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An Efficient Neutrosophic Approach for Evaluating Possible Industry 5.0 Enablers in Consumer Electronics: A Case Study

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Abstract: With the use of cutting-edge technologies like artificial intelligence (AI), robotics, and the Internet of Things (IoT), Industry 5.0 represents a breakthrough move towards a sustainable and human-centered industrial future. Industry 5.0 endeavors to transform industries such as consumer electronics by emphasizing sustainability and collaboration, in contrast to its predecessors, who only concentrated on automation and efficiency. Along with improved manufacturing efficiency and product innovation, this change in the consumer electronics sector also redefines the human-machine interaction. This paper proposes a novel hybrid integrating model that combines the Entropy Weight Method (EWM), Best-Worst Method (BWM), and an acronym in Portuguese for Interactive Multi-criteria Decision Making (TODIM) using single-valued neutrosophic trapezoidal numbers to evaluate Industry 5.0 enablers. The EWM provides objective weight for criteria, while the BWM captures the subjective preferences of decision-makers. The TODIM method ranks alternatives based on these weighted criteria using single-valued neutrosophic trapezoidal numbers, which effectively handle uncertainties and imprecise information inherent in decision-making processes. The proposed hybrid model effectively evaluates the Industry 5.0 consumer electronics sector using an empirical study emphasizing personalization, sustainability, resilience, and smart manufacturing criteria. The model enhances decision-making by balancing objective metrics with subjective preferences, thus guiding stakeholders toward informed and sustainable technological investments. The hybrid EWM-BWM-TODIM method with single-valued neutrosophic trapezoidal numbers demonstrated robustness in accommodating subjective and objective criteria weights. Sensitivity analysis revealed variations in aggregation methods and θ values significantly influenced final rankings, emphasizing the method's adaptability and responsiveness to decision-maker preferences and environmental changes.

Keywords: Industry 5.0, Entropy Weight Method, Best-Worst Method, TODIM, SVTNN, TOPSIS.

1. Introduction

The next phase of the industrial revolution, "Industry 5.0," focuses on the collaboration between humans and machines to create a more sustainable and human-centered future. It builds upon the foundations of Industry 4.0, centered on digital transformation and automation [2]. In Industry 5.0, AI-powered systems will take over repetitive tasks, allowing people to focus on more productive and value-adding tasks [3]. However, Industry 5.0 presents unique issues, such as energy management, perception, and company readiness to embrace these new operational approaches [5]. Despite these challenges, Industry 5.0 is expected to create a more resilient and environmentally aware future. Industry 5.0 seeks to improve the human element in industrial processes, in contrast to Industry 4.0, which emphasizes automation and data interchange in industrial processes [6]. It aims to establish a symbiotic relationship between intelligent machines and human workers by utilizing cutting-edge technology like artificial intelligence (AI), robotics, and the Internet of Things (IoT). Industry 5.0 enablers encompass the technologies, strategies, and methodologies that drive the shift towards this innovative industrial framework [7]. These enablers are crucial for achieving the human-centric, sustainable, and collaborative objectives of Industry 5.0. Artificial intelligence (AI) solutions improve human decision-making, expedite procedures, and support predictive maintenance [8]. Advanced robotics, such as collaborative robots (cobots), are designed to work alongside human workers, undertaking repetitive or hazardous tasks, which allows humans to engage in more intricate and creative endeavors [9]. IoT devices and sensors provide real-time monitoring and data collection from machines, processes, and environments, fostering more intelligent and adaptive manufacturing systems [10]. Before implementing changes in the actual world, digital twins—virtual representations of physical assets, processes, or systems—allow for modeling, monitoring, and optimization in a virtual environment [11].

In the Industry 5.0 era, the consumer electronics sector is expected to undergo a profound Industry 5.0 represents a significant milestone in the industrial revolution, where the fusion of advanced technologies and human creativity is set to revolutionize industries worldwide. Unlike previous industrial revolutions focused solely on automation and efficiency, Industry 5.0 prioritizes the collaborative relationship between humans and machines, seeking to leverage their respective strengths to achieve unparalleled innovation, productivity, and sustainability [12]. One of the most dynamic sectors experiencing this paradigm shift is consumer electronics. Traditionally driven by rapid technological advancements and consumer demands for smarter, more intuitive devices, the consumer electronics industry is now poised at the forefront of Industry 5.0's evolution [13]. This era promises incremental improvements in product performance and design and a fundamental reimagining of how electronics are conceived, manufactured, and integrated into everyday life. Furthermore, Industry 5.0 will focus on developing energy-efficient and self-sustaining consumer electronics by leveraging advanced power management and energy harvesting technologies [14]. Industry 5.0 enables consumer electronics manufacturers to offer highly personalized products and experiences. This can include customizable features, adaptive interfaces, and tailored functionalities that cater to individual preferences and needs [11]. This involves leveraging IoT, AI, and data analytics to optimize manufacturing processes in real time. Smart manufacturing improves efficiency, quality control, predictive maintenance, and customization capabilities in consumer electronics, contributing to faster production cycles and reduced costs [15]. The global Consumer Electronics market is expected to reach $1.43 trillion by 2025, growing at a CAGR of 6.3% from 2020 to 2025 [16]. The Industry 5.0 enablers market in Consumer Electronics is expected to reach $143.8 billion by 2027, growing at a CAGR of 24.1% from 2020 to 2027 [17].

