

Comparing Fuzzy TOPSIS and Hierarchical COMET: A Mathematical Perspective on Uncertain Decision-Making

Selin İrem Aşlakcioğlu, Beste Çetin, Lara Dinçer and Syed Shah Sultan Mohiuddin Qadri

Department of Industrial Engineering

Çankaya University Ankara, Türkiye

c2312008@student.cankaya.edu.tr, c2312016@student.cankaya.edu.tr,

c2312022@student.cankaya.edu.tr, syedshahsultan@cankaya.edu.tr

Abstract

This study compares an inherently fuzzy decision framework-the Characteristic Objects Method (COMET)-and a traditional fuzzified methodology, Fuzzy TOPSIS, to evaluate how their underlying mathematical foundations influence gaming CPU rankings. Utilizing an empirical comparison, thirteen modern processors are evaluated across six technical and economic criteria: core count, thread count, thermal design power (TDP), cache, price, and average gaming frames per second (FPS). Architectural criteria are represented as crisp triangular fuzzy numbers (c, c, c) , while FPS and price are modeled as fluctuating triangular fuzzy numbers (l, m, u) . The Entropy Weighting Method (EWM) utilized for objective criterion weighting, which is integrated into Fuzzy TOPSIS, and a Simple Additive Weighting (SAW) benchmark solved via GAMS. Furthermore, a multi-scenario sensitivity analysis involving a ($\pm 10\%$) perturbation across price, TDP, and FPS was executed, alongside rank correlation measures (Spearman's ρ , Kendall's τ , Goodman-Kruskal's γ and WS coefficient). Results reveal a significant ranking divergence; Hierarchical COMET ranks the AMD Ryzen 7 9700X first, whereas Fuzzy TOPSIS prioritizes 3D V-Cache models such as the AMD Ryzen 7 5800X3D. Both models demonstrate robust stability under parameter perturbations, maintaining high rank correlation coefficients across all scenarios. Consequently, this paper demonstrates that final decision outcomes are more sensitive to the chosen methodological structure than to variations in input parameters, providing critical theoretical and practical insights for multi-constraint hardware selection problems.

Keywords

Fuzzy MCDM, Fuzzy TOPSIS, Hierarchical COMET, Entropy-weighting, Hardware Selection.

1. Introduction

Decision-making problems involving uncertainty, ambiguity, and conflicting criteria are increasingly common in engineering, management, sustainability, and technology related applications. Therefore, Multi-Criteria Decision-Making (MCDM) methods have become important analytical tools for supporting complex decision-making processes through structured evaluation frameworks (Bhole and Deshmukh 2018; Kumar 2025).

Traditional MCDM methods generally operate under deterministic assumptions using precise numerical information. However, many real-world decision environments involve vague and linguistically expressed information that cannot be represented accurately using crisp values alone. To address this limitation, fuzzy logic has been extensively integrated into classical MCDM methods, enabling decision makers to incorporate uncertainty and subjective judgments into evaluation processes (Nădăban et al. 2016). Fuzzy MCDM approaches have been widely applied in supplier selection, sustainability analysis, healthcare systems, and engineering optimization problems (Chen et al. 2019).

Among fuzzy MCDM approaches, Fuzzy TOPSIS remains one of the most widely used methods due to its computational simplicity and intuitive ranking mechanism (Baral et al. 2025). In contrast, COMET represents an inherently fuzzy decision-making framework based on characteristic objects and fuzzy preference structures (Faizi et al. 2020). Although COMET provides stable ranking behavior, standard COMET implementations may become computationally expensive as the number of criteria increases. Therefore, hierarchical COMET structures have been proposed to improve scalability and reduce computational complexity.

In addition to decision methodology selection, criterion weighting also significantly influences MCDM results. Among objective weighting techniques, the Entropy Weighting Method (EWM) has gained significant attention because it reduces dependence on subjective judgments (Li et al. 2022; Wang and Lee 2009). Despite the growing literature on fuzzy MCDM approaches, limited studies have directly compared fuzzified classical methods such as Fuzzy TOPSIS with inherently fuzzy frameworks such as hierarchical COMET. Therefore, this study investigates the methodological trade-offs between these two approaches within a mathematical modeling-supported fuzzy MCDM framework using entropy-based objective weighting, sensitivity analysis, and rank correlation measures.

The remainder of the paper is organized as follows. Section 2 presents the related literature, Section 3 describes the proposed methodology, Section 4 provides data collection, Section 5 provides the results, and Section 6 concludes the study.

1.1 Objectives

The primary objective of this study is to conduct a systematic methodological comparison between the Characteristic Objects Method (COMET)-an inherently fuzzy, rule-based decision framework-and the classical fuzzified MCDM approach, Fuzzy TOPSIS; Secondly to integrate entropy-based objective weighting to eliminate subjective bias in criterion importance; Furthermore, the study seeks to validate the robustness of these rankings through sensitivity analysis and rigorous rank correlation measures to implement and solve SAW models in GAMS as mathematical benchmarks.

2. Literature Review

This section reviews the existing literature on fuzzy MCDM methods, criterion weighting techniques, and comparative decision-making frameworks relevant to this study. MCDM methods such as TOPSIS, VIKOR, ELECTRE, PROMETHEE, and COMET have been widely applied in engineering, healthcare, logistics, sustainability, and technology evaluation problems (Bhole and Deshmukh 2018; Kumar 2025).

