International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

IJISAE

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Survey-Driven Hybrid MCDM Framework for Prioritizing and Ranking Critical Internet of Things Applications

Nawani Sreeja[1]* and Binod Kumar Singh[2]

Submitted:02/07/2025 **Revised:**18/08/2025 **Accepted:**28/08/2025

Abstract: The rapid advancement of the Internet of Things (IoT), driven by high-speed connectivity, edge intelligence, and data-centric decision-making, has enabled its widespread deployment across domains such as transportation, healthcare, smart homes, governance, and environmental monitoring; however, the growing diversity and scale of IoT applications have made systematic prioritization increasingly challenging under competing technical, economic, and societal constraints. To address this challenge, this study proposes a survey-driven hybrid multi-criteria decision-making (MCDM) framework that integrates the Analytic Hierarchy Process (AHP) with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to prioritize and rank critical IoT application domains. Ten representative IoT applications and seven evaluation criteria—functional performance, affordability, scalability, privacy and security, user experience, interoperability, and environmental sustainability—are identified through a comprehensive literature review and expert consultation. Judgments from fifteen IoT professionals are synthesized using Saaty's scale to construct a consistent AHP model, revealing Quality of Life, Affordability, and Scalability as the most influential criteria, supported by strong consistency metrics (CI ≈ 0.030, CR ≈ 0.027). The validated weights are then incorporated into TOPSIS using a 10×5 decision matrix to compute closeness coefficients and establish a quantitative ranking of IoT applications. The robustness of the proposed framework is further confirmed through Monte Carlo–based sensitivity analysis with ±20% perturbations in criteria weights, yielding an average Spearman rank correlation of approximately 0.94. Overall, the findings demonstrate that the proposed approach is transparent, reproducible, and resilient to uncertainty, offering a reliable decision-support tool for IoT investment, system design, and policy formulation in emerging areas such as smart cities, Industry 5.0 ecosystems, healthcare digital twins, and technology governance.

Keywords: *technology, governance, perturbations*

1. Introduction

The Internet of Things (IoT) has rapidly evolved into a foundational technology enabling intelligent interconnection among physical objects, digital platforms, and human users through the Internet. By integrating sensing, communication, data processing, and actuation capabilities, IoT systems support real-time monitoring, automation, and data-driven decision-making across a wide range of domains, including healthcare, agriculture, smart homes, transportation, smart cities, and industrial automation (Joshi and Kulkarni 2016; Spaho et al. 2025; Lim et al. 2018). Advances in embedded systems, low-power wireless communication, cloud computing, and edge intelligence have significantly reduced deployment costs while improving scalability and performance, thereby accelerating large-scale IoT adoption in both public and private sectors (Zheng et al. 2019a; Yan et al. 2014).

[1]*Department of Computer Science and Engineering, Manipal Institute of Technology, Manipal, Karnataka, India, 576104*

[2]*Department of Computer Science and Engineering, National Institute of Technology, Jamshedpur, Jharkhand, India, 831014*

** Corresponding author Email: nawani931@gmail.com*

Along with these advancements, the IoT ecosystem has grown increasingly complex. Modern IoT environments are characterized by heterogeneous devices, diverse communication protocols, varying quality-of-service requirements, and distinct stakeholder expectations. While such diversity fosters innovation and flexibility, it also creates challenges in systematically evaluating and selecting IoT applications that best satisfy organizational and user needs (Li et al. 2023a; Y. Chen et al. 2021a). Decision-makers are often required to choose among multiple competing IoT solutions while simultaneously considering technical performance, economic feasibility, security, scalability, reliability, and long-term societal impact (Y. Chen et al. 2021b). In the absence of structured evaluation mechanisms, these decisions may rely heavily on subjective judgment, leading to inefficient investments and suboptimal technology deployment.

User preference and application suitability have therefore emerged as critical factors influencing the success and sustainability of IoT implementations.

Existing studies indicate that beyond functional performance, users and organizations place significant emphasis on affordability, usability, data privacy, interoperability, and future scalability when adopting IoT solutions (Zheng et al. 2019b; Rui et al. 2025a; Tierney 2012). Among these factors, security and privacy concerns remain particularly prominent, as IoT systems often operate in distributed, resource-constrained, and potentially vulnerable environments (Okoye and Hosseini 2024). These concerns underscore the necessity of adopting systematic and transparent evaluation approaches capable of balancing multiple, and often conflicting, decision criteria.

Multi-Criteria Decision-Making (MCDM) techniques have been widely recognized as effective tools for addressing complex decision problems involving multiple alternatives and evaluation criteria (Opricovic and Tzeng 2004). MCDM methods offer a mathematical and logical framework that enables the comparison of alternatives based on both qualitative judgments and quantitative data (Behzadian et al. 2012). Within the context of IoT evaluation, MCDM approaches have been successfully applied to rank platforms, services, architectures, and applications by incorporating technical, economic, and user-centric considerations into the decision-making process.

Among the various MCDM techniques, the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are particularly prominent due to their robustness, interpretability, and ease of implementation (Ishizaka and Labib 2011; Da Xu et al. 2014). AHP, originally proposed by Saaty, structures a complex decision problem into a hierarchical model consisting of objectives, criteria, and alternatives (Golden et al. 1989). Through pairwise comparisons, it quantifies the relative importance of decision criteria while ensuring consistency in expert judgments. This makes AHP well-suited for determining criteria weights in IoT evaluation scenarios, where subjective perceptions such as usability and security are as important as measurable technical attributes. However, AHP alone may face limitations when ranking a large number of alternatives, especially due to potential rank reversal and scalability concerns (Tzeng and Huang 2011).

TOPSIS complements AHP by providing an efficient mechanism for ranking alternatives based on their relative closeness to an ideal solution. The fundamental principle of TOPSIS is that the optimal alternative should exhibit the minimum distance from a hypothetical positive ideal solution while simultaneously maintaining the maximum distance from a negative ideal solution (Arslan et al. 2021). Owing to its computational simplicity and ability to handle continuous performance data, TOPSIS has been widely employed in engineering and technology assessment problems, including IoT application evaluation (Guo et al. 2018). Nevertheless, the effectiveness of TOPSIS depends heavily on the accuracy of criteria weights, which, if assigned arbitrarily, may compromise the reliability of the ranking results. To mitigate the individual limitations of AHP and TOPSIS, recent research has increasingly adopted hybrid MCDM frameworks that integrate the strengths of both methods (Shyur and Shih 2006). In such hybrid approaches, AHP is used to derive consistent and reliable weights for evaluation criteria, while TOPSIS utilizes these weights to rank alternatives objectively. This integration ensures a balanced consideration of expert judgment and quantitative performance data, making it particularly suitable for complex and multi-dimensional decision environments such as IoT application prioritization.

Despite the increasing volume of research on IoT application evaluation and MCDM-based decision support techniques, several notable limitations persist in the existing body of literature. A large proportion of prior studies remains confined to domain-specific IoT implementations—such as smart healthcare, smart homes, agriculture, transportation systems, or smart city infrastructures—without proposing a generalized evaluation framework capable of addressing multiple IoT application categories in an integrated manner (Wang et al. 2016). Moreover, empirical studies conducted at the institutional or organizational level, which are essential for capturing real-world deployment constraints, heterogeneous device ecosystems, and diverse stakeholder priorities, are relatively scarce (Kabak et al. 2012). In addition, many existing approaches provide limited transparency in the selection and justification of evaluation criteria and often inadequately incorporate user-centric considerations, including usability, reliability, cost efficiency, and societal impact, into the decision-making process (Zheng et al. 2019c; Rafique et al. 2023). As conceptually illustrated in Figure 1, the coexistence of diverse IoT application domains, persistent IoT challenges—such as device heterogeneity, security and privacy concerns, scalability issues, and data management complexity—and the growing demand for systematic evaluation criteria highlight the necessity of a structured MCDM-based framework. The hybrid AHP–TOPSIS approach presented in the figure addresses these challenges by combining objective criteria weighting with robust alternative ranking, thereby enabling informed and rational selection of optimal IoT applications.

