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Assessing AI-Driven Personalization in Smart Cities Using Hybrid Machine Learning and MCDM Approach

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Abstract

This study aims to assess AI-driven personalization strategies in smart cities, focusing on promoting digital inclusion across diverse urban populations. As artificial intelligence becomes increasingly central to urban service delivery, ensuring equitable and effective personalization is critical to preventing the amplification of digital inequality. To address this challenge, a hybrid evaluation framework is proposed, integrating Multi-Criteria Decision Making (MCDM) techniques, specifically Step-wise Weight Assessment Ratio Analysis (SWARA), Linguistic q-Rung Orthopair Fuzzy Numbers (Lq-ROFNs), and the Multi-Attributive Border Approximation Area Comparison (MABAC) with a Machine Learning (ML) classification model based on Random Forest. The framework is applied to stakeholder input from ten Indonesian smart cities, evaluating personalization readiness across five dimensions: accessibility, affordability, user engagement, privacy, and personalization effectiveness. The results indicate that accessibility and user engagement are the most influential criteria, while affordability and privacy are areas requiring strategic policy focus. The integrated model classifies cities by readiness level and identifies sensitivity patterns relevant to inclusive digital policy-making. The novelty of this research lies in its synthesis of MCDM and ML approaches to produce a transparent, scalable, and data-driven tool for evaluating AI personalization. This contributes to inclusive smart city development by aligning AI implementation with broader social equity objectives.

Keywords: Machine Learning; MCDM; Data-Driven Evaluation; AI Personalization; Classification; Smart City.

1. Introduction

The emergence of smart cities represents a strategic response to accelerating urbanization, focusing on enhancing infrastructure, public services, and sustainability by integrating advanced technologies [1, 2]. Among these technologies, Artificial Intelligence (AI) plays a pivotal role, particularly through AI-driven personalization, which enables services

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to dynamically adapt to individual user needs [3]. This transformation is further supported by hybrid approaches combining Machine Learning and Multi-Criteria Decision-Making methodologies, facilitating more data-informed and context-sensitive decision-making [4]. While AI-based personalization holds great promises for improving efficiency, responsiveness, and citizen satisfaction, it also poses significant risks of exacerbating digital inequality if inclusivity and equity are not prioritized explicitly [3, 5]. As smart cities increasingly adopt AI to optimize public services, ensuring the fair distribution of benefits across socio-economic groups is essential. Scholars have highlighted the need to embed social sustainability principles, such as inclusion, equity, and citizen participation, throughout the smart city development process to ensure these systems are just and inclusive [6, 7].

Recent studies have demonstrated AI's capacity to transform urban governance through real-time analytics and predictive service delivery, enhancing both the efficiency of public services and the quality of life for residents [8]. However, ethical concerns, including privacy, autonomy, and algorithmic bias, have emerged as major challenges. As Lawelai et al. [9] argue, algorithmic systems may inadvertently reinforce existing social inequalities without participatory safeguards, emphasizing the need for inclusive and transparent evaluation frameworks. Achieving sustainable smart city digitalization necessitates frameworks prioritizing community engagement, equitable access, and accountability. While several value-sensitive design approaches have been proposed [10, 11], many existing evaluation models for AI-driven personalization fail to comprehensively address key aspects of digital inclusion, such as accessibility, affordability, digital literacy, and infrastructure gaps. Moreover, few frameworks provide policymakers with structured tools to assess trade-offs and make evidence-based, inclusive decisions that consider the needs of all urban populations [12].

From a methodological perspective, integrating MCDM and Machine Learning offers a balanced approach to urban evaluation by combining qualitative reasoning with quantitative insights. MCDM facilitates prioritizing complex urban objectives, such as environmental impact, affordability, and user satisfaction, while ML enhances classification and predictive analysis capabilities [13]. The importance of hybrid methods that incorporate public sentiment to enhance trust and adoption of AI technologies has been emphasized. However, despite these advancements, challenges remain concerning data governance and unequal access to AI-driven services, which impede the equitable implementation of smart city technologies [14, 15].

The integration of ML and MCDM into AI-driven personalization evaluations marks a significant advancement in assessing these strategies to improve digital inclusion in smart cities [16]. Therefore, this study proposes a hybrid evaluation framework that integrates fuzzy MCDM methods, namely SWARA, Lq-ROFNs, and MABAC with a Random Forest classifier to assess AI personalization readiness across five dimensions: accessibility, affordability, user engagement, privacy, and personalization effectiveness. Using expert-based data from ten Indonesian smart cities, the framework is empirically validated to demonstrate its applicability in real-world urban contexts.

This study makes three key contributions to literature. First, it conceptualizes an inclusive and empirically validated framework for evaluating AI-driven personalization in smart cities. Second, it integrates fuzzy logic-based MCDM techniques SWARA, Lq-ROFNs, and MABAC with Random Forest classification to support interpretable and robust analysis. Third, it demonstrates the framework's practical utility in enabling evidence-based, inclusive digital governance across diverse urban contexts.

The objectives of this study are to: (1) identify and prioritize key criteria that influence AI personalization in smart cities, (2) evaluate the readiness of urban regions using expert-based fuzzy assessments, and (3) validate the evaluation through supervised classification. The framework aims to assist policymakers in designing data-driven, inclusive AI strategies for urban development.

The structure of this paper is organized as follows. Section 1 introduces the study and outlines the research background. Section 2 reviews the state-of-the-art literature on AI-driven personalization in smart cities, with a focus on identifying existing methodological gaps. Section 3 describes the research methodology, emphasizing the proposed hybrid ML and MCDM framework and the techniques implemented. Section 4 presents the empirical analysis and discusses its implications for smart city policy development. Finally, Section 5 concludes the paper by summarizing key findings and outlining directions for future research.

2. Literature Review

2.1. Theoretical Background

This structured approach is complemented by the integration of Machine Learning algorithms that discuss how intelligent data collection and processing can significantly improve decision-making outcomes in the context of transportation systems [17]. The utilization of ML technology offers a different understanding of system dynamics and provides a foundation for resilient and adaptive transportation networks in the ever-evolving smart city landscape. In addition, the application of the MCDM method in smart cities is well documented. For instance, it illustrates how data-driven preference learning can effectively address the challenges of interacting with various criteria, thereby improving decision-making in urban environments [18]. This is further supported by research using the hybrid MCDM method to evaluate urban mobility systems, which demonstrates the practical application of this technique in real-world scenarios [19]. Methodologies like these are critical in ensuring that urban mobility solutions are efficient and equitable and meet the needs of all citizens.

AI-based systems can analyze large amounts of data to tailor services to individual preferences, thereby driving digital inclusion. For example, developing an intelligent decision support system that combines ML and MCDM methodologies can improve service personalization [20]. These integrations enable the understanding and prediction of more diverse user needs, which is critical to fostering an inclusive digital environment. In addition, the impact of the application of AI on the decision-making process in smart cities is enormous, highlighting that AI and the Internet of Things can significantly improve intelligent decision-making capabilities and drive social innovation [21]. This perspective aligns with the findings of those who argue that the synergy between AI and big data analytics creates a robust framework for informed decision-making in smart cities [22]. Frameworks like these are critical to addressing urban areas' challenges, including sustainability, resource management, and community.

2.2. Challenges in AI Personalization Evaluation

AI-driven personalization holds considerable potential for enhancing service delivery and promoting sustainability within smart cities [23]. However, existing evaluation frameworks often fail to address critical challenges, particularly digital inequality, where AI systems may disproportionately benefit individuals with higher levels of digital literacy, better access to technology, and greater socio-economic resources. This issue is further compounded by inequitable access, especially in low-income areas, where large segments of the population are excluded from the benefits of AI systems. Ethical concerns, including privacy violations, algorithmic bias, and threats to user autonomy, further complicate the adoption of AI technologies. Current evaluation models predominantly focus on technical and economic criteria, while neglecting social dimensions, thus limiting their capacity to ensure fairness and inclusiveness in AI systems. Brito et al. [24] underscores the importance of incorporating fairness and inclusivity within AI systems to mitigate digital inequalities.

Furthermore, MCDM models fail to account for the complexities inherent in digital inclusion and often overlook the inclusion of stakeholder input, particularly from marginalized groups [25]. This challenge extends to adopting AI-driven recommendation systems, which are central to personalization efforts in smart cities. In addition, existing frameworks often lack transparency and scalability, making it difficult for stakeholders to comprehend the decision-making processes underpinning AI systems, thus undermining public trust. Furthermore, most models fail to address the diverse and complex needs of larger cities, limiting their applicability across varied urban environments. Data governance remains a significant issue, as many frameworks lack comprehensive guidelines for safeguarding personal data, thereby compromising privacy [26]. The unequal distribution of access to AI technologies exacerbates the digital divide, with only certain segments of the population benefiting from technological advancements. These gaps in current methodologies highlight the urgent need for the development of inclusive, scalable frameworks capable of comprehensively assessing AI personalization, ensuring that technological benefits are equitably distributed across all urban populations.

2.3. MCDM in Smart City Performance Evaluation

The sheer number of indicators and complexity involved in assessing urban performance in smart cities necessitates the application of multicriteria evaluation methods, which are often associated with ambiguity and uncertainty [27]. Comparison of cities is important to provide an overview of the situation of cities globally. In recent years, the concept of smart city has attracted more and more attention, leading to increased competition between cities [28]. For example, a study by Ozkaya & Erdin evaluated smart cities using the MCDM approach [29] to help identify and analyse key criteria, such as quality of life, infrastructure, and social and environmental sustainability. However, due to the complexity and multitude of factors to consider, more flexible and adaptive methods are needed. MCDM is an effective tool for dealing with uncertainty [30], because it allows decision-making by considering various criteria simultaneously [31].

3. Method

3.1. Identification of Criteria

AI-based personalization evaluation in smart cities requires a comprehensive framework that addresses a range of key criteria related to accessibility, affordability, user engagement, privacy and security, and effectiveness. Each of these criteria includes a variety of subcriteria that are important for ensuring equitable access and outcomes for diverse socio-economic groups. Accessibility is a fundamental criterion that includes several subcriteria of technology accessibility, language accessibility, accessibility for people with disabilities, and geographical accessibility. Emphasizing the importance of addressing social structures that limit access to AI technology suggests that equitable benefit distribution can only be achieved through an inclusive design and implementation process [32]. Additionally, the need to invest in digital infrastructure to ensure equitable access to AI tools in urban and rural areas was highlighted in a study that underscored the importance of reliable internet access and hardware availability [33]. Affordability is another important criterion, which includes access costs, data costs, hardware requirements, and long-term affordability. Economic evaluations of the application of AI, particularly in health and education, show that cost barriers can significantly hinder access for socio-economic groups [34]. For instance, it discusses how AI-equipped educational tools can adapt to individual learning needs but emphasizes that they must be affordable to ensure widespread adoption [35].

