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An Integrated Bipolar pqr-Spherical Fuzzy Decision Framework for the Selection of AI-driven Security System

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ABSTRACT

With rising urbanization and urban population growth, enhancing public safety has become a significant component of sustainable smart city development. Therefore, it is essential to select a reliable, adaptive, and effective security system to ensure a safe urban environment. The implementation of artificial intelligence in smart cities offers a promising solution to address these challenges. However, selecting a security system that enhances public safety while ensuring privacy and sustainability is often a challenging task, as its implementation requires a meticulous evaluation of all relevant criteria. Under these circumstances, the need for multi-criteria decision-making arises. In this regard, this study employs an integrated decision-making framework that integrates the Symmetry Point of Criterion (SPC) approach with the Aczel–Alsina Weighted Assessment (ALWAS) technique under a bipolar pqr-spherical fuzzy environment to select the optimal AI-driven security system. The study considers four security systems as potential alternatives, evaluated based on ten criteria categorized into technical, economic and environmental, and social dimensions. The assessment data are expressed using bipolar pqr-spherical fuzzy sets, while the weights of the criteria are determined using the SPC approach, and the alternatives are ranked using the ALWAS technique. Furthermore, the consistency and stability of the results are validated through comparative analysis and sensitivity analysis, respectively.

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1. Introduction

The swift urbanization and technological progress of the 21st century led to the emergence of smart cities, which began to take shape and gain popularity in recent years [1]. A smart city is a broad and intricate system that utilizes advanced technologies, predominantly driven by Information and Communication Technology (ICT) and the Internet of Things (IoT), digital infrastructure, and data science to improve the overall safety, efficiency, and quality of life of its dwellers [2]. They are evolving into an indispensable framework, particularly in the context of urban development and sustainability. Various sectors contribute to the progress of smart cities, including energy, education, governance, healthcare, infrastructure development, transportation, and telecommunications.

As urbanization continues to rise, cities are turning out to be the primary region for people to reside in. The presence of insecurity, fear, and various threats significantly diminishes the quality of life, particularly in contemporary urban settings. Urban security concerns have emerged as critical social issues that shape the quality of life in densely populated urban areas. Hence, urban safety is one of the crucial challenges in the development and operation of smart cities [3]. In light of this rationale, there arises artificial intelligence (AI), which can transform several aspects of urban life. AI performs a major role in unleashing the complete ability of smart cities. They can be executed in almost all portions of human life [4]. Traditional security systems cannot completely adapt to the varying risk factors of smart cities. By implementing AI-driven technologies into security systems, smart cities can better enhance the safety of their residents and provide a sustainable quality of life.

However, selecting an optimal sustainable AI-driven security system for smart cities is a crucial task since it involves structured planning and programming, technical expertise, financial resources, and an extensive assessment of all relevant attributes. Multi-criteria decision-making (MCDM) stands out as a potential tool for addressing such real-world decision-making problems. The adaptability of MCDM methodologies to consider multiple conflicting criteria to provide an optimal solution is its key feature. Moreover, the incorporation of fuzzy set theory to handle the vagueness and imprecision of the evaluation data has enabled the expansion of MCDM across multiple domains, including industries, banking, healthcare, energy, transportation, and so on.

2. Literature review

Since the introduction of fuzzy sets by Zadeh [5], which deals with membership degree $(\xi \in [0,1])$ to handle the imprecision and uncertainty of data associated with diverse real-world problems, numerous researchers contributed various expansions and generalizations of fuzzy sets to the literature, particularly to deal with ξ as well as non-membership degree (δ). Notable extensions include intuitionistic fuzzy sets (IFS) by Atanassov [6] $(\xi + \delta \leq 1)$, Pythagorean fuzzy sets (PyFS) by Yager [7] $(\xi^2 + \delta^2 \leq 1)$, Fermatean fuzzy sets by Senapati and Yager [8] $(\xi^3 + \delta^3 \leq 1)$, $q-$rung orthopair fuzzy sets (q-ROFS) by Yager [9] $(\xi^q + \delta^q \leq 1, q \geq 1)$, $p, q-$quasirung orthopair fuzzy sets by Seikh and Mandal [10] ($\xi^p + \delta^q \leq 1,$ where $p, q \in \mathbb{Z}^+$ such that $p = q, p > q$ or $p < q$).

Furthermore, to make uncertainty handling more flexible, Cuong [11] proposed picture fuzzy sets which corresponds to ξ, δ, and neutral degree (β) where $\xi + \delta + \beta \leq 1$. Further generalizations include spherical fuzzy sets (SFS) presented by Kutlu Gündoğdu & Kahraman [12] with the constraint $\xi^2+\delta^2+\beta^2 \leq 1$ and T-spherical fuzzy sets (T-SFS) proposed by Mahmood *et al.* [13] where $\xi^t+\delta^t+\beta^t \leq 1, t \geq 2$.

However, decision makers are restricted to utilize the same value of parameter t for ξ, β, and δ in a T-spherical environment, which can substantially impact the result of the decision-making framework. To exclude this shortcoming, Ali and Naeem [14] developed a new extension of T-SFS, named r, s, t-spherical fuzzy sets (in some works, this was reframed as p, q, r-spherical fuzzy sets (pqr-SFS)), which has the liberty to consider different values of parameter for ξ, β, and δ. This relationship is expressed as $\xi^p + \beta^q + \delta^r \leq 1$, where $p, r \in Z^+$ with $q = LCM(p, r)$. The pqr-SFS has been efficiently implemented in the works of Rahim *et al.* [15] and Kang *et al.* [16]. In addition, Karaaslan and Karamaz [17] and Rahim *et al.* [18] extended this notion to interval-valued pqr-SFS.

Bipolar-valued fuzzy sets (BFS) is a generalization of fuzzy sets which captures the dual aspect of nature ($+$ve and $-$ve), whose membership degree range is $[-1, 1]$. Several extensions of BFS exist in the literature, including bipolar IFS [19], bipolar PyFS [20], bipolar q-ROFS [21], and bipolar n, m-rung orthopair fuzzy sets [22]. Furthermore, Princy and Mohana [23] introduced spherical bipolar fuzzy sets and Wang *et al.* [24] developed bipolar T-spherical fuzzy sets (BT-SFS). The BT-SFS includes both $+$ve and $-$ve values of ξ, β, and δ where $\xi^+, \beta^+, \delta^+ \in [0, 1]$ and $\xi^-, \beta^-, \delta^- \in [-1, 0]$ satisfying the conditions $0 \leq (\xi^+)^t + (\beta^+)^t + (\delta^+)^t \leq 1$ and $-1 \leq (\xi^-)^t + (\beta^-)^t + (\delta^-)^t \leq 0$ for some $+$ve integer $t \geq 2$. However, in certain cases, there is a need for decision-makers to assign different values of parameters for $+$ve ξ, β, and δ as well as $-$ve ξ, β, and δ. To eliminate such limitations, Ameen *et al.* [25] introduced the concept of bipolar pqr-spherical fuzzy sets ($B_{pqr}SFS$), which enables decision-makers to consider different parameters (p, q, and r) to $\xi^+, \beta^+, \delta^+ \in [0, 1]$ and $\xi^-, \beta^-, \delta^- \in [-1, 0]$ satisfying the conditions $0 \leq (\xi^+)^p + (\beta^+)^q + (\delta^+)^r \leq 1$ and $-1 \leq (\xi^-)^p + (\beta^-)^q + (\delta^-)^r \leq 0$ for $p, q, r \in Z^+$.

MCDM refers to choosing an optimal solution from the list of alternatives in relation to the specified set of criteria. MCDM techniques fall into two categories: the weighting of criteria and the ranking of alternatives. Evaluating the criteria weights is a crucial phase in the MCDM model, as they have significant influence on the final ranking of alternatives [26,27]. Generally, the weighting approaches are split into two groups, including subjective and objective methods. Subjective approaches take the opinion of the decision-makers, while objective approaches depend solely on the decision matrix to acquire the criteria weights. Various authors have effectively employed the objective weighting approach to obtain the criteria weights. In this regard, Gligorić *et al.* [28] proposed an objective weighting technique called symmetry point of criterion (SPC). This approach is based on assessing the features of the criterion that is established by its symmetry point. The symmetry point lies in the interval $[a, b]$ where a and b signify the minimum and maximum value of the criterion, respectively. In the aftermath, various studies exist in the literature that utilized the SPC approach. Chatterjee *et al.* [29] applied the SPC method for the selection of delivery drones. Alrasheedi *et al.* [30] extended the SPC approach within the fermatean fuzzy environment for evaluating sustainable suppliers in the healthcare supply chain. Van Dua [31] utilized this method for selecting the woodworking machinery for small business in Vietnam. Furthermore, Durdu [32]integrated SPC technique with the LOPCOW method for evaluating the financial performance of firms.

Next, the ranking method selection plays a major role in the assessment of MCDM. Each method is known for its unique computation algorithm. Pamucar *et al.* [33,34] proposed a new ranking method called Aczel-Alsina weighted assessment (ALWAS) which employs the concept of Aczel-Alsina nonlinear functions to enhance the flexibility of the method. However, there are only limited works in the literature that incorporated ALWAS technique. Notably, Gokasar *et al.* [35] applied the ALWAS method for the selection of metaverse integrated connected autonomous vehicles. Unal [36] employed the ALWAS approach to assess the ranking among clustered universities under p, q-quasirung orthopair fuzzy operators. Gürol *et al.* [37] utilized the ALWAS technique for the selection of terminal operating system in green ports under intuitionistic fuzzy environment.