Industry 5.0 enablers are a range of technologies and practices that improve productivity, sustainability, and resilience in consumer electronics. To fully understand and optimize the impact of these enablers, it's crucial to use multi-criteria decision-making (MCDM) methods. MCDM provides a structured approach to evaluating alternatives based on various criteria, including personalization, sustainability, resilience, and technological integration. This framework helps identify the best solutions and ensures that decisions align with environmental and societal imperatives, striking a balance between technological progress and ethical responsibility. In this paper, a novel hybrid integrating model that combines the Entropy Weight Method (EWM), Best-Worst Method (BWM), and an acronym in Portuguese for Interactive Multi-criteria Decision Making (TODIM) using Trapezoidal Neutrosophic Sets (TNS). Neutrosophic sets, introduced by Smarandache (1999), are a generalization of fuzzy sets and intuitionistic fuzzy sets [18]. They handle uncertain, imprecise, and incomplete information in decision-making problems. Single-valued neutrosophic trapezoidal numbers are a type of neutrosophic number that represents uncertain information using a trapezoidal membership function. They are used to model uncertain and imprecise information in decision-making problems [19]. Deli and Subas [19] and Biswas et al. [20]

studied the ranking of single-valued neutrosophic trapezoidal numbers, an essential step in solving MCDM problems. The ranking process involves comparing and ordering the neutrosophic numbers based on membership values. Single-valued trapezoidal neutrosophic numbers have been widely used in various applications and integrated with many MCDM methods. Irvanizam Irvanizam and Novi Zahara provide a novel approach to evaluating healthcare service quality using neutrosophic numbers and the RAFSI method [21]. Liang Ruxia et al. [22] propose an integrated approach for assessing e-commerce websites using single-valued trapezoidal neutrosophic numbers with the help of the DEMATEL method.

The EWM-BWM-TODIM method is a comprehensive approach within MCDM that can be particularly effective in evaluating Industry 5.0 enablers in consumer electronics. The Entropy method is a widely used objective method for determining weights of criteria in MCDM problems [23]. In this paper, the EWM is applied using the trapezoidal neutrosophic decision matrix to obtain the objective weights. Mengdi Kong et al. [24] used the AHP-EWM-GFCE method to evaluate a medical waste gasification low-carbon multi-generation system. Hongjun Sun et al. [25] propose EWM-based TOPSIS to evaluate the passive turbulence control-based hydrokinetic energy harvester. Ziyuan Luo et al. [26] proposed the EWM-TOPSIS method for flood risk evaluation of a coastal city. Josy George et al. [27] conducted a comparative study of MCDM techniques (TOPSIS, VIKOR, and MOORA) integrated with the EWM method for vendor selection in the manufacturing industry. Irik Mukhametzyanov [28] applied EWM with the CRITIC method. Best-Worst Method (BWM) determines the subjective weights of the criteria based on the decision-maker's preferences [29]. BWM helps identify the best and worst alternatives for each criterion. By comparing alternatives against each criterion, it highlights the most advantageous and the least advantageous options [30]. The Improved BWM is an extension of the original BWM method, which addresses some limitations [31]. Himanshu Gupta [32] assessed organizations' performance based on GHRM practices using BWM and Fuzzy TOPSIS. Bhosale Akshay Tanaji et al. [33] proposed neutrosophic fuzzy sets using BWM integrated with the VIKOR method for cybersecurity risk assessment of connected and autonomous vehicles. Yanbing Ju et al. [34] proposed a novel framework using BWM and the SMAA-MARCOS method [34] Eren Kamber et al. [35] used fuzzy BWM & CODAS methodology for prioritization of drip-irrigation pump alternatives in agricultural applications [35]. TODIM (TOmada de Decisao Interativa Multicriterio) ranks the alternatives based on the criteria weights and the decision matrix [36]. TODIM is a well-established MCDM method widely used in various fields and environments. Fangfang Xia proposed a novel approach to Multi-Attribute Group Decision Making (MAGDM) using probabilistic hesitant fuzzy sets and two decision-making techniques: TODIM and EDAS [37]. Kun Chen et al. [38] developed a generalized TODIM evaluation approach incorporating a novel score function and trust network under an interval-valued hesitant fuzzy environment. Wen Li et al. [39] proposed an extended CPT-TODIM method based on novel type-2 fuzzy numbers to evaluate and select the most suitable reform models. Liyi Liu et al. [40] developed a supplier selection method for emergency materials in China using a group exponential TODIM method that considers hesitant fuzzy linguistic sets. Ke Zhang et al. [41] presented a novel approach to group decision-making under uncertainty, specifically focusing on interval-valued multiplicative preference relations, and proposed a stochastic group preference acceptability analysis based on the TODIM method. Yushuo Cao et al. [42] proposed an integrated framework, the complex q-rung ortho-pair fuzzy-generalized TODIM method with a weighted power geometric operator, to assess the appropriate technique for food waste treatment. Kavimani Vijayananth et al. [43] used an integrated CRITIC-TODIM approach to evaluate the performance of the composite material. This paper applies the TODIM method to the trapezoidal neutrosophic decision matrix, using the weights obtained from EWM and BWM.

Applying the novel hybrid integrating model (EWM-BWM-TODIM) using trapezoidal neutrosophic sets enhances the decision-making process in evaluating Industry 5.0 enablers for consumer electronics. It enables decision-makers to navigate complexities and uncertainties effectively, promoting informed decisions that balance technological advancement. Jianping Fan et al. [44] develop a comprehensive decision-making approach that combines the strengths of EWM, BWM, and TODIM methods in a Linguistic Pythagorean Fuzzy (LPF) environment. Implementing a sophisticated decision-making framework such as the EWM-BWM-TODIM method using trapezoidal neutrosophic sets involves several challenges. These challenges stem from the inherent complexity of integrating multiple MCDM techniques with advanced trapezoidal neutrosophic set representations and the dynamic nature of Industry 5.0 enablers.