Highlighting the gap in access to generative AI technologies in developing countries, where inadequate infrastructure exacerbates economic disparities [36]. User Engagement is critical to the successful implementation of AI-based services. These criteria include cultural relevance, ease of use, user-centered feedback mechanisms, trust and convenience, and social inclusion. Supporting a sociological perspective on AI, emphasizing the need for user engagement strategies that consider diverse user backgrounds and experiences to encourage inclusiveness [37]. Support this further by advocating for AI tools designed with user input in mind, ensuring that they meet the needs of all community members [38]. Privacy and Security criteria include data anonymization, consent mechanisms, and data storage and transmission security. Emphasizing the importance of ethical considerations in the application of AI, particularly in healthcare, where data privacy and accountability are essential to maintain public trust [39]. Similarly, there is a need for user-centric principles in AI-based healthcare monitoring systems to ensure that privacy issues are adequately addressed [40].

Effectiveness includes impact on targeted outcomes, scalability, sustainability, and adaptability. The effectiveness of AI applications in smart cities can be evaluated based on their ability to provide tangible benefits to users while being scalable and sustainable over time. Furthermore, it advocates for a human-centered design approach that mitigates bias in AI systems, thereby increasing its effectiveness across various populations [41]. In addition, the scalability of AI solutions is essential to meet the growing needs of urban populations, as previous research has proposed cognitive IoT architectures that can adapt to changing urban dynamics [42]. Evaluation of AI-based personalization in smart cities should consider a multi-sided framework that addresses accessibility, affordability, user engagement, privacy and security, and effectiveness. By focusing on their respective criteria and subcriteria, policymakers and city planners can work to create an inclusive and equitable smart city environment that benefits all groups of people.

3.2. Design of Hybrid SWARA, Lq-ROFN, and MABAC

Solving complex problems in real-life scenarios often involves selecting the best alternative from several options based on multiple measurable and non-measurable factors, which is the core purpose of Multi-Criteria Decision-Making (MCDM) methods [43]. Despite their usefulness, conventional MCDM approaches that depend on exact data values struggle to accommodate the uncertain and dynamic nature of real-world systems. These traditional techniques often suffer from limitations such as imprecise data handling, inability to assign appropriate importance to criteria, and inconsistencies when applied to pre-established datasets [44].

In this study, MCDM was applied using three methods, including SWARA, to determine the weight of the criteria and produce a more objective assessment of the importance of each criterion [45]. Lq-ROFNs handle uncertainty by considering varying levels of importance in the data [46]. Finally, MABAC is used to evaluate alternatives by measuring distances within the attribute space, which allows for better comparisons between existing options [47]. The combination of these three methods provides a comprehensive and accurate approach to assessing the performance of smart cities and providing relevant insights into sustainable and inclusive policy development. The procedure comprises the following stages:

Step 1*:* Sum the expert assessments for each criterion and calculate the average value for each opinion, as expressed by Equation 1.

$$\bar{t}_j = \frac{\sum_{k=1}^{r} t_{jk}}{r} \tag{1}$$

where; $\bar{t}_i$ reflect the average expert assessment for criterion j, and t_{jk} reflect the assessment of criterion j by expert k, and r denotes the total number of experts.

Step 2*:* Find the comparative value and the value of the coefficient, as expressed by Equation 2.

$$k_j = \begin{cases} 1 & j=1 \\ S_j + 1 & j>1 \end{cases} \tag{2}$$

where; S_i reflect the comparative value assigned to criterion j, and k_i reflect the coefficient related to this comparative value.

Step 3*:* The weight of each criterion is recalculated based on the coefficient value, as expressed by Equation 3.

$$q_j = \begin{cases} 1 & j=1 \\ \frac{k_j-1}{k_j} & j>1 \end{cases} \tag{3}$$

where; q_j reflect the recalculated weight of criterion j. Recalculation is expressed as $q_j = 1$ when $k_j = 1$, and $q_j = \frac{k_j-1}{k_j}$ when $j > 1$.

Step 4: Determining the final weight for each criterion, as expressed by Equation 4.

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{4}$$

where; w_j reflects the relative importance of criterion j based on the expert evaluations and the recalculated values, that is calculated by dividing the recalculated weight q_j by the sum of all recalculated weights $\sum_{j=1}^{n} q_j$, where n is the total number of criteria.

Step 5: Once the weights for each subcriterion have been determined, the subsequent step involves defuzzifying the aggregated Lq-ROFNs using a score function, as illustrated in Equation 5 [48].

$$Lq\_ROFN_i = (\mu_i - v_i) \tag{5}$$

where; Lq_ROFN_i reflect the resulting fuzzy number for criterion i, which reflects the uncertainty or imprecision in evaluating that criterion. The μ_i reflect the upper bound of the fuzzy number for criterion i. The v_i represents the lower bound of the fuzzy number for criterion i.

Step 6: Aggregating the expert evaluations by incorporating the initial weights derived from the SWARA method. The aggregation is expressed by Equation 6.

$$Lq\_ROFN_{\text{aggregated}} = \sum(w_i - Lq\_ROFN_i) \tag{6}$$

$Lq\_ROFN_{\text{aggregated}}$ reflect the aggregated fuzzy number derived by considering each criterion's weighted evaluations. The w_i reflect the weight assigned to criterion i calculated through the SWARA method. Lq_ROFN_i represents the fuzzy evaluation of the i_{th} criterion. The sum of these weighted fuzzy numbers provides a comprehensive aggregated evaluation for the alternatives being considered, considering the importance of each criterion and the uncertainty inherent in the fuzzy evaluations.

Step 7: Determine aggregation linguistic evaluations with different importance levels for criteria, as expressed by Equation 7.

$$FinalWeight_i = \alpha \times SWARA\_Weight_i + (1 - \alpha) \times Lq\_ROFN_i \tag{7}$$

$FinalWeight_i$ reflect the combined importance of criterion i, considering both expert judgment and the uncertainty of fuzzy evaluations. The coefficient α (ranging from 0 to 1) acts as a scaling factor, determining each method influences the final weight. $SWARA\_Weight_i$ represents the importance of the i-th criterion as calculated through the SWARA technique, while the expression $(1 - \alpha)$ denotes the complementary proportion of weight attributed to the Lq_ROFN_i based evaluation.

Step 8: Format the matrix X by evaluating m alternatives based on n criteria. The alternatives are represented as vectors $A_i = (x_{i1}, x_{i2}, \ldots, x_{in})$, where X_{ij} reflect the value of the *i-th* alternative concerning the *j-th* criterion $i = 1,2,\ldots,m$; $j = 1,2\ldots n$. The format of the matrix can be expressed by Equation 8.

$$X = \begin{array}{c} \\ a_{\_1} \\ a_{\_2} \\ \cdots \\ a_{\_m} \end{array} \begin{array}{c} \begin{array}{cccc} c_{\_1} & c_{\_2} & \cdots & c_{\_n} \end{array} \\ \begin{bmatrix} x_{\_11} & x_{\_12} & \cdots & x_{\_1n} \\ x_{\_21} & x_{\_22} & \cdots & x_{\_2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{\_m1} & x_{\_m2} & \cdots & x_{\_mn} \end{bmatrix} \end{array} \tag{8}$$

The evaluation matrix X is constructed by organizing the assessments of m alternatives across n criteria. Each alternative is represented as a vector $A_i = (x_{i1}, x_{i2}, \ldots, x_{in})$, where each element x_{ij} is the value of the i_{th} alternative according to the *j-th* criterion.

Step 9: The elements of the initial matrix are normalized according to the formulation provided in Equation 9.

$$N = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \cdots & t_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ t_{m1} & t_{m2} & \cdots & t_{mn} \end{bmatrix} \end{array} \tag{9}$$

Normalization ensures that all criteria are on the same scale. The normalized matrix N is calculated by applying a normalization method to each element x_{ij} of the matrix.

***Step 10**:* Determining the normalization of matrix elements, as expressed by Equation 10.

$$\text{Benefit } t_{ij} = \frac{x_{ij}-x_i^-}{x_i^+-x_i^-}, \text{ for Cost } t_{ij} = \frac{x_{ij}-x_i^+}{x_i^- -x_i^+} \quad (10)$$

x_i^+ and x_i^- represent the maximum and minimum values for the i_{th} criterion across all alternatives, respectively. The t_{ij} represents the normalized value for the *i-th* alternative according to the *j-th* criterion.

Step 11: Calculating the elements of the weighted matrix. The calculating of the elements of the weighted matrix V by adjusting the normalized evaluations based on the weights assigned to each criterion. Each element v_{ij} in the matrix is the product of two components: the normalized value of the *i-th* alternative for the j criterion, denoted as t_{ij}, and the weight assigned to the *j-th* criterion, represented by fw_i. The calculation of the elements of the weighted matrix can be expressed by Equation 11.

$$v_{ij} = \text{fw}_i \cdot t_{ij} \quad (11)$$

By multiplying the normalized evaluation t_{ij} by the corresponding weight fw_i, we obtain the weighted value v_{ij}, which reflects both the importance of the criterion and the performance of the alternative for that criterion. This weighting is crucial because it ensures that more important criteria have a greater influence on the decision process.

Step 12: Determining the border approximation area matrix. Once the weighted matrix is obtained, then calculate the border approximation area matrix G for each alternative. This matrix is calculated by taking the geometric mean of the weighted values across all criteria for each alternative. The determining border approximation area matrix can be expressed by Equation 12.

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{\frac{1}{m}} \quad (12)$$

g_i represents the border approximation for the i-th alternative. This is done by multiplying all the weighted values v_{ij} for a particular alternative across the criteria and then taking the m-th root, where m is the number of criteria.

Step 13: Calculate the distance of the border approximation area. Calculating the distance of each alternative helps assess how far each alternative is from the ideal or optimal solution, where the distance is expressed as the difference between the weighted matrix V and the border approximation matrix G, as expressed by Equation 13.

$$Q = V - G \quad (13)$$

Q reflect the distance matrix, where each element q_{ij} reflect the difference between the weighted value v_{ij} of the *i-th* alternative for the *j-th* criterion and the corresponding border approximation value g_i.