Though there exist many studies that implement MCDM in the assessment of smart cities, there are only limited studies which focussed on security management. Demir [38] utilized WENSLO-RAWEC methodology under triangular fuzzy numbers for the security management in smart cities. Bouramdane [39] used AHP method for evaluating the disaster management strategies in smart cities. Fayyaz *et al.* [40] combined MCDM with game theory for the evaluation of smart city street design. The integration of AI into MCDM to optimize road safety was put forth in the work of Ashraf *et al.* [41].

2.1 *Research gaps and contributions*

Based on the reviewed literature, it is evident that limited attention has been paid to the assessment of security management in smart cities, particularly with the incorporation of AI-Analytics and MCDM. No prior study extended the SPC approach and ALWAS technique under $B_{pqr}SF$ environment. Also, the integration of SPC and ALWAS approaches into a single framework for the evaluation of security management remained unexplored. To fill this gap in the literature, this study suggests a $B_{pqr}SF$-SPC-ALWAS framework to select an optimal AI-driven security system for smart cities.
The contributions of this study are as follows:

- The main objective of this study is to propose an enhanced MCDM model based on $B_{pqr}SFS$. The SPC approach and the ALWAS technique aids in choosing an appropriate AI-driven security system for smart cities.
- $B_{pqr}SFS$ was employed to eliminate the vagueness and uncertainty in the evaluation information. To the best of our knowledge, this is the first study to integrate SPC and ALWAS methods under the $B_{pqr}SF$ environment.
- The study considers ten criteria categorized into technical, economic and environmental, and social dimensions. The $B_{pqr}SFS$-based SPC method was developed to obtain the objective weights of the criteria considered.
- Then, the $B_{pqr}SFS$-based ALWAS method was formulated to assess four security systems and determine the optimal system. In addition, the consistency and robustness of the method have been examined through comparative and sensitive analyses.

2.2 *Layout of the paper*

The remainder of the article is structured as follows: Section 2 provides the fundamental definitions and concepts related to $B_{pqr}SFS$. Section 3 explains the SPC and ALWAS techniques. Section 4 presents the case study of the selection of AI-driven security systems. The results and discussion are presented in section 5, along with comparison and sensitive analysis. Section 6 provides the concluding remarks.

3. Preliminaries

This section provides the fundamental definitions and concepts of fuzzy sets employed in this study.

Definition 1 *A bipolar fuzzy set (BFS) $\widetilde{\mathsf{B}^\hbar}$ on the universe $\widetilde{\mathsf{W}^\hbar}$ is expressed as:*

$$\widetilde{\mathsf{B}^\hbar} = \left\{ \left(w, \xi^{+}_{\widetilde{\mathsf{B}^\hbar}}(w), \xi^{-}_{\widetilde{\mathsf{B}^\hbar}}(w) \right) : w \in \widetilde{\mathsf{W}^\hbar} \right\}, \tag{1}$$

where $\xi^{+}_{\widetilde{\mathsf{B}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [0,1]$ signifies the degree of positive membership and $\xi^{-}_{\widetilde{\mathsf{B}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [-1,0]$ signifies the degree of negative membership for every $w \in \widetilde{\mathsf{W}^\hbar}$. The ordered pair $\widetilde{\mathsf{B}^\hbar} = \left(\xi^{+}_{\widetilde{\mathsf{B}^\hbar}}, \xi^{-}_{\widetilde{\mathsf{B}^\hbar}} \right)$ represents a bipolar fuzzy number.

Definition 2 *A pqr-spherical fuzzy set (pqr-SFS) $\widetilde{\mathsf{K}^\hbar}$ on the universe $\widetilde{\mathsf{W}^\hbar}$ is described as:*

$$\widetilde{\mathsf{K}^\hbar} = \left\{ \left(w, \xi_{\widetilde{\mathsf{K}^\hbar}}(w), \beta_{\widetilde{\mathsf{K}^\hbar}}(w), \delta_{\widetilde{\mathsf{K}^\hbar}}(w) \right) : w \in \widetilde{\mathsf{W}^\hbar} \right\}, \tag{2}$$

where $\xi_{\widetilde{\mathsf{K}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [0,1]$, $\beta_{\widetilde{\mathsf{K}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [0,1]$, and $\delta_{\widetilde{\mathsf{K}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [0,1]$ indicates the degree of membership, neutrality, and non-membership functions, respectively, of $w \in \widetilde{\mathsf{W}^\hbar}$ satisfying the condition $0 \leq \left(\xi_{\widetilde{\mathsf{K}^\hbar}}(w)\right)^p + \left(\beta_{\widetilde{\mathsf{K}^\hbar}}(w)\right)^q + \left(\delta_{\widetilde{\mathsf{K}^\hbar}}(w)\right)^r \leq 1$ for each $w \in \widetilde{\mathsf{W}^\hbar}$ and any positive integers p, q, and r. The triplet $\widetilde{\mathsf{K}^\hbar} = \left(\xi_{\widetilde{\mathsf{K}^\hbar}}, \beta_{\widetilde{\mathsf{K}^\hbar}}, \delta_{\widetilde{\mathsf{K}^\hbar}}\right)$ denotes a p,q,r-spherical fuzzy number.

Definition 3 *A bipolar pqr-spherical fuzzy set [25] $(B_{pqr}SFS)$ $\widetilde{\mathsf{G}^\hbar}$ on the universe $\widetilde{\mathsf{W}^\hbar}$ is given by the expression:*

$$\widetilde{\mathsf{G}^\hbar} = \left\{ \left(w, \xi^+_{\widetilde{\mathsf{G}^\hbar}}(w), \beta^+_{\widetilde{\mathsf{G}^\hbar}}(w), \delta^+_{\widetilde{\mathsf{G}^\hbar}}(w), \xi^-_{\widetilde{\mathsf{G}^\hbar}}(w), \beta^-_{\widetilde{\mathsf{G}^\hbar}}(w), \delta^-_{\widetilde{\mathsf{G}^\hbar}}(w) \right) : w \in \widetilde{\mathsf{W}^\hbar} \right\}, \tag{3}$$

where $\xi^+_{\widetilde{\mathsf{G}^\hbar}}, \beta^+_{\widetilde{\mathsf{G}^\hbar}}, \delta^+_{\widetilde{\mathsf{G}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [0,1]$ corresponds to the positive membership, neutral, and non-membership degrees, respectively, and $\xi^-_{\widetilde{\mathsf{G}^\hbar}}, \beta^-_{\widetilde{\mathsf{G}^\hbar}}, \delta^-_{\widetilde{\mathsf{G}^\hbar}} : \widetilde{\mathsf{W}^\hbar} \to [-1,0]$ corresponds to the negative membership, neutral, and non-membership degrees, respectively, such that

$$0 \leq \left(\xi^+_{\widetilde{\mathsf{G}^\hbar}}(w)\right)^p + \left(\beta^+_{\widetilde{\mathsf{G}^\hbar}}(w)\right)^q + \left(\delta^+_{\widetilde{\mathsf{G}^\hbar}}(w)\right)^r \leq 1,$$

and

$$-1 \leq \left(\xi^-_{\widetilde{\mathsf{G}^\hbar}}(w)\right)^p + \left(\beta^-_{\widetilde{\mathsf{G}^\hbar}}(w)\right)^q + \left(\delta^-_{\widetilde{\mathsf{G}^\hbar}}(w)\right)^r \leq 0,$$

for each $w \in \widetilde{\mathsf{W}^\hbar}$ and some $p, q, r \in \mathbb{Z}^+$. A $B_{pqr}SFS$ can be denoted as $\widetilde{\mathsf{G}^\hbar} = \left(\xi^+_{\widetilde{\mathsf{G}^\hbar}}, \beta^+_{\widetilde{\mathsf{G}^\hbar}}, \delta^+_{\widetilde{\mathsf{G}^\hbar}}, \xi^-_{\widetilde{\mathsf{G}^\hbar}}, \beta^-_{\widetilde{\mathsf{G}^\hbar}}, \delta^-_{\widetilde{\mathsf{G}^\hbar}}\right)$ for ease in utilization. This term is referred to as the bipolar pqr-spherical fuzzy number $(B_{pqr}SFN)$.

Definition 4 (25) *Let $\widetilde{\mathsf{G}^\hbar_\jmath} = \left(\xi^+_{\widetilde{\mathsf{G}^\hbar_\jmath}}, \beta^+_{\widetilde{\mathsf{G}^\hbar_\jmath}}, \delta^+_{\widetilde{\mathsf{G}^\hbar_\jmath}}, \xi^-_{\widetilde{\mathsf{G}^\hbar_\jmath}}, \beta^-_{\widetilde{\mathsf{G}^\hbar_\jmath}}, \delta^-_{\widetilde{\mathsf{G}^\hbar_\jmath}}\right)$, for $\jmath = 1, 2, \cdots, \ell$, be a collection of $B_{pqr}SFNs$. Then the expression for bipolar pqr-spherical fuzzy-weighted geometric $(B_{pqr}SFWG)$ operator is determined as follows:*

$$B_{pqr}SFWG\left(\widetilde{\mathsf{G}^\hbar_1}, \widetilde{\mathsf{G}^\hbar_2}, \cdots, \widetilde{\mathsf{G}^\hbar_\ell}\right) = \left(\prod_{\jmath=1}^{\ell} (\xi^+_{\widetilde{\mathsf{G}^\hbar}})^{\tau_\jmath}, \sqrt[2q]{1 - \prod_{\jmath=1}^{\ell} (1 - (\beta^+_{\widetilde{\mathsf{G}^\hbar}})^{2q})^{\tau_\jmath}}, \sqrt[2r]{1 - \prod_{\jmath=1}^{\ell} (1 - (\delta^+_{\widetilde{\mathsf{G}^\hbar}})^{2r})^{\tau_\jmath}}, \right.$$

$$\left. - \sqrt[2p]{1 - \prod_{\jmath=1}^{\ell} (1 - (\xi^-_{\widetilde{\mathsf{G}^\hbar}})^{2p})^{\tau_\jmath}}, - \prod_{\jmath=1}^{\ell} (-\beta^-_{\widetilde{\mathsf{G}^\hbar}})^{\tau_\jmath}, - \prod_{\jmath=1}^{\ell} (-\delta^-_{\widetilde{\mathsf{G}^\hbar}})^{\tau_\jmath} \right), \tag{4}$$

where $\tau = (\tau_1, \tau_2, \cdots, \tau_\ell)$ represents the weight of $\widetilde{\mathsf{G}^\hbar_\jmath}$ for $\jmath = 1, 2, \cdots, \ell \mid \sum_{\jmath=1}^{\ell} \tau_\jmath = 1$ and $\tau_\jmath > 0$.