Among these approaches, TOPSIS has become one of the most widely used MCDM methods because alternatives are ranked according to their relative distances from ideal and anti-ideal solutions (Çelikkilek and Tüysüz 2020). To improve uncertainty handling, fuzzy logic has been integrated into TOPSIS, resulting in Fuzzy TOPSIS methods utilizing fuzzy numbers and linguistic variables (Baral et al. 2025; Nădăban et al. 2016). Previous studies have also discussed issues related to normalization sensitivity, Euclidean distance calculations, rank reversal behavior, and dependency on a single ranking index in TOPSIS based methods (Çelikkilek and Tüysüz 2020).

COMET was proposed as an alternative MCDM framework based on characteristic objects and fuzzy rule-based preference structures (Faizi et al. 2020). Previous studies have applied COMET in product selection and consumer decision-making problems involving multiple conflicting criteria. However, increasing numbers of criteria and characteristic objects may lead to computational complexity issues in standard COMET implementations. Therefore, hierarchical COMET structures have been introduced to improve scalability and computational efficiency.

Criterion weighting also significantly influences MCDM results. Previous studies have shown that EWM improves objectivity by assigning higher weights to criteria with greater information variability (Li et al. 2022). In addition, sensitivity analysis and rank correlation measures are frequently used to evaluate ranking consistency and robustness in MCDM applications (Demir et al. 2024). Previous studies have also integrated mathematical optimization models with MCDM approaches to support multi-constraint decision-making problems (Dordevic et al. 2022; Taherdoost 2023).

Although many studies have investigated fuzzy MCDM methods independently, limited attention has been given to the methodological comparison between fuzzified classical methods and inherently fuzzy frameworks. Therefore, this

study compares Fuzzy TOPSIS and hierarchical COMET under an entropy-based weighting framework to investigate their methodological differences and ranking behavior.

3. Methods

3.1. Research Framework

This paper presents a comparative framework for evaluating gaming CPUs under uncertain and conflicting criteria. The framework integrates entropy-based weighting, fuzzy and inherently fuzzy MCDM methods, mathematical modelling, and ranking convergence analysis.

Gaming-related criteria, including average FPS and market price, were represented using triangular fuzzy numbers to reflect uncertainty. Criterion weights were objectively determined through the entropy method and integrated into Fuzzy TOPSIS (Mavi et al. 2016). To reduce the computational complexity of COMET, a hierarchical structure was adopted (Watrobski et al. 2017). In addition to that, a Subjective Additive Weighting model was implemented in GAMS under equal and entropy-based weighting scenarios to examine ranking convergence with fuzzy MCDM methods.

3.2. Determination of Alternative and Criteria

This study considers thirteen gaming-oriented CPU alternatives available in the Turkish market, including both AMD Ryzen and Intel Core processor families from different performance and price segments. The evaluation is based on six criteria: Core Count, Thread Count, Cache, Thermal Design Power (TDP), Market Price, and Average Gaming FPS. Core Count, Thread Count, Cache, and FPS are considered benefit criteria, while TDP and Price are treated as cost criteria.

Average FPS values were obtained from TechPowerUp benchmark scores, whereas market prices were collected from e-commerce platforms. Due to market and benchmark uncertainty, FPS and Price were represented using triangular fuzzy numbers (l, m, u) . In contrast, Core Count, Thread Count, Cache, and TDP were modeled as crisp triangular fuzzy numbers (c, c, c) since these values remain fixed (Chen 2000).

3.3. Entropy Weighting Method

The Entropy Weighting Method (EWM) is utilized to determine the relative importance of the evaluation criteria objectively which calculates criterion based on the degree of information provided data itself. The methodological flowchart and mathematical execution steps of the Entropy Weighting Method (EWM) are illustrated in Figure 1.

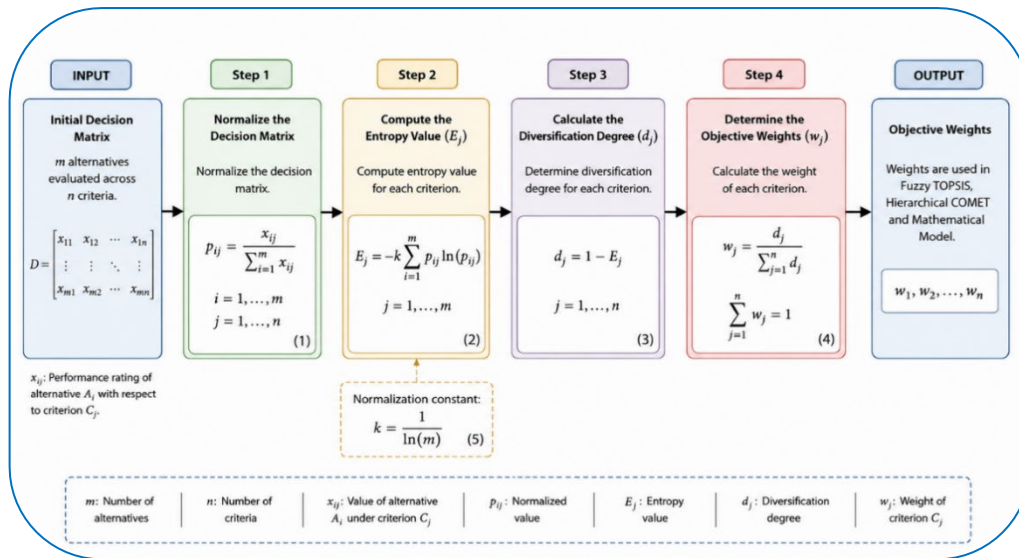


Figure 1. Methodological Flowchart and Mathematical Execution Steps of the Entropy Weighting Method (EWM).