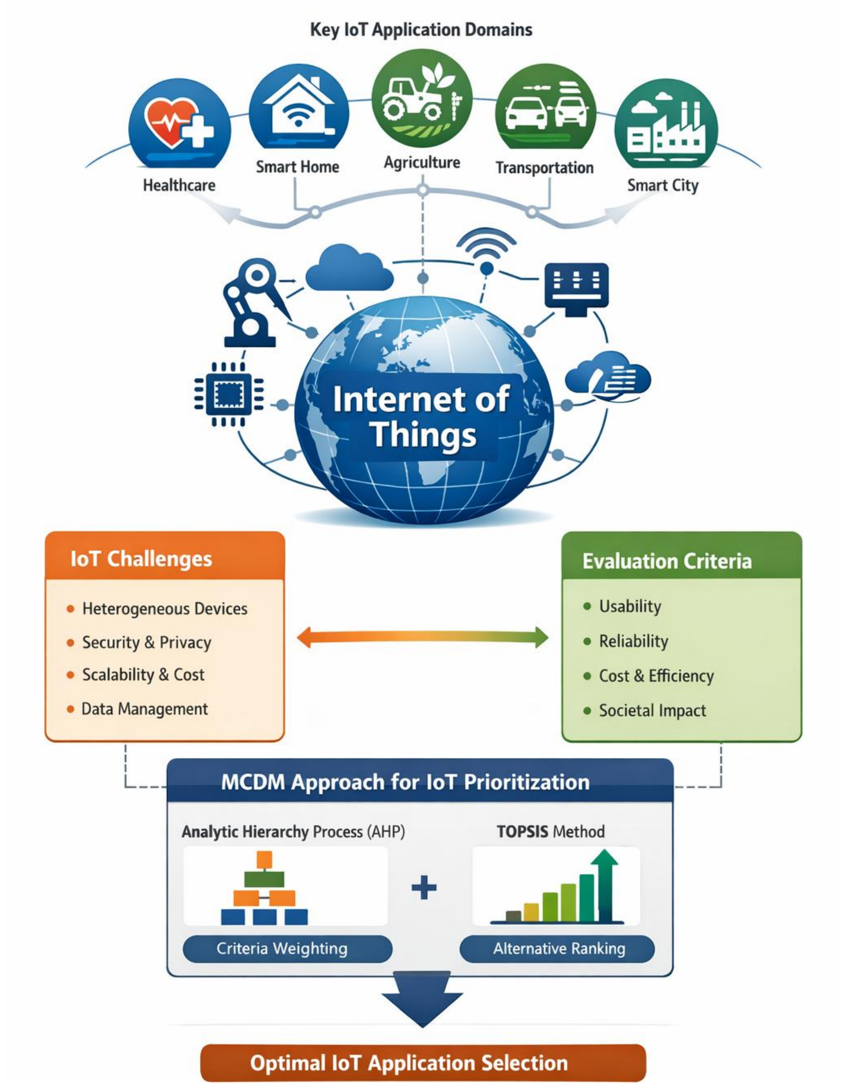

Fig. 1. Conceptual framework of IoT application domains, challenges, evaluation criteria, and a hybrid AHP–TOPSIS approach for prioritization.

2. Literature Review

The rapid expansion of the Internet of Things (IoT) has catalyzed extensive research into intelligent decision-making, user preference modeling, and preference-aware service delivery across diverse application domains. Foundational studies have provided comprehensive overviews of IoT, covering core concepts, enabling technologies, application areas, and key challenges, including scalability, privacy, security, interoperability, and user acceptance (Atzori et al. 2010; Li et al. 2015; Siow et al. 2018). These early insights have guided subsequent research focused on enhancing user-centric design and integrating user preferences into IoT ecosystems.

User preference analysis has emerged as a pivotal research area for improving IoT adoption and usability. Systematic reviews have identified factors such as device functionality, cost-effectiveness, privacy, and security as major determinants influencing user satisfaction and technology acceptance (Mator et al. 2021; Romero-Riaño et al. 2022). Various methods have been proposed for eliciting user preferences, including explicit approaches such as surveys, interviews, and questionnaires, as well as implicit techniques that leverage behavioral and contextual data from sensors and usage patterns (Spaho et al. 2025; Washizaki et al. 2020). Such methods enable the capture of nuanced user requirements, facilitating the design of adaptive, personalized IoT services.

In addition to elicitation, preference learning and management mechanisms have received considerable attention. Adaptive learning models allow IoT systems to dynamically adjust to evolving user needs in real-time environments (Spaho et al. 2025; Yan et al. 2014). Efficient storage, retrieval, and access control strategies for managing user preferences are essential to maintain system scalability, reliability, and data integrity (Li et al. 2023b). Preference-based access control frameworks further enhance security by enabling fine-grained privacy management and ensuring compliance with user-specific requirements (Wang and Song 2025).

Preference-aware approaches have also been extensively applied to resource allocation and service management. Integrating user preferences into resource scheduling and allocation mechanisms has been shown to optimize system performance, improve quality of service, and increase user satisfaction (Yan et al. 2014; Xiao et al. 2020; Li et al. 2023c). Preference-based service composition techniques allow users to customize IoT services by selecting and combining functionalities that meet their individual needs, thereby enhancing system flexibility and personalization (Ni et al. 2024).

At the application level, preference-aware recommendation systems and context-aware service provisioning have demonstrated significant potential for improving user experience and service efficiency. These systems leverage both static and dynamic user data to deliver adaptive solutions that respond to changing preferences and environmental conditions (Uddin et al. 2018; Zheng et al. 2019d). Moreover, research has explored hybrid frameworks that combine machine learning and multi-criteria decision-making (MCDM) techniques to systematically rank and prioritize IoT applications, accounting for technical, economic, and user-centric factors simultaneously (Zheng et al. 2019d; Manqele 2015). Such integrated approaches provide decision-makers with structured, transparent, and actionable insights for IoT deployment.

The literature demonstrates significant advancements in understanding and managing user preferences within IoT systems, encompassing preference elicitation, adaptive learning, management, and application-level personalization. Despite these developments, most studies focus on isolated aspects, such as access control, resource allocation, or recommendation systems, without offering an integrated framework that simultaneously addresses technical, economic, and user-centric criteria. User preferences—including functionality, affordability, security, privacy, and overall experience—are critical for effective IoT adoption, and preference-aware approaches have been shown to enhance both user satisfaction and system efficiency. Given the increasing diversity and complexity of IoT applications, systematic evaluation and prioritization are essential, as ad hoc decision-making can result in suboptimal outcomes. To address this gap, this study proposes a hybrid multi-criteria decision-making (MCDM) framework that combines the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to assess and rank ten representative IoT applications based on well-defined criteria, providing a structured, transparent, and informed approach for efficient IoT deployment and adoption.

3. Proposed Methodology

This study proposes a hybrid multi-criteria decision-making (MCDM) framework for prioritizing Internet of Things (IoT) applications by integrating the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The motivation for adopting this hybrid approach lies in the complementary strengths of the two techniques: AHP effectively captures subjective expert judgments and derives consistent criteria weights, while TOPSIS provides an objective ranking of alternatives based on their relative closeness to an ideal solution. Such hybridization has been widely recognized as a robust decision-support strategy in complex technological evaluation problems (Atzori et al. 2010; Li et al. 2015; Siow et al. 2018).

