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A Social Value-Based Weighting Approach for Advanced Multi-Criteria Decision-Making Methods

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Abstract

Purpose: This study aims to address a key gap in Multi-Criteria Decision-Making (MCDM) methods—namely, their limited incorporation of social and cultural values. While MCDM is widely used for solving complex problems involving multiple, often conflicting criteria, most existing weighting techniques rely mainly on quantitative data or subjective judgments. This research seeks to develop a framework that integrates social values into the weighting process to enhance the alignment of decisions with societal expectations.

Design/Methodology/Approach: The study proposes a new framework termed Social Value-Based Weighting (SVBW). In this approach, baseline weights are first derived using any classical weighting method (subjective, objective, or hybrid). These baseline weights are then adjusted through a Social Priority Index, which reflects the degree to which each criterion aligns with selected social values. Values incorporated into the index include justice, public interest, resource efficiency, harm prevention, and religious democracy. The model is designed to be compatible with any existing MCDM technique, and the strength of value-based adjustments can be customized using flexible parameters. A numerical example and sensitivity analysis are used to evaluate the model's behavior and implications.

Findings: Results from the numerical example and sensitivity analysis demonstrate that integrating a social value layer into the weighting process does not fundamentally change final rankings but significantly enhances the transparency of the decision-making logic. More importantly, it increases the social acceptability of outcomes by explicitly reflecting societal value priorities. The findings highlight the potential of SVBW to reconcile technical decision-making processes with normative public expectations.

Practical Implications: The proposed framework offers wide applicability in areas such as public policy, resource management, investment decisions, and organizational planning. By embedding social values into traditional MCDM procedures, SVBW provides decision-makers with a more socially grounded and context-sensitive tool.

Originality/Value: This study contributes a novel conceptual bridge between quantitative decision analysis and social value considerations. The SVBW framework lays the foundation for developing context-specific, socially embedded MCDM approaches that enhance both technical rigor and societal legitimacy.

Keywords

Multi-Criteria Decision-Making (MCDM); criteria weighting; social values; Social Priority Index (SPI).

Introduction

Over the past decades, Multi-Criteria Decision-Making (MCDM) has emerged as one of the most significant and widely applied tools for solving complex problems that involve diverse and often conflicting criteria (Azhar et al., 2021; Aruldoss et al., 2013). This approach encompasses a broad range of methods, including pairwise comparison, outranking, and distance-based techniques, the most prominent of which can be found in families such as AHP, ANP, ELECTRE, PROMETHEE, TOPSIS, and VIKOR (Azhar et al., 2021). Evidence shows that the use of MCDM techniques has grown exponentially; among them, AHP remains the most widely used standalone method, while hybrid approaches hold the second position (Mardani et al., 2015).

Between 2004 and 2024, the field has rapidly evolved from fundamental models toward more advanced hybrid approaches, which are now increasingly integrated with tools such as artificial intelligence, fuzzy logic, and machine learning (Kumar & Pamucar, 2025). Furthermore, the scope of applications has expanded to domains such as energy, environment, sustainability, urban planning, and healthcare, all of which are aligned with global priorities, including the United Nations Sustainable Development Goals (Mardani et al., 2015; Kumar & Pamucar, 2025).

In such contexts, decision-makers must balance a set of quantitative and qualitative criteria to ultimately select the option that yields the highest overall utility. Consequently, determining appropriate weights for the criteria is recognized as one of the most critical and influential stages in the entire decision-making process. To address this need, numerous weighting methods have been developed, each based on distinct operational principles and computational procedures (Uzhga-Rebrov & Kuļešova, 2023).

These approaches are generally divided into two categories: subjective methods, which are simpler but depend heavily on the judgments of decision-makers; and objective methods, in which weights are derived mathematically and independently of individual preferences (Odu, 2019). The Analytic Hierarchy Process (AHP) and the Analytic Network Process (ANP) emerged in the 1980s as dominant weighting techniques, yet they have been subject to considerable theoretical and practical criticisms (Huang & Inuiguchi, 2015). To overcome these limitations, alternative models were proposed, such as the Diminishing Utility Decision-Making (DUDM) approach, which integrates the concept of diminishing marginal utility with AHP in order to model both primary and interactive weights more effectively while reducing the number of required pairwise comparisons and computational complexity (Huang & Inuiguchi, 2015).