Step 14: Performance classification based on threshold value. The classification helps simplify decision-making by distinguishing between alternatives that perform above a certain threshold, as expressed by Equation 14.

$$Performance = \begin{cases} S_i > k = \ High \\ S_i \le k = \ Moderate \end{cases} \quad (14)$$

S_i reflect a score of the i-th alternative based on the calculated distance from the border approximation. When the score S_i greater than the threshold k, then the alternative is the classified performance as having *High Performance*, meaning it performs well compared to the ideal solution. When the score is less than or equal to k, the alternative is classified as having *Moderate Performance*, indicating that it does not meet the optimal standard. This final classification helps decision-makers easily categorize and compare the alternatives based on their relative performance. The outcomes generated from each stage of the MCDM process serve as inputs for the subsequent classification phase.

3.3. Classification of Random Forest

The integration of Random Forest algorithms within the context of smart cities has garnered significant attention due to their effectiveness in analyzing complex urban data and enhancing decision-making processes. One of the significant advantages of random forests is their flexibility in handling different types of data without requiring strict assumptions about the underlying distribution [49]. Random forest is a classifier that consists of a collection of structured tree classifiers [50], with independently identical distributed random trees, and each tree throws a unit sound for the final classification of the input x. The random forest uses the Gini Index to determine the final class in each tree. The final class of each tree is collected and selected by the weight values to build the final classifier, expressed by Equation 15.

$$Gini\ (T) = 1 - \sum_{j=1}^{n}\left(p_j\right)^2 \quad (15)$$

The Gini Index denoted as $Gini(T)$, reflect a measure of inequality or impurity commonly used in decision trees and classification problems. The term p_i represents the proportion of data points in the j-th class. This is calculated as the number of data points in class j divided by the total number of data points. The summation $\sum_{i=1}^{n} p_i^2$ Sums the squares of the proportions for all classes. When the dataset T is divided into two subsets, T_1 and T_2, with sizes N_1 and N_2, respectively, where the indices in the data split correspond to class n as expressed by Equation 16.

$$Gini_{split}(T) = \frac{N_1}{N}\, gini(T_1) + \frac{N_2}{N}\, gini(T_2) \tag{16}$$

As a complement to the stages implemented in the MCDM process, the Random Forest algorithm plays a role in classifying and predicting test data, where the target class is determined based on the results of the decision from the MCDM method, as expressed by Equation 17.

$$TargetClass = \begin{cases} True\ if\ MCDM\_Result = Classification\_result \\ False\ if\ MCDM\_Result \neq Classification\_result \end{cases} \tag{17}$$

True and False denote the possible values of the TargetClass, reflecting the agreement or disagreement. The conditions outlined specify the criteria for assigning each value based on the equality or inequality of the decisions.

3.4. Proposed Framework

The foundation of any academic research lies in a structured framework that guides researchers through the complexity of investigation. Therefore, this study proposes a structured framework applicable across disciplines to guide systematic research. The framework shown in Figure 1 is designed to be adaptable, allowing researchers to tailor it to their specific needs while still adhering to rigorous academic standards.

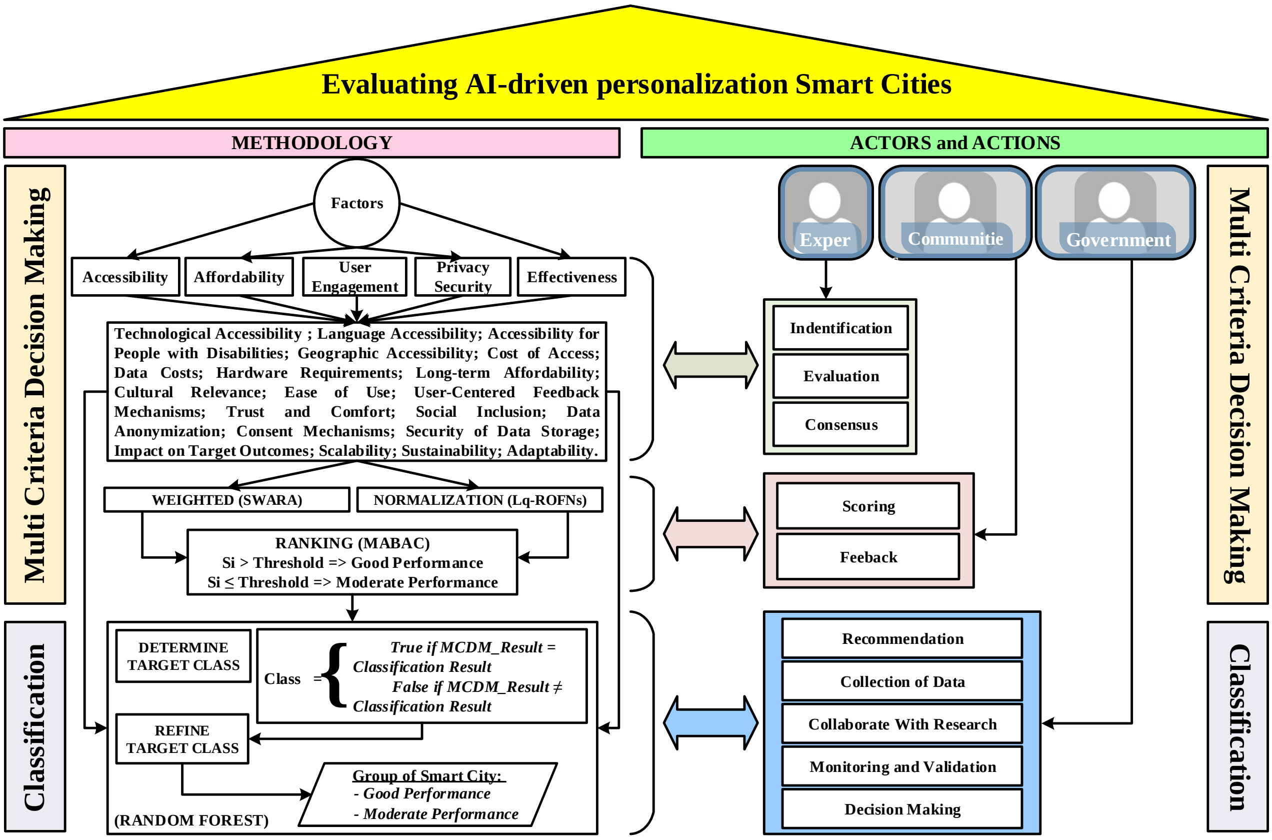

Figure 1. Proposed Framework

Based on the illustration in Figure 1, the framework proposed outlines an approach for assessing AI-driven personalization and promoting digital inclusion by integrating MCDM techniques and machine learning algorithms. The methodology considers accessibility, affordability, engagement, privacy, and effectiveness to evaluate strategies for promoting digital inclusion in smart cities.

3.5. Data Collection

The data of this study comes from a questionnaire distributed to respondents in 10 cities that have implemented smart city technology, including the community, academics, experts, and the government. Necessary instructions and guidance are provided during the filling process to ensure the validity of the questionnaire. A total of 700 questionnaires were distributed offline and online and through micro-interviews by phone, and after screening and analysis, 512 final questionnaires were created, with a return rate of 73.14%. The recommended sample size from previous studies showed that 50 was considered poor, 300 was considered good, 500 was considered excellent, and 1000 was considered outstanding [51]. Therefore, 512 sample data used in this study meet the standard. Overall, the basic information the respondents summarized is shown in Table 1.

Table 1. Basic demographic information the respondents

Type	Options	Frequency	Percentage
Number of years using AI-driven personalization tools	Less than 1 year	130	25.39%
	1–3 years	180	35.16%
	3–5 years	130	25.39%
	More than 5 years	72	14.06%
Types of smart city services used	Public transportation	140	27.34%
	Smart energy management	110	21.48%
	Health monitoring systems	90	17.58%
	Waste management	80	15.63%
	Traffic management and smart parking	55	10.74%
	Environmental monitoring	50	9.77%
	Digital government services	70	13.67%
	Education and learning platforms	45	8.79%
	Telemedicine and health services	60	11.72%
AI-driven personalization techniques used	Recommendation systems	160	31.25%
	Predictive analytics	120	23.44%
	Natural language processing (NLP)	100	19.53%
	Image and video recognition	80	15.63%
	Sentiment analysis	52	10.16%
Frequency of AI-driven personalization use	Daily	210	41.02%
	Weekly	160	31.25%
	Monthly	95	18.55%
	Rarely	47	9.18%
Primary role in smart city initiatives	Government official	100	19.53%
	Engineer/Technical role	130	25.39%
	Researcher	80	15.63%
	Consultant	50	9.77%
	Policy maker	60	11.72%
	Developer	92	17.97%

The questionnaire is designed with scenario design as the main idea so that respondents can quickly provide feedback in real [52]. The questionnaire format is built based on the criteria summarized through literature review and interviews with relevant experts, as shown in Table 2.

Table 2. List of factors and criteria

No.	Factor	Criteria
1	Accessibility	Technological Accessibility, Language Accessibility, Accessibility for People with Disabilities, and Geographic Accessibility.
2	Affordability	Cost of Access, Data Costs, Hardware Requirement, Long-term Affordability.
3	User Engagement	Cultural Relevance, Ease of Use, User-Centered Feedback Mechanisms, Trust and Comfort, and Social Inclusion.
4	Privacy and Security	Data Anonymization, Consent Mechanisms, Security of Data Storage and Transmission
5	Effectiveness	Impact on Target Outcomes, Scalability, Sustainability, Adaptability

The factors and criteria outlined in Table 2 are integral to the stages of the MCDM and classification implementation processes, which will be discussed in detail in the subsequent chapter.

4. Illustrative Study

4.1. MCDM Using Hybrid SWARA, Lq-ROFN, and MABAC

The initial phase of the MCDM implementation involves assigning weights to each criterion using the SWARA approach, in which a ranking index ranging from 1 to 20 affects the corresponding weight values. The relevant data is presented in Table 3.

Table 3. List of the initial weight of criteria

No.	Factors	Code	Criteria	Initial Weight
1	Accessibility	C1	Technological Accessibility	0.03516
		C2	Language Accessibility	0.05907
		C3	Accessibility for People with Disabilities	0.08555
		C4	Geographic Accessibility	0.10889
2	Affordability	C5	Cost of Access	0.12360
		C6	Data Costs	0.12661
		C7	Hardware Requirements	0.11817
		C8	Long-Term Affordability	0.10129
3	User Engagement	C9	Cultural Relevance	0.08027
		C10	Ease of Use	0.05914
		C11	User-Centered Feedback Mechanisms	0.04072
		C12	Trust and Comfort	0.02631
		C13	Social Inclusion	0.01601
4	Privacy and Security	C14	Data Anonymization	0.00921
		C15	Consent Mechanisms	0.00502
		C16	Security of Data Storage and Transmission	0.00260
5	Effectiveness	C17	Impact on Target Outcomes	0.00128
		C18	Scalability	0.00060
		C19	Sustainability	0.00027
		C20	Adaptability	0.00011

To enhance the subjectivity of the initial weights and better capture uncertainty and linguistic judgments, the company employs Lq-ROFNs. A panel of experts evaluates each criterion using predefined linguistic terms—Excellent (E), Good (G), Moderate (M), Below (B), and Poor (P)—which are then mapped to corresponding q-rung orthopair fuzzy values, as detailed in Table 4.

