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Fuzzy Multi-Criteria Decision-Making Based Security Management: Risk Assessment and Countermeasure Selection in Smart Cities

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ABSTRACT

The aim of this study is to develop a fuzzy MCDM based framework for security management in smart cities. The study focuses on the assessment of security risks and the selection of appropriate security measures. To address the uncertainties and complexities in the assessment of security risks and measures, this research employs two different fuzzy methods: weighting the risk factors using the Fuzzy weight by envelope and slope (F-WENSLO) method and selecting the most appropriate security measures using the Fuzzy Ranking Alternatives with Weights of Criterion (F-RAWEC) method. The proposed approach is applied to a case study on identifying and assessing potential security risks in a smart city infrastructure. The risk factors used in the study are identified as flash floods, traffic accidents and transportation security, robbery and public safety threats, cybersecurity threats, health crises and pandemics, and energy infrastructure and outages. Security systems are defined as physical security systems, emergency response and crisis management systems, software and cybersecurity systems, monitoring and surveillance systems, and sensor-based early warning systems. The results show that physical security measures play a critical role in preventing and responding to incidents, while emergency response and crisis management systems perform less well. It is also stated that software and cybersecurity systems provide an effective solution against digital threats, but their integration with other systems is important. The results show that the fuzzy-based model significantly increases the accuracy in prioritizing risks and provides a systematic method for selecting the most effective security measures. This study contributes to the literature by presenting an innovative decision-making tool for security management in smart cities.

1. Introduction

Smart cities aim to make urban life more efficient, sustainable and secure with digital technologies, big data analytics and artificial intelligence-based solutions. However, the acceleration of urbanization and the spread of technological infrastructure also bring security threats [1]. Issues such as crime rate analysis, emergency management, traffic safety and public order protection are among the biggest security problems faced by smart cities [2,3].

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Traditional security management approaches cannot fully adapt to dynamic and variable risk factors. Therefore, new methods that take uncertainties into account in security management and are supported by multi-criteria decision making (MCDM) techniques are needed. In this study, security risk factors in smart cities will be weighted using the F-WENSLO method and the most appropriate security measures will be determined with the F-RAWEC method.

Fuzzy logic-based multi-criteria decision making (FMCDM) approaches aim to reduce the impact of uncertainties by providing decision makers with more flexible and adaptable analyses [4-6]. These approaches, unlike traditional decision-making methods, have the capacity to process uncertain and fuzzy data, allowing decision makers to approach complex problems more effectively and accurately [7]. FMCDM methods allow for more flexible evaluations between alternatives by taking into account the uncertainty of each criterion [8]. In this way, it allows for more robust and reliable results, especially in the evaluation of various risk factors and security measures. At the same time, it allows decision makers to make more consistent and understandable decisions even in cases where different views and information are combined [9,10]. In our study, a decision support model is proposed to determine the most appropriate strategies by analyzing different security factors. This model will guide security managers and city planners to better understand existing security threats and develop effective intervention strategies.

Although various studies exist in the literature on assessing security risks and determining appropriate security measures, this research stands out by developing a novel decision support model that integrates the F-WENSLO and F-RAWEC methods. Specifically, the key contributions of this study to literature are as follows:

- ✓ Methodological Innovation: This study provides a more robust and flexible approach to decision-making under uncertainty by dynamically weighting risk factors using the F-WENSLO method and selecting the most appropriate security measures using the F-RAWEC method. While traditional multi-criteria decision-making (MCDM) methods often rely on predefined or expert-derived weighting techniques, this study employs a performance-based dynamic weighting approach.
- ✓ Integrated Security Management Model: While most existing studies in the literature focus on individual risk factors or specific security systems, this research conducts a holistic security assessment, analyzing various security risks that smart cities may encounter. The study comprehensively evaluates critical risk factors, including cybersecurity threats, traffic accidents, crime rates, natural disasters, energy outages, and health crises, alongside five different security measures: physical security, monitoring and surveillance, early warning systems, cybersecurity, and emergency response systems.
- ✓ Real-World Application: A case study was conducted using a smart city scenario (MetroCity) to demonstrate how theoretical methods can be integrated into practical decision support processes. This application provides city administrators with a concrete decision-making tool. The findings indicate that physical security measures (SS1) play a crucial role, while emergency response systems (SS5) exhibit lower performance, offering important insights for policymakers.
- ✓ Advancing the Use of Fuzzy MCDM: While previous studies on smart city security primarily rely on classical decision-making models that operate with precise data, this study adopts a fuzzy logic-based approach, enabling the management of uncertainty. This allows for greater flexibility in incorporating expert opinions and uncertain datasets into the decision-making process.

In conclusion, this research expands the existing literature by introducing a new methodological approach to risk management and security measure selection in smart cities. Additionally, it provides a data-driven, dynamic, and integrated security management model, offering valuable contributions to both academic research and practical applications. In the rest of this article, first of all, existing security management and FMCDM applications in the literature will be examined, then the proposed methodology will be detailed. Finally, the applicability of the model will be evaluated through a case study and the results will be discussed.

2. Literature Review

Security management in smart cities is a rapidly developing field, and the assessment of risks and selection of appropriate security measures are of great importance. In recent years, traditional security management methods have evolved to take into account the dynamic structure and data richness of smart cities [11]. While traditional MCDM techniques consider a large number of factors, fuzzy logic-based methods can better handle uncertainties and imprecise data. Fuzzy MCDM is used as an important tool in weighting risk factors and selecting security measures. Fuzzy logic offers security managers flexibility that allows them to make better decisions in uncertain environmental conditions [12]. Methods such as F-WENSLO and F-RAWEC are widely used in the processes of more accurate risk assessment and precaution selection.

Security in smart cities is not limited to the protection of physical infrastructure. IoT (Internet of Things) technology provides critical data to optimize city security. While IoT-based sensors are used for early detection of security threats and risk assessment, FMCDM techniques make significant contributions in analyzing this data and selecting appropriate precautions [13]. In this context, studies in the field of security management in smart cities increasingly adopt the integration of IoT and FMCDM.

In addition, studies conducted in recent years show that these methods are not only limited to security measures, but also provide efficient use of resources and reduced operational costs. These studies emphasize the importance of weighing risks and finding the most appropriate solutions for the correct selection of security measures.

Smart cities are modern residential areas that aim to make services within the city more efficient by using advanced information and communication technologies. Studies on critical factors such as sustainability, security, energy efficiency and transportation are increasing in these cities. Most studies adopt MCDM methods and fuzzy logic-based approaches to solve various problems in cities. Such methods allow for more accurate management of uncertainty and unclear data.

Fayyaz *et al.,* [14] determined security as the most critical factor in the design of city streets for the integration of autonomous vehicles (AVs) and bicycles in smart cities by using a combination of interval-fuzzy multi-criteria decision making and game theory. The study emphasizes that green infrastructure and smart technology integration are optimal strategies, and these strategies help to provide a balance between bicycles and AVs, making the transportation system more efficient and sustainable. Similarly, *Kaveh et al.,* [15] developed a strategic framework combining MCDM and mathematical optimization methods, considering sustainability, resilience and smart cities for disaster management. The study emphasized the importance of infrastructure, health centers, transportation networks in the pre-disaster preparation and risk reduction stages, and determined the most suitable locations and suppliers for optimal emergency preparedness.

