Applied Decision Analytics Volume 2, Issue 1 (2026) 150-180

Applied Decision Analytics

Journal homepage: www.ada-journal.org
ISSN: 3104-2945

A Review of the Application of MCDM Methods in Business Analytics

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ARTICLE INFO

Article history:
Received 20 September 2025
Received in revised form 29 November 2025
Accepted 21 December 2025
Available online 4 February 2026

Keywords:
Multi-Criteria Decision-Making (MCDM), Business analytics, Hybrid MCDM, AHP, TOPSIS, Predictive analytics, Decision support systems

ABSTRACT

Multi-Criteria Decision-Making (MCDM) techniques have become quite important in solving complex business decision-making problems that involve numerous conflicting criteria and uncertainty. This review provides a full discussion of theoretical backgrounds, methodological development, and practical implementation of MCDM within the framework of business analytics in marketing, finance and supply chain management, operations, human resource management, and strategic management. Classical methods such as AHP, ANP, TOPSIS, VIKOR, DEMATEL, COPRAS, Entropy, WASPAS, and MOORA have proved to be effective in prioritization, performance evaluation, and risk assessment. Hybrid structures that combine fuzzy logic, DEMATEL, ANP, and AI-based predictive analytics are additionally used to gain robustness, interpretability, and real-time decision support. The analysis identifies major methodological trends, gaps in the research, and uncharted areas and offers a systematic roadmap on which future research can be directed. These results emphasize the strategic importance of MCDM as a decision-support facilitator that incorporates ordered multi-criteria reasoning with data-driven evaluations that encourage transparency, resilience, and sustainability of managerial choices.

1. Introduction

In the contemporary digital economy, Business Analytics (BA) has become an indispensable discipline that enables organizations to transform data into actionable intelligence for strategic and operational decision-making. BA employs statistical modeling, machine learning, and data visualization to analyze complex datasets and optimize business performance across diverse functional areas including marketing, finance, supply chain, and human resources [1, 2]. Through descriptive, predictive, and prescriptive analytics, organizations are now capable of not only understanding past trends but also forecasting future outcomes and identifying optimal courses of action. Despite these advancements, decision-making in modern enterprises has become increasingly complex, primarily due to the growing uncertainty, dynamic market behavior, and conflicting performance objectives.

Business Analytics (BA) is a discipline that has grown to be essential in the modern digital economy that helps organizations to convert data into operational and strategic intelligence. BA

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uses statistical modeling, machine learning, and data visualization to process complex datasets and enhance the business performance of various functional areas such as marketing, finance, supply chain and human resources [1, 2]. With the help of descriptive, predictive, and prescriptive analytics, organizations are now able to comprehend trends of the past in addition to predicting the future and determining the best courses of action. Regardless of these developments, decision making in contemporary enterprises has been devolving with more complexity; mainly brought about by the escalating levels of uncertainty, dynamic market performance and competing performance goals.

In this case, standard single-criterion optimization strategies do not tend to reflect the multidimensionality of business issues. Most of the time, managers must make trade-offs among conflicting goals like cost and quality, profitability and sustainability or risk and return [1]. To cope with this natural complication, scholars have resorted to MCDM techniques - a set of formal analytical tools that are intended to assist in making rational and transparent choices when a number of, and typically conflicting, criteria have to be evaluated at the same time [2]. MCDM offers methodological basis to break down decision problems into hierarchical or networked decision problems, a relative importance of the criteria, and priorities or ranking of alternatives in the face of uncertainty.

The MCDM techniques integration into Business Analytics have attracted much attention during the last decade as organizations aim to add more data-based insights with formal decision frames. BA offers quantitative evidence and prediction potential whereas MCDM offers qualitative judgment, modeling of stakeholder preferences, and comparative analysis [2]. Such synergy increases the effectiveness of the managers in different fields of business. As an example, in strategic management, MCDM can be used to analyse investment portfolio and corporate growth decisions [3]; in marketing analytics, it can be used to support customer segmentation and product selection [4]; in operations and supply chain management, it can be used to analyse suppliers and optimise processes [5]; and in financial analytics, it can be used to analyse risk and allocate capital [6]. This increase in the integration between these two fields indicates the wider trend of creating hybrid decision-support systems which incorporate computational intelligence with multi-criteria reasoning.

Furthermore, due to the growing volatility and data-intensiveness of business environments, decision-makers need tools that will be able to process vast amounts of data simultaneously and be interpretable. MCDM can be hybridized with BA (and, consequently, with artificial intelligence (AI) and big-data models), and this approach offers an avenue to this balance [3, 4]. New uses show that MCDM can be incorporated into business analytics pipelines to prioritize predictive model results, indicate stakeholder opinions on automated dashboards, and enhance the overall transparency of decisions.

Although research in both areas has grown, there is a lack of a syntactic effort to understand the application of MCDM techniques to business analytics. Common reviews do not give a comprehensive picture of the methodological trends, integration strategies and practical results but concentrate on single applications or industries [2, 5]. Thus, the proposed research is going to fill that gap by conducting a systematic review and classifying the utilization of MCDM approaches in business analytics. This review would have fourfold objectives:

i. To classify the literature based on the business areas and the MCDM approaches applied;
ii. To test the methodological assimilation of MCDM techniques into the data-driven decision-making models;

iii. The aim of the study is to examine the performance of MCDM methods to deal with complex, uncertain, and multi-criteria business problems; and
iv. To determine the major gaps in the research and the way forward in developing MCDM-BA integration.

The article has made contributions both to theory and practice: it adds to academic knowledge about how MCDM is currently changing its role in business analytics and offers a systematic roadmap to practitioners on how to adopt hybrid decision-support methodologies in strategic, financial, operational, and marketing situations [3, 4]. The sections that follow further expound on the methodology of the review provide a comparative discussion of the widely used MCDM techniques, and systematically discuss their uses in different business sectors.

2. Methodology of the Review

They have made an adoption of a systematic and transparent review methodology to have a full coverage of the literature on the utilization of MCDM methods in the aspect of business analytics [4, 6]. The methodology was designed as a search strategy that was structured, had inclusion and exclusion criteria that were well defined, and a system of categorization of the gathered studies.

2.1 Literature Search Strategy

The given review is efficient in describing the systematic and methodological procedure of identifying the relevant research materials on the use of MCDM techniques in the context of the business analytics. Such stringent and transparent search strategy in academic reviews is constructive especially on comprehensiveness, replicability and methodological validity- features that Baydas et al. [7] and Silva et al. [8] argue out in systematic literature review. The presence of peer-reviewed databases, including Scopus, Web of Science, IEEE Xplore, and Google Scholar, demonstrates compliance with high-quality academic requirements, as all of them have interdisciplinary coverage of the research in the field of engineering, management science, and data analytics.

The keywords chosen such as MCDM, AHP, ANP, TOPSIS, DEMATEL, and business analytics are deeply suitable as they are the most frequent sets of methodological and thematic overlap between decision science and data-driven business processes. Other recent bibliometric and systematic review studies have also been done using such key word strategies, including in the study of MCDM using in supply chain sustainability [9] and the study of MCDM hybrid integration with artificial intelligence to predictive analytics [10]. The Boolean operators (AND, OR) enable selective search of the articles and reduce the number of irrelevant publications included in the search results, but increase the scope of the results according to business functions and analytical paradigms.

The time horizon (2013-2025) will guarantee that the review addresses not only the state-of-the-art approaches to methodological bases, but also more recent developments in hybridized and data-driven MCDM frameworks. This time frame coincides with the fact that Business Analytics (BA) is evolving very fast, and MCDM methods are evolving towards a higher level of computing power in the Industry 4.0 era [11]. As an example, hybrid MCDM models, incorporating fuzzy logic, machine learning, and big data analytics, are rapidly increasing in the post-2015 literature [12], which has moved to a paradigm shift in which purely mathematical models are being replaced by intelligent decision-support models.

Moreover, the omission of grey literature, non-peer-reviewed sources as well as the studies lacking methodological rigor are excluded as the exclusion criteria, which enhances the academic integrity and credibility of the review. Since emphasis is placed on peer-reviewed, empirically based studies, the researcher is likely to avoid bias and make certain that the synthed findings will be credible and replicable [13]. The review is linguistically consistent by restricting to materials written in English, but this potentially creates a slight regional bias as observed by Basilio et al. [14] who mentioned the language challenges in research on global management.

Overall, this search strategy is an effective literature search strategy that indicates a balanced scope of search. It guarantees the incorporation of traditional MCDM models as well as the innovative hybrid models applicable in business analytics applications [10, 11]. The stringent selection and the inclusion of extensive key-wording makes the review be in good position to provide substantial information on how techniques in methodology have developed, how interdisciplinary and how pragmatic the adoption patterns of MCDM tools as business decision optimization tools have been.

2.2 Inclusion and Exclusion Criteria

It shows that this section has a strict and precise structure of sifting the relevant studies, so the review will be focused on the intersection of MCDM with Business Analytics (BA). Specification of inclusion and exclusion parameters is important to systematic and integrative reviews since it improves methodological transparency, reproducibility and scholarly plausibility [13, 14]. With the use of structured criteria, this review narrows in the high-quality research that does not only use MCDM techniques but has a significant contribution to the decision-making practices in the real business analytic scenarios.

The inclusion criteria favor the studies that implement the traditional methods of MCDM including AHP, ANP, TOPSIS, VIKOR, DEMATEL and COPRAS-techniques that have been extensively recognized in the decision science literature as being used to deal with multi-dimensional and conflicting criteria [12]. The choice provides a mixed methodological diversity and, paradoxically, conceptual consistency of all the works reviewed. As an example, AHP, ANP, or TOPSIS and VIKOR are now common in hierarchical decision-making frameworks in marketing and strategic planning [15], whereas TOPSIS and VIKOR have become popular in financial and operational analytics to perform a ranking and optimization of performance [16]. The inclusion of the established techniques offers a great basis to evaluate methodological progress and hybridization, i.e., their integration with fuzzy logic, big data analytics, or machine learning systems.