3.4. Fuzzy TOPSIS

Fuzzy TOPSIS was applied to rank the CPU alternatives based on their closeness to the Fuzzy Positive Ideal Solution (FPIS) and Fuzzy Negative Ideal Solution (FNIS) (Chen 2000). The entropy-based weights obtained from EWM were integrated into the fuzzy evaluation process.

Step 1: Normalize the Fuzzy Decision Matrix: The fuzzy decision matrix is normalized using linear scale transformation to maintain the structural integrity of triangular fuzzy ranges. The applied formulations for benefit and cost criteria are provided below:

For benefit criteria:

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*} \right), \quad u_j^* = \max_i u_{ij} \quad (1)$$

For cost criteria:

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}} \right), \quad l_j^- = \min_i l_{ij} \quad (2)$$

Step 2: Construct the Weighted Normalized Fuzzy Decision Matrix: The obtained Entropy weights were multiplied by the normalized fuzzy scores to account for the relative importance of each criterion.

$$\tilde{v}_{ij} = \tilde{r}_{ij} \cdot w_j = (w_j l_{ij}, w_j m_{ij}, w_j u_{ij}) \quad (3)$$

Step 3: Determine Fuzzy Positive Ideal Solution (A^+) and Fuzzy Negative Ideal Solution (A^-): Ideal solutions are determined by identifying the maximum upper bounds and minimum lower bounds across alternatives:

$$A^+ = \{\tilde{v}_1^*, \dots, \tilde{v}_n^*\} \text{ where } \tilde{v}_j^* = \max_i \tilde{u}_{vij} \quad (4)$$

$$A^- = \{\tilde{v}_1^-, \dots, \tilde{v}_n^-\} \text{ where } \tilde{v}_j^- = \min_i \tilde{l}_{vij}$$

Step 4: Calculate the Distance of Each Alternative from the Ideal Solutions S_i^+ and S_i^- : The relative distances of each alternative from the fuzzy positive and negative ideal solutions are calculated using the n-dimensional Vertex method:

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{[(l_a - l_b)^2 + (m_a - m_b)^2 + (u_a - u_b)^2]}{3}} \quad (5)$$

$$S_i^+ = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*), \quad S_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-), \quad i = 1, \dots, m \quad (6)$$

Step 5: Compute the Relative Closeness Coefficient (C_i^*): To determine the final ranking in descending order closeness coefficient is calculated where rank order is inversely proportional to C_i^* value:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-}, \quad i = 1, \dots, m \quad (7)$$

3.5 Hierarchical COMET

Traditional COMET method, introduced by Sałabun, provides an inherently fuzzy approach for multi-criteria decision-making by utilizing characteristic objects and fuzzy preference structure (Kizielewicz et al. 2024; Sałabun, 2015). However, the number of characteristic objects increases exponentially as the number of criteria grows, leading to high computational complexity. To overcome this limitation, hierarchical decomposition is employed to reduce computational burden while preserving the core structure of the original COMET methodology. The following Algorithm 1 provides the pseudocode of procedure of Hierarchical COMET.

Algorithm 1: Hierarchical COMET for Gaming CPU Evaluation

Input:

$A = \{A_1, A_2, \dots, A_{13}\}$ // CPU alternatives

$C = \{C_1, C_2, \dots, C_6\}$ // Evaluation criteria

Output:

Final ranking of CPU alternatives

BEGIN

1. Define characteristic values for each criterion:

$$C_j = \{c_{j1}, c_{j2}, \dots, c_{jk}\}$$

2. Construct hierarchical sub-models:

$$S_1 = \{C_1, C_2\} \quad // \text{ Computational performance}$$

$$S_2 = \{C_4, C_6\} \quad // \text{ Gaming performance}$$

$$S_3 = \{C_3, C_5\} \quad // \text{ Cost-efficiency}$$

3. FOR each criterion C_j DO

Determine x_{min} and x_{max}

Compute fuzzy boundaries:

$$BL = x_{min} + (x_{max} - x_{min})/3$$

$$BH = x_{min} + 2(x_{max} - x_{min})/3$$

Define triangular fuzzy numbers:

$$A_j^{Low} = (x_{min}, x_{min}, BL_j)$$

$$A_j^{Med} = (x_{min}, BL_j, BH_j)$$

$$A_j^{High} = (BH_j, x_{max}, x_{max})$$

END FOR

4. FOR each sub-model S_k DO

Generate Characteristic Objects (CO_s)