Various studies are also being conducted on environmental and energy efficiency issues. *Otay et al.,* [16] used multi-expert interval-fuzzy BWM and TOPSIS methodology while evaluating sustainable energy systems in smart cities. According to the results of the study, environmental sustainability criterion was determined as the most important criterion, and other factors such as energy technology investments and transportation systems were also listed. Chaurasiya and Jain [17] presented a hybrid MCDM framework to improve waste management in smart cities in developing countries such as India. In the study, they determined the most suitable IoT-based waste management technologies using Pythagorean fuzzy MEREC, SWARA and ARAS methods.

Fuzzy logic and MCDM methods find application in many areas in smart cities due to their ability to manage uncertainties. Rani and Potika [18] developed a model that manages such uncertainties while assessing forest fire risks in smart cities. This model ranks the fire risk status of various cities using factors such as weather, vegetation and terrain characteristics. Makki and Alqahtani [19] studied the barriers in smart cities and used DEMATEL (Decision-Making Trial and Evaluation Laboratory) approach to overcome these barriers. In this study, factors such as technical problems, infrastructure deficiencies and high costs were identified as the main barriers and comprehensive strategies were proposed to solve these barriers. Maniratinam *et al.,* [20] developed a new MCDM method to analyze user satisfaction for micro-mobility vehicles (e.g., electric scooters). This method includes evaluation criteria for increasing sustainable clean energy transportation in smart cities. The results of the study show that users evaluate the quality of micro-mobility services according to criteria such as accessibility, reliability, responsiveness and performance.

The studies reveal the importance of MCDM and fuzzy logic approaches in the evaluation of various systems in smart cities, especially in sustainability, energy efficiency, security and transportation. These methods help cities to be managed efficiently while also managing uncertainties and complexities more effectively.

3. Methodology

This research aims to optimize the risk assessment and precaution selection processes by using FMCDM methods to improve security management in smart cities. The flow diagram describing the analysis process of the research is given in Figure 1.

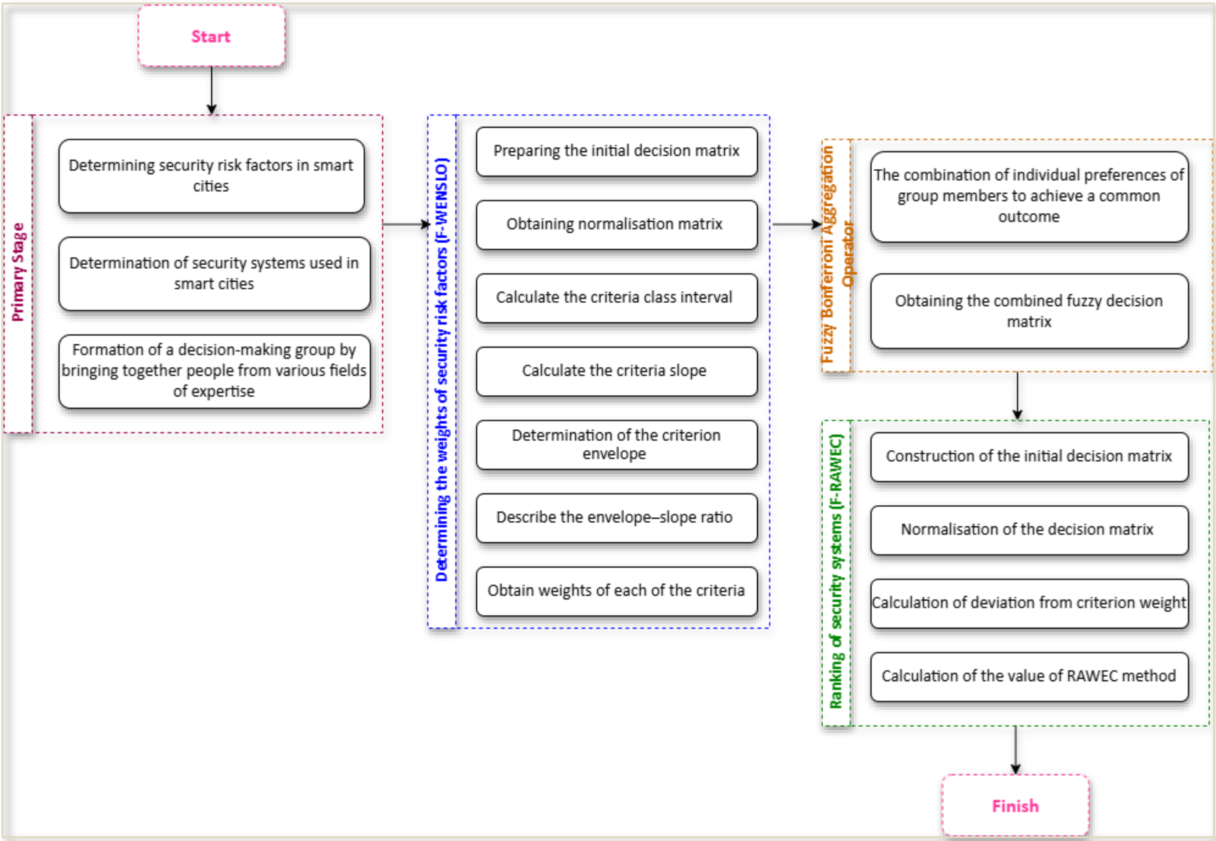

Fig. 1. Flow chart

At the end of these steps in Figure 1, security risk factors in smart cities are weighted, individual decisions are converted to a common result, and security systems are ranked according to the determined criteria. This process aims to optimize risk management in smart cities using FMCDM methods.

3.1 Data Collection

The data collection phase will be carried out to determine security risks in smart cities and the measures that can be taken against these risks. In this process, the existing literature on security measures in smart cities will be examined and data obtained from IoT (Internet of Things) based systems will be used.

3.1.1 Security Risk Factors

Security risk factors in smart cities are given in Table 1 with their explanations.

Table 1.
Security risk factors in smart cities

Risk Factor	Description	References
Cybersecurity Threats (RF1)	The digital infrastructures of smart cities are vulnerable to cyber-attacks. Threats such as hacking, data breaches, and malware can damage city infrastructure and put citizens' personal information at risk.	Chatterjee *et al.*, [21]; Elmaghraby and Losavio, [22]

Traffic Accidents and Transportation Safety (RF2)	Emerging technologies such as smart traffic management systems and autonomous vehicles may lead to traffic accidents. Infrastructure deficiencies or system failures can threaten traffic safety.	Jagatheesaperumal *et al*., [23]; Adewopo *et al*., [24]
Crime Rates and Public Safety (RF3)	In smart cities, crime rates can be monitored through security cameras and facial recognition technology. However, these technologies can also be manipulated, leading to ethical concerns such as violations of personal privacy.	Tutak and Brodny, [25]; O'Malley and Smith, [26]
Natural Disasters (Earthquakes, Floods, Fires) (RF4)	Early warning systems and sensors can monitor natural disasters, but large-scale disasters can destroy city infrastructure and increase security risks.	Elvas *et al*., [27]; Nefros *et al*., [28]
Energy Infrastructure and Power Outages (RF5)	Disruptions in energy infrastructure can impact the city. Power outages pose a major security risk, especially for critical infrastructure, and can hinder the operation of other security measures in the city.	Şerban and Lytras, [29]; Jafari *et a*l., [30]
Health Crises and Pandemics (RF6)	Health management systems can be monitored with IoT devices, but major health crises can strain the city's healthcare infrastructure and threaten public safety. Pandemics can disrupt social order.	Petrova and Tairov [31]; Hassankhani *et al*., [32]

Table 1 provides an overview of how each factor can affect the city while addressing the security risks of smart cities from various perspectives.