Table 4. Linguistic terms for evaluation

Linguistic terms	Membership	Non-membership
Excellent (E)	0.9	0.05
Good (G)	0.7	0.2
Moderate (M)	0.5	0.4
Below (B)	0.3	0.6
Poor (P)	0.3	0.85

Based on linguistic terms in Table 4, the experts evaluate the criteria as seen in Table 5.

Table 5. List of final weight of criteria

Code	Criteria	Evaluation (μ ; v)	Lq-ROFN	Final Weight
C1	Technological Accessibility	{ 0.9 ; 0.05 }	0.85	0.36110
C2	Language Accessibility	{ 0.7 ; 0.2 }	0.50	0.23544
C3	Accessibility for People with Disabilities	{ 0.7 ; 0.2 }	0.50	0.25133
C4	Geographic Accessibility	{ 0.9 ; 0.05 }	0.85	0.40533
C5	Cost of Access	{ 0.7 ; 0.2 }	0.50	0.27416
C6	Data Costs	{ 0.7 ; 0.2 }	0.50	0.27597
C7	Hardware Requirements	{ 0.7 ; 0.2 }	0.50	0.27090
C8	Long-term Affordability	{ 0.7 ; 0.2 }	0.50	0.26077
C9	Cultural Relevance	{ 0.9 ; 0.05 }	0.85	0.38816
C10	Ease of Use	{ 0.9 ; 0.05 }	0.85	0.37548
C11	User-Centered Feedback Mechanisms	{ 0.9 ; 0.05 }	0.85	0.36443
C12	Trust and Comfort	{ 0.9 ; 0.05 }	0.85	0.35579
C13	Social Inclusion	{ 0.7 ; 0.2 }	0.50	0.20961
C14	Data Anonymization	{ 0.5 ; 0.4 }	0.10	0.04553
C15	Consent Mechanisms	{ 0.7 ; 0.2 }	0.50	0.20301
C16	Security of Data Storage and Transmission	{ 0.7 ; 0.2 }	0.50	0.20156
C17	Impact on Target Outcomes	{ 0.9 ; 0.05 }	0.85	0.34077
C18	Scalability	{ 0.9 ; 0.05 }	0.85	0.34036
C19	Sustainability	{ 0.5 ; 0.4 }	0.10	0.04016
C20	Adaptability	{ 0.5 ; 0.4 }	0.10	0.04007

Table 5 presents the evaluation outcomes, aggregated values, and final decision weights for each criterion. In the Lq-ROFNs computation process, the coefficient α is set at 0.6. An illustrative example of weight determination using both the SWARA and Lq-ROFNs methods is provided below:

$$FinalWeight_i = \alpha \times SWARA\_Weight_i + (1 - \alpha) \times LqROFN_i$$
$$FinalWeight_{C1} = 0.6 * 0.03516 + (1 - 0.6) * 0.85 = 0.36110.$$

Overall, the comparison of the initial weight value and the evaluation results is shown in Figure 2.

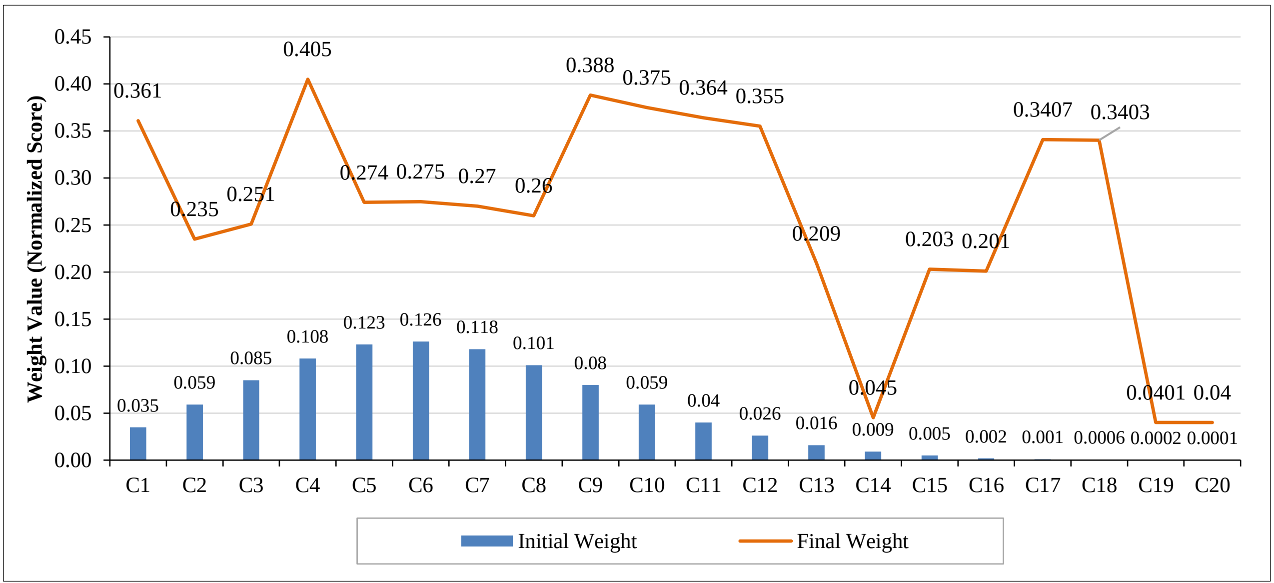

Figure 2. Comparison of initial and final weights of criteria C1–C20

The chart illustrates a clear shift in the distribution of criterion importance between the initial and final weights across 20 criteria. Several criteria, such as C4, C9, C10, C11, C17, C18, experienced significant increases in final weight, indicating their elevated relevance after a more refined evaluation potentially through expert judgment or advanced MCDM methods. In contrast, criteria such as C14, C15, C19, and C20 were assigned minimal final weights, suggesting they were considered less impactful or redundant. Some criteria like C5, C6, C7, C8 and C16 maintained relatively stable weights, reflecting consistent perceived importance. Overall, the final weighting emphasizes a focused prioritization on a smaller subset of criteria, likely enhancing decision-making efficiency and model clarity by concentrating influence on the most critical factors. In complex MCDM scenarios involving numerous and often conflicting criteria, fully subjective approaches may fall short in capturing the full complexity of the decision context.

The integration of SWARA with Lq-ROFNs offers a scalable hybrid solution, enabling the simultaneous consideration of both qualitative judgments and quantitative data in more intricate decision-making processes.

This study utilized 24 pioneering smart cities and regencies in Indonesia as the basis for data collection. Respondent data was gathered through online questionnaires to facilitate faster and more convenient responses. Based on the collected feedback, the MABAC method was employed to define the matrix structure for each smart city alternative. The results of the Weighted Matrix Elements (V) calculations are presented in Table 6. Subsequently, the Estimated Border Area (G) Matrix for each criterion was computed by taking the geometric mean of all alternatives under each criterion. The outcomes of this calculation are illustrated in Figure 3.

Table 6. Results of calculation of the weighted matrix elements (V)

CITY	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	:	C14	C15	C16	C17	C18	C20
Batam	0.361	0.313	0.418	0.540	0.548	0.459	0.451	0.521	0.776	0.500	:	0.045	0.270	0.268	0.454	0.340	0.066
Bandung	0.601	0.392	0.418	0.405	0.365	0.275	0.451	0.260	0.517	0.375	:	0.060	0.270	0.268	0.454	0.340	0.053
Jakarta	0.722	0.392	0.335	0.675	0.365	0.367	0.361	0.260	0.776	0.375	:	0.060	0.338	0.201	0.681	0.453	0.080
Semarang	0.601	0.470	0.335	0.540	0.456	0.367	0.270	0.260	0.388	0.625	:	0.045	0.270	0.335	0.340	0.453	0.080
Surabaya	0.722	0.235	0.502	0.540	0.365	0.367	0.270	0.521	0.776	0.500	:	0.091	0.270	0.335	0.567	0.453	0.080
Denpasar	0.361	0.235	0.335	0.540	0.548	0.459	0.270	0.260	0.776	0.625	:	0.091	0.338	0.268	0.681	0.340	0.040
Medan	0.601	0.235	0.418	0.540	0.548	0.551	0.541	0.347	0.646	0.375	:	0.060	0.406	0.201	0.681	0.680	0.080
Balikpapan	0.481	0.470	0.418	0.675	0.456	0.275	0.270	0.347	0.776	0.500	:	0.060	0.203	0.268	0.567	0.453	0.053
Sleman	0.481	0.470	0.418	0.810	0.365	0.367	0.451	0.434	0.646	0.750	:	0.075	0.406	0.335	0.681	0.340	0.053
Palembang	0.481	0.235	0.251	0.405	0.274	0.367	0.361	0.434	0.388	0.375	:	0.075	0.270	0.403	0.454	0.567	0.040
Bojonegoro	0.481	0.470	0.335	0.540	0.274	0.367	0.361	0.521	0.517	0.750	:	0.091	0.203	0.268	0.567	0.340	0.066
Manado	0.601	0.235	0.418	0.675	0.274	0.275	0.361	0.260	0.388	0.375	:	0.091	0.406	0.335	0.681	0.453	0.080
Malang	0.481	0.235	0.502	0.810	0.274	0.551	0.270	0.347	0.517	0.750	:	0.060	0.338	0.335	0.567	0.453	0.040
Tangerang	0.361	0.235	0.335	0.675	0.365	0.367	0.451	0.521	0.646	0.625	:	0.045	0.338	0.201	0.681	0.340	0.066
Depok	0.361	0.235	0.335	0.810	0.548	0.367	0.270	0.260	0.646	0.750	:	0.045	0.338	0.201	0.681	0.567	0.053
Bekasi	0.361	0.313	0.418	0.405	0.274	0.275	0.451	0.434	0.646	0.750	:	0.075	0.270	0.335	0.681	0.567	0.040
Solo	0.481	0.235	0.335	0.675	0.365	0.459	0.361	0.347	0.388	0.625	:	0.075	0.338	0.335	0.681	0.340	0.080
Banjarmasin	0.722	0.235	0.335	0.675	0.456	0.275	0.361	0.260	0.517	0.750	:	0.075	0.203	0.403	0.340	0.680	0.053
Pontianak	0.601	0.470	0.251	0.405	0.365	0.459	0.270	0.347	0.646	0.750	:	0.045	0.270	0.201	0.340	0.680	0.040
Makassar	0.722	0.392	0.502	0.810	0.456	0.275	0.451	0.347	0.776	0.375	:	0.045	0.406	0.201	0.681	0.680	0.040
Badung	0.722	0.313	0.335	0.810	0.548	0.275	0.361	0.347	0.646	0.375	:	0.075	0.338	0.201	0.567	0.340	0.080
Banyuwangi	0.601	0.313	0.335	0.540	0.274	0.367	0.361	0.434	0.517	0.375	:	0.060	0.203	0.201	0.340	0.340	0.040
Yogyakarta	0.481	0.470	0.502	0.810	0.548	0.551	0.541	0.434	0.646	0.375	:	0.045	0.406	0.335	0.681	0.567	0.053
Kulon Progo	0.361	0.235	0.335	0.810	0.548	0.275	0.361	0.347	0.388	0.625	:	0.060	0.406	0.268	0.567	0.340	0.080

