Journal of Analytical Uncertainty
Vol. 1, No. 1, December 2025 Page. 35-45
E-ISSN: 3124-6818
https://doi.org/10.63924/jau.v1i1.269

Multi-Criteria Decision Making for Smart City Implementation Using Fuzzy Soft Maut Method

Adem Yolcu[1]*, Taha Yasin Öztürk[2]

[1,2]Department of Mathematics, Kafkas University, Kars, Türkiye
*Corresponding author's email: yolcu.adem@gmail.com

Abstract

Smart city development requires making choices based on multiple and competing criteria. Thus, in these kinds of environment, the opinions of experts are often given in terms of vague language rather than specific numbers. This paper investigates this challenge by developing a Fuzzy Soft Multi-Attribute Utility Theory (MAUT) system for assessing the readiness of metropolitan municipalities to implement a smart city. This is a hybrid method which integrates the parameter-based structured approach of soft sets with the ability to model uncertainty in fuzzy sets and usefulness aggregation rules of MAUT. Triangular fuzzy numbers are employed for the representation of an expert's judgment. A procedure is followed in order to aggregate, normalize the assessments, and then combine them in an overall utility score. The model is developed to help decision-makers in creating a transparent and flexible method to address numerous criteria in uncertain situations in the context of urban and smart city planning.

Keywords: Fuzzy Soft, Method, Smart City, Planning, Decision Making

Article history: Submitted 12/10/2025|Revised 07/11/2025|Accepted 25/12/2025|Online first 28/12/2025

1. Introduction

The fast growth of information and communication technologies (ICT) has changed the way cities and buildings are planned and managed. Issues such as comfort, safety, energy use, and environmental impact are now closely linked with digital systems. Within this setting, intelligent buildings and smart cities have become key concepts, since they bring together technological infrastructure, energy management, environmental performance, and user–oriented services. These systems are not driven by a single factor. They depend on many interacting criteria, including technological capacity, sustainability, service quality, and financial feasibility. For this reason, their evaluation naturally requires a structured multi–criteria decision–making (MCDM) framework [1, 2, 5, 4, 3].

Fuzzy set theory, introduced by Zadeh [7], offers a way to represent such imprecise and linguistic information in mathematical form. At the same time, Molodtsov's soft set theory provides a parameter–based structure that can model uncertainty without the need for strict membership functions [8]. By combining these two ideas, fuzzy soft sets, as proposed by Maji et al. [9, 10], create a flexible framework in which both fuzziness and parameter dependence can be handled together.

Many recent studies have shown that fuzzy and soft set based decision models are well suited for problems in engineering, sustainability, and smart infrastructure assessment [11, 12, 13]. These approaches are often better at reflecting human reasoning and system complexity than classical crisp models. In particular, the integration of fuzzy logic with MAUT has been reported to improve the reliability of decisions by accounting for expert hesitation and uncertainty. This need is especially visible in smart city and intelligent building applications, where technological, environmental, and socio–economic factors are closely intertwined [1].

Multi-Attribute Utility Theory (MAUT) [16, 6] is a systematic method that helps decisionmakers select the best alternative in complex situations involving multiple and often conflicting criteria. While traditional MAUT relies on precise numerical data, hybrid models such as "Fuzzy MAUT" and "HF-MAUT" (Hesitant Fuzzy MAUT) have been developed by integrating Fuzzy Logic and Hesitant Fuzzy Sets to model real-world uncertainties and human judgments [17, 18]. In the literature, Fuzzy MAUT and its derivatives (HF-MAUT) have been applied to various industrial and environmental problems. Kahraman and Kaya [18] proposed a fuzzy multi-criteria benefit model to evaluate the performance of smart buildings. Narayanamoorthy et al. [17] used HF-MAUT and HF-CRITIC methods to select the best use alternative (e.g., groundwater recharge) for reclaimed water in India. Anchan et al. (2024) [20] integrated Fuzzy AHP and Fuzzy MAUT to evaluate the performance of Public Sector Undertakings (PSU) stocks and investment funds. Ahmed et al. (2019) developed a framework incorporating Fuzzy MAUT and Fuzzy AHP for prioritizing and allocating risks in construction projects in Egypt [19].

