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Review

Multi-Objective Optimization in the Digital and AI Eras: A Review of Methodological Evolution and Cross-Domain Applications

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Abstract

With the rapid advancement of digitalization, data-intensive computing, and artificial intelligence (AI), multi-objective optimization (MOO) has shifted from traditional mathematical modeling and algorithmic solving toward integrated decision-support frameworks that incorporate data-driven learning, decision-maker preferences, and complex contextual factors. However, existing literature reviews still exhibit four major gaps: a lack of integrated cross-period evolutionary perspectives, insufficient links between methodological advances and cross-domain decision values, an incomplete synthesis of emerging challenges in AI-driven MOO, and a scarcity of comprehensive frameworks encompassing resilience, sustainability, equity, and public value. To bridge these gaps, this review synthesizes 140 core analytical publications (2000–2026) indexed in the Web of Science Core Collection to establish a cross-period evolutionary framework, integrate major methodological approaches, evaluate decision values across diverse fields, and outline future research directions in the AI era. We trace the development of MOO across three analytical stages: Information-Based Computing (2000–2010), Data-Intensive Decision-Making (2011–2015), and AI-Driven Optimization (2016–present). Furthermore, we examine the evolution of five core paradigms—mathematical programming, evolutionary multi-objective optimization, multi-criteria decision-making, uncertainty and robust modeling, and AI-assisted and data-driven optimization—across seven application domains. Our findings reveal that the research paradigm of MOO has shifted from computational efficiency and solution-set quality toward data-driven adaptability, dynamic response, trustworthy decision-making, and cross-domain value balance. The primary contribution of this study lies in proposing an integrated "Technology Evolution–Mathematical Methods–Application Value" review framework that aligns methodological features with domain-specific needs, facilitates cross-domain comparisons, and highlights future avenues emphasizing interpretability, reliability, human preferences, and public value.

Keywords: multi-objective optimization; methodological evolution; artificial intelligence; cross-domain applications; decision value

MSC: 90C29

Check for updates

Academic Editors: Ye Tian and James Liou

Received: 2 September 2026
Revised: 30 September 2026
Accepted: 1 October 2026
Published: 4 October 2026

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1. Introduction

1.1. Research Background and Significance

With the rapid development of globalization, digital transformation, and intelligent technologies, modern engineering systems, industrial management, and social governance problems have gradually exhibited characteristics of high complexity, uncertainty, and multi-objective conflicts. Many practical decision-making problems can no longer be adequately described by a single performance metric; instead, they must simultaneously account for interrelated factors such as cost, quality, efficiency, risk, sustainability, and equity. Traditional single-objective optimization (SOO) seeks an optimal solution primarily by defining a single objective function. However, in real-world decision-making environments, unavoidable trade-off relationships typically exist among different objectives, making it difficult for a single optimal solution to fully reflect system requirements and decision preferences [1,2].

Such multi-objective conflicts are ubiquitous across diverse decision-making systems. In engineering design and production systems, decision-makers need to balance objectives such as cost, performance, reliability, and energy efficiency to enhance overall system performance [3–5]. In logistics and supply-chain management, enterprises must consider supply risk, system resilience, and environmental sustainability requirements alongside cost reduction and service-level improvement, shifting supply-chain decision-making from a pure efficiency orientation toward a multi-objective coordination paradigm [6–8]. In healthcare systems, the allocation of limited resources involves multiple considerations, including service efficiency, care quality, equitable resource distribution, and long-term management benefits [9,10]. Consequently, establishing decision-making methods capable of handling multiple conflicting objectives and complex constraints simultaneously has become an important research direction in optimization research and management science [1].

Thus, multi-objective optimization (MOO) has gradually evolved into an essential mathematical framework for addressing complex decision-making problems. Unlike SOO, which seeks an optimal solution under a single objective, MOO considers two or more conflicting objective functions simultaneously. It identifies feasible alternatives under different target trade-offs through the nondominance relation, thereby forming a Pareto-optimal set [2]. This concept transforms the traditional optimization mindset of "searching for a single best answer", allowing method selection and final solutions to align with problem information and decision preferences [1].

The development of MOO is primarily built upon the foundations of mathematical programming and evolutionary computation, forming a closely complementary relationship with multi-criteria decision-making (MCDM). Mathematical programming and evolutionary methods are mainly responsible for formulating multi-objective problems and generating feasible solution sets under different trade-offs. Conversely, MCDM is primarily used to express decision preferences, compare candidate solutions, and select an appropriate compromise solution from the Pareto set. Therefore, this paper treats MCDM as a preference integration and alternative selection layer within a generalized multi-objective decision-making process rather than a concept identical to MOO. Early studies focused mainly on multi-objective mathematical models and generative solution strategies [11,12]. With advancements in computing power, evolutionary multi-objective optimization (EMO) gradually became a dominant research direction. Deb et al. [13] proposed the Non-dominated Sorting Genetic Algorithm II (NSGA-II), which improved the convergence and diversity of the solution set using fast nondominated sorting, crowding distance, and elitism, making it a critical benchmark for subsequent research. Since then,

avenues such as decomposition-based search and indicator-driven selection have further expanded the capabilities of EMO in solution-set generation and evaluation [14,15].

In recent years, the evolution of data environments and artificial intelligence (AI) technologies has further reshaped the research landscape of MOO. The abundance of big data, real-time information, and dynamic operations of complex systems present new challenges to traditional optimization methods that rely on fixed models in terms of computational cost, environmental changes, and decision timeliness. To address these challenges, approximation approaches such as surrogate models approximate computationally expensive objective functions to reduce the burden of function evaluations, primarily addressing computationally expensive multi-objective optimization problems. Meanwhile, evolutionary dynamic multi-objective optimization focuses on tracking the moving Pareto set and its Pareto front as the environment changes, thereby addressing dynamic multi-objective optimization problems [16,17]. Building on these foundations, multi-objective reinforcement learning extends MOO to sequential decision-making. Digital twin (DT) technology supports closed-loop optimization through real-time interaction between physical systems and virtual models [18,19]. Furthermore, large language models (LLMs) are progressively applied to problem formulation and automated code generation [20]. These advancements not only improve solution efficiency but also enhance the capacity of MOO to handle computationally expensive and dynamic multi-objective optimization problems. Concurrently, model interpretability, the integration of decision-maker preferences, and human oversight have emerged as vital research topics [21–23].

Beyond algorithmic evolution, the application scope of MOO has gradually expanded from traditional engineering problems to diverse social and environmental systems. Studies in engineering and industrial domains cover production scheduling, manufacturing systems, and data-driven design [3,24,25]. In supply chains, research has extended from network design to sustainability and resilience management [6–8]. The healthcare field emphasizes resource allocation and capacity coordination across different levels of medical services [9,10]. In education and emergency management, MOO is applied to curriculum and educational resource scheduling, as well as emergency logistics distribution [26,27]. Research in public policy and environmental decision-making utilizes multi-criteria frameworks to integrate preferences from diverse stakeholders while balancing the long-term impacts of decisions [28,29]. Collectively, these studies demonstrate that the practical value of MOO is no longer confined to enhancing computational performance but extends to coordinating solution feasibility and multifaceted value alignment.

Against this background, the following section identifies the specific research gaps that motivate the present review.

1.2. Research Gaps

In recent years, MOO-related research has formed a multifaceted methodological framework encompassing mathematical programming, EMO, MCDM, uncertainty and robust modeling, as well as AI-assisted and data-driven optimization. Existing reviews have separately synthesized general MOO and EMO approaches [1,30], computationally expensive multi-objective optimization problems [16], dynamic multi-objective optimization problems [17], and preference-based EMO [22], laying an essential knowledge foundation for understanding diverse methods and specific problem categories. However, these reviews predominantly focus on specific methodologies, problem types, or application scopes as their primary analytical targets. Few have placed the evolution of computational and data environments, the functional shifts and integration paradigms of different methods, and the cross-domain application values involving efficiency, resilience, sustainability, equity, and public value under a unified framework for systematic analysis. As MOO

progressively expands from traditional offline optimization to data-driven, dynamically updated, and AI-collaborative decision-making environments, there remains a critical need to adopt a comprehensive cross-period, cross-method, and cross-domain perspective to re-examine its overarching development. To address this, the present study synthesizes four primary research gaps:

(1) Insufficient integrated analysis of cross-period evolutionary frameworks: Although existing reviews provide in-depth explanations of distinct methods and problem types, they predominantly use specific technical branches as their basic unit of analysis, rarely placing changes in computational power, data roles, and decision outputs within a single historical framework. The development of MOO reflects not merely improvements in algorithmic performance, but the joint influence of changes in computational capability, data environments, and practical decision-making requirements. Without an integrated cross-period perspective, the evolution of different methods can easily be perceived as mutually independent technological updates, failing to illuminate how advancements in information infrastructure, data availability, and system complexity have reshaped the developmental trajectory of MOO. Consequently, establishing a review framework that links technological environment dynamics with methodological evolution is necessary to achieve a more complete understanding of MOO's development context.

(2) Lack of a systematic link between methodological development and cross-domain application values: Existing methodological reviews primarily explain the mechanics of models or algorithms, whereas domain-specific studies evaluate solutions within specific contexts. A common evaluative scale capable of comparing problem structures, data requirements, validation standards, and decision values between these two lines of research remains lacking. Engineering research typically emphasizes physical feasibility and computationally expensive evaluation management [31], whereas supply-chain management focuses on network coupling, sustainability, and disruption resilience [7,8]. Healthcare and public decision-making place greater emphasis on accessibility, equity, and procedural legitimacy [28,32], while environmental decision-making further involves long-term risks and spatial spillovers [33]. Existing literature predominantly addresses these values within their respective domains, leaving the applicability conditions and evidence standards of identical methods across different contexts insufficiently articulated. Therefore, establishing a cross-domain comparative framework that connects methodological capabilities, application contexts, and decision values is essential.

(3) Comprehensive synthesis of emerging challenges in AI-driven MOO remains lacking: Existing reviews have separately addressed surrogate models, dynamic optimization, and preference-based EMO, touching upon fundamental issues such as function approximation, environmental updates, and human preferences [16,17,22]. However, in recent years, AI, machine learning (ML), reinforcement learning (RL), DT, and LLMs have progressively intervened in MOO's problem formulation, function approximation, search control, policy updating, and decision communication, expanding their roles beyond isolated algorithmic components [18–20]. Existing literature still overwhelmingly focuses on computational performance, lacking an integrated discussion regarding model interpretability, preference quality, and human oversight in high-stakes decision-making [21–23]. Therefore, in addition to addressing how AI enhances optimization performance, MOO research must analyze how AI functions under conditions of trustworthiness, interpretability, and alignment with decision-making requirements.

(4) Lack of a comprehensive evaluation perspective integrating multidimensional decision values: Existing methodological studies predominantly focus on objective function values, computational efficiency, convergence, diversity, and solution-set quality as their primary evaluative metrics [34,35], rarely comparing solutions across domains in terms of the practical values generated at organizational, social, and public levels. Although these metrics are crucial for algorithmic comparisons, solution value within complex systems depends further on domain-specific evidence and consequences. Healthcare and public governance must account for service accessibility, value conflicts, and procedural legitimacy [28,32]; environmental decision-making involves stakeholder perspectives, long-term risks, and resource allocation [29,33]. Consequently, the evaluation framework for MOO needs to expand beyond traditional efficiency orientations toward multidimensional analysis encompassing resilience, sustainability, equity, and public value. Taken together, these gaps motivate the research objectives defined below.

1.3. Research Objectives

Grounded in the identified gaps in the literature, this paper develops a comprehensive review framework that bridges technological evolution, methodological paradigms, and domain-specific applications within the MOO landscape. Specifically, this work pursues the following fourfold objective:

(1) To establish a multi-period evolutionary framework for MOO by analyzing transitions in computational environments, data roles, problem complexity, dominant methodological functions, and decision-output paradigms across three analytical stages: Information-Based Computing, Data-Intensive Decision-Making, and AI-Driven Optimization;
(2) To compare the functional roles and applicability conditions of two optimization approaches—mathematical programming and EMO—with MCDM as a complementary decision-support approach while also examining uncertainty and robust modeling and AI-assisted and data-driven optimization as cross-method enhancement layers;
(3) To compare MOO applications across engineering and industrial management, logistics and supply-chain management, healthcare systems, education, emergency management, public governance, and environmental sustainability, with particular attention to objective conflicts, constraints, evidence requirements, and decision values;
(4) To identify emerging opportunities and open research challenges in AI-enabled MOO, specifically focusing on model interpretability, decision reliability, human preference integration, dynamic adaptability, and practical deployment.

1.4. Research Contributions

Anchored in the identified research gaps and study objectives, this review provides an integrative perspective on the evolution, methodological taxonomy, and cross-domain decision-making value of MOO. Specifically, its primary contributions are fourfold:

(1) It provides an evidence-based, longitudinal analytical framework that interprets the evolution of MOO by examining transitions in computational and data environments, core methodological functions, decision outputs, and validation paradigms across three developmental stages.
(2) It establishes a functional methodological architecture that delineates mathematical programming and EMO as primary optimization paradigms, integrates MCDM as a complementary decision-support mechanism, and positions uncertainty and ro-

bust modeling alongside AI-assisted and data-driven optimization as cross-method enhancement layers.

(3) It develops a cross-domain comparative framework that evaluates how problem structures, operational constraints, evidential requirements, and decision values vary across seven application domains, thereby systematically bridging methodological capabilities with domain-specific needs.

(4) It advances the review into the AI era by systematically bridging emerging methodological opportunities with critical dimensions of algorithmic interpretability, decision reliability, human preference integration, governance oversight, and real-world deployment constraints.

These contributions, along with their alignment with the four identified research gaps, three analytical stages, core methodological paradigms, and seven application domains, are systematically synthesized in Figure 1.

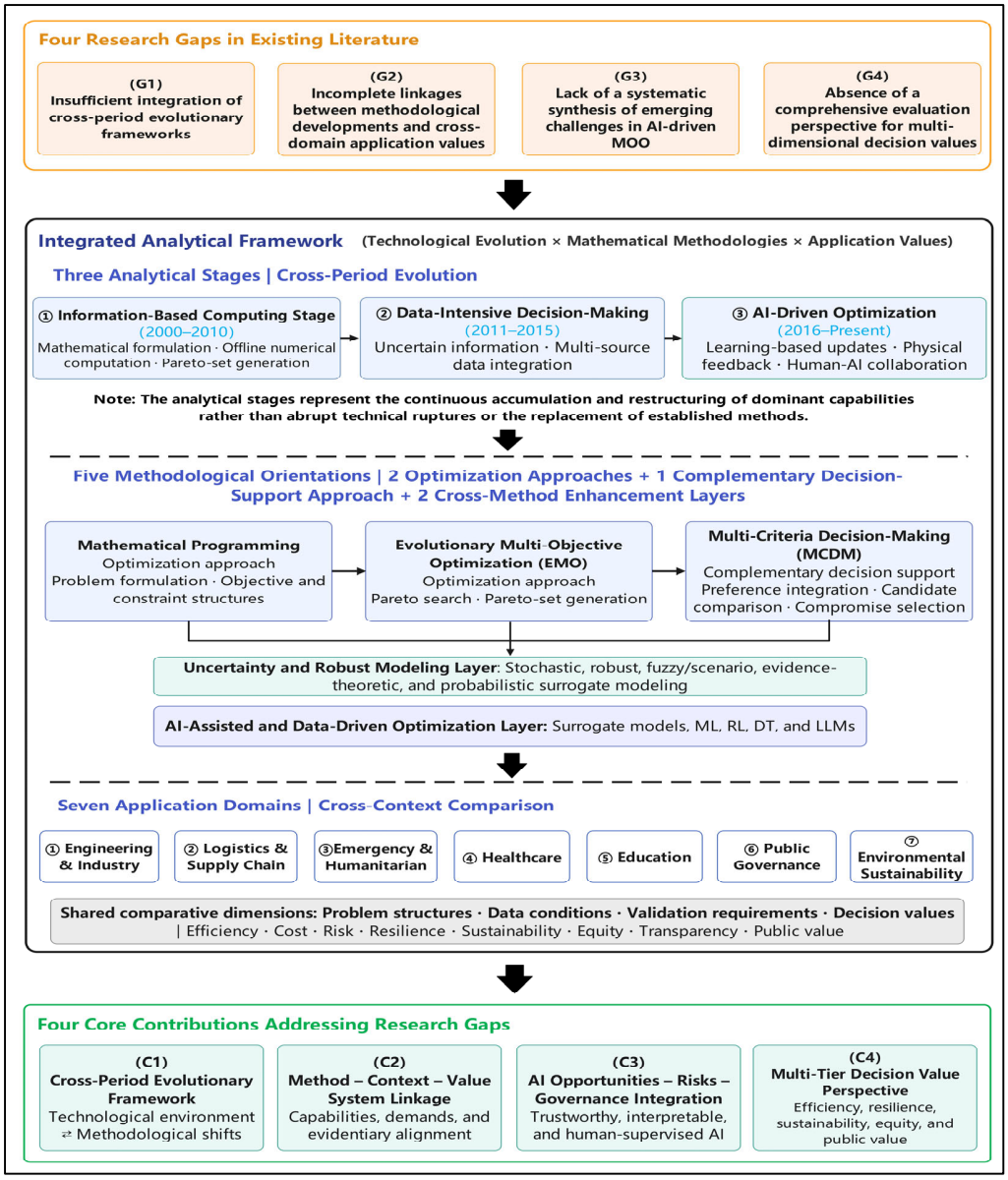


Figure 1. Conceptual framework of the integrative review on MOO. Note: The arrows indicate the logical progression from the identified research gaps through the integrated analytical framework to the corresponding research contributions.

