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Enhancing Ethical Leadership Responses: Application of Dimension Reduction and Fermatean Fuzzy MEREC-WASPAS Methods

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ABSTRACT

Identifying priority strategies for improving the ethical leadership response model in companies is essential for the effective allocation of financial and human resources. This study aims to evaluate and improve the performance of the ethical leadership response model by developing a novel fuzzy decision-making framework. In the first stage, decision-maker weights are calculated using a dimensionality reduction method. In the second stage, the weights of the selected criteria are determined using Fermatean fuzzy MEREC. In the third stage, policy alternatives are ranked using Fermatean fuzzy WASPAS. The findings indicate that sustainable risk policies constitute the most important criterion for improving the performance of the ethical leadership response model. Furthermore, rewarding employees is identified as the most effective policy alternative for enhancing ethical leadership performance. The main contribution of this study lies in the development of a novel framework that integrates machine learning with fuzzy decision-making theory to provide a comprehensive evaluation of strategies for improving ethical leadership responses. The machine learning approach enables the computation of expert weights, while the use of Fermatean fuzzy sets helps account for uncertainty in the evaluation process. Consequently, the proposed framework facilitates the identification of more effective policy alternatives for leaders' responses to employees.

1. Introduction

Ethical leadership response model is an approach that explains how leaders should react to the ethical problems they encounter. It is possible to talk about many benefits of this model for the

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business. The main purpose of this approach is to develop values such as transparency and honesty within the business. Therefore, thanks to this model, customers' and employees' trust in the business is increased. Similarly, it is easier to increase employee satisfaction in this environment [1]. In this way, the motivation of employees will increase, which allows the organizational effectiveness of the business to be increased. In addition to them, ethical leadership enables early detection of potential problems. As a result, it is possible to minimize the problems that may occur within the business. Another advantage of ethical leadership is ensuring long-term sustainability. This situation allows businesses to increase their competitiveness. Legal compliance is another benefit of ethical leadership. Due to this condition, the possibility of businesses being exposed to legal penalties can be minimized.

There are some important factors and strategies that need to be considered for this model to be successful. In this context, first the core values of the business should be fully defined. In this context, ethical principles should be clearly adopted by all employees. To achieve this goal, the written ethical guide of the business must be defined [2]. Another issue that affects the performance of this process is the qualification of the managers of the business. This situation supports the more successful implementation of ethical rules in the business. Moreover, transparency is another element that significantly affects the success of this model. In this context, employees must have detailed information about the activities of the top management. Similarly, by creating an effective feedback system, problems experienced within the business should be easily reported to the upper management. Furthermore, for this model to be successful, it must be examined periodically whether the business acts in accordance with ethical rules. In this way, it will be possible to solve possible problems early and the necessary measures can be taken in a timely manner.

Identifying how leaders should prioritize response strategies when confronting unethical pro-organizational behavior remains a challenging issue, particularly under conditions of ethical ambiguity and limited organizational resources. While ethical leadership research has extensively examined antecedents and behavioral outcomes, less attention has been devoted to how leaders systematically evaluate and rank alternative response options from a decision-support perspective. In practice, leaders often rely on normative judgment rather than empirical performance metrics when ethical dilemmas arise, which highlights the need for analytically structured prioritization frameworks rather than purely descriptive models. Rather than claiming a general lack of ethical leadership research, this study addresses a more specific methodological gap: the limited use of expert-based multi-criteria decision-making approaches to structure managerial judgment in ethical leadership response design. Existing studies frequently rely on qualitative assessments, case discussions, or performance indicators, whereas formal prioritization tools capable of integrating multiple ethical criteria under uncertainty remain underexplored in this context.

Accordingly, the objective of this manuscript is to develop a decision-support framework that systematically prioritizes ethical leadership response strategies based on expert evaluations. The study aims to identify (i) which ethical criteria are considered relatively more important when assessing unethical pro-organizational behavior and (ii) how alternative leadership response strategies can be comparatively ranked under uncertainty. To achieve this objective, an expert-based multi-criteria evaluation is conducted. First, expert importance weights are derived using a dimension reduction–based weighting approach. Next, the relative importance of ethical criteria is determined through Fermatean fuzzy MEREC. Finally, leadership response alternatives are ranked using Fermatean fuzzy WASPAS.