The key challenges behind the current work are presented as follows:

- Industry 5.0 enablers are complex and multifaceted, making evaluating their performance and impact on the consumer electronics sector difficult.
- The evaluation of Industry 5.0 enablers involves dealing with uncertain and ambiguous information, which can be challenging to model and analyze using traditional MCDM methods.
- Combining EWM, BWM, and TODIM methods into a coherent framework requires meticulous planning and execution. The calculations involved in EWM, BWM, and TODIM, especially when using trapezoidal neutrosophic sets, are mathematically intensive and computationally demanding.
- Gathering accurate and comprehensive data on Industry 5.0 enablers for all criteria and alternatives is challenging, especially in rapidly evolving sectors like consumer electronics. Data quality and availability may impact the EWM-BWM-TODIM method's effectiveness.
- Balancing subjective weights from BWM with objective weights from EWM can be difficult, requiring careful calibration and validation.
- The importance of criteria may change over time due to technological advancements or market shifts, necessitating regular updates to the weighting scheme.

Methodological Contributions of the Study:

- The study applies the hybrid model to the specific context of Industry 5.0 enablers in consumer electronics, demonstrating its practical relevance and effectiveness in this emerging industrial domain.
- The methodological innovations presented in this study provide a foundation for future research in MCDM and Industry 5.0. The hybrid model can be adapted and extended to other sectors and decision-making scenarios, promoting further advancements in the field.
- Developing a novel hybrid integrating model that combines the Entropy Weight Method (EWM), Best-Worst Method (BWM), and TODIM using single-valued neutrosophic trapezoidal numbers to evaluate Industry 5.0 enablers in consumer electronics. The study provides a robust decision-making framework. This framework can navigate the complexities and uncertainties of evaluating Industry 5.0 enablers in consumer electronics.
- The use of trapezoidal neutrosophic sets in the decision-making process effectively handles uncertain, imprecise, and incomplete information. This enhances the model’s ability to represent real-world complexities in evaluating Industry 5.0 enablers.
- The model incorporates objective (EWM) and subjective (BWM) methods for determining criteria weights. This dual approach ensures a balanced evaluation that reflects the importance of inherent criteria and decision-makers' preferences.

The rest of the part is arranged as follows: Section 2 briefly overviews the basic concepts and definitions of single-valued neutrosophic trapezoidal numbers and their operations. Section 3 introduces a novel hybrid method integrating EWM, BWM, and TODIM using single-valued neutrosophic trapezoidal numbers. Section 4 presents an empirical study evaluating possible industry 4.0 enablers in consumer electronics. Section 5 compares existing methods and a sensitivity analysis to validate the effectiveness and robustness of the proposed method. Section 6 concludes the research work by summarizing the main contributions and findings of the study.

2. Basic Ideas of Single-Valued Neutrosophic Trapezoidal Numbers

A single-valued trapezoidal Neutrosophic Number (SVTNN) is an extension of neutrosophic numbers designed to handle uncertain, imprecise, and incomplete information in decision-making [19]. Neutrosophic sets generalize fuzzy sets and intuitionistic fuzzy sets, incorporating degrees of truth (T), indeterminacy (I), and falsity (F) [18]. Deli and Subas present SVTNN using these degrees, providing a more flexible and comprehensive way to model uncertainty.

A single-valued trapezoidal neutrosophic number (SVTNN) $\breve{a} = ((a_1, b_1, c_1, d_1); T_a, I_a, F_a)$ characterized by three trapezoidal membership functions, truth (T), indeterminacy (I), and falsity (F), representing as follows:

Truth Membership Function $T_a(x) = f(x) = \begin{cases} \frac{(x - a_1)T_a}{(b_1 - a_1)}, & a_1 \leq x \leq b_1 \\ T_a, & b_1 \leq x \leq c_1 \\ \frac{(d_1 - x)T_a}{(d_1 - c_1)}, & c_1 \leq x \leq d_1 \\ 0, & otherwise \end{cases}$

Indeterminacy Membership Function $I_a(x) = f(x) = \begin{cases} \frac{(b_1 - x + I_a(x - a_1))}{(b_1 - a_1)}, & a_1 \leq x \leq b_1 \\ I_a, & b_1 \leq x \leq c_1 \\ \frac{(x - c_1 + I_a(d_1 - x))}{(d_1 - c_1)}, & c_1 \leq x \leq d_1 \\ 1, & otherwise \end{cases}$

Falsity Membership Function $F_a(x) = f(x) = \begin{cases} \frac{(b_1 - x + F_a(x - a_1))}{(b_1 - a_1)}, & a_1 \leq x \leq b_1 \\ F_a, & b_1 \leq x \leq c_1 \\ \frac{(x - c_1 + F_a(d_1 - x))}{(d_1 - c_1)}, & c_1 \leq x \leq d_1 \\ 1, & otherwise \end{cases}$

Where $0 \leq T_a \leq 1$; $0 \leq I_a \leq 1$; $0 \leq F_a \leq 1$ and $0 \leq T_a + I_a + F_a \leq 3$; $a_1, b_1, c_1, d_1 \in R$.

Various operations can be performed on SVTNN to facilitate their use in decision-making processes suppose $\widetilde{A_1} = ((a_1, a_2, a_3, a_4); T_1, I_1, F_1)$ and $\widetilde{A_2} = ((b_1, b_2, b_3, b_4); T_2, I_2, F_2)$ are two single-valued trapezoidal neutrosophic numbers. Below are some common operations:

Addition $\widetilde{A_1} \oplus \widetilde{A_2}$:

$$= \left((a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4); \min(T_1, T_2), \max(I_1, I_2), \max(F_1, F_2)\right) \quad (1)$$

Multiplication $\widetilde{A_1} \otimes \widetilde{A_2}$:

$$= \left((a_1 b_1, a_2 b_2, a_3 b_3, a_4 b_4); \min(T_1, T_2), \max(I_1, I_2), \max(F_1, F_2)\right) \quad (2)$$

Scalar Multiplication:

$$\lambda\widetilde{A_1} = \left((\lambda a_1, \lambda a_2, \lambda a_3, \lambda a_4); \min(T_1, T_2), \max(I_1, I_2), \max(F_1, F_2)\right) \quad (3)$$