1.5. Research Organization

The remainder of this paper is organized as follows. Section 2, "Literature Development and Analytical Framework", develops an interpretive periodization of MOO-related research and compares representative methodological developments and research-domain composition across the three analytical stages. Section 3, "Mathematical Methods and Theoretical Framework", elaborates on the principal methodological framework of MOO, first comparing two optimization approaches—mathematical programming and EMO—with MCDM as a complementary decision-support approach, then analyzing two cross-method enhancement layers—uncertainty and robust modeling—alongside AI-assisted and data-driven optimization, exploring their core mechanisms, integration paradigms, and applicability contexts. Section 4, "Cross-Domain Applications and Decision Value", analyzes the applications of MOO across engineering optimization and industrial engineering management, logistics and supply-chain management, healthcare systems, education, emergency management, public governance, and environmental sustainability, demonstrating how MOO supports decision-making in complex systems. Finally, Section 5, "Conclusions and Implications," synthesizes the main research findings, proposes a future research agenda encompassing problem-feature–methodology adaptability, continuous trustworthiness, human–AI collaborative decision-making, and multidimensional decision values, highlights practical application implications, and addresses the limitations of this study.

2. Literature Development and Analytical Framework

Section 2 presents the review methodology and the three-stage analytical framework, detailing literature identification and taxonomy, evidence evaluation, stage-specific features, and cross-stage synthesis.

2.1. Review Methodology and Analytical Procedures

2.1.1. Review Design, Literature Identification and Analytical Periodization

This study adopts a structured integrative review methodology guided by a purposive and iterative literature selection strategy. The Web of Science (WOS) Core Collection served as the primary data source, retrieving English-language journal articles and review papers indexed in the Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), and Emerging Sources Citation Index (ESCI). The sampling timeframe spans from 2000 to 2026, with the final retrieval executed on 30 June 2026. Guided by the "developmental stage–methodological orientation–research domain" analytical framework, literature was identified iteratively through multiple combinations of keywords related to multi-objective optimization, mathematical methodologies, intelligent technologies, and cross-domain applications. The review process emphasized transparent literature identification, analytical relevance, and integrative synthesis, consistent with the review-design principles discussed by Xiao and Watson [36] and Snyder [37].

Literature identification and selection followed an iterative, two-stage screening protocol. Publications retrieved via the predefined keyword combinations were first screened by title and abstract to assess topical relevance, methodological focus, key findings, and application domains. Candidate articles were subsequently evaluated through comprehensive full-text review, scrutinizing problem formulation, objective modeling, methodological design, substantive contributions, and conceptual alignment with our analytical framework. Publications meeting the inclusion criteria and providing sufficient information for substantive analysis and classification were retained as core analytical publications.

Studies were eligible for inclusion if they met the following criteria: (1) formulated an identifiable multi-objective or multi-criteria decision structure; (2) utilized or substantially informed at least one of the core methodological orientations identified in this

review—namely, mathematical programming, EMO, MCDM, uncertainty and robust modeling, or AI-assisted and data-driven optimization; and (3) supplied adequate methodological or empirical evidence addressing at least one analytical dimension across developmental stages, methodological orientations, or application domains. Specifically, MCDM studies were incorporated only if functionally linked to multi-objective trade-offs via preference or weight elicitation, Pareto-set filtering, compromise-solution selection, or integrated optimization–decision frameworks.

Conversely, studies were excluded if they: (1) focused exclusively on generic AI, broad management concepts, or single-objective optimization without explicit multi-objective or multi-criteria formulations; (2) were restricted to stand-alone indicator evaluations or routine alternative ranking; or (3) constituted conference abstracts, editorials, book reviews, duplicate records, or publications lacking sufficient full-text detail for rigorous analytical classification.

Through this iterative identification, review, and selection process, 140 publications were retained as the core analytical corpus and subsequently classified by developmental stage, methodological orientation, and research domain, as summarized in Figure 2. The 140 publications constituting the fixed analytical corpus are listed as References [1–140] and form the basis for all descriptive statistics and cross-stage analyses reported in this review. Among these, 127 publications were mapped to the five core methodological orientations, whereas 13 were categorized as review and research-support literature and subsequently excluded from the proportional calculations across the five orientations. Foundational theoretical references [141,142] and additional recent or contextual references [143–148] are used to support theoretical interpretation, methodological discussion, and emerging or future research directions and are not included in the statistical analyses of the 140 core analytical publications.

The final total of 140 publications was not predetermined as a statistical sample; rather, it represents a core analytical corpus systematically established through an iterative process of identification, screening, comparative appraisal, and cross-referencing, guided by our research objectives, analytical framework, and the five selection principles delineated below. Literature selection continued until the three analytical stages, the principal methodological orientations, and the seven application domains were each represented by sufficient literature to support the comparative and integrative analyses undertaken in this review.

Literature selection was guided by five complementary principles: foundational significance, methodological representativeness, methodological evolutionary linkage, recent methodological and application relevance, and relevance to the analytical framework. Foundational significance refers to studies that establish or consolidate core concepts, mathematical foundations, canonical methods, or evaluation principles in MOO. Methodological representativeness prioritizes publications that exemplify core algorithmic families, problem structures, or foundational technical pathways. Methodological evolutionary linkage captures studies that delineate how established paradigms are extended, hybridized, or transformed into subsequent methodological innovations. Recent methodological and application relevance encompasses state-of-the-art advances in data-driven, AI-assisted, dynamic, or cross-domain MOO research. Relevance to the analytical framework requires that a publication provide substantive evidence for at least one of the three analytical dimensions used in this review: developmental stage, methodological orientation, or research domain.

These selection principles were informed by established literature-review methodology and reporting guidance [36–42] and representative MOO reviews. Xiao and Watson [36] and Snyder [37] emphasize alignment among review purpose, literature identification, selection, and synthesis. Within the MOO field, Marler and Arora [1], Coello Coello [77],

Zhou et al. [30], and Emmerich and Deutz [2] demonstrate the importance of organizing the literature around mathematical foundations, representative methodological families, historical development, and emerging methodological trajectories. Accordingly, earlier publications primarily serve to establish theoretical and methodological foundations, represent pivotal technical pathways, and trace evolutionary trajectories. Conversely, more recent literature is utilized to capture cutting-edge methodological innovations, data- and AI-driven paradigms, and emerging cross-domain applications. Consequently, the publication counts and proportional distributions reported in subsequent sections reflect the internal composition of this curated 140-publication analytical corpus.

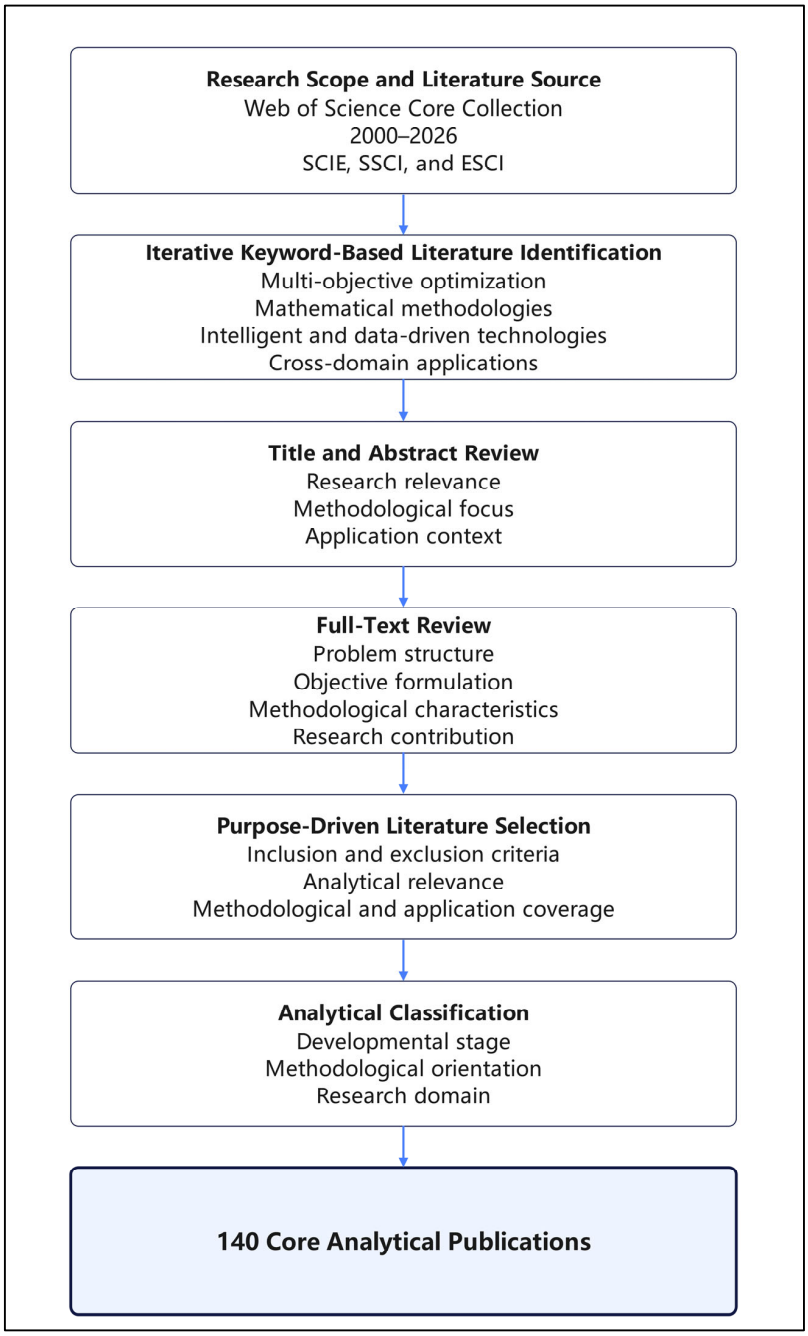


Figure 2. Literature identification, selection, and analytical classification framework. Note: The two foundational papers by Zadeh and Saaty serve solely as theoretical bases and are excluded from the 140 core analytical papers and their statistical summaries.

This review proposes an evidence-grounded, three-stage analytical periodization of the MOO literature: Information-Based Computing (2000–2010), Data-Intensive Decision-Making (2011–2015), and AI-Driven Optimization (2016–present). The designation of "Information-Based Computing" serves as a conceptual heuristic operationalized specifically for this study rather than an established disciplinary term. It delineates a foundational era primarily characterized by explicit mathematical formulation, offline numerical computation, and Pareto-set generation, prior to the widespread emergence of large-scale data integration, adaptive learning mechanisms, and real-time feedback loops in MOO research. These boundaries are operational rather than abrupt historical breaks and are defined by shifts across five analytical dimensions: computational environment, role of data, problem complexity, dominant methodological function, and decision-output paradigm. The first stage is grounded in foundational and representative studies that consolidated mathematical formulations, Pareto-based solution generation, and evolutionary multi-objective optimization, as reflected in Marler and Arora [1] and Coello Coello [77]. The 2010/2011 boundary reflects the convergence, in the early 2010s, of developments associated with complex EMO, robust optimization, surrogate-assisted computation, and multi-objective sequential decision-making, as documented by Zhou et al. [30], Bertsimas et al. [52], Jin [56], and Roijers et al. [57]. The 2015/2016 threshold is similarly conceptualized as an operational inflection point—one that reflects the convergence of cyber–physical connectivity, data-intensive computation, surrogate-assisted modeling, and subsequent AI-driven adaptive decision support rather than positing an abrupt emergence of AI-enabled MOO in 2016. Representative developments around this transition are illustrated by Monostori et al. [4] and Díaz-Manríquez et al. [85]. Across the three analytical stages, the principal interpretive trajectory is summarized as offline modeling and Pareto-set generation → uncertainty, multi-scenario, and data integration → learning, dynamic updating, and AI-assisted decision support. Figure 3 and Table 1 therefore provide descriptive views of the temporal and methodological composition of the 140 core analytical publications rather than estimates of global MOO publication trends.

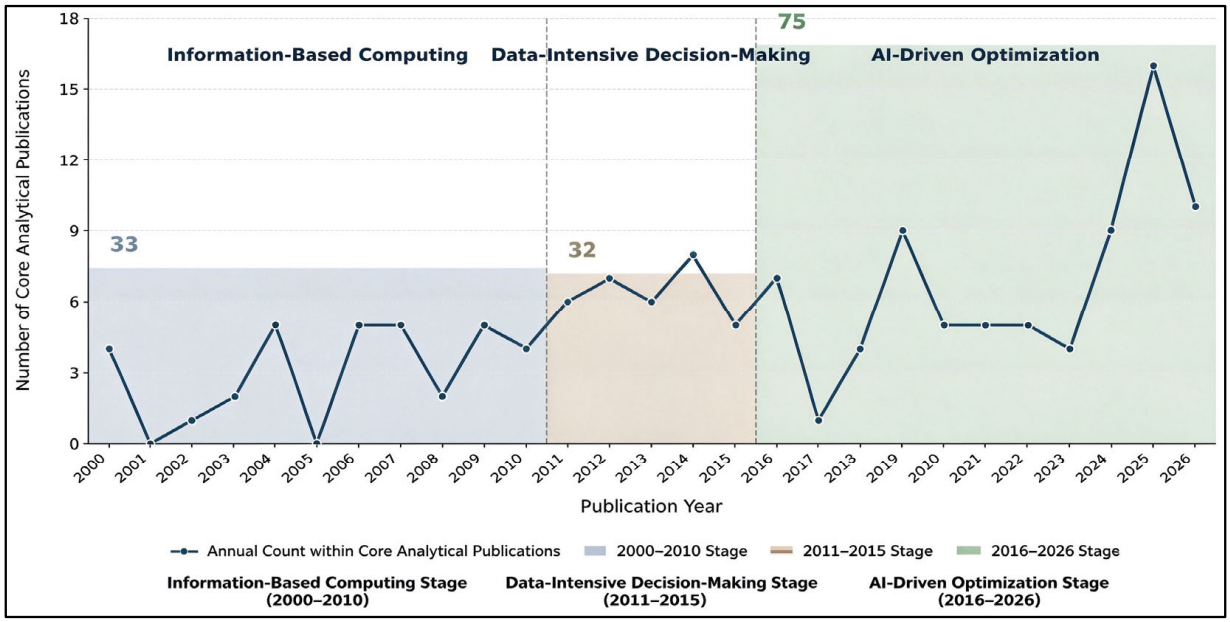


Figure 3. Temporal distribution of the 140 core analytical publications. Note: Publication counts per year and stage describe the temporal distribution of the 140 core analytical publications; data for 2026 are reported through 30 June 2026.

Table 1. Distribution of core analytical publications across the three developmental stages and primary methodological orientation.

Developmental Stage	Mathematical Programming	EMO	MCDM	Uncertainty	AI-Assisted	Review and Research-Support Literature	Total
Information-Based Computing Stage (2000–2010)	10	11	5	2	2	3	33
Data-Intensive Decision-Making Stage (2011–2015)	13	8	4	5	2	0	32
AI-Driven Optimization Stage (2016–Present)	8	12	14	4	27	10	75
Total	31	31	23	11	31	13	140

Note: Includes 13 publications classified as review and research-support literature, which are excluded from the proportional calculations of the five methodological orientations; the percentages for the five orientations are calculated using the remaining 127 publications as the denominator.

2.1.2. Classification, Coding, and Evidence Assessment

Each of the 140 core analytical publications was assigned one primary methodological orientation and one primary research domain for mutually exclusive descriptive analysis. Each publication's primary methodological orientation was assigned based on four criteria: the nature of its research problem, the technique executing the dominant analytical or optimization function, its core methodological innovation, and its primary theoretical or empirical contribution. For example, when mathematical programming and MCDM were combined, mathematical programming was treated as the primary orientation if the principal contribution concerned model formulation or Pareto-solution generation, whereas MCDM was treated as primary when the main contribution concerned preference integration, alternative comparison, or compromise-solution selection. The primary research domain was determined according to the principal decision context, data source, validation setting, and ultimate application purpose.

To accommodate hybrid and cross-domain studies without compromising the mutually exclusive categorization required for descriptive statistics, secondary methodological and domain attributes were coded as auxiliary labels for qualitative synthesis. Consequently, primary classifications served as the sole baseline for stage- and method-level statistical distributions, while secondary methodologies, hybrid architectures, and interdisciplinary traits were qualitatively preserved to prevent double-counting. Among the 140 core analytical publications, 127 were classified into five analytical methodological orientations—mathematical programming, EMO, MCDM, uncertainty and robust modeling, and AI-assisted and data-driven optimization—while the remaining 13 were classified as review and research-support literature and excluded from the proportional calculations of the five orientations. Publications were classified under "AI-assisted and data-driven optimization" as their primary orientation only when AI or data-driven techniques actively drove core optimization mechanisms—specifically function approxima-

tion, algorithmic search, parameter updating, or decision-support processes—within a multi-objective context.

Two authors independently classified all 140 core analytical publications using the same coding rules. The initial classification agreement was 73.6%, while 26.4% of the publications (37 of 140) showed classification differences. For publications with inconsistent initial classifications, all authors jointly re-examined the research problem, dominant methodological function, application context, and principal contribution, and the final classification was determined through discussion and consensus.

