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Review

Best-worst multi-criteria decision-making method: A review of the literature

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ABSTRACT

The Best-Worst Method (BWM) has emerged as a powerful and efficient technique in the field of Multi-Criteria Decision-Making (MCDM), renowned for its simplicity, computational efficiency, and ability to address complex decision-making problems involving multiple conflicting criteria. As one of the leading MCDM methods, BWM has received significant attention across a wide range of disciplines and application areas. This paper aims to provide a comprehensive review and bibliometric analysis of BWM-related research from 2015 to June 2025. This study investigates the integration of BWM with other Multi-Attribute Decision-Making (MADM) techniques. It also systematically examines BWM's application in environments characterized by uncertainty and ambiguity, addressing critical methodological challenges. Furthermore, the research categorizes and evaluates real-world applications of BWM, demonstrating its practical relevance and effectiveness across various domains. The bibliometric analysis covers multiple dimensions, including document analysis to track publication growth and trends, keyword analysis to identify emerging research themes, source analysis to highlight influential journals and conferences, author analysis to recognize leading contributors, affiliation analysis to map institutional and geographical contributions, citation analysis to assess impactful studies, and application analysis to explore BWM's diverse real-world uses. By offering valuable insights into the current state of BWM research, this study provides a foundation for future research and promotes the broader adoption of BWM in decision-making processes.

1. Introduction

Decision-making is a fundamental aspect of human activity, influencing a wide range of fields, including business management, engineering, healthcare, and public policy (Wiecek et al. [1]; Zavadskas & Turskis [2]; Zopounidis et al. [3]; Glaize et al. [4]). In an increasingly complex and interconnected world, it often involves navigating conflicting criteria, where trade-offs are unavoidable. Consequently, the need for systematic, reliable, and efficient methods to support decision-makers in making informed choices has become more critical (Stewart [5]; Aruldoss et al. [6]; Thakkar [7]; Kulkarni [8]). Multi-Criteria Decision-Making (MCDM) methods have emerged as indispensable tools, enabling the structured evaluation and prioritization of alternatives while accounting for diverse and occasionally contradictory factors (Yu [9]; Ferreira et al. [10]; Kumar [11]).

MCDM techniques provide a formalized approach to managing decision-making complexities, offering clarity and analytical depth for sound judgments. MCDM is broadly categorized into two main branches: Multi-Attribute Decision-Making (MADM) and Multi-Objective Decision-Making (MODM) (Taherdoost & Madanchian [12]). MADM focuses on evaluating and selecting the best alternative from a finite set of options based on predefined criteria, making it particularly useful for discrete decision problems (Tzeng & Huang [13]; Zavadskas et al. [14]). In contrast, MODM deals with designing or optimizing solutions in continuous domains, aiming to achieve the best possible outcomes for multiple, often competing objectives (Tanino et al. [15]; Hwang & Masud [16]). Both branches provide structured frameworks, aiding decision-makers in navigating complex, multidimensional problems across various domains.

MADM methods can be classified into several categories based on their primary functions and applications. The first category includes weighting methods, which focus on determining the relative importance

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(weights) of criteria. These methods often rely on pairwise comparisons or other techniques to calculate weights. Examples of weighting methods include the Analytic Hierarchy Process (AHP) (Vargas [17]; Vaidya & Kumar [18]; Emrouznejad & Marra [19]; Zyoud & Fuchs-Hanusch [20]), Analytic Network Process (ANP) (Sipahi & Timor [21]; Asadabadi et al. [22]; Chen et al. [23]; Kheybari et al. [24]), Full Consistency Method (FUCOM) (Pamucar et al. [25]; Everest et al. [26]), Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) (Bana E Costa & Vansnick [27]; Ferreira & Santos [28]), and Stepwise Weight Assessment Ratio Analysis (SWARA) (Keršuliene et al. [29]; Mardani et al. [30]).

The second category comprises ranking methods, which are used to rank alternatives based on multiple criteria. These methods evaluate and compare alternatives to determine their relative performance. Notable examples of ranking methods include the Elimination Et Choice Translating Reality (ELECTRE) (Figueira et al. [31]; Govindan & Jepsen [32]; Durucasu et al. [33]), Multi-Attributive Border Approximation Area Comparison (MABAC) (Pamucar & Ćirović [34]; Demir et al. [35]), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) (Behzadian et al. [36]; Durucasu et al. [36]; Ishak & Akmaliah [37]), Tomada De Decisao Interativa Multicriterio (TODIM) (Llamazares [38]; Chakraborty et al. [39]), Technique for Order Preference and Similarity to Ideal Solution (TOPSIS) (Behzadian et al. [40]; Zyoud & Fuchs-Hanusch [41]; Çelikbilek & Tüysüz [42]; Taherdoost & Madanchian [43]), and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Yazdani & Graeml [44]; Gul et al. [45]; Mardani et al. [46]).

The third category involves hybrid assessment methods, which combine multiple techniques to evaluate and rank alternatives. These methods often integrate weighting and ranking approaches to provide more comprehensive results. Examples of hybrid methods include the Additive Ratio Assessment (ARAS) (Zavadskas & Turskis [47]; Chakraborty et al. [48]), Complex Proportional Assessment (COPRAS) (Chatterjee et al. [49]; Chakraborty et al. [50]), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA) (Chakraborty et al. [51]; Singh et al. [52]), Simple Additive Weighting (SAW) (Afshari et al. [53]; Kaliszewski & Podkopaev [54]), and Weighted Aggregated Sum Product Assessment (WASPAS) (Chakraborty & Zavadskas [55]; Mardani et al. [56]). The fourth category consists of relational and efficiency analysis methods, which focus on analyzing relationships between criteria or evaluating the efficiency of alternatives. These methods are particularly useful for understanding interdependencies and optimizing resource allocation. Examples include the Data Envelopment Analysis (DEA) (Emrouznejad & Yang [57]; Peykani et al. [58]; Peykani et al. [59]; Peykani et al. [60]; Mergoni et al. [61]), and Decision-Making Trial and Evaluation Laboratory (DEMATEL) (Shieh et al. [62]; Si et al. [63]; Alinezhad et al. [64]).

Notably, from another perspective, MADM methods are broadly categorized into individual and group-based approaches. Individual methods focus on single decision-makers, while group methods involve multiple stakeholders to reach a consensus (Zahedi Khameneh & Kılıçman [65]). This classification ensures flexibility, addressing diverse decision-making scenarios for both personalized and collaborative contexts.

Among the various MCDM techniques, the Best-Worst Method (BWM) has garnered significant attention for its innovative framework and practical utility (Mi et al. [66]; Tu et al. [67]). Its ability to simplify decision-making processes while ensuring a high degree of consistency and reliability makes it particularly well-suited for addressing real-world challenges. The growing adoption of BWM underscores its relevance in contemporary decision-making contexts, where precision and adaptability are essential. BWM, first introduced by Rezaei [68], distinguishes itself as an innovative approach within the realm of MCDM techniques, leveraging a pairwise comparison mechanism that centers exclusively on the best and worst criteria. This unique feature significantly reduces the decision-makers' cognitive effort by eliminating the need for exhaustive comparisons among all criteria, a notable drawback of traditional methods such as the AHP (Saaty [69]; Saaty [70]; Saaty [71]; Saaty [72]; Saaty [73]).

By concentrating on the extremes of preference, specifically identifying the best and worst criteria, the BWM significantly simplifies the comparison process while improving the internal consistency of evaluations (Cavallo & Ishizaka [74]). This approach enables the derivation of highly accurate weight vectors with minimal computational effort, making it a practical and efficient tool for both theoretical research and real-world applications (Mi et al. [66]; Liang et al. [75]; Corrente et al. [76]). Its versatility across various disciplines, from operations research to environmental management, highlights its broad applicability, empowering researchers and practitioners to tackle complex decision-making challenges with precision and clarity (Pamucar et al. [77]; Wu et al. [78]). The method's structured framework ensures reliable outcomes, fostering confidence in its use for high-stakes decisions.

The significance of BWM extends beyond its methodological efficiency; it serves as a powerful tool to overcome critical challenges inherent in MCDM (Hasan et al. [79]; Ahmad et al. [80]). By reducing the subjectivity involved in assessing criteria importance, BWM fosters more objective and reliable decision-making processes. Its structured approach to pairwise comparisons improves consistency, ensuring that derived weights are both logical and representative of real-world priorities. Additionally, its computational simplicity, grounded in linear programming principles, allows for seamless integration into decision-support systems (Rezaei [81]; Brunelli & Rezaei [82]). By providing a systematic framework to evaluate the relative importance of criteria and alternatives, BWM has proven its value as an indispensable methodology in addressing multifaceted decision-making challenges.

Over the past decade, the best-worst method has been extensively applied across diverse fields, including business, economics, energy, engineering, finance, management, medicine, social sciences, and technology (Mi et al. [66]). These applications underscore the method's versatility and practicality in addressing complex decision-making scenarios. In addition to its practical applications, BWM has also spurred a wave of methodological advancements and hybrid approaches. Researchers have explored extensions of BWM to handle fuzzy environments, interval data, and group decision-making settings (Guo & Zhao [83]; Hafezalkotob et al. [84]; Mohammadi & Rezaei [85]; Kouaissah & Hocine [86]; Cheng & Chen [87]; Dong & Wan [88]; Li et al. [89]). These extensions aim to enhance the method's applicability in situations characterized by uncertainty, imprecision, and the involvement of multiple stakeholders. Moreover, the integration of BWM with other MADM methods and optimization techniques has further broadened its scope and potential for innovation (Yadav et al. [90]; Liu et al. [91]; Munim et al. [92]; Liang et al. [93]; Foroozesh et al. [94]; Gul & Yucesan [95]; Chowdhury & Haque Munim [96]; Guo & Chen [97]).

Given the extensive applications, significance, and rising prominence of the BWM in MCDM, this paper conducts a comprehensive survey and systematic bibliometric analysis of research in this field. Accordingly, the integration and comparison of BWM with other MADM techniques are examined. Furthermore, the BWM field under conditions of uncertainty and ambiguity is systematically analyzed. Additionally, real-world applications of BWM are categorized and reviewed, demonstrating its practical relevance. Finally, by analyzing a Scopus dataset of 2672 studies published between 2015 and June 2025, this review encompasses document, keyword, source, author, affiliation, citation, and thematic analyses. It explores research trends, citation patterns, and thematic developments, providing valuable insights into BWM's growth, versatility, and potential for broader adoption in decision-making contexts.

The structure of the paper is as follows: In Section 2, a review of integrated studies combining the BWM with other multi-attribute decision-making techniques is presented. Section 3 provides an overview of the BWM field under conditions of uncertainty and ambiguity. Section 4 offers a comprehensive review of the applications of BWM in various

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real-world problems. Following this, Section 5 presents a detailed bibliometric analysis of studies in the BWM domain. Section 6 provides a critical evaluation of BWM studies. Section 7 outlines both theoretical and practical directions for future research. Finally, Section 8 synthesizes the study's key findings and presents the final conclusions.

2. A survey of BWM and MADM techniques

Since its introduction, the BWM has garnered significant attention in the field of MADM due to its simplicity, efficiency, and reliability. Researchers have increasingly explored its integration with other decision-making techniques to enhance the robustness and precision of analytical outcomes. These hybrid approaches leverage the strengths of BWM, particularly its ability to reduce the complexity of decision-making processes by focusing on the best and worst criteria, thereby minimizing the number of required pairwise comparisons. Comparative studies have consistently demonstrated BWM's effectiveness and reliability, often highlighting its advantages over traditional methods in terms of consistency, computational efficiency, and ease of application. Such attributes have solidified BWM's position as a valuable tool for both theoretical research and practical problem-solving across diverse fields, including supply chain management, sustainability assessment, and healthcare. In the following section, a comprehensive review of integrated studies combining BWM with other MADM methods, as illustrated in Fig. 1, will be presented. This review underscores the growing significance of BWM in decision-making science, shedding light on its evolving role and potential for addressing increasingly complex real-world challenges.

By integrating the best-worst method with complementary methodologies, researchers aim to enhance the robustness, precision, and practical applicability of decision-making frameworks. This analysis highlights key studies demonstrating how such integrations address complex decision-making challenges, optimize computational efficiency, and yield more reliable outcomes in both theoretical and practical contexts. The focus is on exploring how BWM synergizes with other MADM techniques to improve decision accuracy and adaptability. The most notable integrations of BWM with prominent MADM approaches are systematically examined, showcasing their contributions to advancing decision science and addressing real-world complexities.

- **Analytic Hierarchy Process (AHP):** The integration of BWM with AHP marks a significant advancement in overcoming the limitations of traditional AHP. By leveraging BWM's structured comparison approach, these hybrid models streamline the number of pairwise comparisons required while preserving the quality of decision-making (For example, please see Chowdhury & Haque Munim [96]).
- **Analytic Network Process (ANP):** The ANP effectively addresses interdependencies among criteria but is often hindered by its complex comparison requirements. The integration of BWM with ANP provides a more streamlined approach to managing these interdependencies (For example, please see Khanmohammadi et al. [98]).
- **Additive Ratio Assessment (ARAS):** The ARAS method greatly benefits from BWM's precise weight determination capabilities, resulting in a powerful hybrid model for evaluating alternatives (For example, please see Liao et al. [99]; Ramezanali et al. [100]; Erden et al. [101]).
- **Complex Proportional Assessment (COPRAS):** The integration of COPRAS with BWM establishes a balanced approach, effectively addressing both beneficial and non-beneficial criteria (For example, please see Amoozad Mahdiraji et al. [102]; Bahrami et al. [103]; Masoomi et al. [104]).
- **Data Envelopment Analysis (DEA):** The combination of DEA and BWM establishes a powerful methodology, merging efficiency evaluation with preference-based weighting for enhanced decision-making (For example, please see Fan et al. [105]; Omrani et al. [106]; Omrani et al. [107]; Guo & Chen [97]; Omrani et al. [108]; Yu & Khezrimotlagh [109]; Tadić et al. [110]).
- **Decision-Making Trial and Evaluation Laboratory (DEMATEL):** The integration of DEMATEL with BWM enhances causal relationship analysis through precise weight determination (For example, please see Liu et al. [91]; Govindan et al. [111]; Karuppiah et al. [112]; Kumar et al. [113]; Ma et al. [114]; Yadav et al. [115]).
- **Elimination Et Choice Translating Reality (ELECTRE):** The combination of the ELECTRE method with BWM enhances precision in criteria weighting, making it especially effective for outranking-based decision problems (For example, please see You et al. [116]; Yadav et al. [90]; Kumar et al. [117]; Koohathongsumrit & Luangpaiboon [118]).
- **Full Consistency Method (FUCOM):** The integration of the FUCOM with BWM establishes a highly consistent framework for criteria weighting while reducing mathematical complexity (For example, please see Fazeli & Peng [119]).

Fig. 1. Integration and comparison of BWM with other MADM methods.