Score function:

$$S(\widetilde{A_1}) = \left(\frac{1}{12}\right)(a_1 + a_2 + a_3 + a_4)(2 + T_1 - I_1 - F_1) \quad (4)$$

accuracy function:

$$a(\widetilde{A_1}) = \left(\frac{1}{12}\right)(a_1 + a_2 + a_3 + a_4)(2 + T_1 - I_1 + F_1) \quad (5)$$

3. Novel EWM-BWM-TODIM Method within Single-Valued Neutrosophic Trapezoidal Numbers

The hybrid integration of the EWM, BWM, and TODIM within the context of SVTNNs presents a robust approach to tackling MCDM problems. This method leverages the strengths of each technique while effectively managing the uncertainties inherent in decision-making scenarios. Figure 1 represents the overall methodology flowchart for the EWM-BWM-TODIM method using single-valued neutrosophic trapezoidal numbers. The steps to implement this hybrid technique are as follows:

Phase 1. Construct the Decision Matrix with SVTNNs

Step 1.1. Identify Alternatives and Criteria: List all alternatives $A_1, A_2, A_3, \ldots\ldots, A_m$ and criteria $C_1, C_2, C_3, \ldots\ldots, C_n$.
Step 1.2. Collect Expert Opinions: Gather expert evaluations of each alternative against each criterion, represented as SVNTN $\widetilde{A_1} = ((a_1, a_2, a_3, a_4); T_1, I_1, F_1)$ using linguistic terms as represented in Table 1.
Step 1.3. Formulate the Decision Matrix: Using a score function in Eq. (5), we can convert the SVTNNs into crisp numbers.
Step 1.4. Aggregate the Decision Makers' Matrix: The decision makers' matrix can be aggregated using a suitable aggregation method, such as the average method to construct the decision matrix.

Table 1. SVTNN scale.

Linguistic Scale	Trapezoidal Number ($l, M1, M2, U$)	Truth-Membership (T)	Indeterminacy-Membership (I)	Falsity-Membership (F)	Score Function
Strongly very low (SVL)	(0, 0.1, 0.2, 0.3)	0.1	0.8	0.9	0.020
Very low (VL)	(0.1,0.2,0.3,0.4)	0.2	0.7	0.8	0.058
Low (L)	(0.2,0.3,0.4,0.5)	0.3	0.7	0.7	0.105
Median low (ML)	(0.3,0.4,0.5,0.6)	0.5	0.4	0.5	0.240
Medium (M)	(0.4,0.5,0.6,0.7)	0.6	0.3	0.4	0.348
Medium-high (MH)	(0.5,0.6,0.7,0.8)	0.7	0.3	0.3	0.455
High (H)	(0.6,0.7,0.8,0.9)	0.8	0.1	0.2	0.625
Very high (VH)	(0,7,0.8,0.9,1)	0.9	0.2	0.1	0.737
Strongly very high (SVH)	(0.8,0.9,1,1)	1.0	0.1	0.1	0.863

Phase 2. Apply the Entropy Weight Method (EWM): The EWM is an objective weighting method used to determine the importance of each criterion by following these steps [24].
Step 2.1. Normalize the Decision Matrix: Normalize the SVTNN decision matrix to ensure comparability across different criteria using the following:

$$\mathcal{P}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad \textit{Where } 1 \leq i \leq m \quad , 1 \leq j \leq n \tag{6}$$

Step 2.2. Calculate the Entropy of Each Criterion: Compute the entropy value for each criterion $j$based on the normalized decision matrix as follows:

$$e_j = -k \sum_{i=1}^{m} (\mathcal{P}_{ij} . \ln \mathcal{P}_{ij}) \quad \text{Where } 1 \leq j \leq n \text{ and k} = {}^{1}\!/_{\ln m} \tag{7}$$

Step 2.3. Determine the Degree of Divergence: Calculate the degree of divergence for each criterion by this equation;

$$d_j = \left|1 - e_j\right| \quad \text{Where } 1 \leq j \leq n \tag{8}$$

Step 2.4. Calculate the Weights of Criteria: Derive the objective weight by

$$\mathcal{W}_j = \frac{g_j}{\sum_{i=1}^{m} g_j} \tag{9}$$

Phase 3: Apply the Best-Worst Method (BWM): BWM is a subjective weighting method based on the decision maker's preferences, which identifies the best and worst criteria and compares all other criteria with them [29] by the following steps:
Step 3.1. Identify the Best and Worst Criteria: Decision-makers select the most important (best) and least important (worst) criteria.
Step 3.2. Construct Pairwise Comparison Vectors: giving the best criterion (BO) more importance than other criteria and giving other criteria (OW) less importance than the worst criterion as :
$A_B = (a_{B1}, a_{B2}, \ldots., a_{Bn})$ where a_{Bj} is the importance of the best criterion relative to the jth criterion (a_{BB}, = 1, clearly) (10)
$A_W = (a_{W1}, a_{W2}, \ldots., a_{Wn})$ where a_{Wj} the importance of the worst criterion relative to the jth criterion (a_{WW}, = 1, clearly) (11)

Step 3.3. Determine the Optimal Weights: Determine the optimal subjective weights by solving the BWM optimization problem using this model:

$$\min \zeta \; s.t \begin{cases} \left|\frac{W_B}{W_j} - a_{Bj}\right| & \leq \zeta \\ \left|\frac{W_j}{W_W} - a_{Wj}\right| & \leq \zeta \\ \sum_{j=1}^{n} W_j = 1 \\ j = 1,2, \ldots, n \end{cases} \tag{12}$$

Step 3.4. Integrate EWM and BWM Weights: Integrate the objective weights from EWM and subjective weights from BWM to obtain the combined weights by taking the average of the two sets of weights.