Based on these considerations, this study develops a fuzzy soft set based MAUT framework for evaluating urban readiness for smart city implementation. The proposed model combines the clear utility structure of MAUT with the flexible representation of fuzzy soft sets. In this way, linguistic expert judgments, multiple criteria, and uncertainty can be handled at the same time, without losing the additive logic of utility theory. By applying the model to a real decision problem, the study contributes both to the methodology of decision science and to practical urban planning.

2. Preliminaries

Definition 1. [8] *Let U be an initial universe set and E be a set of parameters. Let* $\mathrm{P}(U)$ *denote the power set of U. A pair* (F,E) *is called a soft set over U, where F is a mapping given by:*

$$F : E \rightarrow \mathrm{P}(U).$$

In this context, a soft set is a parameterized family of subsets of the universe U.

Definition 2. [9] *Let U be a universal set and E be a set of parameters. Let* F(U) *be the set of all fuzzy subsets of U. A pair* (F,E) *is called a fuzzy soft set over U, where F is a mapping:*

$$F : E \to \mathrm{F}(U).$$

For each parameter $e \in E$, $F(e)$ is a fuzzy set in U characterized by a membership function $\mu_{F(e)}(x) \in [0,1]$.

Definition 3. *A triangular fuzzy number (TFN) $\tilde{A}$ is defined as $\tilde{A} = (l,m,u)$, where $l \le m \le u$ and $l,m,u \in \mathbb{R}$. Its membership function is given by*

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l, \\ \dfrac{x-l}{m-l}, & l \le x \le m, \\ \dfrac{u-x}{u-m}, & m \le x \le u, \\ 0, & x > u. \end{cases}$$

Let $\tilde{A}_1 = (l_1,m_1,u_1)$ and $\tilde{A}_2 = (l_2,m_2,u_2)$ be two TFNs and let $k > 0$ be a real scalar. The basic arithmetic operations are defined as [11, 13]*:*

$$\tilde{A}1 \oplus \tilde{A}2 = (l1 + l2,\ m1 + m2,\ u1 + u2),\ k \otimes \tilde{A}_1 = (k\, l_1,\ k\, m_1,\ k\, u_1).$$

For TFNs $\tilde{A}_j = (l_j,m_j,u_j)$ and weights $w_j \ge 0$ with $\sum_{j=1}^{n} w_j = 1$, their linear combination is

$$\sum_{j=1}^{n} w_j \otimes \tilde{A}_j = \left(\sum_{j=1}^{n} w_j l_j,\ \sum_{j=1}^{n} w_j m_j,\ \sum_{j=1}^{n} w_j u_j \right).$$

These operations allow the model to aggregate weighted utility scores while maintaining the fuzzy boundaries of the initial assessments, a feature that classical crisp methods fail to provide.

3. Fuzzy Soft MAUT: Proposed Methodology

The purpose of this section is to formalize the proposed Fuzzy Soft MAUT framework. The goal is to integrate fuzzy soft sets with the additive utility structure of MAUT. This allows expert uncertainty and parameter dependence to be handled in a unified way. The section presents the complete mathematical procedure used to compute and rank alternatives.

Let $A = \{A_1,...,A_m\}$ be alternatives. Let $E = \{e_1,...,e_n\}$ be criteria. Let U be the universe.

A fuzzy soft set is (F,E) with

$$F : E \to \mathrm{F}(U).$$

For $e_j \in E$ and $A_i \in A$,

$$F(e_j)(A_i) = \tilde{x}_{ij}.$$

Each $\tilde{x}_{ij}$ is a TFN:

$\tilde{x}ij = (lij,mij,uij)$, $0 \le lij \le mij \le uij \le 1$. Step 1:

Expert evaluations. Assume K experts. Expert k gives

$$\tilde{x}_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)}).$$

Step 2: Aggregation. Use FWGM [15]:

$$\tilde{x}_{ij} = \left(\prod_{k=1}^{K}(l_{ij}^{(k)})^{1/K}, \prod_{k=1}^{K}(m_{ij}^{(k)})^{1/K}, \prod_{k=1}^{K}(u_{ij}^{(k)})^{1/K}\right).$$

Set $\tilde{D} = [\tilde{x}_{ij}]$.

