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Integrating decision tools for efficient operations management through innovative approaches

Weidong Liu[1] & Xuewu Lai[2]✉

In a dynamic business environment, operations management (OM) is essential for enhancing efficiency, minimizing costs, and promoting sustainable growth. Traditional OM methods frequently encounter difficulties in balancing various criteria, including cost, quality, resource utilization, and adaptability, resulting in a lack of clear guidance for organizations in selecting optimal strategies. This study presents a novel decision-support framework that combines objective and subjective insights to improve OM strategy selection. This research is distinguished by its innovative integration of three advanced methodologies: CRITIC (Criteria Importance Through Intercriteria Correlation) for objective weighting, CIMAS (Criteria Importance Assessment) for subjective weight determination, and WASPAS (Weighted Aggregated Sum Product Assessment) for comprehensive strategy ranking. This hybrid weighting approach signifies a notable progression in operations management research, facilitating a balanced and practical evaluation of competing strategies. This study assesses five advanced OM approaches: lean management, automation, sustainability-driven operations, flexible workforce allocation, and data-driven decision-making, in relation to eight essential performance criteria. Our findings indicate that data-driven decision-making is a prominent strategy for achieving operational excellence, whereas alternative approaches exhibit distinct advantages across various performance dimensions. The results highlight the significant potential of multi-criteria decision-making (MCDM) techniques in assisting operations management leaders and policymakers in making informed, performance-oriented decisions. This study redefines the future of operations management by addressing efficiency and sustainability goals, offering a practical roadmap for organizations facing complex operational challenges.

Keywords Operations management, Risk analysis, Decision-making, Sustainable growth

In modern OM, using innovative decision-making tools has become essential for boosting efficiency and staying competitive across different industries. With today's fast-changing business world, organizations are under growing pressure to improve efficiency, cut costs, and maintain an edge over their rivals. OM is essentially the design, execution, and optimization of the resources and procedures of an organization that are absolutely essential for achieving its objectives[1]. This change marks a departure from perceiving decision-making tools as just wanted extras and towards a more systems-oriented approach in which they are vital for improving efficiency, boosting strategic planning, and motivating operational innovation. The development of smart tools that can help companies make choices under difficult circumstances is one of the most important topics presently under investigation in the area of organisational management. Data analytics and simulation tools are becoming more and more important for companies in order to forecast operational results, maximise resource management, and react fast to market developments. These developments not only raise customer happiness and service quality but also maximize resource[2]. OM's alignment with the larger objectives of the company helps the operational system of the company to be better generally. Recent study shows how organizational management (OM) could improve value chains and help a business be generally successful[3,4]. Moreover, studies imply that different strategies could improve operational performance and provide companies a competitive advantage in many different markets. For instance, the healthcare sector has seen major financial gains from the use of specialized training and management improvements, thereby demonstrating how these tools might be suitable for the particular requirements of a broad spectrum of companies[5] Strategic resource management increases adaptability to changing market needs, hence preserving the competitive edge of healthcare companies[6]. Using creative OM in production mostly focuses on highly defined and orderly processes. These methods simplify

[1]Business School, Quzhou University, Quzhou 324000, China. [2]Business School, Xi'an International University, Xi'an 710071, China. ✉email: l_xuewu@163.com

both creation and administration, therefore enabling continuous increase in productivity. These models are very helpful as they allow one to balance the thirst for new ideas with resource allocation grounded on reality[7].

Another important trend is the use of decision-making frameworks that add value in competitive environments. Real-time analytics, control systems, and integration platforms help organizations make fast, well-informed decisions when it counts[8]. Today, automation and digital transformation are core parts of OM. Many companies use automation to reengineer business processes, boosting productivity and allowing them to adapt quickly to any shifts in operations-key to staying competitive[9]. At the same time, integrating information systems for project and process management enhances how well firms can respond to market changes and improve efficiency[10]. In the dynamic realm of decision-making, decision-makers (DMs) face significant challenges in selecting the optimal option from the available options as systems become increasingly complex. Measuring the difficulty of doing a task is a challenging but manageable endeavour. Businesses usually have to balance a lot of conflicting interests when making choices since employee motivation, goal formulation, and organisational perspective moulding are complicated processes. DMs are focusing more on creating reliable and useful methods to successfully navigate and manage the issues that arise in real-world situations. When given complicated situations that call for the evaluation of many competing criteria, DMs may depend on the rigorous analytical framework known as MCDM. In MCDM, DMs attempt to determine the optimal choice from a range of options by concurrently assessing each option's performance across many factors. Several models, techniques, and procedures have emerged within the framework of MCDM in order to solve the natural difficulties in decision-making. These instruments are supposed to help decision-makers reach more informed and whole conclusions. They achieve this by collecting pertinent data, assessing workable answers depending on many contradicting criteria, and finally finding a compromise. Early studies on MCDM most often focused on deterministic situations with numerical criteria values. But as society and technology have developed, decisions now provide fewer obvious answers and more complex problems. Producing precise numerical numbers that fairly represent the criteria becomes challenging for decision-makers (DMs). An efficient solution to this problem is provided by Zadeh[11] using her fuzzy set (FS) theory. Extension of the idea of characteristic functions in this theory includes membership functions. This theory holds that depending on the criteria satisfied, membership functions give every universal object a membership grade (MG) ranging from zero to one. MGs are one approach the FS theory addresses uncertainty in decision-making. Many academics from many fields have developed several FS extensions to handle issues of complexity and uncertainty. Extended to incorporate MGs and non-membership grades, the intuitionistic fuzzy set (IFS)[12]

Organisational management has recently paid a lot of attention on instruments supporting decision-making. MCDM approaches have now shown to be very helpful in ranking and evaluating alternatives depending on different performance criteria. Sadly, the fact that many modern MCDM models rely on reliable data or expert judgements usually results in little adaptability. Organisations would gain from a more all-encompassing approach including both objective information and personal opinions.

Research gap

Despite the increasing emphasis on OM for improving efficiency, reducing costs, and ensuring sustainable growth, existing decision-making frameworks often face significant limitations:

- Traditional OM strategy selection methods frequently rely on either objective or subjective weighting techniques, leading to potential biases or incomplete assessments. The absence of a hybrid weighting approach combining both perspectives creates a gap in achieving a balanced and holistic evaluation of strategies.
- Most existing OM frameworks fail to comprehensively address multiple critical factors such as cost, quality, resource utilization, and adaptability. This limitation restricts their applicability in dynamic business environments where trade-offs among these criteria are essential.
- Conventional methods often struggle to rank and compare OM strategies effectively due to their inability to handle the complexities of MCDM. This results in a lack of clear guidance for organizations in selecting optimal strategies tailored to their specific operational challenges.
- While several MCDM techniques have been applied in OM, there is a noticeable gap in the integration of advanced methodologies CRITIC, CIMAS, and WASPAS in a unified framework. The synergistic potential of these techniques for robust strategy selection remains underexplored.
- Despite the availability of several MCDM approaches, there is a deficiency of research that systematically evaluates their effectiveness in assessing operational management strategies. Many studies utilize approaches such as AHP, TOPSIS, or VIKOR without sufficiently justifying their selection. This study fills the gap by integrating CRITIC, CIMAS, and WASPAS, demonstrating their combined advantages in managing trade-offs, reducing bias, and improving ranking accuracy in dynamic corporate environments.

This study addresses these gaps by introducing a novel decision-support framework that integrates CRITIC for objective weighting, CIMAS for subjective weighting, and WASPAS for comprehensive ranking.

Contribution

This study contributes to the literature and practice on OM by introducing an innovative MCDM model that:

- Proposes an innovative MCDM framework that integrates both objective (using CRITIC) and subjective (using CIMAS) evaluations, offering a balanced and comprehensive assessment of criteria by leveraging data-driven analysis alongside expert input to enhance decision-making in OM.
- Utilizes the WASPAS method to rank OM strategies, ensuring a comprehensive evaluation that highlights the most efficient and effective approaches.

- Evaluating five OM strategies-Lean Management, Automation, Sustainability, Workforce Flexibility, and Data-Driven Decision-Making-across eight essential criteria, this study offers managers a comprehensive view of strategy effectiveness.
- Aids decision-makers in aligning operational strategies with key goals such as cost-efficiency, flexibility, sustainability, and quality improvement, enhancing the relevance and applicability of the framework.
- Offers a practical tool for managers and policymakers to make informed, performance-oriented choices, bridging the gap between theoretical models and real-world application in OM.

Literature review

The first studies on MCDM problems conducted in deterministic environments In these situations, the qualifying thresholds were usually determined using precise figures. But as society and technology have developed, the environment in which judgements are taken has become more complex and shadowful. As a result, DMs may find it challenging to provide precise numerical values that meet the requirement. This problem is effectively addressed by the FS theory, which was presented by Zadeh[11]. Membership functions that give each universal object a MG between 0 and 1 depending on preset criteria are an extension of characteristic functions, according to this theory. Fuzziness in the decision-making process is successfully addressed by FS theory via the usage of MGs. To deal with the complexity and uncertainty in a variety of disciplines, several scholars have developed a number of FS extensions. An extension of fuzzy sets that offers MGs and non-membership grades is IFS[12].

Key operators and attributes were presented by Cuong and Hai[13,14]. Wei et al.[15–17] contributed by offering projection models[15], generalised dice similarity measurements[16], and specialised similarity measures[17] created especially for PFSs.

Singh developed specific metrics for evaluating connections within PFSs in his work on "correlation coefficients for picture fuzzy sets"[18]. Son[19] presented a new clustering method specifically designed for PFSs. A work by Phong et al.[20] looked at the basic properties of fuzzy relations within PFSs. New concepts, including generalised simplified neutrosophic Einstein AOs and a unique distance metric for fuzzy collections of cubic PFSs, were presented by Ashraf et al.[21,22] and Li et al.[23]. The writers came up with both of these concepts. Constraints on PFSs, especially when combined values were larger than one, led to the discovery of "spherical fuzzy sets" (SFS)[24,25].