Despite such advances, the issue of objectivity in determining criteria weights remains one of the fundamental challenges in the MCDM field (Uzhga-Rebrov & Kuļešova, 2023). Put differently, a central question is still left unanswered: on what basis should criterion weights be established, and can this foundation truly reflect the real values and priorities of society or the governing system?

A review of the scholarly literature reveals extensive efforts to overcome the limitations of traditional weighting methods. For example, Al-Aomar (2022) developed a hybrid AHP–Entropy method to integrate subjective and objective approaches and to address the challenge of heterogeneous data in preference judgments. Similarly, Wang and Lee (2009) introduced the fuzzy TOPSIS approach, which combines subjective weights derived from decision-makers' preferences with objective weights obtained through Shannon's entropy theory. In addition, Zavadskas and Podvezko (2016) proposed the IDOCRIW method, which merges entropy with the Criterion Impact Loss (CILOS) technique, thereby improving the accuracy of objective weight estimation. Odu (2019), in a comprehensive review, also emphasized that while subjective approaches are generally simpler, objective approaches provide the advantage of mathematically rigorous and unbiased weight derivation.

Collectively, these studies demonstrate that researchers have consistently sought solutions to balance subjective preferences with data-driven objectivity in the weighting process.

Nevertheless, most of these efforts have remained confined to the technical dimension of the problem, paying little attention to underlying social or cultural values. In fact, in many of these methods, the "importance of criteria" is either determined based on the individual judgment of the decision-maker or derived solely from data characteristics, while fundamental social principles and cultural values are absent from the decision-making process. The literature also highlights a significant gap between conventional MCDM methods and socio-cultural contexts.

Keykha et al. (2025) argue that methods such as Shannon's entropy rely exclusively on data or subjective judgments, rendering the results highly sensitive to modeler choices. Similarly, Ayan et al. (2023) stress that even recent weighting approaches continue to focus predominantly on technical aspects, overlooking cultural values. Al-Aaidroos et al. (2016) criticize utilitarian decision-making models for reflecting secular norms and for being misaligned with certain social values; they propose instead the adoption of altruistic utility and value-sensitive terminologies to align decision models with ethical considerations. Finally, Al-Qur'an (2023) introduces a council-based framework, emphasizing the necessity of integrating ethics and mutual consultation into the decision-making process, consistent with behavioral decision-making theories.

As a result, in societies where values and ethics play a fundamental role in social and political life, neglecting them in the decision-making process can create a disconnect between decision outcomes and public expectations. Within such a context, principles such as justice, public interest, resource efficiency, harm prevention, and religious democracy hold a central position. Ignoring these principles not only undermines the acceptability of decisions but may also reduce their long-term effectiveness. This raises a critical question: can the weighting process in MCDM be redesigned in a way that reflects prevailing social values and brings decision outcomes closer to the cultural expectations and priorities of society?

The significance of weighting in multi-criteria decision-making (MCDM) can be examined from three perspectives: scientific, social, and governance. From a scientific standpoint, criteria weighting forms the core of all MCDM methods. If the assigned weights fail to reflect the true importance of the criteria, the entire decision-making process will lead to unreliable outcomes (Öztürk & Batuk, 2007; Odu, 2019). Comprehensive studies have shown that a variety of weighting approaches have been developed, each with substantial differences in their operational principles and computational procedures (Uzhga-Rebrov & Kuļešova, 2023). Although methods such as ranking, pairwise comparison, trade-off analysis, and fuzzy logic have been proposed to address uncertainty (Öztürk & Batuk, 2007), several challenges remain unresolved, including decreased consistency of judgments as the complexity of criteria increases and inefficiencies at different levels of decision-making (Mostofi et al., 2022).

Despite this progress, relatively few approaches have explicitly focused on *value-based* or *socially oriented* weighting. Thus, developing a framework that systematically incorporates prevailing social values into the weighting process represents not only a novel contribution but also a promising avenue for expanding the literature on MCDM.

In societies where policymaking and large-scale decision-making are not aligned with prevailing cultural and social values, outcomes often face resistance from the public. Under such conditions, even decisions that are economically or technically optimal may lack broad social acceptance. Incorporating social values into the weighting process of criteria directly reflects the priorities of society in decision-making—an approach that significantly enhances the acceptance of results.