Incorporating business analytics applications, such as marketing analytics, financial optimization, supply chain management, operations, and HR analytics, will make the review reflect the multi-dimensional character of the contemporary business environment. Recent research points out that MCDM tools have been important in managing the unpredictability, ranking of strategic objectives and real-time information-based data decision systems in the areas [17]. To give an example, hybrid MCDM models like AHP-DEMATEL-TOPSIS have been used in supply chain analytics to assess supplier sustainability and performance [18], and in human resource analytics, DEMATEL-ANP models can be used to determine competency and performance of leadership. Therefore, this criterion makes sure that the chosen literature does not only have a methodological rigor but also a business-related value.

The need to prove empirically or by case proves is also an additional boost to the credibility of the review since it eliminates theoretical or conceptual papers. The necessary foundation to the evaluation of how MCDM models operate in data-driven business settings, where decision contexts tend to be dynamic and multi-layered, is empirical grounding [19]. Quantitative analysis, simulation models, or empirical study-based studies which combine MCDM with predictive analytics or optimization algorithms, provide actionable information and practical value which is in keeping with current trends in evidence based management.

Conversely, the exclusion criteria can be the quality control measures that are used to filter the works that are not contributing any substantive empirical or analytical contribution. The elimination of papers that are more theoretical or domain irrelevant (e.g. those that are about mechanical or engineering applications) helps to avoid thematic dilution and keep the review focused on business decision contexts. Similarly, by filtering out reviews, opinion pieces and editorials, only primary studies containing original research would be considered- in line with best practices on systematic reviews [20]. This conclusion reinforces the relevance of conclusions made on the basis of the analyzed literature.

In general, such an inclusion-exclusion framework provides a reasonable trade-off between the rigor of methods and their practical use [14, 18]. It makes sure that the chosen studies do not only prove the existence of strong MCDM applications but also give a reflection on the developing discussion of how the use of data-driven approaches can improve strategic, financial, and operational decision-making in contemporary companies. The method is comparable to other systematic reviews in the business and management worlds [19, 20], which provides a valid basis to synthesize research findings and determine emerging methodological directions in the business analytics based on MCDM.

2.3 Classification of Studies

The review provides a powerful and multi-dimensional structure of the reviewed literature organization, which will help to capture the methodological and contextual diversity in the implementation of MCDM methods to Business Analytics (BA). The dual classification, based on MCDM methodology and business functional/domain is indicative of a thorough and methodical framework, which permits substantive comparisons made between analytical methods and managerial situations. Closely related two-dimensional models have been effectively used in previous reviews that are MCDM-centric, including the reviews by Hapsari et a. Over the significance of balancing the rigor aspects of methodology and the practical relevance in decision-making research, Alsanousi et al. [21] and [22] argue.

MCDM Techniques, the first dimension, points to the variety and development of the decision-making models in business. The classical procedures like AHP (Analytic Hierarchy Process) and ANP (Analytic Network Process) are still used as the basic approaches to the hierarchical structuring of decisions and interdependency analysis among the criteria [18]. Such approaches are especially appreciated in strategic management and marketing to rank alternatives by the expert judgment [15]. Contrarily, the distance-based ranking schemes like TOPSIS, VIKOR, and COPRAS are more information-focused and have been effectively implemented in performance assessment, supplier selection and risk analysis context.

Additionally, the classification acknowledges the recent surge in hybrid and integrated methods, including fuzzy AHP-TOPSIS or DEMATEL-ANP that have become popular because of their capability to deal with uncertainty, interrelations, and non-linearity in the business world [7, 11]. As an example, customer segmentation and product selection models based on the use of fuzzy AHP-TOPSIS have found extensive application in marketing analytics, whereas the use of DEMATEL-ANP frameworks is favored in strategic decision-making to determine cause-effect relationships between organizational competencies [12]. Equally, objective measures of weighting, such as

Entropy, WASPAS, and MOORA, assist in the objective weighting of criterion, particularly when the area of decision has substantial amount of data, such as financial risk models and the analysis of supply chains [8-10]. This aspect, therefore, summarizes the methodological frontier of MCDM studies and how it is constantly evolving to keep up with computational and analytical innovations.

The second dimension - Business Function and Domain - sorts the reviewed studies into the given domains of managerial use and includes the interdisciplinary scope of MCDM in business analytics. MCDM methods have been utilized in marketing analytics, e.g., brand valuation, market entry strategy, and evaluation of digital campaign [21]. Financial analytics Hybrid MCDM models like AHP-DEMATEL-TOPSIS have been applied in portfolio optimization, credit rating, and risk in investments [21, 22]. Likewise, operations and supply chain management have become the new ruling areas, and MCDM assists in selection of suppliers, logistics planning and sustainable procurement decision making [23]. Integrated models, including DEMATEL-ANP or AHP-ISM in the human resource and strategic management, have facilitated a non-random assessment of their competencies, leadership potential and readiness of their organizations to change.

Notably, this classification system also considers the combination of the MCDM with the new data-driven paradigms, such as artificial intelligence (AI), machine learning (ML), and big data analytics. This hybridization also demonstrates a current trend in the methodology whereby MCDM models are augmented with computational intelligence to assist predictive and prescriptive analytics in dynamic business settings [16, 17]. As an illustration, AI-based MCDM models have been applied in the prediction of customer churn and demand forecasting, whereas MCDM models with ML have enhanced the assessment of multi-dimensional financial performance [11, 12]. This intersection of MCDM and AI and big data is one of the critical points in decision science - the transformation of conventional decision-support frameworks into an intelligent, adaptive, and automated analytics system.

Overall, the use of this classification methodology implies a systematic synthesis of the reviewed literature, which allows revealing methodological trends, specific innovations in the domain, and interdisciplinary connections. The systematic mapping of studies in terms of analysis techniques and business uses, the review captures not only the scope of MCDM implementation, but also the basis of further sections to extract domain-specific findings, gaps in research, and future focus.

2.4. Data Extraction and Synthesis

Data extraction and synthesis step constitute one of the key steps towards methodological rigor and analytical coherence of systematic literature reviews. In this case, the data that was extracted consisted not only of the employed MCDM techniques but the contextual dimensions that were used to analyze the situation: decision goals, analytical integration and sectoral focus [22, 23]. Such a thorough extraction made it possible to do a multi-layered synthesis process to combine both qualitative and quantitative dimensions. The comprehensive range of criteria, such as the number of criteria, selection of alternatives, and combination with analytical tools (e.g., artificial intelligence or big data analytics) was a guarantee of the review capturing the methodological depth and breadth of the application that was consistent with the already established practices of systematic reviews in decision sciences.

Qualitative synthesis Thematic analysis was used to identify common patterns in methodologies such as the growing number of hybrid models using subjective (AHP, ANP) and objective (Entropy, CRITIC) weighting schemes and specific application of MCDM methods to business decisions. The strategy echoes the systematic reviews of the past as carried out by Zhang et al. [24] and Qin et al.

[25] who pointed at the importance of determining methodological tendencies and innovation patterns in MCDM studies. The study has also pointed out the change in the traditional deterministic models to the more adaptable, uncertainty-managing models, such as fuzzy and grey-based versions of MCDM, as already mentioned by Barasin et al. [26].

Frequency analysis of the method use by domain, i.e. the prevalence of AHP and TOPSIS in strategic and financial decisions, or the integration of DEMATEL-ANP into supply chain analysis, to the quantitative side assisted in outlining both stable and developing research interests. Recent meta-analyses have followed a similar path to synthesis [19-23], showing that this type of an integrative framework has a greater power to make inferences about the applicability and performance of MCDM methods. This synthesis methodology ultimately was effective in organizing the findings as well as facilitating comparative insights that add weight to the validity and reproducibility of the results of the review.

3. Overview of MCDM Techniques Used in Business Analytics

The MCDM approaches have been required in the business analytics to organize complex decision-making, to cope with multiple conflicting criteria, to aid in making rational and data-based decisions. The number of MCDM methods developed and adapted to different business decision-making situations has been extensive over the past decades, such as the cases of performance evaluation, risk assessment, strategic planning, and forecasting.

3.1 AHP and ANP

The AHP and the ANP take the middle stage in the literature and practice of MCDM since they propose intuitive models to convert expert opinions into quantitative priorities. The main contribution of AHP is its hierarchical structure in terms of which a complex decision is split into goal-criteria-sub criteria-alternatives levels and that a pair-wise comparison is employed to obtain relative weight and ranks [27]. This breakdown renders AHP especially appealing to those problems that require decision makers to integrate quantitative measures as well as qualitative judgments-such as in integrating financial measures with managerial preferences in investment appraisal or in integrating technical requirements with consumer preferences in product choice [23-27]. A large body of applied work demonstrates AHP's versatility: it has been deployed extensively for supplier selection, combining AHP with TOPSIS for final ranking, project and portfolio selection, marketing strategy evaluation, and public-sector decisions.

ANP was introduced to overcome AHP's limitation of strictly hierarchical (acyclic) structures by allowing interdependencies and feedback among criteria and alternatives [28]. Where AHP forces unidirectional parent–child logic, ANP models problems as networks of clusters and nodes, enabling the capture of influence relationships (e.g., how service quality influences customer satisfaction, which in turn affects brand perception and future product design). This makes ANP better suited to managerial contexts characterized by mutual causation—strategic planning, organizational capability assessment, and interdependent risk evaluation being prime examples [29]. Recent empirical and review studies report ANP's growing application in economics, finance and sustainability decision problems where factor interrelations are non-negligible.

Methodologically, both AHP and ANP have undergone significant refinements and hybridizations. Traditional issues, such as inconsistency in judgment when comparing two items at the same time, sensitivity to scale, and subjectivity, have led to the creation of consistency indices, ratio scale alternatives, and group decision-making models [29, 30]. The fuzzy AHP variants (triangular, trapezoidal, intuitionistic and, more recently, Fermatean and Pythagorean fuzzy extensions) have been developed and reviewed extensively to reduce ambiguity and deal with vagueness in the human judgments, where fuzzy set theory is embedded in pairwise comparisons [30]. Fuzzy AHP has particularly been eminent in areas with a preponderance of qualitative criteria, such as customer ratings, service quality measurement, and sustainability measurements, to assist analysts to exchange linguistic measurements with strong numeric weights.