Munir et al.[26] created T-SF Einstein hybrid aggregation procedures for decision-making with several characteristics. Zeng et al.[27] used T-SF Einstein interactive aggregation operators to study the selection of photovoltaic cells. The strength of T-SF Liu et al.[28] investigated the use of Muirhead mean operators in group decision-making with several features. Ullah et al.[29] investigated the use of T-SF Hamacher aggregation operators in search and rescue robot testing.

A T-SF DEMATEL technique was used by Zdemirci et al.[30] to assess potential social banking systems. In the framework of T-SF Hypersoft, Sarkar et al.[31] examined aggregation operators based on Sugeno-Weber triangular norms. In order to choose the best construction company, Gurmani et al.[32] proposed a MCDM model with many characteristics that use the linguistic interval-valued T-SF TOPSIS approach. These contributions enhance our comprehension and use of T-SFSs across several domains, proving their efficacy in complex decision-making situations.

Diakoulaki et al.[33] were the first to establish the CRITIC approach . This method offers a dependable answer to the difficult issue of allocating relative significance to different MCDM criteria. Ratio analysis is used by CRITIC for comparison. It calculates each criterion's relative value via pairwise comparisons. Ali[34] presented the CRITIC-MARCOS strategy, which expanded on the fundamental concepts of CRITIC and included a unique scoring function based on spherical fuzzy information. This development enhanced CRITIC's usefulness in decision-making scenarios and demonstrated how adaptable it is to different information architectures.

Mukhametzyanov[35] improved the understanding of objective weight-finding techniques, emphasising CRITIC's capacity to handle the intricacy of weight determination in MCDM scenarios. By incorporating CRITIC into a blockchain assessment system, Zafar et al.[36] demonstrated its adaptability and showed its value in examining complex systems. Technology evaluations like the 5G industry assessment[37], the automobile industry's material selection[38], and the evaluation of sustainable practices in green energy sources[39] also demonstrate CRITIC's flexibility.

CRITIC's capacity to adapt to various decision-making settings was proved by its integration with the grey relational analysis for investment portfolio selection[40] and its use in the virtual reality metaverse for customer needs ranking[41]. Meena et al.[42] use a hierarchical framework to examine how coopetition strategically integrating cooperation and rivalry affects digital transformation business performance. They identify organizational culture, information exchange, and trust as significant factors using M-TISM and PLS-SEM, providing strategic management and operational efficiency insights. Vadivel et al.[43] highlighted the significance of CRITIC in the context of green supplier selection, or sustainable supply chain management. The CRITIC-CODAS method was used by Kumari and Acherjee[44] to choose unconventional machining techniques. Their study used a comprehensive approach, including CODAS for overall decision-making and CRITIC for criteria weight determination. Khargotra et al.[45] focused on the design optimisation and thermo-hydraulic characterisation of delta-shaped barriers in a solar water heating system. Hafidy et al.[46] present a conceptual framework that examines the integration of Industry 4.0 with Operations Management to improve supply chain resilience. The literature analysis underscores the synergistic advantages of these approaches, highlighting the potential of their hybridisation to effectively tackle intricate supply chain issues. The use of MCDM techniques has grown significantly across a range of industries, with a focus on techniques like WASPAS. MCDM techniques were investigated bibliometrically by Büşra and Abacolu[47]. This work provides a fundamental analysis of the MCDM study setting. The VIKOR-WASPAS-entropy technique was shown to be useful in the realm of quiet Genset selection by Vaid et al.[48].Dehshiri et al.[49] present a decision-making framework that combines blockchain technology with strategic partnerships to improve sustainability in the RESC. The study employs CRITIC and F-CoCoSo methodologies to demonstrate how blockchain's transparency and traceability enhance trust and optimizing energy supply and demand management. Dehshiri et al.[50] approach blends Knowledge Management (KM) with Lean, Agile, Resilient, and Green (LARG) paradigms to improve Supply Chain performance. Their study uses SWARA-G and MARCOS-G MCDM methods to emphasise the relevance of coordination and collaboration in automobile efficiency and communication costs. Eghbali-Zarch et al.[51] used fuzzy IDOCRIW and WASPAS algorithms to rank feasible solutions for managing garbage from construction and demolition. This application showed how flexible WASPAS is when dealing with complex waste management issues. To choose an overseas payment mechanism, Nguyen et al.[52] offered a spherical fuzzy WASPAS-based entropy target weighting. This demonstrated WASPAS's financial flexibility. Al-Barakati et al.[53] used an extended interval-valued Pythagorean fuzzy WASPAS approach to assess renewable energy sources. With an emphasis on sustainability, this study helped evaluate renewable energy choices. Masoomi et al.[54] investigated the strategic supplier selection issue in the context of renewable energy supply chains using a fuzzy BWM-WASPAS-COPRAS model. Darzi[55] assesses e-waste mitigation strategies through the lens of Industry 5.0 enablers, utilising an integrated scenario-based BWM and Fuzzy VIKOR approach to prioritise sustainable solutions. Kumar[56] offers a thorough examination of MCDM methods, their applications, and emerging trends, emphasizing their importance in complicated decision-making processes. Bathrinath et al.[57] used fuzzy AHP-WASPAS techniques to study variables impacting long-term performance at construction sites. Our knowledge of sustainable construction approaches has improved as a result of this study. Thanh and Lan[58] examined the deployment of solar energy for Vietnam's sustainable future using a hybrid SWOC-FAHP-WASPAS model. They provided a thorough analysis of solar energy's advantages and disadvantages in sustainable development. Kshanh and Tanaka[59] conduct a comparative examination of MCDM approaches for evaluating energy efficiency projects, emphasising their importance in sustainable industrial energy management within a petrochemical complex. Yu et al.[60] present a comprehensive MCDM framework for assessing Environmental, Social, and Governance sustainable company performance, providing valuable insights for strategic decision-making. The WASPAS approach was used by Handayani et al.[61] in the context of online English course selection. The adaptability of WASPAS in educational decision-making processes was shown by this application. Dehshiri et al.[62] assess the viability of implementing Solar Industrial Process Heat (SIPH) within Iran's textile sector to enhance cleaner production practices. The study employs MCDM methods such as SWARA and MARCOS-G to determine that Isfahan is the most suitable province, emphasising SIPH's capacity for cost-effective energy production and substantial reductions in CO2 emissions in the context of future pollution tax policies. Dehshiri and Zanjirchi[63] propose an extensive framework for assessing hydrogen production from wind energy through MCDM methodologies. The study employs SWARA and WASPAS approaches to identify Bandar Abbas in Iran's Hormozgan province as the most suitable location, emphasising its capacity to generate substantial hydrogen and energy for industrial requirements.

Although decision-making in OM has been widely researched, most existing models don't fully integrate both objective and subjective weighting methods, which are crucial for covering all operational priorities. Many traditional OM frameworks tend to focus on either numbers or opinions alone, often resulting in evaluations that don't fully capture the necessary trade-offs between cost, quality, sustainability, and flexibility. Additionally, while there's plenty of study on individual OM strategies, few studies offer a systematic, multi-criteria comparison of various approaches in a single, unified framework.

The limited use of advanced MCDM techniques, such as the integration of CRITIC for objective weighting with CIMAS for subjective assessment, leaves a gap in methodologies capable of holistically evaluating OM strategies. Further, the underutilization of MCDM models, like WASPAS, that are designed to rank and prioritize alternatives effectively, indicates a need for more sophisticated approaches that can handle the complexity and diversity of modern OM criteria. Addressing these gaps, this study develops a comprehensive, hybrid MCDM framework to support more informed and balanced OM decision-making.

Motivation
In today's fast-paced and competitive world, organizations are leaning heavily on (OM to boost their performance, cut costs, and adapt to ever-changing market conditions. However, making decisions in OM isn't always straightforward. Leaders often find themselves juggling different factors, such as cost efficiency, quality, and sustainability, which can sometimes clash with one another. Many traditional methods in OM tend to focus on just one performance measure or rely on personal judgments, which can miss the bigger picture when evaluating and ranking different strategies. This issue becomes even clearer as businesses strive to meet the rising demands for sustainability, flexibility, and insights driven by data. With this challenge in mind, this study aims to develop a decision-making framework that combines both objective information and subjective insights. By doing so, we hope to create a balanced and practical approach to help organizations choose the best strategies in OM

Structure of the paper
The study is organised logically, beginning with Section 2, which provides an overview of T-spherical fuzzy Sets (T-SFSs) and associated operations. This section lays a solid foundation by illuminating fundamental ideas, mathematical formulae, and important T-SFS properties. Section 3 then goes into depth about the CRITIC-WASPAS technique, which combines the CRITIC and WASPAS approaches for aggregation and criteria weight computation. CRITIC and CIMAS-WASPAS are applicable in Section 4. We discuss the methodology's results, ramifications, and prospects for further study in Section 5. We wrap up by providing a succinct overview that emphasises the methodology's importance in creating frameworks for decision-making

Preliminaries
Definition 1 [64] A T-SFS in Z is defined as:

$$\phi = \{\langle o, \upsilon_\phi(o), \kappa_\phi(o), \chi_\phi(o) | o \in Z \rangle\}, \tag{1}$$

where $\upsilon_\phi(o), \kappa_\phi(o), \chi_\phi(o) \in [0,1]$, such that $0 \leq \upsilon^t_\phi(o) + \kappa^t_\phi(o) + \chi^t_\phi(o) \leq 1$ for all $o \in Z$. $\upsilon_\phi(o), \kappa_\phi(o), \chi_\phi(o)$ denote membership degree (MD), abstinence degree (AD) and non-membership degree (N-MD) respectively for some $o \in Z$. We denote this pair as $E^\varpi = (\upsilon_{E^\varpi}, \kappa_{E^\varpi}, \chi_{E^\varpi})$. Throughout this article it is called T-SFN with the conditions $\upsilon_{E^\varpi}, \kappa_{E^\varpi}, \chi_{E^\varpi} \in [0,1]$ and $\upsilon^t_{E^\varpi} + \kappa^t_{E^\varpi} + \chi^t_{E^\varpi} \leq 1$.

