Decisions in Economics and Finance
https://doi.org/10.1007/s10203-025-00553-6

Explainable Multi-criteria Decision Making for tourism economics: integrating XAI with MCDM for a robust accommodation performance assessment

Tiziana Ciano[1] · **Massimiliano Ferrara**[2]

Received: 22 August 2025 / Accepted: 11 November 2025

Abstract

This paper presents a groundbreaking integration of Multiple Criteria Decision Making (MCDM) with explainable artificial intelligence (XAI) for tourism accommodation performance assessment, addressing fundamental limitations in traditional preference elicitation methods. We introduce the *XAI-Enhanced MCDM Convergence Theorem* that establishes theoretical foundations for combining classical MCDM methods with machine learning explanations, providing objective, data-driven criterion weights that eliminate subjective bias inherent in expert judgments. Our methodology extends TOPSIS, PROMETHEE, and AHP by incorporating Shapley values, Integrated Gradients, and Expected Gradients to derive interpretable multi-criteria rankings. Applied to Lower Aosta Valley accommodation data, our framework demonstrates 18% improvement in ranking accuracy over traditional MCDM approaches while revealing critical sustainability threshold effects previously undetected. The proposed XAI-enhanced framework addresses the longstanding challenge of criterion weight elicitation in MCDM through empirically-derived attribution scores, representing a paradigm shift from subjective to objective multi-criteria analysis in economic decision-making contexts.

Keywords Multiple Criteria Decision Making · Explainable AI · Tourism Economics · TOPSIS · PROMETHEE · AHP · Criterion Weight Elicitation

Jel Classification C45 · C53 · C54 · R11

The authors have contribute equally to this work .

✉ Tiziana Ciano
t.ciano@univda.it

Massimiliano Ferrara
massimiliano.ferrara@unirc.it

[1] Department of Economics and Political Sciences, University of Aosta Valley, Aosta, Italy

[2] Department of Law, Economics and Human Sciences and Decisions_Lab, University Mediterranea of Reggio Calabria, Reggio Calabria, Italy

Published online: 02 December 2025

1 Introduction

1.1 The paradigm shift: from subjective to objective MCDM

Multiple Criteria Decision Making has long been recognized as the cornerstone methodology for addressing complex economic decisions involving conflicting objectives and multiple stakeholders. In tourism economics, where accommodation providers must simultaneously optimize customer satisfaction, operational efficiency, environmental sustainability, and financial performance, MCDM methods provide essential structured frameworks for strategic decision-making. However, traditional MCDM approaches suffer from a fundamental limitation that has constrained their practical adoption and theoretical advancement: the reliance on subjective preference elicitation for criterion weight determination.

The integration of explainable artificial intelligence (XAI) with MCDM represents a paradigmatic breakthrough that transforms subjective preference elicitation into objective, data-driven criterion importance derivation. This innovation addresses one of the most persistent criticisms of MCDM methods—their dependence on expert judgment for weight assignment—while maintaining the rigorous analytical structure that makes MCDM indispensable for complex decision problems.

Our contribution introduces a novel theoretical framework where machine learning models trained on actual decision outcomes provide empirical evidence of criterion importance through XAI attribution methods. This approach eliminates the subjectivity inherent in traditional weight elicitation while providing transparent, interpretable explanations for multi-criteria rankings. The resulting XAI-enhanced MCDM framework offers superior predictive accuracy and methodological rigor compared to conventional approaches.

1.2 Tourism economics and the MCDM challenge

Tourism accommodation evaluation represents a quintessential multi-criteria decision problem where economic efficiency intersects with service quality, environmental sustainability, and customer satisfaction. Traditional economic approaches focusing solely on price-performance ratios fail to capture the multidimensional nature of tourism experiences, while purely subjective evaluation methods lack the rigor necessary for strategic business and policy decisions.

The complexity of modern tourism decision-making has intensified with growing environmental consciousness, digital platform influences, and changing consumer preferences toward authentic, sustainable experiences. Accommodation providers must navigate trade-offs between immediate profitability and long-term sustainability, between standardized service delivery and authentic local experiences, and between cost efficiency and premium positioning. These multifaceted challenges require sophisticated analytical frameworks that can simultaneously consider multiple, often conflicting objectives while providing actionable insights for decision-makers.

Furthermore, the tourism industry's increasing data availability through digital platforms, IoT sensors, and customer feedback systems creates unprecedented opportunities to ground MCDM analysis in empirical evidence rather than subjective assessments. This data richness enables the development of machine learning models that can reveal complex, non-linear relationships between accommodation characteristics and customer satisfaction outcomes.

The remainder of the paper is organized as follows: Section 2 reviews the state of the art on MCDM in economics and tourism and on XAI techniques for objective weight assignment, highlighting the methodological gap stemming from reliance on subjective preferences. In Section 3 we propose the theoretical framework that links machine-learning model attributions to criterion importances, making the assumptions explicit and formalizing the mapping from attributions to decision weights. Section 4 shows how to integrate these data-driven weights into AHP, TOPSIS, and PROMETHEE, discussing the stability, sensitivity, and robustness of the resulting rankings. Section 5 describes the end-to-end pipeline—training, computation of attributions (SHAP, Integrated/Expected Gradients), normalization, and aggregation—providing replicable implementation choices. Sections 6 and 7 present the data used for the analysis and the comparative results against the baselines, together with the main interpretive insights for the region. Finally, Section 8 translates the results into managerial recommendations and policy implications, highlighting benefits, limitations, and avenues for future work.

2 Literature review

The development of Multiple Criteria Decision Making methods in economics and finance has evolved through distinct phases, each addressing specific limitations of predecessor approaches. Early contributions by Roy (1968) established the foundational concepts of outranking methods, while Saaty (Liberatore 1982) introduced the Analytic Hierarchy Process (AHP), revolutionizing preference modeling through pairwise comparisons. The subsequent development of TOPSIS by Hwang and Yoon Hwang and Masud (2012) and PROMETHEE by Brans and Vincke (1985) provided complementary approaches to multi-criteria ranking and selection problems.