Definition 5 (25) *Let $\widetilde{\mathsf{G}^\hbar} = \left(\xi^+_{\widetilde{\mathsf{G}^\hbar}}, \beta^+_{\widetilde{\mathsf{G}^\hbar}}, \delta^+_{\widetilde{\mathsf{G}^\hbar}}, \xi^-_{\widetilde{\mathsf{G}^\hbar}}, \beta^-_{\widetilde{\mathsf{G}^\hbar}}, \delta^-_{\widetilde{\mathsf{G}^\hbar}}\right)$ represent a $B_{pqr}SFN$. Then, the score function of $\widetilde{\mathsf{G}^\hbar}$ is given as:*

$$Score(\widetilde{\mathsf{G}^\hbar}) = \frac{1}{2} \left\{ 1 + (\xi^+_{\widetilde{\mathsf{G}^\hbar}})^p \left(1 - (\beta^+_{\widetilde{\mathsf{G}^\hbar}})^q - (\delta^+_{\widetilde{\mathsf{G}^\hbar}})^r \right) - |\xi^-_{\widetilde{\mathsf{G}^\hbar}}|^p \left(1 - |\beta^-_{\widetilde{\mathsf{G}^\hbar}}|^q - |\delta^-_{\widetilde{\mathsf{G}^\hbar}}|^r \right) \right\}. \tag{5}$$

4. Methodology

This section provides the MCDM techniques utilized in this study. The initial step is to build a decision matrix which indicates the performance of alternatives on the basis of evaluation criteria, as shown in Eq. (6). Let $\widetilde{\mathbb{M}_c} = \widetilde{\mathbb{M}_1}, \widetilde{\mathbb{M}_2}, \widetilde{\mathbb{M}_3}, \cdots, \widetilde{\mathbb{M}_s}$ represent the set of alternatives to be ranked and $\widetilde{\mathbb{V}_d} = \widetilde{\mathbb{V}_1}, \widetilde{\mathbb{V}_2}, \widetilde{\mathbb{V}_3}, \cdots, \widetilde{\mathbb{V}_t}$ represent the set of criteria employed to rank the alternatives. g_{st} indicates the performance of the c^{th} alternative on the basis of the d^{th} criterion.

$$\widetilde{\mathsf{G}^{\hbar}} = [g_{cd}]_{s\times t} = \begin{array}{c} \\ \widetilde{\mathbb{M}_1} \\ \widetilde{\mathbb{M}_2} \\ \vdots \\ \widetilde{\mathbb{M}_s} \end{array} \begin{array}{c} \begin{array}{cccc} \widetilde{\mathbb{V}_1} & \widetilde{\mathbb{V}_2} & \cdots & \widetilde{\mathbb{V}_t} \end{array} \\ \begin{pmatrix} \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{11}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{11}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{11}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{11}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{11}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{11}}}\right) & \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{12}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{12}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{12}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{12}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{12}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{12}}}\right) & \cdots & \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{1t}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{1t}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{1t}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{1t}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{1t}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{1t}}}\right) \\ \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{21}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{21}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{21}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{21}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{21}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{21}}}\right) & \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{22}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{22}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{22}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{22}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{22}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{22}}}\right) & \cdots & \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{2t}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{2t}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{2t}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{2t}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{2t}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{2t}}}\right) \\ \vdots & \vdots & \ddots & \vdots \\ \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{s1}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{s1}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{s1}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{s1}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{s1}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{s1}}}\right) & \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{s2}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{s2}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{s2}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{s2}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{s2}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{s2}}}\right) & \cdots & \left(\xi^{+}_{\widetilde{\mathsf{G}^{\hbar}_{st}}}, \beta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{st}}}, \delta^{+}_{\widetilde{\mathsf{G}^{\hbar}_{st}}}, \xi^{-}_{\widetilde{\mathsf{G}^{\hbar}_{st}}}, \beta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{st}}}, \delta^{-}_{\widetilde{\mathsf{G}^{\hbar}_{st}}}\right) \end{pmatrix} \end{array} \tag{6}$$

where $c = 1, 2, \cdots, s$ and $d = 1, 2, \cdots, t$. The performance of each alternative was gathered using $B_{pqr}SFS$. The relative importance of the criteria was determined by the SPC approach, after which the ALWAS technique was utilized to obtain the optimal solution.

4.1 SPC method

The SPC approach utilizes the symmetry point of the criterion, specifically the criterion's symmetry modulus, to assess its impact on the criteria weights. A higher modulus value signifies a greater criterion weight. The SPC technique's computation procedure is explained as follows:

- **Step 1:** Compute the symmetry point (Ψ_d) for each criterion utilizing Eq. (7).

$$\Psi_d = \frac{min(g_{cd}) + max(g_{cd})}{2} \qquad (c = 1, 2, \cdots, s; \;\; d = 1, 2, \cdots, t), \tag{7}$$

where $min(g_{cd})$ and $max(g_{cd})$ are the worst and best outcomes of criterion d, respectively, while g_{cd} is the initial score value of the c^{th} alternative on the basis of the d^{th} criterion.

- **Step 2:** Construct the absolute distance matrix (Λ) using Eq. (8).

$$\Lambda = \left|\left|\lambda_{cd}\right|\right|_{s\times t} = \begin{Vmatrix} \left|g_{11} - \Psi_1\right| & \left|g_{12} - \Psi_2\right| & \cdots & \left|g_{1t} - \Psi_t\right| \\ \left|g_{21} - \Psi_1\right| & \left|g_{22} - \Psi_2\right| & \cdots & \left|g_{2t} - \Psi_t\right| \\ \cdots & \cdots & \ddots & \cdots \\ \left|g_{s1} - \Psi_1\right| & \left|g_{s2} - \Psi_2\right| & \cdots & \left|g_{st} - \Psi_t\right| \end{Vmatrix}, \tag{8}$$

where λ_{cd} is the absolute distance element of matrix Λ.

- **Step 3:** Develop the matrix of moduli of symmetry (Θ) employing Eq. (9).

$$\Theta = \left|\theta_{cd}\right|_{s\times t} = \begin{vmatrix} \frac{\frac{\sum_{c=1}^{s}\lambda_{c1}}{s}}{g_{11}} & \frac{\frac{\sum_{c=1}^{s}\lambda_{c2}}{s}}{g_{12}} & \cdots & \frac{\frac{\sum_{c=1}^{s}\lambda_{ct}}{s}}{g_{1t}} \\ \frac{\frac{\sum_{c=1}^{s}\lambda_{c1}}{s}}{g_{21}} & \frac{\frac{\sum_{c=1}^{s}\lambda_{c2}}{s}}{g_{22}} & \cdots & \frac{\frac{\sum_{c=1}^{s}\lambda_{ct}}{s}}{g_{2t}} \\ \cdots & \cdots & \ddots & \cdots \\ \frac{\frac{\sum_{c=1}^{s}\lambda_{c1}}{s}}{g_{s1}} & \frac{\frac{\sum_{c=1}^{s}\lambda_{c2}}{s}}{g_{s2}} & \cdots & \frac{\frac{\sum_{c=1}^{s}\lambda_{ct}}{s}}{g_{st}} \end{vmatrix}, \tag{9}$$

where s denotes the total number of alternatives.

- **Step 4:** Formulate the modulus of symmetry of criterion (Φ) utilizing Eq. (10).

$$\Phi = \left|\phi_d\right|_{1\times t} = \left|\begin{matrix} \frac{\sum_{c=1}^{s}\theta_{c1}}{s} & \frac{\sum_{c=1}^{s}\theta_{c2}}{s} & \dots & \frac{\sum_{c=1}^{s}\theta_{ct}}{s} \end{matrix}\right| \qquad (d = 1, 2, \cdots, t). \tag{10}$$

- **Step 5:** Compute the criteria weights (Ω) using Eq. (11).

$$\Omega = \left|\omega_d\right|_{1\times t} = \left|\begin{matrix} \frac{\phi_1}{\sum_{d=1}^{t}\phi_d} & \frac{\phi_2}{\sum_{d=1}^{t}\phi_d} & \cdots & \frac{\phi_d}{\sum_{d=1}^{t}\phi_d} \end{matrix}\right| \qquad (d = 1, 2, \cdots, t). \tag{11}$$

4.2 ALWAS method

The ALWAS technique utilizes Aczel-Alsina non-linear functions to determine weighted alternative functions. Weighted functions interpret the preliminary measure of alternatives and determine its final assessment scores. The following describes the computing process of the ALWAS approach:

- **Step 1:** Standardize the initial decision matrix $\widetilde{\mathsf{G}^{\hbar}} = [g_{cd}]_{s\times t}$ utilizing Eq. (12), which defines the standardized decision matrix $\widetilde{\widetilde{\mathsf{G}^{\hbar}}} = [\tilde{g}_{cd}]_{s\times t}$, as this step entails translating the initial information into normalized values between 0 and 1.

$$\tilde{g}_{cd} = \begin{cases} \frac{g_{cd}}{g'_d}, & if\ d \in Benefit\ criterion \\ -\frac{g_{cd}}{g'_d} + \max\limits_{1\le c\le s}\left(\frac{g_{cd}}{g'_d}\right) + \min\limits_{1\le c\le s}\left(\frac{g_{cd}}{g'_d}\right), & if\ d \in Cost\ criterion \end{cases} \tag{12}$$

where $g'_d = \max\limits_{1\le c\le s}(g_{cd})$ and g_{cd} is the initial score value of the c^{th} alternative based on the d^{th} criterion.

