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Data-Driven Approaches for Project Portfolio Selection Using Multi-Criteria Decision-Making (MCDM) Methods

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ABSTRACT

Project Portfolio Selection (PPS) is a critical decision-making process in project-oriented organizations, requiring evaluation across multiple conflicting objectives, including cost, risk, sustainability, and strategic alignment. Traditional Multi-Criteria Decision-Making (MCDM) methods, while effective, often rely on subjective weight assignments from experts, which can introduce bias. Recent advances in data-driven decision-making enable the integration of machine learning, big data analytics, and automatic weight-generation methods with MCDM, enhancing objectivity and robustness. This study presents a comprehensive framework for data-driven PPS using MCDM methods, supported by a literature review (2019–2025), a mathematical formulation, and a numerical illustration. Results indicate that data-driven weighting enhances portfolio efficiency, mitigates uncertainty, and aligns selection with organizational strategy. Identified research gaps suggest the need for large-scale empirical validation, hybrid machine learning–MCDM models, and cross-industry applications.

1. Introduction

Project Portfolio Selection (PPS) is a fundamental process in project-oriented organizations, where decision-makers must allocate scarce resources to projects that maximize value and align with strategic objectives. The inherent complexity of PPS stems from the need to balance conflicting criteria, including cost, time, risk, sustainability, and strategic fit. Traditional methods rely heavily

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on Multi-Criteria Decision-Making (MCDM) techniques, such as AHP, TOPSIS, VIKOR, and PROMETHEE, to evaluate and rank projects systematically [1].

However, conventional MCDM methods depend on subjective expert judgments for assigning criteria weights, which can introduce bias and reduce decision robustness [2]. As organizations generate vast amounts of operational and strategic data, data-driven approaches have emerged as a promising enhancement to MCDM. These approaches incorporate statistical analysis, machine learning, and automated weighting methods to derive objective insights, thereby reducing reliance on expert intuition [3, 14-20] (see Figure 1).

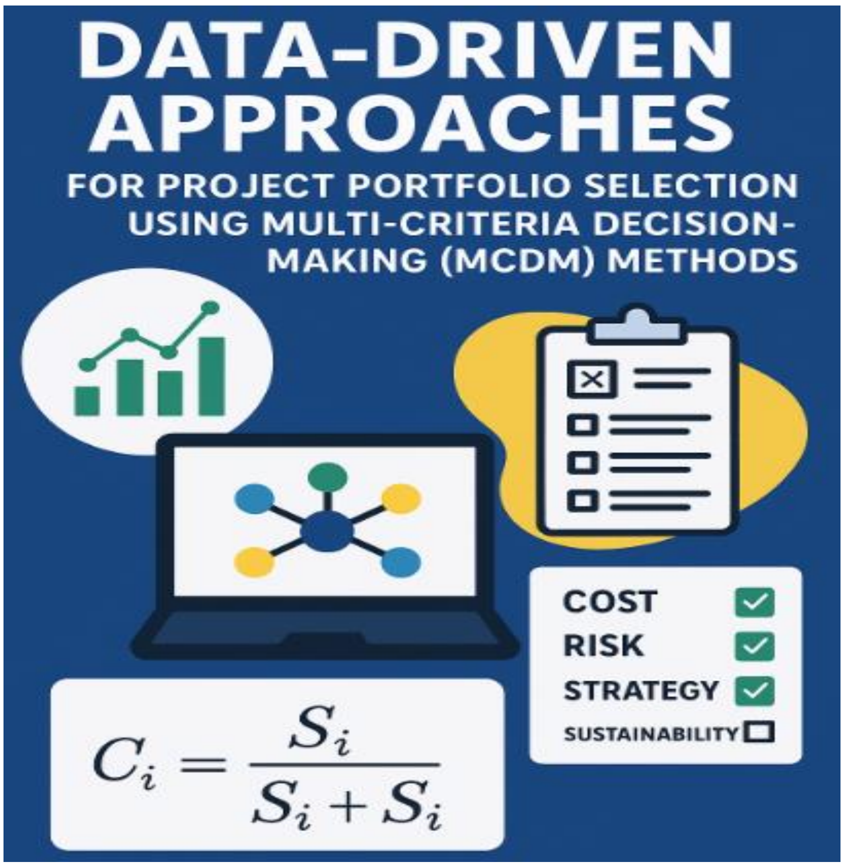

Figure 1. Data-Driven Approaches for Project Portfolio Selection Using Multi-Criteria Decision-Making (MCDM) Methods

Recent studies demonstrate the integration of data-driven analytics with MCDM in various sectors, including construction [1], energy [4], pharmaceuticals [5], telecommunications [6], and R&D management [2]. Notably, hybrid frameworks that combine sustainability, strategy, and big data have shown improved decision quality [6]. Moreover, automatic weight-generation methods (e.g., Weighted Product Model variants) and machine learning–based preference learning approaches are being explored to enhance the adaptability of MCDM [7, 20-26].