- **Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH):** The combination of MACBETH with BWM enhances its practicality, resulting in a semantically rich yet computationally efficient framework (For example, please see Pishdar et al. [120]).
- **Multi-Attributive Border Approximation Area Comparison (MABAC):** The integration of MABAC with BWM establishes a balanced approach for evaluating alternatives, supported by precise criteria weights (For example, please see Luo & Xing [121]; Muravev & Mijic [122]; Pamucar et al. [123]; Chen et al. [124]).
- **Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA):** The MOORA method achieves enhanced precision through BWM integration, resulting in an efficient hybrid for multi-criteria optimization problems (For example, please see Petrović et al. [125]; Riahi et al. [126]; Mota et al. [127]).
- **Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE):** The integration of PROMETHEE and BWM enhances outranking precision by combining BWM's rigorous criteria prioritization with PROMETHEE's robust pairwise comparisons. This synergy ensures reliable, well-structured multi-criteria decision outcomes through systematic weight calibration (For example, please see Luo & Xing [121]; Liu et al. [128]; Kheybari et al. [129]; Chowdhury & Haque Munim [96]; Taghipour et al. [130]).
- **Simple Additive Weighting (SAW):** The combination of BWM and SAW enhances MADM by integrating BWM's precise, pairwise-derived criteria weights with SAW's simplicity, ensuring transparent and reliable prioritization in complex decision-making scenarios (For example, please see Stević et al. [131]; Aryafar & Roshanravan [132]; Alkan et al. [133]; Trivedi et al. [134]).
- **Stepwise Weight Assessment Ratio Analysis (SWARA):** The integration of SWARA with BWM establishes a balanced approach to criteria weighting, leveraging the complementary strengths of both methods (For example, please see Karakuş [135]; Swain et al. [136]).
- **Technique for Order Preference and Similarity to Ideal Solution (TOPSIS):** The TOPSIS is one of the most frequently integrated methods with BWM, forming a powerful framework for evaluating alternatives based on their relative closeness to ideal solutions (For example, please see You et al. [137]; Xiong et al. [138]; Lahri et al. [139]; Gul & Yucesan [95]; Asadabadi et al. [140]; Majumder et al. [141]; Trivedi et al. [134]).
- **Tomada De Decisao Interativa Multicriterio (TODIM):** The integration of TODIM with BWM establishes a psychologically grounded decision framework that incorporates prospect theory to account for risk aversion while ensuring precise criteria weights (For example, please see Celik et al. [142]; Tang et al. [143]; Govindan et al. [144]).
- **VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR):** The integration of VIKOR with BWM enhances compromise solution identification by combining BWM's structured pairwise weighting with VIKOR's proximity-based ranking, ensuring balanced and transparent outcomes in multi-criteria decision contexts (For example, please see Shojaei et al. [145]; Wu et al. [146]; Rafieyan et al. [147]; Aleksić et al. [148]).
- **Weighted Aggregated Sum Product Assessment (WASPAS):** The WASPAS gains enhanced precision through BWM integration, creating a balanced framework that leverages both summation and product-based aggregation (For example, please see Xiong et al. [138]; Ma et al. [149]; Masoomi et al. [104]; Firoozzare et al. [150]; Kavus et al. [151]).

3. A classification of BWM under uncertainty

Decision-makers often grapple with incomplete information, conflicting criteria, and unpredictable outcomes, underscoring the growing need for effective frameworks to navigate these complexities. Uncertainty and ambiguity are inherent in many real-world scenarios, posing significant challenges to traditional decision-making approaches (Peykani et al. [152–155]). These conventional methods frequently fall short, as they rely on assumptions of certainty and clarity that seldom align with practical realities. Consequently, there is a pressing need to adopt more sophisticated methodologies, such as the BWM, which is specifically designed to address the intricacies of decision-making in uncertain and ambiguous environments. The general classification of the Uncertain Best-Worst Method (UBWM) field is illustrated in Fig. 2.

This section delves into the systematic examination and classification of the BWM under varying conditions of uncertainty and ambiguity. Accordingly, the following prominent UBWM approaches are surveyed: the Fuzzy Best-Worst Method (FBWM), Interval Best-Worst Method (IBWM), Probabilistic Best-Worst Method (PBWM), Grey Best-Worst Method (GBWM), Rough Best-Worst Method (RBWM), Z-Number Best-Worst Method (ZNBWM), Robust Best-Worst Method (ROBWM), Belief-Based Best-Worst Method (BBWM), and Hybrid Uncertain Best-Worst Method (HUBWM).

- **Fuzzy BWM:** The FBWM is the most widely adopted approach for addressing uncertainty within the BWM framework, leveraging Fuzzy Set Theory (FSS) to model imprecision and vagueness in decision-making. This variant integrates various extensions of fuzzy set theory, including Type-1 Fuzzy Sets (T1FS), Type-2 Fuzzy Sets (T2FS), Interval Type-2 Fuzzy Sets (IT2FS), Intuitionistic Fuzzy Sets (IFS), Hesitant Fuzzy Sets (HFS), Pythagorean Fuzzy Sets (PFS), Spherical Fuzzy Sets (SFS), Fermatean Fuzzy Sets (FFS), and Neutrosophic Sets (NS), to effectively capture the inherent vagueness and imprecision in experts' judgments (Li et al. [89]). Numerous variants of FBWM have been developed, each tailored to specific applications and decision-making contexts. The most significant variants of FBWM, designed to address diverse challenges and scenarios, are as follows:
  - o **Triangular Fuzzy BWM:** Utilizes triangular fuzzy numbers to represent preferences, offering computational simplicity while capturing basic uncertainty. This method is particularly effective for decision-making problems where a balance between simplicity and adequate uncertainty representation is required (For example, please see Moslem et al. [156]; Dong et al. [157]).
  - o **Trapezoidal Fuzzy BWM:** Employs trapezoidal fuzzy numbers to provide more flexibility in uncertainty modeling at the cost of increased computational complexity. This method is well-suited for scenarios where decision-makers need to capture a wider range of uncertainty with greater precision (For example, please see Sofuoğlu [158]; Debnath et al. [159]).
  - o **Type-2 Fuzzy BWM:** Extends uncertainty modeling to the membership function itself, providing a second-order representation of uncertainty. This approach is ideal for highly complex decision-making environments where traditional fuzzy sets fail to adequately capture the depth of uncertainty (For example, please see Goldani et al. [160]; Yucesan et al. [161]).
  - o **Intuitionistic Fuzzy BWM:** Incorporates both membership and non-membership degrees to model hesitation in preference judgments. This method is particularly useful in situations where decision-makers face significant ambiguity or conflicting information, requiring a more nuanced representation of preferences (For example, please see Cheng & Chen [87]; Wan et al. [162]).
  - o **Hesitant Fuzzy BWM:** Employs hesitant fuzzy sets to represent preferences, allowing for the expression of multiple possible membership values. This method is ideal for scenarios where decision-makers exhibit hesitation in expressing their preferences (For example, please see Ali & Rashid [163]; Li et al. [164]).
  - o **Pythagorean Fuzzy BWM:** Uses Pythagorean fuzzy sets to model uncertainty, addressing the limitations of traditional and intuitionistic fuzzy sets. This method is suitable for situations requiring

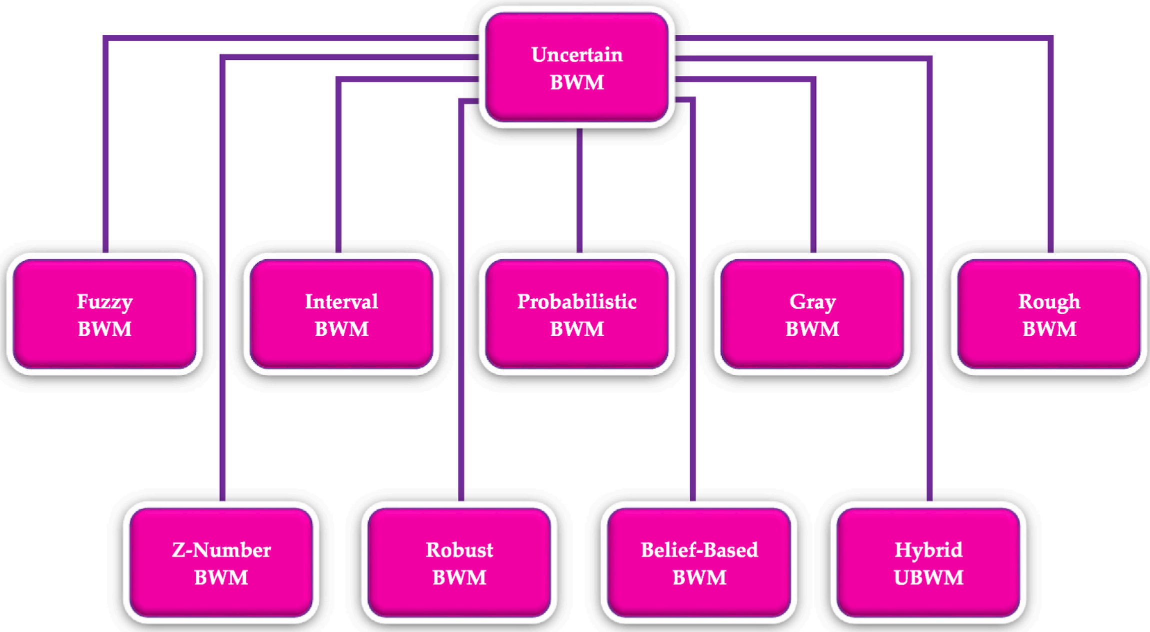

Fig. 2. Classification of Uncertain BWM

greater flexibility in expressing preferences (For example, please see Fan et al. [165]; Otay et al. [166]).

- o **Spherical Fuzzy BWM:** Leverages spherical fuzzy sets to model uncertainty, enabling the simultaneous expression of membership, non-membership, and indeterminacy degrees. This method is ideal for scenarios requiring a more comprehensive representation of uncertainty (For example, please see Bonab et al. [167]; Haseli et al. [168]).
- o **Fermatean Fuzzy BWM:** Utilizes Fermatean fuzzy sets to model uncertainty, providing greater flexibility in expressing membership and non-membership degrees. This method is suitable for situations requiring higher precision in preference representation (For example, please see Wei et al. [169]; Gao et al. [170]).
- o **Neutrosophic BWM:** Utilizes neutrosophic sets to model uncertainty, incorporating degrees of membership, non-membership, and indeterminacy. This method is particularly effective in capturing the complexity of decision-making scenarios where ambiguity, inconsistency, and incomplete information coexist (For example, please see Vafadarnikjoo et al. [171]; Yucesan & Gul [172]; Li & Yazdi [173]).

- **Interval BWM:** The IBWM represents uncertainty through interval numbers rather than precise values, enabling decision-makers to specify ranges of possible preference values. In this approach, preference values are expressed as intervals, where the lower and upper bounds define the range of possible preference values. This method is particularly suitable for scenarios where decision-makers can identify bounds for their preferences but are unable to determine exact values, providing a flexible and practical framework for handling imprecision in judgment (For example, please see Hafezalkotob et al. [84]; Xu et al. [174]).
- **Probabilistic BWM:** The PBWM incorporates probabilistic frameworks to represent uncertainty in preference judgments and criteria weights. This approach models uncertainties using probability distributions, enabling a statistical interpretation of the variability in preferences. Unlike methods that rely on single values or intervals, PBWM characterizes preferences and weights through probability density functions, which capture the likelihood of different possible values, providing a comprehensive and nuanced representation of uncertainty (For example, please see Mohammadi & Rezaei [85]; Shi et al. [175]).
- **Grey BWM:** The GBWM integrates Grey Systems Theory (GST) with the BWM to address decision-making problems involving incomplete or partially unknown information. Grey theory, specifically developed to handle such uncertainties, provides a unique framework for modeling imprecision in BWM. In GBWM, preferences and weights are represented as grey numbers, which are defined as intervals with lower and upper bounds, representing a range of possible values without requiring any assumptions about their distribution (For example, please see Mahmoudi et al. [176]; Muhammad Muneeb [177]; Bitarafan et al. [178]; Razavian et al. [179]; Krstić et al. [180]; Tadić et al. [110]).
- **Rough BWM:** The RBWM combines Rough Set Theory (RST) with BWM to handle imprecise or incomplete data. It uses rough numbers, such as Classical Rough Numbers (CRN), Fuzzy Rough Numbers (FRN), and Interval Rough Numbers (IRN), to represent preferences and weights through lower and upper approximations. This approach effectively models uncertainty without requiring distributional assumptions, making it a flexible tool for complex decision-making in data-scarce environments (For example, please see Stević et al. [181]; Chang et al. [182]; Deveci et al. [183]; Kazemitash et al. [184]; Haqbin al [185]).
- **Z-Number BWM:** The ZNBWM employs Z-numbers to simultaneously model both the uncertainty in preferences and the reliability of the provided information. Z-numbers consist of two components: the first component represents a fuzzy restriction on the value of a variable, capturing the imprecision in preferences, while the second component represents the reliability of this restriction as a probability measure. This dual representation enables ZNBWM to effectively capture both the vagueness in decision-makers' judgments and the confidence level associated with those judgments (For example, please see Aboutorab et al. [186]; Moslem [187]).
- **Robust BWM:** The ROBWM integrates Robust Optimization (RO) techniques with BWM to address decision-making problems under uncertainty. This approach combines robust optimization with various uncertainty sets, such as box, ellipsoidal, and polyhedral sets, as well as their combinations, to model deep uncertainty. By leveraging these uncertainty sets, ROBWM provides a flexible

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framework for handling variability in preferences and weights, ensuring reliable and stable solutions even in the presence of data fluctuations. This makes it a powerful tool for complex decision-making scenarios where robustness and precision are critical (For example, please see Sadjadi & Karimi [188]; Bahadori et al. [189]).

- **Belief-Based BWM:** The BBWM incorporates evidence theory, specifically Dempster-Shafer theory, to handle uncertainty and incomplete information in preference judgments. BBWM employs belief structures to represent uncertainty, enabling the explicit modeling of ignorance, partial knowledge, and conflicting information. Preferences are expressed as basic probability assignments over possible preference values, providing a more nuanced and flexible representation of uncertainty compared to traditional probability or fuzzy approaches (For example, please see Liang [190]; Liang et al. [191]).
- **Hybrid Uncertain BWM:** The HUBWM combine multiple uncertainty-handling frameworks to leverage their complementary strengths. These approaches recognize that different uncertainty representations excel at capturing distinct aspects of imprecision. By integrating multiple frameworks, such as fuzzy sets, rough sets, and probabilistic models, HUBWM aims to provide a more comprehensive and flexible approach to uncertainty modeling, enabling decision-makers to address complex and multifaceted uncertainties effectively (For example, please see Pamucar et al. [192]; Chen et al. [193]; Zhang et al. [194]; Liu et al. [195]; Tavana et al. [196]).

Notably, incorporating uncertainty handling mechanisms into the BWM is essential for realistic representation, robustness, confidence assessment, and flexibility. Real-world preferences are rarely precise, and uncertainty-aware models better reflect actual decision processes. These methods yield solutions less sensitive to input variations, provide reliability measures, and accommodate diverse information types, such as interval judgments or linguistic assessments. Uncertainty in decision-making arises from epistemic gaps, linguistic vagueness, inherent randomness, and ambiguity, all of which challenge conventional BWM's reliance on precise data.