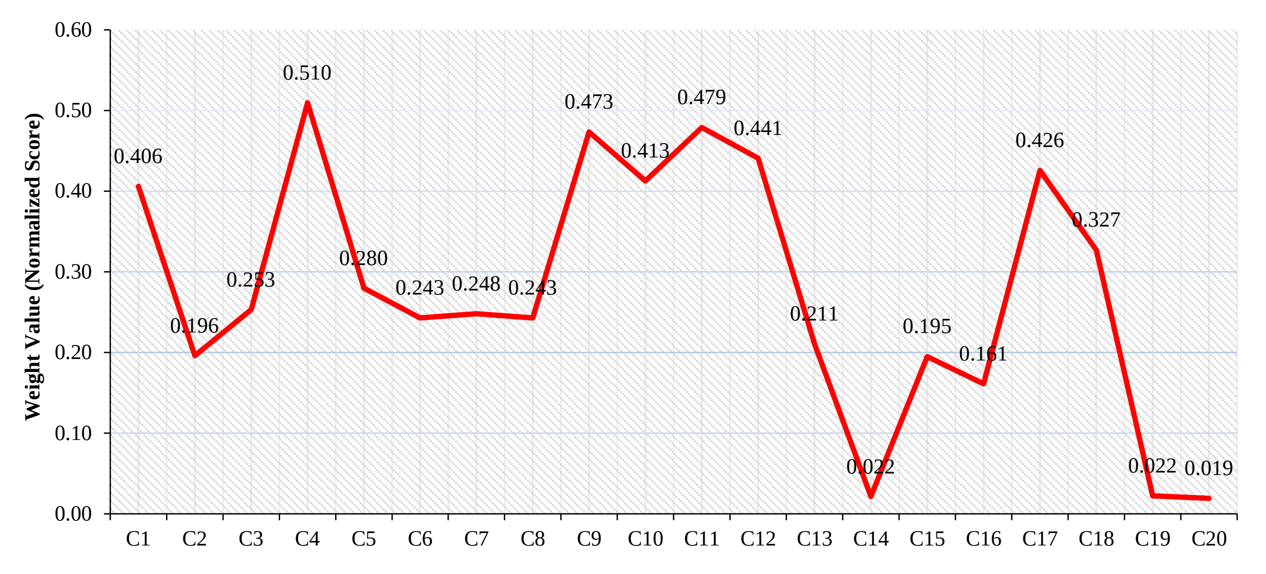

Figure 3. Final normalized weight values of criteria (c1–c20) based on the estimated border area matrix

The Estimated Border Area Matrix calculation results in Figure 3 illustrate significant variations in the collective performance between the evaluated criteria. Criteria such as C4 (0.510), C11 (0.479), and C9 (0.473) occupy the highest scores, indicating that most cities have performed well and consistently in aspects such as geographical accessibility, ease of use, and trust in digital systems. These high values represent the system's strength that can be used as a strategic pillar for strengthening AI-based service personalization policies. On the other hand, criteria with the lowest G-values such as C14 (0.022), C19 (0.022), and C20 (0.019) indicate inequality and weaknesses that need to be addressed immediately, as they reflect the low average performance of cities in these dimensions. Therefore, the recommended managerial approach is to focus policy interventions on low-value criteria to improve digital readiness equally, while maintaining and expanding excellence in high-value areas to ensure sustainability and inclusivity in the development of AI-based smart cities.

The final stage of the MABAC process involves calculating the Alternative Distance Matrix Element derived from the Approximate Border Area (Q), as depicted in Figure 4.

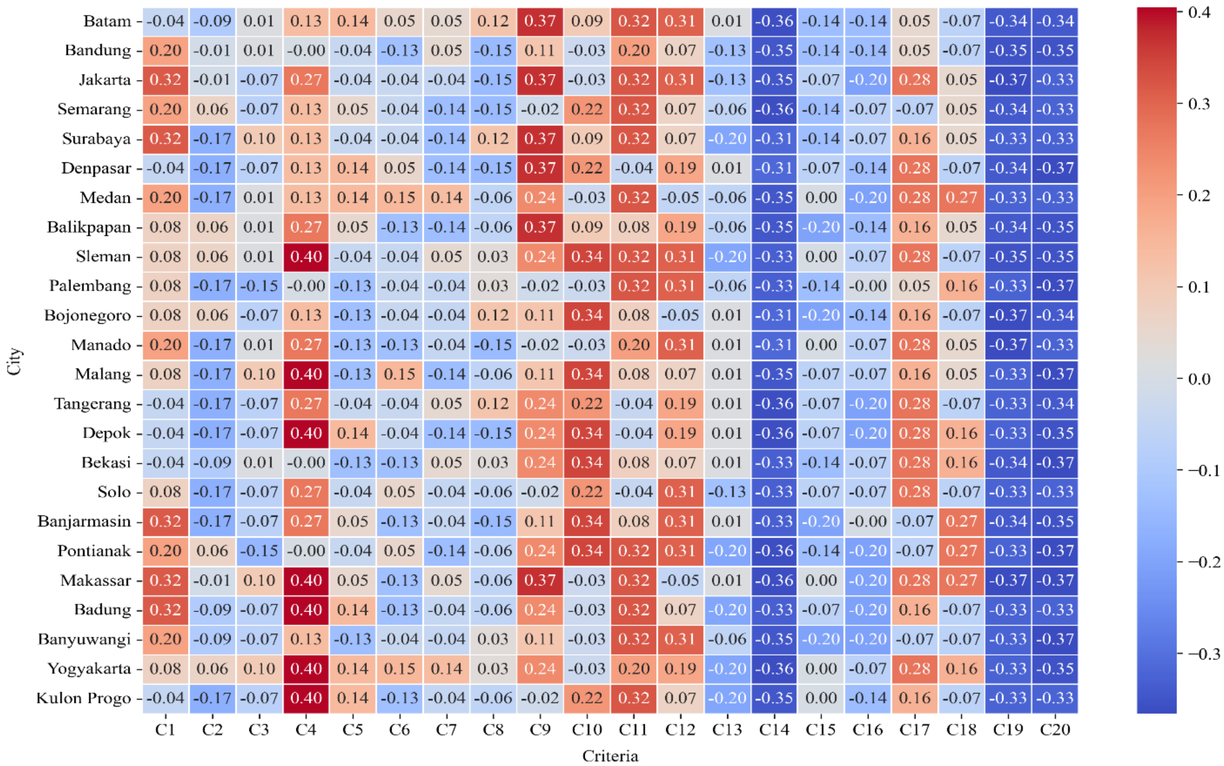

Figure 4. The result of calculating the alternative distance matrix element with the approximate border area

The MABAC method calculates the result to determine the class as the initial target for each smart city. The outcomes of the MCDM process are presented in Table 7.

Table 7. Result of calculation of MABAC method

No.	City	Value	Initial Class
1	Batam	0.1468	Good
2	Bandung	-1.1906	Moderate
3	Jakarta	0.0898	Good
4	Semarang	-0.6537	Moderate
5	Surabaya	-0.0225	Moderate
6	Denpasar	-0.5011	Moderate
7	Medan	0.3149	Good
8	Balikpapan	-0.3408	Moderate
9	Sleman	0.6773	Good
10	Palembang	-0.8623	Moderate
11	Bojonegoro	-0.6587	Moderate
12	Manado	-0.4246	Moderate
13	Malang	-0.1188	Moderate
14	Tangerang	-0.4013	Moderate
15	Depok	-0.1861	Moderate
16	Bekasi	-0.3677	Moderate
17	Solo	-0.5550	Moderate
18	Banjarmasin	-0.0867	Moderate
19	Pontianak	-0.2378	Moderate
20	Makassar	0.5924	Good
21	Badung	-0.2840	Moderate
22	Banyuwangi	-0.9401	Moderate
23	Yogyakarta	0.8259	Good
24	Kulon Progo	-0.6123	Moderate

Based on the results obtained through all stages of the MCDM implementation, it is known that of the 24 smart cities designated as samples, 6 cities are in the Good-Performance class, and 18 are in the Moderate-Performance class.

4.2. Sensitivity Analysis

The application of MDCM, which involves many alternatives and criteria, requires measuring a data set through performance analysis [53]. A sensitivity analysis was conducted on the MCDM results by incrementally increasing each criterion weight by 0.02. The outcomes of this assessment are detailed in Tables 8 and 9.