Definition 2 [64] Classifying T-spherical fuzzy numbers (T-SFNs) is essential when applying them to real-world scenarios. T-SFN is the "score function" (SF) for this. $E^\varpi = (\upsilon_{E^\varpi}, \kappa_{E^\varpi}, \chi_{E^\varpi})$ be defined as:

$$S(E^\varpi) = \upsilon^t_{E^\varpi} - \chi^t_{E^\varpi}. \tag{2}$$

However, it is impossible to determine which is superior since the aforementioned function is insufficient for classifying T-SFNs under different situations. To do this, define an accuracy function H of E^ϖ as follows:

$$\hbar^\wp(E^\varpi) = \upsilon^t_{E^\varpi} + \kappa^t_{E^\varpi} + \chi^t_{E^\varpi}. \tag{3}$$

We will provide operational guidelines for T-SFN aggregation.

Definition 3 [28] Let $E^\varpi{}_1 = \langle \upsilon_1, \kappa_1, \chi_1 \rangle$ and $E^\varpi{}_2 = \langle \upsilon_2, \kappa_2, \chi_2 \rangle$ be two T-SFNs, then:

$$E^{\varpi C}_1 = \left\langle \chi_1, \kappa_1, \upsilon_1 \right\rangle, \tag{4}$$

$$E^\varpi{}_1 \vee E^\varpi{}_2 = \left\langle max\{\upsilon_1, \upsilon_2\}, min\{\kappa_1, \kappa_2\}, min\{\chi_1, \chi_2\} \right\rangle, \tag{5}$$

$$E^\varpi{}_1 \wedge E^\varpi{}_2 = \left\langle min\{\upsilon_1, \upsilon_2\}, max\{\kappa_1, \kappa_2\}, max\{\chi_1, \chi_2\} \right\rangle, \tag{6}$$

$$E^\varpi{}_1 \oplus E^\varpi{}_2 = \left\langle \sqrt[t]{\upsilon^t_1 + \upsilon^t_2 - \upsilon^t_1\upsilon^t_2}, \kappa_1\kappa_2, \chi_1\chi_2 \right\rangle, \tag{7}$$

$$E^\varpi{}_1 \otimes E^\varpi{}_2 = \left\langle \upsilon_1\upsilon_2, \sqrt[t]{\kappa^t_1 + \kappa^t_2 - \kappa^t_1\kappa^t_2}, \sqrt[t]{\chi^t_1 + \chi^t_2 - \chi^t_1\chi^t_2} \right\rangle, \tag{8}$$

$$\sigma E^\varpi{}_1 = \left\langle \sqrt[t]{1 - (1 - \upsilon^t_1)^\sigma}, \kappa^\sigma_1, \chi^\sigma_1 \right\rangle, \tag{9}$$

$$E^{\varpi\sigma}_1 = \left\langle \upsilon^\sigma_1, \sqrt[t]{1 - (1 - \kappa^t_1)^\sigma}, \sqrt[t]{1 - (1 - \chi^t_1)^\sigma} \right\rangle. \tag{10}$$

Definition 4 Let $E^\varpi{}_1 = \left\langle \upsilon_1, \kappa_1, \chi_1 \right\rangle$ and $E^\varpi{}_2 = \left\langle \upsilon_2, \kappa_2, \chi_2 \right\rangle$ be two T-SFNs and $\mathbb{E}, \mathbb{E}_1, \mathbb{E}_2 > 0$ be the real numbers, then we have:

1. $E^\varpi{}_1 \oplus E^\varpi{}_2 = E^\varpi{}_2 \oplus E^\varpi{}_1$.
2. $E^\varpi{}_1 \otimes E^\varpi{}_2 = E^\varpi{}_2 \otimes E^\varpi{}_1$.
3. $\mathbb{E}\left(E^\varpi{}_1 \oplus E^\varpi{}_2\right) = \left(\mathbb{E}E^\varpi{}_1\right) \oplus \left(\mathbb{E}E^\varpi{}_2\right)$.
4. $\left(E^\varpi{}_1 \otimes E^\varpi{}_2\right)^{\mathbb{E}} = E^{\varpi\mathbb{E}}_1 \otimes E^{\varpi\mathbb{E}}_2$.
5. $\left(\mathbb{E}_1 + \mathbb{E}_2\right) E^\varpi{}_1 = \left(\mathbb{E}_1 E^\varpi{}_1\right) \oplus \left(\mathbb{E}_2 E^\varpi{}_2\right)$.
6. $E^{\varpi\mathbb{E}_1+\mathbb{E}_2}_1 = E^{\varpi\mathbb{E}_1}_1 \otimes E^{\varpi\mathbb{E}_2}_2$.

Definition 5 For T-SFNs $T_j = (j = 1, 2, 3, \ldots, s)$, the T-spherical fuzzy weighted geometric (T-SFWG) operator is defined as

$$\text{T-SFWG}(S_1, TS_2, \ldots, S_s) = \prod_{j=1}^{s} S_j^{\omega_j},$$

where $w = (w_1, w_2, \ldots, w_s)^T$ is the weighted vector of $G_j = (j = 1, 2, 3, \ldots, s), \omega_j > 0$, and $\sum_{j=1}^{s} \omega_j = 1$. Based on Definition 5, the outcome described in Theorem 6 can be derived as a result.

Theorem 6 The aggregated value of a collection of $T-SFNs\ G_j\ (j = 1, 2, 3, \ldots, s)$ using the T-SFWG operator is also a $T-SFN$, and

$$\text{T-SFWG}(S_1, S_2, \ldots, S_s) = \left(\prod_{j=1}^{s}(\upsilon_j^a + \chi_j^a)^{\omega_j^a} - \prod_{j=1}^{s}\chi_j^{a\omega_j^a},\right. \\ \left.\prod_{j=1}^{s}\chi_j^{a\omega_j^a},\ \sqrt[n]{1 - \prod_{j=1}^{s}\left(1 - \kappa_j^{a\omega_j^a}\right)}\right). \tag{11}$$

CRITIC and CIMAS-WASPAS method for MCDM based on T-SFSs

The proposed model is systematically summarised in this section. The objective weights assigned to each criteria are determined using the T-SF CRITIC approach. Following that, solutions are evaluated using the T-SF CoCoSo approach in accordance with the highlighted limitations. By contributing their expertise based on the language factors listed in Table 1, DMs aid in the assessment process.

Algorithm: T-SFNs based CRITIC and CIMAS-WASPAS technique
Step 1: In a decision-making scenario involving DMs, we are given a set of criteria indicated by $B^\beta = B^\beta{}_1, B^\beta{}_2, ..., B^\beta{}_n$ and a set of alternatives denoted by A $= V^\psi{}_1, V^\psi{}_2, ..., V^\psi{}_m$. Each criteria $B^\beta{}_j$ is evaluated by multiple DMs using T-SFNs for every alternative $V^\psi{}_i$. The T-SF-DM matrix $T = (\upsilon_{ij}^{*(k)})_{m\times n}$ is used by DMs, identified as $D_1, D_2, ..., D_k$, to express their evaluations. Here, $\upsilon_{ij}^{*(k)}$ represents the k-th expert's assessment of criteria $B^\beta{}_j$ for option $V^\psi{}_i$.

$$\begin{array}{c} \\ V^{\Psi}{}_1 \\ V^{\Psi}{}_2 \\ \vdots \\ V^{\Psi}{}_m \end{array} \begin{array}{c} \begin{array}{cccc} B^{\beta}{}_1 & B^{\beta}{}_2 & & B^{\beta}{}_n \end{array} \\ \begin{bmatrix} \langle \upsilon_{11}, \kappa_{11}\chi_{11} \rangle & \langle \upsilon_{12}, \kappa_{12}\chi_{12} \rangle & \cdots & \langle \upsilon_{1n}, \kappa_{1n} \rangle \chi_{1n} \rangle \\ \langle \upsilon_{21}, \kappa_{21} \rangle, \chi_{21} \rangle & \langle \upsilon_{22}, \kappa_{22} \rangle, \chi_{22} \rangle & \cdots & \langle \upsilon_{2n}, \kappa_{2n} \rangle, \chi_{2n} \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle \upsilon_{m1}, \kappa_{m1} \rangle, \chi_{m1} \rangle & \langle \upsilon_{m2}, \kappa_{m2} \rangle, \chi_{m2} \rangle & \cdots & \langle \upsilon_{mn}, \kappa_{mn} \rangle, \chi_{mn} \rangle \end{bmatrix} \end{array}$$

Step 2: Examine the weights w_k of the DMs by:

$$w_k = \frac{\upsilon_{E\varpi}^t - \chi_{E\varpi}^t}{\sum_{k=1}^{t}\left[\upsilon_{E\varpi}^t - \chi_{E\varpi}^t\right]} \tag{12}$$

where $w_k \geq 0$ and $\sum_{k=1}^{t} w_k = 1$.

Step 3: The DMs believe that in order to get the aggregated T-SFDWA that is described in Equation 13, all of the various tables must be combined into one group.