In practice, AHP is often applied as a weight elicitation procedure in hybrid MCDM pipelines. The popular structure of applied research is AHP (to compute subjective weights) then an objective ranking technique, like TOPSIS or VIKOR (to rank and score alternatives). Numerous supplier-selection and sustainability studies adopt this pattern—AHP to obtain criterion weights from procurement experts, and TOPSIS/VIKOR to generate the final ranking based on performance data [31]. In finance, AHP-based weighting combined with TOPSIS or fuzzy extensions has been used for portfolio construction and risk ranking, illustrating how AHP helps incorporate managerial risk tolerance alongside quantitative indicators (recent portfolio selection studies 2024–2025).

ANP-based practices are similarly hybridized, often combined with DEMATEL to identify causal linkages before feeding into ANP's supermatrix for weight synthesis, or used alongside fuzzy logic to capture both interdependence and judgmental uncertainty [28, 29]. Studies in strategic outsourcing, competency evaluation, and organizational performance have illustrated that DEMATEL–ANP hybrids can reveal which capabilities drive others and how priorities shift when interrelationships are accounted for—insights that hierarchical AHP would obscure.

The recent trends also indicate that AHP/ANP can interact with data-driven analytics and AI. As an example, feature selection has been informed directly or model outputs have been prioritized in ensemble predictive systems using weight vectors based on AHP; machine learning models on the other hand have been used to provide performance scores that are fed back into the ranks of AHP/ANP [22, 24]. This two-way linkage assists in mediating interpretability (human-understandable weights and trade-offs) and predictive ability (data-driven scoring), which is an appealing feature of managerial dashboards and decision-support systems.

However, they are still limited and should be considered in the next studies. AHP and ANP continue to face a high dependency on expert elicitation with all the associated biases, consensus, and reproducibility concerns, particularly in group decision-making by a heterogeneous population [26, 27]. The computationally complexity in ANP can increase exponentially where networks are extensive and pair-wise comparisons are abundant as this poses scalability problems in practice. Besides, although fuzzy adaptations decrease vagueness, they present methodological options (type of fuzzy set, defuzzification method) which influence results and make comparability across studies more complex.

Overall, AHP and ANP are considered the cornerstones of MCDM methods in business analytics since they provide clear, systematic methods of introducing managerial judgment to multi-criteria analyses. Their flexibility, through fuzzy extensions, hybrid pipelines (AHP+TOPSIS, DEMATEL+ANP), and combination with AI, is the reason they remain and will continue to be used in supplier selection, portfolio optimization, marketing strategy, HR competency evaluation, and strategic planning [30, 31]. The next-generation work in the direction of intensive validation, scalable applications (especially of ANP), and standard descriptions of how AHP/ANP may be combined with data-driven analytics to increase the levels of reproducibility and managerial confidence should be pursued.

3.2 TOPSIS, VIKOR, and COPRAS

The distance-based MCDM techniques, namely, TOPSIS (Technique of order of preference by similarity to ideal solution), VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje), and COPRAS (Complex Proportional Assessment), have become an unavoidable part of business analytics as they are computationally efficient, transparent and can be adapted to the hybrid decision context [27]. The similarity between these approaches lies in the fact that they are all based on a common conceptual approach: every alternative is judged on its geometric/proportional distance to a hypothetical solution that is an optimal approach to performing all the tasks and a hypothetical solution that is a negative ideal.

TOPSIS compares the Euclidean distance between each alternative and the optimal solution and negative-optimal solution and yields a relative closeness coefficient which is the ranking index. It is one of the most popular tools used in all spheres of business because of its simplicity, the logic of its use, and the capacity to consider the qualitative and quantitative criteria [32]. TOPSIS has also found application in marketing analytics where it has been applied to select brands, rank products and segments in order to more easily present decision-makers with rankings that are easy to interpret and combine both subjective and objective data [31, 32]. Financial analytics: A great many studies have applied AHP-TOPSIS and Entropy-TOPSIS optimization models to portfolio maximization, credit rating, and financial risk measurement, demonstrating how the approach aids rational and informed decision making based on the available data and using expert preferences [29,31]. Hybrid AHP-TOPSIS or Fuzzy-TOPSIS methods are frequently adopted in supply chain management supplier evaluation, logistics performance measurement, and sustainability evaluation because they are resistant to uncertainty or multi-stakeholder scenario.

VIKOR builds on the ideal-solution approach through the addition of a compromise programming model, which aims to find a tradeoff in maximizing the group utility (maximum satisfaction of a majority) and the individual regret (minimum dissatisfaction). This approach is especially useful in decision conflicts between decision-makers or criteria characteristic of strategic and financial decisions where trade-offs are entailed [33]. Over the recent years, VIKOR has become popular in sustainability and ESG-related monetary examination, risk prioritization, and innovation capability assessment, in which the decision-makers have to moderate the economic performance, environmental performance and social performance [34]. Fuzzy and interval-valued VIKOR extensions have also been used to add value to it in dealing with linguistic uncertainty and ambiguous data that frequently occurs in managerial situations [33, 34]. Besides, the combination of VIKOR and AI and big data analytics have facilitated forecasting risk and real-time decision-making in operations and finance.

COPRAS offer a less complicated, but very efficient proportional assessment framework which estimates the relative value and degree of utility of each option regarding advantages and unwanted criteria. It is computationally efficient due to its linear normalization and relative importance computed directly, which is significant when working with large datasets, as much of the business analytics of big data is over big data [35]. COPRAS have been effectively used in the financial benchmarking, selection of suppliers, prioritization of projects, and investment decision making when the quantity and dimensionality of data is large [34, 35]. As an example, entropic copras models have been applied in corporate finance to determine the performance of firms in a state of uncertainty, whereas Fuzzy-copras models have been utilized in optimization of portfolio diversification in the context of varying market situations.

Hybridization has been very vital in the extension of the three distance-based methods. A new category of structures, moving towards being standard in multi-domain use, includes AHP-TOPSIS, DEMATEL-VIKOR, and Entropy-COPRAS hybrids [36]. These blends exploit the advantages of the various methods- subjective weight elicitation with AHP or DEMATEL and objective ranking with distance-based analysis to produce decisions that can be interpreted and are data-robust. Besides, Fuzzy, Grey, and Neutrosophic extensions have become popular in order to model uncertainty, since the decision-makers tend to use vague linguistic-judgments to assess the intangible characteristics like reputation, trust or innovation capacity.

Recent articles show that TOPSIS, VIKOR, and COPRAS have been integrated into data-driven business analytics systems, as organizations continue to integrate MCDM with machine learning, data mining and predictive modeling. As an illustration, TOPSIS combined with neural networks has been applied to customer churn prediction and credit risk assessment, in which MCDM-based weights can be used to interpret model results [31, 32]. On the same note, VIKOR that is intertwined with fuzzy clustering has helped in supporting market segmentation and resource allocation issues, whereas COPRAS-based models with optimization algorithms have improved supply chain resilience and performance assessment.

These methods, though very common, however, are not without limit. TOPSIS also involves a set of linear trade-offs between criteria and this can be too simple of a model that overlooks the interrelationships between the criteria. The sensitivity of VIKOR to the choice of weight and normalization methods may change the ranking and thus require the use of strong sensitivity analysis [34, 35]. COPRAS is computationally simpler but not necessarily rich enough in terms of interpretation to be used in the context of highly interdependent or dynamic decisions. Future studies would focus on combining these distance based models with AI-based adaptive weighting, real-time analytics, and fuzzy-probabilistic hybrid structures to respond to these changing business scenarios with greater scalability and contextual flexibility.

In conclusion, TOPSIS, VIKOR and COPRAS are critical tools of business analytics. They are conceptually straightforward, flexible, and can be combined with other MCDM, fuzzy and AI techniques, which is why they are best suited to multi-domain application, such as financial forecasting, supplier assessment, sustainability ranking and strategic planning where quality of decision, transparency and computational efficiency are of paramount importance.

3.3 DEMATEL and ISM

Two powerful MCDM-based decision models include the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and the Interpretive Structural Modeling (ISM) which are used to reveal the cause and effect relationships and hierarchies in complex decision systems among associated variables [37]. Such approaches are especially useful in business analytics where several variables are dynamically related to each other to affect strategic, financial, operational, and organizational results.

The DEMATEL method was initially invented in the Battelle Geneva Research Centre and is commonly known to be the best at projecting cause-and-effect interdependencies among criteria as well as being able to distinguish between cause (influential) and effect (dependent) variables. This procedure is a transformation of expert judgments into a cause effect diagram using pairwise comparisons and normalization of direct-relation matrices. As time has elapsed, the concept of DEMATEL has spread to fuzzy, grey, and rough set settings to tackle the issue of uncertainty and vagueness in evaluations by experts [37, 38]. These fuzzy and hybrid versions find particular application in business contexts that involve uncertain, incomplete, or linguistic information- e.g. in market behavior forecasting, organizational risk mapping and supplier risk assessment.

The use of DEMATEL in supply chain and operations analytics has grown tremendously in the last ten years. As an example, Taherdoost and Madanchian [39] applied fuzzy DEMATEL to determine the key success factors affecting the management of the green supply chain, and Petrillo et al. [40] combined DEMATEL with ANP (DANP) to rank the drivers of sustainability and obstacles in supplier selection. DEMATEL has been employed in marketing and strategic management, to establish the cause and effect relationships between brand loyalty determinants and customer satisfaction measures [38-40]. On the same note, DEMATEL-based models have been used to assess systemic financial risk and dependency among investment requirements in the financial decision-making based on which organizations can determine the pathways of major influence and reduce cascading failures.

Interpretive Structural Modeling (ISM) technique is a complementary approach to DEMATEL, which is based on the creation of a hierarchical structural model of interactions between the elements of the system. ISM draws on the expertise to establish contextual associations and uses reachability templates to establish a multi-level framework to explain the impact of variables on each other in a hierarchical manner. This visualization feature renders ISM a useful approach to strategic planning, organizational designing, and risk evaluation [40, 41]. ISM has been applied in business analytics to determine significant enablers of digital transformation, key success factors in the adoption of business intelligence, and innovation capability drivers [33,36]. Higher-level enablers, e.g. government support and commitment of the top management, were revealed in the higher levels of interdependency models among sustainable manufacturing practices applied by Punetha and Jain [42], based on the model of higher-level enablers.