Step 3: Normalization. Let B be benefit criteria. Let C be cost criteria. If $e_j \in B$, define

$$u_j^* = \max_i u_{ij}, \qquad \tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right).$$

If $e_j \in C$, define

$$l_j^- = \min_i l_{ij}, \qquad \tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right)$$

Step 4: Weighting. Let $w_j \geq 0$ and $\sum_{j=1}^{n} w_j = 1$. For $\tilde{r}_{ij} = (l'_{ij}, m'_{ij}, u'_{ij})$,

$$w_j \otimes \tilde{r}_{ij} = (w_j l'_{ij},\ w_j m'_{ij},\ w_j u'_{ij}).$$

Step 5: Fuzzy utility. Compute

$$\tilde{U}_i = \sum_{j=1}^{n} w_j \otimes \tilde{r}_{ij}.$$

Thus

$$\tilde{U}_i = \left(\sum_{j=1}^{n} w_j l'_{ij}, \sum_{j=1}^{n} w_j m'_{ij}, \sum_{j=1}^{n} w_j u'_{ij}\right).$$

Step 6: Defuzzification. Let $\tilde{U}_i = (l_i, m_i, u_i)$. Set

$$U_i = \frac{l_i + 2m_i + u_i}{4}.$$

Step 7: Ranking. If $U_i > U_k$, then $A_i \succ A_k$. Sort U_i in descending order.

The computational flow of the proposed Fuzzy Soft MAUT method is illustrated in Fig. 1. The diagram summarizes how expert fuzzy soft evaluations are transformed into normalized scores, aggregated through weighted utilities, and finally converted into crisp values for ranking. This visual representation provides a concise overview of the complete decisionmaking process.

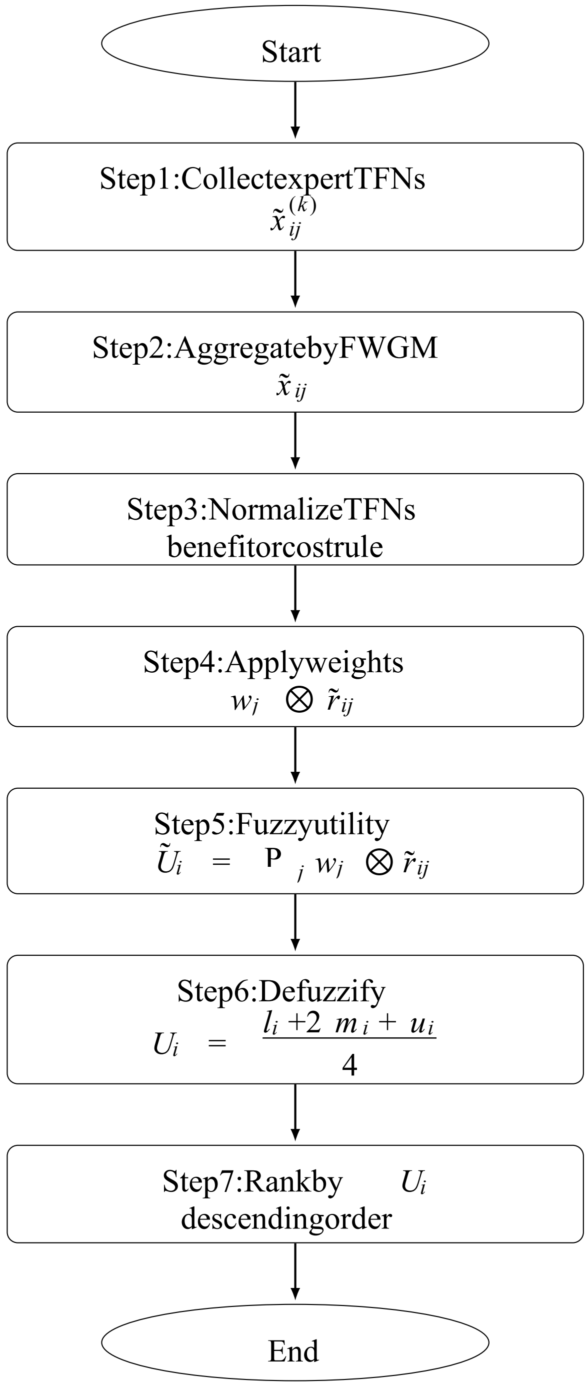

Figure 1. Flowchart of the proposed Fuzzy Soft MAUT procedure.