To evaluate the empirical grounding of the reviewed literature, the 140 core publications were systematically categorized across six principal validation paradigms: theoretical or methodological derivation, benchmark or numerical testing, simulation and scenario-based experimentation, real-world case or empirical validation, operational deployment or longitudinal evidence, and comprehensive review or synthesis. The classification reflected the principal form of evidence used to support each study's main claims rather than assigning a numerical quality score. Accordingly, benchmark tests, simulations, empirical cases, operational deployments, and review studies were not treated as evidentially equivalent; instead, their findings were interpreted in relation to the type and setting of validation reported in each publication. This evidence classification was used to qualify the strength and transferability of the conclusions drawn in the subsequent synthesis.

Figure 3 illustrates the chronological distribution of the 140 core analytical publications evaluated in this review. The observable concentration of studies in recent years reflects the internal composition of this curated corpus and should not be construed as an empirical estimate of the overall publication volume or annual growth rate of the global MOO literature. Accordingly, temporal patterns in Figure 3 are used descriptively, whereas the interpretation of methodological evolution is based on the substantive characteristics of representative studies and the five analytical dimensions defined in Section 2.1.1.

2.2. Information-Based Computing Stage (2000–2010)

The Information-Based Computing stage is primarily characterized by computerized modeling, offline numerical computation, and Pareto set generation, shifting multi-objective problems from pre-weighted single outcomes toward the systematic generation and comparison of non-dominated solution sets. Of the 140 core analytical publications, 33 fall within this analytical stage, representing 23.57% of the total corpus. Methodologically, EMO accounts for 11 publications in this stage, followed closely by mathematical programming with 10. These counts describe the internal composition of the analytical corpus; the interpretation of parallel developments in explicit mathematical modeling and population-based Pareto search is based on the representative methodological studies discussed below rather than on publication counts alone. Regarding mathematical programming, Ehrgott and Gandibleux [11] established a problem and methodology classification for multi-objective combinatorial optimization (MOCO); Marler and Arora [1] synthesized MOO methods based on whether preference articulation occurs before, during, or after the solving process, emphasizing that methodological selection must align with problem information and decision-making requirements. Generative methods also progressively enhanced practical feasibility; for instance, the Augmented ε-Constraint Method (AUGMECON) avoids weakly Pareto-optimal solutions and reduces redundant computations [12]. Table 2 synthesizes representative theoretical, algorithmic, and applied research in this stage.

Table 2. Representative research in the Information-Based Computing Stage (2000–2010).

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Ehrgott and Gandibleux (2000) [11]	Establish a general formulation of MOCO and synthesize main theoretical and problem types.	Survey and classification of MOCO problems and methods.	Systematized MOCO formulations and solution approaches.	Multi-objective combinatorial optimization.
Knowles and Corne (2000) [43]	Approximate non-dominated fronts using a concise evolutionary framework.	PAES with archive-based evolutionary search.	Established a concise approach for Pareto-front approximation.	General MOO benchmark problems.
Deb et al. (2002) [13]	Improve non-dominated sorting, elitism preservation, and solution set diversity.	NSGA-II with fast sorting, elitism, and crowding distance.	Improved convergence, diversity, and computational efficiency.	Benchmark and constrained MOO problems.
Zitzler et al. (2003) [34]	Clarify how the quality of approximation sets can be quantified and compared.	Performance indicators and approximation-set assessment.	Clarified the evaluation and comparison of MOO solution sets.	MOO performance assessment.
Marler and Arora (2004) [1]	Consolidate engineering MOO concepts, terminology, and method selection.	Review and classification of MOO methods.	Organized MOO methods according to preference articulation and method selection.	Engineering optimization.
Farina et al. (2004) [45]	Establish the research foundation for tracking time-varying Pareto fronts.	Dynamic MOO test problems and baseline EMO.	Established test cases for tracking of time-varying Pareto fronts.	Dynamic multi-objective optimization.
Knowles (2006) [46]	Solve computationally expensive MOO under extremely limited exact evaluations.	ParEGO and Gaussian process surrogate modeling.	Reduced exact evaluations through surrogate-assisted sequential search.	Expensive multi-objective optimization.
Zhang and Li (2007) [14]	Reduce the collaborative search cost of multi-objective evolutionary search.	MOEA/D decomposition and neighborhood information sharing.	Reduced search complexity and generated well-distributed solution sets.	Knapsack and continuous MOO problems.
Beume et al. (2007) [15]	Incorporate solution set quality directly into the selection process.	SMS-EMOA and hypervolume-based selection.	Combined hypervolume-based selection with non-dominated sorting to generate well-distributed solution sets.	Benchmark and aeronautical optimization problems.
Mavrotas (2009) [12]	Efficiently generate Pareto solution sets for multi-objective mathematical programming.	AUGMECON/ε-constraint method.	Avoided weakly Pareto-optimal solutions and redundant iterations.	Multi-objective mathematical programming.

Table 2. *Cont.*

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Sabri and Beamon (2000) [6]	Simultaneously integrate supply-chain strategic and operational planning.	Multi-objective supply-chain mathematical modeling.	Integrated cost, customer service, flexibility, and uncertainty across the supply chain network.	Supply-chain design and planning.

(1) EMO also formed four far-reaching technical pathways during this stage: archive-based local search represented by Pareto Archived Evolution Strategy (PAES) [43], elitist non-dominated sorting represented by NSGA-II [13], the decomposition framework of Multiobjective Evolutionary Algorithm Based on Decomposition (MOEA/D) [14], and indicator-based selection represented by S-Metric Selection Evolutionary Multiobjective Optimization Algorithm (SMS-EMOA) [15]. Together, these pathways laid the research foundation for subsequent EMO developments in solution-set generation, evolutionary selection, and performance comparison.

(2) As solution-set generation capabilities advanced, performance evaluation emerged as an independent research focus. Distinct indicators separately capture the distance to the reference front, coverage spread, and distributional uniformity of a solution set; consequently, a single indicator can rarely encompass all quality dimensions [34]. Meanwhile, fast hypervolume computation facilitated its widespread application in algorithm comparison and selection [44]. Since then, convergence, diversity, and computational cost have progressively become the fundamental verification requirements for MOO methodologies.

(3) Prototypes of dynamic and surrogate-assisted optimization also emerged during this stage. Farina et al. [45] extended the research scope from static front approximation to time-varying Pareto front tracking; meanwhile, Pareto Efficient Global Optimization (ParEGO) leveraged Gaussian processes to solve expensive multi-objective problems under limited evaluation budgets [46], with subsequent metamodels beginning to simultaneously express predicted values and model uncertainties [47]. These studies established the fundamental rationale of utilizing learning models to reduce exact simulation costs.

(4) Applied research also began transitioning from methodological validation toward practical systems. Supply-chain models integrated cost, service, resilience, and uncertainty [6]; production scheduling expanded from single completion times to multiple conflicting performance metrics [3]; and healthcare operations research addressed operating-room planning and patient appointment scheduling [48,114].

Overall, this stage established the common language of Pareto solution sets, the two primary solving paths of mathematical programming and EMO, and evaluation standards such as convergence and diversity, thereby laying the groundwork to address high-dimensional data and uncertainty in subsequent stages.

2.3. Data-Intensive Decision-Making Stage (2011–2015)

The data-intensive decision-making stage is characterized not by ML having become mainstream but by the growth of objective counts, contextual data, uncertain information, and cross-system constraints, rendering fixed parameters and low-dimensional test problems insufficient to reflect real-world decision-making. Mathematical programming and EMO remained the primary tools, but robust/stochastic modeling, surrogate models,

sequential decision-making, and MCDM preference integration began jointly addressing risk and data complexity. Of the 140 core analytical publications, 32 are attributed to this developmental stage, representing 22.86% of the corpus. Notably, five publications within this cohort focus on uncertainty and robust modeling, up from two in the preceding stage. This comparison serves a purely descriptive purpose; our substantive interpretation regarding the expanding role of uncertainty handling is anchored in the representative studies on robust optimization, stochastic modeling, uncertain MCDM, and associated methodological advances examined below. Table 3 synthesizes representative research in this stage across many-objective optimization, uncertainty, surrogate modeling, sequential decision-making, and applications.

Table 3. Representative research in the Data-Intensive Decision-Making Stage (2011–2015).

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Rais and Viana (2011) [9]	Synthesize optimization problems and techniques in healthcare operations research.	Review of healthcare OR models and optimization techniques.	Synthesized resource allocation, scheduling, and treatment-planning research.	Healthcare systems.
Zhou et al. (2011) [30]	Integrate developments of EMO algorithms in decomposition, dynamic, expensive, and constrained discrete problems.	Frontier review and algorithm taxonomy.	Expanded EMO from basic frameworks to complex problem types.	General MOO and cross-domain applications.
Jin (2011) [56]	Synthesize how surrogate models reduce expensive evaluations in evolutionary computation.	Surrogate-/metamodel-assisted evolutionary computation.	Established model management and future challenge agendas.	Expensive, dynamic, and constrained problems.
Bertsimas et al. (2011) [52]	Integrate theory, computation, and applications of robust optimization.	Uncertainty sets, adjustable, and multi-stage robust optimization.	Balanced tractability with uncertainty representation.	Finance, machine learning, and engineering.
Behzadian et al. (2012) [58]	Classify Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methodologies and cross-domain applications.	Review of 266 documents and nine application classifications.	Demonstrated the diffusion and hybrid application trends of MCDM.	Supply chain, engineering, healthcare, energy, etc.
Durbach and Stewart (2012) [55]	Synthesize uncertain evaluation and preference processing in multi-criteria decision analysis (MCDA).	Probability, risk, fuzzy numbers, and scenario analysis.	Established a tool system for MCDM under uncertainty.	General decision analysis.
Ben Abdelaziz (2012) [54]	Classify deterministic transformations and solution methods for multi-objective stochastic programming.	Random variables, efficiency concepts, and model transformations.	Systematically synthesized solution methods for stochastic multi-objective problems.	Planning and risk decision-making.

Table 3. *Cont.*

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Roijers et al. (2013) [57]	Determine when multi-objective sequential decision-making cannot be reasonably scalarized.	Scalarization, policy types, and solution-form classifications.	Linked preferences, policy sets, and Pareto outputs.	Planning and learning.
Mavrotas and Florios (2013) [51]	Obtain exact Pareto sets for multi-objective integer programming.	AUGMECON2	Improved the efficiency and accuracy of generative methods in multi-objective integer programming.	Combinatorial and integer programming.
Deb and Jain (2014) [49]	Maintain search pressure and distribution in many-objective problems.	NSGA-III and reference points.	Expanded EMO to 3–15 objectives.	Many-objective optimization.
Li et al. (2015) [50]	Classify many-objective evolutionary algorithms.	Review of 7 categories of many-objective evolutionary algorithm frameworks.	Highlighted research directions including dominance resistance, preferences, and dimensionality reduction.	General many-objective problems.
Hulshof et al. (2012) [10]	Link different decision levels of healthcare capacity planning and control.	Operations research/management science taxonomy and structured review.	Assisted in identifying relationships among strategic, tactical, and operational decisions.	Healthcare systems.
Caunhye et al. (2012) [27]	Synthesize pre-disaster and post-disaster logistics optimization models.	Content analysis and structural model classification.	Systematically synthesized gaps in facility location, distribution, and casualty transportation.	Emergency logistics.
Bozorgi-Amiri et al. (2013) [60]	Balance relief costs and regional shortage equity under multiple uncertainties.	Multi-objective robust stochastic programming.	Integrated supply, demand, facility disruption, and equity.	Disaster relief.
Eskandarpour et al. (2015) [59]	Evaluate objectives, tools, and industrial contexts in sustainable supply chain network models.	Optimization-oriented review of 87 documents.	Highlighted research gaps in life cycle, social metrics, and uncertainty.	Sustainable supply chains.
Huang et al. (2011) [29]	Analyze a decade of application and methodological trends in environmental MCDM.	WOS literature search, application, and methodology classifications.	Linked technical evidence, stakeholder values, and environmental decision-making.	Environmental governance.

(1) An increase in objective dimensionality altered the design requirements of EMO. EMO research expanded to cover decomposition, dynamic, noisy, constrained, discrete, and expensive problems; in many-objective scenarios, candidate solutions are largely non-

dominated by one another, causing the selection pressure of traditional dominance relations to deteriorate. The Non-dominated Sorting Genetic Algorithm III (NSGA-III) utilizes reference points to maintain the solution set distribution in high-dimensional objective spaces, while related methods have also developed alternative pathways, such as relaxed dominance, performance indicators, decision-maker preferences, and dimensionality reduction [49,50].

(2) Mathematical programming also processed integer decisions and uncertain parameters more systematically. Methodologically, the improved Augmented ε-Constraint Method (AUGMECON2) substantially accelerated the generation of exact Pareto-optimal sets for multi-objective integer programming [51]. Simultaneously, robust optimization incorporated uncertainty sets, adjustable decision structures, and multi-stage formulations [52,53], whereas stochastic programming accommodated probabilistic variations across objective coefficients and constraint parameters [54]. In parallel, MCDM increasingly integrated probability theory, risk measures, fuzzy sets, and scenario analysis to capture pervasive uncertainties in criterion evaluations and decision-makers' preferences [55].

(3) Surrogate models and sequential decision-making also gradually formed independent methodological clusters. Surrogate-assisted evolutionary computation expanded from expensive function approximation to dynamic, constrained, and multimodal problems, with key elements including model updating and precise sample allocation [56]. Multi-objective sequential decision-making, depending on the preference form, produces a single policy, a convex coverage set, or a Pareto policy set, laying the foundation for subsequent multi-objective RL [57].

(4) The diffusion of MCDM reflects the increasing complexity of evaluation attributes, stakeholders, and decision-making contexts. TOPSIS has been widely applied across supply chain, engineering, healthcare, energy, and water resource management domains [58]; environmental decision-making research has similarly utilized MCDM to integrate technical information, stakeholder values, and socio-environmental–economic impacts [29]. Within the MOO workflow, MCDM can articulate preferences a priori, guide regions of interest interactively during search, or rank and compromise among options a posteriori after the Pareto solution set is formed.

(5) Applied research further incorporated risk, sustainability, and equity. Sustainable supply-chain models extended beyond cost and carbon emissions to encompass lifecycle impacts, social performance, and uncertainty [59]; healthcare planning began bridging strategic, tactical, and operational levels [10]; and emergency logistics spanned facility location, inventory pre-positioning, distribution, and casualty transportation [27], utilizing robust stochastic programming to simultaneously address cost, infeasibility risk, and regional shortage equity [60].

Overall, this stage forged a collaborative "model–data–preference" framework: mathematical programming and EMO handled modeling and search, surrogate models reduced evaluation costs, and MCDM alongside uncertainty methods supported preference and risk management, thereby laying the groundwork for AI to directly participate in search and real-time decision-making in subsequent stages.

2.4. AI-Driven Optimization Stage (2016–Present)

The primary characteristic of the AI-driven optimization stage is that ML, RL, DTs, surrogate models, and LLMs have begun directly intervening in function approximation, search control, policy updating, and physical feedback, transforming data from static model inputs into learning resources that continuously update models and policies. Within the 140 core analytical publications, 75 were assigned to the third analytical stage, account-

ing for 53.57% of the corpus. Of these, 27 were classified as AI-assisted and data-driven optimization, while 10 were categorized as review and research-support literature. After excluding the latter, the remaining 65 publications were distributed across the five methodological orientations, with AI-assisted and data-driven optimization accounting for 41.5%. This percentage identifies the largest methodological orientation within the third-stage analytical corpus and is not intended as an estimate of its prevalence in the global MOO literature. The substantive importance of AI- and data-driven approaches is instead evaluated through their demonstrated roles in approximation, search control, updating, sequential decision-making, and physical feedback. While relevant technologies primarily enhance approximation, search, updating, and decision timeliness, their operations remain fundamentally grounded in mathematical programming, EMO, MCDM, and uncertainty modeling. Table 4 synthesizes representative research on AI intervention across different aspects of MOO during this stage.

Table 4. Representative research in the AI-Driven Optimization Stage (2016–Present).

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Chugh et al. (2019) [16]	Classify approximation methods and evolutionary control in computationally expensive MOO.	Review of surrogate-assisted EMO.	Proposed criteria for selecting methods based on dimensionality, budget, and approximation type.	Expensive black-box problems.
Jiang et al. (2023) [17]	Systematically synthesize MOO with time-varying objectives, constraints, and environments.	Taxonomy and review of evolutionary dynamic MOO.	Shifted research focus from static solving to front tracking.	Dynamic systems.
Hayes et al. (2022) [18]	Illustrate problem settings and solution concepts in multi-objective RL and planning.	Taxonomy of policies, preferences, and scalarization.	Linked policy sets, Pareto fronts, and sequential decision-making.	Dynamic decision-making and control.
Tao et al. (2019) [19]	Synthesize DT components, industrial applications, and research gaps.	Review of industrial DT frontiers.	Established a physical–cyber space integration framework.	Smart manufacturing.
Barredo Arrieta et al. (2020) [21]	Establish definitions, taxonomies, and challenges of explainable AI.	Review of model explanation methods.	Linked explainability, fairness, and accountability to responsible AI.	High-risk AI decision-making.
Mehrabi et al. (2021) [70]	Identify AI bias sources and definitions of fairness.	Review and taxonomy of bias and fairness.	Incorporated community impacts into AI system design.	Societal and sensitive decision-making.
Ren et al. (2026) [22]	Analyze how preferences guide EMO to regions of interest.	Preference expression, modeling, and incorporation mechanisms.	Linked evolutionary search, human-centered interaction, and cognitive load.	Preferred decision support.