Research has shown that embedding values such as justice, consultation, fairness, and public interest in strategic management strengthens organizational legitimacy and ethical governance (Putra, 2025). This finding is consistent with the work of Khoiro and Husna (2022), who demonstrate a positive correlation between the perception of cultural-social values and support for educational and social policies, emphasizing that integrating social values into policymaking can lead to more inclusive development. Similarly, Al-Aaidroos et al. (2016) argue that while utilitarian decision-making models can be adapted to social contexts, genuine legitimacy requires modifications that incorporate altruistic utility and ethical considerations. Kalkavan et al. (2021) further highlight that ethical and social principles—particularly justice in income distribution and commercial integrity—play a vital role in sustaining economic development, as adherence to honesty reduces market uncertainty and facilitates growth.

Effective governance requires that social values and principles be integrated into all stages of policymaking, planning, and implementation; within this framework, decision-making without reliance on such values remains incomplete. Numerous studies have demonstrated that embedding social values can enrich governance structures and decision-making frameworks. Batchelor (2014), for instance, identifies justice, consultation, and accountability as pillars of governance and recommends that these principles be systematically incorporated into governance processes through change management approaches. Likewise, Al-Qur'an (2023) emphasizes mutual consultation grounded in social ethics and proposes a framework for strategic decision-making that aligns with behavioral decision-making theories.

Putra (2025) introduces the concept of social strategic management, which integrates values such as justice and trustworthiness into business decision-making processes, thereby enhancing both legitimacy and sustainable competitiveness of organizations. Similarly, Riandari et al. (2024), through the introduction of the Multi-Objective Preference Analysis (MOPA) method for tourism planning, demonstrate that this approach, with a high confidence level (0.917), outperforms traditional MCDA and can serve as a powerful tool for value-oriented decision-making.

Given that MCDM methods are widely applied in governance contexts—ranging from infrastructure project selection to social and economic policy formulation—designing a weighting approach grounded in prevailing social values and principles can provide policymakers and managers with an effective and legitimate decision-support tool.

The primary objective of this study is to design and articulate a weighting approach based on prevailing social values within the framework of multi-criteria decision-making (MCDM). The study seeks to demonstrate how values such as justice, public interest, resource efficiency, and religious democracy can serve as illustrative examples of socio-cultural principles that are translated from theoretical foundations into practical rules for criteria weighting.

To achieve this objective, the research follows three main paths:

1. Explaining how selected social values can be explicitly incorporated into the decision-making process;
2. Providing a mechanism for translating these values into operational weighting rules that can be applied in determining or adjusting criteria weights; and
3. Developing a hybrid framework that can be implemented alongside conventional methods such as AHP, ANP, or objective approaches like entropy.

Through this design, the study offers a conceptual and theoretical foundation that paves the way for future applied and empirical research.

Based on the problem statement and research objectives, the key research questions are as follows:

1. How can social values and principles be translated into explicit and actionable rules within the weighting process?
2. In what ways does the proposed approach differ from classical weighting methods, and how can it be integrated with existing MCDM techniques?
3. What implications does the application of this approach hold for enhancing the social acceptance and cultural alignment of multi-criteria decision-making processes?

1. The Proposed Method: Social Value-Based Weighting (SVBW) in MCDM

The fundamental issue is that in MCDM, the weighting of criteria is usually based either on expert judgments (e.g., AHP, ANP, Direct Rating) or on the statistical properties of data (e.g., Entropy, CRITIC). However, in the context of social governance, it is essential that weights also reflect the values and priorities of society. Therefore, the proposed method—hereafter referred to as SVBW: Social Value-Based Weighting—adds a complementary normative layer to any existing weighting technique by adjusting baseline weights according to an index of "alignment with social values and principles".

The core idea is as follows: baseline weights W_j^0 are first derived using any conventional method (subjective, objective, or hybrid). Then, by calculating a *Social Priority Index* $I_j \geq 0$ for each criterion, the weights are adjusted either multiplicatively or through a convex-combination scheme, followed by normalization. This design offers two main advantages:

1. It is compatible with any MCDM ecosystem; and
2. The intensity of social value influence can be controlled through a tunable parameter, ensuring transparency and enabling sensitivity analysis.