Linguistic terms	**Abbreviations**	**T-SFNs**
Highly Favorable	AD	⟨ 0.90 ,0.03, 0.12)⟩
Above Moderate	BD	⟨0.83, 0.13, 0.09⟩
Moderately Favorable	CD	⟨0.75, 0.19, 0.15)⟩
Equally Viable	DD	⟨0.68, 0.26, 0.20⟩
Slight Preference	ED	⟨0.59, 0.34 0.30⟩
Somewhat Neutral	FD	⟨0.41, 0.47, 0.40⟩
Neutral Position	GD	⟨0.20,0.56, 0.53⟩

Table 1. Linguistic terms.

$$\text{T-SFWG}(S_1, S_2, \ldots, S_s) = \left(\prod_{j=1}^{s} (\upsilon_j^a + \chi_j^a)^{\omega_j^a} - \prod_{j=1}^{s} \chi_j^{a\omega_j^a}, \right. \\ \left. \prod_{j=1}^{s} \chi_j^{a\omega_j^a}, \sqrt[n]{1 - \prod_{j=1}^{s} \left(1 - \kappa_j^{a\omega_j^a}\right)} \right). \tag{13}$$

Step 4: CRITIC Method

Step 4.1: For each T-SFNs F_{ij}, create the score matrix $S^* = (\Phi(F_{ij}))_{m\times n}, \forall$ by:

$$\Phi(F_{ij}) = \upsilon_{E^\varpi}^t - \chi_{E^\varpi}^t. \tag{14}$$

Step 4.2: The necessary process that produces the final matrix, which is the standardised representation of T-SFNs, was explained by equation (15).

$$\widetilde{K}_{ij} = \begin{cases} \frac{\Phi(F)_{ij} - \Phi(F)_j^-}{\Phi(F)_j^+ - \Phi(F)_j^-}, & j \in M_b \\ \frac{\Phi(F)_j^+ - \Phi(F)_{ij}}{\Phi(F)_j^+ - \Phi(F)_j^-}, & j \in M_c \end{cases} \tag{15}$$

where $\Phi(F)_j^+ = \max_i \Phi(F)_{ij}, \Phi(F)_j^- = \min_i \Phi(F)_{ij}, M_b$ and M_c represents the benefit-type and cost-type criteria, respectively.

Step 4.3 Use the provided Equation (16) to approximate the standard deviations for the criterion.

$$Q^\varpi{}_j = \sqrt{\frac{\sum_{i=1}^{n} \left(\Phi(F)_{ij} - \bar{Q}_j\right)^2}{M}}. \tag{16}$$

Where $\bar{Q}_j = \sum_{i=1}^{n} \widetilde{K}_{ij}/n$

Step 4.4: Equation (17) used to determine the correlation coefficient for the criterion, offering a consistent way to assess the connection across the dataset. This method provides a reliable and consistent method for determining the correlation.

$$\urcorner_{jt} = \frac{\sum_{i=1}^{n} \left(\Phi(F)_{ij} - \bar{Q}_j\right)\left(\Phi(F)_{ij} - \bar{\Phi(F)}_t\right)}{\sqrt{\sum_{i=1}^{n} \left(\Phi(F)_{ij} - \bar{Q}_j\right)^2 \left(\Phi(F)_{ij} - \bar{Q}_t\right)^2}} \tag{17}$$

Step 4.5: Equation (18) used to assess the data for each criteria. This often used method finds the relevant data information and connections inside the dataset. This formula provides an organized method for a thorough examination of the requirements.

$$\Pi_j = Q^\varpi \sum_{t=1}^{m} (1 - \urcorner_{jt}) \tag{18}$$

Step 4.6: Use the provided equation (19) to determine the appropriate weight for each criteria.

$$P_j = \frac{\Pi_j}{\sum_{j=1}^{p} \Pi_j} \tag{19}$$

Subjective weights of criteria using T-SF-CIMAS

Step 5: After creating the scoring matrix, the following step is to normalise the data. As a result, the supplied data is arranged between 0 and 1. It makes the choosing process more simpler. Equation (20) describes the normalising strategy that was used.

$$\Delta ij = \frac{\Phi(F)_{ij}}{\sum_{i=1}^{r} \Phi(F)_{ij}} \tag{20}$$

Step 6: Here, we multiply each expert's weight by the normalized data matrix. Equation (21) is used to determine it.

$$\Omega_{ij} = \Delta ij(P_j) \tag{21}$$

Step 7: The primary goal of this step is to determine the maximum and minimum values of each criterion in the expert-weighted matrix.

$$\rho_j = \underset{i}{max}\ (\Omega_{ij}) \tag{22}$$

$$\xi_j = \underset{i}{min}\ (\Omega_{ij}) \tag{23}$$

Step 8: The difference between the lowest and highest points that were acquired in the previous phase is calculated in this phase using equation (24).

$$\beth^{\beta}{}_j = \rho_j - \xi_j \tag{24}$$

Step 9: This step is determining the criterion's relevance using Equation (25), the final weighting equation.

$$R_j = \frac{\beth^{\beta}{}_j}{\sum_{j=1}^{t} \beth^{\beta}{}_j} \tag{25}$$

Step 10: The criterion weights obtained from the T-SF-CIMAS and objective weighting approach CRITIC are aggregated using Equation (26). The final criteria weights are then determined using Equation (27).

$$U_j = \frac{(\tau)R_j + (1-\tau)P_j}{2}, \quad \tau \in [0,1] \tag{26}$$

$$W_j = \frac{U_j}{\sum_{j=1}^{t} U_j} \tag{27}$$

WASPAS

Step 11: Used Equations (28) to apply the cost and benefit criteria standardisation. By changing the values to the same scale, the linked characteristics of the cost and benefit types are appropriately and identically rated.

$$T^{\eta}{}_{ij} = \begin{cases} \frac{\Phi(F)_{ij}}{\max\limits_i \Phi(F)_{ij}}, & j \in \mathrm{Cr}_b \\ \frac{\max\limits_i \Phi(F)_{ij}}{\Phi(F)_{ij}}, & j \in \mathrm{Cr}_c \end{cases} \qquad i = 1, 2, \ldots, u;\ \ j = 1, 2, \ldots, v; \tag{28}$$

Step 12: Use Equation (29) to get the additive relative importance for each option in the weighted normalized data.

$$G^{\xi}{}_{1i} = \sum_{j=1}^{n} T^{\eta}{}_{ij} \cdot \mathrm{W}j \quad i = 1, 2, \ldots, u; \tag{29}$$

Step 13: To get the weighted normalizes multiplicative relative significance, use equation (30).

$$G^{\xi}{}_{2i} = \prod_{j=1}^{n} {T^{\eta}}_{ij}^{\mathrm{W}j} \quad i = 1, 2, \ldots, u; \tag{30}$$

Step 14: In this case, equation (31) provides the joint generalized criteria (J).

$$\gimel^{X}{}_i = \frac{1}{2}\left(\sum_{j=1}^{n} G^{\xi}{}_1 + \prod_{j=1}^{n} G^{\xi}{}_2\right) \quad i = 1, 2, \ldots, u; \tag{31}$$

Equation (32) aims to improve ranking accuracy.

$$\daleth^{X}{}_{i} = \delta^{S}\sum_{j=1}^{n} G^{\xi}{}_{1} + (1-\delta^{S})\prod_{j=1}^{n} G^{\xi}{}_{2} \quad i = 1, 2, \ldots, u; \tag{32}$$

Applications of the proposed framework

In today's highly competitive and dynamic business environment, OM is crucial for organizations aiming to achieve sustainable efficiency and maintain a competitive edge. Despite the wealth of available strategies, OM decision-makers face challenges in selecting the most effective approach due to the complex trade-offs between cost, quality, resource utilization, and other key factors. Traditional decision-making models often fail to address the intricacies and uncertainties involved in managing diverse operational goals concurrently. Therefore, there is a pressing need for a systematic, MCDM framework that integrates advanced decision tools to identify the most efficient operational strategy.

Within the manufacturing and supply chain sectors, this study assesses five alternative operational strategies, each of which possesses unique characteristics, under eight critical performance criteria. The goal is to develop a comprehensive decision-making model that will help organizations enhance operational efficiency while balancing multiple objectives. This study uses MCDM techniques to offer practical insights, helping identify the best strategies for boosting efficiency in OM.

Definition of alternatives

1. **Data-Driven Decision-Making** $(V^{\psi}{}_{1})$: This strategy uses analytics and data-driven insights to support operational decisions. By leveraging big data, predictive analytics, and real-time monitoring, organizations can make informed, precise adjustments in operations, improving overall effectiveness. Awan et al.[65] examined data-driven insights that empower managers to make decisions. The study highlights the importance of developing robust BDA capabilities to support circular economy initiatives emphasising sustainability and resource efficiency. Gong[66] introduces reinforcement learning and stochastic optimization as data-driven decision-making techniques to improve inventory management.
2. **Flexible Workforce Allocation** $(V^{\psi}{}_{2})$: This strategy optimizes labour deployment by aligning workforce availability with fluctuating demand. It includes practices like cross-training employees, flexible scheduling, and real-time resource allocation to meet demand efficiently. Oyetoro[67] explored the pivotal role of operations strategy in aligning organizational goals with operational processes to achieve competitive advantage. The study has shown that selecting optimal facility locations enables organizations to minimize the costs related to transportation and labour. Qin et al.[68] investigate workforce flexibility in OM, emphasizing its significance in improving productivity and adaptability within dynamic business contexts.
3. **Sustainability-Driven Operations** $(V^{\psi}{}_{3})$: This approach prioritizes eco-friendly practices, including energy conservation, waste reduction, and sustainable sourcing. It is aimed at long-term efficiency gains through practices that reduce the environmental impact of operations. Sahoo and Goswami[69] provide a comprehensive review of recent studies on green supplier selection using MCDM approaches. The study emphasized the evolving criteria in green supplier selection, such as life-cycle analysis, carbon footprint, and resource efficiency, which reflect the growing complexity of sustainable supply chain management. Stratton et al.[70] investigate sustainable OM, highlighting approaches that reconcile environmental accountability with operational effectiveness.
4. **Lean Management Implementation** $(V^{\psi}{}_{4})$: This strategy focuses on minimizing waste and optimizing resource allocation. It emphasizes continuous improvement, often through practices like just-in-time (JIT) inventory, to enhance process efficiency and reduce unnecessary expenditures. Cuatrecasas[71] outlines a method for the implementation of lean management, emphasizing the improvement of efficiency and the minimization of waste. Zd?ba-Mozoła et al.[72] investigate the application of lean management tools in healthcare settings, focusing on the analysis of prolonged patient stays at a multi-specialist hospital in Poland. The study demonstrates the use of lean tools, such as value stream mapping, to map patient flow and identify areas where delays or inefficiencies occur.
5. **Automation and Digitization** $(V^{\psi}{}_{5})$: This strategy involves implementing technology-driven solutions, such as robotics and automated data processing, to reduce manual tasks, increase speed, and minimize human error. Digitization also enables real-time monitoring and data-driven decision-making. Trofimov et al.[73] explore the impact of automation and digitalization on the management of service organizations, providing insights into how these technologies can transform operational processes, improve service delivery, and enhance overall organizational efficiency. Schumacher et al.[74] investigate the effects of automation, digitisation, and digitalisation on manufacturing processes, highlighting their significance in improving productivity and fostering innovation.