4. Case Study: Selection of the Most Suitable Municipality

This section applies the proposed Fuzzy Soft MAUT method to a real decision problem. The aim is to identify the Turkish metropolitan municipality that is most ready for smart city implementation.

The alternatives are Ankara (A_1), Istanbul (A_2), Izmir (A_3), Bursa (A_4), and Konya (A_5). The criteria are C_1 (technology), C_2 (sustainability), C_3 (public services), and C_4 (budget efficiency). All criteria are benefit type.

Step 1: Expert TFNs. Five experts provided linguistic assessments for all cities and criteria. These judgments were converted into triangular fuzzy numbers and aggregated by the FWGM operator. Only the final group TFNs are reported in Table–1 and used in all computations.

Each evaluation is recorded as $\tilde{x}_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)})$.

Table 1. Aggregated fuzzy soft decision matrix (group TFNs obtained by FWGM)

City	$\tilde{U}i$	U_i	Rank
Ankara (A_1)	(0.6133, 0.7156, 0.8950)	0.7349	3
Istanbul (A_2)	(0.6983, 0.8006, 0.9028)	0.8006	2
Izmir (A_3)	(0.7656, 0.8678, 0.9700)	0.8678	1
Bursa (A_4)	(0.5583, 0.6606, 0.7628)	0.6606	5
Konya (A_5)	(0.5911, 0.6933, 0.7956)	0.6933	4

Step 2: Aggregation. The group TFNs were computed using the FWGM operator [15]:

$$\tilde{x}_{ij} = \left(\prod_{k=1}^{K} (l_{ij}^{(k)})^{1/K}, \prod_{k=1}^{K} (m_{ij}^{(k)})^{1/K}, \prod_{k=1}^{K} (u_{ij}^{(k)})^{1/K} \right).$$

The aggregated fuzzy soft matrix $\tilde{D} = [\tilde{x}_{ij}]$ is shown in Table 1.

Step 3: Normalization. Since all criteria are benefit type,

$u^*_j = \max_i u_{ij}$,.

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*} \right)$$

Step 4: Weighting. The criteria weights are

$W = (0.30, 0.25, 0.20, 0.25)^T$.

Weighted TFNs are computed as

$w_j \otimes \tilde{r}_{ij}$.

Step 5: Fuzzy utility. The fuzzy MAUT utility of each city is

$$\tilde{U}_i = \sum_{j=1}^{4} w_j \otimes \tilde{r}_{ij}.$$

For Izmir (A_3),

$\tilde{U}_3 = (0.7656, 0.8678,$

$0.9700)$. Step 6: Defuzzification. Crisp utilities are obtained by

$$U_i = \frac{l_i + 2m_i + u_i}{4}.$$

For Izmir,

$U_3 = 0.8678.$

Step 7: Ranking. Alternatives are ranked by U_i. The final order is

$$A_3 \succ A_2 \succ A_1 \succ A_5 \succ A_4.$$

Izmir (A_3) is the best city. Bursa (A_4) is the weakest.

5. Comparative Analysis

This section benchmarks the proposed method. Three references are used. They are Classical MAUT, Fuzzy TOPSIS, and VIKOR on defuzzified TFNs. The same TFN matrix (Table 1) and weights $W = (0.30, 0.25, 0.20, 0.25)^T$ are used. Fuzzy TOPSIS follows Chen [11] and fuzzy VIKOR follows Opricovic [14].

5.1. Classical MAUT. Each TFN is defuzzified by

$$x_{ij}^c = \frac{l_{ij} + 2m_{ij} + u_{ij}}{4}.$$

Then MAUT is

$$U_i^{MAUT} = \sum_{j=1}^{4} w_j x_{ij}^c.$$

The computed scores are in Table 2.