3.1.2 Security Measures

The main security systems used to ensure security in smart cities and the functions of each are described in Table 2. It is emphasized that each security system is a critical element that ensures the security of cities and is of great importance, especially for rapid reactions and effective interventions.

Table 2.
Security systems used in smart cities

Security System	Description
Physical Security Systems (SS1)	Security barriers, doors, and access control systems are physical infrastructure-based security measures. They prevent unauthorized access and protect critical areas of the city.
Surveillance and Monitoring Systems (SS2)	Includes CCTV cameras, facial recognition systems, and smart city monitoring systems. It enables real-time monitoring to detect incidents and provide instant information to security forces.
Sensor-Based Early Warning Systems (SS3)	Utilizes sensors for motion, temperature, smoke, air quality, and water levels to detect environmental threats and alert relevant authorities early. Plays a crucial role in natural disasters and infrastructure issues.
Software and Cybersecurity Systems (SS4)	Covers encryption, anomaly detection, intrusion prevention systems, and AI-powered security software. Protects city infrastructure against cyber threats.
Emergency Response and Crisis Management Systems (SS5)	Includes emergency protocols, evacuation plans, autonomous drones, and robots. Ensures rapid response in crisis situations to minimize losses.

Table 2 describes the 5 main security systems used to ensure security in smart cities and the functions of each. It emphasizes that each security system is a critical element in ensuring the security of cities and is of great importance, especially for rapid reactions and effective interventions.

3.2 Fuzzy sets

Zadeh [33], proposed the concept of fuzzy sets to address uncertainty in variables and parameters. Triangular Fuzzy Number (TFN) is used in various studies to turn qualitative assertions into quantitative ones [34]. A TFN represents each figure with three numerals. The first, second, and third integers that define a fuzzy number reflect the lowest, most, and highest potential values, respectively $\tilde{A}(l, m, u)$. Eq. (1) defines the triangle type membership function for fuzzy numbers.

$$\mu_A(x) = \begin{cases} 0, & x < l \\ \dfrac{x-l}{m-l}, & l \leq x \leq m \\ \dfrac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x > u \end{cases} \tag{1}$$

TFNs can be transformed into crisp values by applying the center of gravity defuzzification technique represented by Eq. (2).

$$A = \frac{l + 4m + u}{6} \tag{2}$$

3.3 Fuzzy Bonferroni Aggregation Operator

Aggregation operators, which are mathematical functions, aggregate group members' individual preferences, evaluations, or judgments to form a common conclusion throughout the group decision-making process. The Bonferroni Aggregation (BA) operator is provided by Eq. (3) [35].

$$BA^{p,q}(a_1, a_2, \dots, a_n) = \left(\frac{1}{n(n-1)} \sum_{i,j=1\ (i \neq j)}^{n} a_i^p a_j^q \right)^{\frac{1}{p+q}} \tag{3}$$

where *n* is the number of experts, $p, q \geq 0$.

3.4 F-WENSLO Method

The reason for selecting the WENSLO method is its simple and comprehensible calculation procedure. The novel WENSLO approach, which determines criterion weights based on envelope-slope ratios, represents a significant methodological innovation. In traditional multi-criteria decision-making (MCDM) frameworks, weights are typically assigned based on predefined values or expert-derived estimations. In contrast, the WENSLO method dynamically adjusts weights based on performance outcomes. This dynamic approach enhances the adaptability of the framework, ensuring better alignment with practical operational conditions. Pamučar et al. [36] presented the WENSLO technique for determining weight coefficients of criterion (crisp version). In this work, the WENSLO technique is fuzzification using triangular fuzzy numbers.

Step 1. Construction of the initial decision matrix

The selected experts prioritized the criteria using linguistic phrases from the fuzzy scale in Table 3.

Table 3.
Fuzzy scale, linguistic expressions and triangular numbers

Fuzzy Linguistic Descriptive	Abbreviation	Fuzzy Number
Absolutely low	AL	(1,1,1)
Very low	VL	(1,1.5,2)
Low	L	(1.5,2,2.5)
Medium	M	(2,2.5,3)
Equal	E	(2.5,3,3.5)
Medium-high	MH	(3,3.5,4)
High	H	(3.5,4,4.5)
Very high	VH	(4,4.5,5)
Absolutely high	AH	(4.5,5,5)

Source: Božanić *et al*. [37].

The combined decision matrix ($\tilde{Z}$) is obtained using Eq. (4).

$$\tilde{Z} = \left[\tilde{z}_{ij}\right]_{kxn} = \begin{bmatrix} \tilde{z}_{11} & \cdots & \tilde{z}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{z}_{k1} & \cdots & \tilde{z}_{kn} \end{bmatrix} \tag{4}$$

$\tilde{z}_{ij} = \left(z_{ij}^{l}, z_{ij}^{m}, z_{ij}^{u}\right)$ represents fuzzy value of criterion j. in alternative i.

Step 2. Creating the normalization matrix $\left(\widetilde{\mathrm{T}}\right)$.

Eq. (5) is used to normalise the combined decision matrix.

$$\tilde{t}_{ij} = \left(t_{ij}^{l}, t_{ij}^{m}, t_{ij}^{u}\right) = \frac{\tilde{z}_j}{\sum_{j=1}^{n}\tilde{z}_j} = \left(\frac{z_j^{l}}{\sum_{j=1}^{n} z_j^{u}}, \frac{z_j^{m}}{\sum_{j=1}^{n} z_j^{m}}, \frac{z_j^{u}}{\sum_{j=1}^{n} z_j^{l}}\right) \tag{5}$$

Step 3. Calculation of criterion class interval ($\tilde{\rho}_j$).

The size of the j-th criteria class interval is determined using Sturges' rule, Eq. (6):

$$\tilde{\rho}_j = \left(\rho_j^{l}, \rho_j^{m}, \rho_j^{u}\right) = \left(\frac{max(z_j^{l}) - min(z_j^{l})}{1 + 3.322 * log(k)}, \frac{max(z_j^{m}) - min(z_j^{m})}{1 + 3.322 * log(k)}, \frac{max(z_j^{u}) - min(z_j^{u})}{1 + 3.322 * log(k)}\right) \tag{6}$$

Step 4. Determination of the criterion slope ($tan\tilde{\varphi}_j$).