Table 4. *Cont.*

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Zhang et al. (2024) [62]	Synthesize how ML enhances multi-objective production scheduling.	Review of ML-/RL-enhanced MOEA.	Highlighted integration issues of search, adaptation, generalization, and explainability.	Production scheduling.
Wang et al. (2026) [25]	Coordinate multidisciplinary coupling, objective trade-offs, and constraint satisfaction.	Data-driven multidisciplinary design optimization and collaborative constraint handling.	Enhanced solving efficiency for complex engineering via dynamic task allocation.	Multidisciplinary engineering design.
Feng et al. (2026) [31]	Improve prediction accuracy for Pareto regions under uncertain environments.	Gaussian processes, active learning, and robust MOO.	Quantified model uncertainty and reduced evaluation costs.	Robust engineering design.
Hu et al. (2025) [61]	Review the evolution of constrained EMO from rule-based handling to learning-driven paradigms.	Penalty functions, feasibility rules, supervi-sion/RL/transfer learning.	Clarified the evolution from penalty-based to learning-driven constrained EMO.	Constrained MOO.
Ding et al. (2024) [63]	Generate a set of real-time scheduling policies under diverse preferences.	Multi-policy deep RL and coevolution.	Approximated the scheduling Pareto surface using policy populations.	Flexible job shops.
Yuan et al. (2024) [68]	Integrate production line data, virtual models, and multi-objective feedback control.	DT-driven coupled optimization.	Simultaneously improved multiple production performance metrics in industrial implementation.	Smart cable production lines.
Zhao and Gu (2025) [72]	Simultaneously optimize outpatient movement, waiting times, collaboration, and costs.	Improved NSGA-II and real-world hospital case study.	Provided quantitative trade-offs for patient-centric allocation.	Healthcare facility allocation.
Khameneh et al. (2026) [74]	Balance humanitarian delivery efficiency and equity under disruptions and misinformation.	NSGA-II, ε-constraint benchmark, and vulnerability weighting.	Explicitly formulated equity as a distribution objective.	Humanitarian logistics.
Azzini and Munda (2025) [75]	Examine the sensitivity of public policy rankings to weight and model assumptions.	Kemeny ranking, Sobol sampling, and robustness analysis.	Revealed rank reversals and enhanced policy transparency.	Public governance.
Macasieb et al. (2025) [67]	Reliably identify groundwater Pareto fronts under limited simulation budgets.	Gaussian processes, probabilistic dominance, and parallel sampling.	Propagated surrogate uncertainty to decision outcomes.	Groundwater management.

Table 4. *Cont.*

Authors (Year) [Citation]	Primary Research Objective	Methodology Used	Research Contribution	Application Domain
Aldana-Martín et al. (2026) [20]	Lower the programming implementation threshold for domain problems in optimization frameworks.	Fine-tuned LLMs and automated code generation.	Linked natural language problem descriptions with jMetal implementations.	Optimization modeling tools.

(1) Expensive, dynamic, and constrained problems gradually formed a learning-enhanced methodological system. Surrogate model research shifted from candidate approximator selection toward model updating, precise sample allocation, and error control [16]; dynamic MOO evolved from outputting static solution sets toward tracking time-varying Pareto fronts [17]. Constrained optimization similarly expanded beyond penalty functions and feasibility rules to encompass supervised learning, RL, and transfer learning, though it still faces challenges such as training costs, cross-problem generalization, and dynamic constraints [61].

(2) ML and RL have conferred greater adaptivity upon search mechanisms and sequential decision-making. Multi-objective sequential decision-making can output a single policy, a set of policies, or a Pareto front depending on preferences and scalarization forms [18]; ML also supports prediction, parameter adaptation, dispatching, and search guidance, though it remains constrained by data requirements, overfitting, and generalization capacity [62]. Multi-policy deep RL and policy transfer are utilized to generate real-time scheduling policies under diverse preferences while coping with dynamic job arrivals and low-carbon requirements [63–65].

(3) Data-driven surrogate models are primarily utilized for computationally expensive, black-box, and multidisciplinary coupled problems. Such studies have begun managing limited exact evaluation budgets through objective–constraint correlations, active sampling, and regional resource allocation [25,31,66], while incorporating surrogate predictive distributions into the uncertainty expression of candidate policies [67]. This shift indicates that research focus in the third stage is no longer limited merely to utilizing surrogate models to approximate computationally expensive objective functions but further encompasses sampling-point selection, constraint-feasibility determination, and surrogate-model error control.

(4) DTs further extended MOO from offline solving to physical–virtual closed loops, though they still face challenges such as model fidelity, data synchronization, and lifecycle management [19,139,140]. Smart production lines can leverage DT to feed operational data into MOO algorithms and return real-time physical feedback [68]; supply chain research also integrates DT, uncertainty modeling, and metaheuristics, allowing resilience and sustainability decisions to update dynamically with changing contexts [69].

(5) Evaluation of AI-driven MOO has expanded beyond search performance to encompass preference quality, interpretability, fairness, and accountability [21,22,70]. Particularly in high-risk systems, beyond hypervolume and computational time, it is essential to examine model transparency, human-in-the-loop review, preference sensitivity, and community impacts [23,71]. Related applications include outpatient scheduling balancing walking, waiting, collaboration, and costs [72]; educational timetabling incorporating realistic constraints [73]; humanitarian delivery integrating social vulnerability into objectives [74]; and public policy evaluation inspecting

weights and model assumptions [75]. These studies indicate that MOO in the AI era not only pursues faster search but also needs to articulate trade-offs among distinct decision-making values.

Collectively, the literature synthesized in this phase demonstrates an evolution from offline solution-set generation toward data-empowered surrogate approximation, real-time adaptation, and continuous feedback, alongside growing scrutiny of data quality, model drift, algorithmic interpretability, and human oversight.

2.5. Cross-Stage Comparative Synthesis and Functional Reconfiguration

A cross-stage synthesis within our interpretive framework indicates that methodological evolution in MOO is best understood as a functional reconfiguration of complementary techniques rather than a linear displacement of established methods by emerging ones. Figure 4 illustrates the internal methodological composition of the analytical corpus across the three developmental stages. During the first stage, the method-specific corpus is co-dominated by mathematical programming (33.3%) and EMO (36.7%). In the second stage, mathematical programming accounts for 40.6%, while uncertainty and robust modeling accounts for 15.6%. In the third stage, following the exclusion of 10 publications classified as review and research-support literature, the adjusted baseline of 65 publications is distributed across the five orientations as follows: AI-assisted and data-driven optimization leads, at 41.5%, followed by MCDM (21.5%), EMO (18.5%), mathematical programming (12.3%), and uncertainty and robust modeling (6.2%). These proportions are descriptive of the core analytical corpus and are not interpreted as estimates of field-wide methodological prevalence. Based on the representative studies synthesized across the three stages, the substantive functional reconfiguration can instead be characterized as follows: mathematical programming and EMO continue to support problem formulation and Pareto search; uncertainty-oriented approaches address risk and solution stability; MCDM contributes preference integration and compromise selection; and AI- and data-driven techniques increasingly support approximation, search guidance, updating, and adaptive decision support.

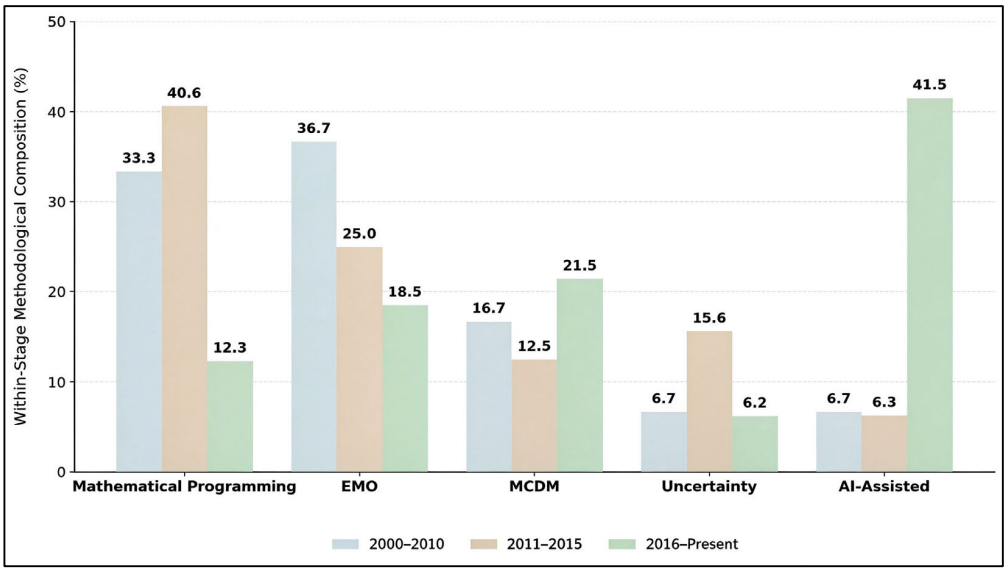


Figure 4. Cross-stage methodological composition. Note: Proportions for each stage are calculated using the five methodological orientations within that stage, excluding review and research-support literature from the denominator. The proportions therefore describe the internal methodological composition of the core analytical corpus.

Figure 5 illustrates the distribution of research domains across the three analytical stages within the 140-publication core corpus. Across these analytical stages, the corpus exhibits differences in application focus: the first stage places greater emphasis on foundational theoretical and methodological developments alongside early applications in supply-chain logistics, healthcare, education, and environmental management; the second stage consolidates representative deployments in supply chains, emergency disaster management, healthcare delivery, and environmental policy; and the third stage exhibits a markedly diversified footprint spanning advanced engineering and industrial systems—leveraging machine-learning scheduling, surrogate-assisted modeling, RL, data-driven design, and DTs—alongside critical applications in public governance, healthcare, education, and environmental sustainability. Importantly, these distributions are intended to delineate the analytical scope of our curated corpus rather than serve as an empirical estimate of global domain-level publication trends.

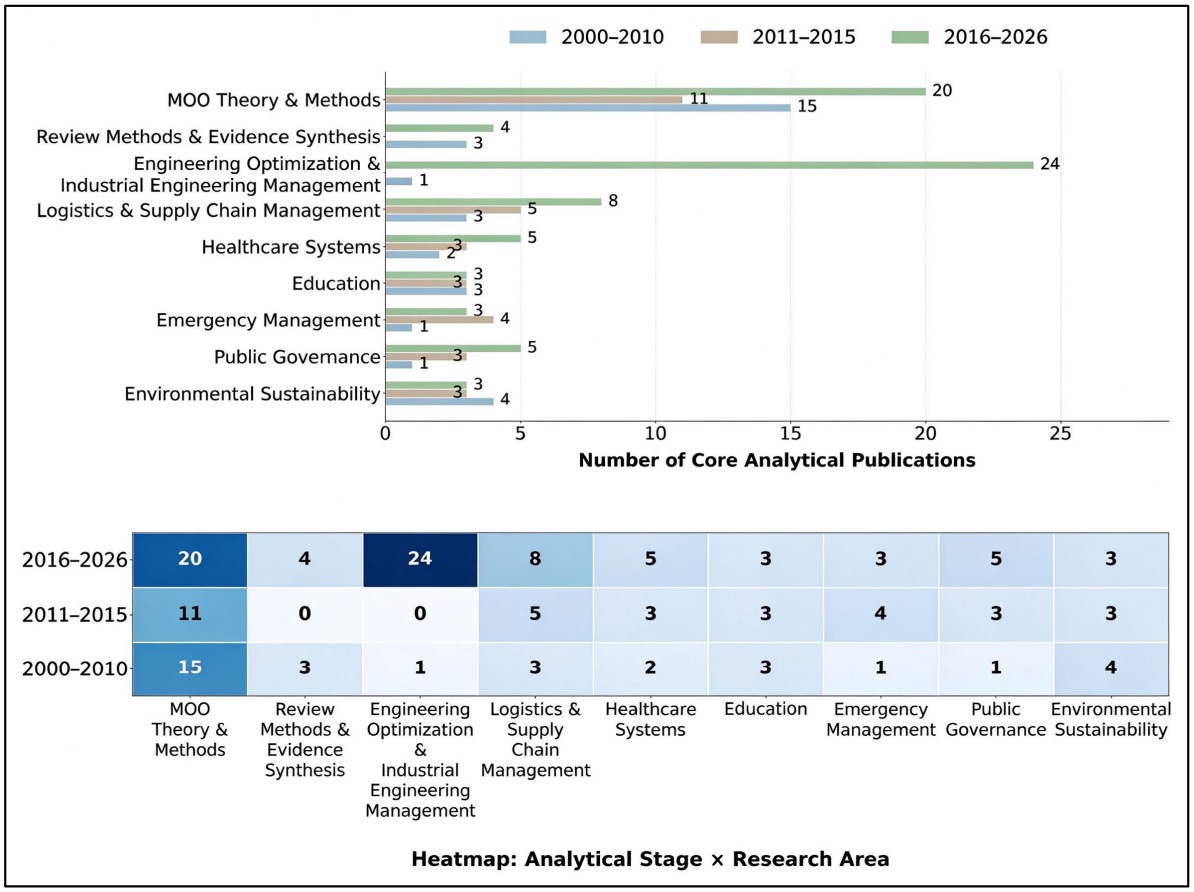


Figure 5. Cross-stage research-domain composition. Note: Research-domain counts describe the internal composition of the 140 core analytical publications and should not be interpreted as estimates of the global distribution or publication volume of MOO research. Darker blue shading indicates a higher number of core analytical publications.

Across stages, problem conditions have expanded from offline static models to high-dimensional, uncertain, expensive, and continuously updating decision-making environments; computational efficiency has likewise extended from single-run algorithmic complexity to the number of simulation evaluations, data costs, surrogate errors, and relearning capabilities. Concurrently, objective sets have broadened beyond performance, cost, and efficiency to encompass risk, resilience, sustainability, equity, and public value. Equity must be explicitly formulated as objectives, constraints, or aggregation rules [129–131], while AI-

generated solution sets require the integration of preference sensitivity, model transparency, data governance, and human-in-the-loop review to evaluate their trustworthiness.

To verify that the substantive findings of our three-stage framework do not hinge upon arbitrary cut-point specifications, a boundary robustness check was conducted across the 140 core analytical publications. As illustrated in Figure 6, sensitivity perturbations were applied independently to each temporal boundary by shifting the cut points forward and backward by one, two, and three years while holding the alternate boundary constant. The overall corpus (N = 140) remained invariant across all perturbation scenarios; solely the stage classifications of boundary-adjacent publications were systematically updated to evaluate structural stability. For the 2010/2011 boundary, the combined share of mathematical programming and EMO within the resulting first-stage five-method corpus remained between 65.0% and 70.0% across the seven specifications, compared with 70.0% under the baseline periodization. For the 2015/2016 boundary, AI-assisted and data-driven optimization remained the largest single methodological orientation within the resulting third-stage corpus under all seven specifications, ranging from 33.3% to 47.2%, compared with 41.5% under the baseline periodization. Figure 6 therefore shows that the principal functional interpretation of the three analytical stages is retained under reasonable boundary adjustments, while reinforcing that the cut points should be interpreted as operational transition points rather than unique historical breakpoints.

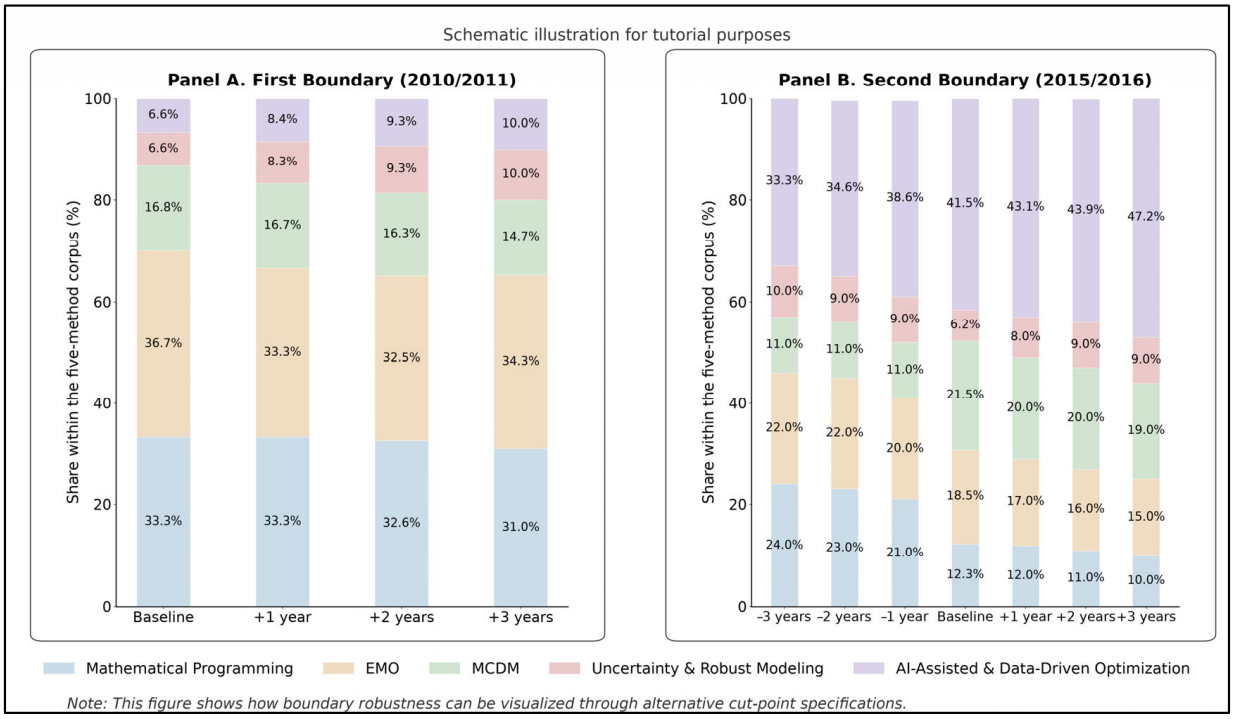


Figure 6. Stage-boundary robustness of the three-stage framework. Note: Percentages are based on the five methodological orientations. Panels A and B test ±1–3-year shifts of the 2010/2011 and 2015/2016 boundaries, respectively. All 140 core analytical publications are retained; only stage assignments change. Data cover 2000–30 June 2026.