Combine fuzzy levels of criteria

FOR each pair (CO_r, CO_s) DO

IF $LvlSum(CO_r) > LvlSum(CO_s)$

$$\alpha_{rs} = 1$$

ELSE IF $LvlSum(CO_r) = LvlSum(CO_s)$

$$\alpha_{rs} = 0.5$$

ELSE

$$\alpha_{rs} = 0$$

END IF

END FOR

Compute preference scores:

$$SJ(CO_r) = \sum_{s=1}^t \alpha_{rs}$$

$$P(CO_r) = \frac{SJ(CO_r)}{t-1}$$

FOR each alternative A_i DO

Compute membership degrees

$$\mu_{Low}, \mu_{Med}, \mu_{High}$$

Compute activation weights:

$$\omega_r = \min(\mu_1, \mu_2, \dots, \mu_q)$$

Compute sub-model score:

$$S_k(i) = \frac{\sum_{r=1}^t \omega_r \cdot P(CO_r)}{\sum_{r=1}^t \omega_r}$$

END FOR

END FOR

5. Construct Final COMET Model:
Inputs = $\{S_1(A_i), S_2(A_i), S_3(A_i)\}$
6. Repeat fuzzy inference procedure
(boundaries, COs, MEJ, memberships)
7. Compute final preference score (P_k):
$$P_k(A_i) = \frac{\sum_{r=1}^t \omega_r \cdot P(CO_r)}{\sum_{r=1}^t \omega_r}$$
8. Rank CPU alternatives
in descending order of $P(A_i)$
- END

3.6. Simple Additive Weighting (SAW)

The Simple Additive Weighting (SAW) method, also known as the Weighted Sum Model (WSM), evaluates alternatives using weighted normalized criterion values (Belton and Stewart 2002). Unlike fuzzy rule-based or distance-based methods, SAW follows a deterministic additive utility structure. In this study, SAW was used as a mathematical benchmark to examine the ranking convergence of additive utility-based models with Fuzzy TOPSIS and Hierarchical COMET under different weighting scenarios. Let:

$$A = \{A_1, A_2, \dots, A_{13}\} \quad (8)$$

Denote the set of CPU alternatives and

$$C = \{C_1, C_2, \dots, C_6\} \quad (9)$$

denote the set of evaluation criteria, classified as benefit criteria and cost criteria:

$$C^+ = \{C_1, C_2, C_4, C_6\}, \quad C^- = \{C_3, C_5\} \quad (10)$$

The decision matrix:

$$X = [x_{ij}]_{13 \times 6} \quad (11)$$

was first normalized using min-max normalization. For benefit criteria and for cost criteria:

$$r_{ij} = \frac{x_{ij} - x_{j,min}}{x_{j,max} - x_{j,min}}, \quad r_{ij} = \frac{x_{j,max} - x_{ij}}{x_{j,max} - x_{j,min}} \quad (12)$$

The composite SAW score of each alternative was then calculated as:

$$P_i = \sum_{j=1}^6 w_j r_{ij} \quad (13)$$

Two weighting scenarios were considered. In the first model (SAW-EQ), equal weights were assigned: $w_j = \frac{1}{6}$. In the second model (SAW-EN), entropy-based weights formulation: $E_j = -k \sum_{i=1}^m p_{ij} \ln(p_{ij})$ used.

The optimal alternative was identified as: $A^* = \arg \max_i \{P_i\}$. Both models were implemented and solved in GAMS using the CPLEX solver.

4. Data Collection

This study evaluates thirteen gaming-oriented CPU alternatives available in the Turkish market. The processors represent both AMD Ryzen and Intel Core families across different performance and price tiers. The six evaluation criteria are: Core Count (C_1), Thread Count (C_2), Cache in MB (C_3), Thermal Design Power — TDP in W (C_4), Market Price in TRY (C_5), and Average Gaming FPS (C_6). Core Count, Thread Count, Cache, and TDP are treated as fixed technical values and modeled as crisp triangular fuzzy numbers (c, c, c) . Average FPS and Market Price involve uncertainty and are represented as triangular fuzzy numbers (l, m, u) .

Average FPS values were sourced from TechPowerUp benchmark databases, which aggregate multi-game performance scores across standardized testing conditions. Market prices were collected from major Turkish e-commerce platforms and reflect prices at the time of data collection. Lower and upper bounds of the fuzzy FPS values capture benchmark variability, while price bounds capture observed market fluctuations. The decision matrix containing all criterion values for the thirteen CPU alternatives is presented in Table 1.

Table 1. Decision Matrix of Gaming CPU Alternatives Across Evaluation Criteria.

	Intel Core i5-12400F	AMD Ryzen 5 5600	AMD Ryzen 5 5600X	AMD Ryzen 5 5500	AMD Ryzen 5 7600	AMD Ryzen 7 5800X3D	Intel Core i5-14600K	Intel Core i5-14400F	AMD Ryzen 7 7800X3D	Intel Core i7-14700K	Intel Core i5-12600K	AMD Ryzen 9 9950X	AMD Ryzen 7 9700X
Core Count	6	6	6	6	6	8	14	10	8	20	10	16	8
Thread Count	12	12	12	12	12	16	20	16	16	28	16	32	16
TDP	65	65	65	65	65	105	125	65	120	125	125	170	65
Cache(MB)	18	32	32	16	32	96	24	20	96	33	20	64	32
Price(₺)	6750	4960	6000	3150	7988	16200	12499	8494	16950	22050	14971	25200	13700
Average FPS	142.7	144.1	147.1	124	170.5	171.7	172.9	149	193.1	182.5	153.4	180	178.4

5. Results and Discussion

5.1 Numerical Results

Table 2 presents the ranking results obtained from all four applied methods -Hierarchical COMET, Fuzzy TOPSIS, SAW with equal weights (SAW-EQ), and SAW with entropy weights (SAW-EN)- across the thirteen gaming CPU alternatives evaluated in this study.

Table 2. CPU Alternatives and Ranking Results Across All Four Applied Methods.