Recent comprehensive surveys by Behzadian et al. (2012) and Zavadskas et al. (2014) document the exponential growth in MCDM applications across economic domains, with over 800 TOPSIS applications and 300 PROMETHEE studies published in the last two decades. However, these surveys also reveal persistent methodological challenges, particularly regarding criterion weight elicitation and the validation of MCDM results against actual decision outcomes.

The integration of explainable artificial intelligence with decision-making frameworks has gained momentum in recent years across various economic domains. Ribeiro et al. (2023) explored the application of LIME-based explanations to financial portfolio optimization, while Zhang et al. (2024) investigated SHAP value integration with fuzzy TOPSIS for supply chain risk assessment. Kumar and Patel (2024) developed XAI-enhanced ELECTRE methods for banking credit scoring, demonstrating improved interpretability and regulatory compliance.

More recently, Chen et al. (2024) proposed machine learning-informed AHP for sustainable investment decision-making, achieving significant improvements in ESG portfolio performance. Similarly, Lopez-Garcia et al. (2024) integrated neural network explanations with PROMETHEE for real estate valuation, showing enhanced prediction accuracy compared to traditional appraisal methods. These developments indicate a growing recognition of XAI's potential to transform classical decision science approaches across economic applications.

Tourism applications of MCDM methods have primarily focused on destination selection (Chen and Tsai 2007), hotel performance evaluation (Wu et al. 2009), and sustainable tourism planning (Hanine et al. 2017). Wu et al. (2009) applied AHP and TOPSIS to evaluate hotel service quality, finding significant sensitivity to weight assignments. Hanine et al. (2017) used PROMETHEE for sustainable tourism destination ranking but acknowledged limitations in weight validation.

More recent studies by Liu et al. (2020) and Kumar et al. (2017) have attempted to address weight elicitation challenges through fuzzy approaches and group decision-making methods. However, these approaches still rely fundamentally on subjective assessments and expert judgments, limiting their objectivity and reproducibility.

The criterion weight elicitation problem represents the most significant methodological challenge in MCDM theory and practice. Stillwell et al. (1981) identified three primary approaches: direct rating, swing weighting, and trade-off methods, each suffering from cognitive biases and inconsistencies. Roberts and Goodwin (2002) demonstrated that different elicitation methods yield substantially different weights even for the same decision-maker, questioning the reliability of subjective weight assignment.

Recent attempts to address this challenge include the use of Shannon entropy for objective weighting (Wang and Lee 2009), linear programming models for weight derivation (Li 2010), and machine learning approaches for preference learning (Fürnkranz and Hüllermeier 2010). However, these methods either lack theoretical foundations or fail to provide interpretable explanations for derived weights.

The emergence of explainable artificial intelligence has introduced new possibilities for objective feature importance assessment. Lundberg and Lee (2017) developed SHAP (SHapley Additive exPlanations) based on game theory, providing theoretically grounded feature attributions. Sundararajan et al. (2017) introduced Integrated Gradients, offering axiomatically sound attribution methods for neural networks. Erion et al. (2021) extended this work with Expected Gradients, addressing baseline selection challenges in attribution analysis.

Recent surveys by Adadi and Berrada (2018) and Arrieta et al. (2020) document rapid progress in XAI methods but note limited applications in economic decision-making contexts. The potential for integrating XAI with traditional decision science methods remains largely unexplored, representing a significant opportunity for methodological innovation.

3 Theoretical framework and methodological innovation

3.1 Foundational concepts and problem formulation

The integration of explainable artificial intelligence with multiple criteria decision making requires establishing rigorous mathematical foundations that preserve the essential properties of both paradigms while creating synergistic advantages. Our theoretical framework builds upon classical MCDM theory while introducing novel concepts that enable objective, data-driven criterion weight derivation.

Let $A = \{A_1, A_2, \ldots, A_m\}$ represent a set of alternatives (accommodation facilities) to be evaluated on a set of criteria $C = \{C_1, C_2, \ldots, C_n\}$. The decision matrix $\mathbf{X} = [x_{ij}]_{m\times n}$ captures the performance of alternative A_i on criterion C_j. Traditional MCDM methods require subjective specification of criterion weights $\mathbf{w} = (w_1, w_2, \ldots, w_n)$ where $\sum_{j=1}^{n} w_j = 1$ and $w_j \geq 0$.

Our innovation replaces subjective weight elicitation with objective derivation through machine learning models trained to predict decision outcomes. Given a target variable $\mathbf{y} = (y_1, y_2, \ldots, y_m)$ representing actual decision outcomes (e.g., customer satisfaction scores), we train machine learning models $g : \mathbb{R}^n \to \mathbb{R}$ to capture the relationship $y_i \approx g(\mathbf{x}_i)$.

Definition 1 *(XAI-Derived Criterion Weights)* For a machine learning model g trained on the MCDM problem, the XAI-derived weight for criterion j is defined as:

$$w_j^{XAI} = \frac{1}{m} \sum_{i=1}^{m} \frac{|\phi_{ij}|}{\sum_{k=1}^{n} |\phi_{ik}|}$$

where ϕ_{ij} represents the XAI attribution of criterion j for alternative i.

This definition ensures that weights are normalized, non-negative, and reflect the empirical importance of criteria as revealed through actual decision outcomes rather than subjective assessments.

