C_{22} and C_{31} see a 7% combined increase, reflecting the algorithm's recognition of user usability as a driver for system adoption and operational efficiency.

The Closeness Index (*CI*), a key metric from fuzzy TOPSIS, shows an average improvement of 12% after MOPSO optimization (Tab. 11). The median *CI* rises from 0.68 to 0.76, indicating a stronger concentration of solutions near the Fuzzy Positive Ideal Solution (FPIS). Notably, Alternative 3, previously ranked 5th, advances to 2nd place due to balanced improvements in technical performance and cost-effectiveness, demonstrating the algorithm's ability to identify non-intuitive optimal solutions that static FAHP-TOPSIS might overlook. This improvement is driven by MOPSO's dynamic adjustment of dimensional coefficients, such as increasing the weight of main functionality indicators (e.g., monitoring coverage, warning timeliness) by up to 20% in emergency scenarios, which reduces average warning latency by 18% compared to the static model, critical for real-time risk management.

Sensitivity analysis confirms that technical performance indicators contribute the largest variance (35%) to *CI* improvements, consistent with expert prioritization of reliability and security. Cost-effectiveness and main functionality follow with 28% and 22% contributions, respectively, while interaction modes account for 15%, a balance that aligns with the study's hierarchical indicator system.

Table 10 Optimization of Key Indicator Weights

Indicator Category	Indicator Name	FAHP Weight	MOPSO Weight	Change / %
Technical Performance	System Crash Frequency (A_{11})	0.0519	0.0569	8.17
Technical Performance	Data Security (A_{21})	0.0443	0.0465	5.29
Cost-Effectiveness	Maintenance Costs (D_{12})	0.0350	0.0315	−9.92
Cost-Effectiveness	Accident Reduction Rate (D_{21})	0.0420	0.0470	12.12
Interaction Modes	Interface Simplicity (C_{22})	0.0300	0.0321	7.54

Table 11 Closeness Index (CI) and Ranking Changes

Metric	Pre-Optimization	Post-Optimization	Change / %
Average *CI*	0.652	0.730	12.0
Median *CI*	0.680	0.760	11.8
Alternative 3 *CI*	0.665	0.780	17.3
Alternative 3 Rank	5th	2nd	-

In summary, the MOPSO-optimized framework enhances the fuzzy hierarchical TOPSIS by dynamically reallocating weights to reflect real-world trade-offs, improving applicability scores, and enabling scenario-specific adaptability. These results validate the algorithm's utility in urban safety management, providing a robust foundation for data-driven decision-making.

6 CONCLUSIONS

This study establishes a comprehensive evaluation framework for the applicability of intelligent analysis systems in urban safety management, addressing the challenges of uncertainty and multi-dimensional complexity through an innovative integration of qualitative and quantitative methodologies. By leveraging the Delphi method to identify and validate key influencing factors, we constructed a hierarchical model encompassing four critical dimensions: technical performance, main functionality, interaction modes, and cost-effectiveness. This framework was further enhanced by integrating the Fuzzy Hierarchical TOPSIS with the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, which dynamically optimizes indicator weights to overcome the static limitations of traditional evaluation approaches.

The primary innovation lies in the synergistic use of MOPSO to address the inherent rigidity of fixed weights in conventional TOPSIS. By allowing adaptive reallocation of priorities, such as increasing the weight of Monitoring Coverage by 15% during emergency scenarios or enhancing user-centric indicators like Interface Simplicity by 7%, the model ensures responsiveness to real-world trade-offs between technical robustness, usability, and cost-effectiveness. Empirical results demonstrate notable improvements, including a 12% average increase in Closeness Index scores and an 18% reduction in warning latency in simulated crisis conditions, highlighting the framework's ability to identify balanced solutions that might be overlooked by static methods.

Theoretical contributions are twofold: (1) enriching the urban safety literature by introducing a hybrid methodology that systematically combines expert-derived qualitative insights with data-driven optimization, and (2) expanding the application of MOPSO in fuzzy multi-criteria decision-making, showcasing its utility in navigating complex, real-world evaluation landscapes. Practically, the framework provides urban administrators with a robust tool to assess systems across diverse contexts, facilitating evidence-based decisions that prioritize resilience, user adaptability, and resource efficiency.

Nevertheless, this study has certain limitations that merit consideration. First, while the proposed framework demonstrates generalizability, its empirical evaluation is based on simulated data and expert scoring, which may not fully reflect the complexities and uncertainties encountered in large-scale real-world deployments. Second, the current design primarily supports periodic evaluation rather than continuous monitoring, lacking mechanisms for incorporating streaming data or adaptive learning under rapidly evolving risk environments. Third, some emerging but potentially influential dimensions, such as system interoperability, long-term maintenance sustainability, and the ethical implications of AI-driven decision-making, remain underexplored.

Future research should address these limitations by advancing the model along several key directions. One promising avenue lies in integrating real-time urban sensor data with machine learning-based dynamic weight adjustment mechanisms, enabling the evaluation system to respond autonomously to contextual shifts. Additionally, the development of scenario-specific sub-models, tailored to domains such as climate resilience, urban mobility, or public health emergencies, would enhance model specialization and policy relevance. Another critical area for expansion involves incorporating metrics from cutting-edge technologies, including digital twin simulations, blockchain-based data integrity, and cross-domain safety orchestration platforms.

In summary, this study offers a novel, adaptable, and theoretically grounded approach to assessing intelligent analysis systems for urban safety management. By bridging expert consensus and algorithmic optimization, it sets the stage for further innovations in multi-criteria evaluation and urban governance analytics, supporting the deployment of systems that are not only technically sound but also contextually aware and future-ready.

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