The essential terms and constructs required for this method include:

1. Alternatives: $A_i: i = \{1,2,\dots,m\}$
2. Criteria set: $C_j: j = \{1,2,\dots,n\}$
3. Baseline weights: W_j^0 for each j, obtained from any classical weighting method
4. Experts: $p = \{1,2,\dots,h\}$
5. Selected social values and principles: $r = \{1,2,\dots,k\}$

2. Methodological Steps

Step 1: Problem and criteria definition

Clearly define the decision problem and its stakeholders, and identify the criteria (with "the more the better" or "the less the better" orientation). Baseline weights for the criteria are determined using any preferred classical method.

Step 2: Identification of relevant social values

Based on the literature, a set of relevant social values is selected, and their relative importance β_r is elicited from experts. This can be accomplished either by constructing a pairwise comparison matrix (e.g., using AHP) or through simpler methods for calculating relative importance.

Step 3: Mapping values to weighting rules

For each value r, one or more *normative rules* are defined. These rules specify how a criterion should receive additional reinforcement or attenuation of weight if it exhibits certain features. Examples of general rules include:

- **Harm prevention rule:** If a criterion plays a significant role in "reducing risks or harms" beyond a given threshold, it receives a reinforcement factor.
- **Justice rule:** If a criterion contributes to improving access or reducing discrimination, it gains additional weight.
- **Public interest rule:** The more broadly collective the benefits of a criterion are, the higher the reinforcement factor it receives.
- **Resource efficiency rule:** Criteria that significantly enhance the efficient use of resources are strengthened.
- **Religious democracy rule:** If a criterion fosters public participation, decision transparency, or managerial accountability, it is assigned a reinforcement factor.

Note: The rules can be defined in linguistic **If–Then** form and subsequently quantified using fuzzy membership functions.

Step 4: Estimating the membership of each criterion in social values

For each criterion c_j, its degree of membership in each value r is assessed, denoted as $\mu_r(j) \in [0,1]$. This evaluation can be conducted using expert panels or documentary evidence.

Step 5: Calculating the Social Priority Index I_j

In this step, a composite index is constructed by combining the inter-value weights β_r (which represent the relative importance of the values in the current decision problem) with the membership scores:

$$I_j = \sum_{r=1}^{k} \beta_r * \mu_r\,(j)$$

subject to:

$$\sum_{r=1}^{k} \beta_r = 1 \ , \beta_r \geq 0$$

To determine the value weights β_r, group decision-making is recommended, either through individual ranking or individual scoring approaches. Differences of opinion among experts regarding values or their relative importance can be managed through these methods.

- In the ranking approach, if experts cannot provide direct scores of criteria with respect to the values, they are asked to assign a rank (from 1 to *n*) for each criterion under each value.
- In the scoring approach, if experts are able to assign explicit scores, they provide value-based evaluations of criteria, which are then aggregated into the index.

Step 6: Computing the final weights $\widetilde{W_J}$

Two main approaches are proposed for adjusting the baseline weights:

a) Multiplicative adjustment

A value-based reinforcement factor is defined for each criterion:

$$M_j = 1 + \alpha \cdot I_j \ ; (\alpha \geq 0)$$

where α controls the intensity of value influence. The final weight is then calculated as:

$$\widetilde{W_J} = \frac{W_j * M_j}{\sum_{j=1}^{m} W_j * M_j}$$

b) Convex (axial–convex) combination

First, "pure value-adjusted" weights are obtained by multiplying and normalizing:

$$M_j = 1 + I_j$$

$$\widehat{W_J} = \frac{W_j * M_j}{\sum_{j=1}^{m} W_j * M_j}$$

Then, a convex combination is computed between the baseline weights and the adjusted weights:

$$\widetilde{W_J} = (1 - \lambda)\, w_j^0 + \lambda\, \widehat{W_J}, \lambda \in [0,1]$$

Here, λ serves as a transparency and sensitivity parameter: if $\lambda = 0$, only baseline weights are applied; if $\lambda = 1$, full social adjustment is applied.

Note: The selection of intensity parameters (α or λ) should be made collaboratively by experts and the decision-making team, often through sensitivity testing. As a guideline, moderate values are recommended at the outset (e.g., $\alpha \in [0.2,0.5]$ or $\lambda \in [0.3,0.6]$).

Normative properties of the SVBW method include:

1. **Non-negativity and normalization:** $\widetilde{W_j} \geq 0, \sum_j \widetilde{W_j} = 1$;
2. **Monotonicity with respect to Ij:** If w_j^0 remains fixed, then with an increase in I_j (while all others remain constant), the adjusted weight $\widetilde{W_j}$ will also increase.
3. **Compatibility with baseline weights:** When $\alpha = 0$ or $\lambda = 0$, the method precisely reduces to the baseline weights w_j^0.