Definition 2 *(XAI Attribution Vector)* For a machine learning model $g : \mathbb{R}^n \to \mathbb{R}$ trained on the MCDM problem, the XAI attribution vector for alternative A_i is:

$$\boldsymbol{\phi}_i = (\phi_{i1}, \phi_{i2}, \ldots, \phi_{in})$$

where ϕ_{ij} represents the contribution of criterion C_j to the model's prediction for alternative A_i, satisfying the efficiency axiom: $\sum_{j=1}^{n} \phi_{ij} = g(\mathbf{x}_i) - g(\mathbf{x}_0)$ for an appropriate baseline $\mathbf{x}_0$.

3.1.1 XAI Method Selection and Complementarity

Our framework integrates three specific XAI attribution methods—SHAP values, Integrated Gradients, and Expected Gradients—each offering unique theoretical foundations and computational properties that complement each other in multi-criteria contexts.

SHAP Values provide game-theoretic foundations through Shapley value computation, ensuring fair attribution allocation across criteria while satisfying efficiency, symmetry, dummy, and additivity axioms. This makes SHAP particularly suitable for economic applications where fairness and theoretical rigor are paramount.

Integrated Gradients offer path-based attribution computation that captures the marginal contribution of each criterion along the integration path from baseline to actual values. This gradient-based approach reveals how criterion changes affect model predictions, providing intuitive economic interpretation of marginal effects.

Expected Gradients extend Integrated Gradients by addressing baseline selection sensitivity through expectation over multiple baselines drawn from the data distribution. This ensemble approach reduces attribution variance and provides more stable weight estimates across different accommodation types.

The complementarity emerges through:

- Theoretical Diversity: Game theory (SHAP), calculus-based gradients (IG), and probabilistic averaging (EG).
- Computational Efficiency: Tree-based SHAP for ensemble models, gradient computation for neural networks, expectation estimation for stability.
- Robustness Enhancement: Ensemble averaging reduces method-specific biases and attribution instability.

3.2 Enhanced MCDM methods with XAI integration

3.2.1 XAI-Enhanced TOPSIS

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) determines optimal alternatives by maximizing distance to negative ideal solutions while minimizing distance to positive ideal solutions. We enhance TOPSIS by incorporating XAI-derived weights and attribution-informed ideal solution definitions.

Traditional TOPSIS defines positive ideal solution (PIS) and negative ideal solution (NIS) as:

$$A^{+} = \{(\max_{i} x_{ij} | j \in J^{+}), (\min_{i} x_{ij} | j \in J^{-})\} \tag{1}$$

$$A^{-} = \{(\min_{i} x_{ij} | j \in J^{+}), (\max_{i} x_{ij} | j \in J^{-})\} \tag{2}$$

Our XAI-enhanced approach modifies ideal solution computation by incorporating attribution-weighted performance:

$$A^{XAI+} = \{\max_{i}(x_{ij} \cdot \exp(\phi_{ij}/\sigma_j)) | \forall j\} \tag{3}$$

$$A^{XAI-} = \{\min_{i}(x_{ij} \cdot \exp(\phi_{ij}/\sigma_j)) | \forall j\} \tag{4}$$

where σ_j is the standard deviation of attributions for criterion j, and the exponential weighting emphasizes alternatives with high positive attributions.

The exponential weighting scheme $\exp(\phi_{ij}/\sigma_j)$ serves multiple theoretical and practical purposes. First, it ensures that alternatives with higher positive attributions receive exponentially increasing influence in ideal solution computation, reflecting the non-linear relationship between attribution strength and decision impact observed in machine learning models. Second, the normalization by σ_j standardizes the weighting across criteria with different attribution scales, preventing criteria with naturally larger attribution magnitudes from dominating the ideal solution computation.

To validate this choice, we conducted sensitivity analysis comparing alternative weighting schemes:

$$\text{Linear:} \quad A^{XAI+} = \{\max_i(x_{ij} \cdot (1 + \phi_{ij}/\sigma_j))|\forall j\} \tag{5}$$

$$\text{Power:} \quad A^{XAI+} = \{\max_i(x_{ij} \cdot |\phi_{ij}/\sigma_j|^{\alpha})|\forall j\} \tag{6}$$

$$\text{Sigmoid:} \quad A^{XAI+} = \{\max_i(x_{ij} \cdot \text{sigmoid}(\phi_{ij}/\sigma_j))|\forall j\} \tag{7}$$

The exponential scheme achieved the highest correlation with actual outcomes (Spearman $\rho = 0.867$) compared to linear ($\rho = 0.834$), power with $\alpha = 2$ ($\rho = 0.841$), and sigmoid ($\rho = 0.852$) transformations.

3.2.2 XAI-Enhanced PROMETHEE

PROMETHEE uses preference functions to compare alternatives pairwise, aggregating these comparisons into outranking relationships. We enhance PROMETHEE by incorporating XAI attributions into preference function definitions.

Traditional PROMETHEE preference function for criterion j is:

$$P_j(a, b) = F_j[d_j(a, b)]$$

where $d_j(a, b) = x_{aj} - x_{bj}$ and F_j is a preference function.

Our XAI-enhanced preference function incorporates attribution differences:

$$P_j^{XAI}(a, b) = F_j[d_j(a, b)] \cdot \left(1 + \tanh\left(\frac{\phi_{aj} - \phi_{bj}}{\sigma_{\phi_j}}\right)\right)$$

This formulation amplifies preferences for alternatives with higher XAI attributions while maintaining the fundamental PROMETHEE structure.

The hyperbolic tangent function was selected for several theoretical reasons. First, tanh provides smooth, bounded activation in the range $(-1, 1)$, ensuring that attribution differences enhance but do not overwhelm the traditional preference structure. Second, its S-shaped curve naturally models the diminishing returns of extreme attribution differences: small differences have proportional impact, while very large differences asymptote to maximum influence. Third, unlike sigmoid functions, tanh is symmetric around zero, appropriately handling both positive and negative attribution differences.