The slope of the criterion is calculated by Eq. (7).

$$tan\tilde{\varphi}_j = \frac{\sum_{i=1}^{k}\tilde{z}_j}{(k-1)\tilde{\rho}_j} = \left(\frac{\sum_{i=1}^{k} z_j^{l}}{(k-1)\rho_j^{u}}, \frac{\sum_{i=1}^{k} z_j^{m}}{(k-1)\rho_j^{m}}, \frac{\sum_{i=1}^{k} z_j^{u}}{(k-1)\rho_j^{l}}\right) \tag{7}$$

Step 5. Determination of the criterion envelope ($\tilde{\varepsilon}_j$)

Eq. (8) calculates the total of the partial Euclidean distances between two consecutive criteria.

$$\tilde{\varepsilon}_j = \left(\sum_{i=1}^{k-1}\sqrt{\left(z_{i+1,j}^{l} - z_{ij}^{l}\right)^2 + \left(\rho_j^{l}\right)^2}, \sum_{i=1}^{k-1}\sqrt{\left(z_{i+1,j}^{m} - z_{ij}^{m}\right)^2 + \left(\rho_j^{m}\right)^2}, \sum_{i=1}^{k-1}\sqrt{\left(z_{i+1,j}^{u} - z_{ij}^{u}\right)^2 + \left(\rho_j^{u}\right)^2}\right) \quad (8)$$

Step 6. Determine the envelope slope ratio ($\tilde{\delta}_j$)

The ratio of the total Euclidean distance to the criteria slope is calculated using Eq. (9).

$$\tilde{\delta}_j = \frac{\tilde{\varepsilon}_j}{tan\tilde{\varphi}_j} = \left(\frac{\varepsilon_j^l}{tan\varphi_j^u}, \frac{\varepsilon_j^m}{tan\varphi_j^m}, \frac{\varepsilon_j^u}{tan\varphi_j^l}\right) \quad (9)$$

Step 7. Obtaining fuzzy weights $\left(\tilde{w}_j\right)$ of each of the criterion

Weights are determined using Eq. (10) depending on the criteria's significance coefficients.

$$\tilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right) = \frac{\tilde{\delta}_j}{\sum_{j=1}^{n}\tilde{\delta}_j} = \left(\frac{\delta_j^l}{\sum_{j=1}^{n}\delta_j^u}, \frac{\delta_j^m}{\sum_{j=1}^{n}\delta_j^m}, \frac{\delta_j^u}{\sum_{j=1}^{n}\delta_j^l}\right) \quad (10)$$

3.5 F-RAWEC Method

The reason for selecting the RAWEC method is to simplify the decision-making process. With its few steps and ease of use, it minimizes the need for complex calculations, making it an efficient and practical alternative for multi-criteria decision-making (MCDM) applications. Moreover, the results obtained using the RAWEC method have shown strong consistency with those of other methods, and its reliability has been well-documented in the literature [38]. Puška et al. [38] presented the RAWEC technique for ranking alternatives (crisp version). In this study, the RAWEC technique is fuzzified using triangular fuzzy numbers.

Step 1. Construction of the initial decision matrix

The selected experts prioritized the criteria using linguistic phrases from the fuzzy scale in Table 3.

The combined decision matrix ($\tilde{X}$) is obtained using Eq. (11).

$$\tilde{X} = \left[\tilde{x}_{ij}\right]_{kxn} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{k1} & \cdots & \tilde{x}_{kn} \end{bmatrix} \quad (11)$$

$\tilde{x}_{ij} = \left(x_{ij}^l, x_{ij}^m, x_{ij}^u\right)$ represents fuzzy value of criterion j. in alternative i.

Step 2. Creating the normalization matrix $\left(\tilde{N}\right)$.

When normalising the initial decision matrix, double normalisation is performed with Eq. (12) for the benefit normalization ($\tilde{n}_{ij}$) and Eq. (13) for the cost normalization $\left(\tilde{n}_{ij}\right)'$.

$$\tilde{n}_{ij} = \left(n_{ij}^l, n_{ij}^m, n_{ij}^u\right) = \frac{\tilde{x}_j}{max(\tilde{x}_{ij})} = \left(\frac{x_{ij}^l}{max(x_{ij}^u)}, \frac{x_{ij}^m}{max(x_{ij}^u)}, \frac{x_{ij}^u}{max(x_{ij}^u)}\right) \quad (12)$$

and

$$(\tilde{n}_{ij})' = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{min(\tilde{x}_{ij})}{\tilde{x}_{ij}} = \left(\frac{min(x_{ij}^l)}{x_{ij}^u}, \frac{min(x_{ij}^l)}{x_{ij}^m}, \frac{min(x_{ij}^l)}{x_{ij}^l}\right) \quad (12)$$

$$\tilde{n}_{ij} = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{min(\tilde{x}_{ij})}{\tilde{x}_{ij}} = \left(\frac{min(x_{ij}^l)}{x_{ij}^u}, \frac{min(x_{ij}^l)}{x_{ij}^m}, \frac{min(x_{ij}^l)}{x_{ij}^l}\right) \quad (13)$$

and

$$(\tilde{n}_{ij})' = (n_{ij}^l, n_{ij}^m, n_{ij}^u) = \frac{\tilde{x}_j}{max(\tilde{x}_{ij})} = \left(\frac{x_{ij}^l}{max(x_{ij}^u)}, \frac{x_{ij}^m}{max(x_{ij}^u)}, \frac{x_{ij}^u}{max(x_{ij}^u)}\right) \quad (13)$$

Step 3. Calculate the deviation from the criteria weight

Eqs. (14) and (15) yield the total deviation from the weight of the criterion after first calculating the deviations of the normalized data from the maximum values denoted by the number 1. The deviation is then multiplied by the weights of the criteria.

$$\tilde{\vartheta}_{ij} = \left(\sum_{i=1}^{n}\left[(1 - n_{ij}^u) * w_j^l\right], \sum_{i=1}^{n}\left[(1 - n_{ij}^m) * w_j^m\right], \sum_{i=1}^{n}\left[(1 - n_{ij}^l) * w_j^u\right]\right) \quad (14)$$

$$(\tilde{\vartheta}_{ij})' = \left(\sum_{i=1}^{n}\left[(1 - (n_{ij}^u)') * w_j^l\right], \sum_{i=1}^{n}\left[(1 - (n_{ij}^m)') * w_j^m\right], \sum_{i=1}^{n}\left[(1 - (n_{ij}^l)') * w_j^u\right]\right) \quad (15)$$

Step 4. Calculation of the value of the RAWEC method

The value of the RAWEC method obtained by Eq. (16) takes a value between (-1,1).

$$\tilde{Q}_i = \frac{(\tilde{\vartheta}_{ij})' - \tilde{\vartheta}_{ij}}{(\tilde{\vartheta}_{ij})' + \tilde{\vartheta}_{ij}} = \left(\frac{(\vartheta_{ij}^l)' - \vartheta_{ij}^u}{(\vartheta_{ij}^u)' + (\vartheta_{ij}^u)}, \frac{(\vartheta_{ij}^m)' - \vartheta_{ij}^m}{(\vartheta_{ij}^m)' + (\vartheta_{ij}^m)}, \frac{(\vartheta_{ij}^u)' - \vartheta_{ij}^l}{(\vartheta_{ij}^l)' + (\vartheta_{ij}^l)}\right) \quad (16)$$

The degree to which the value of an alternative's technique is high determines its superiority. The best option is indicated by the alternative with the highest value.