- **Step 2:** On the basis of Aczel-Alsina norms, the weighted nonlinear functions were defined to describe the final approach for evaluating alternatives. Two weighted functions for the evaluation of alternatives are described as follows:

1. *Aczel-Alsina weighted averaging function (AAWAF)* $\left(\Gamma_c^{(1)\varepsilon}, c = 1, \cdots, s\right)$:

   Let $\tilde{g}_{cd}$ $(c = 1, 2, \cdots, s; d = 1, 2, \cdots, t)$ be a set of elements of matrix $\widetilde{\widetilde{\mathsf{G}^{\hbar}}} = [\tilde{g}_{cd}]_{s\times t}$ and let $\omega_d = (\omega_1, \omega_2, \cdots, \omega_t)^T$ be the vector of weight coefficients of the criteria. Then the *AAWAF* $\left(\Gamma_c^{(1)\varepsilon}\right)$ is defined using Eq.(13).

$$\Gamma_c^{(1)\varepsilon} = \sum_{d=1}^{t}\tilde{g}_{cd}\left(1 - e^{-\left(\sum\limits_{d=1}^{t}\omega_d\left(-ln\left(1 - f\left(\tilde{g}_{cd}\right)\right)\right)^{\varepsilon}\right)^{1/\varepsilon}}\right) \tag{13}$$

   where $f\left(\tilde{g}_{cd}\right) = \frac{\tilde{g}_{cd}}{\sum_{d=1}^{t}\tilde{g}_{cd}}$ and $\varepsilon \ge 0$.

2. *Aczel-Alsina weighted geometric averaging function (AAWGAF)* $\left(\Gamma_c^{(2)\varepsilon}, c = 1, \cdots, s\right)$:

   Let $\tilde{g}_{cd}$ $(c = 1, 2, \cdots, s; d = 1, 2, \cdots, t)$ be a set of elements of matrix $\widetilde{\widetilde{\mathsf{G}^{\hbar}}} = [\tilde{g}_{cd}]_{s\times t}$ and let $\omega_d = (\omega_1, \omega_2, \cdots, \omega_t)^T$ be the vector of weight coefficients of the criteria. Then the *AAWGAF* $(\Gamma_c^{(2)\varepsilon})$ is defined using Eq.(14).

$$\Gamma_c^{(2)\varepsilon} = \sum_{d=1}^{t} \tilde{g}_{cd} \cdot e^{-\left(\sum_{d=1}^{t} \omega_d \left(-ln\left(f\left(\tilde{g}_{cd}\right)\right)\right)^{\varepsilon}\right)^{1/\varepsilon}} \tag{14}$$

where $f\left(\tilde{g}_{cd}\right) = \frac{\tilde{g}_{cd}}{\sum_{d=1}^{t} \tilde{g}_{cd}}$ and $\varepsilon \geq 0$.

- **Step 3:** By integrating the Aczel-Alsina weighted functions Eq.(13) and Eq.(14), the final assessment score (Υ_c) of alternatives is obtained using Eq.(15).

$$\Upsilon_c = \frac{\Gamma_c^{(1)\varepsilon} + \Gamma_c^{(2)\varepsilon}}{1 + \left\{\sigma\left(\frac{1-f(\Gamma_c^{(1)\varepsilon})}{f(\Gamma_c^{(1)\varepsilon})}\right)^{\psi} + (1-\sigma)\left(\frac{1-f(\Gamma_c^{(2)\varepsilon})}{f(\Gamma_c^{(1)\varepsilon})}\right)^{\psi}\right\}^{1/\psi}} \tag{15}$$

where $\psi > 0$, $\sigma \geq 0$, $f(\Gamma_c^{(1)\varepsilon}) = \frac{f(\Gamma_c^{(1)\varepsilon})}{f(\Gamma_c^{(1)\varepsilon})+f(\Gamma_c^{(2)\varepsilon})}$, and $f(\Gamma_c^{(2)\varepsilon}) = \frac{f(\Gamma_c^{(2)\varepsilon})}{f(\Gamma_c^{(1)\varepsilon})+f(\Gamma_c^{(2)\varepsilon})}$.
The alternatives are ranked in decreasing order based on the Υ_c value, where higher the Υ_c value, the best is the alternative.
Figure 1 illustrates the framework of the proposed study.

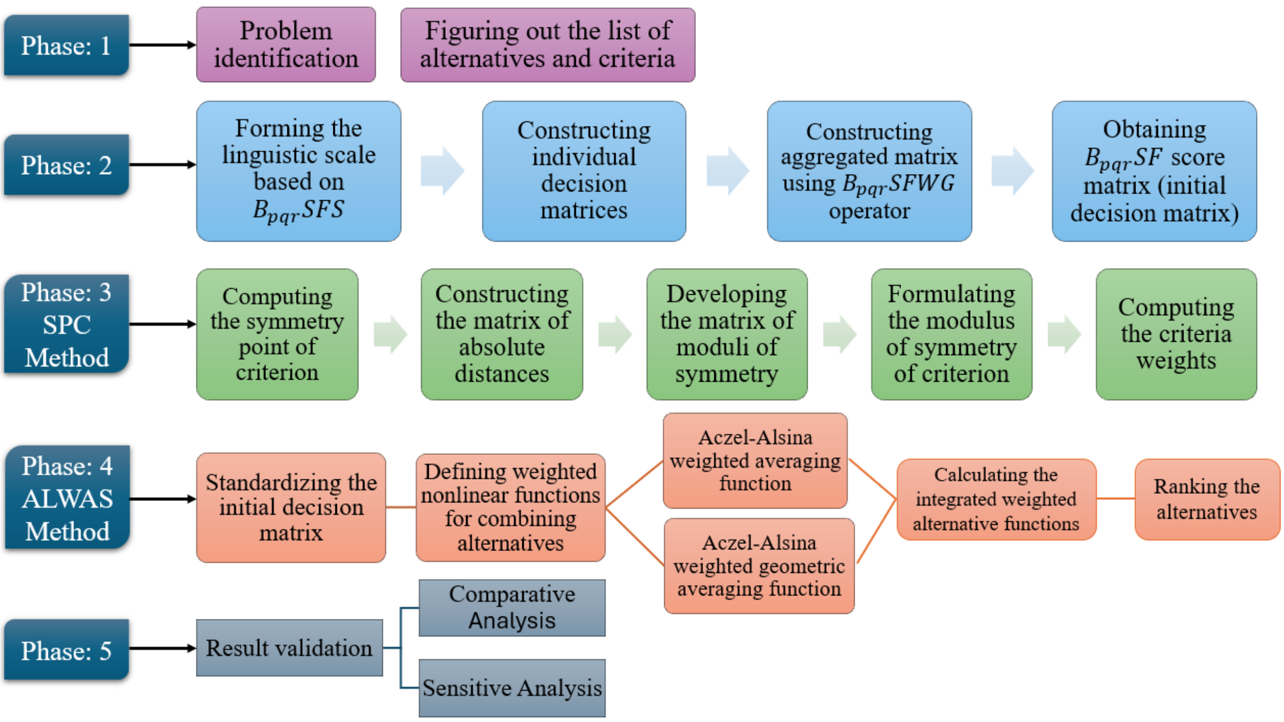

Fig. 1. Framework of the proposed study

5. Case study

A smart city needs to select an effective and sustainable security system in order to provide better protection for its citizens. Integrating AI-analytics with security systems aids in enhancing urban safety and deliver long-term sustainability. On this basis, this study examines four potential AI-driven security systems as alternatives. A brief description of the considered alternatives is defined as follows:

1. **Computer vision-based surveillance ($\widetilde{\mathbb{M}_1}$):**
   Computer vision, also referred to as machine vision, is a surveillance system which utilizes AI-enabled cameras for anomaly detection, object identification, crowd monitoring, licence plate recognition, and threat prediction. They provide sustained real-time monitoring, capturing incidents that humans might fail to catch. They automatically compress the video files and exclude irrelevant data, reducing the time spent on searching videos. However, owing to the fact that they collect extensive data, there often rises significant privacy concerns.

2. **AI-based emergency response systems ($\widetilde{\mathbb{M}_2}$):**
   These systems utilize AI-analytics, including machine learning and deep learning, to automatically detect a wide range of incidents such as accidents, crashes, fires, and medical emergencies, as well as natural catastrophes and dispatch appropriate emergency services. They help in reducing the seriousness of urban incidents by significantly increasing the response time. Moreover, they are privacy-friendly, since they collect minimal amount of data.

3. **Drone-based city monitoring ($\widetilde{\mathbb{M}_3}$):**
   Drones are unmanned aerial vehicles installed with cameras, thermal sensors, and AI-analytics to carry out aerial surveillance. They are extremely effective in covering large areas, traffic monitoring, and, in particular, search and rescue operations. In spite of its strong safety contributions, they might cause disturbance to residents and demands regulatory approval. They require high operational costs and have significant environmental impact due to the usage of batteries.

4. **IoT panic button networks ($\widetilde{\mathbb{M}_4}$):**
   These systems comprise of wearable, fixed or app-based panic buttons that triggers the alarm in the security centre when pressed by citizens during emergencies. They are highly advantageous in favour of women's security, elderly assistance, and vulnerable activities. These systems are privacy-friendly and hold minimal installation and operational costs.