3. Numerical Example

Step 1: Definition of criteria

Four benefit-type criteria are considered. The baseline weights are calculated.

Table 1: Baseline criteria and their initial weights

Criteria (C)	Baseline weight ($\boldsymbol{w_j^0}$)
c1	0.292
c2	0.108
c3	0.413
c4	0.187

Step 2: Determining the set of values and inter-value weights

For simplicity, four values and their relative importance are assumed as follows:

Table 2: Selected social values and their inter-value weights

Social values (r)	Inter-value weights ($\boldsymbol{\beta_r}$)
r1	0.4
r2	0.3
r3	0.2
r4	0.1

Step 3: Estimating membership of each criterion in values ($\boldsymbol{\mu_r(j)}$)

Based on expert judgment, the following membership matrix is adopted:

Table 3: Membership matrix of criteria with respect to social values

Criteria (*C*)	r1	r2	r3	r4
c1	0.1	0.3	0.2	0.2
c2	0.3	0.8	0.3	0.4
c3	1.0	0.5	0.2	0.4
c4	0.2	0.4	0.9	0.3

Step 4: Calculating the Social Priority Index I_j

For example, for c1:

$$I_j = \sum_{r=1}^{k} \beta_r * \mu_r(j) = (0.4 * 0.1) + (0.3 * 0.3) + (0.2 * 0.2) + (0.1 * 0.2) = 0.19$$

Table 4: Computed Social Priority Index (Ij) for each criterion

Criteria (*C*)	Social Priority Index (I_j)
c1	0.19
c2	0.46
c3	0.63
c4	0.41

Step 5: Constructing reinforcement factors M_j and final weights

a) Multiplicative adjustment with $\alpha = 0.5$

For example, for c1:

$$M_j = 1 + \alpha \cdot I_j = 1 + (0.5 * 0.19) = 1.095$$

$$\widetilde{W_j} = \frac{W_j * M_j}{\sum_{j=1}^{m} W_j * M_j} = \frac{0.292 * 1.095}{(0.292*1.095)+(0.108*1.23)+(0.413*1.315)+(0.187*1.205)} = 0.26187$$

Table 5: Reinforcement factors (M_j) and final weights under multiplicative adjustment (α=0.5)

Criteria (*C*)	Reinforcement factor (M_j)	$w_j^0 \times M_j$	Final weight (W_j)
c1	1.095	0.31974	0.26187
c2	1.23	0.13284	0.10880
c3	1.315	0.54310	0.44479
c4	1.205	0.22534	0.18455

b) Convex (axial–convex) combination with $\boldsymbol{\lambda = 0.5}$

For example, for c1:

$M_j = 1 + I_j = 1 + 0.19 = 1.19$

$$\widehat{W_j} = \frac{W_j * M_j}{\sum_{j=1}^{m} W_j * M_j} = \frac{0.292*1.19}{(0.292*1.19)+(0.108*1.46)+(0.413*1.63)+(0.187*1.41)} = 0.2409$$

$$\widetilde{W_j} = (1-\lambda)\, w_j^0 + \lambda\, \widehat{W_j}, \lambda \in [0,1] = (1-0.5) * 0.292 + 0.5 * 0.2409 = 0.2664$$

Table 6: Reinforcement factors, normalized adjusted weights, and final weights under convex combination (λ=0.5)

Criteria (C)	Reinforcement factor ($\boldsymbol{M_j}$)	Normalized value-adjusted weight ($\widehat{\boldsymbol{W_j}}$)	Final weight ($\widetilde{\boldsymbol{W_j}}$)
c1	1.19	0/2409	0/2664
c2	1.46	0/1093	0/1086
c3	1.63	0/4668	0/4399
c4	1.41	0/1828	0/1849

Step 6: Ranking alternatives using WSM (optional)

Consider three hypothetical alternatives, A1, A2, A3, and a performance matrix (scale 0–100):

Table 7: Performance matrix of alternatives (A1,A2,A3) before normalization (scale 0–100)

Criteria	A1	A2	A3
c1	80	70	60
c2	65	75	85
c3	60	70	90
c4	50	60	70

Linear normalization (dividing by the maximum of each row):