4. Case Study: Integrated Security Management in a Smart City – MetroCity Example

People from various fields of expertise were brought together to form a decision-making group to work on integrated security management in the smart city. Table 4 shows the structure of the decision-making group with representatives from each field of expertise.

Table 4.
Structure of the Decision-Making Group

Expert Code	Expertise Area	Role Description
E1	Cybersecurity Expert	Analyzes cyber threats to smart city infrastructure and ensures data security.

E2	Traffic and Transportation Safety Expert	Works on autonomous vehicles, traffic management, and transportation safety.
E3	Disaster Management and Emergency Coordination Expert	Experienced in natural disaster and crisis management, oversees evacuation and response processes.
E4	Public Safety and Crisis Response Expert	Analyzes crime rates, manages surveillance systems, and enhances public safety.

By clearly defining the roles and responsibilities of each expert, the decision-making process is carried out comprehensively and effectively.

MetroCity is a large metropolis that has adopted high-tech, smart city applications. The city administration aims to reduce many risks from cybersecurity to traffic management, from natural disasters to public safety in order to increase security. For this purpose, a comprehensive security management model has been created by integrating different security systems. One day, the following events occur in different residential areas of MetroCity at the same time:

- ✓ Cybersecurity Threat (RF1) - Cyber Attack on City Networks

The central system that manages MetroCity's traffic control systems and energy infrastructure is subject to a large-scale cyber-attack. The goal is to disrupt transportation and create chaos in the city.

- ✓ Traffic Accident and Transportation Safety (RF2) - Autonomous Vehicle Accident

An autonomous vehicle in the city center hits a pedestrian due to a signaling error.

- ✓ Crime Rates and Public Safety (RF3) - Robbery and Public Safety Threat

An organized robbery occurs in a crowded shopping mall.

- ✓ Natural Disaster (RF4) - Flash Flood

Floods occur in some parts of MetroCity due to unexpected heavy rainfall.

- ✓ Energy Infrastructure and Outages (RF5) - Grid Failure

A major outage occurs due to overloading of the main power grid.

- ✓ Health Crisis and Pandemics (RF6) - Infectious Disease Case

A passenger on public transportation in MetroCity is found to have high fever and difficulty breathing.

The results of each expert's assessment of these risks according to Table 3 are given in Table 5.

Table 5.
Expert Assessment of Risk Factors

Risk Factor	E1	E2	E3	E4
RF1	AH	MH	E	H
RF2	M	AH	MH	E
RF3	E	H	MH	AH
RF4	L	E	AH	MH
RF5	H	MH	VH	MH
RF6	MH	E	H	AH

The risk factors in Table 2 were evaluated and scored by each expert within their own area of expertise. This scoring will help determine the weights of the criteria to be used in the final decision-making process. Table 6 shows the evaluation of the security risks experienced in MetroCity and each security system according to Table 3 by four experts.

Table 6.
Experts' evaluation of security systems

Security Systems	Experts	RF1	RF2	RF3	RF4	RF5	RF6
SS1	E1	L	VL	H	M	MH	L
	E2	VL	L	VH	E	H	M
	E3	L	VL	H	M	MH	L
	E4	M	L	VH	E	H	M
SS2	E1	E	VH	AH	E	L	H
	E2	M	AH	AH	MH	M	VH
	E3	MH	H	AH	MH	L	H
	E4	E	VH	AH	MH	M	H
SS3	E1	M	AH	E	AH	H	AH
	E2	M	AH	E	AH	VH	AH
	E3	E	VH	MH	AH	VH	AH
	E4	L	AH	MH	AH	VH	AH
SS4	E1	AH	MH	M	E	AH	E
	E2	AH	E	E	M	AH	E
	E3	AH	E	M	M	AH	MH
	E4	AH	E	E	E	AH	E
SS5	E1	MH	H	VH	AH	E	AH
	E2	H	MH	VH	VH	E	AH
	E3	E	VH	H	AH	MH	AH
	E4	MH	H	VH	AH	E	AH

These evaluations in Table 6 help to understand the strengths and weaknesses of the proposed security systems in the decision-making process and provide information about the criteria to be taken into account in the final selection.

4.1 Determining the weights with F-WENSLO method

The initial decision matrix obtained as a result of the experts' evaluations and presented in Table 5 was normalized using Eq. (5). The normalized matrix obtained is given in Table 7.

Table 7.
Normalized decision matrix

	RF1			RF2			RF3		
E1	0,2647	0,3226	0,3704	0,1290	0,1786	0,2500	0,1471	0,1935	0,2593
E2	0,1765	0,2258	0,2963	0,2903	0,3571	0,4167	0,2059	0,2581	0,3333
E3	0,1471	0,1935	0,2593	0,1935	0,2500	0,3333	0,1765	0,2258	0,2963
E4	0,2059	0,2581	0,3333	0,1613	0,2143	0,2917	0,2647	0,3226	0,3704
max	0,2647	0,3226	0,3704	0,2903	0,3571	0,4167	0,2647	0,3226	0,3704
min	0,1471	0,1935	0,2593	0,1290	0,1786	0,2500	0,1471	0,1935	0,2593

	RF4			RF5			RF6		

E1	0,1000	0,1481	0,2174	0,2000	0,2581	0,3333	0,1765	0,2258	0,2963
E2	0,1667	0,2222	0,3043	0,1714	0,2258	0,2963	0,1471	0,1935	0,2593
E3	0,3000	0,3704	0,4348	0,2286	0,2903	0,3704	0,2059	0,2581	0,3333
E4	0,2000	0,2593	0,3478	0,1714	0,2258	0,2963	0,2647	0,3226	0,3704
max	0,3000	0,3704	0,4348	0,2286	0,2903	0,3704	0,2647	0,3226	0,3704
min	0,1000	0,1481	0,2174	0,1714	0,2258	0,2963	0,1471	0,1935	0,2593

In Table 7, the normalized values of the evaluation of RF1 by E1 are obtained as follows.

$$\tilde{t}_{11} = \left(\frac{4,5}{5+4+3,5+4,5}, \frac{5}{5+3,5+3+4}, \frac{5}{4,5+3+2,5+3,5}\right) = (0,2647 \quad 0,3226 \quad 0,3704)$$

All elements of the matrix were calculated in a similar way.

Then, the criterion class interval was calculated using Eq. (6), the criterion slope Eq. (7), the criterion envelope Eq. (8), the envelope slope ratio Eq. (9) and the fuzzy weight of each criterion Eq. (10) and presented in Table 8.