Moreover, selecting the set of criteria is a crucial step, since it forms the basis for the assessment of alternatives. Choosing the right security system while maintaining public privacy and acceptance, cost efficiency, and sustainability is necessary. Hence, these factors should be taken into account when selecting the criteria. Therefore, following a literary survey, this study considers ten evaluation criteria grouped under three dimensions, viz., technical ($\widetilde{\mathbb{F}_1}$), economic and environmental ($\widetilde{\mathbb{F}_2}$), and social ($\widetilde{\mathbb{F}_3}$) to evaluate the alternatives. A concise description of these criteria is presented in Table 1. The B and C symbols represent the beneficial and cost criteria, respectively. The graphic illustration of the alternatives and criteria considered is shown in Figure 2.

6. Results and discussion

In accordance with the definition of $B_{pqr}SFS$ (Eq. (3)), the linguistic scale is formulated in Table 2 where the values of $p = 3$, $q = 4$, and $r = 5$ were considered. Following a comprehensive review of the existing literature, four distinct decision matrices ($\widetilde{\mathbb{Y}_1}$, $\widetilde{\mathbb{Y}_2}$, $\widetilde{\mathbb{Y}_3}$, and $\widetilde{\mathbb{Y}_4}$) have been developed, assessing the performance of every alternative in relation to each criterion on the basis of $B_{pqr}SFS$. The evaluation data are presented as linguistic terms in Table 3. Next, the $B_{pqr}SFWG$ operator (Eq. (4)) is utilized to obtain the aggregated $B_{pqr}SF$ decision matrix where the weight of each decision matrix is considered to be 0.25. Then, applying Eq. (5), the $B_{pqr}SF$ score matrix is determined, which is given in Table 4. This score matrix functions as the initial decision matrix for further calculations.

Table 1
List of the evaluation criteria

Dimension	Criteria	Description	Type
Technical ($\widetilde{\mathbb{F}_1}$)	Technical feasibility ($\widetilde{\mathbb{V}_1}$)	Potential of the city to readily facilitate the system with existing infrastructure	B
	Reliability ($\widetilde{\mathbb{V}_2}$)	Ability of the system to perform consistently	B
	Cyber security ($\widetilde{\mathbb{V}_3}$)	Resistance of the system to digital threats	B
Economic & Environmental ($\widetilde{\mathbb{F}_2}$)	Ease of maintenance ($\widetilde{\mathbb{V}_4}$)	Effort level required to maintain the system	B
	Cost ($\widetilde{\mathbb{V}_5}$)	Cost required for installation, operation and maintenance of the system	C
	Environmental impact ($\widetilde{\mathbb{V}_6}$)	Capacity of the system to minimize energy utilization, hardware footprint, and emissions	C
Social ($\widetilde{\mathbb{F}_3}$)	Safety enhancement ($\widetilde{\mathbb{V}_7}$)	Effectiveness of the system for real-time detection and prevent incidents	B
	Privacy ($\widetilde{\mathbb{V}_8}$)	Level of personal data gathered or exposed	B
	Social acceptance ($\widetilde{\mathbb{V}_9}$)	Willingness of the public to adopt and utilize the system	B
	User accessibility ($\widetilde{\mathbb{V}_{10}}$)	Ability of the system to be user-friendly for citizens and operators	B

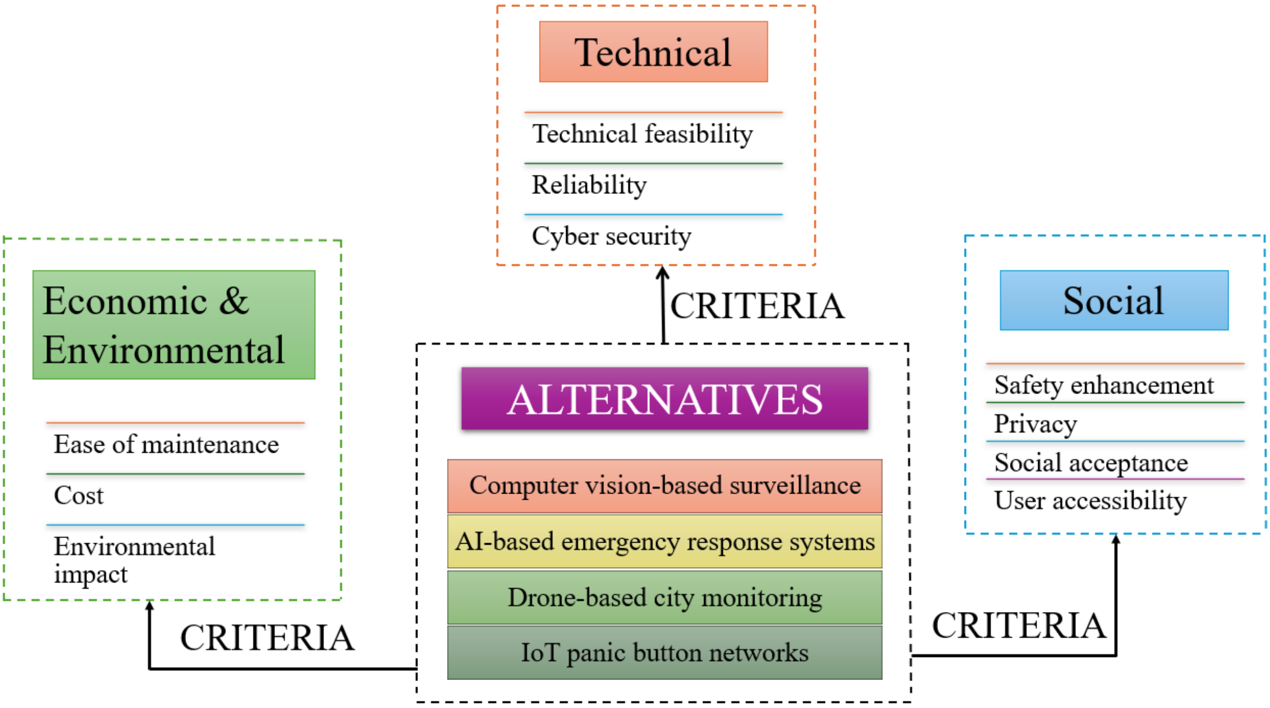

Fig. 2. Graphical Illustration of alternatives and criteria

The primary step of the SPC method is to compute the symmetry point for each criterion utilizing Eq. (7). Subsequent to this step, the absolute distance matrix is constructed using Eq. (8), and their resultant matrix is presented in Table 5. Next, the matrix of moduli of symmetry is created employing Eq. (9), and their outcome is provided in Table 6. Following that, the modulus of symmetry of criterion (ϕ_d) is obtained in Table 7 utilizing Eq. (10). Finally, Eq. (11) is applied to compute the criteria weights which is graphically represented in Figure 3. The results show that $\widetilde{\mathbb{V}_6}$, i.e., environmental impact, has the highest relative importance, followed by privacy ($\widetilde{\mathbb{V}_8}$) and reliability ($\widetilde{\mathbb{V}_2}$), exhibiting a balanced

Table 2
Linguistic scale for $B_{pqr}SFS$

Linguistic term	Abbreviation	$B_{pqr}SFN$
Extremely beneficial	EB	(0.95, 0.10, 0.38, -0.04, -0.02, -0.88)
Highly beneficial	HB	(0.90, 0.13, 0.42, -0.07, -0.04, -0.81)
Considerably beneficial	CB	(0.85, 0.16, 0.46, -0.10, -0.06, -0.74)
Moderately beneficial	MB	(0.80, 0.19, 0.50, -0.13, -0.08, -0.67)
Somewhat beneficial	SB	(0.75, 0.22, 0.54, -0.16, -0.10, -0.60)
Low beneficial	LB	(0.70, 0.25, 0.58, -0.19, -0.12, -0.53)
Negligibly beneficial	NB	(0.65, 0.28, 0.62, -0.22, -0.14, -0.46)

Table 3
Evaluation data of alternatives based on criteria in linguistic terms

		$\widetilde{\mathbb{V}_1}$	$\widetilde{\mathbb{V}_2}$	$\widetilde{\mathbb{V}_3}$	$\widetilde{\mathbb{V}_4}$	$\widetilde{\mathbb{V}_5}$	$\widetilde{\mathbb{V}_6}$	$\widetilde{\mathbb{V}_7}$	$\widetilde{\mathbb{V}_8}$	$\widetilde{\mathbb{V}_9}$	$\widetilde{\mathbb{V}_{10}}$
$\widetilde{\mathbb{Y}_1}$	$\widetilde{\mathbb{M}_1}$	EB	EB	CB	HB	CB	CB	HB	MB	HB	MB
	$\widetilde{\mathbb{M}_2}$	CB	HB	EB	CB	HB	EB	EB	HB	EB	CB
	$\widetilde{\mathbb{M}_3}$	MB	MB	MB	MB	MB	CB	CB	CB	CB	SB
	$\widetilde{\mathbb{M}_4}$	HB	CB	HB	EB	EB	EB	MB	EB	EB	HB
$\widetilde{\mathbb{Y}_2}$	$\widetilde{\mathbb{M}_1}$	HB	HB	MB	CB	CB	MB	EB	SB	CB	CB
	$\widetilde{\mathbb{M}_2}$	MB	EB	HB	SB	MB	CB	HB	CB	CB	EB
	$\widetilde{\mathbb{M}_3}$	SB	CB	CB	NB	LB	LB	MB	MB	MB	NB
	$\widetilde{\mathbb{M}_4}$	CB	CB	EB	HB	HB	HB	SB	HB	HB	EB
$\widetilde{\mathbb{Y}_3}$	$\widetilde{\mathbb{M}_1}$	EB	CB	SB	HB	MB	LB	MB	NB	MB	MB
	$\widetilde{\mathbb{M}_2}$	HB	HB	HB	CB	CB	CB	HB	MB	HB	CB
	$\widetilde{\mathbb{M}_3}$	MB	LB	LB	MB	NB	NB	CB	LB	NB	CB
	$\widetilde{\mathbb{M}_4}$	CB	SB	MB	EB	HB	HB	LB	HB	HB	HB
$\widetilde{\mathbb{Y}_4}$	$\widetilde{\mathbb{M}_1}$	EB	EB	NB	SB	HB	SB	HB	LB	SB	CB
	$\widetilde{\mathbb{M}_2}$	CB	CB	MB	MB	MB	HB	EB	CB	HB	HB
	$\widetilde{\mathbb{M}_3}$	LB	NB	LB	LB	SB	LB	HB	SB	LB	MB
	$\widetilde{\mathbb{M}_4}$	HB	SB	HB	HB	HB	EB	CB	EB	EB	EB