Definition of criteria

1. **Cost Efficiency** (C_1): This criterion is all about finding ways to minimize costs while still achieving the desired results. It's not just about cutting corners but about making smarter decisions. It includes everything from production costs, labor, materials, to ongoing maintenance. A strategy focused on cost efficiency ensures that you're not overspending and helps stretch every dollar to get the best return. It also helps businesses remain competitive in markets where profit margins can be tight, and it fosters long-term financial sustainability.

2. **Time Efficiency** (C_2): Time is money, as the saying goes, and this criterion focuses on how well a strategy reduces time spent on tasks without compromising quality. It's about streamlining processes, cutting down lead times, reducing setup times, and making everything run faster. A strategy that's efficient with time helps businesses stay agile-able to respond to customer demands quickly and keep up with the competition. For customers, this means quicker delivery, and for businesses, it means more capacity to take on new projects without increasing overhead.
3. **Quality Improvement** (C_3): Quality is key to customer satisfaction and loyalty. This criterion looks at how well a strategy helps improve product or service quality. A strong focus on quality means producing goods or services that are reliable, consistent, and meet or exceed industry standards. The benefits of improved quality go beyond just keeping customers happy-it also reduces the likelihood of returns or complaints, lowers costs associated with fixing mistakes, and enhances the brand's reputation. When quality improves, businesses can command better prices and build long-lasting relationships with clients.
4. **Resource Utilization** (C_4): Efficient use of resources is central to any successful business operation. This criterion measures how well a strategy optimizes the use of resources such as labor, raw materials, and equipment. It's about ensuring that every asset is being used effectively to minimize waste and improve productivity. Effective resource utilization not only helps lower operational costs but also reduces environmental impact by minimizing waste and excess consumption. A strategy that maximizes resource use contributes to sustainability while maintaining or increasing output.
5. **Flexibility** (C_5): In a world that is constantly changing, flexibility is critical. This criterion evaluates how well a strategy allows a business to adapt to shifts in market conditions, customer preferences, production needs, or unexpected disruptions. Whether it's a sudden spike in demand or a supply chain hiccup, a flexible strategy allows businesses to pivot and adjust quickly. This could mean adjusting production schedules, switching suppliers, or even rethinking entire processes. A business that can be flexible is more resilient and better equipped to handle unforeseen challenges, which leads to long-term success.
6. **Sustainability** (C_6): Sustainability is no longer just a buzzword-it's a necessity for modern businesses. This criterion reflects how well an operational strategy incorporates eco-friendly practices, such as reducing waste, lowering carbon emissions, and conserving energy. More and more consumers and investors are prioritizing sustainability, so having a strategy focused on environmental responsibility helps businesses attract customers who care about these issues and comply with regulatory requirements. In addition, sustainable practices often lead to cost savings (such as energy efficiency), create a positive brand image, and ensure that businesses contribute to global environmental goals, positioning them for future growth.
7. **Employee Satisfaction** (C_7): A satisfied workforce is a productive one. This criterion assesses how much the strategy influences employee morale and overall job satisfaction. Strategies that focus on creating a positive work environment, offering fair compensation, promoting work-life balance, and providing opportunities for growth contribute to happier, more engaged employees. High employee satisfaction leads to lower turnover, which means less money spent on recruitment and training. It also boosts productivity because motivated employees are more likely to go above and beyond. Furthermore, a healthy and positive workplace culture encourages creativity, collaboration, and long-term loyalty from employees.
8. **Risk Management** (C_8): Risk is inevitable in any business, but how you handle it can make all the difference. This criterion focuses on the ability of an operational strategy to identify potential risks and take proactive steps to manage them. Whether it's supply chain disruptions, unforeseen market changes, or the possibility of equipment failure, a well-thought-out risk management strategy helps reduce the impact of these events. It involves assessing the likelihood of risks, planning for contingencies, and ensuring that the business has the right systems in place to quickly recover.

Experimental results

Step 1: Table 2 presents a tabular record of the DMs' comments. They utilised linguistic term from Table 1 to express their opinions.

Step 2: The weights of DMs is analysing the importance assigned to each DM's area of expertise. Three DMs. comprised this case study. Equation (12) was used to explain the T-SFS linguistic values for the many DMs mentioned in Table 3.

Step 3: To generate the aggregated T-SFNs, individual tables are systematically gathered and categorized according to the viewpoints of the respective DMs. Equation (13) defined the T-SFWG operator, which was used to combine them. Table 4 displays the outcome.

Step 4.1: Equation (14) was used to calculate the score matrix S^* as follows:

$$S^* = \begin{bmatrix} 0.0879 & 0.3769 & 0.0960 & 0.1484 & 0.6715 & 0.4941 & 0.5172 & 0.2769 \\ 0.6565 & 0.0216 & 0.2173 & 0.3443 & 0.4562 & 0.1840 & 0.3917 & -0.0851 \\ 0.1174 & 0.3902 & 0.0080 & 0.3895 & 0.6907 & 0.1555 & 0.0216 & 0.3390 \\ 0.2304 & 0.4749 & 0.6209 & 0.0750 & 0.0966 & 0.5578 & 0.3420 & 0.0488 \\ 0.2885 & 0.6217 & 0.1999 & 0.0767 & -0.0995 & 0.4769 & 0.0795 & -0.1036 \end{bmatrix}$$

Step 4.2: Equation (15) was used to convert the score matrix S^* into the normalised matrix $\widetilde{K}$:

$$\widetilde{K} = \begin{bmatrix} 1 & 0.4079 & 0.1436 & 0.7666 & 0.0243 & 0.1583 & 0 & 0.1403 \\ 0 & 1 & 0.3415 & 0.1437 & 0.2968 & 0.9292 & 0.2532 & 0.9582 \\ 0.9481 & 0.3858 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0.7494 & 0.2446 & 1 & 1 & 0.7518 & 0 & 0.3535 & 0.6557 \\ 0.6472 & 0 & 0.3131 & 0.9946 & 1 & 0.2011 & 0.8832 & 1 \end{bmatrix}$$

Experts	B^{β}_1	B^{β}_2	B^{β}_3	B^{β}_4	B^{β}_5	B^{β}_6	B^{β}_7	B^{β}_8
DM_1	AD	BD	CD	DD	ED	FD	ED	AD
	BD	CD	DD	ED	FD	ED	AD	BD
	CD	DD	ED	FD	ED	AD	BD	CD
	DD	ED	FD	ED	AD	BD	CD	DD
	ED	FD	ED	AD	BD	CD	DD	ED
DM_2	FD	ED	AD	BD	CD	DD	ED	FD
	ED	AD	BD	CD	DD	ED	FD	ED
	AD	BD	CD	DD	ED	FD	ED	AD
	BD	CD	DD	ED	FD	ED	AD	BD
	CD	DD	ED	FD	ED	AD	BD	CD
DM_3	DD	ED	FD	ED	AD	BD	CD	DD
	ED	FD	ED	AD	BD	CD	DD	ED
	FD	ED	AD	BD	CD	DD	ED	FD
	ED	AD	BD	CD	DD	ED	FD	ED
	AD	BD	CD	DD	ED	FD	ED	AD

Table 2. Linguistic terms of given by DMS.

DMs	Qualification	Expertise	Aptitude	Experience	Weights
DM_1	AD	BD	CD	DD	0.3667
DM_2	ED	AD	BD	CD	0.3328
DM_3	DD	ED	AD	BD	0.3005

Table 3. Linguistic terms about DMs.