Table 8. Results of the sensitivity analysis for criteria

City	C1		C2 - C13			C3 - C4 - C5 - C6 - C7					
	Value	Class	Value		Class	Value					Class
Batam	-0.464	M	0.173	0.186	G	0.180	0.173	0.187	0.180	0.180	G
Bandung	-1.788	M	-1.157	-1.163	M	-1.157	-1.170	-1.163	-1.170	-1.157	M
Jakarta	-0.501	M	0.123	0.116	G	0.116	0.123	0.116	0.116	0.116	G
Semarang	-1.251	M	-0.613	-0.620	M	-0.627	-0.627	-0.620	-0.627	-0.633	M
Surabaya	-0.613	M	-0.002	-0.002	M	0.017	0.004	0.004	0.004	-0.002	G
Denpasar	-1.112	M	-0.481	-0.461	M	-0.474	-0.474	-0.461	-0.467	-0.481	M
Medan	-0.283	M	0.334	0.348	G	0.348	0.341	0.355	0.354	0.355	G
Balikpapan	-0.945	M	-0.300	-0.307	M	-0.307	-0.307	-0.307	-0.320	-0.320	M
Sleman	0.073	G	0.717	0.697	G	0.711	0.717	0.704	0.703	0.711	G
Palembang	-1.466	M	-0.842	-0.828	M	-0.842	-0.842	-0.842	-0.835	-0.835	M

Bojonegoro	-1.263	M	-0.618	-0.618	M	-0.631	-0.631	-0.638	-0.631	-0.631	M
Manado	-1.022	M	-0.404	-0.384	M	-0.391	-0.391	-0.404	-0.404	-0.397	M
Malang	-0.723	M	-0.098	-0.078	M	-0.078	-0.078	-0.098	-0.078	-0.098	M
Tangerang	-1.012	M	-0.381	-0.361	M	-0.374	-0.368	-0.374	-0.374	-0.368	M
Depok	-0.797	M	-0.166	-0.146	M	-0.159	-0.146	-0.146	-0.159	-0.166	M
Bekasi	-0.978	M	-0.341	-0.327	M	-0.334	-0.347	-0.347	-0.347	-0.334	M
Solo	-1.159	M	-0.534	-0.528	M	-0.528	-0.521	-0.528	-0.521	-0.528	M
Banjarmasin	-0.677	M	-0.066	-0.046	M	-0.059	-0.053	-0.053	-0.066	-0.059	M
Pontianak	-0.835	M	-0.197	-0.217	M	-0.217	-0.217	-0.211	-0.204	-0.217	M
Makassar	0.001	G	0.625	0.632	G	0.632	0.632	0.626	0.612	0.626	G
Badung	-0.875	M	-0.257	-0.263	M	-0.257	-0.243	-0.243	-0.263	-0.257	M
Banyuwangi	-1.537	M	-0.913	-0.906	M	-0.913	-0.913	-0.920	-0.913	-0.913	M
Yogyakarta	0.221	G	0.865	0.845	G	0.865	0.866	0.866	0.865	0.866	G
Kulon Progo	-1.223	M	-0.592	-0.592	M	-0.585	-0.572	-0.572	-0.592	-0.585	M

Table 9. Results of the sensitivity analysis for criteria (continued)

City	C8 – C9 – C10 - C11 – C12 – C14 – C15 – C16 – C17 – C18 – C19 – C20											Class
	Value											
Batam	0.187	0.187	0.1867	0.187	0.186	0.166	0.173	0.173	0.173	0.166	0.180	0.180	G
Bandung	-1.170	-1.163	-1.157	-1.157	-1.163	-1.163	-1.163	-1.163	-1.163	-1.170	-1.163	-1.163	M
Jakarta	0.11	0.129	0.13	0.129	0.129	0.116	0.123	0.109	0.129	0.116	0.1098	0.129	G
Semarang	-0.632	-0.632	-0.614	-0.614	-0.631	-0.631	-0.632	-0.623	-0.633	-0.633	-0.627	-0.613	M
Surabaya	0.017	0.017	0.017	0.017	0.004	0.017	0.004	0.017	0.017	0.004	0.017	0.017	G
Denpasar	-0.481	-0.461	-0.481	-0.481	-0.467	-0.461	-0.467	-0.474	-0.461	-0.481	-0.467	-0.481	M
Medan	0.342	0.348	0.354	0.354	0.334	0.341	0.354	0.334	0.354	0.354	0.354	0.354	G
Balikpapan	-0.314	-0.3	-0.314	-0.314	-0.307	-0.314	-0.32	-0.314	-0.307	-0.314	-0.307	-0.314	M
Sleman	0.711	0.711	0.7172	0.717	0.717	0.71	0.717	0.71	0.717	0.697	0.703	0.7039	G
Palembang	-0.828	-0.842	-0.822	-0.822	-0.822	-0.828	-0.835	-0.822	-0.835	-0.828	-0.822	-0.842	M
Bojonegoro	-0.618	-0.631	-0.631	-0.631	-0.638	-0.618	-0.638	-0.631	-0.625	-0.638	-0.638	-0.625	M
Manado	-0.404	-0.404	-0.391	-0.391	-0.384	-0.384	-0.384	-0.391	-0.384	-0.397	-0.404	-0.384	M
Malang	-0.092	-0.092	-0.092	-0.092	-0.092	-0.092	-0.085	-0.085	-0.085	-0.092	-0.078	-0.098	M
Tangerang	-0.361	-0.368	-0.381	-0.381	-0.368	-0.381	-0.368	-0.381	-0.361	-0.381	-0.361	-0.368	M
Depok	-0.166	-0.152	-0.166	-0.166	-0.152	-0.166	-0.152	-0.166	-0.146	-0.152	-0.146	-0.159	M
Bekasi	-0.334	-0.334	-0.341	-0.341	-0.341	-0.334	-0.341	-0.334	-0.327	-0.334	-0.334	-0.347	M
Solo	-0.528	-0.534	-0.534	-0.534	-0.514	-0.521	-0.521	-0.521	-0.514	-0.534	-0.514	-0.514	M
Banjarmasin	-0.066	-0.059	-0.059	0.187	-0.046	-0.053	-0.066	-0.046	-0.066	-0.046	-0.053	-0.059	M
Pontianak	-0.211	-0.204	-0.197	-1.157	-0.197	-0.217	-0.211	-0.217	-0.217	-0.197	-0.197	-0.217	M
Makassar	0.619	0.632	0.6323	0.129	0.612	0.612	0.632	0.612	0.632	0.632	0.612	0.612	G
Badung	-0.257	-0.25	-0.243	-0.613	-0.257	-0.25	-0.25	-0.263	-0.25	-0.263	-0.243	-0.243	M
Banyuwangi	-0.906	-0.913	-0.9	0.017	-0.9	-0.913	-0.92	-0.92	-0.92	-0.92	-0.9	-0.92	M
Yogyakarta	0.859	0.859	0.859	-0.481	0.859	0.845	0.865	0.859	0.865	0.859	0.865	0.852	G
Kulon Progo	-0.585	-0.592	-0.572	0.354	-0.585	-0.585	-0.572	-0.585	-0.579	-0.592	-0.572	-0.572	M

Based on the results of the calculation of the sensitivity value for each criterion, it was found that the smart city assessment needs to be focused on criteria that have high sensitivity, namely C1, C2, and C13 because these criteria are proven to have a significant influence on changing class status. Thus, these criteria must be the top priority in the evaluation process to produce more accurate decisions. On the other hand, the criteria C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, C14, C15, C16, C17, C18, C19, and C20 did not show a significant impact on the change in class status, despite an increase in the weight value. Therefore, these criteria can be considered as secondary factors in determining the classification of smart cities and do not require the same attention in decision-making.

4.3. Machine Learning Using MCDM-Random Forest

The application of the classification process in this study began by making improvements to the target class that was worked on by looking for similarities in the results of hybrid SMART, Lq-ROFNs, and MABAC with the random forest decision tree. Supervised learning by random forest requires a labelled target variable to guide the training process [54], which the target variable is essential as it defines the output classes the model aims to predict. This study collected the dataset as the input in Table 10.

Table 10. The dataset as input data in Random Forest

CITY	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	CLASS
Batam	5	4	3	4	2	3	3	2	2	4	2	2	2	5	4	4	4	5	3	3	G
Bandung	3	3	3	5	4	5	3	5	4	5	3	4	4	4	4	4	4	5	4	4	M
Jakarta	2	3	4	3	4	4	4	5	2	5	2	2	4	4	3	5	2	4	5	2	G
Semarang	3	2	4	4	3	4	5	5	5	3	2	4	3	5	4	3	5	4	3	2	M
Surabaya	2	5	2	4	4	4	5	2	2	4	2	4	5	2	4	3	3	4	2	2	M
Denpasar	5	5	4	4	2	3	5	5	2	3	5	3	2	2	3	4	2	5	3	5	M
Medan	3	5	3	4	2	2	2	4	3	5	2	5	3	4	2	5	2	2	2	2	G
Balik	4	2	3	3	3	5	5	4	2	4	4	3	3	4	5	4	3	4	3	4	M
Sleman	4	2	3	2	4	4	3	3	3	2	2	2	5	3	2	3	2	5	4	4	G
Palembang	4	5	5	5	5	4	4	3	5	5	2	2	3	3	4	2	4	3	2	5	M
Bojonegoro	4	2	4	4	5	4	4	2	4	2	4	5	2	2	5	4	3	5	5	3	M
Manado	3	5	3	3	5	5	4	5	5	5	3	2	2	2	2	3	2	4	5	2	M
Malang	4	5	2	2	5	2	5	4	4	2	4	4	2	4	3	3	3	4	2	5	M
Tangerang	5	5	4	3	4	4	3	2	3	3	5	3	2	5	3	5	2	5	2	3	M
Depok	5	5	4	2	2	4	5	5	3	2	5	3	2	5	3	5	2	3	2	4	M
Bekasi	5	4	3	5	5	5	3	3	3	2	4	4	2	3	4	3	2	3	3	5	M
Solo	4	5	4	3	4	3	4	4	5	3	5	2	4	3	3	3	2	5	2	2	M
Banjarmasin	2	5	4	3	3	5	4	5	4	2	4	2	2	3	5	2	5	2	3	4	M
Pontianak	3	2	5	5	4	3	5	4	3	2	2	2	5	5	4	5	5	2	2	5	M
Makassar	2	3	2	2	3	5	3	4	2	5	2	5	2	5	2	5	2	2	5	5	G
Badung	2	4	4	2	2	5	4	4	3	5	2	4	5	3	3	5	3	5	2	2	M
Banyuwangi	3	4	4	4	5	4	4	3	4	5	2	2	3	4	5	5	5	5	2	5	M
Yogyakarta	4	2	2	2	2	2	2	3	3	5	3	3	5	5	2	3	2	3	2	4	G
Kulon Progo	5	5	4	2	2	5	4	4	5	3	2	4	5	4	2	4	3	5	2	2	M

Based on the data in Table 10, the input data is defined as a 2D array, with each row representing a sample of 20 features. The data is split into training (50%) and test (50%) sets. The Random Forest classifier is trained using the training set and applied to predict class labels for new data. The predicted numeric labels are converted to the original class labels: *'Good'* and *'Moderate'*. Figure 5 illustrates the tree formation process.