Table 8.
Calculations according to F-WENSLO method for criteria

	RF1			RF2			RF3		
$\tilde{\rho}_j$	0,0392	0,0430	0,0370	0,0538	0,0595	0,0556	0,0392	0,0430	0,0370
$tan\tilde{\varphi}_j$	0,7147	1,0333	1,5857	0,6194	0,9333	1,4830	0,7147	1,0333	1,5857
$\tilde{\varepsilon}_j$	0,5289	0,5430	0,5471	0,5502	0,5710	0,5593	0,5653	0,5795	0,5471
$\tilde{\delta}_j$	0,3335	0,5255	0,7656	0,3710	0,6118	0,9030	0,3565	0,5608	0,7656
$\tilde{w}_j$	0,0673	0,1551	0,3129	0,0748	0,1806	0,3691	0,0719	0,1655	0,3129
	RF4			**RF5**			**RF6**		
$\tilde{\rho}_j$	0,0667	0,0741	0,0725	0,0190	0,0215	0,0247	0,0392	0,0430	0,0370
$tan\tilde{\varphi}_j$	0,5878	0,9000	1,0000	0,6943	1,1481	1,1667	0,7147	1,0333	1,5857
$\tilde{\varepsilon}_j$	0,6215	0,6420	0,6171	0,5039	0,5206	0,5405	0,5268	0,5403	0,4961
$\tilde{\delta}_j$	0,6215	0,7134	1,0499	0,4319	0,4534	0,7785	0,3322	0,5229	0,6942
$\tilde{w}_j$	0,1254	0,2106	0,4291	0,0871	0,1338	0,3182	0,0670	0,1543	0,2837

All calculations are shown specifically for RF1.

$$\tilde{\rho}_{RF1} = \left(\frac{0,2647-0,1471}{1+3,322*log4}, \frac{0,3226-0,1935}{1+3,322*log4}, \frac{0,3704-0,2593}{1+3,322*log4}\right) = (0,0392 \quad 0,0430 \quad 0,0370)$$

$$tan\tilde{\varphi}_{RF1} = \left(\begin{array}{c} \dfrac{0,2647+0,1765+0,1471+0,2059}{3*0,3704}, \\ \dfrac{0,3226+0,2258+0,1935+0,2581}{3*0,3226}, \\ \dfrac{0,3704+0,2963+0,2593+0,3333}{3*0,2647} \end{array}\right) = (0,7147 \quad 1,0333 \quad 1,5857)$$

$$\tilde{\varepsilon}_{RF1} = \begin{pmatrix} \sqrt{((0{,}1765-0{,}2647)^2+0{,}0392^2)+((0{,}1471-0{,}1765)^2+0{,}0392^2)+((0{,}2059-0{,}1471)^2+0{,}0392^2)}, \\ \sqrt{((0{,}3226-0{,}2258)^2+0{,}0430^2)+((0{,}1935-0{,}2258)^2+0{,}0430^2)+((0{,}2581-0{,}1935)^2+0{,}0430^2)}, \\ \sqrt{((0{,}2963-0{,}3704)^2+0{,}0370^2)+((0{,}2593-0{,}2963)^2+0{,}0370^2)+((0{,}3333-0{,}2593)^2+0{,}0370^2)} \end{pmatrix}$$

$$\tilde{\varepsilon}_{RF1} = (0{,}5289\ \ 0{,}5430\ \ 0{,}5471)$$

$$\tilde{\delta}_{RF1} = \left(\frac{0{,}5289}{1{,}5857}, \frac{0{,}5430}{1{,}0333}, \frac{0{,}5471}{0{,}7147}\right) = (0{,}3335\ \ 0{,}5255\ \ 0{,}7656)$$

$$\widetilde{w}_{RF1} = \begin{pmatrix} \dfrac{0{,}3335}{0{,}7656+0{,}9030+\ldots+0{,}7785+0{,}6942}, \\ \dfrac{0{,}5255}{0{,}5255+0{,}6118+\ldots+0{,}4534+0{,}5229}, \\ \dfrac{0{,}7656}{0{,}3335+0{,}3710+\ldots+0{,}4319+0{,}3322} \end{pmatrix} = (0{,}0673\ \ 0{,}1551\ \ 0{,}3129)$$

Then, the crips weights were obtained using Eq. (2).

$$w_{RF1} = \frac{0{,}0673+4*0{,}1551+0{,}3129}{6} = 0{,}1668$$

Since $\sum_{j=1}^{10} w_j = 1$ should be for all weights, normalized weight values were obtained.

$$\omega_{RF1} = \frac{0{,}1668}{0{,}1668+0{,}1944+\ldots+0{,}1568+0{,}1614} = 0{,}1535$$

Similarly, the same procedures were performed for other weights.

$$\omega_j = (0{,}1535\ \ 0{,}1789\ \ 0{,}1606\ \ 0{,}2143\ \ 0{,}1443\ \ 0{,}1485\ )$$

According to these weight values, the importance of risk factors in MetroCity can be listed as follows:

RF4: Flash Flood (0.2143). It is the most critical risk factor. Flash floods, which are among the natural disasters, have the highest weight value. This indicates that they pose a greater threat compared to other events experienced in the city and that security systems should focus more on them. RF2: Traffic Accident and Transportation Safety (0.1789). Autonomous vehicle accidents are seen as a significant security risk in the city. This indicates that the transportation infrastructure requires more security measures. RF3: Robbery and Public Safety Threat (0.1606). It reveals the seriousness of crime rates and public safety threats in the city. High-security monitoring systems and emergency response systems may need to be strengthened in this area. RF1: Cyber Security Threat (0.1535). Cyber-attacks on MetroCity's central systems are less critical compared to other events, but still pose a serious threat. It is recommended to strengthen cybersecurity systems to better protect digital infrastructure. RF6: Health Crisis and Pandemics (0.1485). The risk of infectious diseases is significant but has a lower priority than other threats. It can be controlled with thermal cameras and digital monitoring systems. RF5: Energy Infrastructure and Outages (0.1443). It is the lowest risk factor. Although energy outages pose a significant risk, they are less critical compared to other factors. This may be due to alternative energy sources in the city or the fact that existing systems are more resistant to such risks.

4.2 Fuzzy Bonferroni aggregation operator application

Decision makers interpreted the performance of security systems according to Table 3. To bring these individual evaluations together, a joint fuzzy decision matrix was obtained using Equation (3) and is given in Table 9.

Table 9.
Combined fuzzy decision matrix

	RF1			RF2			RF3		
SS1	1,4860	1,9896	2,4917	1,2416	1,7440	2,2454	3,7472	4,2475	4,7478
SS2	2,4917	2,9930	3,4940	3,9948	4,4954	4,8734	4,5000	5,0000	5,0000
SS3	1,9896	2,4917	2,9930	4,3732	4,8734	5,0000	2,7462	3,2468	3,7472
SS4	4,5000	5,0000	5,0000	2,6220	3,1225	3,6228	2,2454	2,7462	3,2468
SS5	2,9930	3,4940	3,9948	3,4940	3,9948	4,4954	3,8730	4,3732	4,8734
	RF4			**RF5**			**RF6**		
SS1	2,2454	2,7462	3,2468	3,2468	3,7472	4,2475	1,7440	2,2454	2,7462
SS2	2,8723	3,3727	3,8730	1,7440	2,2454	2,7462	3,6228	4,1231	4,6233
SS3	4,5000	5,0000	5,0000	3,8730	4,3732	4,8734	4,5000	5,0000	5,0000
SS4	2,2454	2,7462	3,2468	4,5000	5,0000	5,0000	2,6220	3,1225	3,6228
SS5	4,3732	4,8734	5,0000	2,6220	3,1225	3,6228	4,5000	5,0000	5,0000

Decision makers individually evaluated the performance of each security system in Table 3. However, since individual evaluations are based on different expert opinions, these evaluations need to be combined appropriately. The Bonferroni aggregation operator is a powerful operator used in the fuzzy decision-making process and was preferred due to the following advantages.