4. A review of BWM applications

In this section, real-world applications and case studies of BWM are

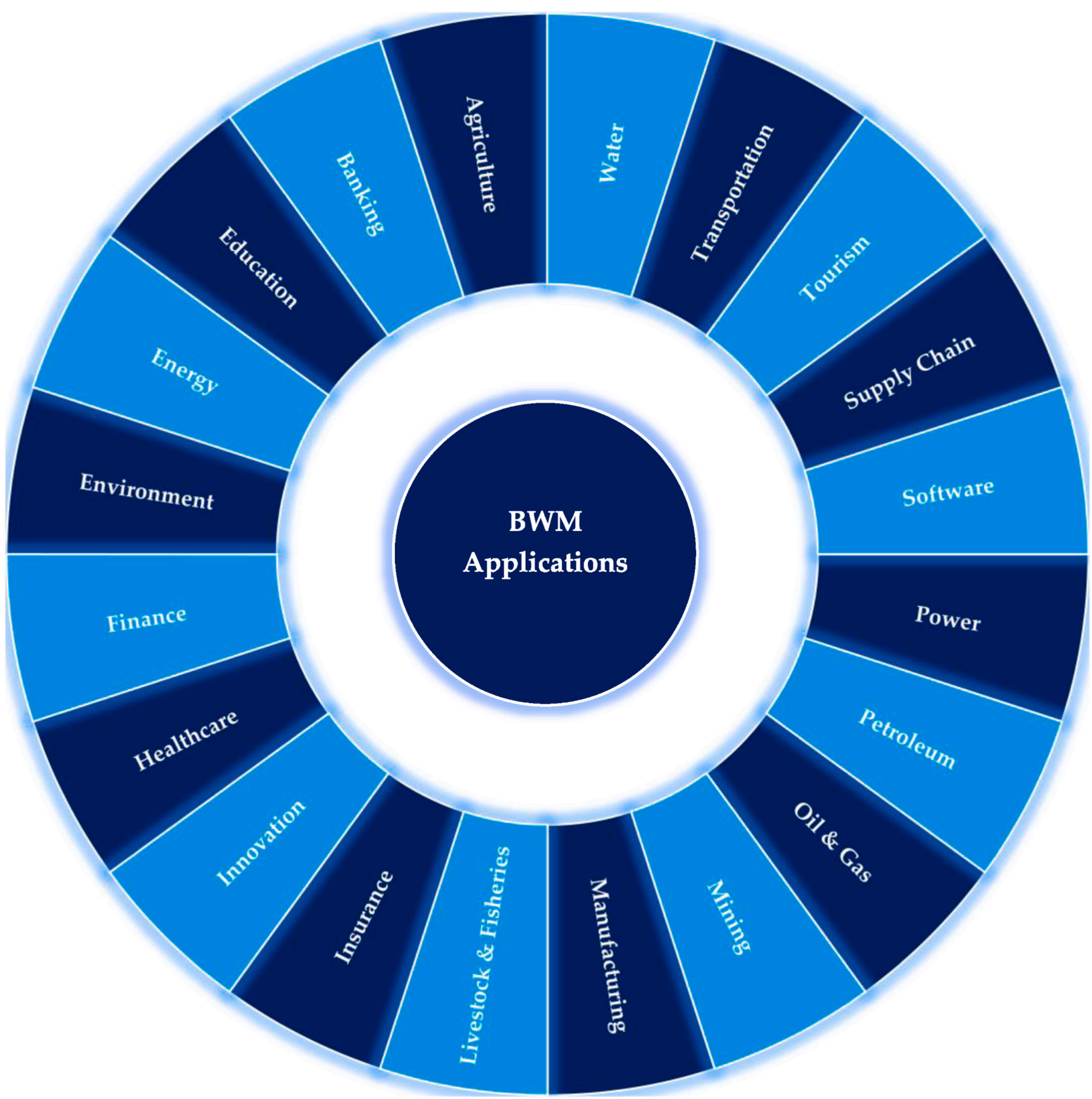

Fig. 3. Implementation cases and practical applications of the BWM

systematically categorized to highlight its versatility across various fields. This method has been successfully applied in diverse areas, demonstrating its ability to handle both qualitative and quantitative data, which makes it a powerful tool for decision-makers facing conflicting criteria. By systematically organizing these applications, researchers and practitioners can gain a deeper understanding of the method's strengths and limitations, paving the way for more informed and effective decision-making processes. The most important application areas, as presented in Fig. 3, will be discussed in detail in the following sections.

- **Agriculture:** The BWM proves invaluable in agriculture by addressing multifaceted challenges with precision. For instance, in sustainable facility relocation, BWM combined with Geographic Information Systems (GIS) optimizes site selection by evaluating trade-offs between economic viability, environmental impact, and social acceptability (Yousefi-Babadi et al. [197]). When applied to land evaluation, BWM systematically ranks factors such as soil fertility, water availability, and climate suitability, enabling informed decisions for paddy cultivation in specific regions, such as northwest Turkey (Everest et al. [198]). In assessing the sustainability of the agricultural sector, BWM helps identify and prioritize critical indicators, offering actionable insights for regions like the Baltic States (Streimikis et al. [199]). This method ensures a balanced, data-driven approach to agricultural planning and resource management.
- **Banking:** The BWM offers a structured approach in the banking sector to tackle complex decision-making scenarios. For instance, it has been used to identify and prioritize key factors influencing customer service experience, enabling banks to enhance client satisfaction strategically (Yadollahi et al. [200]). When assessing industry performance, BWM integrates with intuitionistic fuzzy sets to handle uncertainty, providing a robust framework for evaluating financial and operational metrics (Seyfi-Shishavan et al. [201]). Additionally, in branch efficiency analysis, BWM combines with data envelopment analysis to incorporate decision-makers' preferences, ensuring a balanced evaluation of productivity and service quality (Omrani et al. [108]). This method empowers banks to make informed, customer-centric, and efficiency-driven decisions.
- **Education:** The BWM brings clarity and precision to decision-making in education. For instance, in evaluating cloud-based e-learning providers, BWM helps rank options by considering multiple dimensions such as cost, scalability, and user satisfaction, ensuring institutions select the most suitable platforms (Pour et al. [202]). When assessing school performance, BWM integrates with PROMETHEE to analyze complex datasets like PISA scores, offering a nuanced understanding of educational outcomes (Ishizaka & Resce [203]). In higher education, BWM combines with fuzzy Delphi to measure institutional performance, balancing qualitative and quantitative factors (Petrudi et al. [204]). This method enables educators and policymakers to make data-driven decisions that enhance learning environments and academic excellence.
- **Energy:** The BWM is a powerful tool in the energy sector, particularly for evaluating renewable energy resources and addressing sustainability challenges. For instance, BWM extended with D-Numbers has been applied to assess renewable energy options, considering factors like environmental impact, cost, and feasibility (Mousavi-Nasab & Sotoudeh-Anvari [205]). In decarbonization strategies, BWM helps identify renewable energy potentials and challenges, as seen in its application to Russia's energy transition (Agyekum et al. [206]). Additionally, BWM combined with fuzzy logic effectively uncovers barriers to solar energy development, providing actionable insights for overcoming technical, economic, and regulatory hurdles (Mostafaeipour et al. [207]). By balancing efficiency, cost, and environmental impact, this method supports informed decision-making for a sustainable energy future, making it a valuable framework for policymakers and industry stakeholders.
- **Environment:** The BWM is instrumental in addressing environmental challenges by providing a structured approach to decision-making. For instance, BWM-based weighting models have been used to evaluate environmental performance, balancing factors like resource efficiency and pollution control (Liu et al. [208]). In the context of Lean Six Sigma, BWM helps prioritize enablers that integrate environmental sustainability into business processes, particularly in Indian MSMEs (Singh et al. [209]). Additionally, BWM combined with fuzzy logic assesses the environmental impacts of ship recycling, identifying critical risks and mitigation strategies (Soner et al. [210]). This method ensures a comprehensive and balanced evaluation, supporting sustainable practices and policy-making in environmental management.
- **Finance:** The BWM offers a reliable framework in finance for tackling complex investment and portfolio decisions. For instance, BWM has been integrated with multi-criteria sorting to streamline stock portfolio selection, ensuring an optimal balance between risk and return (Emamat et al. [211]). In evaluating Saudi stocks, BWM combined with TOPSIS provides a hybrid approach to assess financial performance, enabling investors to make data-driven decisions (Alsanousi et al. [212]). Additionally, BWM paired with MOORA-N prioritizes investment funds, considering factors like profitability, stability, and market trends (Mota et al. [127]). This method enhances precision in financial decision-making, helping investors navigate market uncertainties. Its structured and adaptable approach optimizes investment strategies and supports the achievement of long-term financial goals.
- **Healthcare:** The BWM is transforming healthcare decision-making by addressing complex, multi-criteria challenges. For instance, BWM combined with hesitant fuzzy linguistic sets evaluates hospital performance, incorporating qualitative and quantitative metrics while resolving inconsistencies in data (Liao et al. [213]). In total quality management, BWM ranks enablers like patient safety and staff training, helping healthcare establishments prioritize improvement areas (Talib et al. [214]). Additionally, BWM integrated with fuzzy logic assesses service quality in hospitals, focusing on patient satisfaction and operational efficiency (Khanmohammadi et al. [215]). This method ensures a balanced, data-driven approach to healthcare delivery, improving patient outcomes and organizational performance. It enables evidence-based decision-making, supporting higher care standards and operational excellence.
- **Innovation:** The BWM is a game-changer in innovation management, offering a structured approach to evaluate and prioritize complex decisions. For instance, BWM has been used to assess firms' R&D performance, balancing factors like cost, feasibility, and market potential to identify areas for improvement (Salimi & Rezaei [216]). In the fuzzy front end of innovation, BWM combined with fuzzy logic aids in selecting new product ideas, ensuring alignment with strategic goals and market needs (Li et al. [217]). Additionally, BWM integrated with R-Numbers provides a risk-based framework for R&D project selection, addressing uncertainties and optimizing resource allocation (Liu et al. [218]). By enabling organizations to make data-driven decisions, BWM empowers them to drive innovation effectively and sustainably, fostering long-term growth and competitive advantage in dynamic markets.
- **Insurance:** The BWM is revolutionizing performance evaluation in the insurance sector by providing a structured, multi-criteria approach. For instance, BWM integrated with the Balanced Scorecard (BSC) assesses insurance companies' performance across financial, customer, and operational dimensions, ensuring a holistic evaluation (Dwivedi et al. [219]). In non-life insurance, an extended BWM with multiple reference points offers a nuanced assessment, balancing profitability, customer satisfaction, and risk management (Bilbao-Terol et al. [220]). Additionally, BWM combined with

TOPSIS evaluates the Iranian insurance sector, prioritizing key performance indicators to drive strategic improvements (Rahmati & Darestani [221]). This method enables insurers to make data-driven decisions, enhancing competitiveness and customer trust.

- **Livestock and Fisheries:** The BWM is transforming decision-making in livestock and fisheries by addressing supply chain risks, sustainability, and operational efficiency. For instance, BWM combined with fuzzy logic and risk mitigation numbers assesses risks in halal meat supply chains, ensuring compliance and quality (Masudin et al. [222]). In fisheries, BWM evaluates risks in the skipjack tuna supply chain, identifying vulnerabilities and improving resilience in Indonesia's agroindustry (Paillin et al. [223]). Additionally, BWM integrated with GIS and R-numbers selects sustainable livestock sites, balancing environmental, economic, and social factors in Iran (Shahrabi-Farahani et al. [224]). This method supports ethical, sustainable livestock and fisheries management, enabling informed decisions that boost productivity while reducing environmental and social impacts.
- **Manufacturing:** The BWM is reshaping decision-making in manufacturing by addressing sustainability and operational challenges. For instance, BWM has been applied to prioritize barriers to sustainable manufacturing, such as resource scarcity and regulatory compliance, enabling firms to focus on critical areas for improvement (Malek & Desai [225]). In a fuzzy manufacturing environment, BWM helps evaluate complex factors like process efficiency and product quality, providing clarity in uncertain scenarios (Sofuoğlu [158]). Additionally, BWM-based performance evaluation frameworks assess manufacturing firms' operational and strategic metrics, driving continuous improvement (Khan et al. [226]). This method ensures manufacturers can balance sustainability, efficiency, and competitiveness in a rapidly evolving industry.
- **Mining:** The BWM is revolutionizing decision-making in the mining industry by addressing challenges in mineral exploration, safety, and resource optimization. For instance, BWM combined with additive ratio assessment has been used for mineral prospectivity mapping, identifying high-potential copper mineralization sites in Iran (Ramezanali et al. [100]). In safety management, BWM integrated with Human Error Assessment and Reduction Technique (HEART) evaluates human error probabilities in blasting processes, reducing risks and enhancing worker safety (Aliabadi et al. [227]). Additionally, BWM paired with TOPSIS supports mineral potential mapping, balancing geological, environmental, and economic factors to optimize resource extraction (Forson et al. [228]). This method ensures efficient, safe, and sustainable mining operations in a complex and high-risk industry.
- **Oil and Gas:** The BWM is pivotal in the oil and gas industry, addressing sustainability, technology adoption, and performance evaluation. For instance, BWM has been used to assess external forces impacting supply chain sustainability, such as geopolitical risks and environmental regulations, ensuring resilient operations (Ahmad et al. [229]). In technology adoption, BWM combined with Bayesian analysis evaluates blockchain integration in the Norwegian oil and gas sector, highlighting its potential to enhance transparency and efficiency (Munim et al. [230]). Additionally, BWM integrated with hesitant fuzzy sets and an extended Balanced Scorecard evaluates company performance, balancing financial, operational, and environmental metrics (Yazdi et al. [231]). This method enables strategic, sustainable, and innovative decision-making in a highly competitive industry.
- **Petroleum:** The BWM is a game-changer in the petroleum industry, addressing complex decisions in risk management, supply chain optimization, and sustainability. For instance, BWM has been used to select the most appropriate contract strategies for onshore drilling projects, balancing cost, risk, and operational efficiency in the Iranian petroleum sector (Faraji et al. [232]). In supply chain management, BWM integrated with AROMAN enhances practices in national oil corporations, ensuring resilience and efficiency in developing countries (Kiptum et al. [233]). Additionally, BWM combined with fuzzy logic and grey CoCoSo evaluates suppliers in downstream oil and gas, prioritizing sustainability and managing uncertainties (Parsa Rad et al. [234]). This method supports strategic, sustainable, and efficient operations in the petroleum industry.
- **Power:** The BWM is a critical tool in the power sector, enabling optimized decision-making for energy systems. For instance, BWM combined with TOPSIS and fuzzy logic identifies the optimal mix of power plants, balancing cost, efficiency, and environmental impact (Omrani et al. [235]). In renewable energy, BWM integrated with GIS evaluates site suitability for ground-mounted photovoltaic stations, considering factors like solar potential and land use (Fard et al. [236]). Additionally, BWM paired with grey causal modeling assesses risks in electrical power grids, helping mitigate vulnerabilities in India's energy infrastructure (Yash & Rajesh [237]). This method ensures sustainable, efficient, and resilient power systems, empowering stakeholders to make data-driven decisions that enhance energy security, reduce carbon footprints, and support the transition to cleaner energy sources for the future.
- **Software:** The BWM is transforming software development by addressing critical challenges in quality, security, and efficiency. For instance, BWM combined with two-way analysis assesses software vulnerabilities, enabling developers to prioritize and mitigate risks effectively (Anjum et al. [238]). In open-source software, BWM integrated with TOPSIS evaluates code smells, helping teams improve maintainability and reliability (Tandon et al. [239]). Additionally, BWM paired with fuzzy logic supports DevOps implementation, balancing factors like automation, collaboration, and deployment speed (Kumar et al. [240]). This method ensures a structured, data-driven approach to enhancing software quality and operational efficiency in a rapidly evolving tech landscape.
- **Supply Chain:** The BWM is revolutionizing supply chain management by addressing sustainability and operational challenges. For instance, BWM has been used to assess the social sustainability of supply chains, evaluating factors like labor practices and community impact to ensure ethical operations (Ahmadi et al. [241]). In group decision-making, a novel G-BWM approach facilitates consensus among stakeholders, optimizing supply chain strategies (Haseli et al. [242]). Additionally, BWM combined with Delphi identifies and prioritizes challenges in sustainable electric vehicle battery supply chains, such as resource scarcity and recycling (Kumar et al. [243]). This method enables organizations to build resilient, ethical, and efficient supply chains in a rapidly evolving global market. By integrating environmental, social, and economic considerations, BWM supports the development of sustainable supply chains that align with global standards and stakeholder expectations, fostering long-term competitiveness and resilience.
- **Tourism:** The BWM is reshaping decision-making in tourism by addressing strategic and operational challenges. For instance, BWM has been applied to evaluate medical tourism development strategies, balancing factors like infrastructure, cost, and quality of care to identify optimal growth pathways (Abadi et al. [244]). In post-COVID-19 recovery, a rough BWM approach prioritizes solutions for tourism Small and Medium-sized Enterprises (SMEs), focusing on financial resilience and customer engagement (Haqbin et al. [185]). Additionally, BWM helps travelers make informed hotel choices by analyzing online reviews from opinion leaders, ensuring a balance between quality and value (Wu et al. [245]). This method supports sustainable and customer-centric tourism development in a dynamic industry.
- **Transportation:** The BWM is revolutionizing decision-making in transportation by addressing efficiency, sustainability, and service quality. For instance, BWM combined with VIKOR evaluates airline service quality, balancing factors like punctuality, comfort, and customer satisfaction to enhance passenger experiences (Gupta

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[246]). In freight transportation, BWM integrated with fuzzy logic identifies flexibility measures, optimizing logistics operations under uncertain conditions (Shardeo et al. [247]). Additionally, BWM paired with fuzzy Delphi supports sustainable freight solutions in Africa, addressing infrastructure gaps and environmental concerns (Thompson et al. [248]). This method ensures a balanced, data-driven approach to improving transportation systems globally.