CPU Alternatives	COMET	Fuzzy TOPSIS	SAW-EQ	SAW-EN
Intel Core i5-12400F	11	10	11	12
AMD Ryzen 5 5600	10	8	9	10
AMD Ryzen 5 5600X	9	6	10	11
AMD Ryzen 5 5500	13	4	12	13
AMD Ryzen 5 7600	2.5	12	8	9
AMD Ryzen 7 5800X3D	7.5	1	4	4
Intel Core i5-14600K	5	13	6	5
Intel Core i5-14400F	6	11	7	7
AMD Ryzen 7 7800X3D	7.5	2	2	3
Intel Core i7-14700K	2.5	7	1	2
Intel Core i5-12600K	12	5	13	8
AMD Ryzen 9 9950X	4	3	3	1
AMD Ryzen 7 9700X	1	9	5	6

5.2 Graphical Results

5.2.1. Hierarchical COMET Results

The Hierarchical COMET model evaluated 13 gaming CPU alternatives across three sub-models — S1 (Compute: Core Count, Thread Count), S2 (Gaming: Cache, Average Gaming FPS), and S3 (Value: TDP, Price), each comprising 9 Characteristic Objects (COs). The final model integrated their outputs through 27 COs, reducing the dimensionality from the 729 COs that a monolithic formulation would require.

AMD Ryzen 7 9700X achieved the highest preference score ($P_k = 0.857$), while AMD Ryzen 5 7600 and Intel Core i7-14700K shared second place ($P_k = 0.856$, tied rank = 2.5). AMD Ryzen 5 5500 ranked last ($P_k = 0.406$). Sub-model scores reveal a clear trade-off structure: Intel Core i7-14700K and AMD Ryzen 9 9950X led in Compute ($S1 = 1.063$), while AMD Ryzen 7 5800X3D and 7800X3D dominated Gaming ($S2 = 1.063$) owing to their 96 MB 3D V-Cache, but their high TDP and price substantially penalized their Value scores ($S3 = 0.563$), yielding mid-tier final rankings (7.5). 9700X's top position reflects its balanced profile: competitive gaming output ($S2 = 0.719$) combined with the highest Value score among competitive alternatives ($S3 = 0.875$).

5.2.2. Fuzzy TOPSIS Ranking Results

Fuzzy TOPSIS, employing entropy-based criterion weights, ranked AMD Ryzen 7 5800X3D first ($C_i = 0.477$) and AMD Ryzen 7 7800X3D second ($C_i = 0.460$). The entropy procedure assigned the highest weights to Cache (MB) ($w=0.347$) and Price (₺) ($w=0.257$), highlighting the dominant influence of these variables on the model. Consequently, AMD Ryzen 5 7600 and Intel Core i5-14600K, ranked 2.5 and 5 under COMET, were placed 12th and 13th respectively, representing the most pronounced ranking divergence between the two methods.

5.2.3. Mathematical Model Results

Two SAW-based models served as validation benchmarks: SAW with Equal Weights (SAW-EQ) and SAW with Entropy Weights (SAW-EN). SAW-EQ ranked Intel Core i7-14700K first ($P = 0.572$), while SAW-EN identified AMD Ryzen 9 9950X as optimal ($P = 0.690$), as entropy weighting strongly rewarded its maximum core (16) and thread (32) counts. AMD Ryzen 5 5500 ranked last in both models ($P_k = 0.333$ and $P_k = 0.124$, respectively).

The ranking agreement across the applied MCDM methods is visually summarized in Figure 2. The matrix indicates significant methodological divergence between the hierarchical COMET framework and Fuzzy TOPSIS, particularly regarding the evaluation of high-performance gaming CPUs.

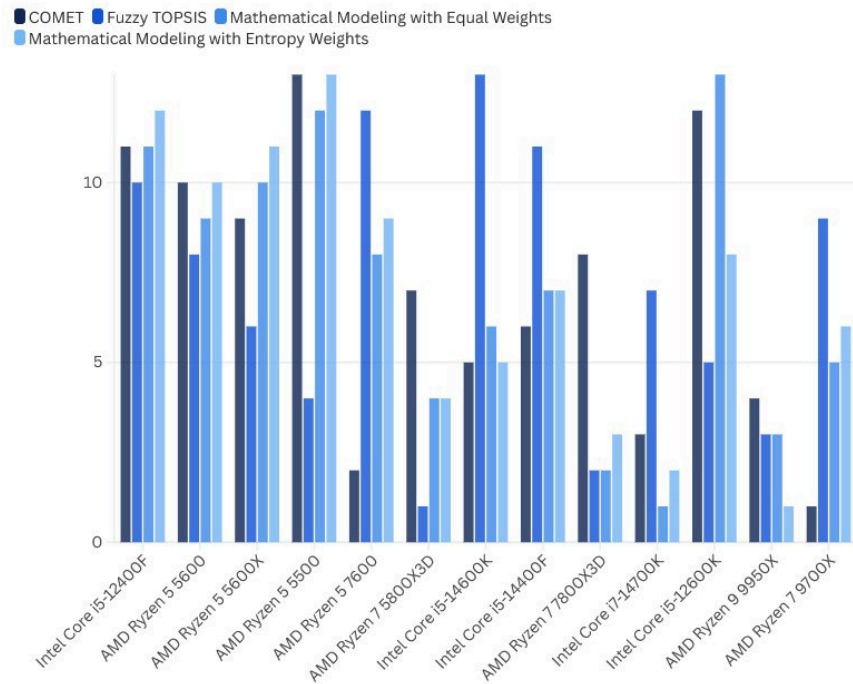


Figure 2. Comparison of ranking results derived from the applied MCDM and mathematical modeling methods for selected gaming CPUs.