The combination of DEMATEL and ISM has become a significant topic since researchers and practitioners are keen on incorporating the strength of causal mapping of DEMATEL with the power of structural visualization of ISM. Experiments like those conducted by Isik et al. [43] and Khulud et al. [44] prove that a hybrid DEMATEL-ISM model increases the interpretability and adds more knowledge to factor groupings. DEMATEL determines cause-effect relationships and calculates influence weights, and ISM translates these relationships into hierarchies, which can help decision-makers, who need to determine leverage points where to intervene. It has been found handy in the strategic risk management process, in the formulation of innovation policy, and in the design of the performance measurement system.

There are also new developments that reveal the hybrid models of DEMATEL-ANP (DANP), DEMATEL-AHP, and DEMATEL-VIKOR as a conjunction of the mapping of the causality relationship and the methods of prioritization and ranking. As an example, Baczekwicz et al. [45] used DANP to examine the correlations between the customer relationship management (CRM) performance measurements, and Rasoanaivo et al. [46] employed DEMATEL-VIKOR to prioritize the supply chain sustainability. These combined models have shown significant advantage in the business intelligence systems in which they increase the transparency and flexibility of the analytical decision making models.

In strategic management and digital transformation research, there has been an increased use of fuzzy DEMATEL-ISM frameworks that provide increased flexibility in modeling uncertainty in qualitative data. As an example, Pelissari et al. [47] and Ayyildiz and Erdogan [48] used fuzzy DEMATEL-ISM to analyze the linkages between Industry 4.0 preparation factors and sustainability enablers to prove their usefulness in dynamic, complicated business scenarios. This type of hybridization promotes strategic alignment that is based on data, i.e., the combination of the MCDM and the state-of-the-art analytics assures not only systemic awareness but also human actionable prioritization.

In general, both DEMATEL and ISM are essential instruments that can be used to model the interdependencies, hierarchies, and feedback loops of today business analytics systems. The combination with fuzzy logic, ANP, and data-driven approaches has increased their use to other areas such as supply chain resilience, organizational risk, marketing performance, innovation management, and digital strategy formulation. Not only do these techniques increase interpretability but also the divide between qualitative managerial understanding and quantitative analytical modeling is reduced, with consequent effects of supporting more holistic and adaptive decision support in more complex business ecosystems.

3.4 Entropy, WASPAS, and MOORA

Objective weighting and ranking systems include Entropy, WASPAS (Weighted Aggregated Sum Product Assessment), and MOORA (Multi-Objective Optimization by Ratio Analysis) have become the quantitative foundation of MCDM systems since they are based on mathematical expressions, and not on the subjective expert assessment of criteria weights and performance scores. Such analytical techniques are becoming more critical in business analytics where judgments need to be made using large and heterogeneous data, which need to be evaluated impartially, transparently, and reproducibly [44, 45]. These methods reduce human bias and improve scalability in computations hence complementing the subjective methods of decision-making such as AHP, ANP, or DEMATEL in a hybrid decision process by focusing on objectivity.

The Entropy weighting technique, which is a product of the information theory of Shannon [39, 40] is a measure of the amount of uncertainty or information in the data attributes in order to ascertain their relative worth. A criterion that has more variability of data (information entropy) has more discriminating power and therefore a greater weight. The approach has found application especially in corporate governance analysis, financial performance evaluation and sustainability analysis where decisions are made based on various quantifiable indicators [48]. As an example, the Entropy-TOPSIS and Entropy-COPRAS models have extensively been applied to bank performance analysis, credit risk rating, and investment ranking, which is expected to remain unbiased in ascertain the importance of factors whilst not compromising on interpretability [44, 45]. Entropy has been applied in the supply chain analytics to calculate objective weights of supplier criteria like cost, quality, delivery reliability, and sustainability measures, and provide strong decision guidance in dynamic context [41, 42]. In addition, Entropy with fuzzy MCDM has been useful in assimilating both quantitative and linguistic information in demanding business situations like e-commerce performance management and intelligent logistics schemes.

The WASPAS approach combines the additive principle of the Weighted Sum Model (WSM) and the multiplicative principle of the Weighted Product Model (WPM), and strikes a balance between simplicity, sensitivity and robustness. This is because WASPAS is a hybrid that is capable of managing both linear and nonlinear trade-offs, which means that it is a strong ranking tool in any business analytics application. WASPAS has been used in financial decision-making, where it has been found to be superior to single-method procedures by optimizing portfolio, appraising investment, and evaluating credit [47]. WASPAS has been used in operational benchmarking to evaluate the efficiency of manufacturing operations, service quality and operational resilience in uncertain or crisis prone business settings [48]. Besides, hybrid AHP-WASPAS, Entropy-WASPAS and Fuzzy-WASPAS models have gained popularity in supplier selection and sustainability assessment research, with subjective inputs combined with objective inputs to increase the reliability and acceptance of the models by stakeholders.

Another efficient and multi-purpose MCDM technique is MOORA which utilizes the ratio analysis to rank the alternatives in terms of both positive and non-positive considerations. It is also computationally easy due to its normalized decision matrix and additive nature of aggregation and it is more applicable in business areas as it can be used up to multiple objectives. MOORA has been widely used in the benchmarking of financial performance and selection of projects and risk management [49]. MOORA has helped in product performance analysis and market entry decisions in marketing analytics and supplier analysis, process enhancement and facility location planning in operations management [50, 51]. The strong points of MOORA are that it is stable to changes in decision matrices, and it can easily process quantitative and qualitative data with low computing power. The Fuzzy-MOORA, over-Grey-MOORA and Neutrosophic-MOORA are advanced versions that have allowed the use of MOORA in uncertain and imprecise business settings, improving certainty in the decision making with incomplete information.

The expanding research base has revealed that Entropy, WASPAS, and MOORA are being incorporated in the hybrid and AI-enhancement business analytics more and more. As an example, Entropy-MOORA has been used to evaluate green supply chain performance, combining sustainability and efficiency measures [27] and WASPAS combined with machine learning has been applied to forecast financial distress and optimize operations [29]. These integrations underscore the suitability of objective weighting models and predictive analytics and intelligent decision systems. Beyond this, there has been recent research on hybrid Entropy-DEMATEL or Entropy-ANP systems to include causal effect as well as objective variability in decision parameters to generate a more holistic analytical system of business strategy formulation.

Entropy, WASPAS, and MOORA are objective approaches that can be used in relation to risk and sustainability analytics to define key performance indicators (KPIs) and evaluate their relative impact on organizational performance [18, 19]. They offer a quantitative base of multi-criteria models because they offer impartial weights, which can subsequently be corroborated with subjective expert decisions using the framework of hybrid MCDMs. This integration makes business analytics decision data-driven and at the same time context-driven to make decisions highly accurate and policy relevant.

To conclude, the Entropy, WASPAS, and MOORA are fundamental tools in the contemporary MCDM-based business analytics owing to their simplicity of computation, objectivity, and flexibility of integration [45]. Their uses cut across a wide range of business operations: financial forecasting, operational benchmarking, supplier assessment, and sustainability assessment, and the development of hybrid and AI-based models highlights the long-term interest of the field in data-driven decision-making.

3.5 Evolution of MCDM in Business Analytics

The MCDM development in business analytics is an evolutionary process of transforming the traditional deterministic models to a hybrid, intelligent and data-driven decision-support systems. The first models of MCDM like AHP [19], TOPSIS [11], and VIKOR [37] were organized tools allowing to rank and select among a variety of quantitative and qualitative criteria. But as the world of business grew more complicated, uncertain, and dynamic, the classical methods started to be constrained in their ability to deal with imprecise information, changing preferences of the stakeholders, and large-dimensional decision space. Therefore, scholars have developed MCDM as hybrids and AI-enhanced frameworks that take into account fuzzy logic, probabilistic modelling, and machine learning to further improve the depth of the analysis and predictive power.

One of the milestones in this development is the incorporation of fuzzy logic in MCDM which gave birth to fuzzy-AHP, fuzzy-TOPSIS, fuzzy-DEMATEL and other hybrid methods. These models deal with this vagueness and subjectivity of the human judgment by converting linguistic judgments into fuzzy numbers [43]. As an example, Fuzzy AHP-TOPSIS models have been widely used in supplier selection, customer satisfaction analysis and product portfolio optimization since they represent both the hierarchical nature of the decision issues and the similarity of the alternatives to the optimal solution [26, 39]. Likewise, Fuzzy DEMATEL-ANP hybrids have been deployed in the fields of risk interdependency, innovation capabilities analysis and strategic business planning where the criteria have very high interrelationships and causal feedback loops [49]. These combinations allow decision-makers to understand complex, uncertain relationships in an intuitively clear way and yet remain mathematically rigorous.

The development of MCDM is also connected with the introduction of big data and artificial intelligence that made MCDM techniques shift towards predictive and prescriptive analytics. To illustrate, a machine learning model with objective weighting approaches, including Entropy, CRITIC, or GRA, can be adjusted in real-time to adapt the weight depending on incoming data streams [33, 34]. The continuous learning of data applies to these data-driven hybrid models in forecasting the financial risk, rating credit, and performance measurement, where adaptability of the model is improved [22]. The development of more AI-centered MCDM systems, including those integrating neural networks, deep learning and evolutionary optimization with conventional MCDM reasoning, has also contributed to decision-making in investment portfolio optimization, supply chain resilience and strategic planning [27]. With the inclusion of computational intelligence, these systems are able to reveal non-linear relationships and complicated trade-offs that MCDM methods might fail to identify.

Moreover, the integration of MCDM and big data analytics is a revolutionary stage of business analytics. The current business environment is characterized by heterogeneous, large volume, and high velocity data, and the combination of MCDM and big data technology including data mining, clustering, and predictive modeling enables solid decision support in the face of uncertainty [45]. As an example, AHP-Entropy-TOPSIS hybrid frameworks deployed on big data platforms have been utilized in real-time supplier ranking and benchmarking of market performance. Equally, predictive business intelligence built in with WASPAS and MOORA combined with the AI algorithms have become used to assist firms to determine the best investment options as well as risk-adjusted decision options [51]. This combination makes it more scalable, continuously learner, and fills the space between human intuition and the accuracy of the algorithms.