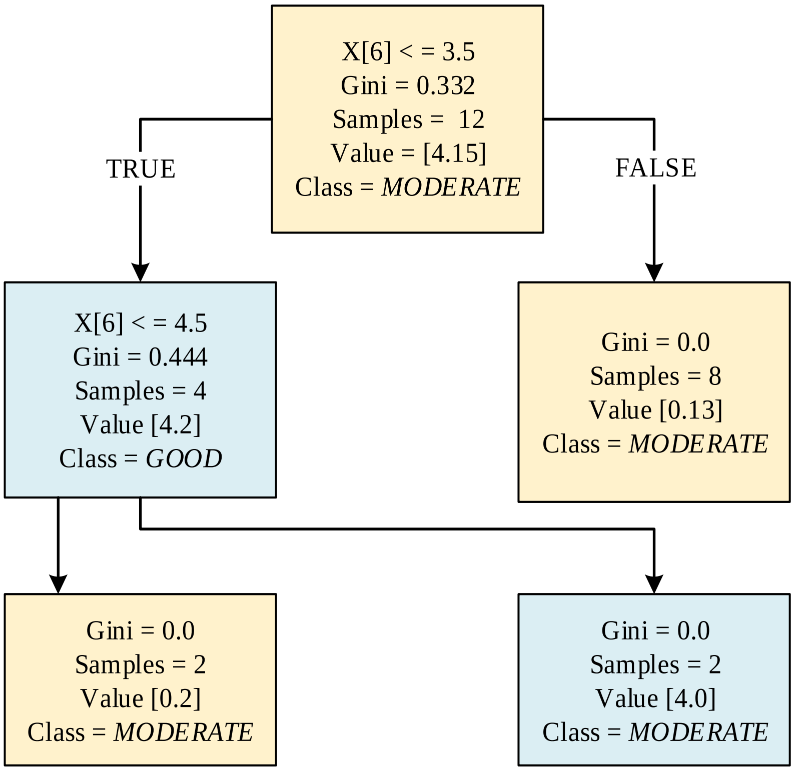

Figure 5. The visual illustration of the tree formation process

Based on the illustration of the process flow, an example of the calculation stages that occur on the Root Node: Top Node: x(6) <= 3 as follows:

- The decision rule here is based on the feature at index 6 (denoted x(6)). When x(6) is less than or equal to 3.5, the samples are classified to the left branch (True). Otherwise, they go to the right branch (False).
- Gini *Indeks: 0.332* = This measures the impurity or disorder in the node.
- Samples*: 12* = 12 samples or data points reach the node.
- *Value: [4, 15]* = This represents the number of samples in each class. In this case, 4 samples are of class '*Good'*, and 15 are of class '*Moderate'*.
- *Class [MODERATE]*= Most of the samples (15 out of 19) belong to the 'Moderate' class, so this node is classified as *'Moderate'*.

The calculation of the Gini value on the Root Node (x(6) <= 3.5) is as follows:

Proportions(*Good*)= $\frac{4}{9}$ = 0.211.

Proportions(*Moderate*) = $\frac{15}{19}$= 0.789.

$Gini_{Root}$ = $1 - 0.211^2 - 0.789^2 = 1 - 0.0445 - 0.6229 = 0.332$.

The $Gini_{Root}$ result for root nodes with a value of about 0.332 indicates moderate impurity with the predominance of the *Moderate* class. This reflects the partial classification of mixtures, which are effectively refined by the Random Forest algorithm, as presented in Table 11.

Based on the result in Table 11, it was known that out of 24 cities, 22 were correctly classified according to their initial labels, showing an accuracy rate of 91.67%. This indicates that the model has good generalization capabilities even though it was trained on a relatively small subset of data that reflects the actual labels of individual cities. In-depth testing was carried out by comparing the performance of the random forest model based on 20%, 30%, 40%, and 50% training data, which are shown in Figure 6.

Table 11. The results of refined the classification

City	Classification		Status
	Before	**After**	
Batam	Good	*Moderate*	Invalid
Bandung	Moderate	*Moderate*	Valid
Jakarta	Good	*Good*	Valid
Semarang	Moderate	*Moderate*	Valid
Surabaya	Moderate	*Moderate*	Valid
Denpasar	Moderate	*Moderate*	Valid
Medan	Good	*Good*	Valid
Balikpapan	Moderate	*Moderate*	Valid
Sleman	Good	*Moderate*	Invalid
Palembang	Moderate	*Moderate*	Valid
Bojonegoro	Moderate	*Moderate*	Valid
Manado	Moderate	*Moderate*	Valid
Malang	Moderate	*Moderate*	Valid
Tangerang	Moderate	*Moderate*	Valid
Depok	Moderate	*Moderate*	Valid
Bekasi	Moderate	*Moderate*	Valid
Solo	Moderate	*Moderate*	Valid
Banjarmasin	Moderate	*Moderate*	Valid
Pontianak	Moderate	*Moderate*	Valid
Makassar	Good	*Good*	Valid
Badung	Moderate	*Moderate*	Valid
Banyuwangi	Moderate	*Moderate*	Valid
Yogyakarta	Good	*Good*	Valid
Kulon Progo	Moderate	*Moderate*	Valid

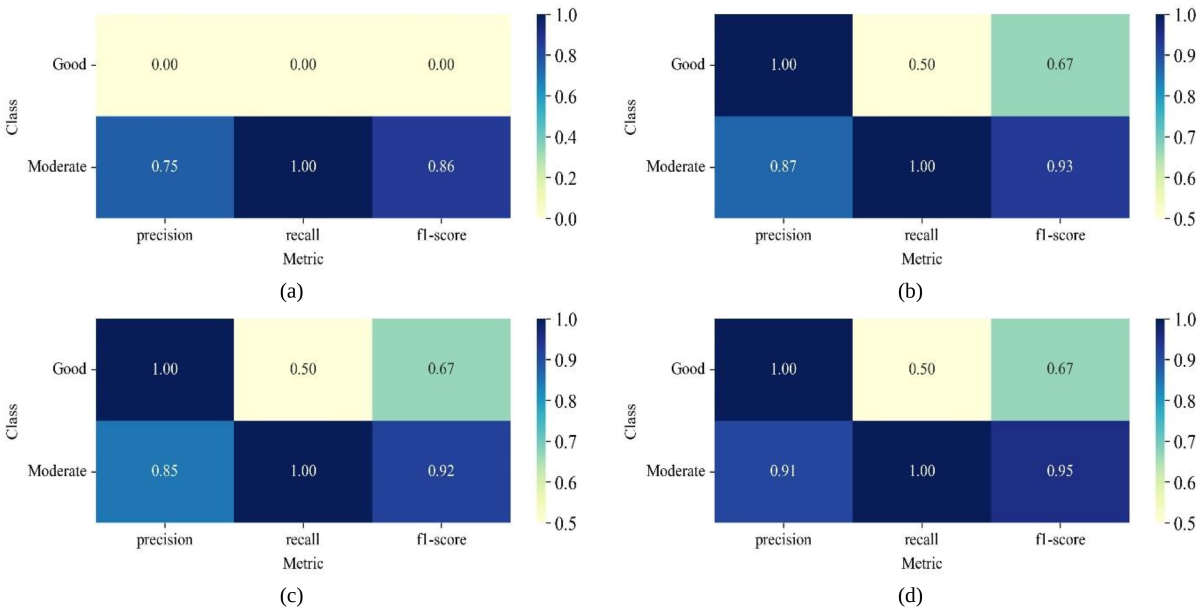

Figure 6. (a) Random forest prediction with 20% training data; (b) Random Forest prediction with 30% training data; (c) Random Forest prediction with 40% training data; (d) Random Forest prediction with 50% training data

Based on the results of the evaluation of the Random Forest model with variations in the proportion of training data of 20%, 30%, 40%, and 50%, it can be seen that the increase in the proportion of training data significantly improves the model's ability to classify both classes, especially the *Good* class which was previously undetected in the proportion of 20% and 30%. At 40% proportion, the model began to show a significant improvement with the recall for the *Good* class reaching 0.50, while the precision remained high. The best performance is achieved at 50% proportions, where the model maintains a balance between precision and sensitivity, with a precision of 1.00 and a recall of 0.50 for the *Good* class, as well as a very high F1 score for the Moderate class. These results indicate that Random Forest is an effective classification approach in mapping the readiness of AI-based personalization at the city level. The high consistency of the classification reinforces the belief that the features used in the model collectively represent critical characteristics in determining a city's digital readiness class.

4.4. Comparison of Evaluation

To evaluate the performance of each classification method in distinguishing the level of city readiness based on digital indicators, tests were carried out on six different machine learning models, namely Random Forest (RF), Decision Tree (DT), K-Nearest Neighbors (K-NN), Logistic Regression (LR), Artificial Neural Network (ANN), and Naïve Bayes (NB). This evaluation used a confusion matrix that compares the actual and prediction labels for two target classes: *Good* and *Moderate*. Visualization of each model's prediction results and overall accuracy value is shown in Figure 7.