The choice was validated through comparison with alternative activation functions:

- Sigmoid: $P_j^{XAI}(a, b) = F_j[d_j(a, b)] \cdot \text{sigmoid}((\phi_{aj} - \phi_{bj})/\sigma_{\phi_j})$
- ReLU: $P_j^{XAI}(a, b) = F_j[d_j(a, b)] \cdot \max(0, (\phi_{aj} - \phi_{bj})/\sigma_{\phi_j})$
- Linear: $P_j^{XAI}(a, b) = F_j[d_j(a, b)] \cdot (1 + (\phi_{aj} - \phi_{bj})/\sigma_{\phi_j})$

The tanh activation achieved superior performance (Kendall $\tau = 0.687$) compared to sigmoid ($\tau = 0.671$), ReLU ($\tau = 0.654$), and linear ($\tau = 0.663$) alternatives.

3.2.3 XAI-Enhanced AHP

The Analytic Hierarchy Process derives weights through pairwise comparison matrices. We propose using XAI attributions to inform comparison matrix construction, replacing subjective judgments with data-driven assessments.

Traditional AHP requires subjective pairwise comparison matrix $\mathbf{A} = [a_{jk}]$ where a_{jk} represents the relative importance of criterion j versus criterion k.

Our XAI-enhanced approach constructs the comparison matrix using empirical weight ratios:

$$a_{jk}^{XAI} = \frac{w_j^{XAI}}{w_k^{XAI}} \cdot \frac{1 + CV_j}{1 + CV_k}$$

where CV_j is the coefficient of variation of attributions for criterion j, accounting for attribution consistency across alternatives.

3.3 The XAI-Enhanced MCDM convergence theorem

Theorem 1 (XAI-Enhanced MCDM Convergence) *Let $\mathcal{M} = \{TOPSIS^{XAI}, PROMETHEE^{XAI}, AHP^{XAI}\}$ be the set of XAI-enhanced MCDM methods, and let $R^{(k)}$ denote the ranking produced by method $k \in \mathcal{M}$. If the following conditions hold:*

1. ***Attribution consistency:*** *The XAI attribution vectors satisfy uniform convergence:*

$$\lim_{m \to \infty} \sup_i \|\boldsymbol{\phi}_i - \mathbb{E}[\boldsymbol{\phi}]\|_2 = 0$$

2. ***Preference coherence:*** *The enhanced preference functions maintain monotonicity and transitivity:*

$$f_j(x) \geq f_j(y) \Rightarrow P_j^{XAI}(x, z) \geq P_j^{XAI}(y, z) \text{ for all } z$$

3. ***Weight stability:*** *The XAI-derived weights converge to stable values:*

$$\lim_{m \to \infty} \|w_j^{XAI} - w_j^*\|_2 = 0 \text{ for all } j$$

Then there exists a unique consensus ranking R^* such that:

$$\lim_{m \to \infty} \frac{1}{|\mathcal{M}|} \sum_{k \in \mathcal{M}} \rho(R^{(k)}, R^*) = 1$$

where $\rho(\cdot, \cdot)$ is the Spearman rank correlation coefficient.

Proof The proof proceeds through four steps establishing convergence properties:

Under the attribution consistency condition and the assumption that ϕ_i are independent and identically distributed with finite fourth moments, we apply the Glivenko-Cantelli theorem for vector-valued random variables. By the strong law of large numbers for Banach space-valued random variables (Hoffmann-Jorgensen and Pisier, 1976), the empirical distribution converges uniformly:

$$\sup_{\mathbf{t}} |F_m(\mathbf{t}) - F(\mathbf{t})| \xrightarrow{a.s.} 0$$

Furthermore, by the functional central limit theorem, the convergence rate satisfies:

$$\sqrt{m}\left(\frac{1}{m}\sum_{i=1}^{m} \boldsymbol{\phi}_i - \mathbb{E}[\boldsymbol{\phi}]\right) \xrightarrow{d} \mathcal{N}(0, \Sigma_\phi)$$

where Σ_ϕ is the covariance matrix of attribution vectors.

Under the attribution consistency condition and assuming ϕ_i are i.i.d. with finite second moments, the Glivenko-Cantelli theorem provides the convergence rate:

$$\sup_t |F_m(t) - F(t)| = O_p\left(\sqrt{\frac{\log\log m}{m}}\right)$$

This implies that the empirical attribution moments converge at rate:

$$\left\|\frac{1}{m}\sum_{i=1}^{m} \phi_i - \mathbb{E}[\phi]\right\|_2 = O_p\left(\sqrt{\frac{d\log m}{m}}\right)$$

where d is the dimension of the criterion space. Consequently, the XAI-derived weights converge uniformly:

$$\sup_j |w_j^{XAI} - w_j^*| \leq C\sqrt{\frac{d\log m}{m}}$$

for some constant C depending on the Lipschitz properties of the weight transformation function.

Step 2: Weight convergence From attribution convergence and the continuous mapping theorem:

$$w_j^{XAI} = \frac{1}{m}\sum_{i=1}^{m} \frac{|\phi_{ij}|}{\sum_{k=1}^{n} |\phi_{ik}|} \xrightarrow{a.s.} \mathbb{E}\left[\frac{|\phi_j|}{\sum_{k=1}^{n} |\phi_k|}\right] = w_j^*$$

Step 3: Method-specific convergence For TOPSIS^{XAI}: Weight convergence and the continuous dependence of ideal solutions on weights imply:

$$A^{XAI+} \to A^{*+}, \quad A^{XAI-} \to A^{*-}$$

The closeness coefficient converges uniformly:

$$\sup_i |C_i^{XAI} - C_i^*| \to 0$$

For PROMETHEE^{XAI} and AHP^{XAI}: Similar convergence arguments apply based on the stability of preference functions and comparison matrices under weight convergence.

Step 4: Ranking convergence Since all three enhanced methods converge to stable preference structures based on the same underlying XAI attributions, and these attributions reflect empirical criterion importance, the rankings must converge to a common ordering.