C_i	V^{ψ}_1	V^{ψ}_2	V^{ψ}_3	V^{ψ}_4	V^{ψ}_5
C_1	$\langle 0.520, 0.315, 0.375\rangle$	$\langle 0.870, 0.155, 0.125\rangle$	$\langle 0.630, 0.415, 0.510\rangle$	$\langle 0.635, 0.305, 0.295\rangle$	$\langle 0.730, 0.390, 0.465\rangle$
C_2	$\langle 0.730, 0.245, 0.230\rangle$	$\langle 0.505, 0.395, 0.475\rangle$	$\langle 0.735, 0.250, 0.190\rangle$	$\langle 0.815, 0.325, 0.405\rangle$	$\langle 0.885, 0.345, 0.415\rangle$
C_3	$\langle 0.615, 0.410, 0.515\rangle$	$\langle 0.665, 0.365, 0.425\rangle$	$\langle 0.430, 0.345, 0.415\rangle$	$\langle 0.870, 0.285, 0.335\rangle$	$\langle 0.665, 0.375, 0.455\rangle$
C_4	$\langle 0.655, 0.425, 0.510\rangle$	$\langle 0.735, 0.315, 0.375\rangle$	$\langle 0.785, 0.365, 0.455\rangle$	$\langle 0.515, 0.335, 0.395\rangle$	$\langle 0.605, 0.435, 0.525\rangle$
C_5	$\langle 0.880, 0.225, 0.215\rangle$	$\langle 0.815, 0.360, 0.440\rangle$	$\langle 0.885, 0.175, 0.135\rangle$	$\langle 0.595, 0.415, 0.485\rangle$	$\langle 0.415, 0.465, 0.555\rangle$
C_6	$\langle 0.835, 0.370, 0.445\rangle$	$\langle 0.615, 0.315, 0.365\rangle$	$\langle 0.635, 0.395, 0.465\rangle$	$\langle 0.825, 0.205, 0.155\rangle$	$\langle 0.805, 0.235, 0.355\rangle$
C_7	$\langle 0.805, 0.215, 0.165\rangle$	$\langle 0.735, 0.245, 0.175\rangle$	$\langle 0.505, 0.385, 0.475\rangle$	$\langle 0.745, 0.335, 0.415\rangle$	$\langle 0.515, 0.325, 0.385\rangle$
C_8	$\langle 0.745, 0.435, 0.515\rangle$	$\langle 0.425, 0.455, 0.545\rangle$	$\langle 0.785, 0.445, 0.525\rangle$	$\langle 0.595, 0.465, 0.545\rangle$	$\langle 0.425, 0.475, 0.565\rangle$

Table 4. Aggregated decision matrix.

B^{β}_1	B^{β}_2	B^{β}_3	B^{β}_4	B^{β}_5	B^{β}_6	B^{β}_7	B^{β}_8
0.4006	0.3688	0.3836	0.4769	0.4457	0.4694	0.4270	0.4612

Table 5. Standard deviations.

Step 4.3: Equation 16 was used to determine the SDs, which are shown in Table 5.

Step 4.4: Equation (17) was used to assess CRCs among criteria. Table 6 contains the findings.

Step 4.5: Equation (18) was used to compute the information amount for each criteria, and the results are shown in Table 7.

Step 4.6: The objective weight for each criteria was determined using Equation (19) and is provided in Table 8.

Step 5: We first used Equation (20) to normalise the score matrix M_{ij}^{Sc} in an attempt to ascertain the subjective weights. The normalised matrix *IN ij* that results is shown below.

$B^{\beta}{}_1$	$B^{\beta}{}_2$	$B^{\beta}{}_3$	$B^{\beta}{}_4$	$B^{\beta}{}_5$	$B^{\beta}{}_6$	$B^{\beta}{}_7$	$B^{\beta}{}_8$
1	-0.6878	-0.1745	0.2833	-0.2124	-0.3913	0.1740	-0.7626
-0.6878	1	-0.1561	-0.6867	-0.5391	0.6448	-0.4597	0.0780
-0.1745	-0.1561	1	0.5819	0.6204	-0.5832	-0.2732	0.4602
0.2833	-0.6867	0.5819	1	0.7097	-0.9768	-0.2189	0.3358
-0.2124	-0.5391	0.6204	0.7097	1	-0.5594	0.2520	0.7771
-0.3913	0.6448	-0.5832	-0.9768	-0.5594	1	0.3408	-0.1698
0.1740	-0.4597	-0.2732	-0.2189	0.2520	0.3408	1	-0.0177
-0.7626	0.0780	0.4602	0.3358	0.7771	-0.1698	-0.0177	1

Table 6. Correlation coefficients.

$B^{\beta}{}_1$	$B^{\beta}{}_2$	$B^{\beta}{}_3$	$B^{\beta}{}_4$	$B^{\beta}{}_5$	$B^{\beta}{}_6$	$B^{\beta}{}_7$	$B^{\beta}{}_8$
1.9196	2.2386	1.2000	1.4841	1.5249	3.2228	2.3593	1.8960

Table 7. The criterion's information quantitative values.

$B^{\beta}{}_1$	$B^{\beta}{}_2$	$B^{\beta}{}_3$	$B^{\beta}{}_4$	$B^{\beta}{}_5$	$B^{\beta}{}_6$	$B^{\beta}{}_7$	$B^{\beta}{}_8$
0.1211	0.1413	0.0757	0.0937	0.0962	0.2034	0.1489	0.1197

Table 8. The objective weights.

$$\Delta ij = \begin{bmatrix} 0.0637 & 0.1999 & 0.0841 & 0.1435 & 0.3699 & 0.2645 & 0.3825 & 0.5817 \\ 0.4755 & 0.0115 & 0.1903 & 0.3330 & 0.2513 & 0.0985 & 0.2897 & -0.1788 \\ 0.0850 & 0.2070 & 0.0070 & 0.3767 & 0.3804 & 0.0832 & 0.0160 & 0.7122 \\ 0.1669 & 0.2519 & 0.5436 & 0.0725 & 0.0532 & 0.2986 & 0.2530 & 0.1025 \\ 0.2090 & 0.3298 & 0.1750 & 0.0742 & -0.0548 & 0.2553 & 0.0588 & -0.2176 \end{bmatrix} \tag{33}$$

Step 6: The normalised matrix WIN_{ij} is generated by calculating the multiplied matrix.

$$\Omega_{ij} = \begin{bmatrix} 0.0077 & 0.0282 & 0.0064 & 0.0134 & 0.0356 & 0.0538 & 0.0570 & 0.0696 \\ 0.0576 & 0.0016 & 0.0144 & 0.0312 & 0.0242 & 0.0200 & 0.0431 & -0.0214 \\ 0.0103 & 0.0292 & 0.0005 & 0.0353 & 0.0366 & 0.0169 & 0.0024 & 0.0852 \\ 0.0202 & 0.0356 & 0.0412 & 0.0068 & 0.0051 & 0.0607 & 0.0377 & 0.0123 \\ 0.0253 & 0.0466 & 0.0133 & 0.0069 & -0.0053 & 0.0519 & 0.0088 & -0.0260 \end{bmatrix} \tag{34}$$

Step 7: Below are the highest (ρ_j) and lowest (ξ_j) values for each column.

$$\rho_j = [0.0077 \quad 0.0016 \quad 0.0005 \quad 0.0068 \quad -0.0053 \quad 0.0169 \quad 0.0024 \quad -0.0260] \tag{35}$$

$$\xi_j = [0.0576 \quad 0.0466 \quad 0.0412 \quad 0.0353 \quad 0.0366 \quad 0.0607 \quad 0.0570 \quad 0.0852] \tag{36}$$

Step 8: To calculate the difference, the equation (24) is used.

$$\daleth^{\beta}{}_j = [0.0499 \quad 0.0450 \quad 0.0406 \quad 0.0285 \quad 0.0419 \quad 0.0438 \quad 0.0546 \quad 0.1113] \tag{37}$$

Step 9: The difference values from matrix $\daleth^{\beta}{}_j$ are used to compute the criteria weights, represented as P_j.

$$R_j = [0.1201 \quad 0.1082 \quad 0.0978 \quad 0.0686 \quad 0.1008 \quad 0.1054 \quad 0.1314 \quad 0.2678] \tag{38}$$

Step 10: Equation (26) computes the aggregated weights from objective and subjective techniques while maintaining $\tau = 0.5$. Figure 1 and Figure2 provide a visual representation of changing parameter τ and its impact of weights.

$$W_j = [0.1190 \quad 0.1233 \quad 0.0859 \quad 0.0804 \quad 0.0975 \quad 0.1525 \quad 0.1387 \quad 0.1902] \tag{39}$$

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Step 11: Equations (28) are used to normalize the cost and benefit criteria. Following normalization, the data may be seen in Table 9.

Step 12, 13 and 14: In the weighted normalized data, the additive relative significance, multiplicative relative importance, and joint generalized criterion for each option were obtained using the formulas (29), (30), and (31), respectively. The values that were obtained are shown in Table (10).

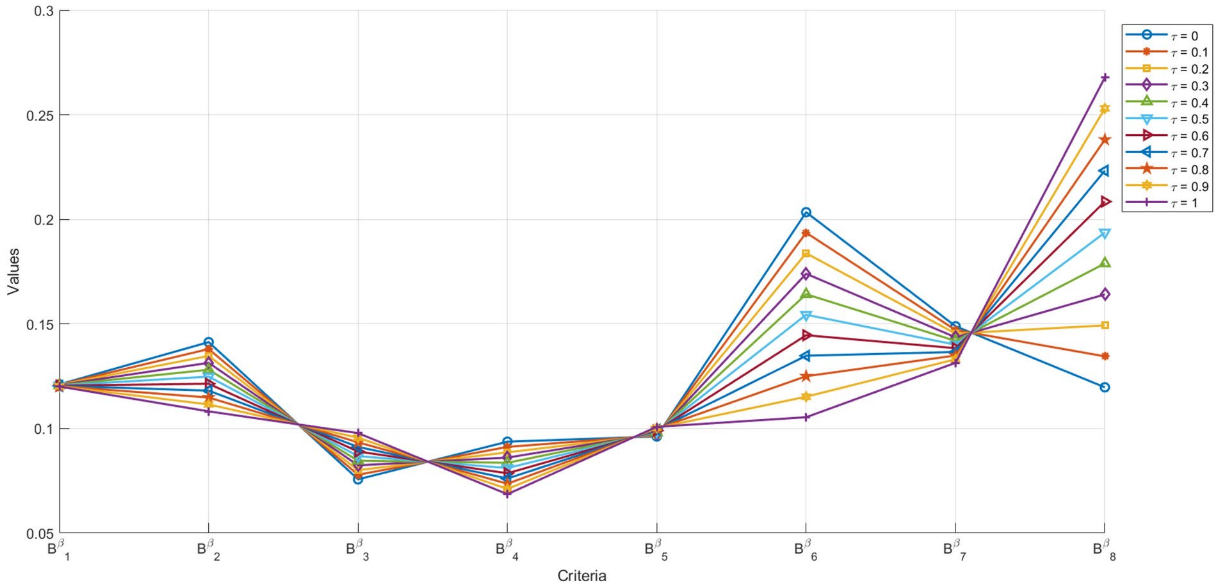

Figure 1. Impact of Parameter (τ) on weights with line graph.