- **Water:** The BWM is a vital tool in water resource management, addressing complex challenges in sustainability and risk assessment. For instance, BWM combined with improved TOPSIS prioritizes watershed management scenarios in arid regions, balancing ecological and socio-economic factors (Alvandi et al. [249]). In water-saving management, BWM identifies and ranks risks across the project lifecycle, ensuring efficient resource use and cost-effectiveness (Ma et al. [250]). Additionally, BWM integrated with TODIMSort and double hierarchy hesitant fuzzy linguistic sets assesses industrial water security, providing a robust framework for risk diagnosis and mitigation (Chao et al. [251]). This method supports informed, sustainable, and resilient water management strategies globally.

Fig. 4. Research methodology and search strategy for BWM field analysis.

In conclusion, it is important to note that the best-worst method has applications beyond the aforementioned domains. For instance, it has been effectively utilized in optimizing theater seating arrangements to boost revenue (Joshi & Lohiya [252]), assessing the life cycle performance of buildings (Amiri et al. [253]), planning emergency facilities (Nyimbili & Erden [254]), selecting technologies for sustainable waste management (Torkayesh et al. [255]), analyzing challenges in Industry 4.0 (Wankhede & Vinodh [256]), evaluating blockchain adoption in automotive supply chains (Dehshiri et al. [257]), measuring urban digital transformation (Vieira et al. [258]), identifying optimal token exchange platforms (Wang et al. [259]), assessing innovation and technology at NASA (Tavana et al. [260]), prioritizing road safety enhancements (Trivedi et al. [134]), determining cryptocurrency trading systems (Yang et al. [261]), evaluating cryptocurrency exchange platforms (Ecer et al. [262]), and designing marketing strategies for halal products (Ghalih & Chang [263]).

5. A comprehensive bibliometric analysis of BWM

Bibliometric analyses provide an in-depth and detailed examination, offering valuable insights into research patterns and advancements (Ellegaard & Wallin [264]; Donthu et al. [265]; Peykani et al. [266]; Passas [267]). The bibliometric capabilities of scientometric tools, such as VOSviewer software and the R Bibliometrix package, are highly effective in supporting quantitative analysis in the fields of Scientometrics and Informetrics. These tools enable the systematic categorization and evaluation of vast volumes of past research data, facilitating the extraction of meaningful insights from large repositories.

Consequently, in the subsequent sections, a comprehensive and detailed bibliometric analysis of studies related to the best-worst method will be undertaken. The search methodology for this review is depicted in Fig. 4. As illustrated, targeted keywords were systematically queried within the “Title, Abstract, and Keywords" fields of publications indexed in the Scopus database, spanning the years 2015 to June 2025. Following the removal of duplicate entries, exclusion of non-English publications, and filtering out grey literature, a refined dataset of relevant documents was curated. These publications were sourced from leading publishers, including Nature, Elsevier, Springer, Taylor & Francis, IEEE, Wiley-Blackwell, Emerald, PLOS, MDPI, Sage, Wolters Kluwer, and Inderscience.

The structure of this section, which provides a detailed exploration of various aspects of bibliometric analysis, is as follows. Subsection 5.1 delves into document analysis, focusing on publication years, publication trends, and document types, shedding light on the temporal patterns and diversity of document formats within the literature. Subsection 5.2 focuses on keyword analysis, identifying key themes and trends in the literature. Subsection 5.3 presents an in-depth source analysis, assessing the origins and distribution of the publications, with particular attention to the top and most influential journals in the field. In Subsection 5.4, the author analysis highlights the contributions and influence of individual researchers. Subsection 5.5 explores affiliation analysis, examining the institutional networks driving research in this field. Subsection 5.6 covers citation analysis and citation network, analyzing the impact and reach of the publications. Finally, Subsection 5.7 provides an overview of thematic analysis, including the evolution of research themes and methods, along with a thematic map.

Following the steps outlined in Fig. 4, the initial broad query retrieved 4490 documents on the topic published between 2015 and June 30, 2025. Upon review, certain terms containing the abbreviation BWM were identified as unrelated to the target methodology. Consequently, these 146 terms were integrated into the second query to filter out irrelevant documents, reducing the total to 3034. Within this subset, some documents used BW or BWM as a unit of measurement, while others referenced the methodology without applying it, often merely suggesting its potential use in future studies. Such cases were excluded, yielding 2738 documents confirmed to have directly employed the methodology. Finally, to restrict the analysis to English-language publications, 66 non-English documents were removed, resulting in a final dataset of 2672 documents. These constitute the foundation of the present study.

5.1. Document analysis

The number of published articles in the BWM field per year from 2015 to June 2025 is shown in Fig. 5, indicating a clear upward trend in research output over the decade. The number of published articles increased dramatically from only 3 in 2015 to a peak of 532 in both 2023 and 2024. In the early years, the growth was relatively modest, with 13 articles in 2016 and 25 in 2017. However, from 2018 onward, the publication rate accelerated significantly, with sharp increases seen each year. By 2020, the number of publications rose to 265, and this growth continued steadily in subsequent years.

The chart also shows that after reaching a peak in 2023, this peak was maintained in 2024. It is worth noting that 312 articles were published in the first half of 2025. This shows that the number of publications in this field has never decreased until 2024. However, the fact that the number of publications in 2024 remained stable compared to 2023 could be a warning of a decrease in publications in this field. The number of publications by the end of 2025 could resolve this concern.

The pie chart in Fig. 6 illustrates the distribution of different document types in the field of the BWM. The majority of publications are articles, which account for 85.30 % of the total, with 2280 documents. This highlights that most of the research related to BWM is presented in journal articles, a common medium for in-depth scientific exploration and rigorous peer-reviewed studies. Conference papers represent the second-largest category at 8.83 % (236 documents), suggesting that BWM is frequently discussed in academic conferences where researchers share early findings and innovations. Additionally, book chapters make up 4.60 % (123 documents), showing that some research on BWM has been included in broader academic volumes. Review papers (18 documents, or 0.67 %) offer a synthesis of existing research, although the relatively small number suggests there may be more opportunities for comprehensive reviews in this field.

Other types of documents are less common. Retracted and Erratum each represent a small percentage of publications, 0.34 % and 0.22 %, respectively. Note and Letter each have a small share of 0.04 %. Overall, the data suggests that while the BWM field is well-established and actively researched, there are still relatively few reviews, books, or corrections, which may indicate areas for future development and consolidation in the literature.

5.2. Keyword analysis

An analysis of the most popular keywords used in research, as well as the most frequently occurring words in paper titles related to the BWM field, is presented in Table 1. This offers insights into recurring themes, methodologies, and areas of application. It should be explained that the left section of Table 1 presents the most popular keywords used in research, while the right section displays the most frequently used words in titles. In both sections, word/phrase frequencies are indicated in parentheses. Notably, unlike the single-word terms typically found in titles, keywords may comprise either individual words or multi-word phrases.

By analyzing the most popular keywords, it can be observed that variations of “Best-Worst Method" and the acronym “BWM" itself dominate the list, appearing with high frequency. This pronounced prevalence not only confirms the methodology’s central role within the research domain but also suggests its widespread adoption as a fundamental analytical tool. The sustained prominence of these terms across the examined literature further indicates BWM’s established position as a core methodological framework in the field. The presence of “Sustainability," “MCDM", and “Multi-Criteria Decision-Making" further

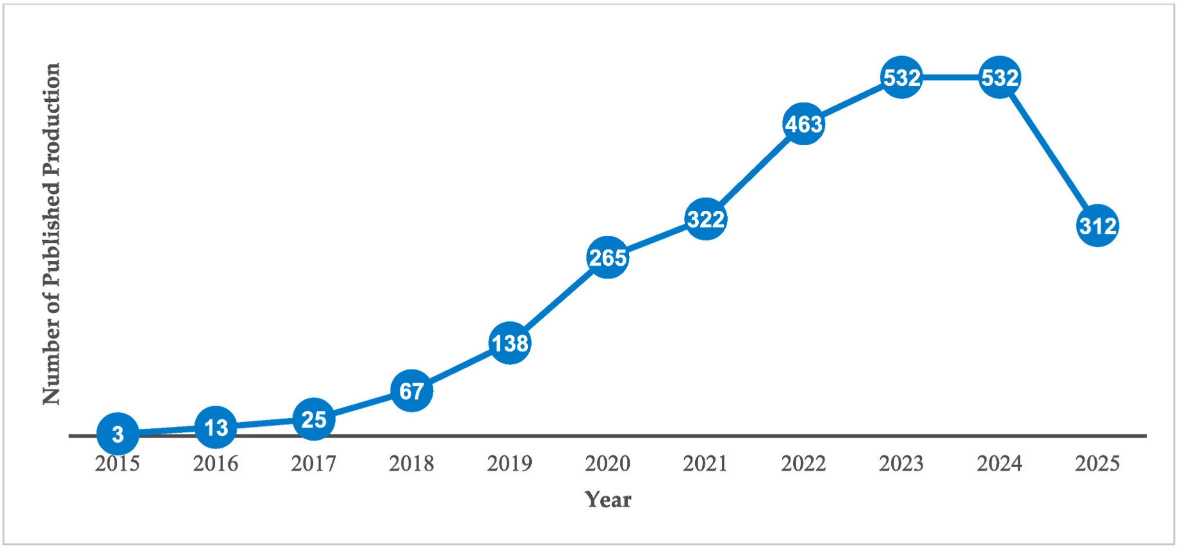

Fig. 5. Publishing trends in the BWM field.

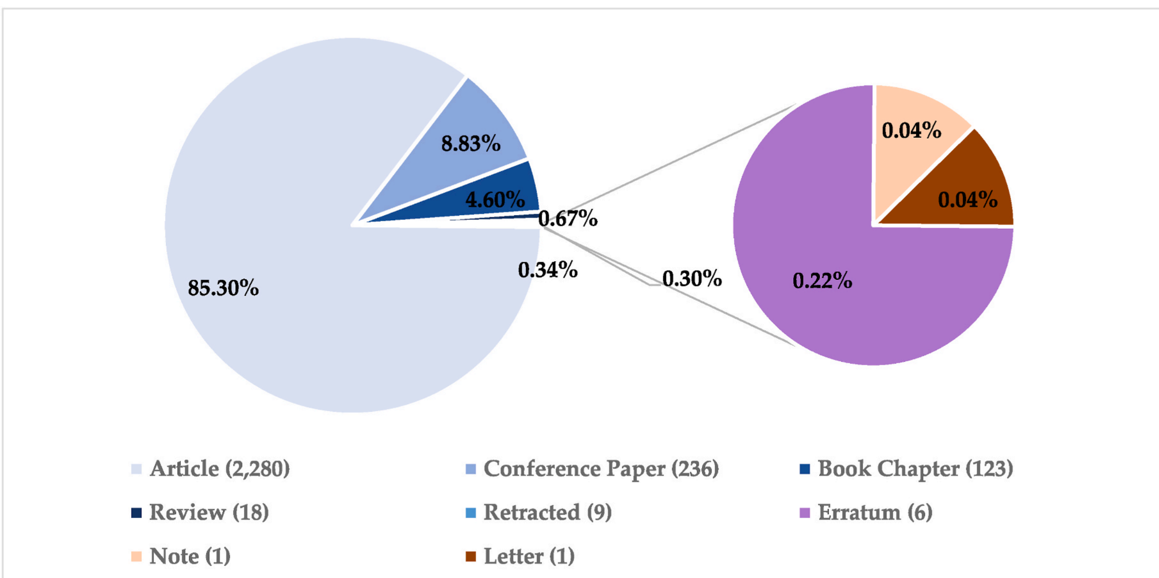

Fig. 6. Document types in the BWM field.

emphasizes the connection between BWM and broader decision-making contexts, particularly those involving multiple criteria and sustainability considerations.

Beyond the core BWM terminology, the table highlights key areas of application and methodological extensions. "Supplier Selection", "Industry 4.0″, "Circular Economy", and "COVID-19″ reveal the diverse range of fields where BWM is being applied. The inclusion of "Fuzzy Best-Worst Method" indicates the integration of fuzzy logic with BWM, a common approach to handling uncertainty and imprecision in decision-making. Other keywords like "Risk Assessment", "Barriers", and "VIKOR" (another MCDM method) suggest the exploration of BWM in conjunction with other methodologies and for addressing specific decision-making challenges.

The next column of the table continues to showcase the breadth of BWM research. Keywords such as "Bayesian Best-Worst Method", "GIS" (Geographic Information Systems), "Group Decision-Making", "Renewable Energy", and "Sustainable Supply Chain" highlight further methodological developments and application areas. The presence of other MCDM methods like "AHP" (Analytic Hierarchy Process), "TOPSIS" (Technique for Order of Preference by Similarity to Ideal Solution), and "DEMATEL" (Decision Making Trial and Evaluation Laboratory) suggests comparative studies and potential integrations with BWM.

On the other hand, the word frequency analysis of document titles shows that the term "Method" occurs most frequently with 810 instances, substantially outpacing all other terms in frequency. Other prominent words related to the core methodology include "Fuzzy", "Approach", "Based", "Selection", and "Model", all appearing over 350 times. The high frequency of these terms highlights the focus on methodological aspects within the BWM domain.

The table also reveals the presence of keywords related to specific applications and areas of interest within BWM research. "Sustainable" and "Sustainability" appear with notable frequencies, suggesting a growing trend towards applying BWM in sustainability-related decision-making. Other terms like "Decision-Making", "Best-Worst", "Supply", and "Evaluation" further emphasize the decision-oriented nature of the field. The inclusion of "Multi-Criteria" reinforces the understanding that

Table 1
Keyword and term frequency analysis in the BWM field.