Table 2. Classical MAUT scores (computed from Table 1)

City	$U_i MAUT$	Rank
Ankara (A_1)	0.7188	3
Istanbul (A_2)	0.7850	2
Izmir (A_3)	0.8500	1
Bursa (A_4)	0.6450	5
Konya (A_5)	0.6800	4

5.2. Fuzzy TOPSIS. Normalization follows the benefit-type rule used in Section 3:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right)$$

$u^*_j = \max_i u_{ij}$,.

Weighted TFNs are

$\tilde{v}_{ij} = w_j \otimes \tilde{r}_{ij}.$

Let $\tilde{v}_{ij} = (l_{ij}^v, m_{ij}^v, u_{ij}^v)$.

FPIS and FNIS are defined componentwise as

$$\tilde{v}_j^+ = \left(\max_i l_{ij}^v, \max_i m_{ij}^v, \max_i u_{ij}^v\right), \qquad \tilde{v}_j^- = \left(\min_i l_{ij}^v, \min_i m_{ij}^v, \min_i u_{ij}^v\right).$$

Chen's vertex distance is used [11]. For $\tilde{a} = (l_1, m_1, u_1)$ and $\tilde{b} = (l_2, m_2, u_2)$:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2}{3}}.$$

Distances are

$$D_i^+ = \sum_{j=1}^{4} d(\tilde{v}_{ij}, \tilde{v}_j^+), \qquad D_i^- = \sum_{j=1}^{4} d(\tilde{v}_{ij}, \tilde{v}_j^-).$$

The closeness coefficient is

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}.$$

All values are computed from Table 1 using the normalization and weighting rules in Section 3. Results are in Table 3.

Table 3. Fuzzy TOPSIS results (Chen [11])

City	$Di+$	$Di-$	CC_i	Rank
Ankara (A_1)	0.1628	0.1239	0.4321	3
Istanbul (A_2)	0.0972	0.1805	0.6500	2
Izmir (A_3)	0.0300	0.2471	0.8918	1
Bursa (A_4)	0.2372	0.0426	0.1523	5
Konya (A_5)	0.2044	0.0754	0.2695	4

5.3. VIKOR on defuzzified TFNs. VIKOR is applied to defuzzified TFN performance values. Each TFN is defuzzified by

$$x_{ij}^c = \frac{l_{ij} + 2m_{ij} + u_{ij}}{4}.$$

For benefit criteria,

$$f_j^* = \max_i x_{ij}^c, \qquad f_j^- = \min_i x_{ij}^c.$$

The normalized regret term is

$$d_{ij} = \frac{f_j^* - x_{ij}^c}{f_j^* - f_j^-}.$$

Opricovic's measures are used [14]:

$$S_i = \sum_{j=1}^{4} w_j d_{ij}, \qquad R_i = \max_{1 \le j \le 4} \left(w_j d_{ij}\right).$$

The compromise index is

$$Q_i = v\frac{S_i - S^*}{S^- - S^*} + (1-v)\frac{R_i - R^*}{R^- - R^*}, \qquad v = 0.5,$$

where

$S^* = \min S_i$, $S^- = \max S_i$, $R^* = \min R_i$, $R^- = \max R_i$. i i i i

A smaller Q_i is better.
Computed results are in Table 4.

Table 4. VIKOR results (Opricovic [14])

City	S_i	R_i	Q_i	Rank
Ankara (A_1)	0.5833	0.2500	0.7052	4
Istanbul (A_2)	0.3576	0.1667	0.3427	2
Izmir (A_3)	0.1000	0.1000	0.0000	1

Bursa (A_4)	0.8318	0.3000	1.0000	5
Konya (A_5)	0.7485	0.2000	0.6931	3

5.4. Ranking consistency. The proposed method yields

$$A_3 \succ A_2 \succ A_1 \succ A_5 \succ A_4.$$

Classical MAUT and Fuzzy TOPSIS match this order. VIKOR swaps A_1 and A_5. Spearman rank correlation is used:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}.$$

Between Fuzzy Soft MAUT and TOPSIS, $\rho = 1.0$. Between Fuzzy Soft MAUT and VIKOR, $\rho = 0.9$.