3. Mathematical Methods and Theoretical Framework

Advancing from the temporal synthesis in Section 2, this section compares the mathematical formulations, functional roles, and application regimes of key MOO optimization and decision frameworks. First, Section 3.1 delineates a shared mathematical foundation and evaluation dimensions. Next, Section 3.2 compares mathematical programming and EMO as primary optimization engines, positioning MCDM as a complementary decision-

support layer. Sections 3.3 and 3.4 evaluate two cross-method enhancement layers: uncertainty and robust modeling and AI-assisted and data-driven optimization, respectively. Lastly, Section 3.5 synthesizes paradigm selection criteria, integration patterns, and validation standards. Together, this architecture illustrates how distinct methods synergize across problem modeling, Pareto generation, preference articulation, uncertainty management, and adaptive updating.

3.1. Mathematical Foundations and Analytical Dimensions

Regarding the theoretical development of MOO and EMO, Coello Coello [77] synthesized major algorithms, applications, and methodological issues of EMO from a historical perspective; Emmerich and Deutz [2] systematically organized the mathematical foundation, representative evolutionary methods, and statistical performance evaluation of MOO. For a general minimization problem, the decision vector can be denoted as x, the objective vector as $F(x)$, and the feasible domain is defined by inequality and equality constraints, as shown in Equation (1).

$$\begin{aligned} \min_{x \in X} F(x) = & [f_1(x), f_2(x), \ldots, f_m(x)]^T \\ \text{s.t. } & g_j(x) \leq 0, j = 1, \ldots, p \\ & \mathrm{h}_k(x) = 0, \; k = 1, \ldots, q. \end{aligned} \tag{1}$$

Here, x represents the decision vector, and $f_i(x)$ denotes the ith objective function, while $g_j(x)$ and $\mathrm{h}_k(x)$ represent the inequality and equality constraints, respectively. Depending on the decision variables, model tractability, and function evaluation costs, problems can be categorized into continuous, discrete, mixed-integer, nonlinear, black-box, or multidisciplinary coupled types. Problems with explicit structures can be solved via mathematical programming; conversely, non-convex, multimodal, black-box, or computationally expensive problems typically employ EMO, surrogate models, or hybrid approaches [1,2,11,78].

Due to conflicting objectives, MOO generally lacks a unique solution that simultaneously optimizes all objectives. If a feasible solution is no worse than another solution across all objectives and strictly better in at least one objective, a Pareto dominance relationship is established, as shown in Equation (2).

$$x^a \prec x^b \Leftrightarrow f_i(x^a) \leq f_i(x^b) \forall i, \; and \; \exists r\text{: } f_r(x^a) < f_r(x^b) \tag{2}$$

Quality evaluation of MOO solution sets typically considers convergence, coverage, distribution uniformity, and computational cost simultaneously. A single quality indicator can only reflect specific features [34]; hypervolume accounts for both convergence and coverage, but its computational cost increases exponentially with the number of objectives [15,44]. Li and Yao [35] systematically classified quality indicators for multi-objective solution sets and compared their evaluation aspects and ideal properties; Bogoya et al. [79] focused on the definition, theoretical properties, and applicability conditions of the average Hausdorff distance. In practical applications, constraint feasibility, sensitivity, robustness, and data extrapolation risks must also be examined.

The subsequent methodological comparison adopts four common dimensions: representation forms of objectives, constraints, and preferences; output types such as a single trade-off solution, Pareto solution set, or ranked alternatives; requirements regarding data, model tractability, computational budget, and uncertainty; as well as functional shifts in methods from offline solving toward data updating, dynamic adaptation, and human–AI collaboration.

3.2. Core Optimization and Decision Methods

Within this review, mathematical programming and EMO are treated as optimization approaches responsible primarily for problem formulation and Pareto-solution generation, whereas MCDM is treated as a complementary decision-support approach for preference articulation, candidate comparison, Pareto-set filtering, and compromise-solution selection. The following discussion compares their core mechanisms, applicability conditions, outputs, and limitations.

(1) Mathematical programming and scalarization: Mathematical programming typically transforms a vector objective into one or more scalar problems. The weighted sum method utilizes non-negative weights w_i to represent the relative importance of each objective, as shown in Equation (3).

$$\min_{x \in X} \sum_{i=1}^{m} w_i f_i(x),\ w_i \geq 0,\ \sum_{i=1}^{m} w_i = 1 \tag{3}$$

This method easily integrates with linear, nonlinear, and mixed-integer models, though its results remain sensitive to weight scaling and normalization schemes, and it may fail to identify unsupported solutions within non-convex Pareto fronts [1,2]. Consequently, studies should specify the origins of assigned weights and perform sensitivity analyses.

The ε-constraint method designates a single primary objective and transforms the remaining objectives into constraints, as shown in Equation (4), thereby systematically scanning the objective space and handling non-convex Pareto fronts. AUGMECON utilizes an augmentation mechanism to avoid weak Pareto solutions and redundant iterations [12], while AUGMECON2 enhances solution efficiency for multi-objective integer programming problems [51].

$$\begin{gathered} \min_{x \in X} f_1(x) \\ \text{s.t.} f_i(x) \leq \varepsilon_i, i = 2, \ldots, m \end{gathered} \tag{4}$$

When a problem involves both discrete and continuous variables, it can be formulated as Mixed-Integer Linear Programming or Mixed-Integer Nonlinear Programming (MINLP), depending on whether the relationships are linear or nonlinear. Jaber et al. [78] pointed out that exact methods for multi-objective MINLP provide optimality bounds and verifiable solutions; however, their computational burden increases exponentially in large-scale, non-convex, or highly coupled problems. Conversely, approximation methods and metaheuristics offer high scalability but generally lack global optimality guarantees. Consequently, recent trends favor combining branch-and-bound, scalarization, decomposition, local search, and population-based approaches into an exact–approximation hybrid framework, rather than viewing the two methodological categories as mutually exclusive choices.

(2) Evolutionary multi-objective optimization: EMO utilizes populations to simultaneously search for multiple candidate solutions, making it well-suited for nonlinear, non-differentiable, non-convex, or analytically intractable problems. PAES approximates non-dominated fronts using local search and an archive [43]; NSGA-II balances convergence and diversity through non-dominated sorting, crowding distance, and elitism [13]; MOEA/D leverages decomposition and neighborhood updating to enhance solution set distribution and scalability [14]; and SMS-EMOA incorporates hypervolume contribution into its selection mechanism [15]. To tackle many-objective problems, NSGA-III employs reference points to maintain solution set distribution [49], whereas other many-objective approaches integrate indicators, preferences, and dimensionality reduction mechanisms [50]. Regarding algorithm comparison, Zitzler et al. [80] systematically evaluated multiple EMO methods using six test functions

with distinct difficulty features; their results demonstrated distinct performance hierarchies among algorithms and highlighted elitism as a crucial factor for improving evolutionary multi-objective search.

Although EMO can generate multiple candidate solutions in a single run, it faces limitations such as high evaluation costs, parameter sensitivity, result stochasticity, and a lack of global optimality guarantees. For combinatorial problems in binary domains, Becerra-Rozas et al. [81] systematically reviewed binarization mechanisms for continuous metaheuristics, pointing out that no single binarization technique is universally applicable and highly efficient; the performance of different transformation strategies must still be validated based on specific problem characteristics. Related research has expanded from low-dimensional benchmarks to expensive, dynamic, noisy, and many-objective problems [30,50,56], while ML and RL are increasingly utilized to predict promising regions, select operators, allocate resources, and handle constraints [61,62,65].

(3) MCDM and preference integration: MCDM structures the evaluation and selection among pre-existing alternatives or generated Pareto-optimal sets using relative weights, utility functions, priority rankings, or outranking models. Furthermore, it embeds decision-maker preferences—such as aspiration levels, reference directions, or weighting vectors—either prior to, during, or following optimization. In our reviewed corpus, prominent MCDM approaches include hierarchical methods (the Analytic Hierarchy Process (AHP) and fuzzy AHP [107,127], as well as the Analytic Network Process (ANP) and fuzzy ANP [106]), distance-to-ideal formulations (classical and entropy-weighted TOPSIS [58,91]), outranking paradigms (Elimination and Choice Expressing Reality (ELECTRE) [82] and the Preference Ranking Organization Method for Enrichment Evaluations [132]), and simple additive weighting [137]. When preference information is introduced before or during optimization, MCDM functions to guide the search or focus it on preferred regions; when it is applied after Pareto solutions have been generated, it supports ex-post comparison, ranking, and compromise selection. In neither case is MCDM treated in this review as replacing the optimization process responsible for generating the Pareto set. TOPSIS ranks alternatives based on their distances to positive and negative ideal solutions, finding widespread applications in engineering, supply chain, healthcare, energy, and water resources domains [58]; ELECTRE utilizes outranking relations to manage structures where criteria cannot fully compensate for one another [82].

Preferences can be incorporated a priori, interactively, or a posteriori. A priori methods offer higher computational efficiency but risk prematurely constraining the search space; a posteriori methods provide a more comprehensive solution set but increase cognitive burden; interactive methods focus exploration on regions of interest but require managing interaction frequency and preference consistency [1,83]. Preference-based EMO further embeds reference points, pairwise comparisons, or preference-learning models directly into the search, the effectiveness of which hinges on preference quality, visualization clarity, and problem characteristics [22].

MCDM has evolved beyond static weighting and a posteriori ranking toward accommodation of multi-source information, stakeholder preferences, interactive search, and preference learning. As data and AI integration deepens, revealing weight origins, normalization schemes, and ranking stability remains necessary to prevent raw data volume from obscuring human value judgments. Table 5 compares the problem structures, applicability conditions, output types, and primary limitations of these optimization and decision-support approaches.

Table 5. Comparison of core optimization and decision methods.

Method Category	Core Mechanisms	Applicability Conditions/ Problem Features	Typical Outputs and Primary Advantages	Primary Limitations	Representative Literature
Mathematical Programming	Scalarization, ε-constraint, decomposition, and exact/ approximation solving.	Objectives and constraints are explicit; feasibility, optimality bounds, or traceable models are required.	A single trade-off solution or Pareto solution set; transparent constraints, capable of reporting optimality gaps.	High computational cost for large-scale, non-convex, and black-box problems; scalarization may miss efficient solutions.	Marler and Arora (2004) [1]; Mavrotas (2009) [12]; Mavrotas and Florios (2013) [51]; Jaber et al. (2024) [78]
EMO	Population search, non-dominated sorting, decomposition, and reference point/indicator guidance.	Nonlinear, non-convex, multimodal, non-differentiable, or black-box problems; requires obtaining multiple trade-off alternatives.	Approximate Pareto solution sets; well-suited for complex search spaces without needing to fix a single weight in advance.	High evaluation costs, parameter sensitivity, result stochasticity, lack of global optimality guarantees.	Knowles and Corne (2000) [43]; Deb et al. (2002) [13]; Zhang and Li (2007) [14]; Deb and Jain (2014) [49]
MCDM	Weights, utility, ideal solution distances, outranking relations, and interactive preferences.	Preference information is available before or during the search, or candidate solutions and Pareto solution sets are available for post-search comparison and selection.	Preferred search regions, alternative rankings, or compromise solutions; can represent value judgments and multi-party preferences.	Weights and normalization schemes may cause rank reversal; unsuitable for standalone search in vast decision spaces.	Marler and Arora (2004) [1]; Behzadian et al. (2012) [58]; Govindan and Jepsen (2016) [82]; Ren et al. (2026) [22]

These optimization and decision-support approaches can form sequential or hybrid architectures based on problem structures, output requirements, and the timing of preference articulation; Section 3.3 further details how uncertainty is embedded into the aforementioned solving and decision-making processes.

3.3. Uncertainty and Robust Modeling

In this review, "Uncertainty and Robust Modeling" (Figure 1) is operationalized as an overarching, cross-method enhancement layer that encompasses paradigms for characterizing, propagating, and mitigating parameter uncertainty and evaluating solution stability; it is deliberately not treated as synonymous with robust optimization. The term robust optimization is reserved strictly in its canonical sense for frameworks formulated via deterministic uncertainty sets, protection levels (budgets of uncertainty), and adjustable/recourse decision policies. In contrast, stochastic programming, fuzzy and scenario-based modeling, evidence-theoretic approaches, and probabilistic surrogate modeling depend on fundamentally distinct informational assumptions and epistemic mechanisms. In practical settings, stochasticity and ambiguity stem from market demand, cost structures, processing times, ambient environmental conditions, algorithmic parameters, measurement noise, and evolving human preferences. If formulations are solved solely under nominal parameter realizations, the resulting deterministic Pareto-optimal sets risk severe performance degradation or constraint violations under real-world perturbations. The subsequent analysis therefore contrasts five foundational paradigms: stochastic MOO, robust and adjustable robust optimization, fuzzy and scenario modeling, evidence theory, and probabilistic surrogate modeling coupled with active learning.

(1) Stochastic multi-objective optimization: Stochastic approaches describe uncertain parameters using probability distributions or scenarios, constructing models via expected values, risk measures, chance constraints, or deterministic equivalents. Distinct transformations can yield different Pareto solutions and risk implications [54]. These methods are well-suited for problems where distributions or scenario probabilities can be reasonably estimated; however, their results remain sensitive to distributional assumptions, scenario design, and sample sizes.

(2) Robust and adjustable robust optimization: Robust optimization seeks solutions that maintain performance within a predefined uncertainty set, thereby mitigating the impacts of tolerances, drifts, and model sensitivity [84]. Uncertainty sets must strike a balance between computational tractability and protection level [52]; meanwhile, adjustable robust models permit two-stage or multistage recourse decisions after uncertain information is revealed, making them suitable for multi-stage problems [52,53]. Overly wide uncertainty sets may result in excessive conservatism, whereas overly narrow sets risk underestimating risk exposure.

(3) Fuzzy and scenario modeling: When information predominantly derives from expert judgment or ill-defined criteria, fuzzy numbers, membership functions, and scenario approaches can be utilized to represent uncertainty [55,141]. Fuzzy methods convert linguistic evaluations into computable mathematical structures; nevertheless, membership functions, linguistic scales, and defuzzification techniques inherit subjectivity, requiring validation through consistency and sensitivity analyses.

(4) Evidence-theoretic and belief-function modeling: Dempster–Shafer evidence theory represents uncertain information through basic probability assignments over sets of hypotheses and derives belief and plausibility measures to express the support and uncertainty associated with alternative propositions. Evidence from multiple sources can subsequently be combined to support decision-making without requiring all uncertain information to be represented by a single precise probability distribution. Beynon et al. [147] demonstrated its applicability to multicriteria decision modeling, while Albogami et al. [148] integrated AHP with Dempster–Shafer evidence theory for project risk assessment. Such approaches are particularly relevant when information is incomplete, imprecise, or derived from heterogeneous sources; however, their results depend on the definition of the frame of discernment, the relationships among evidence sources, and the treatment of conflicting evidence.

(5) Probabilistic surrogate modeling and active learning: Driven by the rapid advancement of surrogate modeling and machine learning techniques, uncertainty management in MOO has expanded beyond exogenous parameter perturbations to directly capture endogenous surrogate prediction errors and structural model ambiguity [31,67]. Specifically, Feng et al. [31] and Macasieb et al. [67] embedded epistemic surrogate uncertainty into infill sampling criteria, Pareto non-dominance classification, and candidate solution fidelity, thereby transforming model approximation error from a passive computational artifact into an active driver of search trajectory. To synthesize these methodological paradigms, Table 6 systematically contrasts their uncertainty representations, operational boundary conditions, decision-support functionalities, and inherent computational limitations across the five surveyed frameworks.

Table 6. Comparison of uncertainty and robust modeling approaches.