Rank	Keywords (Frequency)	Rank	Keywords (Frequency)	Rank	Words (Frequency)	Rank	Words (Frequency)
1	Best-Worst Method (563)	26	Decision-Making (38)	1	Method (810)	26	Sustainability (168)
2	BWM (398)	27	GIS (37)	2	Fuzzy (506)	27	Worst (155)
3	Best Worst Method (216)	28	Decision Making (36)	3	Approach (505)	28	System (150)
4	Sustainability (190)	29	Fuzzy TOPSIS (35)	4	Based (471)	29	Performance (140)
5	MCDM (161)	30	AHP (34)	5	Selection (451)	30	Energy (133)
6	Best-Worst Method (BWM) (153)	31	Fuzzy BWM (33)	6	Model (363)	31	Development (129)
7	Multi-Criteria Decision-Making (149)	32	Supply Chain (33)	7	Sustainable (344)	32	Manufacturing (126)
8	Multi-Criteria Decision Making (116)	33	Blockchain (30)	8	Decision-Making (338)	33	MCDM (125)
9	TOPSIS (100)	34	Fuzzy Sets (28)	9	Best-Worst (334)	34	Barriers (122)
10	Fuzzy Best-Worst Method (86)	35	Group Decision-Making (28)	10	Supply (310)	35	Evaluating (122)
11	Best Worst Method (BWM) (81)	36	Renewable Energy (27)	11	Evaluation (305)	36	Application (121)
12	Supplier Selection (79)	37	Sustainable Supply Chain (27)	12	Multi-Criteria (280)	37	Factors (115)
13	Industry 4 0 (66)	38	Uncertainty (27)	13	Decision (273)	38	Methods (115)
14	Circular Economy (64)	39	Sustainable Supplier Selection (25)	14	Hybrid (271)	39	Bestworst (114)
15	COVID-19 (60)	40	Bayesian BWM (24)	15	Analysis (262)	40	Green (103)
16	Risk Assessment (53)	41	Fuzzy Best Worst Method (24)	16	Chain (258)	41	Criteria (93)
17	Barriers (51)	42	Fuzzy Logic (24)	17	Assessment (253)	42	Service (91)
18	VIKOR (51)	43	Site Selection (24)	18	BWM (252)	43	Linguistic (90)
19	Supply Chain Management (47)	44	FMEA (22)	19	Integrated (249)	44	Economy (87)
20	Sustainable Development (46)	45	MARCOS (22)	20	Framework (248)	45	Optimization (82)
21	DEMATEL (43)	46	Optimization (22)	21	Industry (215)	46	Design (81)
22	Resilience (40)	47	Performance Evaluation (22)	22	Study (213)	47	Systems (80)
23	Sensitivity Analysis (40)	48	Challenges (21)	23	Risk (182)	48	Information (79)
24	Multi-Criteria Decision-Making (MCDM) (39)	49	Fuzzy Set Theory (21)	24	Supplier (178)	49	Quality (77)
25	Bayesian Best-Worst Method (38)	50	TODIM (20)	25	Management (177)	50	Technology (77)

BWM operates within the broader context of multi-criteria decision-making.

The final table's column presents a diverse array of lower-frequency terms, indicative of either specialized applications or emerging research trends. Notable examples include domain-specific terms such as manufacturing, energy, development, green technologies, and systems integration. The explicit inclusion of "MCDM" in several titles further confirms BWM's established position within the broader multi-criteria decision-making framework. Collectively, this frequency analysis of document titles offers valuable insights into both predominant and niche research directions currently shaping the BWM field.

In conclusion, the left section of Table 1 identifies specific keywords and phrases associated with BWM applications and extensions, while the right section demonstrates the predominance of methodology-focused terminology. Both sections underscore BWM's strong connection to multi-criteria decision-making, particularly in sustainability, supply chain management, and risk assessment applications.

Notably, the emergence of industry-specific keywords and contemporary trends (e.g., Industry 4.0 and Circular Economy) reflects BWM's expanding applicability across diverse domains. Furthermore, the methodology's integration with complementary approaches such as fuzzy logic and other MCDM techniques reveals ongoing efforts to enhance its analytical capabilities for addressing complex decision-making challenges.

Finally, the word cloud in Fig. 7 provides a visual representation of the most popular keywords associated with BWM research. The size of each word corresponds to its frequency of appearance in the analyzed text data, providing an immediate visual representation of the dominant themes. As expected, "Best-Worst Method" and its variations, including the acronym "BWM," are the most prominent, highlighting the central focus on this specific methodology. "Multi-Criteria Decision-Making" also appears prominently, reinforcing BWM's role within the broader context of MCDM. "Sustainability" stands out as a significant application area, suggesting the increasing use of BWM in addressing sustainability-

Fig. 7. Word cloud of the most popular keywords in the BWM field.

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related decisions. Beyond these core themes, the word cloud reveals other relevant keywords, albeit with smaller sizes, reflecting their lower but still significant frequencies. Terms like “Fuzzy Best-Worst Method", “Supplier Selection", “Industry 4.0″, “Circular Economy", and “Risk Assessment" indicate specific applications and methodological extensions of BWM. The presence of other MCDM methods like “TOPSIS" and “VIKOR" suggests comparative studies and potential integrations. Overall, the word cloud provides a visually compelling summary of the key themes and trends within the BWM field, confirming the findings from Table 1.

5.3. Source analysis

The top 75 journals and sources that have published research related to the BWM from 2015 to June 2025 are presented in Table 2. The table shows how publication activity in the field has grown over time, with total annual article counts increasing steadily. Leading the list is the *Journal of Cleaner Production*, which published 97 articles on BWM, followed closely by *Sustainability* with 89 articles. Both journals have shown significant contributions since 2020, reflecting increased interest in BWM research in the context of sustainability and environmental management domain. Other highly ranked journals include *Applied Soft Computing*, *Expert Systems with Applications*, and *Computers & Industrial Engineering*, indicating the relevance of BWM in operations research, computer science, and industrial engineering fields.

The classification of journals involves analyzing their scope, aims, and specific fields, resulting in distinct categories based on primary focus areas. This process includes identifying common themes by reviewing each journal’s title and research focus, grouping journals with similar topics to better understand the research landscape, and considering interdisciplinary aspects while classifying them based on their predominant research type. This structured approach helps researchers identify relevant resources and understand where their work fits within the broader context. A total of **six classes** were established, reflecting distinct areas of research:

The **Environmental Science and Sustainability** category includes journals focused on pressing environmental issues and sustainable practices. Notable examples are *Journal of Environmental Management, Renewable and Sustainable Energy Reviews*, and *Sustainable Cities and Society* which address pollution, renewable energy sources, and sustainability challenges.

In the **Artificial Intelligence and Decision-Making** category, journals center on AI methodologies and their applications in decision-making processes. Examples include *Journal of Intelligent & Fuzzy Systems*, *Engineering Applications of Artificial Intelligence*, and *Soft Computing* which explore the integration of fuzzy logic and AI in various fields.

The **Operations and Management** category encompasses journals that focus on strategies and methodologies for effective management and operations research. Key examples are *Annals of Operations Research*, *International Journal of Production Economics*, and *Socio-Economic Planning Sciences* which provide insights into optimizing operations and decision-making in business contexts.

Journals in the **Engineering and Technology** category emphasize innovations and applications in engineering disciplines. Notable examples include *IEEE Access, Technological Forecasting and Social Change,* and *Applied Energy*, which highlight advancements in engineering technology and energy solutions.

The **Mathematics and Theoretical Applications** category features journals that delve into mathematical theories and their practical applications. *Mathematics* and *Mathematical Problems in Engineering* are prime examples, focusing on theoretical developments and their relevance to engineering problems.

Finally, the **General Science and Interdisciplinary Research** category includes journals that cover a wide range of scientific inquiries. Examples such as *Scientific Reports* and *Plos One* facilitate interdisciplinary studies and broad scientific discussions.

Notably, the BWM can be effectively applied across these categories. It aids in research prioritization by allowing researchers in sustainability to rank urgent environmental issues. In operational research, BWM can help allocate resources to competing projects. Additionally, it can evaluate policy impacts in socio-economic studies, assess project proposals in engineering, and facilitate interdisciplinary collaboration by identifying common ranking criteria.

Research in the field of BWM is being shared and disseminated through a variety of platforms, rather than solely relying on traditional academic journals. This multi-channel approach indicates a broader acceptance and application of BWM research across different fields. One significant outlet for BWM research is the *Lecture Notes in Operations Research* series. This series typically publishes advancements in operations research, which is crucial for decision-making processes in various industries. The inclusion of BWM research in this series underscores its applicability in optimizing operations and facilitating informed decision-making, showcasing its relevance in practical contexts.

Another important series is the *Lecture Notes in Mechanical Engineering*, which covers advancements in mechanical engineering, including both theoretical and practical applications. By publishing BWM research here, it demonstrates the interdisciplinary nature of the methodology and its potential contributions to solving mechanical engineering problems. The AIP Conference Proceedings, published by the *American Institute of Physics*, also plays a vital role in disseminating research findings. These proceedings cover a wide range of topics in physics and engineering, often stemming from conferences. BWM research at this venue enables rapid dissemination and collaboration, highlighting conference presentations’ role in sharing innovative ideas.

Additionally, the *Lecture Notes in Networks and Systems* series addresses topics related to networks and systems, which include computational methods and algorithms relevant to BWM. This indicates that BWM methodologies are being applied to networked systems or decision-making in complex environments, further broadening its scope of influence. Lastly, the *ACM International Conference Proceeding Series* publishes proceedings from ACM conferences, covering various fields within computer science disciplines. The presence of BWM research in this collection highlights its relevance in computational contexts, potentially addressing topics like algorithms, artificial intelligence, or data analysis.

In conclusion, the growing body of research related to the BWM from 2015 to June 2025 underscores its importance across various academic fields, particularly in sustainability, operations research, and engineering. The significant contributions from leading journals such as the *Journal of Cleaner Production* and *Sustainability* reflect an increasing recognition of BWM’s applicability in addressing complex environmental and management challenges. The structured classification of journals into distinct categories not only facilitates a clearer understanding of the research landscape but also highlights the interdisciplinary nature of BWM. This systematic approach enables researchers to identify relevant resources and contextualize their work within broader academic discussions.

Furthermore, the dissemination of BWM research through diverse platforms beyond traditional academic journals illustrates its expanding relevance and acceptance in various domains. Outlets such as the *Lecture Notes in Operations Research* and the *AIP Conference Proceedings* provide vital venues for sharing innovative findings and fostering collaboration among researchers. By integrating BWM methodologies into different contexts, including mechanical engineering and networked systems, the research community can leverage this versatile approach to prioritize urgent issues, optimize decision-making, and enhance interdisciplinary collaboration. As BWM continues to gain traction, its potential to contribute to both theoretical advancements and practical applications remains promising.

Table 2
The top 75 journals and sources contributing to the BWM field.

Rank	Journal	Publication Year											Total
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	
1	Journal of Cleaner Production		1	4	5	6	18	21	15	9	14	4	**97**
2	Sustainability		1	2	6	3	12	10	14	12	16	13	**89**
3	Applied Soft Computing			1	2	1	10	9	5	11	8	3	**50**
4	Expert Systems with Applications	1			2		1	6	12	11	11	5	**49**
5	Computers & Industrial Engineering			1	2	3	7	5	9	10	3	1	**41**
6	Environmental Science and Pollution Research						1	6	9	18	2		**36**
7	Journal of Intelligent & Fuzzy Systems					2	3	5	6	13	2		**31**
8	IEEE Access					6	4	3	5	5	4	3	**30**
9	Soft Computing				1		5	5	4	10	5		**30**
10	Environment, Development, and Sustainability				1		1	2	3	2	13	7	**29**
11	Mathematics					2	5	10	7	1	1	2	**28**
12	Annals of Operations Research						1		1	12	9	3	**26**
13	Information Sciences		1			3	1	4	7	6	3	1	**26**
14	Engineering Applications of Artificial Intelligence						1	2	1	7	6	5	**22**
15	IEEE Transactions on Engineering Management							1	2	4	14	1	**22**
16	Socio-Economic Planning Sciences						3	2	6	5	3	3	**22**
17	Benchmarking: An International Journal				2			1	1	4	6	4	**18**
18	Applied Sciences					1	4	2	1	5	2	2	**17**
19	International Journal of Fuzzy Systems					1		1	9	3	1	2	**17**
20	Business Strategy and the Environment						3		4	3	4	2	**16**
21	Technological Forecasting and Social Change		1	1	1		1	4	4		3	1	**16**
22	Decision Science Letters			1	4	2	1	1	2	2	2		**15**
23	Scientific Reports							1		1	4	9	**15**
24	International Journal of Hydrogen Energy						2	4		1	3	4	**14**
25	Mathematical Problems in Engineering			1	1		4	2	6				**14**
26	Decision Making: Applications in Management and Engineering				1	1	1	1	2	3	4		**13**
27	Energy					2	1	4	1	1	4		**13**
28	Heliyon						1			4	8		**13**
29	Plos One							1	5	2	4	1	**13**
30	Sustainable Cities and Society			1		2		4	5			1	**13**
31	International Journal of Information Technology and Decision Making				1		4	1	3	2		1	**12**
32	Journal of Air Transport Management			1	2		1	1	2	3		2	**12**
33	Kybernetes								4	2	4	2	**12**
34	Symmetry		2	1	2	1	1	2	1	1	1		**12**
35	International Journal of Production Economics						3	1	1	2	2	2	**11**
36	International Journal of Production Research				1	3	2			3	1	1	**11**
37	Sustainable Energy Technologies and Assessments						3	3	2	2	1		**11**
38	Sustainable Production and Consumption					1		5	1	3		1	**11**
39	Buildings							1	2	5	2		**10**
40	Energies			1	2		1		2	3	1		**10**
41	International Journal of Disaster Risk Reduction			1				1	1	5	1	1	**10**
42	International Journal of Environmental Research and Public Health					1	4	4	1				**10**
43	International Journal of Productivity and Performance Management								1		3	6	**10**
44	International Journal of System Assurance Engineering and Management						1	2			5	2	**10**
45	Procedia Computer Science					1			4		4	1	**10**
46	Cleaner Logistics and Supply Chain							2	3		3	1	**9**
47	Complex and Intelligent Systems							3	3	1	2		**9**
48	International Journal of Logistics Research and Applications				1	1	2		1		4		**9**
49	Journal of Environmental Management				1	1				2	1	4	**9**
50	Knowledge-Based Systems			1	2		1	2	2		1		**9**
51	Omega	1	1			1	2	1			2	1	**9**
52	Operations Management Research									4	5		**9**
53	Renewable Energy				1			2	1	1	2	2	**9**
54	Technological and Economic Development of Economy					1	2	2	2		1	1	**9**
55	Applied Energy					1		1		2	1	3	**8**
56	Applied Intelligence							2	2	3	1		**8**
57	Axioms								3	5			**8**
58	Decision Analytics Journal								2	3	3		**8**
59	Engineering, Construction and Architectural Management							1		1	2	4	**8**
60	Informatica				1		2		3	1	1		**8**
61	International Journal of Quality and Reliability Management					1		1	2	1	2	1	**8**
62	Journal of the Operational Research Society								3	3		2	**8**
63	Management Decision					1	1		1	1	1	3	**8**
64	Neutrosophic Sets and Systems						1	1		1	1	4	**8**
65	Technology in Society						1		3		2	2	**8**
66	Energy Conversion and Management						1	1	2	1	2		**7**
67	International Journal of Advanced Manufacturing Technology					1	1	1			3	1	**7**

(*continued on next page*)

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Table 2 (*continued*)

Rank	Journal	Publication Year											Total
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	
68	International Journal of Environmental Science and Technology						1	1	2	2		1	**7**
69	International Journal of Intelligent Systems					2		1	4				**7**
70	Journal of Modelling in Management									1	3	3	**7**
71	Materials Today: Proceedings						1	5		1			**7**
72	Operational Research							1	2	1	2	1	**7**
73	Quality and Reliability Engineering International									1	3	3	**7**
74	Renewable and Sustainable Energy Reviews					1	1		2	2	1		**7**
75	Transport Policy				1				2	1		3	**7**
	Total	**2**	**7**	**17**	**43**	**53**	**128**	**166**	**216**	**235**	**233**	**136**	**1236**

5.4. *Author analysis*

An overview of the most influential authors in BWM research, ranked by their total number of published articles, is provided in Table 3. The table lists the top 25 contributors, offering a detailed breakdown of their publication activity from 2015 to June 2025. The table highlights significant contributors to the BWM field, showcasing a variety of publication outputs from 2015 to 2023. At the forefront is **Jafar Rezaei**, who stands out as the most prolific author with a remarkable total of 56 publications. His consistent contributions over the years indicate a strong commitment to advancing research within this discipline.