$$W_f = AVG\,(EWM_W\,, BWM_W) \tag{13}$$

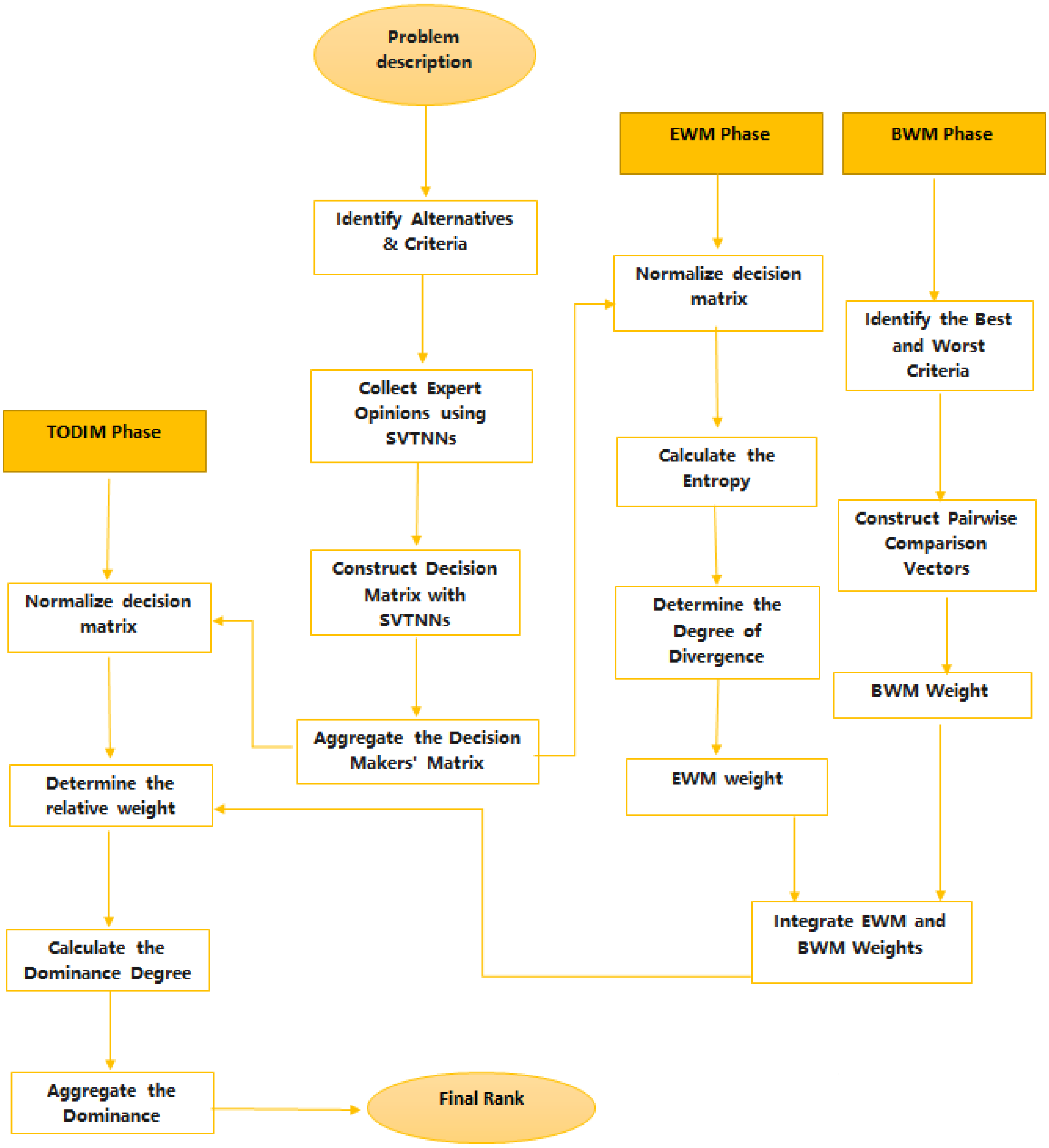

Figure 1. Methodology flowchart.

Phase 4. Apply TODIM Method: TODIM is a multi-criteria decision method that ranks and evaluates the alternatives based on the weight of each criterion [36] the steps of how to accomplish it:
Step 4.1. Calculate Normalized Decision Matrix: Normalize the decision matrix as follows where B shows the set of beneficial criteria, and H represents the set of non-beneficial criteria:

$$\mathcal{P}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad \text{for B} \tag{14}$$

$$\mathcal{P}_{ij} = \frac{1/x_{ij}}{\sum_{i=1}^{m} 1/x_{ij}} \quad \text{for H} \tag{15}$$

Step 4.2. Determine the relative weight using the global weights of criteria obtained from equation 14 using

$$\breve{\mathcal{W}}_j = \frac{w_j}{\breve{w}} \tag{16}$$

Where, $\breve{\mathcal{W}}$ is the maximum amount of weights
Step 4.3. Calculate the Dominance Degree: For each pair of alternatives $(\mathcal{A}_i, \mathcal{A}_j)$ calculate the $\delta(\mathcal{A}_i, \mathcal{A}_j)$ as

$$\boldsymbol{\delta}(\mathcal{A}_i, \mathcal{A}_j) = \sum_{j=1}^{m} \Phi(\mathcal{A}_i, \mathcal{A}_j)$$

$$\Phi(\mathcal{A}_i, \mathcal{A}_j) = \begin{cases} \sqrt{\frac{w_j(\mathcal{P}_i - \mathcal{P}_j)}{\sum_{j=1}^{n} \breve{\mathcal{W}}_j}} & if\ (\mathcal{P}_i - \mathcal{P}_j) > 0 \\ 0 & if\ (\mathcal{P}_i - \mathcal{P}_j) = 0 \\ \frac{-1}{\theta}\sqrt{\frac{\sum_{j=1}^{n} \breve{\mathcal{W}}_j (\mathcal{P}_i - \mathcal{P}_j)}{w_j}} & if\ (\mathcal{P}_i - \mathcal{P}_j) < 0 \end{cases} \tag{17}$$

Where, θ the attenuation factor of the losses value ranges from 1 to 10.
Step 4.4. Aggregate the Dominance Degrees: Calculate the overall dominance degree of each alternative using this equation:

$$\zeta_i = \frac{\sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j) - \min \sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j)}{\max \sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j) - \min \sum_{j=1}^{n} \delta(\mathcal{A}_i, \mathcal{A}_j)} \tag{18}$$

Step 4.5. Rank the Alternatives: Rank the alternatives based on their overall dominance values to determine the best option.