Method Category	Core Mechanisms	Applicability Conditions/Problem Features	Typical Outputs and Primary Advantages	Primary Limitations	Representative Literature
Stochastic Multi-Objective Optimization	Probability distributions, scenarios, risk measures, and chance constraints.	Distributions or scenario probabilities can be reasonably estimated.	Establishes risk–performance trade-offs and quantifies tail risk.	Distribution misspecification and scenario scale affect solution sets and computational cost.	Ben Abdelaziz (2012) [54]
Robust and Adjustable Robust Optimization	Uncertainty sets and post-disclosure decision recourse.	Distributional information is insufficient, but parameter bounds can be specified for high-risk or multi-stage problems.	Maintains feasibility under controlled scenarios and supports multi-stage adaptation.	Overly wide sets yield excessive conservatism; overly narrow sets underestimate risk.	Beyer and Sendhoff (2007) [84]; Bertsimas et al. (2011) [52]; Gabrel et al. (2014) [53]
Fuzzy and Scenario Modeling	Fuzzy numbers, membership functions, linguistic scales, and scenario-based representations.	Expert judgment, linguistic information, or scenario-based uncertainty predominates, or criteria boundaries are difficult to quantify precisely.	Converts qualitative judgments into satisfaction levels, weights, or rankings.	Membership functions and defuzzification inherit subjectivity, requiring sensitivity validation.	Durbach and Stewart (2012) [55]
Evidence-Theoretic/Belief-Function Modeling	Basic probability assignments, belief/plausibility measures, and evidence combination.	Information is incomplete, imprecise, or derived from multiple heterogeneous sources, and precise probability distributions are difficult to specify.	Represents bounded belief and uncertainty and integrates multiple evidence sources to support risk assessment and alternative selection.	Sensitive to frame definition, dependence among evidence sources, and the treatment of conflicting evidence.	Beynon et al. (2000) [147]; Albogami et al. (2021) [148]
Probabilistic Surrogate Modeling and Active Learning	Predictive distributions, model error, and adaptive sampling.	Exact simulation is expensive and predictive uncertainty requires active management.	Incorporates predictive uncertainty directly into sampling and Pareto classification.	Model calibration, prediction error, and stopping criteria impact reliability.	Feng et al. (2026) [31]; Macasieb et al. (2025) [67]

Method selection should correspond to the nature of uncertain information: stochastic approaches are suitable when probability distributions can be estimated, robust methods are suitable when uncertainty sets or parameter bounds can be specified, fuzzy modeling is suitable when linguistic or imprecise judgments dominate, evidence-theoretic approaches are suitable when incomplete or multi-source evidence must be combined, and probabilistic surrogates are suitable when expensive black-box evaluations introduce predictive uncertainty. Studies should report uncertainty sources, distribution or set configurations, evidence-combination assumptions, scenario ranges, and sensitivity results; high-risk applications further necessitate evaluating the decision consequences of model misspecification.

3.4. AI-Assisted and Data-Driven Optimization

Early developments in AI-assisted and data-driven MOO included dynamic Pareto front tracking and surrogate modeling [45–47], subsequently evolving toward model management and multi-objective sequential decision-making [56,57]. Díaz-Manríquez et al. [85]

categorized the integration architectures of surrogate-assisted multi-objective evolutionary algorithms based on the interaction paradigms between multi-objective evolutionary algorithms and surrogate models. Here, a clear distinction must be made between two directions: "AI for MOO" and "optimization for ML". Liu et al. [86] systematically summarized gradient-based, population-based, and regularized optimization methods in ML, discussing their scalability, theoretical guarantees, and robustness; as that study focuses on utilizing optimization methods to support ML rather than direct AI intervention in MOO solving, it is classified in this study as review and research-support literature. As data availability and real-time computing power advance, AI further intervenes in function approximation, search guidance, constraint handling, policy learning, and physical–virtual feedback. The following discussion addresses surrogate models and ML-assisted search, RL and DT closed-loop optimization, as well as generative AI and human oversight.

(1) Surrogate modeling and ML-assisted search: Surrogate models replace computationally expensive exact simulations with low-cost approximators, making them suitable for objective functions that are costly or lack analytical forms. Gaussian process (GP) models simultaneously predict objective values and uncertainty, allocating limited exact evaluations toward candidate solutions with higher information value [46,47]. Subsequent research shifted focus toward the interactions between surrogate models and EMO, update timing, and error control [56,85].

Recent methodologies further integrate active learning, knowledge transfer, and adaptive regional search. Wang et al. [25] coordinated multidisciplinary design through objective–constraint correlations and dynamic task allocation, whereas Feng et al. [31] actively sampled in potential Pareto regions while quantifying model uncertainty. Two-stage search, multitask learning, and local resource allocation can also improve feasibility, convergence, and evaluation efficiency for expensive, constrained, and high-dimensional problems [66,87,88].

Zhang et al. [62] pointed out that ML can support evolutionary search, schedule adaptation, and decision-making in multi-objective production scheduling; however, it remains constrained by data requirements, interpretability, overfitting, scalability, stability, and generalization capability. In constrained EMO, supervised learning, RL, and transfer learning can assist in identifying feasible directions, but insufficient training data may lead to negative transfer or erroneous judgments [61].

(2) RL, dynamic decision-making, and DT closed-loop optimization: RL is well suited for multi-objective sequential decision-making where states, actions, and outcomes evolve over time. Its output can be a single policy, a convex coverage set, or a set of Pareto-optimal policies, depending on preference information and scalarization forms [57]; combining objectives via straightforward linear addition risks obscuring critical trade-offs [18]. Consequently, beyond designing reward functions, studies must address preference integration and policy validity under environment shifts.

Multi-policy deep RL can generate real-time scheduling policy sets corresponding to varying preferences [63], transfer learning enables the application of pre-trained policies to dynamic job arrivals and low-carbon scheduling [64], and Q-learning can adaptively adjust evolutionary operations based on operator contributions [65]. Nevertheless, policy reliability remains dictated by state, action, and reward designs; if proxy rewards fail to capture cost, safety, or fairness requirements, the derived policies may prove unsuitable for actual deployment.

Digital twins (DTs) form a closed loop through physical systems, synchronized virtual models, bidirectional data links, and decision feedback [19,139,140]. Intelligent production lines can feed real-time data into MOO models and route optimal equipment settings

back into the shop floor [68]; supply chain studies further demonstrate the integration of DTs with uncertainty analysis and optimization methods to support decision adaptations that track operational dynamics [69]. However, deployment risks include model synchronization, data governance, communication latency, and fail-safe protection.

(3) Generative AI, reliability, and human oversight: LLMs currently primarily support problem formulation, code generation, and black-box search. Aldana-Martín et al. [20] transformed natural language problem descriptions into jMetal code; Brahmachary et al. [76] explored LLMs as population-based black-box optimizers; nevertheless, hallucinations and generation instability still necessitate code validation, numerical re-verification, and human review.

AI-assisted MOO further requires evaluation of interpretability, fairness, and accountability. Explanation methods must align with the target user and decision context [21], whereas data and model biases may cause highly efficient solutions to adversely impact specific groups [70]. High-risk systems should therefore retain mechanisms for human intervention, override, and review [71], while systematically logging data versions, preference configurations, and decision rationale. Table 7 compares the five functional domains, applicability conditions, and primary risks of AI intervention in MOO.

Table 7. Functional roles and risks of AI-assisted MOO.

AI Intervention Role	Core Mechanisms	Applicability Conditions	Primary Contributions	Key Risks	Representative Literature
Computationally Expensive Function Approximation	Surrogate models such as GP and radial basis function.	Evaluation is expensive and analytically intractable or exact samples are limited.	Reduces simulation counts and quantifies candidate region uncertainty.	Surrogate error, prediction error, and false Pareto fronts.	Knowles (2006) [46]; Emmerich et al. (2006) [47]; Chugh et al. (2019) [16]; Feng et al. (2026) [31]
Search and Constraint Guidance	Classification, prediction, knowledge transfer, and active learning.	High-dimensional, constrained, or expensive problems.	Improves sampling, constraint handling, and resource allocation.	Overfitting, negative transfer, and search bias.	Wang et al. (2026) [25]; Wang et al. (2025) [88]; Hu et al. (2025) [61]; Wang et al. (2026) [66]
Dynamic Policy Learning	Multi-objective RL, transfer learning, and adaptive operators.	Sequential problems where states and actions continuously evolve.	Supports real-time adaptation, policy transfer, and multi-preference policies.	Reward misspecification, policy drift, safety issues, and insufficient generalization.	Roijers et al. (2013) [57]; Hayes et al. (2022) [18]; Ding et al. (2024) [63]; Fan and Tian (2025) [64]; Du et al. (2025) [65]
Physical–Virtual Closed Loop	DT, real-time synchronization, and optimization feedback.	Decisions require online updating and feedback to physical systems.	Connects physical states, virtual models, and MOO.	Model synchronization, latency, data governance, and fail-safe protection.	Tao et al. (2019) [19]; Jones et al. (2020) [139]; Fuller et al. (2020) [140]; Yuan et al. (2024) [68]; Nozari et al. (2026) [69]
Problem Formulation and Generative Assistance	LLMs, code generation, and black-box search.	Textual problems require conversion into executable models or candidate solutions need to be generated via a black-box approach.	Lowers implementation barrier and supports exploration.	Hallucination, semantic errors, prompt sensitivity, and numerical infeasibility.	Aldana-Martín et al. (2026) [20]; Brahmachary et al. (2025) [76]

AI can support function approximation, search guidance, dynamic policy learning, closed-loop control, problem formulation, and generative assistance; its validation must also encompass surrogate errors, policy safety, model synchronization, out-of-distribution generalization, and human review. Section 3.5 further details how these functionalities integrate with core methods and uncertainty handling.

3.5. Method Integration, Selection, and Validation

Method selection and integration must simultaneously account for problem structures, data quality, computational budgets, and deployment environments, as no single universally superior method exists for all problems [1]. Mathematical programming, EMO, and MCDM support problem modeling, Pareto search, and preference selection, respectively, whereas uncertainty and AI modules enhance risk handling, function approximation, and dynamic updating. Figure 7 integrates the aforementioned functionalities and their feedback relationships.

Figure 7 outlines a feedback workflow comprising problem formulation, core solving, uncertainty and AI enhancement, preference selection, and deployment validation. Problems with explicit structures can combine mathematical programming and EMO; when preference integration is required, MCDM can screen the Pareto solution set; computationally expensive or uncertain problems can incorporate robust modeling, surrogate models, and active learning; and dynamic systems can integrate RL or DTs while retaining constraint checks, fail-safe mechanisms, and human oversight. Method selection and validation can be determined according to the following two aspects.

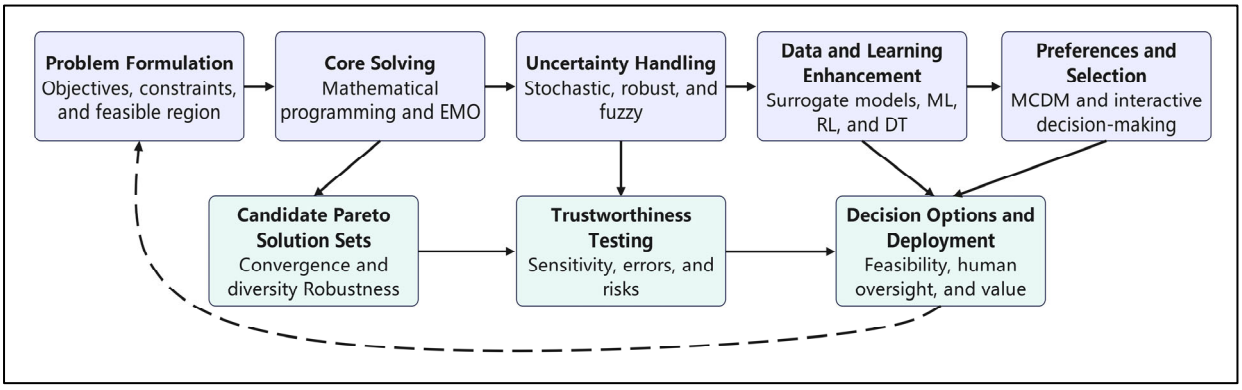


Figure 7. Integrated MOO decision architecture. Note: The evolution across the three analytical stages reflects a continuous restructuring of computational data, uncertainty, and human-interaction modules rather than a sequence of mutual replacements. Solid arrows indicate the main forward workflow, while the dashed arrow represents the feedback loop from deployment and validation to problem formulation.

(1) Method selection should align with problem and data conditions: When objectives and constraints are explicit and optimality information is required, mathematical programming can be adopted; nonlinear, multimodal, or black-box problems are well suited for EMO; when exact evaluation is computationally expensive, surrogate models can be incorporated; dynamic sequential problems can employ RL or DTs; and when preferences, fairness, and public values are involved, MCDM and sensitivity analysis should be integrated. Method selection should not rely solely on benchmark performance, but must also account for data characteristics, uncertainty, computational budgets, decision deadlines, and error consequences.

(2) Validation should align with method types and application risks. Methodological validation must align with each paradigm's operational characteristics: mathematical

programming studies should report solution times, feasibility bounds, and relative optimality gaps; EMO literature requires multiple independent trials under fixed computational budgets alongside rigorous statistical tests [34,35]; surrogate models necessitate high-fidelity validation of candidate solutions and calibrated predictive variances; and RL or digital-twin deployments demand systematic tracking of environmental drift, automated fail-safe mechanisms, and sustained field monitoring. When preferences or public values are involved, weight origins, normalization schemes, and sensitivity analyses should also be disclosed.

Based on this, Table 8 compares the method configurations and validation priorities across three analytical stages.

Cross-stage comparison demonstrates that the primary contribution of the Information-Based Computing stage lay in establishing a common foundation for problem formulation, Pareto search, and quality evaluation; the Data-Intensive Decision-Making stage subsequently integrated multi-scenario conditions, risk, and preferences into decision processes; and the AI-Driven Optimization stage further embedded surrogate models, ML, RL, and DTs into dynamic systems. Correspondingly, application focus shifted from early multi-domain demonstrations toward engineering and industrial systems in the third stage, while continuously expanding into supply chains, healthcare, and public governance—thereby providing the method–scenario alignment contextfor the cross-domain comparisons in Section 4.

Table 8. Cross-stage method configurations and validation priorities.

Development Stage	Problem and Data Conditions	Primary Method Configuration	Validation Priorities
Information-Based Computing (2000–2010)	Computerized modeling, offline numerical computation, and relatively static environments.	Primarily mathematical programming and EMO, supplemented by MCDM and fuzzy/stochastic methods.	Feasibility, convergence, diversity, computational cost, and benchmark testing.
Data-Intensive Decision-Making (2011–2015)	Higher-dimensional objectives, multi-scenario data, increasing uncertainty, and cross-system constraints.	Core methods integrated with robust/stochastic modeling, surrogate models, and sequential decision-making.	Scenario analysis, risk measures, robustness, sensitivity, and cross-model comparison.
AI-Driven Optimization (2016–present)	Real-time data; expensive black-box, dynamic environments; and online updating.	Core methods integrated with uncertainty and AI modules.	Train/test separation, surrogate calibration, generalization testing, drift, safety, and human review.

Note: The three stages represent analytical categorization designed to identify dominant technical conditions and functional shifts; they do not imply that earlier methods ceased to be utilized past the demarcation years. Furthermore, the publication counts across application domains merely reflect the internal structure of the 140 core analytical publications selected in this study.

4. Cross-Domain Applications and Decision Value

This section compares the problem structures, data conditions, validation requirements, and decision value of MOO across various domains, including engineering and industrial systems, logistics, supply chains, emergency systems, healthcare, education, and public governance, as well as environmental sustainability. Section 4.1 establishes a common analytical framework, while Sections 4.2–4.5 expand the analysis domain by domain.

4.1. Cross-Domain Analytical Framework

The value of cross-domain applications cannot be assessed solely based on algorithms or objective functions. Engineering and industrial problems are constrained by physical limitations and high-cost simulations; supply chains and emergency systems face demand fluctuations and disruption risks; healthcare, education, and public governance emphasize fairness, institutional factors, and multi-stakeholder preferences; whereas environmental issues involve long-term time horizons, spatial spillovers, and irreversible impacts. Consequently, the same methodology may require distinct data, feasibility criteria, and validation standards across different domains. This study compares these domain applications across six dimensions: decision context, objectives and constraints, methodology and data, validation levels, decision value, and implementation limitations. Table 9 outlines the core questions and evidentiary criteria for each dimension.

Table 9. Cross-domain analytical dimensions and evidence criteria.

Analytical Dimension	Core Question	Primary Evidence and Criteria	Representative Literature
Decision Context	Who makes decisions and under what institutional and temporal scales?	Decision hierarchy, stakeholders, update frequency, and clarity of decision rights and responsibilities.	Marler and Arora (2004) [1]; Dean (2022) [126]
Objectives and Constraints	Which objectives conflict with one another, and which constraints cannot be violated?	Whether cost, performance, service, risk, fairness, environmental, and safety objectives are measurable, and whether constraints reflect real-world conditions.	Sabri and Beamon (2000) [6]; Khameneh et al. (2026) [74]
Methodology and Data	Do the methods conform to problem structures and data availability?	Consistency in model types, data sources, training scope, constraint handling, and preference integration.	Wang et al. (2026) [25]; Nozari et al. (2026) [69]
Validation Levels	Under what evidentiary conditions do the results hold true?	Whether benchmarks, simulations, real-world cases, sensitivity analyses, or external feedback are utilized to differentiate computational performance, case feasibility, and deployment effectiveness.	Hafsa et al. (2025) [73]; Macasieb et al. (2025) [67]
Decision Value	What does the model improve, and who benefits from it?	Whether efficiency, quality, resilience, accessibility, equity, and environmental benefits are specified, along with the distribution of beneficiary groups and trade-off costs.	Zhao and Gu (2025) [72]; Azzini and Munda (2025) [75]
Implementation Limitations	What conditions might render mathematically feasible solutions unadoptable?	Whether data biases, model misspecification, latency, governance, and accountability issues are identified, and whether failure conditions and human intervention mechanisms are reported.	Baharmand et al. (2022) [112]; Shneiderman (2020) [71]

Accordingly, the core of cross-domain analysis lies in aligning problem characteristics, evidentiary conditions, and decision value. The higher the application risk and public impact, the greater the need to strengthen data trustworthiness, trade-off stability, and human review.