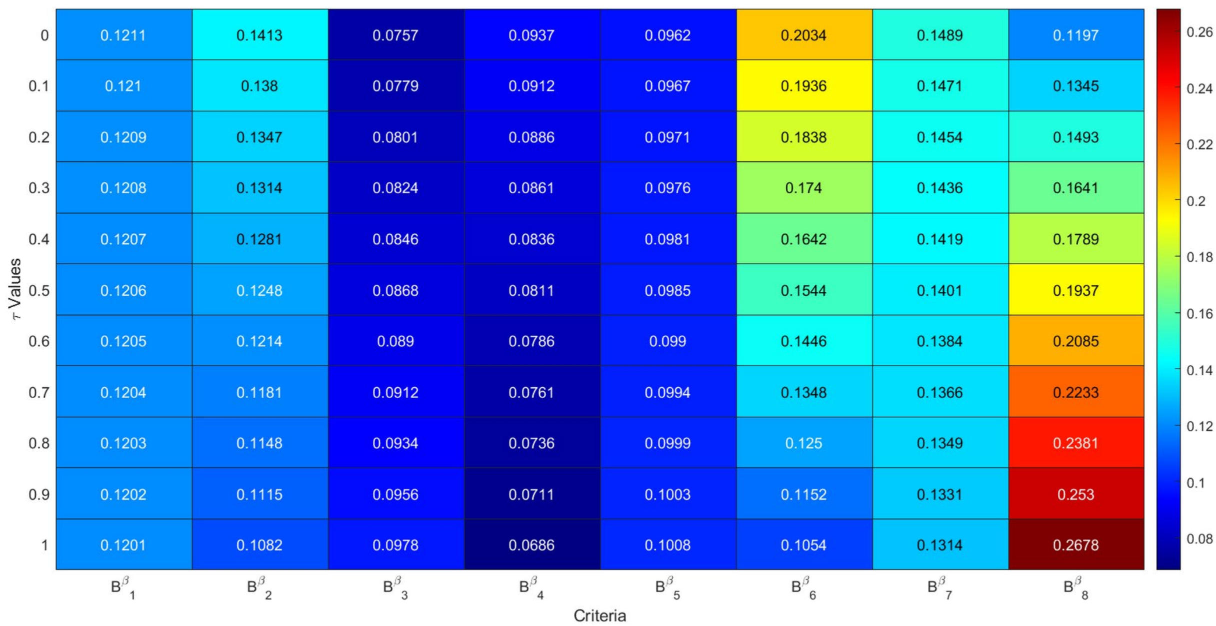

Figure 2. Impact of Parameter (τ) on weights.

B^{β}_1	B^{β}_2	B^{β}_3	B^{β}_4	B^{β}_5	B^{β}_6	B^{β}_7	B^{β}_8
0.1309	0.5613	0.1430	0.2210	1.0000	0.7358	0.7702	0.4124
1.0000	0.0329	0.3310	0.5244	0.6949	0.2803	0.5966	-0.1296
0.1700	0.5649	0.0116	0.5639	1.0000	0.2251	0.0313	0.4908
0.3711	0.7649	1.0000	0.1208	0.1556	0.8984	0.5508	0.0786
0.4641	1.0000	0.3215	0.1234	-0.1600	0.7671	0.1279	-0.1666

Table 9. Normalized matrix.

Alternative	$G^{\xi}{}_1$	$G^{\xi}{}_2$	$\daleth^{X}$	Ranking
$V^{\psi}{}_1$	0.5366	0.4387	0.4877	0.4897
$V^{\psi}{}_2$	0.3972	0.2687	0.3330	0.3350
$V^{\psi}{}_3$	0.3595	0.2037	0.2816	0.2836
$V^{\psi}{}_4$	0.5292	0.3868	0.4580	0.4600
$V^{\psi}{}_5$	0.3731	0.2526	0.3129	0.3149

Table 10. Final ranking.

δ^S	$V^{\psi}{}_1$	$V^{\psi}{}_2$	$V^{\psi}{}_3$	$V^{\psi}{}_4$	$V^{\psi}{}_5$	Ranking	Best alternative
$\delta^S = 0.1$	0.4485	0.2816	0.2193	0.4010	0.2646	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.2$	0.4583	0.2944	0.2349	0.4152	0.2767	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.3$	0.4681	0.3073	0.2505	0.4295	0.2887	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.4$	0.4779	0.3201	0.2660	0.4437	0.3008	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.5$	0.4877	0.3329	0.2816	0.4580	0.3129	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.6$	0.4974	0.3458	0.2972	0.4722	0.3249	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.7$	0.5072	0.3587	0.3128	0.4864	0.3360	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.8$	0.5170	0.3715	0.3284	0.5007	0.3490	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 0.9$	0.5268	0.3843	0.3440	0.5149	0.3619	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$
$\delta^S = 1$	0.5366	0.3971	0.3595	0.5292	0.3748	$V^{\psi}{}_1 \succ V^{\psi}{}_4 \succ V^{\psi}{}_2 \succ V^{\psi}{}_5 \succ V^{\psi}{}_3$	$V^{\psi}{}_1$

Table 11. The effect δ^S on the ranking.

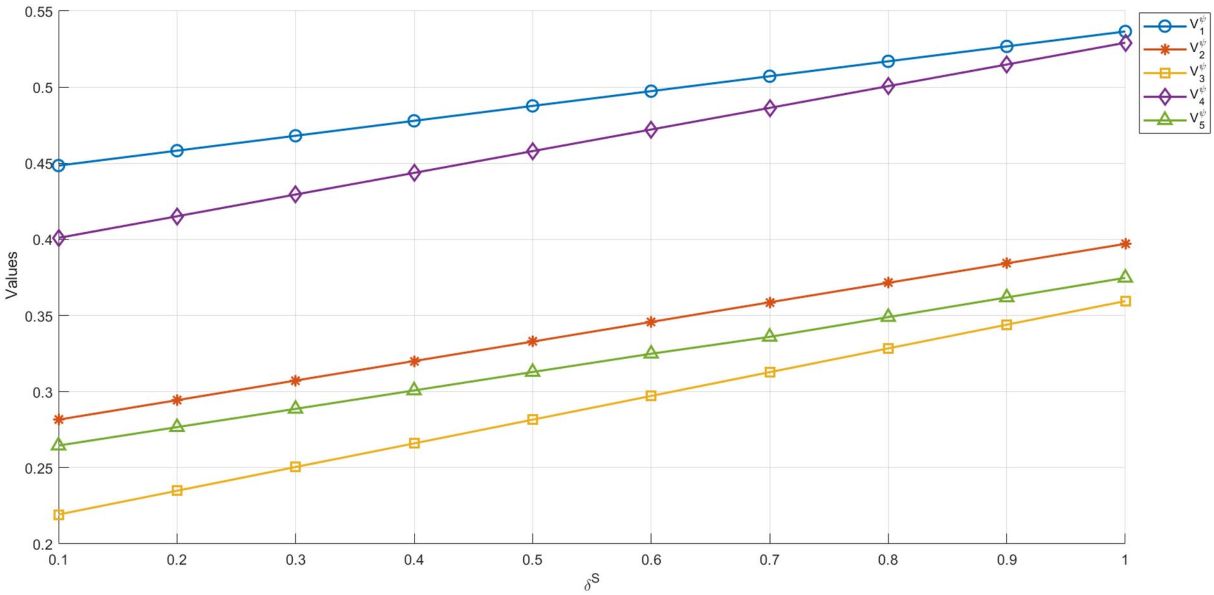

Figure 3. Impact of Parameter (δ^S) with visualization in line graph.

Sensitivity analysis

Sensitivity analysis is an essential stage in the decision-making process since the CIMAS-WASPAS and CRITIC approaches operate in a $T-SF$ environment and the results are shown in Table 11. To better understand the stability and sensitivity of decision findings, a sensitivity analysis may be used to evaluate many alternatives depending on how these properties are altered. Additionally, by quantifying the degree to which changes in input parameters alter choice outcomes, DMs may use sensitivity analysis to priorities efforts to reduce uncertainty and improve decision accuracy. DMs may assess their choices in the context of several fictitious situations using sensitivity analysis, which facilitates scenario-based assessment. The confidence and resilience of decision-making in the area of English education may be increased by taking into account a variety of realistic scenarios and assessing the danger of input parameter ambiguity. Figure 3, Figure4 and Figure5 provide a visual

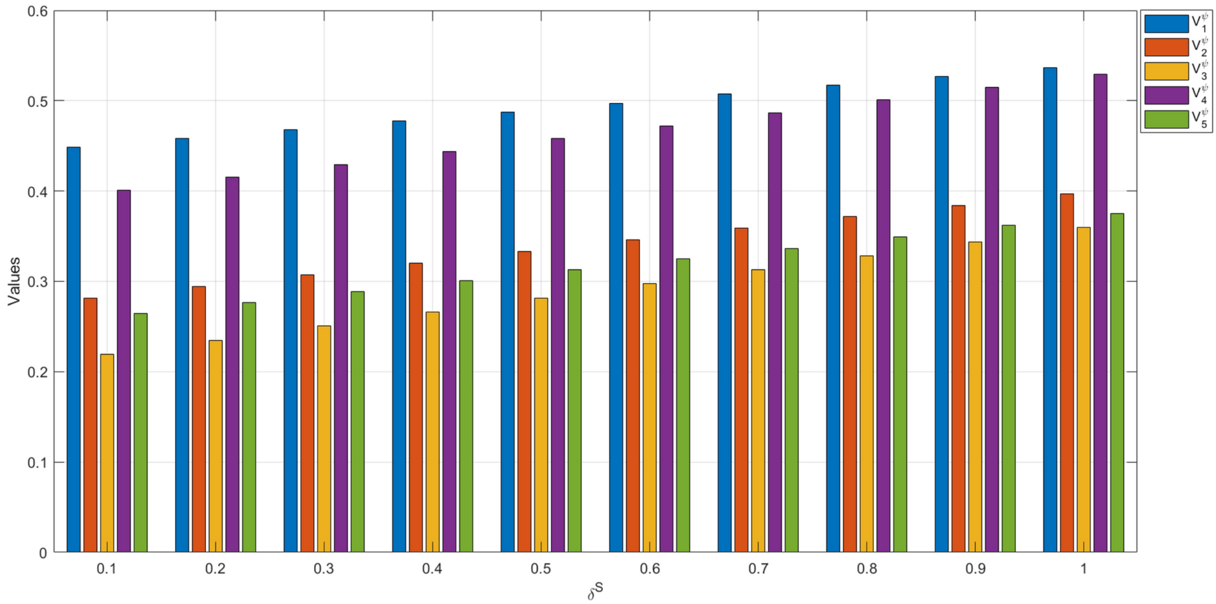

Figure 4. Impact of Parameter (δ^S) with visualization in bar graph.