Table 8: Linearly normalized performance matrix of alternatives

Criteria	A1	A2	A3
c1	1.0	0.875	0.75
c2	0.7647	0.8824	1.0
c3	0.6667	0.7778	1.0
c4	0.7143	0.8571	1.0

1) Using baseline weights w_j^0:

Table 9: Alternative scores and ranking using baseline weights (w_j^0) under WSM

Criteria	A1	A2	A3
c1	0.2920	0.2555	0.2190
c2	0.0826	0.0953	0.1080
c3	0.2753	0.3212	0.4130
c4	0.1336	0.1603	0.1870

Final scores: A1=0.7835, A2=0.8323, A3=0.9270

Ranking: A3≻A2≻A1

2) Using socially adjusted weights $\widetilde{W}_j$:

a) Multiplicative adjustment

Table 10: Alternative scores and ranking using socially adjusted weights under multiplicative adjustment (α=0.5)

Criteria	A1	A2	A3
c1	0.2619	0.2291	0.1964
c2	0.0832	0.0960	0.1088
c3	0.2965	0.3459	0.4448
c4	0.1318	0.1582	0.1845

Final scores: A1=0.7734, A2=0.8293, A3=0.9345

Ranking: A3≻A2≻A1

b) Convex combination

Table 11: Alternative scores and ranking using socially adjusted weights under convex combination (λ=0.5)

Criteria	A1	A2	A3
c1	0/2665	0/2332	0/1999
c2	0/0831	0/0959	0/1087
c3	0/2933	0/3422	0/4399
c4	0/1321	0/1585	0/1849

Final scores: A1=0.7750, A2=0.8297, A3=0.9334

Ranking: A3≻A2≻A1

Interpretation: In this example, the application of the Social Value-Based Weighting (SVBW) approach did not alter the final ranking of the alternatives. However, it enhanced the transparency and defensibility of the ranking logic, enabling decision-makers to clearly demonstrate why one alternative is preferred over another and how this preference is grounded in social values.

3. Sensitivity Analysis within the Proposed Framework

A key component of any multi-criteria decision-making (MCDM) model is sensitivity analysis, as it reveals how robust or fragile the results are to changes in model parameters. Within the proposed SVBW framework, it is also essential to examine how the ranking of alternatives responds under different scenarios. Four main dimensions of sensitivity are considered:

1. **Sensitivity to changes in alternatives:** In this case, the performance data of alternatives are modified, and the rankings are recalculated using socially adjusted weights. Comparing the results indicates whether small variations in the alternatives' values lead to meaningful changes in the final ranking. If the rankings remain stable, the proposed framework can be regarded as more reliable and robust.
2. **Sensitivity to changes in criteria:** Here, the number or type of decision criteria is altered (e.g., adding a new criterion or removing an existing one). The weighting procedure is then repeated, and the resulting rankings of alternatives are observed. This analysis demonstrates how flexible the proposed framework is when facing structural changes in the criteria set.
3. **Sensitivity to changes in social values and principles:** In this scenario, either the relative importance of social values or the degree of association of criteria with those values is varied. This allows identification of which criteria are most influenced by social values and which alternative rankings are more sensitive to shifts in value priorities.

4. Sensitivity Analysis Results

The results of the sensitivity analysis under different scenarios are summarized below.

1) Baseline table

Baseline Weights & Scores (SVBW example) — including criterion weights, scores for A1, A2, A3, and their rankings.

Table 12: Baseline Weights & Scores (SVBW example)

w-set	c1	c2	c3	c4	Score A1	Score A2	Score A3	Rank A1	Rank A2	Rank A3
Base ($\boldsymbol{w_j^0}$)	0.292	0.108	0.413	0.187	0.7835	0.8323	0.9270	3	2	1
Multiplicative (α=0.5)	0.2618	0.1087	0.4447	0.1845	0.7734	0.8293	0.9345	3	2	1
Convex (λ=0.5)	0.2505	0.1822	0.3497	0.2174	0.7750	0.8297	0.9334	3	2	1

2) Sensitivity 1: Changes in alternatives

Two scenarios were tested:

- OPT1: Improvement of A2 on criterion c3 to 0.85
- OPT2: Reduction of A3 on criterion c2 to 0.9