4.2. Engineering and Industrial Systems

Engineering and industrial systems typically feature high-dimensional design variables, strongly coupled constraints, and dependence on computationally expensive simulations or real-time equipment data for performance evaluation. Consequently, the value of MOO in this domain lies not only in enhancing solving efficiency, but also in coordinating trade-offs among performance, cost, energy, safety, and quality within limited computational resources. Taking a bi-objective truss design as an example, Nguyen et al. [89] combined Rao-1 with differential evolution to improve the convergence, coverage, and diversity of trade-off solutions; Yılmaz and Dede [90] jointly incorporated duration, cost, and environmental impacts into construction projects; and Shen et al. [91] simultaneously addressed mechanical performance and geometric constraints in automated refueling arm design. These studies demonstrate that engineering MOO typically requires ensuring physical constraints and design feasibility before evaluating and comparing the quality of Pareto solution sets.

When engineering problems further involve multidisciplinary coupling, black-box simulations, and expensive evaluations, the research focus shifts from expanding the search range toward effectively allocating a limited budget for exact evaluations. Wang et al. [25] utilized objective–constraint correlations and dynamic task allocation to coordinate search and constraint satisfaction in multidisciplinary design; Feng et al. [31] focused active sampling on potential Pareto regions and leveraged surrogate model uncertainty to determine subsequent evaluation locations. To address expensive constrained problems, Wang et al. [87,88] reduced the number of exact evaluations through two-stage search and knowledge transfer, respectively; meanwhile, Zhang et al. [92] and Wang et al. [66] further addressed dynamic and high-dimensional expensive problems. As demonstrated, the role of data-driven engineering optimization extends beyond saving computational time to simultaneously managing surrogate errors, solution feasibility, and sampling bias.

In contrast to engineering design, production and manufacturing systems place greater emphasis on environmental dynamics, execution speed, and low-carbon requirements. Prata [24] reviewed industrial engineering and operations management research over the fifty-year history of Engineering Optimization, noting that production scheduling, production planning and control, transportation logistics, and routing constitute the primary topics, whereas sustainability goals and the integration of ML with metaheuristics represent emerging directions. Ding et al. [63] utilized multi-policy deep RL to generate flexible job-shop scheduling policies under varying preferences, enabling decision-makers to select distinct trade-off solutions based on real-time system states. Li et al. [93] further incorporated makespan, energy consumption, and transport coordination into low-carbon scheduling. To cope with dynamic job arrivals and distributed assembly problems, Fan and Tian [64] and Du et al. [65] enhanced schedule adaptability by leveraging transfer learning and learning-based coordination, respectively. Although these studies shift scheduling from fixed solutions to dynamic policies, system reliability remains dictated by state observability, reward design, cross-scenario generalization, and equipment safety margins.

In addition to efficiency and dynamic adaptation, engineering MOO in recent years has progressively integrated safety, design information, and physical system feedback. Monostori et al. [4] defined Cyber–Physical Production Systems (CPPS) as system architectures in which collaborative computational entities are tightly linked with physical manufacturing processes, accessing and processing data through networks, thereby illustrating that the integration of computing, communication, and manufacturing technologies serves as a vital foundation for achieving smart manufacturing. Sukpancharoen et al. [94] simultaneously addressed cost-effectiveness and safety requirements in multi-story facility layout design; Zhao et al. [95] combined computational fluid dynamics (CFD) results with ML to improve

stirred tank design; and Kenny et al. [96] proposed a progressive data-driven framework that allocates limited evaluation resources across multiple design concepts, performing multi-objective optimization on each individual concept to identify trade-off solutions among distinct design goals. Building upon these advances, Yuan et al. [68] leveraged DTs to connect real-time data, virtual models, and optimization feedback in cable production lines, improving production efficiency, equipment utilization, and product quality through coordinated system-level optimization. This shift demonstrates that engineering optimization has evolved from offline candidate generation toward closed-loop decision-making capable of interacting directly with physical systems.

Overall, MOO in engineering and industrial systems has expanded from traditional performance–cost trade-offs to encompass energy efficiency, low-carbon production, safety, quality, and system resilience. Correspondingly, research validation should not rely solely on benchmark functions, algorithmic metrics, or single simulation results; instead, it should further evaluate surrogate model accuracy, solution-set stability under data variations, control execution timeliness, compliance with physical constraints, as well as fail-safe protection and corrective capabilities under anomalous scenarios.

4.3. Logistics, Supply Chains, and Emergency Systems

Logistics and supply-chain decision-making encompasses interdependent components including facility location, capacity, supplier selection, inventory, transportation, and distribution, where localized improvements risk shifting costs, delays, or risks onto other nodes. Melo et al. [97] emphasized the integration of facility location with other supply-chain design decisions; Ho et al. [98] further highlighted that supplier evaluation and selection requires considering multiple criteria rather than cost alone. Consequently, the role of MOO in supply chains extends beyond minimizing single-node costs to illuminating network-level trade-offs and cascading impacts.

With increasing attention paid to sustainability and supply disruption risks, supply-chain decision-making has progressively expanded beyond costs and service levels to encompass energy consumption, carbon emissions, circular recycling, and system resilience. Dekker et al. [99], Lin et al. [100], and Demir et al. [101] illustrated through logistics operations, green transportation, and freight management, respectively, that environmental impacts must be jointly evaluated with economic and operational performance. Brandenburg et al. [7] and Eskandarpour et al. [59] further highlighted social impacts, uncertainty, and risk in sustainable supply-chain analysis. In response to supply disruptions and systemic shocks, Snyder et al. [102] reviewed operations research/management science (OR/MS) models for supply chain disruptions, while Ivanov and Dolgui [8] extended resilience research toward supply-network viability and survivability.

The emergence of digital platforms and smart supply chains has rendered data updating and cross-organizational coordination critical prerequisites for the practical deployment of optimization models. Guo and He [103] and Chen et al. [104] noted that platform supply chain decisions simultaneously involve pricing, operational coordination, strategic decision-making, and digital technology integration; Chen et al. [105] further emphasized the role of uncertainty analysis and optimization modeling in supply-chain decision-making under uncertainty. Regarding production disruptions that render the original schedule inefficient or infeasible, Holguin Jimenez et al. [5] highlighted that rescheduling should balance the efficiency and stability of newly generated schedules to avoid compounding shop-floor execution difficulties.

Regarding solution evaluation and dynamic updating, MCDM can be applied to organize evaluation criteria, articulate preferences, and compare alternative candidate solutions. Lin et al. [106] employed Fuzzy ANP to evaluate pallet investment options for

supermarket chains, integrating costs, operational efficiency, and interrelationships among factors; Lin et al. [107] first used a modified Delphi method to construct a vaccine cold-chain transportation quality evaluation system comprising 5 criteria and 26 sub-criteria, and subsequently ranked indicator importance via Fuzzy AHP, with results particularly highlighting local weather, topography, road characteristics, cold-chain logistics standardization, and economic development conditions. Nozari et al. [69] further applied DTs, neutrosophic uncertainty modeling, and a hybrid Grey Wolf–Genetic Algorithm to food supply chains, supporting real-time monitoring and decision-making under uncertainty in demand, costs, and capacities.

Compared with general supply chains, emergency response systems face greater time pressure, information gaps, and requirements for resource equity. Altay and Green [108] and Galindo and Batta [109] reviewed OR/MS research in disaster operations management, while Caunhye et al. [27] classified emergency logistics into pre-disaster operations, including short-notice evacuation, facility location, and stock pre-positioning, and post-disaster operations, including relief distribution and casualty transportation. Özdamar and Ertem [110] further emphasized that humanitarian logistics models and their solutions need to be integrated with information technology to enable their practical use. Bozorgi-Amiri et al. [60] incorporated demand and supply uncertainties, as well as shortage-based satisfaction across affected areas, into disaster relief logistics; Mejia-Argueta et al. [111] integrated emergency facility location, humanitarian-aid prepositioning, evacuation, and aid distribution under flood scenarios. Baharmand et al. [112] emphasized that humanitarian logistics optimization models should be grounded in disaster-specific context and field evidence; Khameneh et al. [74] further balanced distribution efficiency and fairness by minimizing total travel distance and delivery-time disparities across affected communities under disrupted and uncertain conditions.

In summary, MOO in logistics, supply chains, and emergency response systems has expanded from balancing cost and service efficiency to embracing multi-faceted decision values, including sustainability, resilience, and equity. Correspondingly, research validation in these domains must extend beyond merely reporting improvements in cost, distance, or lead time; it should also test plan execution feasibility under dynamic scenarios such as supply disruptions, demand and cost fluctuations, traffic blockages, and incomplete information while explicitly comparing disparities across different regions or population groups in waiting times, material shortages, and safety risks.

4.4. Healthcare, Education, and Public Governance

Healthcare, education, and public governance all face challenges associated with resource constraints and divergent group needs, where decision outcomes directly impact service accessibility, quality, and resource distribution. Consequently, the value of MOO in these domains extends beyond improving resource utilization efficiency to balancing equity, institutional regulations, and multi-stakeholder requirements. In contrast to engineering problems, social service domains further demand justification regarding the reasonableness of decision objectives, the representativeness of data across diverse population groups, and the transparency of policy generation and selection processes.

MOO applications in healthcare encompass resource allocation, facility location, outpatient and surgery scheduling, treatment planning, and option evaluation. Rais and Viana [9], Cardoen et al. [48], and Hulshof et al. [10] collectively showed that healthcare OR spans strategic resource allocation and capacity planning as well as operational planning, scheduling, and control, highlighting the need to coordinate decisions across different planning levels. Ahmadi-Javid et al. [113] investigated healthcare facility location, whereas Gupta and Denton [114] analyzed patient appointment scheduling, representing two dis-

tinct strategic and operational decision problems in healthcare systems. Thokala et al. [32], Marsh et al. [115], and Marsh et al. [116] further emphasized structured and explicit MCDA procedures for defining criteria, evaluating alternatives, implementing the analysis, and supporting healthcare decisions. Veenstra et al. [117] integrated facility location with vehicle routing for medication delivery in healthcare logistics. Among recent studies, Zhao and Gu [72] utilized a real hospital case to evaluate how outpatient spatial layouts affect patient walking distance, waiting time, medical staff collaboration, and hospital operating costs, bringing model validation closer to actual operational conditions.

MOO in education primarily addresses course timetabling, examination scheduling, school redistricting, and campus layout design. Lewis [118], MirHassani and Habibi [119], and Pillay [120] highlighted that effective timetabling must first eliminate instructor, student, venue, and time slot conflicts, while concurrently accommodating teaching preferences, enrollment demands, and facility utilization. Nevertheless, variations in institutional rules, faculty structures, and spatial resources across institutions often limit the generalizability of these optimization models. Babaei et al. [121] further argued that the feasibility of large-scale timetabling depends not merely on algorithmic efficacy, but equally on data completeness and cross-departmental coordination. Mumford [26] applied multi-objective approaches to evaluate examination schedules; Caro et al. [122] integrated geographic information systems with integer programming to reconfigure school attendance zones; and Dunke and Nickel [123] formulated lecture and tutorial planning at the tactical level while scheduling individual student tutorial slots at the operational level, thereby seamlessly bridging multi-tier planning horizons in educational scheduling. Zhang et al. [124] subsequently leveraged deep RL to optimize spatial configurations for school districts and educational resources. Furthermore, Hafsa et al. [73] evaluated diverse EMO methods using real-world institutional datasets to generate several actionable timetables, proving that the true utility of educational MOO resides in delivering verifiable decision suites rather than asserting a single optimal solution.

Public governance decisions require harmonizing expert evidence, regulatory frameworks, and societal values. Munda [28] proposed Social Multi-Criteria Evaluation (SMCE), emphasizing that public policies cannot merely pursue overall efficiency; they must also integrate the interests, value stances, and participatory inputs of diverse population groups to prevent offsetting of the losses incurred by one group with the gains of another. da Cruz and Marques [125] applied multi-criteria approaches to evaluate local governance quality; Dean [126] explored how stakeholders participate in decision-making processes; Losada Maestre et al. [127] utilized AHP to support urban development budget allocations; and Costa and Silva [128] synthesized multi-criteria applications in public safety. Azzini and Munda [75] further examined whether policy rankings remain stable under shifting weights and analytical assumptions through sensitivity analysis, expanding policy evaluation from single rankings to robust conclusions.

The aforementioned studies collectively demonstrate that improved overall efficiency does not imply equitable resource distribution, nor does it guarantee sufficient procedural transparency. Bertsimas et al. [129] analyzed the efficiency costs incurred by fairness requirements, and Hooker and Williams [130] integrated Utilitarian objectives with Rawlsian fairness criteria—which maximize the minimum utility—to formalize trade-offs between equity and efficiency, whereas Karsu and Morton [131] systematically organized inequality metrics, fair aggregation functions, and approaches for handling equity and balance. When AI is deployed in high-stakes decision-making such as healthcare, education, or public services, Rudin [23] advocated prioritizing models that are interpretable to both decision-makers and end users; Shneiderman [71] further emphasized maintaining adequate human control under high degrees of computer automation, while defining appropriate bound-

aries between human control and computer control across different operational contexts. Consequently, rigorous validation in these domains must extend beyond average performance to report group disparities, outcome stability, procedural transparency, and governance accountability.

4.5. Environmental Sustainability and Cross-Domain Decision Value

Environmental and sustainability decision-making simultaneously involves economic development, resource utilization, ecological protection, and social acceptance. Because its impacts often extend across different regions, sectors, and generations, evaluating alternatives based on a single metric is inadequate. Huang et al. [29] reviewed MCDM applications in environmental science, illustrating that multi-criteria approaches assist decision-makers in evaluating conflicting environmental, economic, and social objectives. Taking energy planning as an example, Pohekar and Ramachandran [132] and Wang et al. [133] highlighted that energy strategies must account for technical feasibility, environmental impacts, and social acceptance alongside financial costs. In water resources management, Nicklow et al. [134] and Reed et al. [33] demonstrated that EMO can concurrently compare water supply capacity, infrastructure costs, disaster risks, and ecological protection, thereby generating a suite of viable candidate options. Maier et al. [135] further argued that the research focus should shift from individual algorithmic enhancements toward problem formulation, decomposition frameworks, computational efficiency, and authentic decision support under complex, uncertain scenarios.

Another crucial role of MCDM in environmental management lies in incorporating policy goals, expert judgment, scientific data, and societal opinions into a unified evaluation framework. Hajkowicz and Collins [136] noted that multi-criteria decision analysis has been widely applied to water policy, long-term planning, and infrastructure option selection. de Brito and Evers [137] revealed that flood risk research predominantly leverages such methods to compare mitigation measures or regional vulnerability; nevertheless, a portion of these studies still lacks sensitivity testing for data and weights, while rarely enabling sustained stakeholder participation in decision-making processes. Kandakoglu et al. [138] further emphasized that the comprehensiveness of economic, environmental, and social factors, alongside how various participants assign their relative importance, significantly influences solution acceptance. Consequently, beyond providing Pareto optimal solutions, environmental decision-making must articulate whether long-term costs and risks are being shifted onto other regions, population groups, or future generations.

For high-cost simulation problems such as groundwater management, surrogate models facilitate the comparison of candidate alternatives using a reduced number of exact evaluations. Macasieb et al. [67] utilized a GP surrogate model alongside probabilistic Pareto dominance to identify candidate strategies for groundwater management under a constrained simulation budget, visually representing prediction uncertainties via cloudy Pareto fronts. This approach enables decision-makers not only to identify superior alternatives, but also to gauge the trustworthiness of the results. Nevertheless, the reliability of surrogate models remains contingent on whether the training samples encompass primary operational scenarios and whether they undergo validation against high-fidelity simulations; insufficient sampling may lead the model to overlook low-probability, high-consequence environmental risks.

To illustrate the shared structures and distinct variations across application domains, Table 10 compares seven application domains regarding their primary objective conflicts, methodologies and data, core decision values, and evidence and implementation limitations. Cross-domain comparison reveals that while all domains must navigate multiple conflicting objectives under resource constraints, their standards for evaluating solution

superiority and the ramifications of decision failures differ significantly. Engineering and supply chains predominantly measure improvements through cost, performance, energy, and service levels, while healthcare, education, emergency response, and public governance further demand the evaluation of equity, procedural rationality, and accountability, whereas environmental decision-making must additionally account for spatial spillovers and intergenerational impacts.

Table 10. Cross-domain comparison of MOO applications and decision value.