4. Case Study of Evaluating Possible Industry 5.0 Enablers in Consumer Electronics

The consumer electronics industry is undergoing a significant transformation with the advent of Industry 5.0. This new industrial revolution is characterized by integrating humans, machines, and artificial intelligence to create a more sustainable, efficient, and personalized production process. Key to Industry 5.0's impact on consumer electronics is the integration of robotic machinery alongside human critical thinking. This collaboration enhances precision and efficiency in manufacturing processes and fosters creativity and adaptability in product development. Moreover, Industry 5.0 places a significant emphasis on sustainability, urging manufacturers to adopt eco-friendly practices such as using recyclable materials, reducing energy consumption, and implementing economic principles to mitigate environmental impact. To evaluate and rank possible Industry 5.0 enablers in the consumer electronics sector based on multiple criteria to identify the most suitable enabler for implementation. The novel EWM-BWM-TODIM method within the context of SVTNNs is applied to evaluate Industry 5.0 enablers in consumer electronics.

4.1 EWM-BWM-TODIM Method using SVTNNs for Evaluating Industry 5.0 Enablers in Consumer Electronics

Phase 1. Construct the decision matrix with SVTNNs according to experts' opinions.
Step 1.1. Define the decision-making framework:

Criteria: Personalization (C1), Human Socio-technical Environment (C2), Biotechnology (C3), Sustainability (C4), Smart Manufacturing (C5), Green Computing (C6), Resilience (C7).

Alternatives: Bionics (A1), Sustainable Agricultural Production (A2), Cyber-Physical Systems (A3), Smart Materials (A4), AI-based Management Systems (A5).

Step 1.2. The decision matrix consists of SVTNNs based on experts' opinions using linguistic terms represented in Table 1 to get the matrix as shown in Table 2.

Step 1.3. Calculate the score function of each SVTNNs using Eq. (5). The score function of each SVTNN is shown in the last column in Table 1.

Step 1.4. Then aggregate the decision maker's matrix to get the matrix represented in Table 3.

Table 2. Decision matrix of expert's opinions

	Expert 1						
	C1	C2	C3	C4	C5	C6	C7
A1	SVL	VL	L	ML	M	MH	H
A2	VL	L	ML	M	MH	H	VH
A3	L	ML	M	MH	H	VH	SVH
A4	ML	M	MH	H	VH	SVH	SVL
A5	M	MH	H	VH	SVH	SVL	VL
	Expert 2						
A1	VL	L	ML	M	MH	H	VH
A2	L	ML	M	MH	H	VH	SVH
A3	ML	M	MH	H	VH	SVH	SVL
A4	M	MH	H	VH	SVH	SVL	VL
A5	MH	H	VH	SVH	SVL	VL	L
	Expert 3						
A1	ML	M	MH	H	VH	SVH	SVL
A2	M	MH	H	VH	SVH	SVL	VL
A3	MH	H	VH	SVH	SVL	VL	L
A4	H	VH	SVH	SVL	VL	L	ML
A5	VH	SVH	SVL	VL	L	ML	M
	Expert 4						
A1	M	MH	H	VH	SVH	SVL	VL
A2	MH	H	VH	SVH	SVL	VL	L
A3	H	VH	SVH	SVL	VL	L	ML
A4	VH	SVH	SVL	VL	L	ML	M
A5	SVH	SVL	VL	L	ML	M	MH

Table 3. Aggregated decision matrix.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
A1	0.339	0.63	0.89	1.33	1.76	1.95	1.4
A2	0.625	0.89	1.33	1.76	1.95	1.4	1.68
A3	0.890	1.33	1.76	1.95	1.4	1.68	1.03
A4	1.398	1.76	1.95	1.4	1.68	1.03	0.34
A5	1.756	1.95	1.4	1.68	1.03	0.34	0.63

Phase 2. Apply the Entropy Weight Method

Step 2.1. Normalize the aggregate decision matrix in Table 3 using Eq. (6) to get the EWM normalized matrix shown in Table 4.

Step 2.2. Calculate the Entropy of each criterion ej by applying Eq. (7).

Step 2.3. Determine the degree of Divergence dj using Eq. (8).

Step 2.4. Calculate the weights of criteria using Eq. (9) according to Table 5.

Table 4. EWM normalized matrix.

	C1	C2	C3	C4	C5	C6	C7
A1	0.068567	0.095483	0.121514	0.16398	0.224627	0.304447	0.275033
A2	0.126592	0.135814	0.181787	0.216347	0.249254	0.218178	0.331829
A3	0.180062	0.203181	0.239841	0.240066	0.178625	0.263233	0.203217
A4	0.269377	0.268066	0.266135	0.17204	0.215512	0.161208	0.066727
A5	0.355402	0.297455	0.190723	0.207568	0.131983	0.052933	0.123194

Table 5. Final weight.

	C1	C2	C3	C4	C5	C6	C7
Ej	0.916528	0.952381	0.979722	0.993742	0.986325	0.929108	0.921758
dj	0.083472	0.047619	0.020278	0.006258	0.013675	0.070892	0.078242
Wj	0.260496	0.148607	0.063282	0.019529	0.042676	0.221236	0.244174

Phase 3. Apply the Best-Worst Method

Step 3.1. Identify the best and worst criteria: the best criterion is C4 and the worst is C3.

Step 3.2. Construct Pairwise Comparison Vectors: BO and OW matrix are provided in Tables 6, and 7 using the SVTNN scale. But notice $a_{BB}, = 1 and\ a_{WW}, = 1$.