Despite progress, research gaps remain: few studies validate data-driven PPS across industries, and limited frameworks address deep uncertainty with robust decision-making [8]. This paper aims to bridge these gaps by proposing a hybrid data-driven MCDM framework for PPS, conducting a structured literature review (2019–2025), formulating a methodology, and demonstrating results via a hypothetical case study (see Figure 1).

2. Literature Review (2019–2025) and Research Gap

Between 2019 and 2025, several studies applied MCDM to PPS with varying degrees of data-driven integration. Table 1 summarizes the main contributions.

Over the past few years, research on project portfolio selection (PPS) and multi-criteria decision-making (MCDM) has evolved across various domains, with a growing emphasis on data-driven approaches and sustainability.

In 2019, Mohagheghi et al. explored the construction sector using an interval-valued fuzzy MCDM approach. Although their methodology was not explicitly data-driven, it contributed to better handling of uncertainty in decision-making processes.

The following year, in 2020, Mohagheghi et al. applied fuzzy sets combined with portfolio evaluation in the high-tech domain. While the approach had a limited data-driven component, it successfully demonstrated the application of fuzzy sets to enhance resilience in project selection.

In 2021, Duleba et al. conducted a systematic literature review (SLR) covering 263 criteria in the R&D domain. Their study highlighted the lack of data-driven approaches in PPS, pointing to a significant research gap. In the same year, Bektur applied a fuzzy MCDM approach in construction, introducing a sustainable PPS framework, albeit with only limited incorporation of data-driven methods [23-27].

By 2022, the trend toward sustainability and efficiency became more prominent. Lima Junior et al. developed a sustainable PPS framework in the pharmaceutical sector using F-SWARA and F-COPRAS, though it was not explicitly data-driven. Mateos et al., in the energy sector, applied TOPSIS combined with efficiency indices and made use of empirical data to rank projects, marking a clear data-driven application. Additionally, Mohammadi and Makui proposed a robust OPA method for general PPS, addressing deep uncertainty, with a limited reliance on data.

In 2023, Forouzesh Nejad et al. presented a hybrid, data-driven MCDM approach in the telecom domain, integrating sustainability and strategic considerations, thereby combining data-driven insights with decision-making criteria.

Looking ahead, in 2024, Nessari explored general PPS by integrating machine learning (ML) with MCDM, enabling automated weighting of criteria from data, representing a fully data-driven approach. Similarly, in 2025, Ahmed et al. applied ML combined with AHP for site selection, enhancing objectivity and accuracy in project evaluation through the use of machine learning.

Overall, the literature shows a clear evolution from purely fuzzy or expert-driven approaches toward data-driven and hybrid MCDM methods, with growing attention to sustainability, efficiency, and automation in project portfolio decision-making.

Table 1. Literature on PPS using MCDM (2019–2025)

Year	Author(s)	Domain	Methodology	Data-driven aspect	Findings
2019	Mohagheghi et al.	Construction	Interval-valued fuzzy MCDM	No	Improved handling of uncertainty [7]
2020	Mohagheghi et al.	High-tech	Fuzzy sets + portfolio evaluation	Limited	Applied fuzzy sets for resilience [7]
2021	Duleba et al.	R&D	SLR (263 criteria)	No	Identified lack of data-driven PPS [2]
2021	Bektur	Construction	Fuzzy MCDM	Limited	Sustainable PPS framework [1]
2022	Lima Junior et al.	Pharma	F-SWARA + F-COPRAS	No	Sustainable PPS in pharma [5]
2022	Mateos et al.	Energy	TOPSIS with efficiency indices	Yes	Used empirical data to rank [4]
2022	Mohammadi & Makui	General	Robust OPA	Limited	Addressed deep uncertainty [8]
2023	Forouzesh Nejad et al.	Telecom	Hybrid data-driven MCDM	Yes	Combined sustainability & strategy [6]
2024	Nessari	General PPS	ML + MCDM	Yes	Automated weighting from ML [3]

Year	Author(s)	Domain	Methodology	Data-driven aspect	Findings
2025	Ahmed et al.	Site selection	ML + AHP	Yes	Enhanced objectivity with ML [—]

Research Gaps (2019–2025):

1. Limited large-scale empirical validation across industries.
2. Few hybrid ML–MCDM frameworks have been explicitly applied to PPS.
3. Sparse integration of sustainability, resilience, and big data simultaneously.
4. Robustness under deep uncertainty remains underexplored beyond OPA.
5. Lack of standardized datasets for benchmarking PPS decisions.