Application Domain	Primary Objective Conflicts	Methodologies and Data	Core Decision Values	Evidence and Implementation Limitations	Representative Literature
Engineering and Industry	Performance, cost, reliability, duration, energy, quality, and safety	Mathematical programming, EMO, surrogate models, ML, RL, DTs; physical models, simulations, and production-line data	Performance, low carbon, safety, quality, and production resilience	Requires validation of physical feasibility, surrogate errors, dynamic drift, control latency, and fail-safe protection	Prata (2025) [24]; Wang et al. (2026) [25]; Yuan et al. (2024) [68]
Logistics and Supply Chains	Network cost, service, inventory, transportation, emissions, disruption risks, and continuous operations	Mathematical programming, uncertainty modeling, MCDM, DTs; demand, transaction, logistics, and expert data	Efficiency, service, sustainability, resilience, and dynamic responsiveness	Cross-organizational data sharing, demand bias, low-probability disruptions, and model update frequency	Sabri and Beamon (2000) [6]; Chen et al. (2023) [105]; Nozari et al. (2026) [69]
Emergency and Humanitarian Response	Response time, facility damage, delivery coverage, material shortages, information distortion, and equity	Robust/stochastic programming, EMO, multi-criteria analysis; disaster situation, vulnerability, and field data	Rapid response, service coverage, resilience, equity, and accountability	Data timeliness, scenario plausibility, weighting for vulnerable groups, and field execution feasibility	Bozorgi-Amiri et al. (2013) [60]; Baharmand et al. (2022) [112]; Khameneh et al. (2026) [74]
Healthcare	Capacity, facility location, scheduling, waiting time, quality, cost, accessibility, and care value	Operations research, MOO, MCDM, clinical workflows, patient, cost, and expert data	Resource efficiency, service quality, patient accessibility, and equity	Personal data privacy, data bias, clinical acceptability, cross-level coordination, and high-risk review	Hulshof et al. (2012) [10]; Thokala et al. (2016) [32]; Zhao and Gu (2025) [72]
Education	Course and exam conflicts, classrooms, instructor workloads, student preferences, and school district resources	Integer programming, heuristics, EMO, RL; institutional rules, benchmarks, and real-world institutional data	Administrative efficiency, implementable schedules, resource equity, and solution flexibility	Institutional rule heterogeneity, data comparability, dynamic alterations, and preference-articulation cognitive burden	Mumford (2010) [26]; Dunke and Nickel (2023) [123]; Hafsa et al. (2025) [73]

Table 10. *Cont.*

Application Domain	Primary Objective Conflicts	Methodologies and Data	Core Decision Values	Evidence and Implementation Limitations	Representative Literature
Public Governance	Policy performance, resource allocation, public safety, plural values, equity, and legitimacy	MCDM, sensitivity and robustness analysis, policy evidence, expert and stakeholder judgments	Transparency, participation, robust ranking, equity, and accountability	Weighting disputes, non-compensable values, representativeness of participation, and ranking reversal	Munda (2004) [28]; Dean (2022) [126]; Azzini and Munda (2025) [75]
Environmental Sustainability	Energy, water resources, flood hazards, ecological risks, economic development, and intergenerational impacts	EMO, MCDM, surrogate models; monitoring, spatial, scenario, and high-cost simulation data	Resource efficiency, risk control, ecological protection, and long-term sustainability	Long-term extrapolation, spatial risk transfer, extreme events, surrogate credibility, and stakeholder participation	Reed et al. (2013) [33]; de Brito and Evers (2016) [137]; Macasieb et al. (2025) [67]

The functional roles of AI and smart optimization techniques also exhibit distinct variations across different domains. Ding et al. [63] and Yuan et al. [68] utilized RL and DTs, respectively, to support shop-floor scheduling, status updating, and closed-loop control; Nozari et al. [69] leveraged DTs to continuously integrate production, inventory, distribution, and recovery information throughout supply chains. In education, Zhang et al. [124] improved resource allocation using deep RL, whereas Hafsa et al. [73] evaluated EMO algorithms—including NSGA-II, NSGA-III, MOEA/D, Indicator-Based Evolutionary Algorithm, and Strength Pareto Evolutionary Algorithm 2—to generate professional training timetables. In emergency management, Khameneh et al. [74] applied NSGA-II to solve truck–drone humanitarian delivery problems under disruptions and uncertain information, using the ε-constraint method as a comparative benchmark. In environmental research, Macasieb et al. [67] employed surrogate models to mitigate high-cost simulation burdens while estimating prediction errors. In contrast, the selected healthcare and public governance literature relies less directly on AI, where studies place greater emphasis on model interpretability, ranking stability, and human oversight.

From a cross-domain perspective, MOO increasingly underpins dynamic, multi-dimensional decision ecosystems wherein candidate Pareto sets, streaming data updates, and evaluative criteria must synchronously adapt to shifting stakeholder preferences and operational contexts. Consequently, translation into practical utility hinges not merely on conventional algorithmic metrics (e.g., convergence rates and mathematical optimality), but fundamentally on the ecological fidelity of underlying data and constraint boundaries, operational robustness against contextual volatility, and the transparent communication of complex multi-objective trade-offs to end decision-makers.

5. Conclusions and Implications

This section summarizes the principal conclusions, presents theoretical and practical implications, and delineates the study limitations.

5.1. Conclusions

This review synthesizes four principal conclusions concerning the technological evolution, methodological organization, AI integration, and cross-domain decision value of MOO.

(1) The three analytical stages demarcate a progressive functional evolution of MOO rather than discrete, abrupt historical ruptures. Specifically, Information-Based Computing is defined primarily by explicit mathematical formulations, offline numerical solvers, and static Pareto-set generation; Data-Intensive Decision-Making broadens this baseline to accommodate parameter uncertainty, many-objective landscapes, multi-scenario simulations, and cross-system data streams; and AI-Driven Optimization systematically layers on learning-based approximation, adaptive search heuristics, dynamic model updating, and feedback loops responsive to evolving operational environments. Holguin Jimenez et al. [5] documented a comparable shift in production rescheduling from fixed-condition, single-pass solving toward hybrid methods, decision-maker interaction, and dynamic adjustment, while recent surrogate-model, reinforcement-learning, and digital-twin studies further illustrate the expansion of MOO toward adaptive and data-responsive decision processes [31,63,66–68]. These developments indicate that newer capabilities extend rather than replace established optimization foundations.

(2) Mathematical programming and EMO serve as complementary optimization approaches, while MCDM functions as a complementary decision-support approach. Each foundational paradigm serves distinct functional mandates: mathematical programming offers explicit constraint formulations and deterministic optimality bounds; EMO enables effective Pareto search across nonlinear, non-convex, and simulation-based black-box spaces; and MCDM facilitates preference elicitation, candidate ranking, and post-Pareto compromise identification. As Marler and Arora [1] underscored, methodological deployment must tightly match problem structures, preference models, and decision goals—a balance that inherently reflects the classic tension between mathematical exactness and algorithmic scalability highlighted by Jaber et al. [78]. Recent studies further show that AI support, constraint handling, and preference mechanisms make methodological suitability increasingly dependent on data conditions, constraint characteristics, interaction modes, and validation requirements [22,61,62].

(3) AI primarily reshapes the approximation, search, updating, and interaction mechanisms of MOO without replacing its mathematical and decision-theoretic foundations. Surrogate-assisted and adaptive-search studies show how AI can allocate computational resources, approximate expensive functions, guide Pareto search, and incorporate predictive uncertainty into solution evaluation [31,66,67,87]. Recent studies on generative artificial intelligence demonstrate that LLMs can effectively assist in mathematical problem formulation, algorithmic code generation, and heuristic exploration over complex black-box landscapes; nevertheless, their non-deterministic outputs mandate rigorous constraint feasibility verification and downstream numerical benchmarking before practical deployment [20,76].

(4) The cross-domain value of MOO extends beyond efficiency and cost to include resilience, sustainability, equity, transparency, and public value. These priorities vary substantially across application contexts, meaning that identical algorithmic metrics do not carry the same decision significance in every domain. Real-world studies illustrate this distinction: Zhao and Gu [72] evaluated hospital-layout alternatives in an operational healthcare setting, Hafsa et al. [73] addressed implementable timetabling under institutional constraints, Khameneh et al. [74] incorporated relief-distribution and regional-disparity considerations under imperfect information, and Azzini and Munda [75] examined the stability of policy rankings through sensitivity analysis. These studies demonstrate that the practical value of MOO depends not only on solution quality but also on domain-specific feasibility, evidence, validation, and the interpretation of trade-offs.

5.2. Implications

Building on these conclusions, the implications are organized into four theoretical research agendas and four corresponding practical priorities.

5.2.1. Theoretical Implications and Research Agenda

(1) Aligning problem characteristics with method combinations: Future research should examine how objective counts, constraint structures, data availability, preference formats, and computational resources affect the selection and integration of mathematical programming, EMO, MCDM, uncertainty modeling, and AI-assisted components [22,61,62,78]. Recent topology optimization and hybrid surrogate-assisted studies further show that representation and model integration can adapt to problem scale and search stage while being verified through high-fidelity analyses and prototype testing [144,146]. These findings motivate testable "problem characteristics–method functions–validation requirements" mappings that identify applicability boundaries rather than relying solely on average benchmark performance.

(2) Establishing longitudinal trustworthiness across data, models, and decision pipelines: Surrogate-assisted and data-driven MOO literature demonstrates that initial sampling strategies, epistemic approximation errors, constraint boundary handling, and predictive variance directly alter the geometry of Pareto frontiers and subsequent compromise selection [31,66,67,87]. In this context, constraint-aware infill sampling has proven instrumental in enhancing surrogate accuracy across feasible–infeasible boundaries while substantially curbing computationally expensive high-fidelity evaluations [143]. To transition from static benchmarks to resilient real-world deployments, future inquiry must formalize longitudinal validation protocols. These frameworks should systematically evaluate non-stationary data drift, predictive calibration fidelity, Pareto-frontier structural stability, dynamic constraint compliance, and autonomous retraining triggers across extended operational lifecycles.

(3) Constructing interpretable, amendable, and accountable human–AI co-decision-making frameworks: As AI increasingly participates in problem formulation, candidate generation, search guidance, and preference articulation, research should distinguish decision-maker-stated preferences, AI-inferred preferences, and model-generated assumptions, with explicit mechanisms for confirmation, amendment, veto, and traceability. In light of documented vulnerabilities surrounding semantic inaccuracy, prompt sensitivity, and limited explainability [20,22,23,71,76], future benchmarks must assess whether AI-derived formulations, trade-off explanations, and proposed solutions remain transparent and steerable by human decision-makers. Concurrently, studies should systematically measure how tiered human-in-the-loop interventions shape Pareto-frontier topologies and influence compromise selections.

(4) Developing multi-tier decision-value evaluation frameworks: Future research should assess algorithmic quality, model feasibility, organizational adoption, and societal or environmental outcomes as distinct but connected levels of evaluation. Fairness-aware multi-agent deep reinforcement learning in post-disaster task offloading illustrates how AI-driven optimization can explicitly incorporate service fairness alongside operational efficiency [145]. Evidence from healthcare, education, disaster relief, public policy, and related applications further indicates that equity, stability, and long-term risks should not be obscured by a single average performance metric or Pareto indicator [67,72–75].

5.2.2. Practical Implications

For practical implementation, the following four priorities translate the theoretical implications into problem formulation, lifecycle governance, domain-specific validation, and human oversight.

(1) Grounding method selection in rigorous problem formulation: Organizations should formally delineate conflicting objectives, inviolable constraints, data availability, stakeholder priorities, and preference structures prior to choosing among mathematical solvers, EMO heuristics, MCDM ranking, robust models, or AI extensions. Crucially, articulating and logging criteria weights, aspiration levels, and constraint justifications ensures that methodological selection remains anchored in substantive operational needs rather than algorithmic familiarity or tool convenience [22,61,62,78].

(2) Establish lifecycle governance for data, models, and update procedures: Organizations should predefine data-update frequencies, quality checks, outlier handling, model recalibration or retraining, and failure criteria. Studies involving physical–virtual data coupling, uncertainty representation, and surrogate prediction distributions illustrate why data consistency, prediction errors, and model validity require continuous assessment before and during deployment [67–69].

(3) Enforcing phased and domain-consequential validation: Model validation should advance sequentially from synthetic benchmarks to historical backtesting, stochastic simulation, pilot prototyping, field rollout, and continuous post-deployment monitoring. Crucially, validation metrics must reflect domain-specific failure risks: engineering and industrial applications prioritize physical constraints and operational safety; supply-chain and disaster logistics require stress-testing under disruptions and cascading information distortion; public governance, healthcare, and education prioritize equitable access, algorithmic fairness, and stable welfare outcomes; and environmental systems necessitate multi-temporal and spatial impact evaluations [67,72–75].

(4) Establish human oversight and accountability mechanisms for AI-assisted decision-making: Organizations should define who may modify objectives, weights, and constraints; who reviews AI-generated alternatives; and under what conditions automated processes should be suspended or overridden. Records of data sources, model versions, human interventions, and final approvals should be retained for traceability. LLM-assisted and preference-based approaches can support modeling, search, and interaction, but they do not eliminate the need for domain expertise and human control [20,22,23,71,76].

The relationships between the theoretical research agendas and practical priorities are summarized in Table 11.

Table 11. Integrated theoretical and practical implications of MOO in the digital and AI eras.

Core Issue	Theoretical Implications	Practical Implications	Key Validation Focus	Representative Recent Studies
Mismatch between methods and problem conditions	Establish alignment relationships among problem characteristics, data conditions, preference formats, and method selection	Define problem conditions prior to selecting or combining appropriate methods	Compare component contributions and identify applicability boundaries	Jaber et al. (2024) [78]; Zhang et al. (2024) [62]; Hu et al. (2025) [61]; Ren et al. (2026) [22]
Coexistence of dynamic, uncertain, and expensive evaluations	Integrate sampling, approximation errors, constraint feasibility, and longitudinal stability	Continuously update data and calibrate models using high-fidelity results	Check data drift, prediction errors, and option stability	Wang et al. (2024) [87]; Feng et al. (2026) [31]; Wang et al. (2026) [66]; Macasieb et al. (2025) [67]

Table 11. *Cont.*

Core Issue	Theoretical Implications	Practical Implications	Key Validation Focus	Representative Recent Studies
AI penetration in modeling, search, and preference articulation	Construct interpretable, amendable, and accountable human-AI co-decision-making frameworks	Delineate responsibilities across AI recommendations, manual modifications, and final approval sign-offs	Check semantic errors, prompt sensitivity, preference consistency, and human oversight	Aldana-Martín et al. (2026) [20]; Brahmachary et al. (2025) [76]; Ren et al. (2026) [22]
Disparities in cross-domain value and failure ramifications	Evaluate technical, organizational, societal, and environmental outcomes via tiered frameworks	Establish pilots, monitoring, and accountability procedures tailored to application domains	Report average efficacy, group disparities, sensitivity, and failure scenarios simultaneously	Zhao and Gu (2025) [72]; Hafsa et al. (2025) [73]; Khameneh et al. (2026) [74]; Azzini and Munda (2025) [75]

5.3. Limitations

The conclusions and implications of this study must be interpreted within the boundary conditions of its data sources, analytical design, and inferential scope, with five principal limitations outlined below.

(1) Literature sources and language scope: This study relies primarily on English-language journal articles and review papers indexed in WOS, omitting exhaustive coverage of other databases, books, conference proceedings, technical reports, and non-English studies. Consequently, this paper presents a representative research trajectory bounded by specific retrieval and selection criteria, rather than an all-inclusive census of global MOO outputs from 2000 to 2026.

(2) Temporal demarcation and coverage limitations: The three evolutionary stages serve as interpretive, literature-anchored lenses rather than macroscopic estimates of global MOO research output. Stage-specific counts and shares reflect solely the internal distribution of the 140 analyzed core publications. In addition, whereas the third stage captures the ongoing paradigm shift from 2016 to the present, our literature retrieval and selection period ended on 30 June 2026. Given the fluid nature of this current phase, future contributions may further refine and contextualize the specific properties observed in this review.

(3) Residual simplification in the classification scheme: Although secondary methodological and cross-domain characteristics were retained to represent hybrid studies, the descriptive statistics still rely on one primary methodological orientation and one primary research domain for each publication. This preserves mutually exclusive denominators and comparability across stages, but may not fully capture the intensity, sequencing, or functional interaction of multiple methods within highly hybrid studies. Accordingly, the reported category proportions should be interpreted as primary-orientation distributions rather than complete representations of all methodological combinations.

(4) Cross-domain comparability: Clear disparities exist across the seven application domains regarding problem scales, data sources, objective formulations, and validation levels; accordingly, this paper adopts a comparative synthesis rather than measuring all studies through a single effect size. The resulting conclusions serve to identify transferable methodological mechanisms and necessary contextual adaptations, rather than providing universally applicable algorithm rankings across domains.

(5) Heterogeneity in evidence and validation maturity: Although this review distinguishes the principal evidence and validation types of the core analytical publications, these categories are not converted into a single numerical quality score or an ordinal

hierarchy. Benchmark studies, simulations, empirical cases, operational deployments, and review studies therefore provide different forms of support and should be interpreted within their respective validation settings. This limitation is particularly relevant to rapidly developing AI-assisted approaches, including LLM-assisted modeling, AI-guided search, and human–AI interaction, for which much of the current evidence remains concentrated in methodological demonstrations, simulations, or case-based validation, while long-term deployment and cross-context evidence remain comparatively limited. Continued assessment based on open benchmarks, longitudinal operational records, and real-world deployment outcomes is therefore necessary.

These limitations define the scope within which the proposed review framework and its conclusions should be interpreted.

Author Contributions: Conceptualization, H.-L.L.; Methodology, H.-L.L.; Formal analysis, H.-L.L.; Data curation, H.S.; Writing—original draft, H.-L.L., H.S. and Y.-Y.M.; Writing—review and editing, H.-L.L., H.S. and Y.-Y.M.; Supervision, H.-L.L. and Y.-Y.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Fujian Provincial Federation of Social Sciences, grant number FJ2022T006; the Fujian Provincial Department of Science and Technology, grant numbers 2024R0099, 202335040124, and 202435040200; and Sanming University, grant number 23YG03S.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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