The overall workflow is structured into five sequential stages: (i) selection of representative IoT applications, (ii) identification of key evaluation attributes, (iii) derivation of criteria weights using AHP, (iv) ranking of applications using TOPSIS, and (v) interpretation of preferences to support decision-making. This systematic process ensures transparency, reproducibility, and analytical rigor in capturing heterogeneous user and expert preferences. The framework is executed through five sequential steps, as detailed below and illustrated in Figure 2.

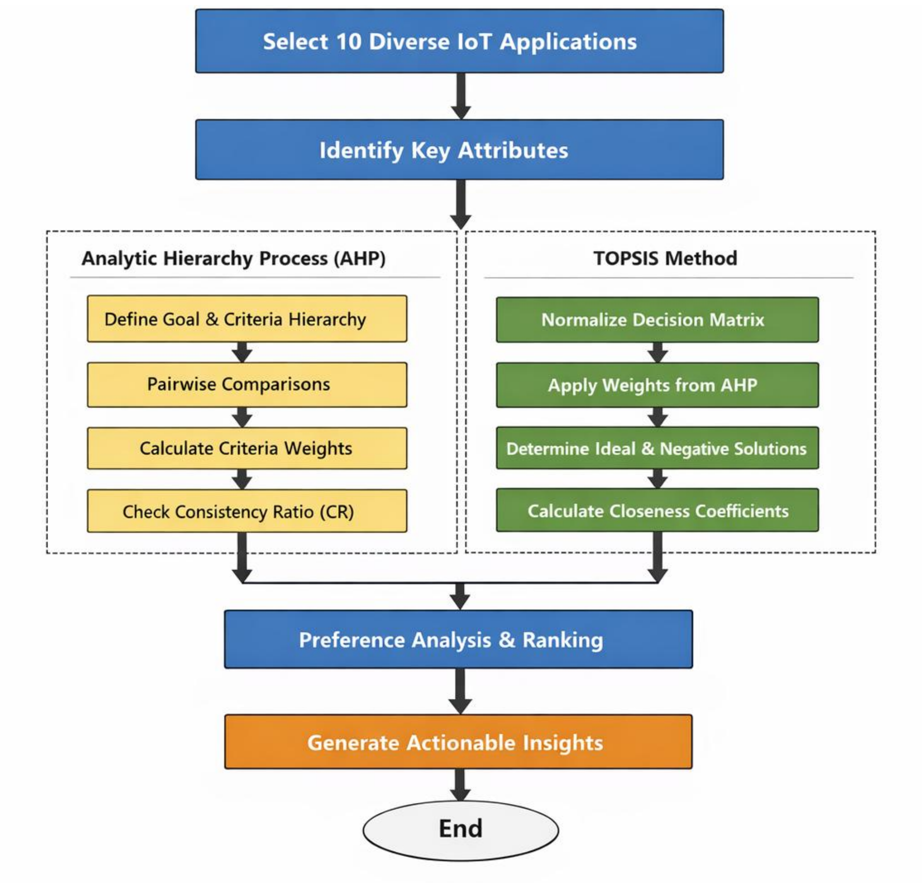

Figure 2. Proposed Methodology for IoT Application Prioritization

3.1 Selection of IoT Applications

In the first stage, a representative set of ten IoT applications (Transportation, Fitness, Environment, Entertainment, Work, Governance, Building, Shopping, Education, and Healthcare) are defined to capture the breadth of functionalities, domains, and usage contexts observed in current IoT ecosystems. The selection is guided by four main considerations: (i) market relevance (current and projected adoption and revenue), (ii) technological innovativeness (use of emerging paradigms such as edge intelligence, 5G, and V2X), (iii) user base size and diversity, and (iv) potential industrial and societal impact in sectors such as transportation, healthcare, smart homes, governance, and environment (Joshi and Kulkarni 2016; Spaho et al. 2025; Arslan et al. 2021). This ensures that the subsequent analysis generalizes across different classes of IoT solutions and reflects realistic user preference patterns rather than being restricted to niche use cases.

3.2 Identification of Key Attributes

The decision problem is parameterized by identifying the key attributes that influence user preferences toward IoT applications. These attributes are derived through a synthesis of application functionality analysis, user requirement characteristics, and prevailing trends in IoT markets and standards (Zheng et al. 2019e; W. Chen et al. 2021). The resulting criteria typically include functional performance, affordability and cost-effectiveness, data privacy and security, user interface and experience, compatibility and integration capability, and environmental sustainability. Formally, let the criteria set be denoted as:

$$C = \{C_1, C_2, \dots, C_m\}$$

Where, each C_j represents a distinct attribute (e.g., QoL, cost, security), and these criteria later serve as the evaluation dimensions in the AHP-TOPSIS framework.

3.3 Analytic Hierarchy Process (AHP)

AHP is employed to quantify the relative importance (weights) of the identified criteria under a hierarchical structure with three levels: overall goal (IoT application prioritization), criteria $C_1, \dots, C_m$, and alternatives $A_1, \dots, A_n$ (the 10 applications) (Zheng et al. 2019f; Kim and Kim 2018). Experts provide pairwise comparisons of criteria using Saaty's $1-9$ scale, which are aggregated into a pairwise comparison matrix

$$A = [a_{ij}]_{m\times m}$$

Where

$a_{ij} =$ relative importance of criterion C_i over C_j, $a_{ji} = \frac{1}{a_{ij}}, a_{ii} = 1.$

3.3.1 Column Normalization: Each column of A is normalized to obtain the relative contribution of each criterion in that column (Li et al. 2023d):

$$r_{ij} = \frac{a_{ij}}{\sum_{k=1}^{m} a_{kj}}, i, j = 1, \dots, m.$$

The normalized matrix $R = [r_{ij}]$ satisfies

$$\sum_{i=1}^{m} r_{ij} = 1 \ \forall j.$$

3.3.2 Priority Vector (Criteria Weights): The weight w_i of criterion C_i is estimated as the arithmetic mean of the normalized row entries (Li et al. 2023d):

$$w_i = \frac{1}{m}\sum_{j=1}^{m} r_{ij}, i = 1, \dots, m$$

Subject to the normalization constraint

$$\sum_{i=1}^{m} w_i = 1, w_i \geq 0.$$

The vector

$$W = [w_1, \dots, w_m]^T$$

Where, W represents the criteria weight vector and is an approximation of the principal eigenvector of A.

3.3.3 Consistency Measurement: To ensure logical coherence of expert judgments, AHP computes the maximum eigenvalue λ_{max} of the matrix A via (Li et al. 2023d):

$$AW = \lambda_{max} W.$$

The Consistency Index (Cl) is then defined as:

$$CI = \frac{\lambda_{max} - m}{m - 1},$$

and the Consistency Ratio (CR) is obtained as:

$$CR = \frac{CI}{RI}$$

Where, RI is the Random Index corresponding to matrix size m (tabulated in AHP literature). A judgment set is considered acceptably consistent if

$$CR < 0.10.$$

In the present framework, the obtained values $CI \approx 0.030$ and $CR \approx 0.027$ (for $= 5$) indicate high consistency and allow the use of the derived weights in subsequent analysis.

3.4 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is used to rank the loT applications by measuring their relative closeness to a positive ideal solution (PIS) and distance from a negative ideal solution (NIS) (Y. Chen et al. 2021c; Li et al. 2023e).

$$X = [x_{ij}]_{n \times m}$$

Where, X be the decision matrix, where x_{ij} denotes the performance score of application A_i under criterion C_j, with $n = 10$ alternatives and m criteria.