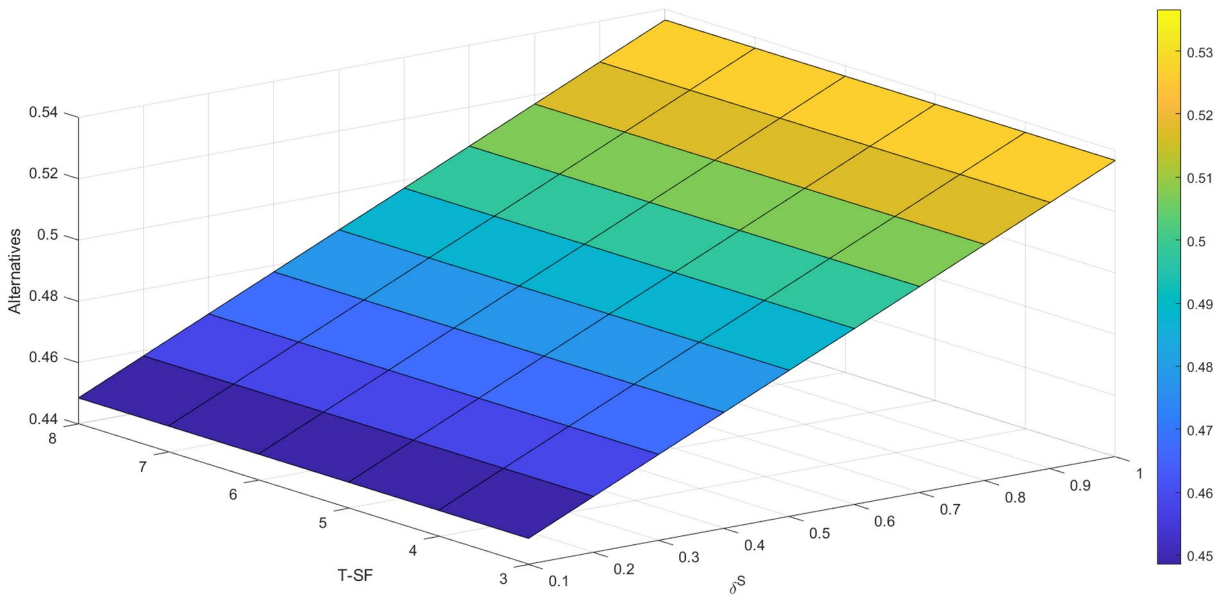

Figure 5. Impact of Parameter (δ^S) with visualization 3D surface.

representation of the findings. Simulated extreme conditions like market priority shifts or resource limits to assess the framework's flexibility under multiple operational settings. When sustainability criteria were given a larger weight, V_{ψ_4} was a close competitor to V_{ψ_1}. This emphasizes the need to balance the weights of the criteria with organizational priorities and external factors.

Comparative analysis

Comparing the results of the CRITIC and CIMAS-WASPAS techniques against those of other well-known decision-making approaches demonstrates the reliability and robustness of the proposed strategy in a T-SF context. This comparison shows the dependability and strength of the suggested technique from Table 12. These inquiries help to explain the existence of changing parameters. This cross-case study shows in a range of decision-making situations the reliability of the CRITIC and CIMAS-WASPAS approaches.

Author	Method	Ranking of alternatives	The optimal alternative
Kumari and Mishra[75]	COPRAS method	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Chen[76]	VIKOR	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Rouyendegh[77]	ELECTRE model	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Ju et al.[78]	TODIM	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Stanujkić and Karabašević[79]	WASPAS method	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Fan et al.[80]	COPRAS	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Akdag AND Menekse[81]	CRITIC-REGIME	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Zhang and Wei[82]	D-CRITIC and CPT-CoCoSo	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Ali[34]	CRITIC-MARCOS	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Yazdi[83]	TOPSIS method	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$
Proposed	CRITIC and CIMAS-WASPAS	${V^{\psi}}_1 \succ {V^{\psi}}_4 \succ {V^{\psi}}_2 \succ {V^{\psi}}_5 \succ {V^{\psi}}_3$	${V^{\psi}}_1$

Table 12. Comparison with some existing methods.

Limitations of the method

- Dependency on Accurate Input Data: The model's effectiveness relies on the accuracy and reliability of input data, both for objective and subjective weights. Errors or biases in data collection can affect the model's outcomes, particularly in subjective assessments through CIMAS.
- The model's performance is highly sensitive to the choice and definition of criteria, which may vary across organizations and industries. Selecting inappropriate or incomplete criteria could lead to suboptimal strategy recommendations.
- While the CIMAS method allows for subjective weighting, it also introduces the potential for expert bias. The model's objectivity could be compromised if subjective weights overly influence the final rankings.
- The model performs a static evaluation of strategies based on predefined criteria, potentially limiting its adaptability in dynamic environments where operational priorities and external conditions evolve over time.
- The proposed framework presents several significant advantages that enhance its utility in OM decision-making. By integrating CRITIC, CIMAS, and WASPAS, the model facilitates a balanced approach that merges objective data-driven insights with subjective expert judgement, allowing for a comprehensive evaluation of strategies. This hybrid methodology is especially beneficial in tackling complex, multifaceted challenges where solely quantitative or qualitative methods may be inadequate.

Discussion of the paper

In an increasingly competitive and dynamic business environment, the significance of effective OM cannot be overstated. Organizations are constantly seeking ways to optimize their processes, reduce costs, and enhance overall performance. The complexity of today's operational challenges makes traditional decision-making procedures in organizational management useless, especially when it comes to balancing a wide range of components that may occasionally contradict one another. The aim of this study is to create a decision-support system combining objective and subjective evaluations to help companies choose their strategies more wisely. Though decision-making processes have come a long way, little study has been done on how to combine objective and subjective criteria for assessing organizational management methods. Since they solely employ quantitative or qualitative data, many of the currently in use frameworks do not provide a thorough overview of the many approaches. OM's criteria' complexity and connectivity call for the creation of a strong model able to evaluate and analyses several operational strategies totally. This work proposes a MCDM model combining elements of the CRITIC, CIMAS, and WASPAS in order to handle these issues. Five operational factors were investigated using the framework; eight criteria in all were taken into account. Objective weight in the CRITIC method is derived from intercriteria correlation. But the CIMAS method is used to get professional opinions and insights that mirror the strategic goals of the company for subjective weight evaluation. It was evident that all operational processes were followed once the weighted criteria from the WASPAS assessments of the many approaches were gathered. The assessment process was improved, the researchers found, by combining objective and subjective weighting approaches. Using data-driven decision-making in increasing operational performance proved to be most effective. Extensive analysis of the technique revealed the requirement of merging expert viewpoints with factual data.

Conclusions and Implications

This paper aims to study new OM techniques by means of a hybrid MCDM framework. By combining subjective and objective weighing techniques, including the CIMAS and CRITIC, the framework allows a thorough and objective assessment of the numerous operational options accessible. The results of the case study, which examine five different OM techniques to eight crucial criteria, indicate that the model could provide significant insights for decision-makers. One might compare many approaches. The findings of the study imply that the most effective approach to improve general performance, efficiency, and sustainability is data-driven decision-making. The ability of the framework to highlight trade-offs between competing criteria not only aids in the selection of optimal strategies but also empowers organizations to align their operational goals with broader strategic objectives. This study contributes significantly to the field of OM by addressing critical gaps in existing methodologies. It equips practitioners with a robust decision-support tool that enhances the strategic selection of operational approaches, ultimately promoting greater efficiency and adaptability in an increasingly complex business landscape.

Future directions of the study

There are numerous significant ways in which future research can expand upon the methodologies and findings of this work. The proposed hybrid MCDM framework can be utilized across various industries and sectors, facilitating its validation and adaptation in diverse operational contexts. Broadening the criteria used in the evaluation process would improve the thoroughness of the analysis, yielding more profound insights into the complex nature of operational strategies. The creation of a dynamic MCDM model that adjusts to fluctuating market conditions and changing organisational objectives presents a valuable direction for future research, overcoming the constraints of static assessments. Performing sensitivity analyses to evaluate the influence of changes in weights and criteria on decision outcomes will yield important insights into the model's stability and reliability, thereby confirming its robustness in practical applications. In light of the increasing focus on sustainability within business operations, future research should prioritise the assessment of strategies that highlight environmental and social dimensions, in accordance with global trends towards sustainable and responsible management practices. This study addresses its limitations and suggests advancements in multi-criteria decision-making methodologies relevant to contemporary operational challenges.

Data Availability

The data used to support the study's findings are included within the article.

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Additional information
Correspondence and requests for materials should be addressed to X.L.