The sustainability, resilience, and inclusivity of stakeholders in business decision-making are other areas of evolution of MCDM. The latest research has been focused on green supply chain management, corporate social responsibility (CSR), and the assessment of the ESG (Environmental, Social, and Governance) based on hybrid MCDM models [39, 40]. Multi-objective models can be used to ensure that the operational efficiency of businesses is in line with long-term social and environmental objectives by incorporating sustainability criteria into them. In addition, hybrid MCDM models, including Entropy-DEMATEL-ANP-TOPSIS or Fuzzy-ISM-MICMAC, have proven useful in charting out the interdependences of the factors of sustainability, to enable strategic planning with informed decision-making in uncertain global markets.

To conclude, the development of MCDM in business analytics is an exemplary paradigm shift, whereby, the deterministic, criteria-driven ranking models give way to hybrid, smart and adaptive systems, which are able to handle uncertainty, complexity and non-linearity. Fuzzy logic integration, AI and big data analytics do not only increase the computational resilience of the MCDM models, but also expand their scope to dynamic decision situations, including financial forecasting and supply chain management, strategic innovation and sustainability analytics. The future of MCDM is that it can be synergistically combined with AI-based analytics, real-time data systems, and human reasoning, thus positioning it as a foundation of business decision intelligence in the present. Table 1 is an example of some of the most common MCDM techniques, where they are mostly used in business analytics, and an example of hybrid or combined methods.

Table 1
Summary Table of MCDM Methods

MCDM Method	Primary Applications	Hybrid/Integrated Approaches
AHP	Supplier selection, product portfolio, marketing strategy	Fuzzy AHP, AHP-TOPSIS, AHP-DEMATEL
ANP	Strategic planning, project prioritization	ANP-DEMATEL, Fuzzy ANP, ANP + Big Data
TOPSIS	Portfolio ranking, performance assessment	Fuzzy TOPSIS, TOPSIS + AHP/Entropy, AI-enhanced TOPSIS
VIKOR	Compromise decision-making	Fuzzy VIKOR, VIKOR + weighting, predictive integration
COPRAS	Performance benchmarking, project evaluation	Fuzzy COPRAS, COPRAS-TOPSIS, AI integration
DEMATEL	Risk analysis, interdependency mapping	DEMATEL-ANP, Fuzzy DEMATEL, process analytics integration
ISM	Hierarchical modeling of factors	ISM-DEMATEL, ISM-AHP
Entropy	Objective weighting, financial evaluation	Entropy-TOPSIS, Entropy-MOORA, predictive analytics integration
WASPAS	Supplier selection, multi-criteria evaluation	Fuzzy WASPAS, WASPAS + AHP/Entropy, AI-based ranking
MOORA	Performance evaluation, risk assessment	Fuzzy MOORA, MOORA + Entropy, MOORA-TOPSIS hybrids

4. Applications of MCDM in Business Analytics

4.1 Marketing Analytics

Within the marketing analytics field, MCDM techniques have now become essential in organizing more complicated decision issues, in assessing decision alternatives, and in aiding in the development of strategies based on data. Marketing decisions as such are always based upon a number of conflicting criteria, including but not limited to price, quality, brand recognition, and customer loyalty, and thus the conventional single-criteria approaches are insufficient. Through MCDM methods, decision-makers are able to prioritize the products, segments or campaigns in an organized manner and they can involve both the quantitative and the qualitative measures or judgments.

Hybrid approaches, particularly AHP-TOPSIS and AHP-DEMATEL-TOPSIS, have been common in marketing analytics. AHP-TOPSIS has also been used extensively in ranking products, prioritizing campaign, and selecting a supplier or vendor, with hierarchical weight elicitation capability of AHP and distance-based ranking of TOPSIS [51, 52]. As an illustration, AHP entraps professional assessments of such marketing variables like brand awareness, perceived quality and market share, whereas TOPSIS computes the relational proximity of the alternatives to the ideal solution, creating plain rankings of marketing projects. The related approaches have fuzzy extensions, namely fuzzy

AHP-TOPSIS and fuzzy AHP-VIKOR, enabling managers to address the linguistic assessments and imprecise customer likes, which are especially useful in the new markets where data can be limited or be unpredictable.

Hybrids between AHP-DEMATEL and TOPSIS increase this analytical power by charting the cause-effect relationships among marketing factors and then rank alternatives. DEMATEL determines the critical drivers including customer satisfaction and loyalty as well as brand advocacy and simulates the relationships between the drivers. This network is the outcome that informs the AHP weighting process and improves the ranking process of TOPSIS with the integration of interdependency information within the decision-making framework [51]. The applications of such hybrid frameworks include in campaign effectiveness measurement, market entry strategy choice, and investment priority in digital marketing, which helps organizations to make more sound and practical marketing choices.

In addition to the conventional hybrid models, MCDM techniques have been combined with machine learning, clustering and big data analytics in marketing contexts. As an example, TOPSIS with K-means clustering enables a marketer to divide customers into segments according to a set of multi-criteria behavioral as well as demographic traits and rank the most desirable segments on which a targeted campaign is conducted [50, 51]. On the same note, fuzzy AHP with sentiment analysis based on social media data has been used to measure brand reputation, customer perceptions, and strategic interventions priority [52]. These integrations help marketers to make use of predictive intuitions and at the same time maintain interpretability so that the automated analytics does not replace the managerial judgment.

MCDM is also applicable in marketing analytics to digital marketing, new product development and omni-channel strategy. An illustration is that, under new product development, fuzzy AHP-TOPSIS is applied to rank product concepts based on a number of factors such as cost, market potential, technical, and customer preference [43]. The hybrid MCDM models in digital marketing are used to allocate budgets between campaigns and channels based on clickstream data, conversion rates, and customer lifetime value indicators and generated a multi-criteria rank of data-driven digital initiatives.

Recently, the focus on sustainability and ethical aspects in marketing choices has been highlighted and MCDM has been employed to compare green products, responsible advertising and ethical branding methods. The application of entropy-TOPSIS, WASPAS and MOORA has been used to measure performance in various dimensions of sustainability which integrates both objective data and managerial inclinations in marketing strategy development.

Finally, marketing analytics MCDM methods offer clear, hierarchical, and flexible structures to solve multi-dimensional marketing decisions [53]. The fact that they can integrate hierarchical organization, causal modeling, and ranking based on distance, which is supplemented with fuzzy logic and AI-driven analytics, makes them essential in product assessment, customer grouping, prioritization of campaigns, and market entry strategy. Such combination of traditional and intelligent MCDM models will assure that the marketing decisions made are data and context sensitive in order to contribute to increased managerial performance in competitive and dynamic markets.

4.2 Financial Analytics

MCDM methods have significantly been used in financial analytics because of the growing complexity, interdependence and uncertainty of financial markets. When making investment decisions, risk assessments and credit evaluations, it is important to put into consideration various quantitative and qualitative criteria such as return on investment, liquidity, market volatility, credit worthiness, regulatory compliance and sustainability factors. The systematic method of bringing these diverse criteria together proposed by MCDM allows decision-makers to rank the available options and make clear and evidence-based decisions.

The hybrid models, especially, AHP-TOPSIS, ANP-based models, and Fuzzy ANP-DEMATEL-TOPSIS, are popular in the spheres of financial decision-making as all of these tools provide an ability to integrate hierarchical structuring, cause-effect relationships, and distance-related rankings. These techniques are used in investment portfolio optimization, which combines various financial indicators: expected returns, risk measures, liquidity and ESG performance, enabling investors to rank portfolios based on both quantitative measures and expert judgment [52, 53]. ANP-based methods can also be useful when financial criteria are not independent with each other, since they capture the feedback between risk factors, asset relationships and market conditions resulting in a more robust prioritization.

MCDM is also used widely in credit scoring and loan evaluation, where a bank and other financial institutions are required to estimate the relative significance of various attributes of their borrowers such as their performance in terms of income stability, repayment history, collateral and credit behaviour. The Fuzzy ANP-DEMATEL-TOPSIS models can be used to incorporate linguistic expert judgments typically used in financial risk assessment into a quantitative ranking system [54]. These models help enhance the precision and transparency of credit risk classification by modeling interdependencies between risk factors and measuring their relative importance.

MCDM is applied in risk prioritization and financial stress testing to identify the risk drivers that are the most important, in a systematic manner, to provide the organization with resources to mitigate the risk. DEMATEL-based hybrids have been used, including the DEMATEL-ANP and fuzzy DEMATEL-ANP, to measure systemic financial risks and comprehend the cause and effect relationships among the macro-economic, market, and operational risk factors [54, 55]. These models assist in building the cause-effect chain of financial indicators, which enhance planning and formulation of policies to control risks.

MCDM can also be used in conjunction with predictive analytics and other methods of forecasting, which adds additional value to MCDM in the financial field. As an illustration, forward-looking investment analysis, financial performance forecasting, and scenario planning can be carried out with the help of Entropy-TOPSIS, MOORA, and WASPAS frameworks together with time-series forecasting, regression models, or neural networks [52]. This type of hybrid systems enables decision-makers to consider alternatives in the context of uncertainty and provides an opportunity of combining both past information and judgment of experts, which facilitates proactive financial strategies.

Other uses include sustainable finance and ESG investment decision-making, in which the hybrid MCDM models can order investment opportunities by financial performance and social, environmental, and governance factors. Fuzzy AHP-TOPSIS, Entropy-DEMATEL and WASPAS-based models have been used as a way of prioritizing sustainable projects, assessing corporate performance and optimizing socially responsible portfolios [51, 52]. These strategies offer the comprehensive decision-making platform that incorporates financial gain with moral and regulatory concerns.

To sum up, the MCDM in financial analytics offers a multi-dimensional transparent and robust decision support system. MCDM techniques also improve the optimization of a portfolio, analysis of risk, credit analysis and predictive finance due to hierarchical structuring, mapping of causal relationships, distant based ranking, and fuzzy reasoning. This is due to the combination of objective and subjective criteria, hybrid-based models, and predictive analytics that are AI-based and make sure that financial decisions are not only made based on data, but also contextual, which helps institutions navigate through the complex and uncertain financially interdependent environment.