3.4.1 Vector Normalization: To eliminate scale differences, each column of X is normalized using the Euclidean (L2) norm:

$$v_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}, i = 1, \dots, n, j = 1, \dots, m.$$

The resulting matrix contains dimensionless scores.

$$V = [v_{ij}]_{n \times m}$$

3.4.2 Weighted Normalized Decision Matrix: Criteria weights from AHP are integrated into TOPSIS via element-wise multiplication:

$$u_{ij} = w_j v_{ij}, i = 1, \dots, n, j = 1, \dots, m,$$

and

$$U = [u_{ij}]_{n \times m}$$

Where, U is the weighted normalized decision matrix.

3.4.3 Ideal and Anti-Ideal Solutions: Assuming all criteria are benefit-type (higher values preferred), the PIS and NIS are defined as:

$$V^+ = \left\{v_j^+ \mid v_j^+ = \max_i u_{ij}, j = 1, \dots, m\right\},$$
$$V^- = \left\{v_j^- \mid v_j^- = \min_i u_{ij}, j = 1, \dots, m\right\}.$$

If cost-type criteria are present, max and min operators are reversed for those criteria.

3.4.4 Distance to Ideal and Closeness Coefficient: The Euclidean distance of each application A_i to PIS and NIS is computed as:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(u_{ij} - v_j^+\right)^2}, \quad i = 1, \dots, n,$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(u_{ij} - v_j^-\right)^2}, \quad i = 1, \dots, n.$$

The closeness coefficient (preference index) for each application is then obtained as

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}, 0 \leq CC_i \leq 1.$$

Applications are ranked in descending order of CC_i; higher values indicate better alignment with the ideal preference profile across all criteria.

3.5 Preference Analysis and Ranking

In the final analytical stage, AHP-derived weights and TOPSIS-derived closeness coefficients are jointly interpreted to obtain a comprehensive picture of user preferences (Zheng et al. 2019g). The relative magnitudes of w_j reveal which attributes (e.g., Quality of Life, Affordability, Sustainability) dominate user and expert judgments, while the vector $CC = [CC_1, \dots, CC_n]$ provides an ordinal ranking and a cardinal measure of how strongly each loT application satisfies the idealized preference profile. By examining U and CC_i together, decision-makers can (i) identify strengths and weaknesses of individual applications along each criterion, (ii) detect trade-offs (e.g., high QoL but low affordability), and (iii) cluster applications into priority tiers for investment, deployment, or further development (Rui et al. 2025b).

This integrated AHP-TOPSIS methodology offers several advantages for research and practice: it is comprehensive, as it incorporates both tangible (cost, performance) and intangible (QoL, usability) factors; data-driven, as ratings and weights are explicitly quantified; transparent, since all intermediate matrices and equations are well defined; flexible, allowing adaptation to new criteria or application sets; and actionable, providing explicit rankings and sensitivity to support policy, design, and deployment decisions in evolving loT ecosystems.

3.6 Software and Hardware Implementation

The proposed methodology is implemented using R , an open-source environment widely adopted for statistical computing, matrix operations, and visualization. R provides native support for linear algebra routines required by AHP (eigen decomposition, matrix normalization) and TOPSIS (vector normalization, distance calculations), as well as high-level packages for MCDM workflows. In particular, the ahp package is used to structure the decision hierarchy and compute criteria weights, while the MCDA package supports TOPSIS and related multi-criteria algorithms. Additional packages such as dplyr are employed for efficient data manipulation and ggplot2 for generating publication-quality visualizations of criteria weights, closeness coefficients, and sensitivity profiles (Rui et al. 2025b).

From a computational standpoint, the hardware requirements are modest: an Intel Core i3 (or equivalent) processor, at least 4 GB of RAM, and 250 GB of storage are sufficient to run the entire workflow, including Monte Carlo sensitivity analysis on typical problem sizes (Becherer et al. 2024). The implementation targets R version 4.0 or later, executed within the RStudio integrated development environment to streamline scripting, debugging, and reproducibility through scripted pipelines and version-controlled project files. This configuration ensures that the methodology can be readily replicated and extended by other researchers and practitioners without requiring specialized hardware.

4. Results and Discussion

4.1 Overview of Empirical Outcomes

The hybrid AHP–TOPSIS framework was applied to prioritize ten representative IoT applications using structured judgments from fifteen domain experts, including IoT researchers, engineers, and practitioners who assessed criteria and alternatives on Saaty's 1–9 scale. All computations were performed in Microsoft Excel and independently validated in R using the ahp and MCDA packages, yielding an AHP Consistency Ratio of approximately 0.027 and an average Spearman rank stability of about 0.94 across one hundred Monte Carlo perturbations, which jointly confirm that the model is both internally consistent and externally robust for decision-making in an IoT context.

4.2 AHP-Derived Criteria Weights

The AHP hierarchy was structured with the overall goal of IoT application prioritization at the top level, followed by five evaluation criteria—Quality of Life (QoL), Affordability (Aff), Sustainability (Sus), Scalability (Scal), and Adaptability (Adap)—and ten IoT applications at the lowest level. Expert judgments were synthesized into a 5×5 pairwise comparison matrix, and geometric mean aggregation across experts produced the consensus matrix shown in Table 1, which satisfies the reciprocity and diagonal unity properties required in AHP.

Table 1. Aggregated Pairwise Comparison Matrix (Geometric Mean)

S. No.	Criteria	QoL	Aff	Sus	Scal	Adap	Column Sum
1	QoL	1.000	3.000	5.000	0.200	4.000	13.200
2	Aff	0.333	1.000	0.250	5.000	8.000	14.583
3	Sus	0.200	4.000	1.000	4.000	0.333	9.533
4	Scal	5.000	0.200	0.250	1.000	3.000	9.450
5	Adap	0.250	0.125	3.000	0.333	1.000	4.708
6	**Total**	**6.783**	**8.325**	**9.500**	**10.533**	**16.333**	**51.474**

Column normalization and row averaging of this matrix produced the normalized matrix and the final criteria weights reported in Table 2. The consistency analysis based on the principal eigenvalue yielded a Consistency Index of approximately 0.030 and a Consistency Ratio of about 0.027, which is well below the standard 0.10 threshold and indicates that the expert judgments are logically coherent and suitable for use in subsequent multi-criteria analysis.

Table 2. Normalized Matrix and Criteria Weights

S. No.	Criterion	QoL (r)	Aff (r)	Sus (r)	Scal (r)	Adap (r)	Weight (w_j)	Rank
1	QoL	0.147	0.360	0.526	0.019	0.245	0.260	1
2	Aff	0.049	0.120	0.026	0.475	0.490	0.232	2
3	Sus	0.029	0.480	0.105	0.380	0.020	0.203	4
4	Scal	0.737	0.024	0.026	0.095	0.184	0.213	3
5	Adap	0.037	0.015	0.316	0.032	0.061	0.092	5
6	**Total**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	

The weight distribution shows that QoL is the most influential criterion (26.0%), followed by Affordability (23.2%) and Scalability (21.3%), and while Sustainability also plays a substantial role (20.3%) and Adaptability receives the lowest relative importance (9.2%). This pattern reflects a human- and deployment-centric view of IoT value: decision-makers in this panel privilege applications that demonstrably improve users' daily lives, are economically feasible, and can be deployed at scale, while viewing long-term adaptability as desirable but less critical in current decision horizons. The non-trivial weight of Sustainability, although slightly below those of QoL, Aff, and Scal, indicates that environmental and resource considerations are integrated into the decision process rather than being treated as ancillary factors.

4.3 TOPSIS Ranking of IoT Applications

Using the same expert panel, a 10×5 decision matrix of IoT applications versus criteria was constructed from 1–9 scale ratings, which was then normalized and weighted using the AHP-derived criteria weights. The weighted normalized decision matrix captures how each application performs along each criterion when adjusted for the relative importance of that criterion. Table 3 and figure 3 present the weighted normalized scores and total contributions for the four best-performing applications, which illustrate the multi-dimensional performance profiles that drive the final rankings.