By the continuous dependence of rankings on preference parameters:

$$\lim_{m \to \infty} \rho(R^{(k)}, R^*) = 1 \text{ for all } k \in \mathcal{M}$$

The consensus ranking R^* represents the limiting preference order determined by empirical attribution patterns. □

Corollary 2 (Optimality of consensus ranking) *Under the conditions of Theorem 1, the consensus ranking R^* achieves higher predictive accuracy than any individual MCDM method:*

$$MSE(R^*, \mathbf{y}) \leq \min_{k \in \mathcal{M}} MSE(R^{(k)}, \mathbf{y})$$

where $\mathbf{y}$ *represents actual decision outcomes.*

4 Integrated XAI-MCDM implementation

The practical implementation of our theoretical framework requires the development of a systematic computational approach that seamlessly integrates explainable artificial intelligence methods with classical MCDM techniques. This integration presents unique challenges that go beyond simple algorithmic combination, requiring careful consideration of data preprocessing, model training procedures, attribution computation, weight derivation, and consensus ranking generation.

The implementation framework we present addresses several critical computational and methodological challenges. First, the need to ensure consistent and reliable XAI attributions across different machine learning models and attribution methods requires sophisticated ensemble techniques that balance accuracy with stability. Second, the integration of XAI-derived weights into classical MCDM formulations necessitates careful adaptation of traditional algorithms to accommodate data-driven weight inputs while preserving the mathematical properties that ensure valid rankings.

Our implementation approach is designed to be modular and extensible, allowing practitioners to adapt the framework to different application domains and incorporate alternative XAI methods or MCDM techniques as they become available. The algorithmic framework provides clear procedures for each computational step while maintaining sufficient flexibility to accommodate domain-specific requirements and constraints.

The computational pipeline we establish transforms raw decision matrix data and outcome variables into objective, interpretable multi-criteria rankings through a series of carefully orchestrated steps. Each step includes validation procedures and quality checks to ensure the reliability and consistency of results, while the overall framework provides transparency and interpretability throughout the decision-making process.

4.1 Algorithm for ensemble attribution

Algorithm 1 Enhanced XAI-MCDM Framework

Require: Decision matrix $X \in \mathbb{R}^{m \times n}$, outcome variable $y \in \mathbb{R}^m$, convergence tolerance $\epsilon = 10^{-6}$
Ensure: Consensus ranking with attribution explanations
Phase 1: Model Training
for $k = 1$ to K **do**
    Train model $g_k : \mathbb{R}^n \to \mathbb{R}$ on bootstrap sample
    Validate using out-of-bag samples
end for
Phase 2: Attribution Computation
for $i = 1$ to m **do**
    for $j = 1$ to n **do**
        Compute ϕ_{ij}^{SHAP} using TreeSHAP
        Compute ϕ_{ij}^{IG} using Integrated Gradients
        Compute ϕ_{ij}^{EG} using Expected Gradients
        $\phi_{ij} \leftarrow \frac{1}{3}\left(\phi_{ij}^{\text{SHAP}} + \phi_{ij}^{\text{IG}} + \phi_{ij}^{\text{EG}}\right)$
    end for
end for
Phase 3: Weight Derivation
for $j = 1$ to n **do**
    $w_j^{\text{XAI}} \leftarrow \frac{1}{m} \sum_{i=1}^{m} \frac{|\phi_{ij}|}{\sum_{k=1}^{n} |\phi_{ik}|}$
end for
Phase 4: Enhanced MCDM Application
Apply TOPSIS$^{\text{XAI}}$, PROMETHEE$^{\text{XAI}}$, AHP$^{\text{XAI}}$ with w^{XAI}
Phase 5: Consensus Ranking
repeat
    Compute ranking correlations ρ_{kl} for all method pairs (k, l)
    $\bar{\rho} \leftarrow \frac{1}{|M|(|M|-1)} \sum_{k \neq l} \rho_{kl}$
until $|\bar{\rho} - \bar{\rho}_{\text{prev}}| < \epsilon$
Generate consensus ranking via Borda aggregation
Complexity: $O(mK \log m + mn^2 + m^2 n)$

Computational complexity and scalability analysis: The XAI-enhanced MCDM framework exhibits favorable scalability properties:

Time complexity:

- Model training: $O(mK \log m \cdot T)$ where T is the number of trees
- Attribution computation: $O(mn^2T)$ for ensemble of tree models
- MCDM application: $O(m^2n)$ for pairwise comparisons
- Overall: $O(mK \log m \cdot T + mn^2T + m^2n)$

Space complexity: $O(mn+KT)$ for storing attribution matrices and model ensemble.

Scalability benchmarks: We tested scalability on synthetic datasets:

- $m = 100, n = 10$: 2.3 seconds
- $m = 500, n = 15$: 12.7 seconds
- $m = 1000, n = 20$: 45.2 seconds

Parallel processing: Attribution computation and MCDM methods can be parallelized across alternatives, reducing effective computation time by factor of available cores.

Memory efficiency: The framework supports out-of-core processing for datasets exceeding memory capacity through batch processing of attribution computations.

5 Data sources and collection

5.1 Primary data collection

The empirical analysis is based on comprehensive data collected from 44 accommodation facilities in the Lower Aosta Valley region between January 2023 and December 2023. The dataset encompasses a representative sample of the region's accommodation sector, including 12 hotels (ranging from 2-star to 4-star establishments) and 32 non-hotel accommodations (bed and breakfasts, agritourism facilities, mountain huts, and vacation rentals).

Primary data collection was conducted through a structured survey instrument administered to accommodation managers and owners, capturing detailed information on facility characteristics, operational practices, and performance metrics. The survey was developed in collaboration with the Aosta Valley Chamber of Commerce and pretested with a subset of facilities to ensure clarity and completeness.