4.3 Supply Chain & Operations Analytics

The MCDM methods are critical to improving decision-making in the context of supply chain and operations analytics in the context of complexity, uncertainty, and multi-dimensional performance requirements. The current supply chains are dynamic and in most cases extend to the global networks, have many stakeholders, limited by cost and quality and time and sustainability factors. MCDM offers a methodology to analyze and process alternatives and optimization of operating strategies with quantitative measurements, professional expertise, and real-time data.

One of the most noticeable uses of MCDM in operations management is supplier selection. The conventional approaches such as AHP, TOPSIS, VIKOR and COPRAS enable companies to assess the suppliers based on various standards such as cost effective, product quality, reliability with delivery, flexibility and environmental influence [56]. As an example, fuzzy AHP-TOPSIS has been popularly applied to consider the vagueness in expert perceptions in ranking suppliers and this offers a more refined measure of trade-offs amid expenses, quality and sustainability [57]. Moreover, hybrids based on ANP and DEMATEL are able to model interdependencies and causation between the selection criteria and, furthermore, contribute to more accurate and strategically relevant rankings.

MCDM also helps in logistics and optimization of operations. The TOPSIS, VIKOR, and MOORA techniques are used to consider transportation routes, warehouse locations, inventory policies, and production schedules depending on the cost, lead time, reliability, flexibility and carbon footprint among others [54, 55]. Uncertainty in the logistics decision has been managed with hybrid frameworks, such as fuzzy DEMATEL-ANP or Entropy-TOPSIS and facilitates the use of real-time operational data, allowing more agile and resilient supply chains [54]. These strategies can also be used to consider both the financial efficiency and environmental sustainability at once that is getting more and more important in green supply chain management.

The combination of AI, machine learning, and analytics based on the IoT has changed the conventional MCDM applications by moving them into dynamic real-time decision-support systems. Taking the example, IoT-based sensors supply real-time inventory, transportation, and supplier metrics, which may be integrated into hybrid MCDM-AI systems of predictive logistics and flexible planning [41, 42]. In a like manner, machine learning algorithms, together with fuzzy MCDM, help predict demand, improve production plans, and re-rank suppliers dynamically according to the performance indicators [56, 57]. These hybrid systems enable operations managers to quickly react in response to the volatility of the market as well as supply disruption and sustainability needs, thereby maintaining efficiency and resiliency.

MCDM equally plays a very important role in sustainability evaluation and green operations. Entropy-TOPSIS, WASPAS and MOORA techniques have been used to assess the use of carbon emissions, energy consumption, and resource utilization in supply chain networks [32, 34]. Moreover, fuzzy DEMATEL-ISM systems represent relationships among sustainability enablers, including government policy, technological adoption, and supplier commitment that enable organizations to find leverage points on strategic improvement [28]. The strategies enable the making of decisions that are sustainable in operational performance to meet the social and environmental goals.

Moreover, multi-objective and hybrid MCDM models have gained even more popularity in the production planning, capacity optimization, and risk assessment. Examples of studies using

DEMATEL-ANP, fuzzy TOPSIS, and hybrid MOORA-WASPAS models show that they are able to balance cost, time, quality and sustainability trade-offs especially in complex global supply chains [57, 58]. These approaches make use of quantitative operational data and expert judgment, which give actionable information about resource allocation, supplier negotiating, and performance benchmarking.

To sum up, MCDM applications to supply chain and operations analytics can provide systematic, adaptive, and multi-dimensional structures to assess options, optimize operations and guarantee sustainability. The combination with AI, IoT, and predictive analytics increases responsiveness in real-time which allows organizations to address the difficult supply chain, organization operational uncertainty, and environmental goals. MCDM has integrated analytical rigor and managerial intelligence to make it one of the foundations of modern operations and supply chain decision-making.

4.4 Human Resource and Strategic Management

MCDM has become an important tool in the sphere of human resource (HR) and strategic management, offering a systematic way of assessing performance, competencies, and strategic choices in environments that have many, often mutually incompatible criteria. HR decision-making, including employee appraisal, leadership evaluation, training needs analysis, and succession planning should be carefully balanced between qualitative and quantitative criteria, which include skills, experience, behavioral characteristics, and impact on the organization. In the same measure, strategic management is the process of considering growth activities, mergers and acquisitions, decision to invest in innovation projects, and resource allocation processes, which require multi-dimensional analysis.

AHP and AHP-DEMATEL hybrids find extensive use in HR analytics to assess competencies, as well as conduct appraisal and leadership. AHP divides complex HR decisions issues into hierarchical stages of criteria and sub-criteria allowing to compare employees or leaders with performance and competency indicators on a pair-wise basis [58]. The combination of DEMATEL represents the cause-effect relationships between competencies, including the impact of communication skills on team performance or leadership effectiveness, giving managers practical insights about specific interventions and development initiatives to make [27,39]. Moreover, fuzzy AHP-DEMATEL models can deal with the subjective and imprecise quality of human judgments, and therefore, the HR managers can consider linguistic judgments and expert opinions during the decision-making process.

MCDM in strategic management helps to evaluate and rank the corporate growth options, mergers and acquisitions (M&A) and innovation projects. The Balanced Scorecard (BSC) systems are also frequently used alongside MCDM to incorporate financial, customer, internal process, and learning and growth views into a multi-criteria assessment system [58, 59]. Hybrid MCDM methods (e.g., AHP-TOPSIS, ANP- VIKOR, and Fuzzy DEMATEL- ANP) are used to evaluate the strategic choices considering both quantitative measures (e.g., expected ROI, market share, operational efficiency) and qualitative (e.g., fit to the organizational culture and support by the leadership, potential innovativeness) ones [19, 22]. These models help organizations to sing out the most promising strategic initiatives taking into consideration the interdependency, trade-offs and uncertainties that accompany high-level decision-making.

MCDM is also very significant in the talent management and succession planning where it is used to rank employees in terms of promotion, prioritizing of training and retention strategy. MCDM achieves the objective, transparent, and strategic human capital decisions by incorporating various performance measures and competencies [59]. Moreover, the HR analytics has been applied to the entropy-based and WASPAS to be able to objectively prioritize criteria, including employee performance scores, skill gaps, and engagement metrics, and thus provide a complement to subjective ones.

MCDM techniques aid multi-objective appraisals of R and D schemes, adoption of technology and expansion of the market in strategic planning. Fuzzy logic, DEMATEL, and ANP hybrid frameworks assist managers to integrate interdependencies between strategic elements that include market potential, technological feasibility, resource allocation and competitive positioning to offer a holistic evaluation of strategic options [55, 56, 59]. The integration of objective measures and human judgement is the way to make sure that sophisticated strategic choices are evidence-based and nevertheless pertinent to the context.

Lastly, MCDM supports the scenario analysis, sensitivity testing, and robustness checks in HR and strategic management. Organizations can make resilient and adaptive decisions in uncertain environments by considering changes in criteria weights or interdependencies to change employee rankings, leadership evaluation, or strategic project prioritization.

Conclusively, MCDM in HR and strategic management gives a systematic, open, and multi-dimensional method of choosing the employees, leaders, and strategic initiatives. Hierarchical structuring, causal mapping, fuzzy reasoning and hybrid ranking techniques allow MCDM to make data-driven, context-sensitive and long-term objectives-oriented human capital and strategic decisions.

4.5 Data-Driven & Hybrid Business Intelligence Systems

MCDM techniques are widely used in data-driven and hybrid business intelligence (BI) systems to improve the process of decision-making, to optimize the resource distribution, and to offer useful insights based on big and heterogeneous data sets. The conventional MCDM methods are good when dealing with structured, decision problems, but have weaknesses in their capacity to deal with high dimensional, real-time and unstructured data that characterizes the contemporary business world. Combining MCDM and machine learning, data mining, predictive analytical techniques and a high order of visualization aids, organizations can use the benefits of structured multi-criteria evaluation as well as data-driven intelligence, to create a strong decision-support system.

A product with much popularity is Fuzzy AHP and clustering algorithms. Data Clustering Partitions customers into homogenous clusters based on behavioral or demographic or transactional data, and fuzzy AHP values and ranks these clusters on a number of strategic criteria (profitability potential, loyalty, or responsiveness to marketing campaigns) [60]. This mixed method allows the companies to discover high-value customer bases, tailor marketing, and allocate resources optimally and deal with the uncertainty of human behavior and survey-based measurements.

The use of TOPSIS simulated with AI and machine learning models has also been a feature of predictive analytics. Predictive outputs (e.g., sales forecast, risk score, or customer churn probability) generated by AI models (e.g. neural networks, decision trees, or ensemble learning algorithms) can be included in MCDM models to rank and prioritize decisions [52, 53]. By being integrated in this way, decision-makers can integrate predictive insights and structured evaluation, which will ensure that recommendations are both forward-looking and multi-dimensional. As an example, in financial portfolio choice or operational performance evaluation, AI-enhanced versions of TOPSIS or VIKOR models prioritize alternatives with regard to the predicted performance, risk aspects and sustainability criteria in one step.

The development of interactive BI dashboards that use MCDM increases the transparency, interpretability, and engagement of the stakeholders in decisions. The platforms enable users to visualise trade-offs between two or more criteria, to search through scenario analysis and dynamically manipulate criteria weights in real-time [57, 58]. Fuzzy MCDM with Entropy weighting and predictive analytics dashboards allow managers to track key performance indicators (KPIs), understand bottlenecks, and model a what-if environment in the marketing, finance, operations, and HR sectors. This interactive nature enhances evidence-based task execution and data-driven strategy formulation, which minimizes the use of intuition.

Moreover, hybrid MCDM-BI systems have been used in sustainability analytics, risk management and innovation evaluation. As an example, Entropy-WASPAS dash boards with real-time environmental and operational data have been applied to trace the sustainability of supply chain as well as evaluate the performance of green project and prioritize various strategic initiatives according to the diverse objectives [59, 60]. Equally, MCDM models together with machine learning and big data-systems allow organizations to weigh innovation initiatives, R&D investments, and adoption strategies of the technology, with a view of evaluating the potential returns, technical feasibility, and strategic alignment.

In general, the incorporation of MCDM into data-driven and hybrid BI systems is a pointer towards the intelligent, adaptive and interactive decision support frameworks. With a mix of classical multi-criteria reasoning, fuzzy and objective weighting systems, predictive analytics, and visualization systems, these hybrid platforms promote the quality, speed, and strength of business decisions. They equip managers with usable information across fields, aid in multi-dimensional assessment and scenario analysis in addition to strategic planning in more complex, uncertain and data-saturated business environments.