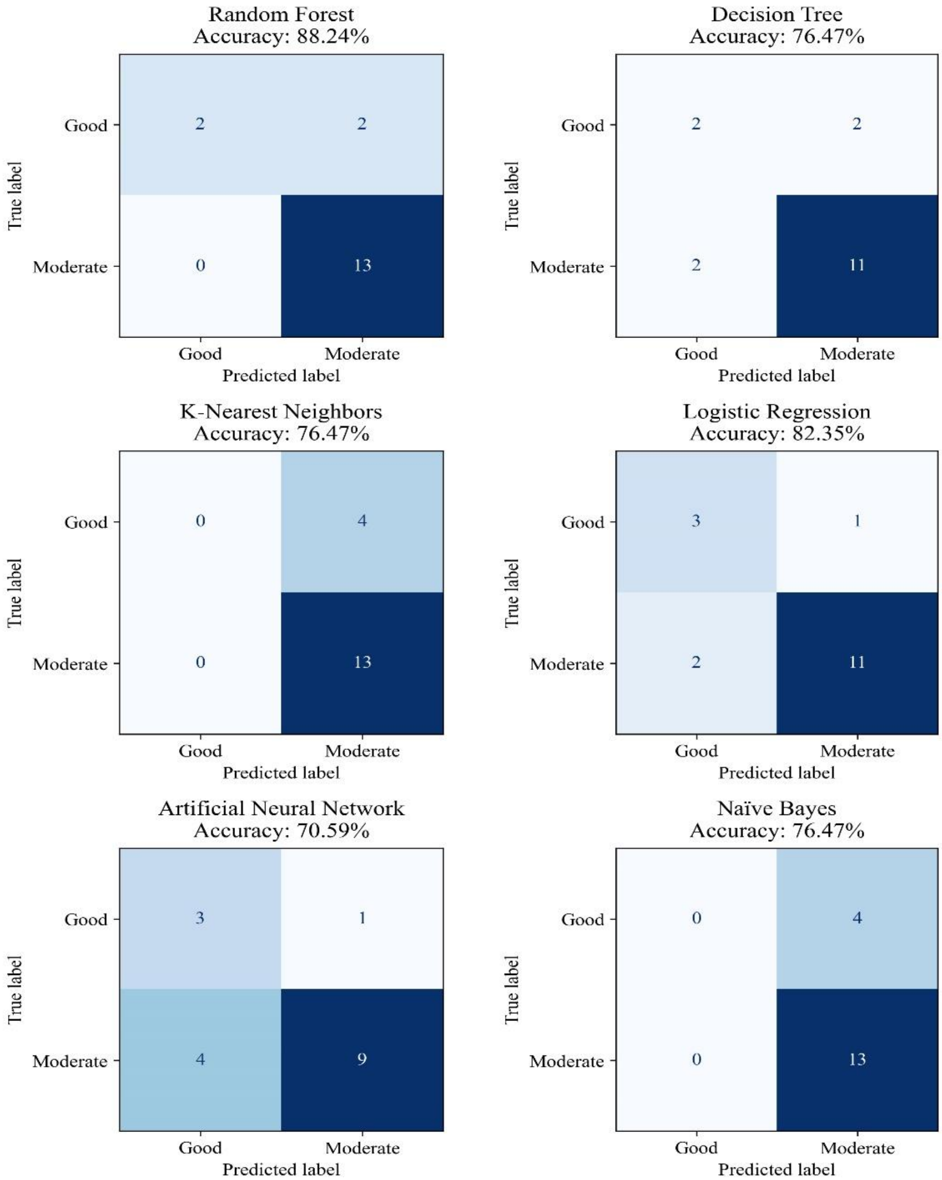

Figure 7. Comparative confusion matrix visualization of classification models

The confusion matrices in Figure 7 demonstrate that high accuracy does not necessarily indicate balanced performance across classes, particularly in datasets with class imbalance. Consequently, model evaluation should not rely solely on accuracy but incorporate additional metrics such as precision, recall, and F1-score. To provide a comprehensive assessment, precision, recall, and F1-score calculations were conducted for the KNN, Decision Tree, Logistic Regression, Artificial Neural Network, Naïve Bayes, and Random Forest methods in identifying the *Good* and *Moderate* classes. Results are displayed in Figure 8.

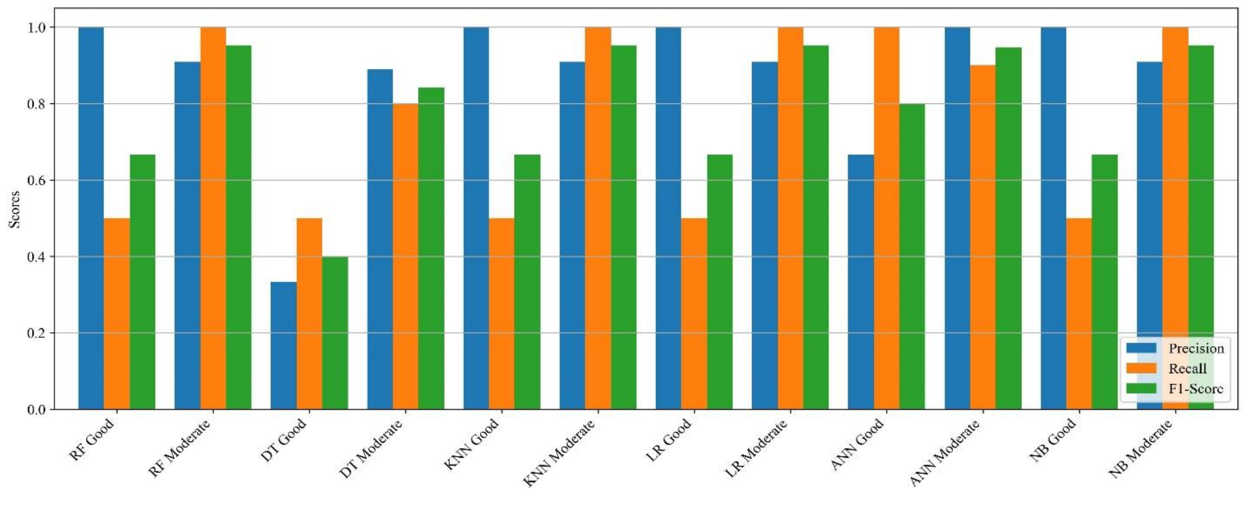

Figure 8. Result of Precision, Recall, and F1-Score for different models

Based on the evaluation and visualization results of the model performance comparison, Random Forest showed the best classification performance compared to other methods. The Random Forest performed most consistently with a precision score of 1.00, a recall of 0.83, and an F1-score of 0.91 in the *Good* class, as well as a precision of 0.86, a recall of 1.00, and an F1-score of 0.92 in the *Moderate* class. Meanwhile, ANN recorded a precision of 0.75, a recall of 0.60, and an F1-score of 0.67 in the *Good* class, a precision of 0.81, a recall of 0.90, and an F1-score of 0.85 in the *Moderate* class. The Logistic Regression and Decision Tree are at medium performance levels; for instance, the Decision Tree produces an F1-score of 0.67 (*Good*) and 0.83 (*Moderate*), while Logistic Regression records an F1-score of 0.73 (*Good*) and 0.82 (*Moderate*). On the other hand, K-Nearest Neighbors shows an imbalance in performance, with an F1-score of just 0.57 in the *Good* class despite reaching 0.86 in the *Moderate* class. Naïve Bayes recorded high performance in the *Moderate* class (F1-score 0.86) but very low in the *Good* class (F1-score 0.50), showing weakness in dealing with dependency between features.

The in-depth analysis results show that although Random Forest is worthy of being recommended as the main model in supporting digital-based urban readiness classification decision-making, other models can be used selectively or after advanced parameter tuning and optimization.

4.5. Comparison with Previous Studies

The integration of fuzzy MCDM methods with Random Forest classification in this study contributes to the evolving research on evaluating AI-driven personalization in smart cities. This hybrid approach aligns with prior methodological advancements and extends them through empirical validation and uncertainty modeling.

Fayyaz et al. (2024) [55] introduced a comprehensive framework combining fuzzy Delphi, Analytical Network Process (ANP), and Game Theory to optimize smart city street design, thereby emphasizing the utility of multi-method decision-making models in addressing urban complexity. Similarly, a recent study published in Scientific Reports proposed a decision-support system that integrates machine learning-based feature selection (RF-RFE) with fuzzy MCDM, particularly q-Rung Orthopair Fuzzy Sets (q-ROFS), to facilitate sustainable urban planning under conditions of uncertainty. These studies underscore the importance of combining ML with fuzzy logic to enhance decision quality in complex urban environments.

Aljohani [2] explored the role of AI and deep learning in optimizing energy systems in smart cities, they often lack a structured evaluation of inclusivity or personalization readiness. Our framework addresses this gap through both quantitative evaluation and classification validation. Khanyile [56] further demonstrated the comparative performance of Fuzzy Overlay and Random Forest classification in post-mining land assessment, concluding that fuzzy methods offer superior accuracy in capturing spatial ambiguity. Building upon these insights, our study introduces a novel application of a fuzzy MCDM–RF hybrid framework tailored specifically to assess AI personalization readiness. The incorporation of Lq-Rung Orthopair Fuzzy Numbers (Lq-ROFNs) allows for more nuanced representation of expert uncertainty, while the Random Forest model enables robust and interpretable classification. This framework provides a replicable and scalable tool for policymakers to assess digital inclusion and personalization maturity within smart city ecosystems.

4.6. Limitation of the Study

While this study offers a robust framework for evaluating AI-driven personalization in smart cities by integrating fuzzy MCDM and Random Forest classification, some limitations must be acknowledged. Firstly, empirical validation is limited to 24 cities in Indonesia, which can limit the generalization of findings to other national or regional contexts with different levels of digital maturity or governance frameworks. Secondly, the framework presents a static evaluation, not considering dynamic shifts in AI implementation or personalization maturity over time. Lastly, contextual factors such as infrastructure disparities and the power of policy enforcement are not explicitly modeled, although they are likely to influence the outcomes of AI personalization. Future research can overcome these limitations by combining longitudinal data, expanding algorithmic comparisons, and exploring broader cross-regional applications.

5. Conclusion

This study proposed and validated a hybrid evaluation framework that integrates fuzzy Multi-Criteria Decision-Making techniques, specifically using SWARA and MABAC with the Random Forest classifier to assess AI personalization readiness in smart cities. The framework was empirically applied to ten Indonesian cities, evaluating five critical dimensions of AI-driven service delivery: accessibility, affordability, user engagement, privacy, and personalization effectiveness. The results indicate that accessibility and engagement are pivotal for fostering inclusive AI service delivery, whereas affordability and privacy remain underdeveloped. Theoretically, this research contributes to the growing body of knowledge by integrating fuzzy MCDM with supervised machine learning to enable robust and interpretable evaluations. The use of Lq-ROFNs enhances the handling of uncertainty in expert-based assessments, while the Random Forest classifier strengthens empirical validation and readiness classification. This methodological synthesis supports the development of transparent, adaptive tools for digital governance.

Despite its strengths, the study is constrained by its reliance on expert judgment, which may introduce subjectivity, and its geographic focus on Indonesian cities, potentially limiting the generalizability of findings. Future research should apply the framework across diverse urban contexts and incorporate longitudinal data to capture temporal dynamics in AI personalization readiness. This research advances the field by offering a replicable, scalable, and data-driven decision-support model for inclusive AI personalization strategies. It provides practical utility for urban policymakers and offers novel insights into how hybrid intelligent systems can bridge the gap between technological innovation and social equity in smart city ecosystems. Additionally, it underscores the need to examine how infrastructure disparities and governance mechanisms shape personalization readiness across different socio-political settings.

6. Declarations

6.1. Author Contributions

Conceptualization, M.F. and T.K.A.R.; methodology, M.F., T.K.A.R., and S.; software, E.M.H. and S.W.; validation, B.E.W.A., I.M., and D.; formal analysis, M.F. and I.D.M.W.; investigation, E.M.H. and S.; resources, D. and B.E.W.A.; data curation, I.M.; writing—original draft preparation, M.F.; writing—review and editing, S.W. and S.; visualization, B.E.W.A. and I.D.M.M.; supervision, T.K.A.R.; project administration, M.F.; funding acquisition, M.F., I.M., and D. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

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6.4. Acknowledgments

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6.5. Institutional Review Board Statement

Not applicable.

6.6. Informed Consent Statement

Not applicable.

6.7. Declaration of Competing 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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