The contribution of this study lies not in behavioral validation or policy prescription, but in providing a theoretically informed and methodologically transparent prioritization structure that supports managerial reasoning in ethical leadership contexts. By framing ethical leadership responses as a multi-criteria decision problem, the study complements existing behavioral research with a normative evaluation tool that can guide future empirical investigations and practitioner-oriented applications. In this process, different techniques are integrated to increase the superiority of the proposed model. Some advantages of this recommended model are explained below. (i) Rather than employing predictive or data driven machine learning algorithms, the proposed framework utilizes an unsupervised dimension reduction procedure mathematically analogous to principal component analysis to derive expert importance weights from demographic information. Accordingly, the term machine learning is used in a broad methodological sense referring to feature transformation and dimensionality reduction rather than prediction or model training. This clarification improves the transparency of the proposed framework and avoids interpreting the methodology as a conventional artificial intelligence model. (ii) Considering the Fermatean fuzzy sets also contributes the superiority of the proposed model. With the help of these sets, a wide range of evaluation areas can be taken into consideration. These cases help to minimize uncertainty problem in the analysis process. This issue is accepted as the most critical problem of the decision-making analysis. Thus, owing to Fermatean fuzzy sets, this problem can be overcome more effectively. Hence, more appropriate findings can be identified. (iii) Using MEREC and WASPAS methods also provides a few advantages to the proposed model. MEREC focuses on the change in the state of the alternative in the absence of a criterion. In this process, the criterion whose absence causes major change is considered important. In other words, a very sensitive calculation process is carried out in weighting the criteria. On the other hand, WASPAS requires a more comprehensive analysis by combining the weighted sum and product values of the alternative. With the help of this condition, more effective policy alternatives for leaders' responses to employees can be identified.

The main points in the literature evaluation are given in the second section. In the following part, necessary details are provided for the recommended model. Analysis findings, discussion and conclusion are underlined.

2. Literature Review

A specific form of unethical behavior, unethical pro-organizational behavior, is defined as “actions intended to promote the effective functioning of the organization or its members, yet which violate core societal mores, laws, values or standards of proper conduct” [3]. UPB includes two conflicting components: being unethical and pro-organizational. In contrast, third parties may also respond to UPB by simultaneous activation of disgust and admiration [4].

UPB can trigger different reactions [5]. In the present paper we operationalize five leader responses to employee UPB drawing on research on creativity, deviance, and leadership [6,7] from an interactionist perspective [8,9]. The identified leader responses are forgiving, rewarding, punishing, ignoring, and manipulating.

Forgiving refers to the leaders' forgiveness and ability to let go of negative feelings in response to employee unethical behavior [10]. Without actual punishment, forgiving cautions employees to abstain from UPB in the future. Additionally, it indicates that the leader abandoned negative feelings and retaliation intentions with an empathetical point of view [11]. Forgiving acknowledges well-intended motives to benefit the organization while it also signals that UPB is a violation of acceptable norms and values. However, forgiving does not mean that future UPB acts will be forgiven or tolerated. Forgiveness is associated with positive outcomes such as satisfaction and engagement at work [12].

Ignoring refers to the intentional lack of a response from the leader by not providing feedback or communication to employees' UPB. Similarly to forgiving, ignoring may be a one-time event that does not guarantee future ignoring of UPB. However, leaders may show ignoring when unethical behavior is deemed necessary for high employee performance [13]. Leader's absence, low levels of reactance and avoidance may signal acceptance of unethical behavior and misconduct norms within the organization [14]. Supervisor's bottom line mentality referring to prioritizing bottom-line outcomes such as profit or other financial outcomes may lead them to ignore or undermine the importance of other values such as adhering to moral principles [15]. Considering the paradoxical nature of UPB consisting of pro-social and unethical components, leader's ignorance may be characterized as either reward or punishment omission [16] depending on the consequences of UPB or perception of the employee engaging in UPB [17].