Table 13: Sensitivity – Option Changes

Scenario	w-set	Score A1	Score A2	Score A3	Rank A1	Rank A2	Rank A3
OPT1: A2@c3→0.85	Base (w_j^0)	0.7835	0.8621	0.9270	3	2	1
	Multiplicative (α=0.5)	0.7732	0.8611	0.9342	3	2	1
	Convex (λ=0.5)	0.775	0.8549	0.9334	3	2	1
OPT2: A3@c2→0.9	Base (w_j^0)	0.7835	0.8323	0.9162	3	2	1
	Multiplicative (α=0.5)	0.7732	0.829	0.9234	3	2	1
	Convex (λ=0.5)	0.775	0.8297	0.9152	3	2	1

3) Sensitivity 2: Changes in criteria

Two scenarios were examined:

- CRIT1: Removing criterion c4 (with re-normalized weights)
- CRIT2: Reducing the importance of c1 by 20% (with re-normalized weights)

Table 14: Sensitivity – Criteria Changes

Scenario	w-set	Adjusted Weights	Score A1	Score A2	Score A3	Rank A1	Rank A2	Rank A3
CRIT1: remove c4	Base ($\boldsymbol{w_j^0}$)	{c1:0.3592, c2:0.1328, c3:0.508}	0.7994	0.8266	0.9102	3	2	1
	Multiplicative (α=0.5)	{c1:0.3211, c2:0.1334, c3:0.5455}	0.7868	0.8230	0.9197	3	2	1
	Convex (λ=0.5)	{c1:0.3202, c2:0.2329, c3:0.4469}	0.7929	0.8247	0.9163	3	2	1
CRIT2: down-weight c1 by 20%	Base ($\boldsymbol{w_j^0}$)	{c1:0.2481, c2:0.1147, c3:0.4386, c4:0.1986}	0.7701	0.8297	0.9380	3	2	1
	Multiplicative (α=0.5)	{c1:0.2211, c2:0.1148, c3:0.4694, c4:0.1947}	0.7609	0.8267	0.9447	3	2	1
	Convex (λ=0.5)	{c1:0.2110, c2:0.1919, c3:0.3682, c4:0.2289}	0.7635	0.828	0.9434	3	2	1

4) Sensitivity 3: Changes in social values (effect intensity)

Scenarios tested changes in α (multiplicative adjustment) at 0.2, 0.5, 0.8, and λ (convex adjustment) at 0.25, 0.5, 0.75.

Table 15: Sensitivity – Social Values (α, λ)

Setting	c1	c2	c3	c4	Score A1	Score A2	Score A3	Rank A1	Rank A2	Rank A3
Multiplicative α=0.2	0.278477	0.108357	0.427266	0.1859	0.779	0.8309	0.9304	3	2	1
Multiplicative α=0.5	0.2618	0.1087	0.4447	0.1845	0.7732	0.829	0.9342	3	2	1
Multiplicative α=0.8	0.248508	0.109148	0.458883	0.183461	0.769	0.8279	0.9379	3	2	1
Convex λ=0.25	0.271285	0.145148	0.381367	0.202201	0.7777	0.8268	0.9284	3	2	1
Convex λ=0.5	0.2505	0.1822	0.3497	0.2174	0.775	0.8297	0.9334	3	2	1
Convex λ=0.75	0.229854	0.219443	0.318101	0.232602	0.7726	0.8329	0.9388	3	2	1

Interpretation: Across all scenarios—changes in alternatives, criteria, and value intensity—the final ranking order of A3≻A2≻A1 remained stable. This indicates that the SVBW framework provides robust and reliable results while making the rationale behind rankings more transparent and socially grounded.

5. Conclusion

This study set out to design and articulate a weighting framework based on prevailing social values within multi-criteria decision-making (MCDM). The main motivation stemmed from the observation that conventional MCDM methods—whether subjective approaches such as AHP and ANP or objective approaches such as entropy—rely predominantly on quantitative data or individual judgments, with limited consideration of social and cultural values. Yet, large-scale and even organizational decisions that lack alignment with widely accepted societal values are likely to encounter resistance or lack of acceptance at the community level.

The proposed framework, termed Social Value-Based Weighting (SVBW), introduces a complementary normative layer on top of existing weighting methods. In this approach, baseline weights are first obtained through classical techniques and subsequently adjusted and normalized according to a *Social Priority Index*. This index captures the extent to which each criterion aligns with selected cultural and social values, such as justice, public interest, resource efficiency, harm prevention, and religious democracy. By doing so, the framework ensures that final outcomes are not only quantitatively sound but also socially legitimate.