- ✓ Balances Extreme Evaluations: It produces a more balanced result by softening the extremes between individual expert opinions.
- ✓ Better Reflects Dependent and Interactive Data: Instead of the classical arithmetic average, it takes into account the interaction and dependency between evaluations.
- ✓ Produces a Compromise Solution: If there are extremes between the opinions of decision makers, it creates the most appropriate fuzzy decision matrix by finding the middle ground.

4.3 F-RAWEC method application

Benefit and cost normalized decision matrices are obtained by using Eq. (12) and Eq. (13). These matrices are given in Table 10 and Table 11, respectively.

Table 10.
Benefit normalization matrix

	RF1			RF2			RF3		
SS1	0,5964	0,7469	1,0000	0,5530	0,7119	1,0000	0,4729	0,5286	0,5992

SS2	0,4253	0,4965	0,5964	0,2548	0,2762	0,3108	0,4491	0,4491	0,4990
SS3	0,4965	0,5964	0,7469	0,2483	0,2548	0,2839	0,5992	0,6916	0,8176
SS4	0,2972	0,2972	0,3302	0,3427	0,3976	0,4735	0,6916	0,8176	1,0000
SS5	0,3720	0,4253	0,4965	0,2762	0,3108	0,3554	0,4607	0,5134	0,5798
		RF4			**RF5**			**RF6**	
SS1	0,6916	0,8176	1,0000	0,4106	0,4654	0,5372	0,6351	0,7767	1,0000
SS2	0,5798	0,6658	0,7817	0,6351	0,7767	1,0000	0,3772	0,4230	0,4814
SS3	0,4491	0,4491	0,4990	0,3579	0,3988	0,4503	0,3488	0,3488	0,3876
SS4	0,6916	0,8176	1,0000	0,3488	0,3488	0,3876	0,4814	0,5585	0,6651
SS5	0,4491	0,4607	0,5134	0,4814	0,5585	0,6651	0,3488	0,3488	0,3876

The benefit normalized values for the RF1 risk factor of the SS1 security system are obtained as follows.

$$\tilde{n}_{11} = \left(\frac{1,4860}{2,4917}, \frac{1,4860}{1,9896}, \frac{1,4860}{1,4860}\right) = (0,5964 \;\; 0,7469 \;\; 1,0000)$$

All elements of the matrix are calculated similarly.

Table 11.
Cost normalization matrix

		RF1			**RF2**			**RF3**	
SS1	0,2972	0,3979	0,4983	0,2483	0,3488	0,4491	0,7494	0,8495	0,9496
SS2	0,4983	0,5986	0,6988	0,7990	0,8991	0,9747	0,9000	1,0000	1,0000
SS3	0,3979	0,4983	0,5986	0,8746	0,9747	1,0000	0,5492	0,6494	0,7494
SS4	0,9000	1,0000	1,0000	0,5244	0,6245	0,7246	0,4491	0,5492	0,6494
SS5	0,5986	0,6988	0,7990	0,6988	0,7990	0,8991	0,7746	0,8746	0,9747
		RF4			**RF5**			**RF6**	
SS1	0,5492	0,6494	0,6494	0,7494	0,8495	0,3488	0,4491	0,5492	0,5492
SS2	0,6745	0,7746	0,3488	0,4491	0,5492	0,7246	0,8246	0,9247	0,6745
SS3	1,0000	1,0000	0,7746	0,8746	0,9747	0,9000	1,0000	1,0000	1,0000
SS4	0,5492	0,6494	0,9000	1,0000	1,0000	0,5244	0,6245	0,7246	0,5492
SS5	0,9747	1,0000	0,5244	0,6245	0,7246	0,9000	1,0000	1,0000	0,9747

The cost normalized values for the RF1 risk factor of the SS1 security system are obtained as follows.

$$(\tilde{n}_{11})' = \left(\frac{1,4860}{5,0000}, \frac{1,9896}{5,0000}, \frac{2,4917}{5,0000}\right) = (0,2972 \;\; 0,3979 \;\; 0,4983)$$

All elements of the matrix are calculated in a similar way.

Then, deviations from the criterion weights are obtained by Eq. (14) and Eq. (15). These matrices are given in Table 12 and Table 13, respectively.

Table 12.
Deviations from criteria weights (Benefit)

		RF1			**RF2**			**RF3**	

SS1	0,0272	0,0393	0,0000	0,0335	0,0520	0,0000	0,0379	0,0780	0,1254
SS2	0,0387	0,0781	0,1263	0,0558	0,1307	0,2544	0,0396	0,0912	0,1568
SS3	0,0339	0,0626	0,0792	0,0563	0,1346	0,2643	0,0288	0,0511	0,0571
SS4	0,0473	0,1090	0,2096	0,0492	0,1088	0,1943	0,0222	0,0302	0,0000
SS5	0,0423	0,0891	0,1575	0,0542	0,1245	0,2379	0,0388	0,0806	0,1315
		RF4			**RF5**			**RF6**	
SS1	0,0387	0,0384	0,0000	0,0514	0,0715	0,1473	0,0245	0,0345	0,0000
SS2	0,0527	0,0704	0,0937	0,0318	0,0299	0,0000	0,0417	0,0891	0,1471
SS3	0,0691	0,1160	0,2150	0,0560	0,0805	0,1749	0,0436	0,1005	0,1738
SS4	0,0387	0,0384	0,0000	0,0567	0,0872	0,1949	0,0348	0,0681	0,0950
SS5	0,0691	0,1136	0,2088	0,0452	0,0591	0,1065	0,0436	0,1005	0,1738

Deviations from the criterion weight for the RF1 risk factor of the SS1 security system are obtained as follows.

$$\tilde{\vartheta}_{11} = \big((1-0{,}5964)*0{,}0673\;\;(1-0{,}7469)*0{,}1551\;\;(1-1)*0{,}3129\big) = (0{,}0272\;\;0{,}0393\;\;0{,}0000)$$

All elements of the matrix are calculated similarly.

Table 13.
Deviations from criteria weights (Cost)

		RF1			RF2			RF3	
SS1	0,0473	0,0934	0,1570	0,0563	0,1176	0,2033	0,0180	0,0249	0,0473
SS2	0,0338	0,0623	0,0942	0,0150	0,0182	0,0093	0,0072	0,0000	0,0338
SS3	0,0405	0,0778	0,1256	0,0094	0,0046	0,0000	0,0324	0,0580	0,0405
SS4	0,0067	0,0000	0,0000	0,0356	0,0678	0,1017	0,0396	0,0746	0,0067
SS5	0,0270	0,0467	0,0629	0,0225	0,0363	0,0372	0,0162	0,0208	0,0270
		RF4			**RF5**			**RF6**	
SS1	0,0158	0,0691	0,0949	0,1505	0,0306	0,0335	0,0479	0,0436	0,0850
SS2	0,0000	0,0534	0,0685	0,0967	0,0567	0,0737	0,1434	0,0185	0,0271
SS3	0,0784	0,0125	0,0000	0,0000	0,0196	0,0168	0,0081	0,0067	0,0000
SS4	0,1097	0,0691	0,0949	0,1505	0,0087	0,0000	0,0000	0,0319	0,0580
SS5	0,0079	0,0157	0,0053	0,0000	0,0414	0,0503	0,0876	0,0067	0,0000

Deviations from the criterion weight for the RF1 risk factor of the SS1 security system are obtained as follows.

$$\big(\tilde{\vartheta}_{11}\big)' = \big((1-0{,}7028)*0{,}0673\;\;(1-0{,}6021)*0{,}1551\;\;(1-0{,}5017)*0{,}3129\big)$$
$$= (0{,}0473\;\;0{,}0934\;\;0{,}1570)$$

All elements of the matrix are calculated in a similar way. The RAWEC method value is obtained with Eq. (16) and is given in Table 14.