Following **Rezaei**, **Himanshu Gupta** emerges as another prominent figure, demonstrating a substantial number of published articles (46 publications), especially in recent years. This uptick suggests that **Gupta** is actively engaged in current research trends and may be addressing pressing issues within the BWM field. Similarly, **Anish Kumar**, **Muhammet Gul**, and **Jingzheng Ren** also exhibit significant publication records, highlighting their ongoing contributions to the body of knowledge in this area.

The yearly contributions from these authors reveal varied patterns, with some showing spikes in specific years. This variability could reflect changes in research focus, collaboration opportunities, or responses to emerging topics within the field. Notably, there are authors like **Zhiru Li** and **Xinyu Zhang** who, while having fewer total publications, demonstrate increasing trends in their output. This rise suggests they may be gaining influence as their research evolves.

Moreover, the data may hint at collaborative efforts among authors, especially if multiple individuals exhibit similar spikes in publication during particular years. Such collaborations can significantly impact the advancement of research and the sharing of ideas within the academic community. Additionally, authors with a long-term presence in the field, consistently publishing over the years, signify dedication and a solid foundation of expertise in BWM.

In conclusion, the authors listed in the table represent a diverse array of publication behaviors, from established leaders to emerging voices. Analyzing their contributions provides valuable insights into the dynamics of research within the BWM field, illustrating its evolution and the active engagement of its contributors.

5.5. *Affiliation analysis*

Complementary insights into the global research landscape of the Best-Worst Method are provided, highlighting both the geographical distribution of contributions and the most cited countries in this field, as shown in Fig. 8 and Table 4. It should be explained that Fig. 8 presents a global distribution of research contributions, using a choropleth map to visualize publication output by country, where darker blue hues indicate greater research productivity. China is clearly the leading country in

Table 3
The top 25 contributing authors and their number of published articles in the BWM field.

Rank	Authors	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	Total
1	Jafar Rezaei	3	3	5	5	9	14	3	7	3	4		**56**
2	Himanshu Gupta		1	2	4	2	5	5	2	9	9	7	**46**
3	Anish Kumar					1	9	6	5	7	8	2	**38**
4	Muhammet Gul					1	3	6	8	11	3	4	**36**
5	Jingzheng Ren			2	2	4	9	7	2	6	3	1	**36**
6	Yi Liu				1	1	3	5	7	7	4	3	**31**
7	Md. Abdul Moktadir				1	3	4	3		10	4	2	**27**
8	Edmundas Kazimieras Zavadskas			1	5	3	9	3	4	1	1		**27**
9	Dragan Pamucar			1		2	3	5	5	1	7	2	**26**
10	Zhiwu Li			1		4	4	8	3		5	1	**26**
11	Melih Yucesan					1	1	4	7	7	3	2	**25**
12	Yanlin Li						4	1	1	3	10	5	**24**
13	Sen Guo			2	4	4	2	4	2	3	1	2	**24**
14	Maghsoud Amiri					2	4	5	3	6	2	1	**23**
15	Xiong Wang						3	4	2	8	4	2	**23**
16	Haoran Zhao			3	8	3			4	2	1	2	**23**
17	Madjid Tavana						4	6	4	3	4	2	**23**
18	Huchang Liao		1	1		6	6	1	3	2	1	1	**22**
19	Peide Liu					1	1	5	11	2	2		**22**
20	Xinyu Zhang					2	5	2	3	2	6	1	**21**
21	Jun Wang	1			2		3	3	2	2	5	2	**20**
22	Yongsheng Wang				2	1	1	2	5	2	5	2	**20**
23	James J. H. Liou				2	4	5	3	1	3	2		**20**
24	Geerten van de Kaa			2	1	2	4	3	2	2	1	2	**19**
25	Jiquan Zhang						1		5	6	3	4	**19**
	Total	**4**	**5**	**20**	**37**	**56**	**107**	**94**	**98**	**108**	**98**	**50**	**677**

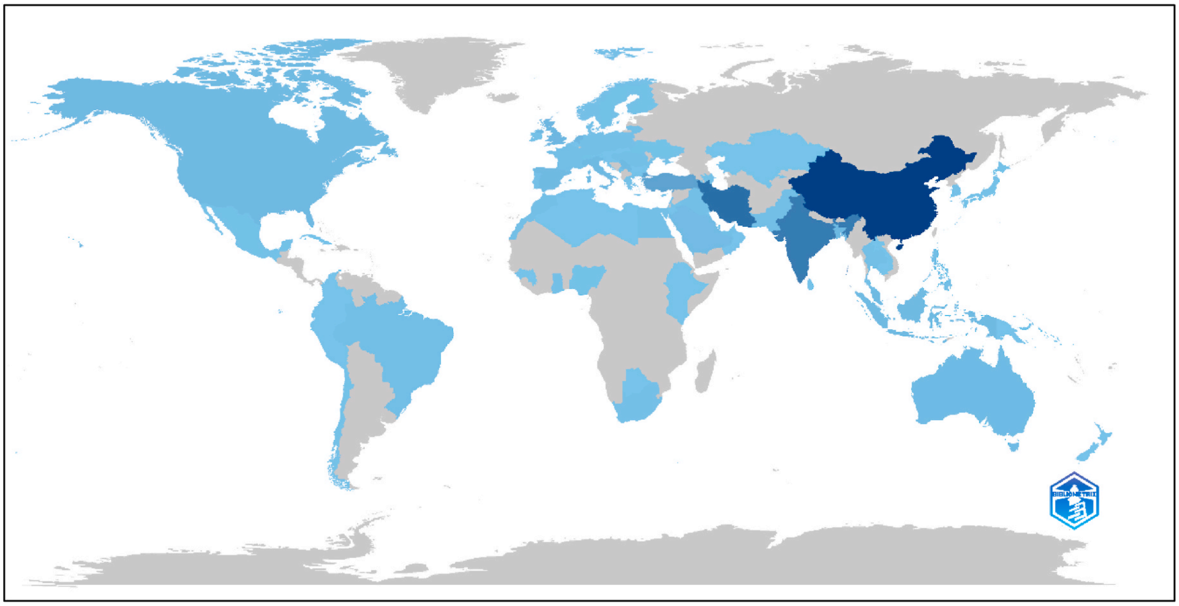

Fig. 8. Geographical distribution of contributing countries in the BWM field.

Table 4
The top 25 most contributing countries and affiliations in the BWM field.

Rank	Country	Frequency	Total Citations	Rank	Affiliation	Country	Frequency
1	China	2517	16,095	1	University of Tehran	Iran	334
2	Iran	1570	7945	2	Islamic Azad University	Iran	197
3	India	1335	8202	3	North China Electric Power University	China	165
4	Turkey	611	3785	4	Delft University of Technology	Netherlands	148
5	Netherlands	223	4774	5	The Hong Kong Polytechnic University	China	109
6	United Kingdom	212	1817	6	Sichuan University	China	85
7	Bangladesh	209	1027	7	Bangladesh University of Engineering and Technology	Bangladesh	78
8	USA	183	1559	8	Central South University	China	73
9	Italy	162	441	9	Iran University of Science and Technology	Iran	69
10	Malaysia	156	785	10	Munzur University	Turkey	68
11	Indonesia	153	59	11	Shiraz University	Iran	68
12	Canada	148	1145	12	Shadong University of Finance and Economics	China	64
13	Spain	146	690	13	Vilnius Gediminas Technical University	Lithuania	59
14	Serbia	142	1929	14	Ferdowsi University of Mashhad	Iran	57
15	Australia	136	1290	15	University of Belgrade	Serbia	57
16	Saudi Arabia	124	508	16	Wuhan University of Technology	China	55
17	Brazil	87	140	17	Urmia University of Technology	Iran	53
18	Lithuania	81	709	18	University of Jaén	Spain	46
19	France	78	285	19	Chongqing University	China	45
20	Thailand	74	215	20	Indian Institute of Technology	India	45
21	Pakistan	67	186	21	Universiti Teknologi Malaysia	Malaysia	44
22	Philippines	66	74	22	National Taipei University of Technology	Taiwan	43
23	Morocco	60	137	23	Allameh Tabataba'i University	Iran	42
24	Egypt	54	561	24	University of Dhaka	Bangladesh	42
25	Iraq	53	154	25	Tarbiat Modares University	Iran	41

BWM research, indicated by its dark blue color on the map, reflecting the highest frequency of contributions. The left section of Table 4 confirms this, showing that China ranks first with 2517 publications and a total of 16,095 citations, with an average of 25.7 citations per article. This makes China not only the most prolific in terms of publication volume but also one of the most impactful in terms of total citations.

Countries such as Iran, India, Turkey, and the United Kingdom also appear prominently on the map and in the table. Accordingly, Iran is ranked second in Table 4, with 1570 publications and 7945 citations, averaging 19.3 citations per article. Similarly, India is ranked third with 1335 publications and 7027 citations (23.6 average citations). Turkey, despite having fewer publications (611), demonstrates significant impact with 3785 total citations and a strong average of 18.6 citations per article.

Furthermore, the left section of Table 4 provides additional insight into countries with high average article citations despite fewer publications. For instance, the Netherlands ranks ninth in terms of publication frequency but has a remarkable average of 78.3 citations per article, highlighting the influence of Dutch research in the BWM field. Similarly, the United Kingdom shows a high average of 30.3 citations per article, despite only 212 publications. This suggests that countries with fewer publications can still have a substantial impact if their research is highly cited.

The combination of Fig. 8 and Table 4 reveals that while the volume of research output is concentrated in a few major countries like China, Iran, and India, the academic impact, measured by citations, varies significantly. Countries like the Netherlands and United Kingdom punch above their weight in terms of average citations, demonstrating that quality and influence are not solely dependent on quantity. The geographical distribution suggests that BWM research is growing globally, but certain regions, particularly in Africa and Central Asia, remain underrepresented, indicating areas where the method could potentially expand in the future.

On the other hand, the right section of Table 4 highlights the top 25 academic institutions contributing to research on the best-worst method, a multi-criteria decision-making approach. University of Tehran (Iran) leads with 334 published articles, followed by Islamic Azad University (Iran) with 197 articles, and North China Electric Power University (China) with 165. Notably, Table 4 reveals a global distribution of research efforts, with affiliations from countries like Iran, China, the Netherlands, Bangladesh, and Serbia among the top contributors. This indicates a widespread interest and active research community focused on advancing and applying the BWM across diverse geographical regions.

The table not only identifies the leading institutions in BWM research but also provides insights into the collaborative landscape of the field. The presence of multiple universities from the same country, such as Iran and China, suggests strong national research networks dedicated to BWM. Furthermore, the table highlights the international nature of BWM research, with contributions from institutions across different continents. This global representation underscores the versatility and applicability of BWM as a decision-making tool in various contexts. Overall, the data presented in Table 4 serves as a valuable resource for researchers, practitioners, and policymakers seeking to understand the key players and institutional contributions driving the advancement of the BWM field.

5.6. Citation analysis

An analysis of citations from 2015 to June 2025, highlighting trends in total citations, cumulative citations, and the number of articles published annually, is presented in Table 5. In the early years, from 2015 to 2020, the total number of citations steadily increased, peaking in 2020 with 12,882 citations. Simultaneously, the number of articles published also grew significantly, rising from just 3 articles in 2015 to 265 in 2020. This growth in publications reflects an expansion in research output, likely contributing to the overall rise in citations. However, despite the increasing number of articles, the mean total citations per article gradually decreased, with a notable drop from 217.38 citations per article in 2016 to 33.17 in 2021, suggesting that the average impact or visibility of each paper may be diminishing as more articles are published.

From 2021 onward, while the number of articles continued to rise, reaching a peak of 532 in 2023, there is a noticeable decline in both total and mean citation rates. By 2024, the total citations dropped to 2,895, with the mean total citations per article falling to just 3.80. This trend might indicate a saturation point in the field, where an increase in the volume of publications results in fewer citations per article. The cumulative total citations, however, continue to grow, reaching 66,955 by June 2025, indicating the ongoing accumulation of citations across all years. Overall, the data suggests that while research output is increasing, the average impact of each individual paper, as measured by citations, is declining over time.

Table 6 provides a comprehensive overview of the top 100 publications in the BWM, showcasing the significant contributions made by various researchers. The table is structured to highlight the rank, authors, year of publication, source journal, total citations, and citations per year for each publication. This format allows for a clear assessment of the impact and relevance of these works within the academic community.

The most notable entry is by Rezaei, whose 2015 publication in Omega has garnered an impressive total of 3239 citations, translating to a remarkable 294.45 citations per year. This high citation count underscores the publication's foundational role in the BWM field, indicating that it continues to be a crucial reference for ongoing research. Rezaei's subsequent publication in 2016, also in *Omega*, follows closely with 1384 total citations, further establishing him as a leading figure in this area.

Other significant authors include Guo & Zhao [83] and Pamucar et al. [25], whose works *in Knowledge-Based Systems* and *Symmetry*, respectively, have also made substantial contributions, with citation counts of 730 and 622. These figures reflect the broader themes explored in their research, suggesting a growing interest in the methodologies and applications relevant to BWM.

The table also highlights the importance of recent publications, such as those by Yadav et al. [268] and Gupta & Barua [269], which have been published in high-impact journals like the *Journal of Cleaner Production*. These works demonstrate not only significant total citations but also robust citations per year, indicating their ongoing relevance in current discussions and research trends within the field.

Additionally, the diversity of journals represented, including *Resources, Conservation and Recycling and Process Safety and Environmental Protection*, illustrates the interdisciplinary nature of BWM research. The presence of multiple entries from the *Journal of Cleaner Production* indicates a strong focus on sustainability and environmental issues, which are critical areas of exploration in contemporary research.

In conclusion, Table 6 serves as a valuable resource for understanding the landscape of impactful research in the BWM field. By analyzing the top publications, one can identify key contributors, emerging trends, and foundational studies that continue to shape the direction of research and practice in this evolving discipline.

At the conclusion of this subsection, Fig. 9 presents a citation network (literature review map) that visualizes relationships among the most cited research papers in BWM field. Within this diagram, each node corresponds to an individual study, conventionally labeled by author names and publication year. The larger nodes indicate more influential papers, while the smaller nodes represent less cited works, providing a visual representation of the impact of each study within the academic community. The lines connecting the nodes signify citations or references between the papers. A line from one node to another suggests that the first paper has cited the second, demonstrating how research builds upon prior work. This connectivity highlights the collaborative nature of academic research, showcasing how new studies are informed by and

Table 5
Annual total citations per year in the BWM field.

Year	Total Citations	Cumulative Total Citations	Articles	Mean Citations per Article	Citable Years	Mean Citations per Year
2015	3597	3597	3	1198.67	11	108.97
2016	2826	6423	13	217.38	10	21.74
2017	3563	9986	25	142.52	9	15.84
2018	7038	17,024	67	105.04	8	13.13
2019	7440	24,464	138	53.91	7	7.70
2020	12,882	37,346	265	48.61	6	8.10
2021	10,681	48,027	322	33.17	5	6.63
2022	8922	56,949	463	19.27	4	4.82
2023	6858	63,807	532	12.89	3	4.30
2024	2895	66,702	532	5.44	2	2.72
2025	253	66,955	312	0.81	1	0.81

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Table 6
The top 100 publications in the BWM field.