5.3 Proposed Improvements

Some improvements for future research are suggested to increase the methodological rigor and practical application of this study. It can be extended by incorporating mechanisms that integrate e-commerce pricing data dynamically, going beyond snapshots to provide dynamic decision support, as discussed above. Second, in the light of the fact that no current solution takes into account the single decision maker assumption, further research could be conducted to

create separate hierarchical COMET systems for specific user profiles like gaming requirements, budget considerations, and professional performance. Third, an empirical rank reversal analysis is needed to assess the robustness of Hierarchical COMET when new CPU alternatives are introduced or old ones are dropped. Fourth, the reliability of the model can be further improved by integrating with the interval-based modeling technique of the criteria, for example, Cache and TDP, to compensate the uncertainty of the benchmarks and a comparative analysis of different weighting technique (AHP or SWARA) can be done to eliminate the effect of different weight technique on the final result ranking. Finally, comparison of the CPU options in local currency prices with the international offerings would give a more complete idea of the effect of currency volatility on the ranking results.

5.4 Validation

5.4.1. Sensitivity Analysis

COMET ranking robustness was assessed by varying Price, Average Gaming FPS, and TDP by $\pm 10\%$. Price variations produced near-perfect stability ($\rho_s = 0.997$, $\tau = 0.974$), as no CPU crossed a TFN boundary under this perturbation (BL = 10,500€, BH = 17,850€). FPS variations produced the greatest sensitivity ($\rho_s = 0.876$, $\tau = 0.795$ for $+10\%$; $\rho_s = 0.788$, $\tau = 0.615$ for -10%), confirming gaming performance as the most influential dynamic criterion. TDP variations yielded strong stability in both directions ($\rho_s > 0.929$, $\tau > 0.872$). All coefficients exceeded 0.60 across all six scenarios, confirming ranking stability under realistic perturbations.

Similarly, evaluating the Fuzzy TOPSIS model under the identical $\pm 10\%$ criteria shifts revealed a highly coherent and resilient behavior. The preference structure proved to be remarkably stable, particularly at the top of the hierarchy, where premium options like the AMD Ryzen 7 5800X3D and AMD Ryzen 7 7800X3D consistently locked in their 1st and 2nd places throughout all test cases. Although minor 1–2 position adjustments were observed in mid-range alternatives—such as the Intel Core i7-14700K reacting to specific price and TDP fluctuations—these minimal variations do not compromise the overall framework, confirming that both multi-criteria tools deliver dependable and solid alignment under uncertainty.

5.4.2 Rank Correlation Analysis

Ranking agreement across COMET, Fuzzy TOPSIS, SAW-EQ, and SAW-EN was assessed using Spearman's ρ_s , Kendall's τ , the WS coefficient, and Goodman-Kruskal's γ , with tied ranks assigned as averages. COMET showed strong agreement with SAW-EQ ($\rho_s = 0.731$, $\tau = 0.564$, WS = 0.694, $\gamma = 0.579$) and moderate-to-strong agreement with SAW-EN ($\rho_s = 0.641$, $\tau = 0.462$, WS = 0.643, $\gamma = 0.474$), validating the COMET ranking against the mathematical benchmarks. SAW-EQ and SAW-EN exhibited very strong mutual agreement ($\rho_s = 0.896$, $\tau = 0.795$, WS = 0.903, $\gamma = 0.795$).

In contrast, COMET and Fuzzy TOPSIS produced negative correlations ($\rho_s = -0.321$, $\tau = -0.231$, $\gamma = -0.237$), while the WS coefficient remained positive (WS = 0.370), indicating that methodological disagreement is concentrated among lower-ranked alternatives with partial agreement preserved at the top. Fuzzy TOPSIS also showed weak agreement with both SAW-EQ ($\rho_s = 0.209$, $\tau = 0.077$) and SAW-EN ($\rho_s = 0.286$, $\tau = 0.128$).

This divergence is most strikingly illustrated by AMD Ryzen 7 5800X3D, ranked 1st by Fuzzy TOPSIS yet 7.5th by COMET, and by AMD Ryzen 7 9700X, ranked 1st by COMET yet 9th by Fuzzy TOPSIS. Fuzzy TOPSIS's entropy-weighted ideal solution approach rewards the 5800X3D's exceptional cache and thread count, while COMET's hierarchical structure penalizes its 105 W TDP and 16,200€ price through the Value sub-model ($S_3 = 0.563$). 9700X's competitive gaming output with low TDP (65 W) and moderate price (13,700€) is rewarded under COMET's equal sub-model weighting but overlooked under entropy-driven criterion importance. These methodological differences are visually summarized in the Spearman rank correlation matrix presented in Figure 3. Furthermore, the detailed numerical values of these correlations including Spearman's ρ , Kendall's τ , WS coefficient, and Goodman-Kruskal's γ are provided in Table 3 to facilitate a precise quantitative comparison between the evaluated frameworks.

Table 3. Rank Correlation Coefficients Across the Applied MCDM and Mathematical Modeling Methods.