Table 14.
Ranking of appropriate security systems
for risk factors

	$\tilde{\boldsymbol{\vartheta}}_{ij}$			$(\tilde{\boldsymbol{\vartheta}}_{ij})'$			$\tilde{\boldsymbol{Q}}_i$			$\boldsymbol{Q}_i$	**Rank**
SS1	0,2130	0,3137	0,2727	0,2648	0,4494	0,7023	-0,0080	0,1778	1,0240	0,2878	1
SS2	0,2603	0,4893	0,7782	0,1846	0,2498	0,3651	-0,5192	-0,3240	0,2356	-0,2633	3
SS3	0,2876	0,5452	0,9642	0,1212	0,1572	0,2121	-0,7167	-0,5524	-0,1849	-0,5185	4
SS4	0,2488	0,4417	0,6937	0,1916	0,2953	0,4400	-0,4429	-0,1986	0,4340	-0,1339	2
SS5	0,2931	0,5673	1,0161	0,1296	0,1594	0,1957	-0,7315	-0,5614	-0,2304	-0,5346	5

The ranking value of the SS1 security system is obtained as follows.

$$\tilde{Q}_1 = \left(\frac{0{,}2648 - 0{,}2727}{0{,}7023 + 0{,}2727}, \frac{0{,}4494 - 0{,}3137}{0{,}4494 + 0{,}3137}, \frac{0{,}7023 - 0{,}2130}{0{,}2648 + 0{,}2130}\right) = (-0{,}0080 \;\; 0{,}1778 \;\; 1{,}0240)$$

Table 14 evaluates the performance of different security systems and ranks them in terms of effectiveness. When Q_i values are examined, Physical Security Systems (SS1) have the highest impact among security systems (Q_i = 0,2878), while Emergency Response and Crisis Management Systems (SS5) have the lowest performance (Q_i = -0,5346). The results show that security systems should be addressed with an integrated approach. In particular, it has been revealed that physical security measures (SS1) play a critical role in preventing and responding to incidents. However, Software and Cyber Security Systems (SS4) (Q_i = -0,1339) have a high level of impact in terms of preventing digital threats and should be considered as a complementary element to physical security measures.

In contrast, Monitoring and Surveillance Systems (SS2) (Q_i= -0,2633), Sensor-Based Early Warning Systems (SS3) (Q_i= -0,5185) and Emergency Response Systems (SS5) (Q_i= -0,5346) showed relatively lower performance. This situation reveals that these systems alone may be insufficient and should be integrated with other security measures.

5. Discussion, practical and managerial implications

This study was conducted to evaluate various risk factors occurring in MetroCity and to determine the effectiveness of security systems against these risks. As a result of the analysis, the importance weights of the risk factors were determined and it was seen that the most critical risk was flash flood (RF4=0,2143). This was followed by autonomous vehicle accident (RF2=0,1789) and crime rates and public safety threat (RF3=0,1606). The lowest weighted risk factors were determined as network failure (RF5=0,1443) and infectious disease cases (RF6=0,1485). These findings reveal the need for the city administration and relevant stakeholders to focus their resources on the most critical risks. In addition, the performance of security systems was determined by Q_i values. While physical security systems (SS1=0,2878) stood out as the most effective solution, software and cyber security systems (SS4=-0,1339) came in second. While monitoring and surveillance systems (SS2=-0,2633) and sensor-based early warning systems (SS3=-0,5185) were found to be moderately effective, emergency response and crisis management systems (SS5=-0,5346) had the lowest effectiveness.

5.1 Practical and Managerial Implications

- ✓ Restructuring Risk Management Strategies: The results showed that flash floods and traffic accidents are the most critical risk factors. Therefore, municipalities and infrastructure managers need to invest more in disaster management systems. The high-risk level of autonomous vehicle accidents reveals the need to strengthen smart traffic systems and signaling infrastructure.

- ✓ Integration and Optimization of Security Systems: The determination of physical security systems (SS1) as the most effective solution indicates that more investments should be made in these systems in the future. The fact that emergency response and crisis management systems (SS5) have the lowest level of effectiveness reveals the need to improve the integration and operational efficiency of these systems.
- ✓ Determination of Technological Investment Areas: Integrating advanced artificial intelligence and machine learning-based systems with monitoring, sensor and software-based systems can increase system effectiveness. The cyber security infrastructure needs to be strengthened to effectively prevent cyber security threats (RF1).
- ✓ Policy Recommendations for Decision Makers: Municipalities and decision makers should focus on the most critical risk factors (RF4 and RF2) to ensure more effective allocation of resources. In order to increase the effectiveness of security systems, the integration between physical and software-based security systems should be strengthened. The findings of this study contribute to both academic literature and provide guidance for practical applications. Future studies can be supported by different decision-making methods, focusing on the integration and increased effectiveness of security systems.

6. Conclusions, limitations and future directions

This study was conducted to evaluate various risk factors that may occur in MetroCity and to determine the effectiveness of different security systems against these risks. The findings show that flash floods and autonomous vehicle accidents are the most critical risk factors. The factors with the lowest risk level are network failure and infectious disease cases. When evaluated in terms of security systems, physical security systems were determined to be the most effective system, while emergency response and crisis management systems were found to have the lowest performance.

6.1 Limitations of the Study

- ✓ Data Scope: The data used in the study is specific to MetroCity and different results may be obtained in other cities.
- ✓ Number of Decision Makers: The limited number of experts participating in the evaluation process may limit the generalizability of the results.
- ✓ Methodological Scope: The decision-making methods used are based on certain assumptions and different results may be obtained when different methodologies are used.

6.2 Future Directions

- ✓ Real-Time Data Usage

Risk management strategies can be developed by integrating real-time data and artificial intelligence-supported analyses in city management processes.

- ✓ Comparative Studies for Different Cities

Similar analyses can be conducted in cities with different geographical and demographic characteristics to test the generalizability of the findings.

This study provides significant contributions to the optimization of security systems in the context of smart city security. Future research is expected to offer more integrated solutions based on technological developments and data analysis.

Author Contributions

For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, GD.; methodology, GD.; software, GD.; validation, GD.; formal analysis, GD.; investigation, GD.; resources, GD.; data curation, GD.; writing—original draft preparation, GD.; writing—review and editing, GD.; visualization, GD.; supervision, GD.; project administration, GD.; funding acquisition, GD. All authors have read and agreed to the published version of the manuscript." Authorship must be limited to those who have contributed substantially to the work reported.

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