The comparative results show a strong agreement between the proposed Fuzzy Soft MAUT and Fuzzy TOPSIS, with a perfect Spearman correlation. This indicates that the utilitybased fuzzy soft aggregation captures the same preference structure as the distance-based fuzzy TOPSIS model. Fuzzy VIKOR produces a very similar ranking but slightly interchanges Ankara and Konya, which reflects its emphasis on the maximum individual regret. Overall, Izmir remains the dominant alternative across all methods, confirming the stability of the decision outcome.

6. Sensitivity Analysis

This section tests weight sensitivity. Only weights are changed. The TFN matrix stays fixed. The full procedure is recomputed.

We use six scenarios. They are $S0$–$S5$. All criteria are benefit type.

6.1. Weight scenarios. The tested weight vectors are given in Table 5. Table 5.

Weight scenarios used in the sensitivity test

Scenario	w_1	w_2	w_3	w_4
$S0$ (Base)	0.30	0.25	0.20	0.25
$S1$ ($C_1 \uparrow$)	0.60	0.14	0.12	0.14
$S2$ ($C_2 \uparrow$)	0.12	0.60	0.14	0.14
$S3$ ($C_3 \uparrow$)	0.15	0.12	0.60	0.13
$S4$ ($C_4 \uparrow$)	0.14	0.12	0.14	0.60
$S5$ (Equal)	0.25	0.25	0.25	0.25

6.2. Recomputation rules. For each scenario, the same steps are applied. Normalization is benefit-type:

$$u_j^* = \max_i u_{ij}, \qquad \tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right).$$

Fuzzy utilities are:

$$\tilde{U}_i = \sum_{j=1}^{4} w_j \otimes \tilde{r}_{ij}.$$

Defuzzification is:

$$U_i = \frac{l_i + 2m_i + u_i}{4}.$$

Ranking is by decreasing U_i.

6.3. Results. Table 6 reports the crisp utilities. Ranks are shown in parentheses.

Table 6. Sensitivity results: crisp utilities U_i and ranks

Scenario	A_1	A_2	A_3	A_4	A_5	Leader
$S0$	0.7349 (3)	0.8006 (2)	0.8678 (1)	0.6606 (5)	0.6933 (4)	A_3
$S1$	0.7312 (3)	0.8433 (1)	0.8387 (2)	0.6353 (5)	0.6960 (4)	A_2
$S2$	0.6868 (4)	0.7949 (2)	0.8864 (1)	0.6849 (5)	0.6953 (3)	A_3
$S3$	0.7711 (3)	0.7887 (2)	0.8783 (1)	0.7187 (4)	0.6800 (5)	A_3
$S4$	0.7693 (2)	0.7509 (3)	0.8844 (1)	0.6369 (5)	0.6953 (4)	A_3
$S5$	0.7389 (3)	0.7944 (2)	0.8722 (1)	0.6694 (5)	0.6917 (4)	A_3

7. Discussion.

The leader is stable in five scenarios. Izmir (A_3) stays first in $S0$, $S2$, $S3$, $S4$, $S5$. A change appears in $S1$. This is the technology-dominant case. In $S1$, Istanbul (A_2) becomes first. Its C_1 score is the highest. Thus the dominance of w_1 matters. Lower ranks are more sensitive. A_1 and A_5 change positions. This occurs under $S2$, $S3$, $S4$. The last place is stable. Bursa (A_4) remains last in all scenarios.

7. Conclusion

This study examined a fuzzy soft MAUT framework for smart city evaluation. The objective was to integrate parameterized fuzzy information into a utility–based structure. This integration allows expert uncertainty to be represented in a systematic form. The model was applied to five metropolitan municipalities in Turkey using four key criteria. The results indicated that Izmir is the most suitable city for smart city implementation. This outcome was also supported by the rankings obtained from Fuzzy TOPSIS and Fuzzy VIKOR, which strengthens the reliability of the findings. The sensitivity analysis showed that the leading position of Izmir is largely stable under different weight configurations. Only when technological infrastructure was assigned to dominant weight did Istanbul slightly outperform Izmir, reflecting its strong technological capacity. An important feature of the proposed approach is that it preserves both fuzzy uncertainty and parameter dependence while maintaining a clear utility–based ranking mechanism. This makes the framework suitable for complex urban decision problems that involve both qualitative and quantitative criter This study has some limitations. The utility function is linear and the number of experts is limited. These aspects may be refined in future research. Future work may extend the framework by incorporating neutrosophic or hesitant fuzzy soft structures. The development of a decision support system based on the proposed model also represents a meaningful direction for further investigation.