5. Discussion and Research Gaps

5.1 Synthesis of Insights

The synthesis of the literature review shows that MCDM has a transformational role in decision-making in various business fields such as marketing, finance, operations, human resource, and strategic management. MCDM offers a methodical model to organize the issues of complexities, deal with conflicting standards and combine quantitative and qualitative information, which is crucial in present business conditions of uncertainty and swift change [14, 17]. In numerous fields, such classical techniques as AHP, ANP, TOPSIS, VIKOR, COPRAS, DEMATEL, and ISM continue to reveal their application in prioritization, ranking, risk assessment, and performance evaluation as transparent and rational means of decision support to the managers.

The review suggests that hybridization of MCDM techniques is a strong way of promoting analytical power of MCDM methods. Indicatively, fuzzy AHP-TOPSIS, fuzzy ANP-DEMATEL-TOPSIS combine hierarchical structuring and interdependency mapping and distance-based rankings to support uncertainty and subjectivity in the decision problem more effectively [24, 26]. On one side, in marketing, hybrid MCDM frameworks enable prioritizing products, customer segmentation, and campaign evaluation, whereas on the other, they assist in portfolio optimization, credit scoring, and risk assessment [11, 13, 16]. Hybrid models are useful in supply chain applications and operations, such as supplier evaluation, optimization of the logistics, sustainability evaluation, but the HR and strategic management use MCDM to examine competencies, leadership and strategic growth.

The predictive and real-time MCDM is further enhanced with the integration of information-based analytics, artificial intelligence, and BI systems. As an example, TOPSIS or WASPAS should be combined with machine learning to enable organizations to use predictive capabilities and keep multi-criteria assessment to monitor performance in real-time, control risks, and plan their activities [8, 12]. Equally, fuzzy AHP with clustering or sentiment analysis can help in the subtle segmentation and prioritization of dynamic marketing and customer analytics scenarios [44,48]. These hybrid methods do not only increase the accuracy and robustness of computations, but also increase interpretability and the usability by managers, all the way between analytical rigor and managerial decision-making.

Another trend that the literature focuses on is the increasing tendency toward sustainability, ethical issues, and the incorporation of ESG into the applications of MCDM. The hybrid models, that is, Entropy Topics, TOPSIS, Fuzzy DEMATEL-ANP, and MOORA are used to assess environmental, social and governance aspects in addition to conventional financial and operating principles [57, 60]. This assimilation allows companies to effectively coordinate strategic and operational choices with the long-term sustainability goals that illustrate the changing face of MCDM as not an exclusive technical instrument, but also a strategic facilitator of responsible choices.

Essentially, the integration of insights validates that MCDM is effective in terms of the quality of decisions, transparency, and strategic alignment in various business fields. Its combination with fuzzy logic, AI, and data-driven analytics offer predictive, real-time and multi-dimensional decision support capabilities to organizations, able to respond to complex, uncertain, and dynamic business issues. The interplay of the classical rigor in MCDM and smart analytics makes it a fundamental approach to evidence-based decision-making and strategic planning in the contemporary world.

5.2 Methodological Trends

The current trends in methodology developed as per the literature show a gradual shift in how MCDM has been applied in business analytics with an incremental sophistication, hybridization and combination with newer computational methods. One of the trends is that there is a tendency to hybridize classical approaches to MCDM with fuzzy logic, DEMATEL, ANP, and objective weighting techniques, and that improves the capacity of decision-makers to be able to deal with uncertainty, vagueness, and interdependences between criteria. As an example, fuzzy AHP-TOPSIS and fuzzy ANP-DEMATEL-TOPSIS models have been extensively used to encompass linguistic decisions, to model the cause and effect relations, and to rank the alternatives in a multi-dimensional decision making process [39]. These mixed models permit stronger prioritization and review, especially in areas in which qualitative measurements and the subjective specialist view are exceptionally important, including HR skill assessment and marketing strategy choice.

Integration of MCDM and artificial intelligence (AI) and Big Data analytics is another broadly important methodological trend, which allows real-time, predictive and adaptable decision support. A combination of machine learning models, clustering algorithms, neural networks, and predictive forecasting methods with MCDM frameworks like TOPSIS, VIKOR, and WASPAS is increasingly used to rank alternatives based on the past and future predictions [17, 25]. This integration will not only increase the accuracy and reliability of in-service but also allows dynamism in rapidly evolving business circumstances, including financial risks, supply chain impact(s), and eMarketing campaigns.

The literature also sheds light on the adaptation of MCDM approaches to sector, which is the adaptation of methods to business problems peculiar to a field. As an illustration, the hybrid fuzzy AHP+TOPSIS are used in marketing analytics, i.e. customer segmentation and prioritization of campaign, and the DEMATEL-ANP models and MOORA-WASPAS models in supply chain management, i.e. supplier evaluation, logistics optimization and sustainability assessment [14, 19, 26]. ANP–DEMATEL–TOPSIS models can be used in finance to optimize portfolio and credit score, AHP-DEMATEL and balanced scorecard-based MCDM models are applicable in HR and strategic management to assess competencies, leadership, and strategic growth choices [30, 32]. This domain-specific tailoring ensures that MCDM approaches meet business specific goals, operational and performance indicators of each industry.

Another trend of the methodology is the creation of multi-layered decision models composing hierarchical and network-based analysis to mirror the intricacy of the business systems in the real world. The hierarchies used in AHP allow the breakdown of the problems into problem levels of criteria and sub-criteria, whereas the network-based methods, like ANP and DEMATEL, can account to the interdependencies and feedback amongst factors [41]. These multi-layered structures give a more detailed representation of the contexts of decision making, and the direct and indirect effects of criteria can be properly evaluated, which is especially applied in strategic planning, risk management, and sustainability analysis.

To conclude, the trend of the methodological development of MCDM in business analytics is hybridization with fuzzy logic and interdependency modeling, incorporation into AI and Big Data, customization to the specifics of the sector, and modeling based on hierarchies and networks. All these trends increase the strength, flexibility and predictability of MCDM frameworks that allow organizations to approach complicated, uncertain, as well as multi-dimensional business issues in a methodical and data-oriented fashion.

5.3 Research Gaps and Limitations

Although MCDM has been increasing in the field of business analytics, literature shows that there are a number of research gaps and limitations that need to be addressed in order to further advance the theory as well as practice. The second area of weakness is insufficient development of dynamic and real time MCDM models. Majority of the available studies dwell on fixed assessment systems, which fail to meet the dynamic business environment, dynamic market environment or dynamic operational information [56]. This weakness restricts the capacity of organizations to make responsive and quick decisions, particularly in situations when financial trading, managing supply chain disruptions, and digital marketing campaigns demand instantaneous response and forecasting.

The other notable gap is the under-research of some of the business areas such as human resource (HR) analytics, environmental, social, and governance (ESG) decision-making and innovation management. Although marketing, finance, and operations are most commonly used with MCDM, HR-related analyses, including employee performance, talent retention, and development of leadership are relatively small [11, 16]. In the same vein, ESG-related decision-making that necessitates incorporating sustainability measures into the conventional performance measures remains in its early phases, and there are few solid structures that ensure that the complexity and multi-dimensionality of these requirements are fulfilled [18, 42]. Even the management of innovations involving R&D prioritization and technology adoption do not have frameworks based on thorough MCDM, which restricts the organizations in the opportunity to analyse strategic innovation projects in a systematic way.

Another weakness is the absence of strong validation, benchmarking and standardization of MCDM structures. Most of the researches depend on single case study, experience or validation by simulation and limit the generalization and reproducibility of results [56, 57]. There is a lack of comparison among other MCDM models, hybrid models or across business environments, which leaves the managers with difficulties in adopting evidence-based best practices.

Also, the issue of computational complexity and scalability is critical, especially in reference to hybrid and multi-layered models, which combine fuzzy logic, DEMATEL, ANP, or AI-based analytics. The more criteria, choices, and dependencies are present, the higher the level of computational load, and this may be a barrier to its practical implementation in a large-scale organizational or supply chain network [59, 60]. These challenges are not well realized by efficient algorithms, parallel computing and heuristic optimization.

Last but not least, the combination of MCDM and the next-generation analytics system, including Big Data platforms, Internet of Things (IoT), and powerful machine learning models is at its inception. Although there are a few promising hybrid frameworks suggested, the full potential of real-time, predictive, and adaptive decision support is unexploited, especially when it is necessary to have continuous streams of data, automated learning, and dynamic re-ranking of alternatives.

Finally, the gaps in the research indicate that it is necessary to have dynamic, domain-diverse, validated, scalable, and technologically integrated MCDM frameworks. By overcoming these constraints, MCDM techniques will be able to assist in solving complex, real time and multi-dimensional business decisions, thus filling the gap between theory and practice in the context of the modern business

5.4 Future Research Directions

The literature review indicates that there are a number of opportunities in terms of future research that can facilitate the effectiveness and applicability of MCDM in business analytics. One of the main trends is the emergence of moving and adaptive MCDM frameworks that can deal with real-time data, changing business circumstances and immediate decision-making demands. These structures would include ongoing audit of criteria, automatic ranking changes, and predictive changes, which could allow the organisations to react to changes in the market, supply chain crises, and changes in customer behaviour efficiently [12, 18]. Addition of adaptive mechanisms of weighting and feedback in the hierarchical and network based MCDM models has the potential to enhance accuracy and strength of decision making in the presence of uncertainty.

The other significant opportunity is to extend MCDM applications to new underutilized areas, such as HR analytics, ESG-based decision-making, and innovation management. Future research in the field of HR analytics may focus on creating models that will combine employee performance, competencies, engagement index, and succession planning in multi-criteria models, which will facilitate evidence-based talent management [22, 29]. To use MCDM frameworks in sustainability and ESG-centric decision-making, financial, environmental, social and governance metrics may be paired with predictive analytics to inform corporate sustainability strategies and responsible investment appraisal [34, 50]. Cutting-edge MCDM models might be applied in the management of innovation in the evaluation of R and D projects, technology adoption and strategic growth options, incorporating expert judgment with quantitative data to achieve the optimal distribution of resources and innovation.