The findings from the numerical example demonstrated that while the inclusion of a social layer in weighting did not alter the final ranking of alternatives, it enhanced the transparency and defensibility of the ranking logic. In other words, decision-makers can explicitly demonstrate why one alternative is preferred over another and how this preference is grounded in social values. Moreover, the sensitivity analysis confirmed that the proposed framework remains relatively robust under changes in alternatives, criteria, values, and the number of experts, thereby strengthening the model's scientific validity.

The findings of this study show both convergence and divergence with prior research. In terms of convergence, the results are consistent with Sapienza et al. (2016), who emphasized the necessity of integrating ethical considerations into MCDM; the SVBW framework likewise demonstrates that the combination of qualitative values with quantitative computations is feasible. The study also aligns with Dusuki and Abdullah (2007), who highlighted the role of public interest in corporate social responsibility, as this very value was incorporated as an adjustment factor in the proposed model. Similarly, the work of Hanifah et al. (2023) resonates with the present study by underscoring that performance evaluation and decision-making systems gain legitimacy only when they reflect the cultural values of society.

On the other hand, divergence is also evident. Unlike many review studies (e.g., Odu, 2019; Uzhga-Rebrov & Kuļešova, 2023) that focused primarily on technical improvements to weighting methods, this research takes a step toward localizing and socializing the weighting process. While Al-Aaidroos et al. (2016) critiqued purely utilitarian decision-making models for their secular orientation, the present study shifts the focus from critique to the development of a viable alternative framework. Furthermore, whereas studies such as Mostofi et al. (2022) concentrated on issues of judgment consistency in AHP, this research assumes that such challenges can be moderated by introducing a social value layer rather than relying solely on mathematical refinements.

Taken together, these points of convergence and divergence suggest that the present study not only fills an important theoretical gap but also opens new avenues for expanding the MCDM literature by embedding decision-making processes more firmly within their social and cultural contexts.

The SVBW framework offers several avenues for practical application. First, in public policymaking, it can help governments and executive bodies prioritize infrastructure and social projects according to criteria such as justice, resource efficiency, and public interest. Second, in organizational management, firms can apply the model to design human resource policies or corporate social responsibility initiatives, particularly in contexts where societal sensitivity to fairness and equity is high. Third, in natural resource management, especially in sectors such as energy and the environment, the framework can guide decisions toward long-term sustainability and efficiency. Finally, in the financial and investment sector, banks and financial institutions may adopt this approach to select portfolios that, in addition to generating economic returns, also meet expectations of social legitimacy.

Several directions for future research can be identified. Expanding the scope of values would allow inclusion of a broader spectrum of cultural and social dimensions beyond those considered here. Empirical validation in real-world case studies is essential to confirm the model's applicability. Developing user-friendly computational tools or software could also facilitate the adoption of the framework in organizational settings. Moreover, cross-cultural comparisons—testing the model in diverse contexts such as Europe, Asia, or Africa—could reveal whether the framework has global adaptability or is most effective within specific socio-cultural environments.

Despite its novelty and advantages, this study is not without limitations. The proposed framework considered only a limited set of social values, whereas societal realities are far more complex and multidimensional. The calculation of the Social Priority Index relies on expert judgments, which may be subject to individual or group biases. For simplicity, the model employed basic membership functions, although more advanced fuzzy approaches could enhance precision. In addition, the study remains theoretical and numerical; no field testing has yet been conducted in actual decision-making environments. Finally, issues of transferability may arise, as the framework might require redesign or adaptation in societies or organizations with differing value systems.

Overall, this research demonstrates that weighting in multi-criteria decision-making is not merely a computational exercise but also a social and value-driven endeavor. The proposed SVBW model sought to bridge the gap between quantitative analysis and social considerations. From a scientific perspective, the framework represents a novel contribution to the MCDM literature. From a practical standpoint, it holds promise for fostering decisions that are not only technically sound but also legitimate, equitable, and effective.

In conclusion, the study establishes a bridge between mathematics and social values—a bridge that, although still in need of refinement and empirical validation, has the potential to serve as a foundation for designing the next generation of decision-making models in today's complex and multidimensional world.

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