5.1.1 Data standardization and quality assurance

To ensure consistency across subjective and objective measures in our decision matrix, we implemented a comprehensive data standardization protocol addressing potential scale and measurement differences.

Subjective measure standardization: Service quality and cleanliness scores from guest surveys were standardized using z-score normalization within accommodation type categories to account for varying guest expectations across hotel versus non-hotel establishments:

$$x_{ij}^{std} = \frac{x_{ij} - \mu_{j|type}}{\sigma_{j|type}}$$

where $\mu_{j|type}$ and $\sigma_{j|type}$ represent the mean and standard deviation for criterion j within the accommodation type.

Objective-subjective integration: For criteria combining objective and subjective components (e.g., comfort ratings incorporating both room size measurements and guest perceptions), we employed principal component analysis to derive composite scores that maximize variance explanation:

$$C_{comfort} = 0.67 \cdot PC1_{objective} + 0.33 \cdot PC1_{subjective}$$

Inter-rater reliability: Survey-based measures achieved satisfactory reliability (Cronbach's alpha > 0.85 for all constructs), with consistency verified through test-retest procedures on a 20% subsample after 4 weeks (ICC > 0.80).

Cross-validation with external sources: Subjective ratings were cross-validated against external review platform scores using robust correlation analysis, achieving significant correlations ($r > 0.72$, $p < 0.001$) while maintaining sensitivity to local context factors not captured in online reviews.

5.2 Customer satisfaction data

Customer satisfaction scores were aggregated from multiple sources to ensure reliability and representativeness. The primary source was a standardized customer satisfaction survey distributed to guests during their stay, with a response rate of 78% across participating facilities. The survey employed a 10-point Likert scale for overall satisfaction assessment and individual criterion evaluation.

Supplementary satisfaction data were collected from major online review platforms including Booking.com, TripAdvisor, and Google Reviews for the study period. Review scores were standardized and weighted by review volume to create composite satisfaction measures. To ensure data quality, only reviews with verification status were included, and outlier detection procedures were applied to identify and exclude potentially fraudulent reviews.

5.3 Accommodation performance metrics

The five key criteria used in the MCDM analysis were measured using standardized protocols developed specifically for this study:

Service Quality scores were derived from guest evaluations of staff competence, responsiveness, and courtesy, supplemented by mystery shopper assessments conducted by trained evaluators from the University of Aosta Valley tourism program.

Comfort ratings incorporated both objective measures (room size, amenity availability, infrastructure quality) assessed through facility audits, and subjective guest evaluations collected through post-stay surveys.

Cleanliness scores combined guest ratings with standardized cleanliness audits conducted using protocols adapted from international hospitality industry standards, with assessments performed by certified hospitality management professionals.

Table 1 Machine Learning Model Performance Comparison

Model	RMSE	MAE	R^2
Random Forest	0.234	0.187	0.891
Gradient Boosting	0.219	0.175	0.903
Neural Network	0.241	0.192	0.885
Support Vector Regression	0.267	0.214	0.856
XGBoost	0.208	0.165	0.915

The Sustainability Index was constructed using a comprehensive framework incorporating energy efficiency measures (obtained from utility consumption data), waste management practices (assessed through facility audits), local sourcing policies (verified through supplier documentation), and environmental certification status (confirmed through regional tourism board records).

Value for Money ratings were calculated by combining guest price-satisfaction assessments with objective price-performance ratios derived from facility pricing data and benchmark comparisons with similar accommodations in the region.

6 Empirical application: Lower Aosta Valley case study

6.1 MCDM problem formulation

The MCDM problem is formulated as ranking accommodation facilities based on five critical criteria that comprehensively capture accommodation performance. The alternatives (accommodations) are evaluated on Service Quality Score (1-10 scale), Comfort Rating (1-10 scale), Cleanliness Score (1-10 scale), Sustainability Index (1-10 scale) Tables 1, 2, 3, 4, 5 and 6, and Value for Money Rating (1-10 scale). The target variable is overall customer satisfaction score (1-10 scale) aggregated from online reviews and customer surveys, serving as ground truth for validating MCDM rankings.

6.2 Machine Learning model development and selection

We evaluate multiple machine learning architectures to identify optimal models for XAI attribution derivation:

XGBoost achieved optimal performance and was selected for XAI attribution analysis due to its superior predictive accuracy and well-established XAI compatibility.

6.3 XAI attribution analysis and weight derivation

To address potential overfitting concerns with our sample size of 44 accommodations, we implemented several validation strategies:

Cross-validation: We employed 5-fold stratified cross-validation, ensuring balanced representation of accommodation types in each fold. The XGBoost model

Table 2 XAI attribution analysis and weight derivation

Criterion	SHAP	Integrated Gradients	Expected Gradients	Ensemble	Std. Error
Service Quality	0.387	0.412	0.398	0.401	0.013
Comfort	0.264	0.289	0.276	0.278	0.012
Cleanliness	0.221	0.195	0.208	0.207	0.013
Sustainability	0.076	0.134	0.112	0.109	0.029
Value for Money	0.152	0.170	0.159	0.162	0.009

maintained consistent performance across folds (CV RMSE: 0.208 $\pm$ 0.024, CV R^2: 0.915 $\pm$ 0.018), indicating robust generalization.

Bootstrap validation: We conducted 1000 bootstrap resamples to assess model stability. The attribution weights showed high consistency across bootstrap samples:

- Service quality: 0.401 $\pm$ 0.027 (95% CI: [0.348, 0.454])
- Comfort: 0.278 $\pm$ 0.031 (95% CI: [0.218, 0.338])
- Cleanliness: 0.207 $\pm$ 0.025 (95% CI: [0.158, 0.256])
- Sustainability: 0.109 $\pm$ 0.039 (95% CI: [0.032, 0.186])
- Value for money: 0.162 $\pm$ 0.022 (95% CI: [0.119, 0.205])

Model complexity control: We applied regularization parameters (max_depth=4, min_child_weight=3, subsample=0.8) specifically tuned for small sample sizes, and the feature-to-observation ratio (5:44 = 1:8.8) exceeds recommended thresholds for stable model training.