Alternatively, leaders may choose to reward employee UPB. These leaders appreciate their employees' effort to benefit the organization and praise the employees to take the risk of engaging in UPB. Rewarding offers greater autonomy in future unethical decision-making. Although UPB is regarded as a form of an unethical behavior, employees engaging in UPB may have good performance evaluations [18]. Additionally, recent research suggests that managers often regard employees' UPB as a form of valuable exchange resource providing reciprocation or strategic benefit. In parallel, leader's positive attitudes toward UPB can enhance the positive aspects of UPB for the individual involved and foster a sense of psychological entitlement [19,20]. Most research has concentrated on the more subtle forms of leaders' rewarding behavior in response to employee UPB, such as expressions of gratitude [21]. Although this form of recognition is not a direct reward, it influences how employees make sense of their work environment through social cues affecting their own behaviors in line with social information processing model. Thus, leader's gratitude behavior associated with respect and recognition of employee's efforts conveying positive emotions [22] that could potentially encourage further UPB. Furthermore, the leader's rewarding UPB is signaling acceptability of the unethical behavior and encouraging employees to engage moral disengagement to justify immoral behavior [23].

Conversely, punishing is a negative response that acts upon disciplinary acts by perceiving UPB as serious misconduct without toleration [24]. It includes high levels of deterrence in future UPB and clearly indicates that nonconformity will not be tolerated [25]. In competitive contexts that highly value achievement and success, punishment alone is not sufficient because the work culture with high levels of demand and workload may promote it indirectly. Punishment may sometimes backfire for inducing anger and resentment in employees leading to lower contribution and employees are more likely to accept punishment if they believe it is fair and the source of the punishment is a legitimate authority. If employees perceive leaders' punishment response to UPB is unfair, it may be associated with decrease in motivation, so legitimacy of the source of punishment and employees' fairness perceptions are crucial.

Finally, leaders may respond to employee UPB by manipulation to maximize personal gains. Manipulating response differs from the other leader responses to UPB because it depends on the leader's judgment of UPB plausible consequences [26]. If UPB is associated with success and positive outcomes, the leader legitimizes it and attempts to take credit for the success. If UPB results in adverse outcomes, the leader places responsibility on the employee, whose actions they may be punished or ignored. Highly narcissistic or Machiavellian leaders lack empathy for others and accordingly seek to gain success or power, by promoting ethically questionable behaviors to exploit others [27]. Thus, self-interested leaders' manipulation of UPB and their exploiting of others for personal gains is important factor shaping employee behavior following UPB.

The identification of leadership response alternatives followed a theory-driven literature review rather than an a priori selection. Previous research on ethical leadership, unethical pro-organizational behavior, creative deviance, and managerial reactions to norm violations consistently distinguishes between a limited set of recurrent response patterns. These patterns are commonly conceptualized as positive reinforcement (e.g., rewarding), negative reinforcement (e.g., punishing), non-response or omission (e.g., ignoring), moral restoration (e.g., forgiving), and self-interested strategic behavior (e.g., manipulating). Drawing on this stream of literature, the present study operationalizes five representative leadership response alternatives: rewarding, punishing, ignoring, forgiving, and manipulating. These alternatives reflect dominant theoretical categories repeatedly discussed across leadership and organizational behavior research rather than an exhaustive list of all possible responses. Their selection is guided by conceptual relevance, theoretical clarity, and applicability to unethical pro-organizational behavior contexts. While additional response types could be identified in specific organizational settings, incorporating a broader set of alternatives would substantially increase model complexity without necessarily improving analytical insight. Accordingly, the selected alternatives are intended to provide a theoretically grounded and analytically tractable representation of leadership response strategies suitable for multi-criteria decision-making analysis.