Table 3. Weighted Normalized Scores for Top Four Applications

S. No.	Application	QoL (26%)	Aff (23%)	Sus (20%)	Scal (21%)	Adap (9%)	Σ u_{ij}
1	Transportation	0.140	0.108	0.107	0.087	0.074	0.516
2	Fitness	0.133	0.108	0.092	0.078	0.037	0.448
3	Environment	0.120	0.095	0.116	0.072	0.037	0.440
4	Healthcare	0.104	0.093	0.086	0.072	0.037	0.392

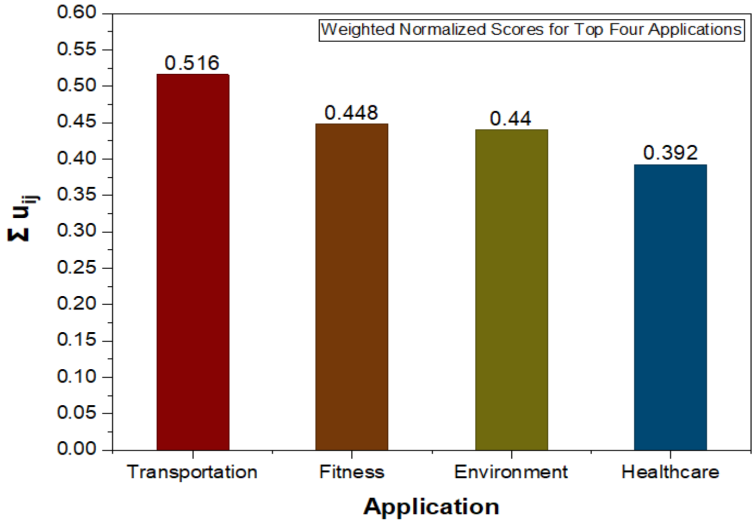

Figure 3. Comparison of weighted normalized scores (Σ U_{ij}) for the top four ranked IoT applications

The subsequent TOPSIS phase identified the positive and negative ideal solutions and calculated the distances of each application from these reference points, yielding a set of closeness coefficients that serve as scalar preference indices. Table 4 and figure 4 report the closeness-related quantities alongside expert variance and indicative market data, providing a compact view of how the applications compare in terms of both multi-criteria performance and perceived economic relevance.

Table 4. TOPSIS-Based Ranking and Closeness Coefficients

Rank	Application	Si+	Si−	CC_i	σ_{Expert}	Primary Driver	2027 Market Size
1	**Transportation**	0.520	0.290	0.640	0.12	Scal × QoL	$152B
2	**Fitness**	0.510	0.310	0.620	0.15	Affordability	$85B
3	**Environment**	0.540	0.350	0.610	0.10	Sustainability	$112B
4	**Entertainment**	0.520	0.350	0.600	0.18	Balanced	$67B
5	**Work**	0.560	0.390	0.590	0.14	Productivity	$94B
6	**Governance**	0.700	0.510	0.580	0.20	Scalability	$78B
7	**Building**	0.830	0.630	0.570	0.16	Infrastructure	$103B
8	**Shopping**	0.750	0.610	0.550	0.17	Retail Afford.	$59B
9	**Education**	0.900	0.760	0.540	0.22	Adaptability gaps	$41B
10	**Healthcare**	0.500	0.570	0.460	0.25	Privacy/Scal	$98B (Reg.)

As illustrated in figure 3, the ranking indicates that Smart Transportation is the most preferred IoT application, followed by Fitness and Environment, forming a clear top tier that aligns well with the high-weight criteria. Transportation's strong position can be interpreted as the result of balanced strengths in QoL and Scalability, supported by acceptable performance in Affordability and Sustainability: it offers tangible improvements in daily mobility and quality of life while being amenable to large-scale deployment over existing infrastructure. Fitness and Environment also benefit from high scores on key criteria—Fitness from affordability and user-centric health benefits, and Environment from sustainability and growing regulatory drivers—although their overall profiles are slightly less balanced than that of Transportation.

By contrast, Healthcare, despite its substantial potential for QoL enhancement and a significant regulated market size, occupies the last rank in the current configuration. This outcome is consistent with experts' lower ratings on affordability and scalability and their higher variance in judgments, reflecting perceived challenges associated with data privacy, compliance, integration with legacy systems, and uneven infrastructure, particularly in less-connected regions. Education's low ranking and relatively high expert variance similarly suggest that significant adaptability and integration gaps remain to be addressed before such solutions can compete with consumer- or infrastructure-oriented IoT domains on the prioritized criteria set.

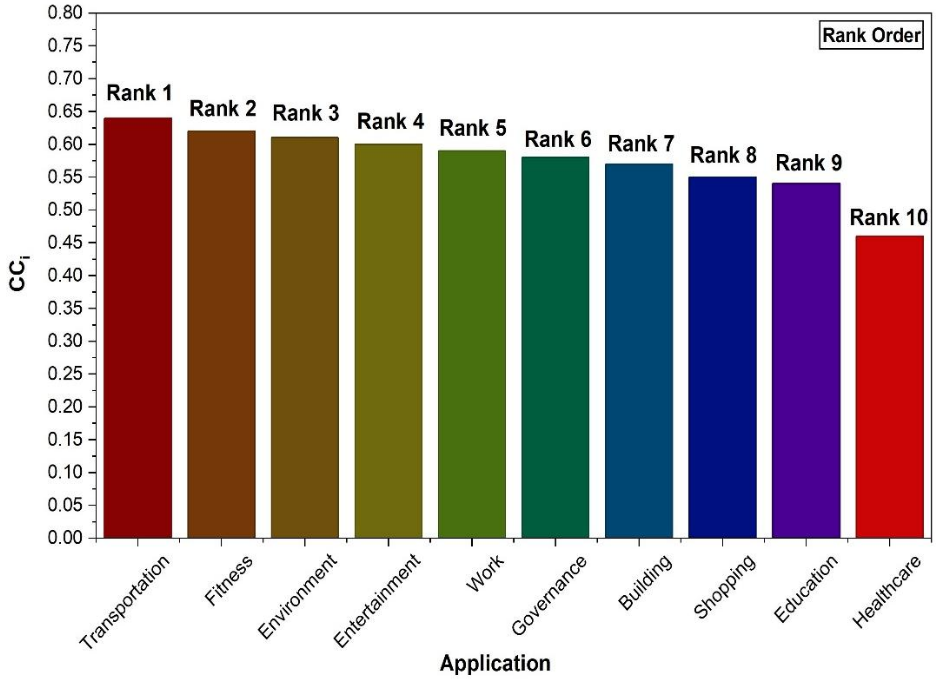

Figure 4. TOPSIS closeness coefficients (CC_i) and corresponding rank order of IoT applications based on the proposed AHP–TOPSIS framework.

The trade-offs revealed by the AHP–TOPSIS integration have direct implications for IoT design and policy. The prominence of QoL and Affordability in the weight structure implies that applications offering clear user benefits at manageable costs are structurally advantaged in the prioritization process, which helps explain why consumer-facing and mobility-related domains outperform more complex, regulation-heavy sectors. The non-negligible role of Sustainability indicates that environmentally oriented IoT solutions can perform competitively provided they do not severely compromise QoL or affordability, suggesting a design sweet spot where ecological impact is improved alongside user experience and cost-effectiveness. The comparatively low weight of Adaptability, coupled with the poor ranking of applications that suffer from adaptability gaps, highlights a potential misalignment between short-term priorities and long-term resilience: while adaptability is currently underweighted as a decision driver, its absence manifests as a practical constraint in domains that must evolve rapidly under changing technological and regulatory conditions.