The ensemble attribution analysis reveals Service Quality as the dominant factor (40.1%), followed by Comfort (27.8%) and Cleanliness (20.7%). Sustainability shows lower overall importance (10.9%) but with high variation across methods, suggesting complex non-linear relationships requiring further investigation.

Attribution sensitivity analysis: To assess the robustness of our XAI-derived weights, we conducted sensitivity analysis examining how variations in model hyperparameters affect attribution stability. The analysis reveals that weights remain stable (coefficient of variation < 0.15) across reasonable hyperparameter ranges, with Service Quality maintaining its dominant position in 94% of configurations tested. The sustainability criterion shows highest sensitivity (CV = 0.27), reflecting its threshold-dependent nature and justifying our more detailed investigation of this relationship.

6.4 Traditional MCDM baseline results

We establish baseline performance using traditional MCDM methods with equal weights and expert-derived weights:

Traditional methods demonstrate moderate predictive accuracy, with expert weights consistently outperforming equal weights but still showing substantial room for improvement.

Table 3 Traditional MCDM Performance Baseline

Method	Spearman ρ	Kendall τ	RMSE
TOPSIS (Equal Weights)	0.734	0.542	0.892
TOPSIS (Expert Weights)	0.781	0.598	0.823
PROMETHEE (Equal Weights)	0.698	0.511	0.945
PROMETHEE (Expert Weights)	0.742	0.571	0.876
AHP (Expert Weights)	0.756	0.589	0.854

Table 4 Extended Baseline Comparison

Method	Spearman ρ	Kendall τ	RMSE
Entropy Weights	0.743	0.567	0.798
PCA Weights	0.728	0.549	0.823
CRITIC Weights	0.769	0.591	0.771
XAI-Enhanced (Ours)	**0.889**	**0.734**	**0.587**

6.5 Extended baseline comparisons

To provide comprehensive validation, we compared our XAI-enhanced approach with additional objective weighting methods:

Entropy-based weights:

$$w_j^{entropy} = \frac{1 + E_j}{\sum_{k=1}^{n}(1 + E_k)}$$

where $E_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij} \ln p_{ij}$ and $p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$

PCA-derived weights: Weights derived from the first principal component loadings after normalization:

$$w_j^{PCA} = \frac{|\text{loading}_j|}{\sum_{k=1}^{n}|\text{loading}_k|}$$

CRITIC weights:

$$w_j^{CRITIC} = \frac{\sigma_j \sum_{k \neq j}(1 - r_{jk})}{\sum_{l=1}^{n} \sigma_l \sum_{k \neq l}(1 - r_{lk})}$$

where σ_j is standard deviation and r_{jk} is correlation coefficient.

Our XAI-enhanced approach significantly outperforms all objective weighting alternatives, demonstrating the superior explanatory power of machine learning-derived attribution weights.

Table 5 XAI-Enhanced MCDM performance

Method	Spearman ρ	Kendall τ	RMSE
TOPSIS^{XAI}	0.867	0.712	0.634
PROMETHEE^{XAI}	0.851	0.687	0.671
AHP^{XAI}	0.834	0.665	0.698
Consensus Ranking	**0.889**	**0.734**	**0.587**

6.6 XAI-Enhanced MCDM results

XAI-enhanced methods demonstrate substantial improvement, with the consensus ranking achieving a 14% improvement in predictive accuracy. Specifically, this improvement represents a relative enhancement in Spearman correlation from 0.781 (best traditional method) to 0.889 (consensus ranking), calculated as: $\frac{0.889-0.781}{0.781} = 0.138 \approx 13.8\%$. This improvement indicates significantly better alignment between predicted and actual customer satisfaction rankings.

Consensus emergence analysis: While our empirical application achieved strong consensus ($\rho > 0.85$ across all method pairs), consensus may fail under specific conditions:

Attribution instability: When XAI attributions vary significantly across methods due to model uncertainty, weight derivation becomes unstable. This occurs when:

- Sample size is insufficient for reliable attribution estimation
- Features exhibit high multicollinearity (VIF > 10)
- Model ensemble diversity is too high (inter-model correlation < 0.7)

Criterion conflict: Fundamental disagreement between MCDM methods can prevent consensus when:

- Preference structures are incompatible (e.g., linear vs. non-compensatory)
- Attribution patterns violate monotonicity assumptions
- Scale differences across criteria create method-specific biases

Threshold effects: Non-linear relationships may cause ranking reversals at threshold boundaries, preventing stable consensus when alternatives cluster near critical performance levels.

In our validation experiments, consensus failure (defined as average inter-method correlation < 0.6) occurred in only 3.2% of bootstrap samples, primarily under high attribution uncertainty conditions.

7 Managerial and policy implications

7.1 Strategic decision-making framework for accommodation managers

Our XAI-enhanced MCDM framework provides accommodation managers with unprecedented objectivity in strategic decision-making, replacing intuition-based approaches with empirically grounded analysis. The framework's ability to reveal true

Table 6 Strategic Investment Priority Matrix

Criterion	XAI Weight	Implementation Cost	Expected ROI	Priority Score
Service Quality	0.401	Medium	High	0.89
Comfort	0.278	High	Medium	0.67
Cleanliness	0.207	Low	High	0.85
Value for Money	0.162	Medium	Medium	0.54
Sustainability	0.109	Variable	Threshold-dependent	0.43*

*Conditional on crossing 6.5 threshold

criterion importance through data analysis rather than subjective assessment enables more effective resource allocation and competitive positioning.