Table 4
$B_{pqr}SF$ score matrix

	$\widetilde{\mathbb{V}_1}$	$\widetilde{\mathbb{V}_2}$	$\widetilde{\mathbb{V}_3}$	$\widetilde{\mathbb{V}_4}$	$\widetilde{\mathbb{V}_5}$	$\widetilde{\mathbb{V}_6}$	$\widetilde{\mathbb{V}_7}$	$\widetilde{\mathbb{V}_8}$	$\widetilde{\mathbb{V}_9}$	$\widetilde{\mathbb{V}_{10}}$
$\widetilde{\mathbb{M}_1}$	0.908	0.873	0.703	0.795	0.799	0.718	0.840	0.673	0.769	0.772
$\widetilde{\mathbb{M}_2}$	0.799	0.858	0.840	0.757	0.784	0.842	0.891	0.799	0.858	0.842
$\widetilde{\mathbb{M}_3}$	0.708	0.691	0.705	0.682	0.673	0.671	0.799	0.718	0.691	0.703
$\widetilde{\mathbb{M}_4}$	0.828	0.744	0.840	0.891	0.875	0.891	0.718	0.891	0.891	0.891

evaluation of the dimensions considered.

Table 5
Matrix of absolute distances

	$\widetilde{\mathbb{V}_1}$	$\widetilde{\mathbb{V}_2}$	$\widetilde{\mathbb{V}_3}$	$\widetilde{\mathbb{V}_4}$	$\widetilde{\mathbb{V}_5}$	$\widetilde{\mathbb{V}_6}$	$\widetilde{\mathbb{V}_7}$	$\widetilde{\mathbb{V}_8}$	$\widetilde{\mathbb{V}_9}$	$\widetilde{\mathbb{V}_{10}}$
$\widetilde{\mathbb{M}_1}$	0.100	0.091	0.069	0.009	0.025	0.063	0.036	0.109	0.022	0.025
$\widetilde{\mathbb{M}_2}$	0.009	0.076	0.069	0.029	0.010	0.061	0.086	0.017	0.067	0.045
$\widetilde{\mathbb{M}_3}$	0.100	0.091	0.066	0.104	0.101	0.110	0.006	0.064	0.100	0.094
$\widetilde{\mathbb{M}_4}$	0.020	0.039	0.069	0.104	0.101	0.110	0.086	0.109	0.100	0.094

Table 6
Matrix of moduli of symmetry

	$\widetilde{\mathbb{V}_1}$	$\widetilde{\mathbb{V}_2}$	$\widetilde{\mathbb{V}_3}$	$\widetilde{\mathbb{V}_4}$	$\widetilde{\mathbb{V}_5}$	$\widetilde{\mathbb{V}_6}$	$\widetilde{\mathbb{V}_7}$	$\widetilde{\mathbb{V}_8}$	$\widetilde{\mathbb{V}_9}$	$\widetilde{\mathbb{V}_{10}}$
$\widetilde{\mathbb{M}_1}$	0.063	0.085	0.097	0.077	0.074	0.120	0.064	0.111	0.094	0.084
$\widetilde{\mathbb{M}_2}$	0.072	0.086	0.081	0.081	0.076	0.102	0.060	0.093	0.084	0.077
$\widetilde{\mathbb{M}_3}$	0.081	0.107	0.097	0.090	0.088	0.128	0.067	0.104	0.104	0.092
$\widetilde{\mathbb{M}_4}$	0.069	0.100	0.081	0.069	0.068	0.096	0.075	0.084	0.081	0.072

Table 7
Modulus of symmetry of criterion

	$\widetilde{\mathbb{V}_1}$	$\widetilde{\mathbb{V}_2}$	$\widetilde{\mathbb{V}_3}$	$\widetilde{\mathbb{V}_4}$	$\widetilde{\mathbb{V}_5}$	$\widetilde{\mathbb{V}_6}$	$\widetilde{\mathbb{V}_7}$	$\widetilde{\mathbb{V}_8}$	$\widetilde{\mathbb{V}_9}$	$\widetilde{\mathbb{V}_{10}}$
ϕ_d	0.071	0.094	0.089	0.080	0.076	0.112	0.066	0.098	0.091	0.081

Following this, the ALWAS method is applied to assess the alternatives and establish the optimal security system. The first step is to standardize the decision matrix employing Eq. (12). Next, using the Aczel-Alsina nonlinear functions, the AAWAF $(\Gamma_c^{(1)\varepsilon=1})$ and AAWGAF $(\Gamma_c^{(2)\varepsilon=1})$ were determined using Eq. (13) and Eq. (14), respectively. Finally, by integrating the weighted functions, the final assessment score Υ_c was obtained utilizing Eq. (15), and their results are shown in Table 8. The alternatives are ranked in decreasing order based on the Υ_c value, where higher the Υ_c value, the best is the alternative. Figure 4 represents the ranking results of the alternatives.

$$\Gamma_c^{(1)\varepsilon=1} = \begin{array}{c} \widetilde{\mathbb{M}_1} \\ \widetilde{\mathbb{M}_2} \\ \widetilde{\mathbb{M}_3} \\ \widetilde{\mathbb{M}_4} \end{array} \begin{bmatrix} 0.894 \\ 0.917 \\ 0.847 \\ 0.909 \end{bmatrix} \qquad \Gamma_c^{(2)\varepsilon=1} = \begin{array}{c} \widetilde{\mathbb{M}_1} \\ \widetilde{\mathbb{M}_2} \\ \widetilde{\mathbb{M}_3} \\ \widetilde{\mathbb{M}_4} \end{array} \begin{bmatrix} 0.891 \\ 0.915 \\ 0.842 \\ 0.903 \end{bmatrix}$$

It is evident from the results that AI-based emergency response systems ($\widetilde{\mathbb{M}_2}$) ranks first followed by IoT panic button networks ($\widetilde{\mathbb{M}_4}$), Computer vision-based surveillance $\widetilde{\mathbb{M}_1}$, and Drone-based city monitoring $\widetilde{\mathbb{M}_3}$. Safety and privacy are the main concerns in the development of smart cities. $\widetilde{\mathbb{M}_2}$ emerged as the optimal solution due to its safety effectiveness and strong privacy protection. It can

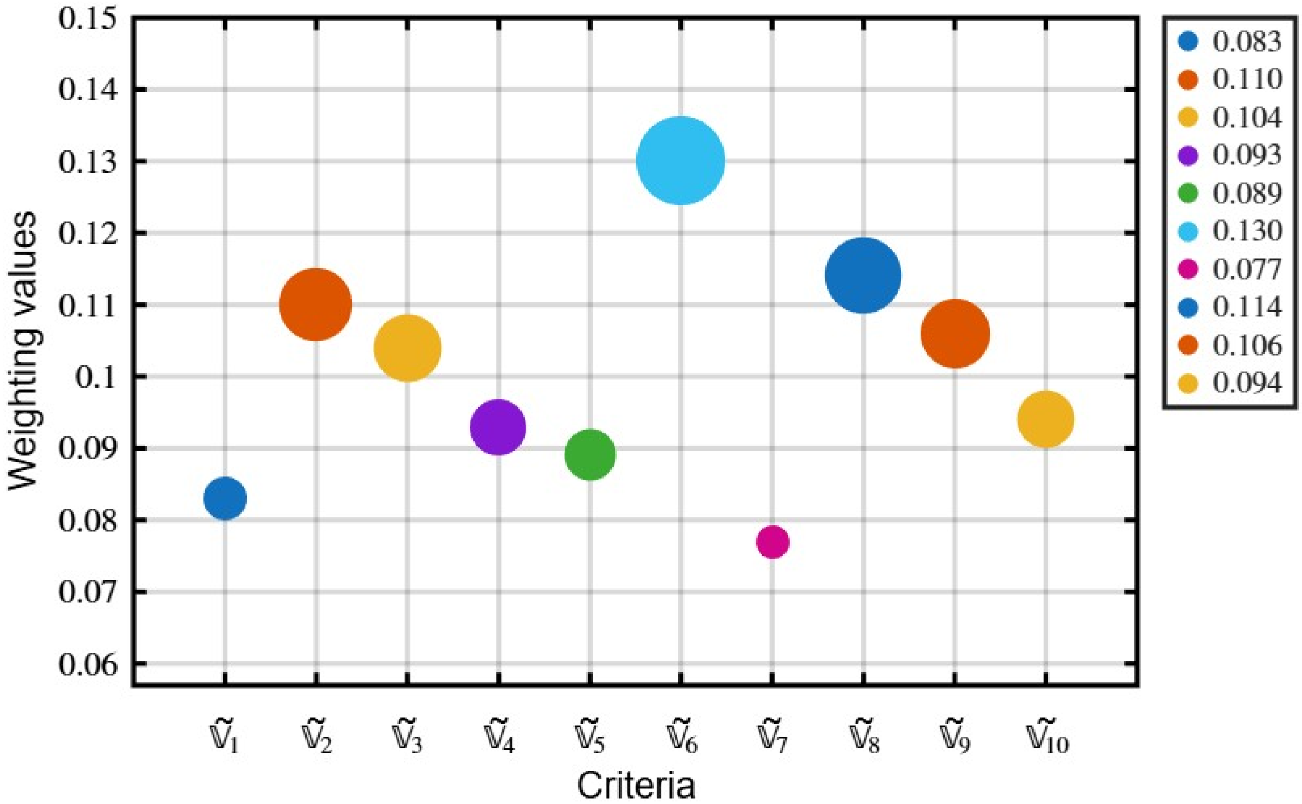

Fig. 3. Weights of the criteria

Table 8
Final assessment score and ranking of alternatives

Alternatives	Υ_c	Rank
$\widetilde{\mathbb{M}}_1$	0.893	3
$\widetilde{\mathbb{M}}_2$	0.916	1
$\widetilde{\mathbb{M}}_3$	0.845	4
$\widetilde{\mathbb{M}}_4$	0.906	2