Step 3.3. Use the Eq. (12) model to determine the optimal weights, as indicated in Table 8.

Step 3.4. Integrate EWM and BWM Weights by taking the average EWM weight in Table 5 and BWM in Table 8 to get the final weight in Table 8.

Table 6. BO matrix.

Best to Others	c1	C2	C3	C4	C5	C6	C7
C4	M	MH	SVL	SVH	H	MH	ML
Score function	0.34833333	0.455	0.02	1	0.625	0.105	0.17333333

Table 7. WO matrix

Others to the Worst	C3	Score function
C1	VH	0.73666667
C2	H	0.625
C3	SVH	1
C4	SVL	0.02
C5	ML	0.17333333
C6	L	0.105
C7	H	0.625

Table 8. Final weight.

	C1	C2	C3	C4	C5	C6	C7
BWM weight	0.19049893	0.14583984	0.28191875	0.03599775	0.07922529	0.05996084	0.20655859
EWM-BWM weight	0.225498	0.147223	0.1726	0.027763	0.060951	0.140598	0.225366

Phase 4. Apply the TODIM Method

Step 4.1. Calculate the normalized decision matrix using Eq. (14), and Eq. (15) taking into account that the beneficial criteria are C1, C2, C4, C5, and C6 and the non-beneficial criteria are C3 and C7, the TODIM normalized matrix is shown in Table 9.

Step 4.2. Determine the relative weight using the EWM-BWM weight in Table 8 as provided in the last row in Table 9.

Step 4.3. Calculate the Dominance Degree by Eq. (17) as shown in Table 10.

Step 4.4. Aggregate the Dominance Degrees using Eq. (18) as ζi shown in Table 10.

Step 4.5. Rank the alternatives: Rank the alternatives based on their overall dominance values to determine the best option as indicated in Table 10.

Table 9. TODIM normalized matrix.

	C1 +	C2 +	C3 -	C4 +	C5 +	C6 +	C7 -
A1	0.068567	0.095483	0.305923	0.16398	0.224627	0.304447	0.10486
A2	0.126592	0.135814	0.204491	0.216347	0.249254	0.218178	0.086912
A3	0.180062	0.203181	0.154994	0.240066	0.178625	0.263233	0.141917
A4	0.269377	0.268066	0.13968	0.17204	0.215512	0.161208	0.432209
A5	0.355402	0.297455	0.194911	0.207568	0.131983	0.052933	0.234101
$\breve{\mathcal{W}}$	1	0.652882	0.765419	0.123121	0.270294	0.623503	0.999416

Table 10. Final rank.

	$\delta(\mathcal{A}_i, \mathcal{A}_i)$	Zi	RANK
A1	-13.4058	0	5
A2	-9.17353	0.809956	3
A3	-8.18049	1	1
A4	-8.90488	0.861369	2
A5	-10.7333	0.511453	4

According to the EWM-BWM-TODIM method using SVTNNs, Cyber-Physical Systems (A3) are the most suitable Industry 5.0 enabler for the consumer electronics industry, followed by Smart Materials (A4), and Sustainable Agricultural Production (A2).

5. Comparison and Sensitivity Analyses

5.1 Comparison with other Methods

To validate the effectiveness of the EWM-BWM-TODIM method using Single Valued Neutrosophic Trapezoidal Numbers (SVTNNs), we compare the results with those obtained from the Evaluation based on Distance from Average Solution (EDAS) [45] and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods [46,47]. Applying the EDAS and TOPSIS methods to get the final rank of the two methods. Then, compare the rankings obtained from the EWM-BWM-TODIM method with those from EDAS and TOPSIS, as provided in Table 11.

Table 11. Comparison analysis.

Alternatives	EWM-BWM-TODIM Rank	EDAS Rank	TOPSIS Rank
A1	5	4	4
A2	3	5	5
A3	1	3	3
A4	2	2	2
A5	4	1	1

The comparison of the rankings reveals some differences between the methods: EWM-BWM-TODIM: The rankings produced show Cyber-Physical Systems (A3) as the top alternative, followed by Smart Materials (A4) and Sustainable Agricultural Production (A2) in third place. AI-based Management Systems (A5) and Bionics (A1) are ranked lower. EDAS and TOPSIS: AI-based Management Systems (A5) is ranked highest, with Smart Materials (A4) in second place and Cyber-Physical Systems (A3) in third place. Bionics (A1) and Sustainable Agricultural Production (A2) are ranked lower.

The EWM-BWM-TODIM method offers a comprehensive framework that combines the strengths of multiple MCDM techniques while effectively handling uncertainty through SVTNNs. Its ability to integrate objective and subjective weights provides a balanced and detailed evaluation. Comparing it with EDAS and TOPSIS highlights its robustness and effectiveness, particularly in the context of Industry 5.0 enablers for consumer electronics. The comparison reveals that while AI-based Management Systems (A5) consistently rank high in EDAS and TOPSIS, the EWM-BWM-TODIM method ranks Cyber-Physical Systems (A3) higher, demonstrating its unique perspective in handling multiple criteria under uncertainty. This underscores the importance of using a hybrid approach in complex decision-making scenarios to achieve a more balanced and informed outcome.

5.2 Sensitivity Analysis

The sensitivity analysis is conducted in two stages to examine the robustness of the EWM-BWM-TODIM method.

5.2.1 Changing the Way of Combining the EWM and BWM Weights

In this stage, the weights obtained from the EWM and BWM methods are combined using different aggregation operators to examine their impact on the final rankings by summing both weights and once again by multiplying both weights. The final rank of these methods is shown in Table 12 and Figure 2.

$$W_f = Sum\ (EWM_W\ , BWM_W) \tag{19}$$

$$W_f = Multi\ (EWM_W\ , BWM_W) \tag{20}$$

Table 12. Sensitivity analysis on weight.