8. References

[1] Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis G. & Portugali, Y. (2012). Smart cities of the future. The European Physical Journal Special Topics, 214(1), 481-518.

[2] Triantaphyllou, E. (2000). Multi-criteria decision making methods. In Multi-criteria decision making methods: A comparative study (pp. 5-21). Springer, Boston, MA.

[3] Yolcu, A. (2023). Intuitionistic fuzzy hypersoft topology and ıts applications to multi-criteria decisionmaking. Sigma Journal of Engineering and Natural Sciences, 41(1), 106-118.

[4] Yolcu, A. (2022). Bipolar spherical fuzzy soft topology with applications to multi-criteria group decisionmaking in buildings risk assessment. Symmetry, 14(11), 2362.

[5] Yolcu, A., & Ozturk, T. Y. (2021). Fuzzy hypersoft sets and it's application to decision-making. Theory and application of hypersoft set, 50.

[6] Keeney, R. L., & Raiffa, H. (1993). *Decisions with Multiple Objectives: Preferences and Value TradeOffs*. Cambridge University Press.
[7] Zadeh, L. A. (1965). Fuzzy sets.*Information and Control*, 8(3), 338–353.
[8] Molodtsov, D. (1999). Soft set theory—First results. *Computers & Mathematics with Applications*, 37(4–5), 19–31.
[9] Maji, P. K., Biswas, R., & Roy, A. R. (2001). Fuzzy soft sets. *Journal of Fuzzy Mathematics*, 9(3), 589–602.
[10] Maji, P. K., Roy, A. R., & Biswas, R. (2002). An application of soft sets in a decision making problem. *Computers & Mathematics with Applications*, 44(8–9), 1077–1083.
[11] Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems*, 114(1), 1–9.
[12] Govindan, K., Rajendran, S., Sarkis, J., & Murugesan, P. (2015). Multi criteria decision making approaches for green supplier evaluation and selection: A literature review. *Journal of Cleaner Production*, 98, 66–83.
[13] Zimmermann, H.J., 2011. Fuzzy Set Theory—And its Applications. Springer Science & Business Media.
[14] Opricovic, S., & Tzeng, G. H. (2004). Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS. European journal of operational research, 156(2), 445-455.
[15] Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems*, 17(3), 233–247.
[16] Jansen, S.J.T. (2011). The Multi-attribute Utility Method. In: Jansen, S., Coolen, H., Goetgeluk, R. (eds) The Measurement and Analysis of Housing Preference and Choice. Springer, Dordrecht. https://doi.org/10.1007/978-90-481-8894-9-5
[17] Narayanamoorthy, S., Annapoorani, V., Kang, D., & Ramya, L. (2019). Sustainable assessment for selecting the best alternative of reclaimed water use under hesitant fuzzy multi-criteria decision making. IEEE Access, 7, 137217-137231.
[18] Kahraman, C., & Kaya, I. (2012). A fuzzy multiple attribute utility model for intelligent building˙ assessment. Journal of civil engineering and management, 18(6), 811-820.
[19] Ahmed, R., Afifi, M., & Nassar, A. (2019, June). Using multi-criteria decision making (MCDM) methods in Egyptian construction projects. In Canadian Society for Civil Engineering Annual Conference.
[20] Anchan, V., Vaidya, S., Jain, A., & Chaplot, R. (2024). Synergizing Fuzzy AHP and MAUT for Integrated Evaluation of PSU Stocks and Mutual Fund Schemes. International Journal of Multidisciplinary research and analaysis. 7(11), 5137-5151. DOI: 10.47191/ijmra/v7-i11-20.