automatically detect emergency incidents and dispatch services accordingly. They do not depend on continuous monitoring and facial recognition protecting citizens privacy and are devoid of data breaches. They are also effective due to its low environmental impact and high public acceptance. $\widetilde{\mathbb{M}}_4$ takes the second position because they also exhibit the same features as $\widetilde{\mathbb{M}}_2$, but are only reactive. $\widetilde{\mathbb{M}}_1$ ranks third mainly due to its privacy concerns. $\widetilde{\mathbb{M}}_3$ takes the last position due to its privacy concerns, high cost, and regulatory approval.

6.1 Comparative Analysis

A comparison study was conducted utilizing the same dataset considered by the proposed approach, to demonstrate its consistency and effectiveness. The evaluation compared the results of the ALWAS method with the results of the frequently utilized MCDM techniques, such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), EDAS (Evaluation based on Distance from Average Solution), MOORA (Multi-Objective Optimization based on Ratio Analysis), COPRAS (COmplex

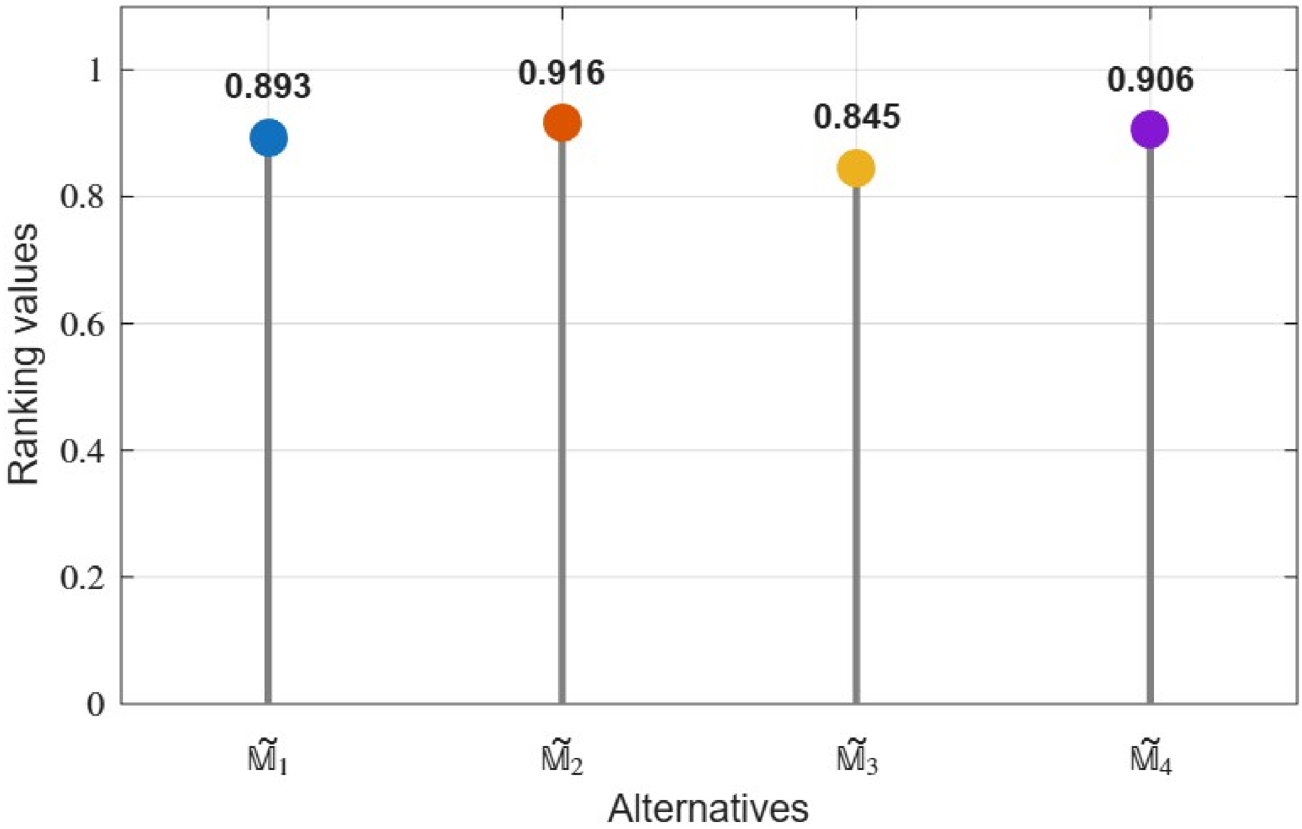

Fig. 4. Ranking of alternatives

PRoportional ASsessment), and MABAC (Multi-Attributive Border Approximation area Comparison). The ranking results obtained from all these techniques are similar to those of our proposed ALWAS method, establishing its consistency and efficiency. The comparison results are summarized in Table 9, and graphically depicted in Figure 5.

Table 9
Comparative analysis results

Alternatives	TOPSIS	Rank	EDAS	Rank	MOORA	Rank	COPRAS	Rank	MABAC	Rank	Proposed method	Rank
$\widetilde{\mathbb{M}}_1$	0.510	3	0.574	3	0.281	3	0.250	3	0.057	3	0.893	3
$\widetilde{\mathbb{M}}_2$	0.561	1	0.740	1	0.294	1	0.256	1	0.193	1	0.916	1
$\widetilde{\mathbb{M}}_3$	0.415	4	0.240	4	0.255	4	0.238	4	-0.173	4	0.845	4
$\widetilde{\mathbb{M}}_4$	0.537	2	0.724	2	0.290	2	0.255	2	0.139	2	0.906	2

6.2 *Sensitivity Analysis*

Sensitivity analysis plays a crucial role in decision-making, which evaluates the decision model's robustness by observing how modifications in the input variables affect its final result. The analysis was conducted in two phases. In the first phase, the criteria weights were altered, while the second phase includes the modification of parameters σ and ψ that were employed in the combination of weighted alternative functions in the ALWAS approach.

1. *Variation in criterion weights:* The criteria weights were modified based on two distinct cases.
   Case I: In this case, equal weights were assigned to all criteria, where $\widetilde{\mathbb{M}}_2$ holds the first position, followed by $\widetilde{\mathbb{M}}_4$, $\widetilde{\mathbb{M}}_1$, and $\widetilde{\mathbb{M}}_3$. Here, the ranking order stayed unchanged after modifying the