Another opportunity of research can be seen in the integration of MCDM with explainable AI and advanced predictive analytics. Integrating MCDM with machine learning, neural networks and deep learning models may provide predictive ranking of alternatives using data, as well as explainable AI methods that may allow managers to make decisions remain transparent and comprehensible [57]. This integration would be helpful in providing real-time, multi-criteria decision support where needed, filling the gap between computational intelligence and managerial insight.

More research in the future should also be done on sound benchmarking and comparative analysis of MCDM techniques across industries. Comparison of classical, hybrid, and AI-combined MCDM models in various fields of business: marketing, finance, operations, HR, and strategy would help to gain valuable information regarding the methodological performance, reliability, and applicability [5, 8, 9]. This would help in the identification of best practices, context-dependent frameworks, and domain-optimized models hence increasing the confidence of the managers in the application of MCDM.

Lastly, scalable, interactive, and user-friendly decision-support platforms should be developed that will incorporate MCDM with BI dashboards, visualization tools, and real-time analytics. These platforms would enable managers to perform trade-offs between several criteria, perform scenario analysis, and/or adjust criteria weights in a dynamic business environment and simulate the results to give actionable insights [7, 21, 36]. Large datasets, multiple decision-makers and complex interdependencies would also be served by scalable architectures, and this makes them practical in multinational organizations and supply networks of complex nature.

To conclude, the new direction of AI should be making dynamic, adaptive, domain-diverse, AI-integrated, and interactive MCDM frameworks in the future. These developments will allow organizations to make stronger, more open, and more context-responsive decisions and be able to use the full capabilities of multi-criteria reasoning in contemporary, multi-data-intensive and quickly changing business settings.

5.5 Theoretical Contributions

The theoretical outcomes of this study on the use of MCDM approaches in business analytics can be expressed in the following way.

Generalized Overview of MCDM Applications in Business Analytics: The article consolidates and categorically classifies the various applications of classical and hybrid MCDM techniques to various business applications such as marketing, finance, supply chain, operations, human resources, and strategic management. This synthesis of the scattered literature offers a unitary theoretical insight into the way MCDM aids structured and multi-criteria decision-making in data-driven business scenarios.

Development of Hybrid MCDM Frameworks: The study points out the future development of MCDM as hybrid models that include fuzzy logic, DEMATEL, ANP, objective weighting, AI, and predictive analytics [39, 44]. Through the synthesis of these developments, the study has a theoretical contribution through its ability to exhibit how the hybridization enhances the robustness, adaptability, and interpretability of decision models especially in the circumstances of uncertainty, interdependency and dynamic business environments.

Combination with Data-Driven and Predictive Analytics: The research presents conceptual knowledge regarding how MCDM is synergically integrated with big data, machine learning and predictive modeling and how these interactions yield real-time-supportive decisions, predictive ranking, and scenario analysis [56, 60]. This contribution fills this gap between classical multi-criteria reasoning and modern data-intensive models of analytics, enhancing the conceptual connection between structured decision-making and advanced analytics.

Establishment of Methodological Trends: The work is theoretically valuable as it describes the prevailing trends in the methodology of the field such as hybridization with fuzzy logic, adoption of AI and Big Data, domain-specific adaptation, multi-layered hierarchical-network modeling. This trend analysis offers a conceptual model to the development of MCDM approaches and their growing consistency with business issues that are complex and realistic.

Emphasizing Research Gaps and Directions: By pinpointing weaknesses, including failure to develop dynamic models, little-explored areas (HR analytics, ESG, innovation management), the research issues of computational scalability, and the early adoption of integrated analytics instruments, the research provides a theoretical basis in future research. It provides a roadmap on how to continue developing MCDM theory by creating dynamic and scalable, explainable, structures that will be more appropriate in modern and data-intensive business settings.

Strategic Decision-Making Perspective: The paper highlights the theoretical significance of MCDM as not just a tool of analysis but also as a strategy decision-enabler [32, 33]. Through the connection of multi-criteria thinking with business insights and data-oriented intelligence, it promotes cognitive processing concerning the contribution of structured evaluation models to transparency, reliability, and sustainability of managerial decision making.

In short, the theoretical contributions of the research are in the form of a comprehensive framework that incorporates classical and hybrid MCDM models, emphasis on the evolution of methods, connecting MCDM to the current state of analytics, the identification of research gaps, and the conceptualization of MCDM as the strategic enabler of sound business decisions.

5.6 Managerial Implications

The results of the study offer a number of effective implications to managers and organizations, who may advance the decision-making processes by implementing MCDM in the business analytics.

Improved Quality and Transparency of decisions: Managers are able to prepare alternatives based on various conflicting criteria in a systematic way through the application of classical and hybrid MCDM models like AHP, ANP, TOPSIS, VIKOR, DEMATEL, and fuzzy-integrated models [27, 36]. This formalized method enhances transparency, traceability as well as justification of decisions that is essential in high stakes situations like investment planning, vendor choice as well as strategic prioritization.

Computer-Assisted and Data-Driven/Predictive Analytics: The hybridization of MCDM with AI, machine learning, and big data analytics can help organizations to provide real-time, predictive, and adaptive decision-making [45]. An example is TOPSIS or WASPAS with forecasting models which enable managers to foresee the trends in the market, predict risks, rank alternatives according to historical and predictive information, and improve proactive and evidence-based strategies.

Strategic Prioritization by Business Domains: The study illustrates how the MCDM can be used in marketing, finance, supply chain, operations, HR and strategic management domains and allows managers to match resources allocation with the strategic goals [10, 15, 31]. Multi-dimensional assessment that takes into account both quantitative measures as well as qualitative judgments is facilitated by hybrid frameworks (e.g., fuzzy AHP-TOPSIS to customer segmentation or DEMATEL-ANP to risk prioritization).

Promoting Sustainability and ESG efforts: Managers have the opportunity to implement MCDM models that include the environmental, social, and governance parameters in addition to the traditional financial and operational indicators [37, 46]. Entropy-TOPSIS or fuzzy DEMATEL-ANP are the methods that allow the organization to achieve the goals of profitability and sustainability that allow the company to make responsible decisions in the long term and ensure corporate social responsibility.

Scenario Analysis and Risk Management: MCDM integration with multi-layered hierarchical and network-based models enables the manager to consider interdependencies among the criteria, conduct scenario analysis and determine the indirect impact of a strategic decision [53, 58]. This ability is especially useful in risk assessment, operational planning and contingency management in uncertain and dynamic environments.

Interactive Decision-Support Platforms: The research identifies the opportunities of the BI dashboards and interactive MCDM platforms that integrate visualization, fuzzy evaluation, and predictive analytics [13, 16, 19]. The trade-offs, which managers are able to explore, the weightings of the criteria are dynamically adjustable, and simulation of alternative outcomes leads to more informed, collaborative, and agile decision-making processes.

Recommendation on Multi-Criteria Resource Allocation: MCDM techniques have been used to offer quantitative rankings and prioritization processes to aid managerial decisions on the allocation of resources efficiently in projects, investments, or departments (operational and strategic planning) [41, 59]. This not only minimizes subjective biases but also keeps it in line with organizational objectives, and also maximizing efficiency of operations.

Overall, managerial impacts of this study include the fact that MCDM is a robust decision-support facilitator, which offers structured, transparent and data-driven solutions to multi-dimensional and uncertain business challenges. Combining classical and hybrid MCDM techniques with predictive and AI-based analytics, managers will be able to enhance the accuracy of decisions, their strategic orientation, sustainability, and operational efficiency, thus it is one of the most important tools in the contemporary business setting.

6. Conclusion

The given review is a detailed summary of the usage of MCDM techniques in business analytics and the pieces of advice it might offer. The discussion indicates that classical MCDM methods; namely SPH, ANP, TOPSIS, VIKOR, DEMATEL, COPRAS, Entropy, WASPAS, and MOORA are applied successfully in different business areas, including marketing, finance, supply chain management, operations, human resources and strategic management. Such techniques make it easy to make structured decisions since they assist in considering and ranking options on the basis of several, often competing, criteria and thus enhancing the levels of transparency, consistency, and rationality in managerial decisions.

The review also highlights how MCDM has evolved to become hybrid systems incorporating fuzzy logic, DEMATEL, ANP, objective weighting schemes and AI-based analytics. This kind of hybridization provides the capability to manage uncertainty, the nature of interdependence and the complex interactions between decision criteria and therefore MCDM is appropriate in the dynamic and data intensive business world. As an illustration, ANP hybrids based on fuzzy AHP-TOPSIS have been extensively used in supplier selection and modelling customer preferences, and the ANP hybrids with DEMATEL are useful in the assessment of interdependence in risk factors and strategic priorities. Real-time decision support, scenario analysis and predictive ranking of alternatives are further fortified by the integration with big data, machine learning, and predictive analytics.

This review offers a cohesive roadmap to scholars and practitioners by organizing the applications systematically, emphasizing the trend in the methodology, and the gaps in the research: there is still much to understand about ESG and HR analytics, and it requires a substantial validation. Its results highlight that MCDM is not simply a calculational instrument but a strategic facilitator of decision-making and it can be used to incorporate data-driven information with multi-criteria decision-making to increase the transparency, strength, and sustainability of a business decision.

The review also points out major directions towards future studies that recommend the creation of dynamic, adaptive, scalable and explainable MCDM frameworks. These innovations will enable organizations to react to business problems in real-time to complex business problems, integrate predictive analytics, and achieve interpretability and trustworthiness. Besides, the implementation of new applications in the unexplored areas, benchmarking protocols, as well as interactive decision-support systems, will contribute even more to managerial effectiveness, evidence-based strategy development, and operational resilience.

Overall, this paper concludes that MCDM has now become a serious facilitator of contemporary business analytics, with a methodological rigor, a hybrid intelligence, and a useful applicability. Its further development is bound to eradicate the distance between systematic decision assessment and novel data-driven technologies, thus enabling companies to attain strong, clear, and sustainable results in the business environment that has been growing more complicated and unpredictable.

Acknowledgement
This research was not funded by any grant.

Conflicts of Interest
The authors declare no conflicts of interest.

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