In recent years, multi criteria decision making methods have been increasingly adopted across a wide range of research domains due to their ability to evaluate complex problems involving multiple conflicting criteria under uncertainty. Recent studies have successfully applied advanced fuzzy MCDM approaches to electric vehicle charging infrastructure planning, renewable energy source selection, business analytics, and augmented reality decision making, demonstrating their flexibility and practical applicability in diverse decision environments. Moreover, continuous methodological developments, including the integration of Fermatean fuzzy sets, Z numbers, and personalized decision frameworks, have significantly enhanced the capability of MCDM techniques to model uncertainty and expert hesitation more effectively. These studies also indicate that different decision problems require different methodological combinations depending on the characteristics of uncertainty and evaluation structure. Considering these developments, the present study adopts the Fermatean fuzzy MEREC and WASPAS methods because they provide an appropriate combination of objective criterion weighting and comprehensive alternative ranking while effectively representing uncertainty in expert judgments. This methodological choice is therefore consistent with recent advances in the MCDM literature and supports a transparent and systematic evaluation of ethical leadership response strategies.

Multi-criteria decision-making (MCDM) methods have experienced substantial methodological development over the last decade through the integration of objective weighting techniques, fuzzy set extensions, and hybrid decision frameworks designed to improve robustness under uncertainty. Recent review studies demonstrate that hybrid MCDM approaches are increasingly preferred because they combine the strengths of complementary weighting and ranking algorithms while mitigating the limitations associated with individual techniques. Objective weighting methods such as MEREC reduce subjective bias by deriving criterion importance directly from decision data, whereas ranking methods such as WASPAS provide stable compromise solutions by integrating additive and multiplicative aggregation principles. These methodological characteristics explain the growing adoption of hybrid MCDM frameworks across engineering, management, healthcare, sustainability, and public policy applications and provide the theoretical rationale for selecting the Fermatean fuzzy MEREC–WASPAS framework in the present study.

Fermatean fuzzy sets (FFSs), introduced as an extension of intuitionistic and Pythagorean fuzzy sets, provide a more flexible framework for representing uncertainty by allowing decision makers to express higher degrees of membership and non-membership simultaneously while satisfying the Fermatean constraint [28]. This additional flexibility enables FFSs to model ambiguous and imprecise expert judgments more effectively, particularly in complex decision environments where uncertainty cannot be adequately represented by conventional fuzzy structures [29]. Owing to these characteristics, Fermatean fuzzy numbers have been successfully integrated into numerous MCDM methods, including TOPSIS, VIKOR, COPRAS, MARCOS, ARAS, CODAS, EDAS, and WASPAS, across applications in sustainable energy, healthcare management, supply chain optimization, environmental assessment, financial decision making, and engineering system evaluation. These studies consistently demonstrate that Fermatean fuzzy environments improve the representation of linguistic uncertainty while preserving computational tractability, making them particularly suitable for expert-based decision support models.

The basic computational operations employed in the present study, including addition, multiplication, score function, and accuracy function, follow the standard definitions proposed in the original Fermatean fuzzy literature and are directly incorporated into the subsequent MEREC–WASPAS computation procedure. Recent studies have successfully employed Fermatean fuzzy environments in energy planning, supplier selection, sustainable manufacturing, healthcare management, financial risk assessment, transportation planning, and public policy evaluation by integrating FFSs with various MCDM techniques [30]. These applications demonstrate the adaptability of Fermatean fuzzy representations across diverse decision contexts characterized by high uncertainty and linguistic assessments.

3. Methodology

In this study, a new model is created to make evaluation to improve the performance of the ethical leadership response model. Firstly, the weights of decision makers are computed using dimension reduction. After that, selected criteria are weighted using Fermatean fuzzy MEREC. Finally, the policy alternatives are ranked via Fermatean fuzzy WASPAS. This section consists of the theoretical background of these approaches. It is important to clarify the scope and nature of the empirical contribution of this study. While the research is theoretically grounded in the ethical leadership and organizational behavior literature, the proposed model does not aim to measure actual leadership behaviors, employee reactions, or organizational performance outcomes through behavioral or survey-based data. Instead, the study adopts a normative decision-support perspective by structuring expert knowledge to prioritize ethical leadership response strategies under conditions of uncertainty. The empirical component of the study relies on expert-generated evaluations, which are systematically aggregated using dimension reduction–based machine learning and Fermatean fuzzy multi-criteria decision-making methods. Accordingly, the findings should be interpreted as a structured expert consensus regarding the relative importance of ethical leadership criteria and response strategies, rather than direct indicators of leadership effectiveness or observable organizational outcomes. This approach is particularly suitable for complex ethical decision-making contexts, where behavioral data are difficult to observe, ethical outcomes are multidimensional, and managerial judgments play a central role. By transforming expert knowledge into an analytically rigorous prioritization framework, the study contributes to the ethical leadership literature by offering a methodological tool that supports policy formulation and strategic decision-making, rather than behavioral prediction. Therefore, the primary contribution of this research lies in methodological advancement—integrating machine learning–based expert weighting with Fermatean fuzzy MEREC and WASPAS—while providing a theoretically informed decision-support framework for ethical leadership response design.