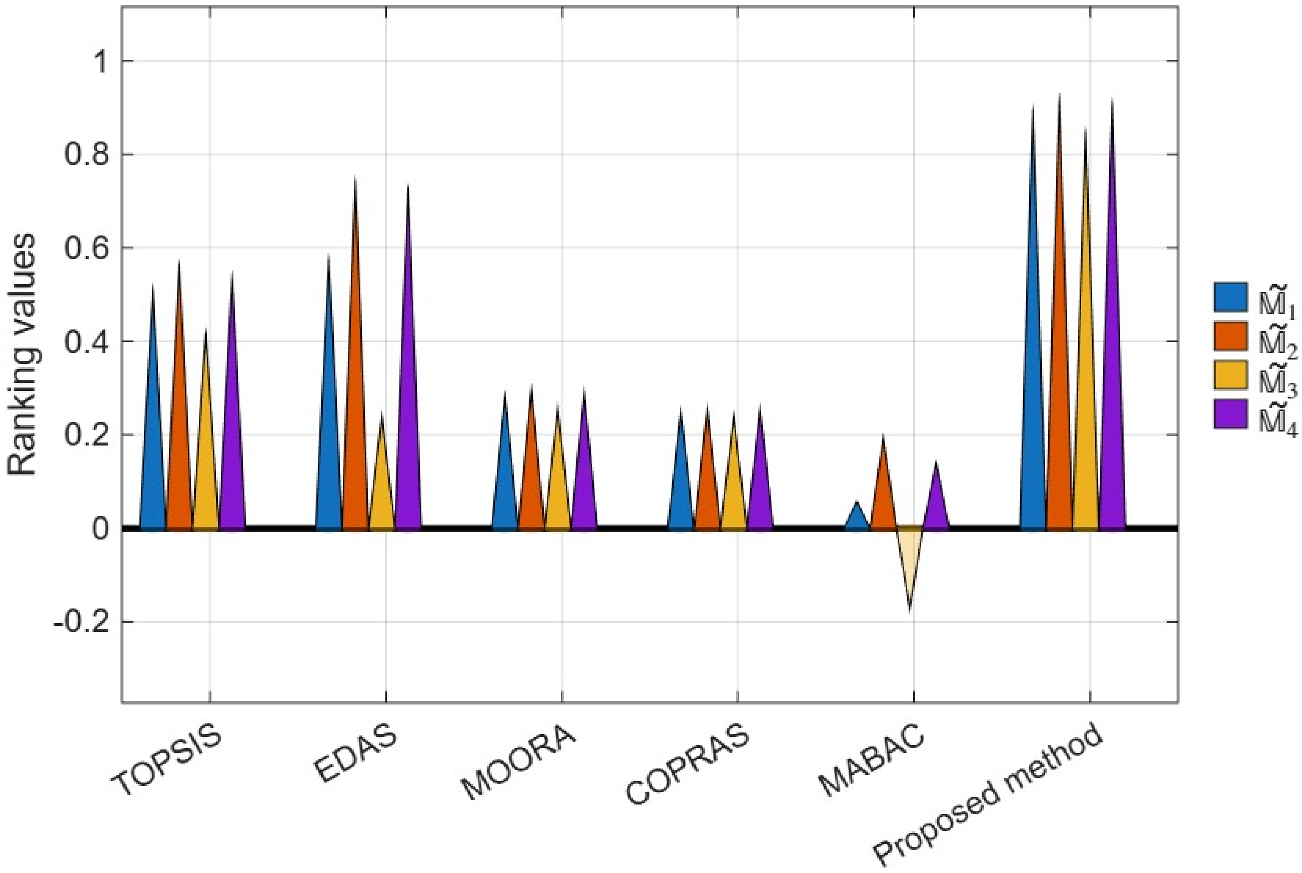

Fig. 5. Graphical representation of comparative analysis

criterion weights.
Case II: In this case, the criteria weights are reversed from the highest value to the lowest value and vice versa,in which $\widetilde{\mathbb{M}}_2$ ranks first, followed by $\widetilde{\mathbb{M}}_4$, $\widetilde{\mathbb{M}}_1$, and $\widetilde{\mathbb{M}}_3$. This shows that despite changing the importance order of the criteria, the ranking remained the same.
The results obtained by varying the criteria weights is shown graphically in Figure **??**.

2. *Variation of σ and ψ parameters:* The σ and ψ parameters indicate the stabilization functions that combines the weighted alternative functions. The values $\sigma = 0.5$ and $\psi = 1$ were considered to compute the initial solution. The modification of the aforementioned parameters was simulated in two cases. The change of the parameter $0 \leq \sigma \leq 1$ was simulated in the first case, while the change of the parameter $1 \leq \psi \leq 50$ was simulated in the second case. Figure 6 and Figure 7 represents the influence of changes in parameters $0 \leq \sigma \leq 1$ and $1 \leq \psi \leq 50$, respectively. In both the cases, the ranking remained unchanged with $\widetilde{\mathbb{M}}_2$ holding the first position, followed by $\widetilde{\mathbb{M}}_4$, $\widetilde{\mathbb{M}}_1$, and $\widetilde{\mathbb{M}}_3$.

Overall, the above-mentioned scenarios signifies that the original ranking is unaffected by changes in the input variables, indicating the robustness of the proposed model.

7. Conclusions, Limitations and Future Research

This research examines the problem of selecting an appropriate AI-driven security system for smart cities. Ensuring public safety while maintaining privacy and sustainability is often a challenge. Their selection requires a careful assessment of all relevant factors. In this context, we develop an enhanced

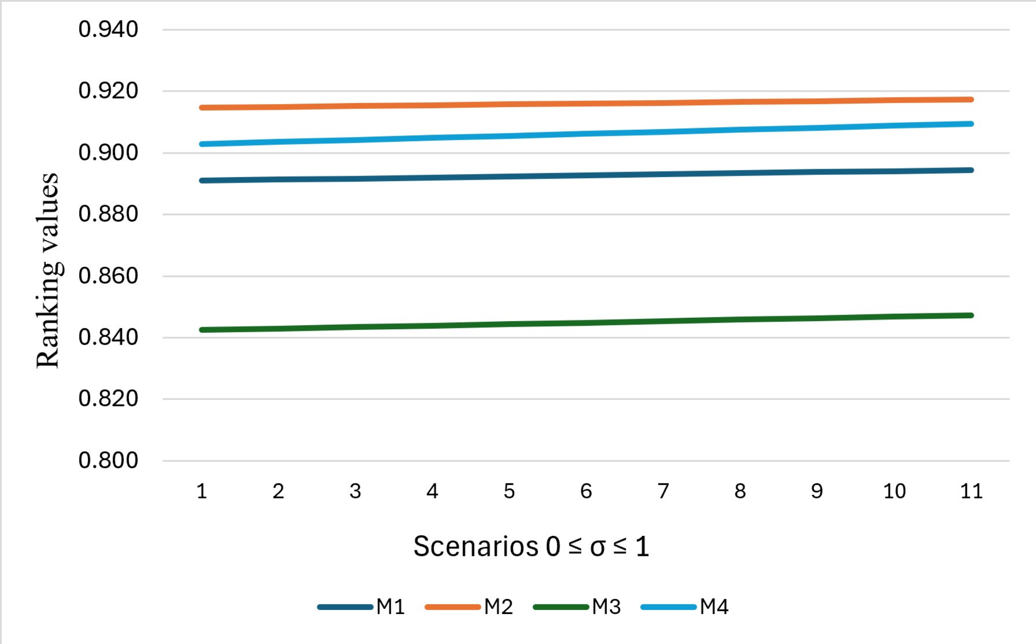

Fig. 6. Influence of parameter σ

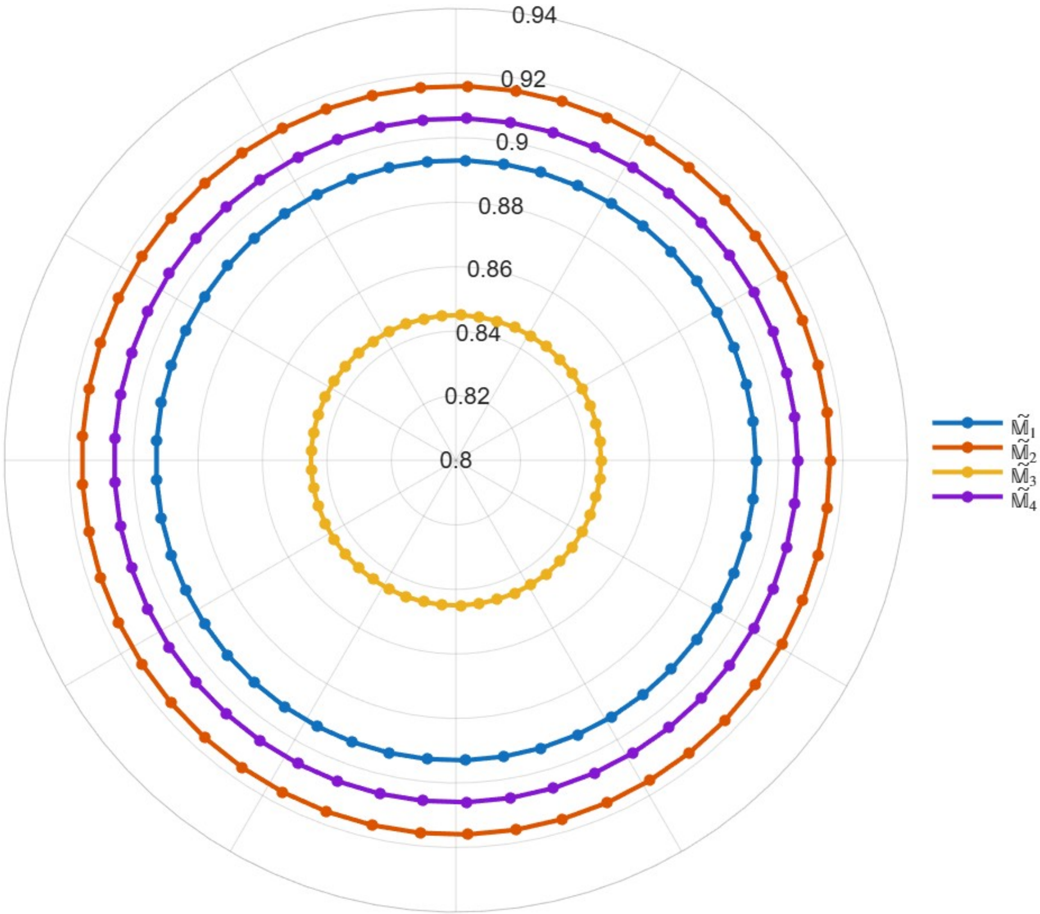

Fig. 7. Influence of parameter ψ

MCDM framework which integrates the SPC and ALWAS techniques under $B_{pqr}SF$ environment. The case study process considered four types of security system as possible alternatives evaluated based on ten criteria which were grouped under technical, economic and environmental and social dimensions. The relative importance of each criterion is obtained using the SPC weighting method, which provides a reliable criterion weighting system for decision-makers. The alternatives are ranked based on the ALWAS approach, where $\widetilde{\mathbb{M}_2}$ turned out to be the best system. Additionally, the results of the proposed method were compared with TOPSIS, EDAS, MOORA, COPRAS, and MABAC approaches to verify its consistency, and two phases of sensitivity analysis were performed to examine its robustness. Ultimately, the proposed $B_{pqr}SFS$-based SPC-ALWAS framework shall facilitate various researchers and policy makers in solving numerous complex problems.

The limitations of the present study include the omission of expert's opinion and utilizing the sole objective method. It can be combined with other subjective or objective methods, providing a new hybrid weighting method for more accurate weight calculation. Furthermore, the absence of direct real-world case study constraints the practical implementation of the proposed work. Future work might involve conducting a real-world case study along with site selection to support security management.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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