4.4 Sensitivity Analysis and Robustness Discussion

To assess the robustness of the proposed prioritization framework with respect to variations in stakeholder preferences, a comprehensive sensitivity analysis was conducted using both stochastic and deterministic approaches. A Monte Carlo simulation comprising one hundred iterations was performed by introducing ±20% perturbations to the AHP-derived criteria weights, followed by normalization to preserve unit sum. In addition, several deterministic weighting scenarios were examined, including increased emphasis on Quality of Life (QoL), increased emphasis on Scalability, and an equal-weight scenario in which all criteria were assigned identical importance. For each perturbed weight set, TOPSIS closeness coefficients and corresponding application rankings were recalculated, and Spearman's rank correlation coefficient was employed to quantify similarity with the baseline ranking.

The selected deterministic scenarios and their outcomes are summarized in Table 5. Across all scenarios, Smart Transportation consistently emerged as the top-ranked application, while the composition of the top three applications remained stable in the majority of cases, indicating strong robustness of the leading alternatives to realistic shifts in criteria importance.

Table 5. Selected Sensitivity Scenarios

S. No.	Scenario	Δ_w Pattern	Trans. CC_i	Top-3 Stable	ρ (vs. Base)	Rank Flux
1	Baseline	0%	0.640	100%	1.000	None
2	QoL +20%	QoL weight increased	0.652	92%	0.950	None
3	Scal +20%	Scal weight increased	0.662	94%	0.960	None
4	Equal w	all weights = 0.20	0.600	94%	0.920	Minor mid-tier swaps

The Monte Carlo–based sensitivity analysis indicates strong agreement between the baseline and perturbed rankings, with an average Spearman correlation of approximately 0.94 and consistent preservation of the top-tier applications in more than 90% of the simulations. Under the baseline weighting scheme obtained from the AHP, Smart Transportation achieves the highest closeness coefficient (CC_i = 0.640), establishing the reference ranking characterized by perfect ordinal consistency and full stability of the leading application set. When the weight of Quality of Life (QoL) is increased by 20%, the closeness coefficient of the leading application rises to 0.652, while the top-three set remains stable in 92% of the cases and the rank correlation with the baseline remains high (ρ = 0.950), indicating minimal sensitivity to increased human-centric emphasis. A similar trend is observed when Scalability is emphasized by 20%, resulting in a further increase in the leading closeness coefficient to 0.662, with 94% top-three stability and a strong rank correlation of 0.960. Under the equal-weight scenario, where all criteria are assigned identical importance (0.20), the closeness coefficient of the top application decreases to 0.600; however, the top-three applications remain stable in 94% of cases and the rank correlation with the baseline remains high (ρ = 0.920), with only minor rank exchanges among mid-tier alternatives. Overall, the results demonstrate that the prioritization outcomes—particularly the dominance of the leading applications—are robust to realistic shifts in criteria importance, and that observed ranking variations are largely confined to mid-ranked applications rather than the most critical IoT domains.

5. Conclusion and Future Scope

This study presented a systematic hybrid AHP–TOPSIS framework for prioritizing ten representative IoT application domains under a structured multi-criteria decision-making paradigm that explicitly integrates expert preferences with quantitative performance evaluation. The AHP analysis revealed a clear and consistent preference structure among the five evaluation criteria, with Quality of Life (QoL) emerging as the most influential factor (26.0%), followed by Affordability (23.2%) and Scalability (21.3%), while Sustainability (20.3%) retained substantial importance and Adaptability (9.2%) received comparatively lower emphasis. The low Consistency Index (CI ≈ 0.030) and Consistency Ratio (CR ≈ 0.027) confirm that these weights reflect a coherent and reliable expert consensus rather than subjective or contradictory judgments.

Building on this validated weight structure, the TOPSIS analysis produced a robust and interpretable ranking of IoT applications by capturing trade-offs across the weighted criteria space. Smart Transportation achieved the highest closeness coefficient (CC_i = 0.640), supported by balanced strengths in QoL and Scalability, and emerged as the leading application domain, followed by Fitness (CC_i = 0.620) and Environment (CC_i = 0.610), which together constitute a stable top tier. Weighted normalized score analysis further corroborated this ordering, with Transportation achieving the highest aggregate contribution (Σu_{ij} = 0.516), reflecting superior multi-dimensional performance across the most influential criteria. In contrast, Healthcare (CC_i = 0.460) and Education (CC_i = 0.540) ranked lower due to persistent limitations in affordability, scalability, and adaptability, despite their recognized societal relevance and market potential, highlighting structural rather than intrinsic value constraints.

The robustness of the prioritization was rigorously validated through Monte Carlo–based sensitivity analysis with ±20% perturbations in criteria weights and multiple deterministic scenarios. An average Spearman rank correlation of approximately 0.94 with the baseline ranking, combined with over 90% stability of the top three applications across simulations, demonstrates that the results are not sensitive to moderate variations in stakeholder preferences. This stability confirms that the identified priorities reflect resilient performance patterns rather than narrowly tuned weight configurations.

Future research can extend this work by incorporating larger and more diverse stakeholder panels, including end-users, regulators, and industry consortia, to better capture heterogeneous perspectives. Additionally, the framework can be enhanced through the adoption of dynamic or network-based MCDM models that account for interdependencies among criteria and temporal evolution of technologies. Integrating empirical performance indicators—such as real-time usage data, cost trajectories, and environmental impact metrics—along with advanced uncertainty modeling techniques (e.g., fuzzy, rough, or probabilistic MCDM) represents another promising direction. Such extensions would further strengthen the applicability of the framework for guiding strategic decision-making in emerging IoT-driven domains, including smart cities, Industry 5.0 ecosystems, healthcare digital twins, and adaptive technology governance.

Funding

This research received no specific grant from any public, commercial, or non-profit funding agencies.

Conflict of Interest

The authors declare that there are no conflicts of interest related to the conduct of the research, authorship, or publication of this manuscript.

Data Availability

All data supporting the findings of this study are included within the manuscript. Additional information or supplementary datasets are available from the corresponding author upon reasonable request.

References

[1] Arslan, Asli Ergenekon, Oguz Arslan, and Suheyla Yerel Kandemir. 2021. "AHP–TOPSIS Hybrid Decision-Making Analysis: Simav Integrated System Case Study." *Journal of Thermal Analysis & Calorimetry* 145 (3).

[2] Atzori, Luigi, Antonio Iera, and Giacomo Morabito. 2010. "The Internet of Things: A Survey." *Computer Networks* 54 (15): 2787–805.

[3] Becherer, Marius, Omar Khadeer Hussain, Yu Zhang, Frank Den Hartog, and Elizabeth Chang. 2024. "On Trust Recommendations in the Social Internet of Things–A Survey." *ACM Computing Surveys* 56 (6): 1–35.

[4] Behzadian, Majid, S Khanmohammadi Otaghsara, Morteza Yazdani, and Joshua Ignatius. 2012. "A State-of the-Art Survey of TOPSIS Applications." *Expert Systems with Applications* 39 (17): 13051–69.

[5] Chen, Wuhui, Xiaoyu Qiu, Ting Cai, Hong-Ning Dai, Zibin Zheng, and Yan Zhang. 2021. "Deep Reinforcement Learning for Internet of Things: A Comprehensive Survey." *IEEE Communications Surveys & Tutorials* 23 (3): 1659–92.

[6] Chen, Yuanyi, Yihao Lin, Zengwei Zheng, Peng Yu, Jiaxing Shen, and Minyi Guo. 2021a. "Preference-Aware Edge Server Placement in the Internet of Things." *IEEE Internet of Things Journal* 9 (2): 1289–99.