Rank Correlation Coefficients	Spearman ρ_s	Kendall τ	WS	Goodman-Kruskal γ
COMET vs Fuzzy TOPSIS	-0.321428571	-0.230769231	0.370165413	-0.236842105
COMET vs SAW-EQ	0.730769231	0.564102564	0.69436536	0.578947368
COMET vs SAW-EN	0.64010989	0.461538462	0.643325069	0.473684211
Fuzzy TOPSIS vs SAW-EQ	0.208791209	0.076923077	0.769454969	0.076923077
Fuzzy TOPSIS vs SAW-EN	0.285714286	0.128205128	0.732974063	0.128205128
SAW-EQ vs SAW-EN	0.895604396	0.794871795	0.903435099	0.794871795

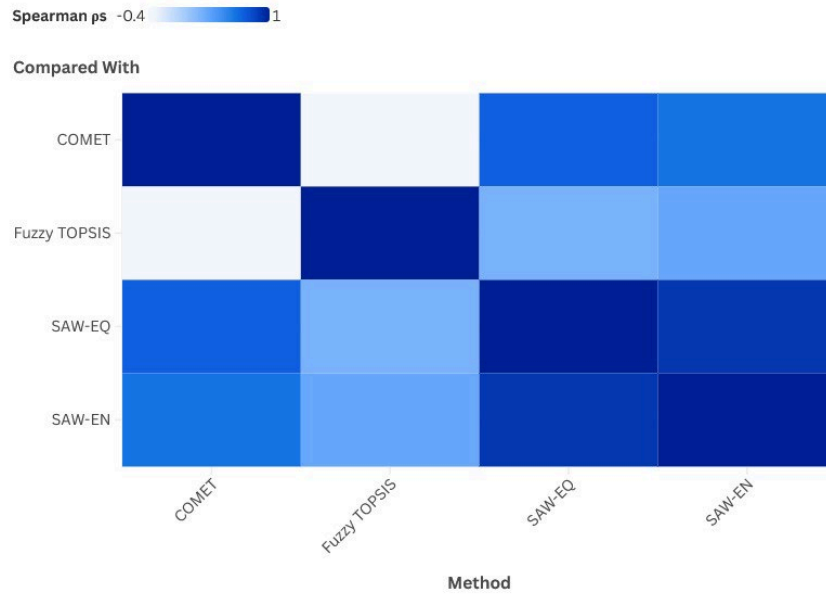


Figure 3. Spearman Rank Correlation Matrix of the Applied MCDM Methods.

6. Conclusion

This study established a mathematical modeling-supported comparative framework for gaming CPU selection, combining Hierarchical COMET, Fuzzy TOPSIS, and two SAW-based benchmark models. The scalability problem of the standard COMET was overcome with the introduction of the framework which is based on the hierarchical decomposition of the standard COMET, reducing the number of Characteristic Objects from 729 to 27, but keeping the same core fuzzy inference structure.

The results show that selection of method has a greater effect on the final rankings than the sensitivity of the input parameters. COMET determined AMD Ryzen 7 9700X to be the best alternative ($P_k = 0.857$) because of its balanced compute, gaming, and value attributes, while Fuzzy TOPSIS found that AMD Ryzen 7 5800X3D is the best alternative ($C_i = 0.477$) because of its entropy-weighted emphasis on cache size and price. Rank correlation analysis showed the strong agreements between COMET and the benchmarks based on the SAW, while the entries of COMET and Fuzzy TOPSIS were negative, due to their fundamentally different decision logics. The results by sensitivity analysis showed that both methods are stable to rank under $\pm 10\%$ deviations of price, TDP and FPS with all the Spearman and Kendall's correlation coefficient greater than 0.60.

The findings provide both theory and practice-based additions to MCDM literature. From the theoretical perspective, the study shows that the ranking divergence among fuzzy MCDM methods does not necessarily indicate methodological errors, but rather it presents two different types of evaluating logic: the criterion weighting and fuzzy rule-based evaluating logic.