Rank	Research	Year	Source	Total Citations	Total Citations per Year
1	Rezaei [68]	2015	Omega	3239	294.45
2	Rezaei [81]	2016	Omega	1384	138.40
3	Guo & Zhao [83]	2017	Knowledge-Based Systems	730	81.11
4	Pamucar et al. [25]	2018	Symmetry	622	77.75
5	Rezaei et al. [270]	2016	Journal of Cleaner Production	514	51.40
6	Yadav et al. [268]	2020	Journal of Cleaner Production	476	79.33
7	Ahmadi et al. [241]	2017	Resources, Conservation and Recycling	460	51.11
8	Gupta & Barua [269]	2017	Journal of Cleaner Production	445	49.44
9	Mi et al. [66]	2019	Omega	374	53.43
10	Moktadir et al. [271]	2018	Process Safety and Environmental Protection	343	42.88
11	Ecer & Pamucar [272]	2020	Journal of Cleaner Production	325	54.17
12	Rezaei et al. [273]	2015	Expert Systems with Applications	324	29.45
13	Mohammadi & Rezaei [85]	2020	Omega	312	52.00
14	Kusi-Sarpong et al. [274]	2019	International Journal of Production Research	311	44.43
15	Aboutorab et al. [186]	2018	Expert Systems with Applications	306	38.25
16	Pamucar et al. [123]	2018	Expert Systems with Applications	289	36.13
17	Wu et al. [146]	2019	Information Sciences	289	41.29
18	Gupta et al. [275]	2021	Journal of Cleaner Production	286	57.20
19	Yazdi et al. [276]	2020	Safety Science	271	45.17
20	Yadav et al. [277]	2020	Computers in Industry	264	44.00
21	Liang et al. [75]	2020	Omega	264	44.00
22	Gupta [246]	2018	Journal of Air Transport Management	255	31.88
23	Gupta & Barua [278]	2016	Technological Forecasting and Social Change	254	25.40
24	Tarei et al. [279]	2021	Journal of Cleaner Production	252	50.40
25	Gupta & Barua [280]	2018	Science of the Total Environment	247	30.88
26	Tian et al. [281]	2018	Applied Soft Computing	244	30.50
27	Bai et al. [282]	2019	International Journal of Production Research	242	34.57
28	Khorram Niaki et al. [283]	2019	Journal of Cleaner Production	241	34.43
29	Rezaei et al. [284]	2018	Transport Policy	239	29.88
30	Lo et al. [285]	2018	Journal of Cleaner Production	224	28.00
31	Salimi & Rezaei [216]	2018	Evaluation and Program Planning	222	27.75
32	Vahidi et al. [286]	2018	Journal of Cleaner Production	220	27.50
33	Rezaei et al. [287]	2018	Tourism Management	219	27.38
34	Gupta et al. [288]	2020	Resources, Conservation and Recycling	216	36.00
35	Moktadir et al. [289]	2020	Business Strategy and the Environment	215	35.83
36	Ahmad et al. [229]	2017	Journal of Cleaner Production	213	23.67
37	Rahimi et al. [290]	2020	Journal of Cleaner Production	207	34.50
38	Dong et al. [157]	2021	Information Sciences	207	41.40
39	Lo & Liou [291]	2018	Applied Soft Computing	196	24.50
40	Ren et al. [292]	2017	Technological Forecasting and Social Change	190	21.11
41	Govindan et al. [293]	2020	International Journal of Production Economics	189	31.50
42	Gupta [294]	2018	Journal of Environmental Management	188	23.50
43	Kumar et al. [295]	2021	Technological Forecasting and Social Change	187	37.40
44	Mou et al. [296]	2016	Information Sciences	186	18.60
45	Ataei et al. [297]	2020	Applied Soft Computing	186	31.00
46	Haeri & Rezaei [298]	2019	Journal of Cleaner Production	185	26.43
47	Kheybari et al. [299]	2019	Applied Energy	182	26.00
48	Lin et al. [300]	2020	IEEE Internet of Things Journal	179	29.83
49	Torabi et al. [301]	2016	Safety Science	177	17.70
50	Moktadir et al. [302]	2020	Journal of Cleaner Production	174	29.00
51	Hafezalkotob & Hafezalkotob [303]	2017	Applied Soft Computing	173	19.22
52	Ghoushchi et al. [304]	2019	Applied Soft Computing	173	24.71
53	Alavi et al. [305]	2021	Sustainable Production and Consumption	173	34.60
54	Darko & Liang [306]	2020	Engineering Applications of Artificial Intelligence	172	28.67
55	Liu et al. [307]	2019	Information Sciences	170	24.29
56	Yazdani et al. [308]	2019	Journal of Civil Engineering and Management	166	23.71
57	Malek & Desai [225]	2019	Journal of Cleaner Production	166	23.71
58	Khalili Nasr et al. [309]	2021	Journal of Cleaner Production	162	32.40
59	Kannan et al. [310]	2020	Science of The Total Environment	158	26.33
60	Nie et al. [311]	2018	Knowledge-Based Systems	156	19.50
61	Yadav et al. [312]	2019	Sustainable Cities and Society	156	22.29
62	Lo et al. [313]	2019	Reliability Engineering & System Safety	155	22.14
63	Torkayesh et al. [314]	2021	Sustainable Cities and Society	153	30.60
64	Gupta et al. [315]	2017	Sustainable Cities and Society	151	16.78
65	Cheraghalipour & Farsad [316]	2018	Computers & Industrial Engineering	150	18.75
66	Pamucar et al. [317]	2019	Computers & Industrial Engineering	146	20.86
67	Javad et al. [318]	2020	Sustainable Futures	145	24.17
68	Elkadeem et al. [319]	2021	Applied Energy	144	28.80
69	Zhou et al. [320]	2020	Energy Conversion and Management	143	23.83
70	Kumar et al. [321]	2020	Tourism Management	140	23.33
71	Şahin [322]	2021	International Journal of Environmental Science and Technology	140	28.00
72	Singh et al. [209]	2021	Journal of Cleaner Production	138	27.60
73	Orji et al. [323]	2020	International Journal of Production Research	137	22.83
74	Sahebi et al. [324]	2020	Technology in Society	136	22.67

(continued on next page)

Table 6 (*continued*)

Rank	Research	Year	Source	Total Citations	Total Citations per Year
75	Van De Kaa et al. [325]	2017	Journal of Cleaner Production	135	15.00
76	Pamucar & Ecer [326]	2020	Facta Universitatis, Series: Mechanical Engineering	135	22.50
77	Zhao et al. [327]	2019	Energy	134	19.14
78	Hashemkhani Zolfani et al. [328]	2018	Soft Computing	132	16.50
79	Abdel-Basset et al. [329]	2020	Journal of Cleaner Production	132	22.00
80	Moktadir et al. [330]	2021	Journal of Cleaner Production	132	26.40
81	Torkayesh et al. [331]	2021	Socio-Economic Planning Sciences	130	26.00
82	Shang et al. [332]	2022	Expert Systems with Applications	130	32.50
83	Pamucar et al. [333]	2017	Sustainability	129	14.33
84	Nawaz et al. [334]	2018	Knowledge-Based Systems	129	16.13
85	Deveci et al. [183]	2021	Applied Soft Computing	129	25.80
86	Torkayesh et al. [255]	2021	Waste Management	128	25.60
87	Kannan et al. [335]	2021	Journal of Cleaner Production	128	25.60
88	Tian et al. [336]	2018	Journal of Cleaner Production	124	15.50
89	Shojaei et al. [145]	2018	Journal of Air Transport Management	123	15.38
90	Karmaker et al. [337]	2023	International Journal of Production Economics	122	40.67
91	Stević et al. [131]	2017	Symmetry	121	13.44
92	Safarzadeh et al. [338]	2018	Computers & Industrial Engineering	121	15.13
93	Moslem et al. [339]	2020	Sustainability	119	19.83
94	Abdel-Basset et al. [340]	2020	Optimization Theory Based on Neutrosophic and Plithogenic Sets	116	19.33
95	Rezaei [341]	2020	International Journal of Information Technology & Decision Making	116	19.33
96	Kumar et al. [342]	2019	Production Planning & Control	114	16.29
97	Pamucar et al. [77]	2020	Mathematics	114	19.00
98	Bai et al. [343]	2022	Journal of Cleaner Production	114	28.50
99	Liao et al. [213]	2019	Journal of Cleaner Production	113	16.14
100	Celik & Gul [344]	2021	Automation in Construction	113	22.60

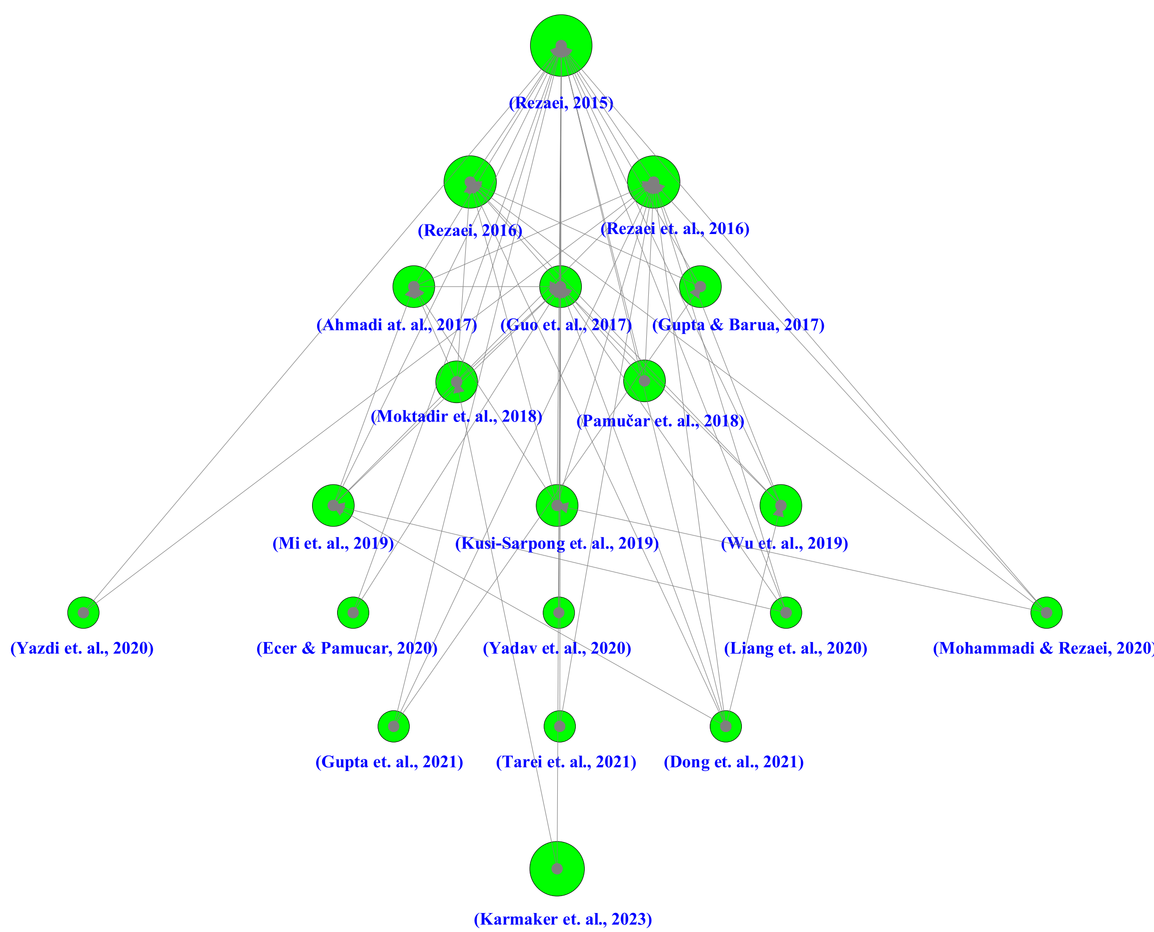

Fig. 9. Graphical presentation of citation network in the BWM field.

contribute to existing literature.

The tree-like structure of the diagram suggests a hierarchical relationship, where foundational or seminal works are positioned at the top, with subsequent studies branching out below. This arrangement indicates the flow of knowledge and illustrates how new research is influenced by earlier studies. The top nodes represent key studies that have significantly impacted the field, serving as essential texts for subsequent research. Analyzing this citation network provides insights into research trends, such as which topics are gaining attention and how certain themes evolve over time. It also highlights the interconnections within the research community, showing how different authors and studies relate to one another. By examining these connections, researchers can identify gaps in the literature and areas for future exploration.

5.7. Thematic analysis

The evolution of research themes and methods in the BWM field from 2015 to June 2025 is visually represented in Fig. 10. It is divided into sections for the years 2015–2017, 2018–2019, 2020–2021, 2022–2023, and 2024–2025, with each section highlighting the prevalent research themes and methodologies during those times. Each colored box in the chart represents a specific research theme, such as "Decision-Making", "Energy Sector", and "Risk Assessment". The colors help differentiate the themes visually, making it easier to identify patterns and shifts. Additionally, boxes labeled "Best-Worst Method" and other methodological approaches indicate the research methods used in conjunction with the themes. The prominence of the "Best-Worst Method" across multiple years suggests its significance in the research landscape.

One notable observation is the continuity and change in themes over time. Some themes, like decision-making, persist across multiple periods, indicating ongoing interest, while others may emerge or fade, reflecting shifts in research focus. The repeated mention of the "Best-Worst Method" highlights its status as a favored approach in recent studies, likely due to its effectiveness in addressing complex decision-making scenarios. The chart also suggests the emergence of new themes in the later years, such as sustainability and multi-objective optimization, which may respond to contemporary challenges or research needs. It should be noted that thematic evolution charts like this one are valuable for understanding the trajectory of research interests and methodologies over time, emphasizing how scholarly focus shifts in response to new challenges, technologies, and insights.

Fig. 11, titled "Thematic Map" and generated by the Louvain Clustering Algorithm, visually represents the relationship between various research themes based on their relevance and development degree. The map is divided into four quadrants, each signifying the status of themes within the research landscape. In the **Niche Themes** quadrant (top left), themes such as "Risk Assessment" and "FMEA Uncertainty" are characterized by low relevance and low development. These themes are emerging but not widely recognized or developed in current research. The **Emerging or Declining Themes** quadrant (bottom left) includes themes that have low relevance but a higher development degree. These themes may be established in the literature but are losing traction in contemporary discussions.

The **Motor Themes** quadrant (top right) features high-relevance, high-development themes, such as "Best-Worst Method" and "COVID-19". These themes are central to current research, indicating strong interest and ongoing development. Conversely, the **Basic Themes** quadrant (bottom right) includes themes like "Sustainability" and "Fuzzy Best-Worst Method", which possess high relevance but may not be as fully developed. While recognized as important, they may require further exploration or advancement. In the central cluster of the map, the "Best-Worst Method" holds a dominant position, indicating its critical role in bridging various themes. This central positioning suggests that it is a pivotal method that connects different areas of research, facilitating more comprehensive studies.

Overall, the thematic map illustrates the dynamics of research trends, emphasizing which themes are currently popular, which are emerging, and which may be in decline. The Louvain Clustering Algorithm effectively categorizes these themes, providing valuable insights into their relevance and development within the academic landscape.