	Average	Sum	Multi
A1	5	5	5
A2	3	3	2
A3	1	1	1
A4	2	2	3
A5	4	4	4

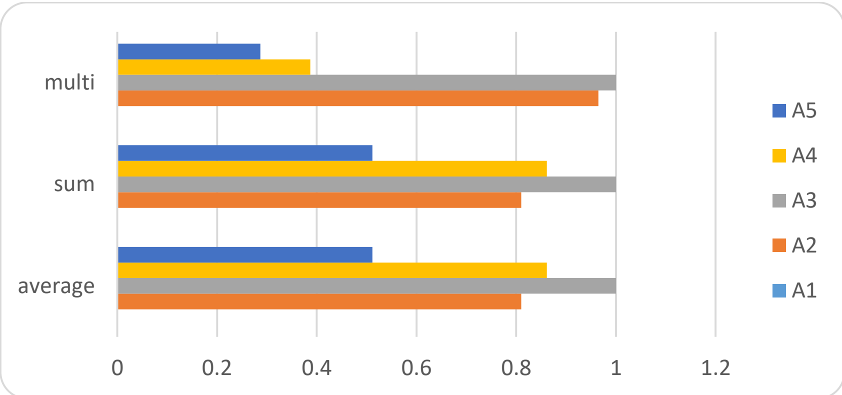

Figure 2. Sensitivity analysis on weight.

The sum method directly adds the weights from EWM and BWM. It also results in equal rankings for all alternatives (A1 to A5) using Eq. (19). The multiplication method is applied using Eq. (20) [48] of weights from EWM and BWM. It leads to different rankings compared to the average and sum methods. The choice of aggregation method significantly impacts the final rankings. While the average and sum methods provide identical rankings, the multiplicative method introduces variability based on the interaction between EWM and BWM weights. The sensitivity analysis shows that combining the EWM and BWM weights can influence the final rankings of the alternatives. While the average and sum methods produced identical rankings, the multiplication method led to slight changes, particularly for alternatives A2 and A4. This highlights the importance of selecting an appropriate method for combining weights in multi-criteria decision-making problems.

5.2.2 Changing the Value of θ in the TODIM Method

In this sensitivity analysis, we will vary the value of θ in the TODIM method to examine its impact on the final rankings of alternatives. θ ranges from 1 to 10, where higher values indicate greater sensitivity to losses relative to gains. Table 13 and Figure 3 show the change of θ value and the final rank of it. It was changed in 6 cases with 6 different values.

Table 13. Sensitivity analysis on TODIM.

	ϴ= 1	**ϴ= 1.5**	**ϴ= 4**	**ϴ= 6.4**	**ϴ= 8.3**	**ϴ= 10**
A1	5	5	5	5	5	4
A2	3	3	4	4	4	5
A3	1	1	3	3	3	3
A4	2	2	1	1	1	1
A5	4	4	2	2	2	2

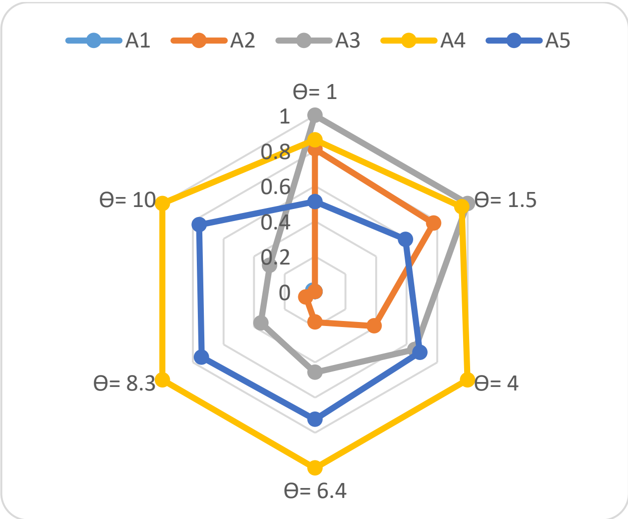

Figure 3. Sensitivity analysis on TODIM.

The sensitivity analysis on θ in the TODIM method illustrates how varying degrees of sensitivity to losses influence the prioritization of alternatives in multi-criteria decision-making. It provides insights into the robustness of decision outcomes under different decision-making contexts. The TODIM method's flexibility in handling different levels of loss aversion allows decision-makers to tailor rankings according to the decision context's specific risk preferences and priorities. By systematically varying θ from 1 to 10 in the TODIM method, this sensitivity analysis illustrates how different levels of loss aversion influence the prioritization of alternatives. Understanding these dynamics helps make informed decisions that effectively balance gains and losses in multi-criteria decision-making scenarios.

6. Conclusion

The evolution towards Industry 5.0 represents a pivotal moment in industrial history, where integrating advanced technologies with human capabilities promises to redefine manufacturing and innovation across sectors. In consumer electronics, this transformation is not merely about incremental improvements but a fundamental rethinking of how global markets conceptualize, produce, and embrace products. In this study, we explored the application of a novel hybrid integrating model that combines the EWM, BWM, and TODIM using single-valued neutrosophic trapezoidal numbers to evaluate Industry 5.0 enablers in the consumer electronics sector. The research addressed the complexities and uncertainties inherent in assessing these enablers, particularly focusing on their impact on personalization, sustainability, resilience, and other critical criteria. The findings of this study provide actionable insights for stakeholders in the consumer electronics industry, enabling informed decision-making processes that align with technological advancements while considering ethical and societal responsibilities. By leveraging advanced technologies like AI, IoT, and robotics within a human-centric framework, Industry 5.0 promises to revolutionize product development, manufacturing processes, and consumer interactions.

Future Research Directions: Future research can expand on this methodology to other industrial sectors and decision-making scenarios. Further advancements could explore additional MCDM techniques or refine the integration of neutrosophic sets in decision analysis

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Author Contributions

All authors contributed equally to this research.

Data availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

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Conflict of interest

The authors declare that there is no conflict of interest in the research.

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