The objective criterion weights derived from our framework enable sophisticated investment prioritization strategies:

This prioritization enables managers to focus limited resources on improvements with highest empirically-validated impact on customer satisfaction.

The sustainability threshold of 6.5 was derived through systematic analysis of attribution patterns and customer satisfaction relationships:

Threshold detection method: We applied a piecewise linear regression approach to identify structural breaks in the sustainability-satisfaction relationship:

$$y_i = \alpha_1 + \beta_1 \cdot \text{Sustainability}_i + \beta_2 \cdot \max(0, \text{Sustainability}_i - \tau) + \epsilon_i$$

The optimal threshold $\tau^* = 6.47$ (rounded to 6.5) minimizes the residual sum of squares and was validated through:

Statistical validation:

- Chow test for structural break: $F = 12.34$ ($p < 0.001$)
- Davies test for threshold existence: LM $= 8.67$ ($p = 0.003$)
- Bootstrap confidence interval for threshold: [6.12, 6.83]

Economic interpretation: Below the 6.5 threshold, sustainability improvements show limited impact on customer satisfaction ($\beta_1 = 0.12$, $p = 0.184$). Above the threshold, sustainability becomes highly significant ($\beta_1 + \beta_2 = 0.48$, $p < 0.001$), suggesting a critical mass effect where sustainability practices become salient to customer experience.

7.2 Regional tourism policy applications

For regional tourism authorities, our framework enables evidence-based policy design and resource allocation. Traditional certification programs rely on subjective criteria weighting, potentially misaligning with actual customer preferences. Our framework enables objective certification tier design based on consensus ranking percentiles and empirically-validated criterion requirements.

The sustainability threshold identification enables targeted support for accommodations approaching critical performance levels, maximizing public investment impact through strategic intervention timing. The framework enables optimal allocation of public resources through focused support programs, prioritized infrastructure investment, targeted training programs, and evidence-based marketing strategies.

7.3 Generalizability and regional transferability

While our framework was developed using Aosta Valley data, several design elements enhance its transferability to other tourism regions:

Methodological universality: The XAI-MCDM integration approach is region-agnostic, requiring only locally relevant performance criteria and outcome measures for adaptation.

Cultural context considerations: The framework can accommodate regional differences through:

- Local criterion selection reflecting cultural tourism values
- Region-specific weight calibration using local satisfaction data
- Adaptation of preference functions to match local decision-making patterns

Scale invariance: The mathematical formulations maintain validity across different market sizes and accommodation densities, though larger datasets may reveal more nuanced threshold effects.

Validation requirements: Successful transfer requires:

- Minimum sample size of 30-40 accommodations for stable attribution estimation
- Representative coverage of accommodation types within the region
- Availability of objective outcome measures (customer satisfaction, occupancy rates, revenue per room)

Pilot implementation strategy: We recommend a phased approach: (1) small-scale validation with 20-30 accommodations, (2) comparison with existing regional evaluation methods, (3) full-scale deployment with sensitivity analysis for local conditions.

8 Conclusion

This paper presents a paradigm-shifting integration of explainable artificial intelligence with multiple criteria decision making, addressing the fundamental limitation of subjective criterion weight elicitation in traditional MCDM approaches. Our theoretical contribution, the XAI-Enhanced MCDM Convergence Theorem, provides rigorous mathematical foundations for this integration while ensuring preservation of essential MCDM properties.

The empirical validation using Lower Aosta Valley accommodation data demonstrates substantial improvements over traditional methods, achieving 18% better correlation with actual decision outcomes while revealing previously undetected sustainability threshold effects. The framework successfully transforms subjective preference elicitation into objective, data-driven criterion importance derivation without sacrificing the structured analytical approach that makes MCDM valuable for complex decision problems.

The practical implications extend beyond tourism to any economic domain where multiple criteria evaluation meets complex data relationships. For accommodation managers, the framework provides objective benchmarking tools and evidence-based investment guidance. For policymakers, it enables the design of certification programs and resource allocation strategies grounded in empirical evidence rather than subjective assessments.

Our convergence theorem demonstrates that different MCDM methods, when enhanced with XAI insights, converge to consensus rankings that reflect true empirical relationships in the data. This finding has profound implications for decision-making theory and practice, suggesting that the combination of structured decision frameworks with machine learning explanations produces more reliable and valid results than either approach alone.

The framework opens several promising research directions:

- Extension to dynamic MCDM with temporal attribution evolution
- Integration with real-time data streams for adaptive decision support
- Application to multi-stakeholder decision contexts with conflicting objectives
- Development of uncertainty quantification methods for attribution-based weights
- Investigation of causal attribution methods for enhanced interpretability

Beyond tourism, potential applications span financial portfolio optimization, sustainable supply chain management, healthcare resource allocation, and urban planning decisions where objective criterion weighting could transform traditional subjective approaches.

The framework opens new research directions at the intersection of decision science and artificial intelligence, with applications extending throughout economics and finance. As organizations increasingly embrace data-driven decision-making, the integration of XAI with MCDM provides a pathway toward more transparent, reliable, and actionable insights for complex multi-criteria problems.

Beyond methodological and practical contributions, this integration also supports broader Sustainable Development Goals by enabling decision processes that balance economic performance with social responsibility and environmental sustainability.

Acknowledgements This paper is part of the NODES project, which received funding from the MUR—M4C2 1.5 of PNRR and was funded by the European Union—NextGenerationEU (Grant agreement no. ECS00000036). We thank the Aosta Chamber of Commerce for providing us with some data.

Funding This research was supported by the NODES project (MUR—M4C2 1.5 of PNRR, European Union—NextGenerationEU, Grant No. ECS00000036).

Data Availability The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflicts of Interest The authors declare that they have no conflict of interest.

Code availability The code used for analysis is available from the corresponding author on reasonable request.

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