To enhance transparency and avoid a black-box interpretation, it is important to clarify the logical role of each methodological component and their integration within the proposed framework. The overall structure of the study follows a sequential decision-support logic rather than a predictive modeling approach. The dimension reduction–based technique, inspired by unsupervised learning principles, is employed exclusively to derive relative expert importance weights from demographic information. This step serves as a preprocessing mechanism that addresses a common limitation in expert-based MCDM studies, where experts are frequently assumed to have equal influence. By transforming multidimensional expert characteristics into a single composite weight, the approach introduces heterogeneity in expert influence without affecting subsequent decision-making calculations. The multi-criteria decision-making stage constitutes the core analytical component of the study. Fermatean fuzzy MEREC is used to objectively determine criterion importance by measuring the sensitivity of alternative performance to the exclusion of individual criteria, while Fermatean fuzzy WASPAS is applied to rank leadership response alternatives through a combined additive and multiplicative evaluation structure. These methods are selected for their compatibility with uncertainty modeling and their ability to provide stable rankings under fuzzy environments. The novelty of the proposed framework does not lie in the individual methods themselves, but in their functional integration. Specifically, the dimension reduction step enhances the reliability of expert aggregation, while the Fermatean fuzzy MCDM components enable the systematic treatment of ethical ambiguity and hesitation. Compared to conventional approaches relying on equal expert weighting or single-method ranking, the proposed structure offers a more transparent and analytically consistent decision-support process rather than a fundamentally new algorithm. Accordingly, the framework should be interpreted as an interpretable, modular, and replicable decision-support system, where each methodological component fulfills a clearly defined role rather than operating as an opaque computational black box.

3.1 Reduction based Machine Learning

In this study, the term machine learning is used in a broad methodological sense to refer to an unsupervised dimension reduction process applied to expert demographic data. More specifically, the procedure is mathematically analogous to principal component transformation, where the covariance structure of the input variables is analyzed and the dominant eigenvector corresponding to the maximum variance is employed to derive expert importance coefficients. The proposed approach does not involve prediction, classification, or iterative model training, nor does it aim to approximate contemporary data-driven machine learning models such as neural networks or ensemble learners. Instead, it functions as a statistically grounded feature transformation technique that reduces multidimensional demographic information into a single composite representation of expert influence. This clarification is essential to prevent misinterpretation of the method as a full-scale machine learning model. The value of the approach lies in its transparency, mathematical rigor, and suitability for expert-weighting within a multi-criteria decision-making framework, rather than in algorithmic learning or predictive performance.

A ML technique called the dimension reduction algorithm makes it possible to divide big data sets into smaller ones. Dimension reduction aims to extract new dimensions in a new space by maximizing the preservation of information or variation in the complex data stack. This procedure computes the covariance values between the matrix's columns and builds the covariance matrix. The eigenvector of the covariance matrix that corresponds to the biggest eigenvalue is used to compute the new data set. Table 1 shows machine learning steps based on dimension reduction [31].