References

- Baral, S. P., Parida, P. K., and Sahoo, D., Fuzzy TOPSIS technique for multi-criteria group decision-making: A study of crude oil price, *Results in Control and Optimization*, vol. 19, 2025. <https://doi.org/10.1016/j.rico.2025.100565>
- Belton, V. and Stewart, T., Multiple Criteria Decision Analysis: An Integrated Approach, *Kluwer Academic Publishers*, 2002.
- Bhole, G. P. and Deshmukh, T., Multi Criteria Decision Making (MCDM) Methods and its applications, *International Journal for Research in Applied Science and Engineering Technology*, vol. 6, no. 5, pp. 899–915, 2018. <https://doi.org/10.22214/ijraset.2018.5145>
- Çelikkilek, Y. and Tüysüz, F., An in-depth review of theory of the TOPSIS method: An experimental analysis, *Journal of Management Analytics*, vol. 7, no. 2, pp. 281–300, 2020. <https://doi.org/10.1080/23270012.2020.1748528>
- Chen, C.-T., Extensions of the TOPSIS for group decision-making under fuzzy environment, *Fuzzy Sets and Systems*, vol. 114, pp. 1–9, 2000.
- Chen, Y. S., Chuang, H. M., Sangaiah, A. K., Lin, C. K., and Huang, W. B., A study for project risk management using an advanced MCDM-based DEMATEL-ANP approach, *Journal of Ambient Intelligence and Humanized Computing*, vol. 10, no. 7, pp. 2669–2681, 2019. <https://doi.org/10.1007/S12652-018-0973-2>
- Demir, G., Chatterjee, P., and Pamucar, D., Sensitivity analysis in multi-criteria decision making: A state-of-the-art research perspective using bibliometric analysis, *Expert Systems with Applications*, vol. 237, p. 121660, 2024. <https://doi.org/10.1016/J.ESWA.2023.121660>
- Dordevic, M., Tešić, R., Todorović, S., Jokić, M., Das, D. K., Stević, Ž., and Vrtagić, S., Development of Integrated Linear Programming Fuzzy-Rough MCDM Model for Production Optimization, *Axioms*, vol. 11, no. 10, 2022. <https://doi.org/10.3390/axioms11100510>
- Faizi, S., Sałabun, W., Ullah, S., Rashid, T., and Wiecekowsk, J., A new method to support decision-making in an uncertain environment based on normalized interval-valued triangular fuzzy numbers and COMET technique, *Symmetry*, vol. 12, no. 4, 2020. <https://doi.org/10.3390/SYM12040516>
- Kizielewicz, B., Shekhovtsov, A., Wiecekowsk, J., Wątróbski, J., and Sałabun, W., The Compromise-COMET Method for Identifying an Adaptive Multi-Criteria Decision Model, *IEEE Access*, vol. 12, pp. 157083–157106, 2024. <https://doi.org/10.1109/ACCESS.2024.3485798>
- Kumar, R., A Comprehensive Review of MCDM Methods, Applications, and Emerging Trends, *Decision Making Advances*, vol. 3, no. 1, pp. 185–199, 2025. <https://doi.org/10.31181/dma31202569>
- Li, Z., Luo, Z., Wang, Y., Fan, G., and Zhang, J., Suitability evaluation system for the shallow geothermal energy implementation in region by Entropy Weight Method and TOPSIS method, *Renewable Energy*, vol. 184, pp. 564–576, 2022. <https://doi.org/10.1016/J.RENENE.2021.11.112>
- Mavi, R. K., Goh, M., and Mavi, N. K., Supplier Selection with Shannon Entropy and Fuzzy TOPSIS in the Context of Supply Chain Risk Management, *Procedia - Social and Behavioral Sciences*, vol. 235, pp. 216–225, 2016. <https://doi.org/10.1016/j.sbspro.2016.11.017>
- Nădăban, S., Dzitac, S., and Dzitac, I., Fuzzy TOPSIS: A General View, *Procedia Computer Science*, vol. 91, pp. 823–831, 2016. <https://doi.org/10.1016/j.procs.2016.07.088>
- Sałabun, W., The characteristic objects method: A new distance-based approach to multicriteria decision-making problems, *Journal of Multi-Criteria Decision Analysis*, vol. 22, no. 1–2, pp. 37–50, 2015.
- Taherdoost, H., Analysis of Simple Additive Weighting Method (SAW) as a MultiAttribute Decision-Making Technique: A Step-by-Step Guide, *Journal of Management Science and Engineering Research*, vol. 6, no. 1, pp. 21–24, 2023. <https://doi.org/10.30564/jmsr.v6i1.5400>
- Wang, T. C., and Lee, H. D., Developing a fuzzy TOPSIS approach based on subjective weights and objective weights, *Expert Systems with Applications*, vol. 36, no. 5, pp. 8980–8985, 2009. <https://doi.org/10.1016/J.ESWA.2008.11.035>
- Watrobski, J., Sałabun, W., Karczmarczyk, A., and Wolski, W., Sustainable decision-making using the COMET method: An empirical study of the ammonium nitrate transport management, *Proceedings of the 2017 Federated Conference on Computer Science and Information Systems*, pp. 949–958, 2017. <https://doi.org/10.15439/2017F455>

Biographies

Selin İrem Aşlakcioğlu is a third year Industrial Engineering student in Çankaya University. Her academic interests center on multi-criteria decision-making (MCDM) methodologies, particularly the application of the Characteristic

Objects Method (COMET). She gained practical experience in production planning through an internship. She has a proficient command of English, which she utilizes for academic research, professional communication and creative writing.

Beste Çetin is a third year Industrial Engineering student at Çankaya University, simultaneously pursuing a degree in Management Information Systems at Anadolu University. Her research focuses on decision-support systems and fuzzy logic integration. She gained practical experience in production planning through an internship at the 3rd Air Maintenance Factory Directorate. Proficient in English with intermediate-level German, she combines her engineering and information systems background to develop analytical decision-support models for hardware selection and production planning problems.

Lara Dinçer is an undergraduate Industrial Engineering student at Çankaya University. Her interests include multi-criteria decision-making (MCDM), operations research, and engineering decision-making. She has worked on projects involving Fuzzy TOPSIS, Fuzzy VIKOR and COMET. She also completed an internship in production planning, gaining experience in manufacturing and planning processes.

Syed Shah Sultan Mohiuddin Qadri is an Assistant Professor in the Department of Industrial Engineering at Çankaya University, Ankara, Türkiye. He holds a Ph.D. in Industrial Engineering from Yasar University, Izmir, Türkiye. Dr. Qadri earned his BS and MS degrees in Applied Mathematics from the University of Karachi and NED University of Engineering & Technology, Karachi, Pakistan, in 2010 and 2013, respectively. He has worked as a researcher on a TÜBİTAK-funded project, and his research interests include simulation optimization, intelligent transportation systems, heuristic optimization, and traffic modeling. Dr. Qadri is dedicated to advancing optimization techniques for solving complex real-world problems.