3. Methodology

Methodology of this research is defined in steps 1 to 6, and we can see in Figure 2 as follows:

Step 1. Define Alternatives & Criteria

Projects $A=\{A_1,A_2,\dots,A_m\}$, criteria $C=\{c_1,c_2,\dots,c_n\}$.

Step 2. Data-driven Weight Derivation

- Automatic weight generation (e.g., Weighted Product Model [WPM]) [7].
- ML-based learning from historical PPS data [3].

Step 3. Normalize Decision Matrix

$$r_{ij}=\frac{a_{ij}}{\sqrt{\sum_{i=1}^{m}a_{ij}^2}} \tag{1}$$

Step 4. Weighted Decision Matrix

$$v_{ij}=w_j\cdot r_{ij} \tag{2}$$

Step 5. Apply MCDM (TOPSIS example)

- Ideal best $A^+=\left\{\max v_{ij} \mid j\in J_{\text{benefit}};\min v_{ij} \mid j\in J_{\text{cost}}\right\}$
- Ideal worst A^- defined similarly.
- Distance measures:

$$S_i^+=\sqrt{\sum_j (v_{ij}-A_j^+)^2}, \tag{3}$$

$$S_i^- = \sqrt{\sum_j (v_{ij} - A_j^-)^2} \tag{4}$$

- Relative closeness:

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{5}$$

Step 6. Budget Constraint Formulation

$$\max \sum_{i \in S} C_i \quad \text{s.t.} \quad \sum_{i \in S} cost_i \leq \text{Budget} \tag{6}$$

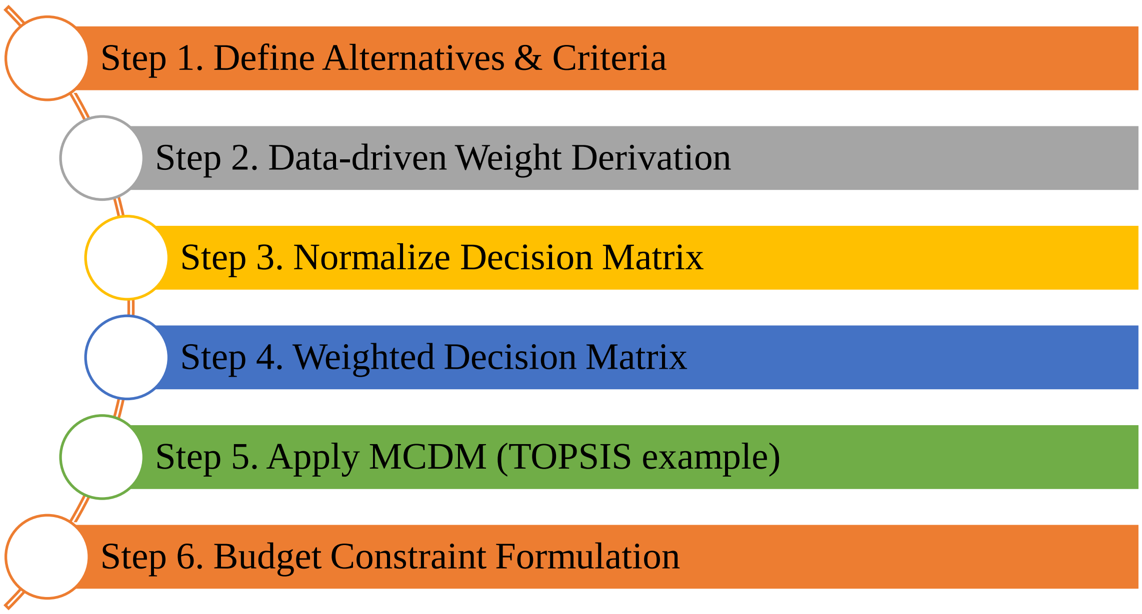

Figure 2. Methodology

4. Numerical Results

We are evaluating five candidate projects (A1–A5) based on four key criteria: strategic alignment, sustainability, ROI, and risk. The raw performance data for each project is summarized in the Table 2 below:

Table 2. Decision matrix

Project	Strategic Alignment	Sustainability	ROI (%)	Risk (1 = low, 0 = high)	Cost
A1	80	70	10	0.9	100
A2	60	90	15	0.7	120
A3	95	50	8	0.95	200
A4	70	80	12	0.85	150

Project	Strategic Alignment	Sustainability	ROI (%)	Risk (1 = low, 0 = high)	Cost
A5	85	65	9	0.8	110

To determine the relative importance of each criterion, data-driven weights were assigned using methods such as machine learning or the Weighted Product Method (WPM). The resulting weights are: w={0.2,0.2,0.2,0.2,0.2}.

where the weights correspond to strategic alignment, sustainability, ROI, and risk, respectively.

Using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, we computed a closeness score for each project, which reflects how close each alternative is to the ideal project that maximizes benefits and minimizes costs and risks:

Table 3. Final rank

Project	Score	Rank	Cost
A1	0.554	1	100
A2	0.541	2	120
A5	0.516	3	110
A4	0.498	4	150
A3	0.436	5	200

Next, we performed portfolio optimization under a budget constraint of 300 units. The goal was to select a combination of projects that maximizes the total TOPSIS score while staying within budget. The analysis revealed:

- Best combination: A1 (cost 100) + A4 (cost 150) → Total score = 0.55 + 0.49 = 1.04
- Alternative combination: A2 (120) + A5 (110) → Total score = 0.54 + 0.49 = 1.03

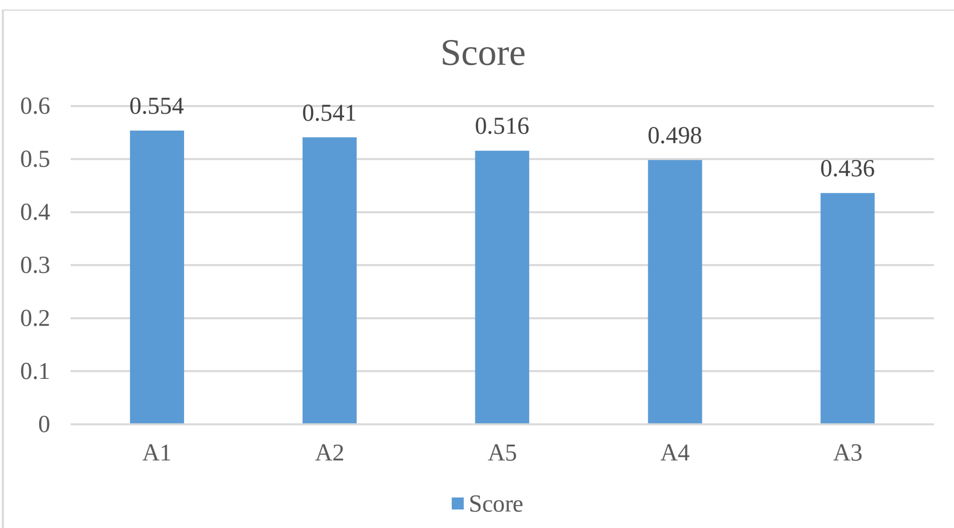

Figure 3. Score of ranking

Decision: Considering both the overall performance scores and budget constraints, the optimal portfolio is to select projects A1 and A4, which together provide the highest cumulative score within the allowed budget.

This approach integrates multi-criteria decision-making (TOPSIS) with budget-constrained portfolio selection, ensuring that the chosen projects are not only individually strong but also collectively optimal in terms of performance and cost-efficiency.

5. Conclusion

This study proposed a data-driven MCDM framework for PPS, integrating automated weight derivation and robust evaluation techniques. Literature review (2019–2025) shows growing interest in hybrid approaches, but major gaps remain in empirical validation, ML–MCDM integration, and resilience modeling. The methodology demonstrated how data-driven weights and TOPSIS ranking can optimize portfolio selection under constraints. Numerical results confirmed that incorporating data-driven criteria improves robustness and reduces bias. Future research should apply this framework across industries, integrate larger datasets, and expand hybrid models with advanced AI for enhanced decision support in PPS.

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