The inclusion of demographic variables such as age and salary in the expert-weighting procedure does not imply that these factors directly determine the correctness or ethical quality of expert opinions. Rather, they are employed as indirect indicators of cumulative professional exposure and organizational embeddedness. Age is used as a proxy for longitudinal experience and repeated exposure to ethical dilemmas across different career stages, while salary level reflects hierarchical positioning and responsibility scope within academic institutions. These variables are not intended to measure normative judgment quality, but to introduce heterogeneity into expert influence that would otherwise be assumed equal in conventional expert-based MCDM studies. The dimension reduction–based weighting approach aggregates multiple demographic characteristics into a composite indicator, thereby avoiding reliance on any single attribute. Nevertheless, it is acknowledged that the relationship between demographic characteristics and ethical judgment is neither linear nor universally valid. The use of age and salary as proxy variables represents a methodological assumption rather than an empirically validated causal mechanism. Accordingly, the resulting expert weights should be interpreted as contextual and indicative rather than definitive measures of expert authority. Future studies may refine the expert-weighting procedure by incorporating alternative indicators such as domain-specific expertise, ethical training, managerial experience, or demonstrated involvement in organizational ethics initiatives.

Table 1
The pseudo-code of Dimension Reduction based Machine Learning

Input: Demographic information f_{ik}
Output: Coefficients of Experts ew_i

Begin
(1) Create a characteristic dataset
F= $[f_{ij}]_{m\times k}$
(2) Calculate the standardize values

$$c_{ij} \leftarrow f_{ij} - \bar{f}_j$$

$$s_{ij} \leftarrow \frac{c_{ij}}{\sqrt{\sum_{i=1}^{m} c_{ij}^2}}\ ; \forall i \in [1,2,\dots,m];\ \forall j \in [1,2,\dots,k]$$

(3) Construct covariance matrix (CM)
(4) Compute CM's eigenvalue (ς)

$$Det(CM - \varsigma I) = 0$$

(5) Find eigenvector ($\mathcal{V}$) of maximum eigenvalue (ς_{max})

$$(CM - \varsigma_{max} I) * \mathcal{V} = 0$$

(6) Define matrix to transformed matrix
Fx $\mathcal{V}\mathcal{H} \leftarrow$
(7) Obtain the coefficients for each expert

$$ew_j \leftarrow \frac{h_j}{\sum_{j=1}^{m} h_j}, \forall j \in [1,2,\dots,n]$$

End

Fermatean fuzzy sets constitute an advanced extension of classical fuzzy environments designed to represent uncertainty and hesitation more effectively in complex decision-making problems. Unlike intuitionistic fuzzy sets and Pythagorean fuzzy sets, Fermatean fuzzy sets provide a wider admissible domain for membership and non-membership degrees through the condition that the cube of their sum does not exceed one. This greater flexibility enables experts to express ambiguous evaluations more realistically while preserving mathematical consistency. In practical applications, Fermatean fuzzy sets employ membership and non-membership functions together with score and accuracy functions to transform linguistic assessments into computationally tractable values for aggregation, weighting, and ranking processes. Owing to these properties, they have become increasingly popular in multi criteria decision making studies where uncertainty, hesitation, and subjective judgments play a significant role.

Recent studies have successfully integrated Fermatean fuzzy sets into various decision-making techniques across diverse application domains. They have been employed in outsourcing vendor selection, renewable energy planning, logistics management, supply chain optimization, and intelligent Industry 5.0 decision support systems, demonstrating their capability to improve the robustness and reliability of expert-based evaluations under uncertainty. These applications indicate that Fermatean fuzzy environments can be effectively combined with different MCDM methods to address complex decision problems involving conflicting criteria and imprecise information. Therefore, the adoption of Fermatean fuzzy sets in the present study is consistent with recent methodological developments and provides an appropriate framework for evaluating ethical leadership response strategies under uncertain decision conditions.

3.2. MEREC with Fermatean Fuzzy Sets

MEREC is an objective multicriteria decision-making method for balancing the requirements specified for an objective. The approach computes the change in the calculation when the criterion is not present. In the other words, MEREC concentrates on the variation in the overall weight of the criterion when that variable is not included in the weight calculation. The approach has several benefits, such as objective weighting, simplicity in comprehension and computation, and a strong mathematical foundation [32]. Table 2 displays the MEREC pseudocode.