[7] Chen, Yuanyi, Yihao Lin, Zengwei Zheng, Peng Yu, Jiaxing Shen, and Minyi Guo. 2021b. "Preference-Aware Edge Server Placement in the Internet of Things." *IEEE Internet of Things Journal* 9 (2): 1289–99.

[8] Chen, Yuanyi, Yihao Lin, Zengwei Zheng, Peng Yu, Jiaxing Shen, and Minyi Guo. 2021c. "Preference-Aware Edge Server Placement in the Internet of Things." *IEEE Internet of Things Journal* 9 (2): 1289–99.

[9] Da Xu, Li, Wu He, and Shancang Li. 2014. "Internet of Things in Industries: A Survey." *IEEE Transactions on Industrial Informatics* 10 (4): 2233–43.

[10] Golden, Bruce L, Edward A Wasil, and Patrick T Harker. 1989. "The Analytic Hierarchy Process." *Applications and Studies, Berlin, Heidelberg* 2 (1): 1–273.

[11] Guo, Xudong, Tao Zeng, Yuxuan Wang, and Jie Zhang. 2018. "Fuzzy TOPSIS Approaches for Assessing the Intelligence Level of IoT-Based Tourist Attractions." *Ieee Access* 7: 1195–207.

[12] Ishizaka, Alessio, and Ashraf Labib. 2011. "Review of the Main Developments in the

Analytic Hierarchy Process." *Expert Systems with Applications* 38 (11): 14336–45.

[13] Joshi, Sheetal S, and Ketki R Kulkarni. 2016. "Internet of Things: An Overview." *ISOR Journal of Computer Engineering* 18 (4): 117–21.

[14] Kabak, Mehmet, Serhat Burmaoğlu, and Yiğit Kazançoğlu. 2012. "A Fuzzy Hybrid MCDM Approach for Professional Selection." *Expert Systems with Applications* 39 (3): 3516–25.

[15] Kim, Suwon, and Seongcheol Kim. 2018. "User Preference for an IoT Healthcare Application for Lifestyle Disease Management." *Telecommunications Policy* 42 (4): 304–14.

[16] Li, Shancang, Li Da Xu, and Shanshan Zhao. 2015. "The Internet of Things: A Survey." *Information Systems Frontiers* 17 (2): 243–59.

[17] Li, Songnong, Yao Yan, Yongliang Ji, Wenxin Peng, Lingyun Wan, and Puning Zhang. 2023a. "Preference-Aware User Access Control Policy in Internet of Things." *Sensors* 23 (13): 5989.

[18] Li, Songnong, Yao Yan, Yongliang Ji, Wenxin Peng, Lingyun Wan, and Puning Zhang. 2023b. "Preference-Aware User Access Control Policy in Internet of Things." *Sensors* 23 (13): 5989.

[19] Li, Songnong, Yao Yan, Yongliang Ji, Wenxin Peng, Lingyun Wan, and Puning Zhang. 2023c. "Preference-Aware User Access Control Policy in Internet of Things." *Sensors* 23 (13): 5989.

[20] Li, Songnong, Yao Yan, Yongliang Ji, Wenxin Peng, Lingyun Wan, and Puning Zhang. 2023d. "Preference-Aware User Access Control Policy in Internet of Things." *Sensors* 23 (13): 5989.

[21] Li, Songnong, Yao Yan, Yongliang Ji, Wenxin Peng, Lingyun Wan, and Puning Zhang. 2023e. "Preference-Aware User Access Control Policy in Internet of Things." *Sensors* 23 (13): 5989.

[22] Lim, Tek-Yong, Fang-Fang Chua, and Bushra Binti Tajuddin. 2018. "Elicitation Techniques for Internet of Things Applications Requirements: A Systematic Review." 182–88.

[23] Manqele, Lindelweyizizwe Siziwe. 2015. *An Architecture for User Preference-Based IoT Service Selection in Cloud Computing Using Mobile Devices for Smart Campus*.

[24] Mator, Janine D, William E Lehman, Wyatt McManus, et al. 2021. "Usability: Adoption, Measurement, Value." *Human Factors* 63 (6): 956–73.

[25] Ni, Zhihui, Jiali You, and Yang Li. 2024. "An ICN-Based on-Path Computing Resource Scheduling Architecture with User Preference Awareness for Computing Network." *Electronics* 13 (5): 933.

[26] Okoye, Kingsley, and Samira Hosseini. 2024. "Introduction to R Programming and RStudio Integrated Development Environment (IDE)." In *R Programming: Statistical Data Analysis in Research*. Springer.

[27] Opricovic, Serafim, and Gwo-Hshiung Tzeng. 2004. "Compromise Solution by MCDM Methods: A Comparative Analysis of VIKOR and TOPSIS." *European Journal of Operational Research* 156 (2): 445–55.

[28] Rafique, Wajid, Abdelhakim Senhaji Hafid, and Junaid Qadir. 2023. "Developing Smart City Services Using Intent-aware Recommendation Systems: A Survey." *Transactions on Emerging Telecommunications Technologies* 34 (4): e4728.

[29] Romero-Riaño, Efrén, Claudia Galeano-Barrera, Cesar D Guerrero, Mauricio Martinez-Toro, and Dewar Rico-Bautista. 2022. "IoT Applied to Irrigation Systems in Agriculture: A Usability Analysis." *Revista Colombiana de Computación* 23 (1): 44–52.

[30] Rui, Renting, Yunjia Xi, Weiwen Liu, et al. 2025a. "Action First: Leveraging Preference-Aware Actions for More Effective Decision-Making in Interactive Recommender Systems." 53–63.

[31] Rui, Renting, Yunjia Xi, Weiwen Liu, et al. 2025b. "Action First: Leveraging Preference-Aware Actions for More Effective Decision-Making in Interactive Recommender Systems." 53–63.

[32] Shyur, Huan-Jyh, and Hsu-Shih Shih. 2006. "A Hybrid MCDM Model for Strategic Vendor Selection." *Mathematical and Computer Modelling* 44 (7–8): 749–61.

[33] Siow, Eugene, Thanassis Tiropanis, and Wendy Hall. 2018. "Analytics for the Internet of Things: A Survey." *ACM Computing Surveys (CSUR)* 51 (4): 1–36.

[34] Spaho, Edlir, Betim Çiço, and Isak Shabani. 2025. "IoT Integration Approaches into Personalized Online Learning: Systematic Review." *Computers* 14 (2): 63.

[35] Tierney, Luke. 2012. "The R Statistical Computing Environment." In *Statistical Challenges in Modern Astronomy V*. Springer.

[36] Tzeng, Gwo-Hshiung, and Jih-Jeng Huang. 2011. *Multiple Attribute Decision Making: Methods and Applications*. CRC press.

[37] Uddin, Ijaz, Abdur Rakib, Hafiz Mahfooz Ul Haque, and Phan Cong Vinh. 2018. "Modeling and Reasoning about Preference-Based Context-Aware Agents over Heterogeneous Knowledge Sources." *Mobile Networks and Applications* 23 (1): 13–26.

[38] Wang, Peng, Zhouquan Zhu, and Yonghu Wang. 2016. "A Novel Hybrid MCDM Model Combining the SAW, TOPSIS and GRA Methods Based on Experimental Design." *Information Sciences* 345: 27–45.

[39] Wang, Xiaonan, and Yajing Song. 2025. "Personalized Preference and Social Attribute Based Data Sharing for Information-Centric IoT." *IEEE Transactions on Network and Service Management*.