6. A critical review of challenges and limitations in BWM studies

A comprehensive critical evaluation of the BWM requires looking beyond the well-documented narrative of its successful applications and extensions. To present a balanced perspective on its scholarly utilization, it is essential to critically examine the systematic limitations,

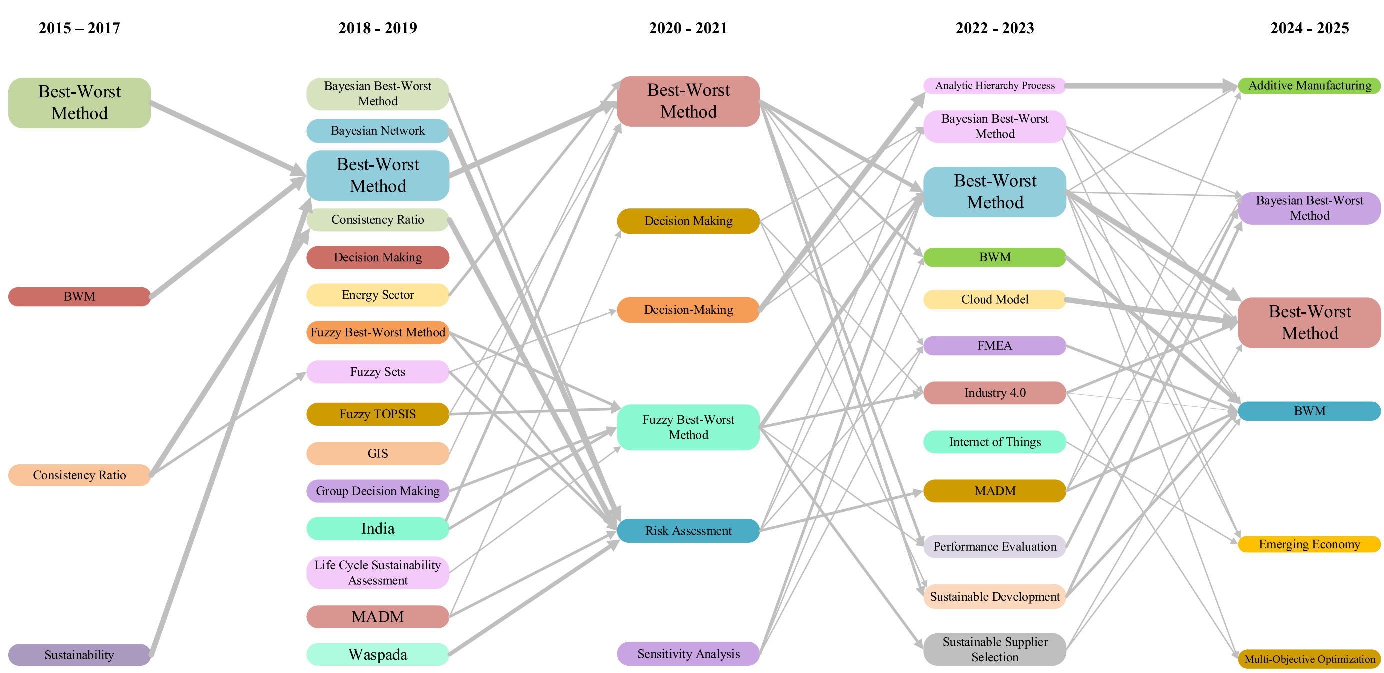

Fig. 10. Thematic evolution in the BWM field.

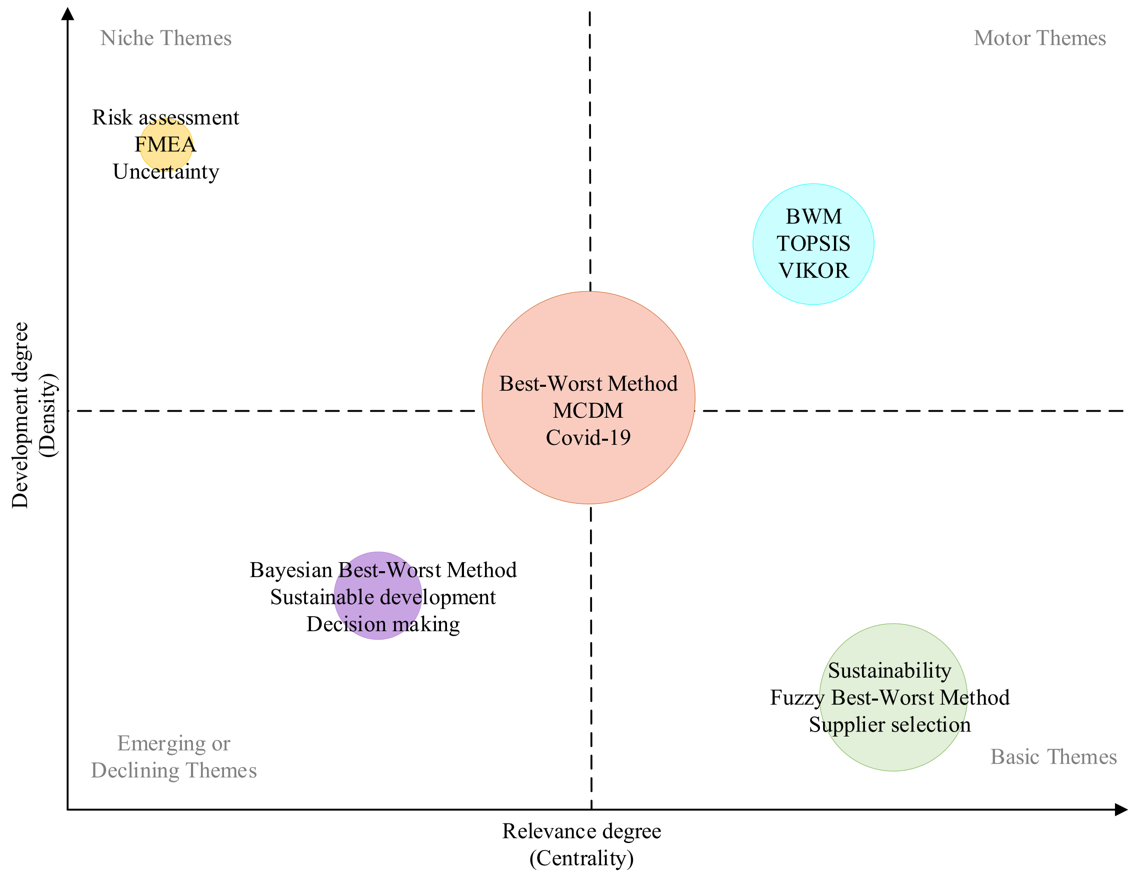

Fig. 11. Thematic mapping and cluster analysis in the BWM field.

common methodological issues, and potential biases that characterize its implementation in case applications. This section, therefore, systematically identifies and discusses these challenges to cultivate a more nuanced and realistic understanding of the method's practical implications and academic application.

6.1. Common methodological issues

A significant strength of the BWM is its structured framework for deriving criteria weights; however, its application is not immune to methodological pitfalls.

- **Over-Reliance on Subjective Judgments:** The core of the BWM, like many MCDM methods, relies on the subjective judgments of decision-makers. This inherent characteristic introduces several challenges:
  - o **Inherent Uncertainty:** Expert judgments are often imprecise and accompanied by ambiguity. Although fuzzy and interval-valued extensions of the BWM have been developed to handle this issue, a considerable number of empirical studies, particularly early applications, utilize the crisp model without adequately addressing the limitations of this assumption. The failure to incorporate uncertainty modelling in contexts where expert knowledge is vague can lead to overstated confidence in the resulting weights.
  - o **Poor Comparison Consistency:** Although the BWM inherently produces more consistent comparisons than methods like AHP due to its structured pairwise format, obtaining a fully consistent comparison set (with a consistency ratio of zero) is often impractical. A common flaw in the literature is the insufficient reporting of the Consistency Ratio (CR) or the lack of a clear protocol for handling matrices with poor consistency (e.g., CR $>$ 0.1). Some studies either omit this crucial validity measure entirely or fail to describe iterative procedures for re-engaging with experts to refine their judgments when consistency is unacceptably low, potentially undermining the reliability of the derived weights.
- **Challenges in Expert Sampling:** The quality and credibility of BWM outcomes are directly contingent upon the selection of appropriate experts. Common limitations in this area include:
  - o **Small Expert Panel Sizes:** Many case studies are conducted with the input of a single expert or a very small panel. While this may be sufficient for certain exploratory studies, an over-reliance on a limited number of viewpoints can threaten the robustness and generalizability of the findings, as the results may be idiosyncratic to that particular individual or group.
  - o **Inadequate Justification of Expert Selection:** A frequent issue is the lack of a transparent and rigorous description of the criteria used for expert selection. Papers often state that "a group of experts was consulted" without specifying the experts' qualifications, years of relevant experience, or organizational roles. This omission makes it difficult for readers to assess the validity and potential biases of the expert input, thereby weakening the study's overall credibility.

6.2. Potential biases in application studies

Beyond methodological issues, the application of BWM in real-world case studies is susceptible to various forms of bias that can skew results and interpretations.

- **Selection Bias:** This occurs when the set of criteria or alternatives is defined incompletely or in a manner that predetermines the outcome. For instance, a study might focus exclusively on economic criteria while neglecting social or environmental dimensions, leading to conclusions that are biased towards a specific perspective. The framing of the decision problem itself, if not done objectively, can inadvertently introduce selection bias before any pairwise comparisons are even made.

- **Confirmation Bias:** This is a significant risk in applied research, where investigators may unconsciously seek out experts who share similar views, interpret ambiguous data in a way that confirms their pre-existing hypotheses, or design the criteria hierarchy to lead to an expected outcome. The subjective nature of the BWM's input phase makes it particularly vulnerable to this cognitive bias if not carefully managed through rigorous research design.
- **Reporting Bias (Publication Bias):** A critical limitation within the broader BWM literature is the tendency to predominantly publish studies with "Successful", clear, and expected results. Cases where the application of BWM encountered significant practical difficulties, such as an inability to reach a consensus among experts, paradoxical results, or poor consistency that could not be resolved, are severely underreported. This creates an incomplete and potentially overly optimistic picture of the method's practical applicability and fails to provide the academic community with valuable lessons learned from challenging implementations.

This critical analysis affirms that the BWM's value as a decision-support tool is contingent upon the rigorous acknowledgment of its inherent methodological limitations and potential biases. Key challenges, including dependency on subjective judgments, difficulties in expert sampling, and various cognitive biases, directly impact the validity of its outcomes. Consequently, the conscious identification and systematic mitigation of these issues are imperative for strengthening the methodological robustness and reliability of future BWM applications. Such diligence is fundamental to ensuring the credibility and practical utility of the method's results in both research and practice.

7. Future research directions

The systematic investigation of BWM's research landscape reveals significant opportunities for advancing methodological development and practical applications. The findings highlight three critical dimensions requiring scholarly attention: (1) theoretical extensions to address current limitations in complex decision scenarios, (2) empirical validation across emerging application domains, and (3) technological integration with contemporary analytical tools. Based on these findings, several guidelines and directions for future research in the field of BWM are proposed, as outlined below.

- The integration of the BWM with Machine Learning (ML) and Deep Learning (DL) algorithms for parameter estimation represents a promising avenue for enhancing decision-making accuracy and efficiency. By leveraging the predictive power of these algorithms, BWM can better handle large-scale, complex datasets and dynamically adapt to changing environments. This synergy could enable more precise weight estimation, reduce subjectivity in preference judgments, and provide data-driven insights, making BWM a more robust and scalable tool for real-world applications across diverse domains.
- The combination of the BWM with other multi-criteria decision-making techniques in Decision Support Systems (DSS) offers a powerful framework for addressing complex, multi-faceted problems. By combining BWM's efficiency in weight determination with the strengths of other MCDM methods, DSS can provide more comprehensive, balanced, and user-friendly solutions. This hybrid approach enhances decision-making accuracy, transparency, and adaptability, particularly in dynamic and data-rich environments.
- Developing new versions of the robust BWM by applying advanced variants of robust optimization, such as scenario-based RO, regret-based RO, light RO, distributionally RO, adaptive RO, and data-driven RO, offers a promising avenue for enhancing decision-making under deep and scenario-based uncertainty. This hybrid approach leverages BWM's efficiency in weight determination and robust optimization's ability to handle data variability, providing more reliable and resilient solutions. By combining these strengths, the framework addresses complex decision-making challenges, improving adaptability and precision in environments characterized by high levels of uncertainty, variability, and complexity.
- Proposing the Adjustable Fuzzy Chance-Constrained Best-Worst Method (AFCCBWM), which integrates Adjustable Possibilistic Programming (APP), General Fuzzy Measures (GFM), and Chance-Constrained Programming (CCP) to address uncertainty and accommodate decision-makers' varying optimistic-pessimistic attitudes. This advanced framework enables flexible modeling of imprecise data and risk preferences, thereby enhancing the robustness of decision outcomes. By effectively balancing optimism and pessimism, AFCCBWM offers a nuanced and adaptive approach to complex decision-making, serving as a versatile tool for managing uncertainty in diverse and challenging environments.
- Extending uncertain frameworks for the BWM to group decision-making provides a powerful approach for tackling complex, collaborative scenarios. By integrating uncertainty modeling with group dynamics, this method accounts for diverse stakeholder perspectives and varying levels of confidence in judgments. It enhances the robustness and adaptability of BWM, ensuring more inclusive, transparent, and reliable decision outcomes. This advancement is particularly valuable in multi-stakeholder environments, where balancing conflicting preferences and managing uncertainty are critical for achieving consensus and effective solutions.

Finally, one of the most valuable research directions for future studies is the application of existing or new extensions of the best-worst method to real-life problems and complex decision-making scenarios. Empirical validation through case studies across various industries, including supply chain optimization, healthcare prioritization, sustainable energy planning, and financial risk assessment, can demonstrate the method's robustness in complex, dynamic environments.

Practical implementation not only tests the scalability of advanced BWM frameworks but also reveals contextual limitations, enabling iterative refinement of the methodology. By bridging theoretical rigor with pragmatic utility, such applications reinforce BWM's relevance as an adaptive decision-making tool while generating actionable insights for policymakers and industry leaders. This synergy between academia and practice ensures continuous methodological innovation aligned with evolving real-world needs.

8. Conclusions

This study provides a thorough examination of the best-worst method across four key dimensions, based on a comprehensive survey and review of the past decade's advancements in the BWM field. First, it reviews the integration of BWM with other multi-attribute decision-making techniques, emphasizing its distinct advantages and methodological contributions in addressing complex decision problems. Second, it systematically investigates the application of BWM in environments characterized by uncertainty and ambiguity, exploring how the method has been adapted to handle incomplete, imprecise, or conflicting information. Third, the research categorizes and evaluates real-world applications and case studies of BWM, showcasing its versatility and effectiveness across diverse fields such as supply chain management, sustainability assessment, healthcare, and risk analysis.

Finally, using the Scopus database as the primary source, the study conducts a comprehensive bibliometric analysis of BWM literature. This analysis includes Document Analysis, which examines the growth and development of publications over time and by document type; Keyword

Analysis, identifying key terms and emerging trends in BWM research; Source Analysis, evaluating influential journals and conferences publishing BWM studies; Author Analysis, highlighting leading researchers and their contributions to the field; Affiliation Analysis, showcasing the institutions and countries driving BWM research; Citation Analysis, investigating the most cited papers and their impact on the discipline; and Thematic Analysis, examining how different research themes relate to one another in terms of relevance and developmental progress. By synthesizing these perspectives, the study offers a comprehensive understanding of BWM's theoretical foundations, methodological advancements, and practical significance.

CRediT authorship contribution statement

Pejman Peykani: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ali Emrouznejad:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Mojtaba Nouri:** Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation.

Data availability

The data used in this study are available from the corresponding author upon request.

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