Table 2
The pseudo-code of MEREC

Input: Evaluations d_{ij}
Output: Weight vector of criteria w_i
Begin
(1) Create the decision matrix
$$\widetilde{D} = \left[\tilde{d}_{ij}\right]_{m\times n}$$
(2) Determine the normalized matrix
(3) Define the defuzzified values (x)
(4) Compute the overall performance (S) of the options
$$S_i \leftarrow \ln\left(1 + \left(\frac{1}{n}\sum_j \left\|ln\left(x_{ij}\right)\right\|\right)\right);\ \forall i \in [1,2,\dots,m]$$
(5) Derive the performance of the options by removing each criterion.
$$S'_{ij} \leftarrow \ln\left(1 + \left(\frac{1}{n}\sum_{k,k\neq j} \|ln(x_{ik})\|\right)\right)$$
(6) Calculate the summation of absolute deviations.
$$V_j \leftarrow \sum_i \left\|S'_{ij} - S_i\right\|$$
(7) Obtain the weight vector of criteria
$$w_j \leftarrow \frac{v_j}{\sum_{j=1}^{m} v_j}, \forall j \in [1,2,\dots,n]$$
End

3.3. WASPAS With Fermatean Fuzzy Sets

WASPAS is a MCDM that combines weighted sum and product values. The purpose of this technique is to rank alternatives. The WASPAS method can provide more accurate results compared to other methods. Another advantage is that it enables the values to be calculated with the highest estimated precision. Table 3 gives the WASPAS pseudocode [33].

4. Analysis Results

The proposed model includes three different stages. The analysis results of these three stages are explained in the following subtitles.

4.1. Determining the weights of decision makers using dimension reduction

Academicians who have academic studies in international databases are invited to participate by e-mail. The demographic information of academics who responded is depicted in Table 4.

Table 3
The pseudo-code of WASPAS

Input: Evaluations d_{ij}; Weight vector of criteria w_i Output: Rank values of alternatives A_i
Begin   (1) Construct the matrix $\widetilde{D} = [\tilde{d}_{ij}]_{m\times n}$ (2) Compute the normalized values ($\widetilde{N}$)   (3) Estimate the $\widetilde{Q_s}$ and $\widetilde{Q_p}$. $\widetilde{Q_{s\iota}} \leftarrow \sum w_j \widetilde{N}_{ij}$ $\widetilde{Q_{p\iota}} \leftarrow \prod \widetilde{N}_{ij}^{\ w_j}$ (4) Define the measure of $\tilde{Q}$ $\tilde{Q}_i \leftarrow v\widetilde{Q_{s\iota}} + (1-v)\widetilde{Q_{p\iota}}$ (5) Calculate the crisped elements of $\tilde{Q}$ (6) Determine the rank values for each alternative   End

Table 4
Demographic Information of the Academics

DM	Age	Experience	Salary (USD/month)	Title
DM1	48	11	3300	Prof
DM2	47	13	2500	Associate Prof.
DM3	45	13	2750	Prof

According to Table 4, three decision makers are academics with at least 11 years of experience. Additionally, academics have between 11 and 13 years of experience. Using this information of academics, the importance weights of decision makers are obtained with the dimensionality reduction-based machine learning technique. First, the standard values are obtained. This matrix is presented in Table 5.

Table 5
Standardized Matrix

DM	Age	Experience	Salary	Title
DM1	0.617	-0.816	0.777	0.408
DM2	0.154	0.408	-0.605	-0.816
DM3	-0.772	0.408	-0.173	0.408

Afterwards, inter-column covariance values are computed with standardized values. The covariance coefficient is shared in Table 6.

The roots of the polynomial of the covariance matrix are calculated with the help of the determinant. In other words, the eigenvalues of the CM are found. The maximum eigenvalue is selected to contain the largest variance in the new data set created. This value is 0.921. Then, the eigenvector is obtained. The value equivalents in the new space are estimated by multiplying the eigenvector with the values in Table 4. Finally, the new values are normalized, and the weights of the decision makers are determined. The weights of the decision makers are summarized in Figure 1.