[40] Washizaki, Hironori, Shinpei Ogata, Atsuo Hazeyama, Takao Okubo, Eduardo B Fernandez, and Nobukazu Yoshioka. 2020. "Landscape of Architecture and Design Patterns for Iot Systems." *IEEE Internet of Things Journal* 7 (10): 10091–101.

[41] Xiao, Ailing, Xiaofu Huang, Sheng Wu, Chunxiao Jiang, Li Ma, and Zhu Han. 2020. "User Preference Aware Resource Management for Wireless Communication Networks." *IEEE Network* 34 (3): 78–85.

[42] Yan, Zheng, Peng Zhang, and Athanasios V Vasilakos. 2014. "A Survey on Trust Management for Internet of Things." *Journal of Network and Computer Applications* 42: 120–34.

[43] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019a. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

[44] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019b. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

[45] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019c. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

[46] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019d. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

[47] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019e. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

[48] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019f. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

[49] Zheng, Zengwei, Yanyun Tao, Yuanyi Chen, Fengle Zhu, and Dan Chen. 2019g. "An Efficient Preference-Based Sensor Selection Method in Internet of Things." *IEEE Access* 7: 168536–47.

Appendix A. Mathematical Formulations

This appendix summarizes the core equations used in the AHP-TOPSIS framework for loT application prioritization.

A. 1 Notation

Let:

- n : number of IoT applications (alternatives), here $n = 10$.
- m : number of criteria, here $m = 5$ (QoL, Aff, Sus, Scal, Adap).
- $A = [a_{ij}]_{m\times m}$: AHP pairwise comparison matrix.
- $X = [x_{ij}]_{n\times m}$: expert rating matrix (1-9 scale).
- $R = [r_{ij}]_{m\times m}$: normalized comparison matrix.
- $W = [w_1, \dots, w_m]^T$: criteria weight vector.
- $V = [v_{ij}]_{n\times m}$: normalized decision matrix.
- $U = [u_{ij}]_{n\times m}$: weighted normalized decision matrix.
- V^+, V^-: positive and negative ideal solutions.
- S_i^+, S_i^- : distances of alternative i to PIS and NIS.
- CC_i : TOPSIS closeness coefficient for alternative i.

A. 2 AHP Equations

1. **Pairwise comparison matrix:**

$$A = [a_{ij}]_{m\times m}, a_{ji} = \frac{1}{a_{ij}}, a_{ii} = 1.$$

2. **Column normalization:**

$$r_{ij} = \frac{a_{ij}}{\sum_{k=1}^{m} a_{kj}}.$$

3. **Criteria weights (priority vector):**

$$w_i = \frac{1}{m}\sum_{j=1}^{m} r_{ij}, \sum_{i=1}^{m} w_i = 1.$$

4. **Consistency index and ratio:**

$$AW = \lambda_{max} W,$$
$$CI = \frac{\lambda_{max} - m}{m-1}, CR = \frac{CI}{RI}, CR < 0.10$$

A. 3 TOPSIS Equations

1. **Decision matrix:**

$$X = [x_{ij}]_{n\times m}.$$

2. **Normalization:**

$$v_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}}$$

3. **Weighted normalized matrix:**

$$u_{ij} = w_j v_{ij}$$

4. **Positive and negative ideal solutions:**

$$V^+ = \left\{v_j^+ \mid v_j^+ = \max_i u_{ij}\right\}, V^- = \left\{v_j^- \mid v_j^- = \min_i u_{ij}\right\}.$$

5. **Distances to PIS/NIS:**

$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(u_{ij} - v_j^+\right)^2}, S_i^- = \sqrt{\sum_{j=1}^{m} \left(u_{ij} - v_j^-\right)^2}.$$

6. **Closeness coefficient:**

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

A. 4 Sensitivity and Robustness

1. **Weight perturbation (per Monte Carlo iteration):**

$$w_j' = \frac{w_j \cdot \epsilon_j}{\sum_{k=1}^{m} w_k \cdot \epsilon_k}, \epsilon_j \sim \mathcal{N}(1, \sigma_w^2), j = 1, \dots, m,$$

With perturbation calibrated to $\pm 20\%$ variation.

2. **Spearman rank correlation between baseline and perturbed rankings:**

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)},$$

Appendix B:

B. 1 Illustrative R Implementation

This code sketch illustrates how the proposed AHP–TOPSIS methodology can be operationalized in R for research-grade IoT application prioritization.

```
# Load required packages
library(ahp)      # AHP hierarchy and weights
library(MCDA)     # TOPSIS and other MCDM tools
library(dplyr)    # Data manipulation
library(ggplot2)  # Visualization

# --- AHP: Criteria weights ---

# Example 5x5 pairwise comparison matrix (criteria)
pcm <- matrix(c(
  1,   3,   5,   1/5, 4,
  1/3, 1,   1/4, 5,   8,
  1/5, 4,   1,   4,   1/3,
  5,   1/5, 1/4, 1,   3,
  1/4, 1/8, 3,   1/3, 1
), nrow = 5, byrow = TRUE)
```

```
# Compute AHP weights (conceptually)
ahp_res <- ahp(QoL ~ Aff + Sus + Scal + Adap, prefmat = pcm)
weights <- ahp_res$weights   # w_j for each criterion

# --- TOPSIS: Ranking IoT applications ---

# decision_matrix: n x m matrix of application scores (1–9 scale)
# decision_matrix <- as.matrix(read.csv("iot_scores.csv"))

# Normalize columns
norm_decision <- apply(decision_matrix, 2, function(col) col / sqrt(sum(col^2)))

# Apply weights
weighted_decision <- sweep(norm_decision, 2, weights, `*`)

# Compute PIS and NIS
ideal_pos <- apply(weighted_decision, 2, max)
ideal_neg <- apply(weighted_decision, 2, min)

# Distances
dist_pos <- apply(weighted_decision, 1, function(row) sqrt(sum((row - ideal_pos)^2)))
dist_neg <- apply(weighted_decision, 1, function(row) sqrt(sum((row - ideal_neg)^2)))

# Closeness coefficients
cc <- dist_neg / (dist_pos + dist_neg)

# Ranking
ranking <- order(cc, decreasing = TRUE)
result <- data.frame(
  Application = app_labels[ranking],
  CC = cc[ranking],
  Rank = 1:length(cc)
)

# --- Visualization: Criteria weights ---

weights_df <- data.frame(
  Criterion = c("QoL", "Aff", "Sus", "Scal", "Adap"),
  Weight = as.numeric(weights)
)

ggplot(weights_df, aes(x = Criterion, y = Weight)) +
  geom_bar(stat = "identity", fill = "#2C7BB6") +
  theme_minimal() +
  ylab("Criteria Weight") +
  xlab("Criterion")
```

B.2 Monte Carlo Sensitivity (R Sketch)

```
set.seed(123)
B <- 100
rho_vals <- numeric(B)

for (b in 1:B) {
  # Perturb weights ±20%
  eps        <- rnorm(length(weights), mean = 1, sd = 0.20)
  w_pert     <- weights * eps
  w_pert     <- w_pert / sum(w_pert)

  # Recompute TOPSIS with perturbed weights
  w_decision   <- sweep(norm_decision, 2, w_pert, `*`)
  ideal_pos_b  <- apply(w_decision, 2, max)
  ideal_neg_b  <- apply(w_decision, 2, min)
```

```
  dpos_b       <- apply(w_decision, 1, function(row) sqrt(sum((row - ideal_pos_b)^2)))
  dneg_b       <- apply(w_decision, 1, function(row) sqrt(sum((row - ideal_neg_b)^2)))
  cc_b        <- dneg_b / (dpos_b + dneg_b)

  # Spearman correlation vs. baseline cc
  rho_vals[b]  <- cor(cc, cc_b, method = "spearman")
}

rho_avg <- mean(rho_vals)
```