Table 6
Covariance Coefficients

	Age	Exp0.	Salary	Title
Age	0.333	-0.252	0.173	-0.063
Exp0.	-0.252	0.333	-0.317	-0.167
Salary	0.173	-0.317	0.333	0.247
Title	-0.063	-0.167	0.247	0.333

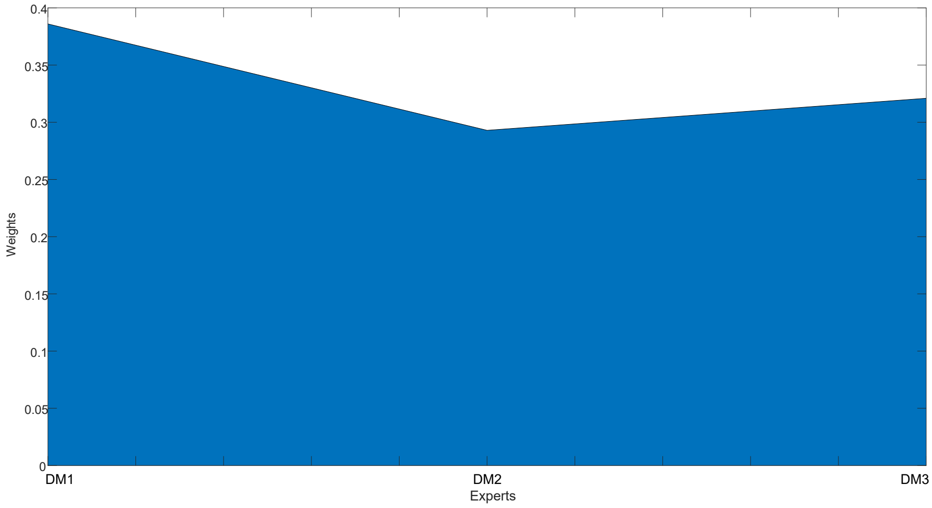

Fig. 1. The Weights of the Academics

According to Figure 1, the importance weight of the 48-year-old academician is the highest, with a value of 0.386. The importance weights of other academics are 0.293 and 0.321, respectively. Then, with these values, weighted decision matrix values are obtained.

4.2. Weighting of the Criteria using Fermatean Fuzzy MEREC

The MEREC method is used with Fermatean Fuzzy numbers to determine the weight vector of the criteria effective on the purpose of the study. For this purpose, criteria are first determined. From search of literature and academician interviews, the selected criteria are shared in Table 7.

Table 7
The Selected Criteria

Codes	Definitions
ETHSTA	Ethical Standards
LEGINF	Legal Infrastructure
CORGOV	Corporate Governance
ORGCUL	Organizational Culture
SUSRPOL	Sustainable Risk Policies

For unethical pro-organizational behavior, five criteria are determined. Additionally, policy alternatives for leaders' responses to employees are defined. The five policy alternatives are shown in Table 8.

The linguistic evaluation scale employed in this study follows the widely accepted nine-point preference structure originally proposed in multi criteria decision making research. This scale provides an appropriate balance between discrimination capability and cognitive simplicity, allowing experts to express different degrees of preference without introducing excessive complexity. Since the subsequent Fermatean fuzzy transformation preserves uncertainty through membership and non-membership functions, the adopted scale serves only as an initial linguistic representation rather than a source of numerical precision. The alternatives in Table 8 are evaluated by three decision makers based on the criteria in Figure 1. The evaluations of the decision makers are tabulated in Table 9.

Table 8
Policy Alternatives for Leaders' Responses to Employees

Codes	Definitions
REWARDING	Rewarding
IGNORING	Ignoring
PUNISHING	Punishing
MANIPULATING	Manipulating
FORGIVING	Forgiving

Table 9
The Evaluations of the Academics

		DM1			
Codes	ETHSTA	LEGINF	CORGOV	ORGCUL	SUSRPOL
REWARDING	9	9	6	8	7
IGNORING	7	7	4	9	6
PUNISHING	7	5	2	8	5
MANIPULATING	6	4	1	4	3
FORGIVING	5	3	3	6	4
		DM2			
Codes	ETHSTA	LEGINF	CORGOV	ORGCUL	SUSRPOL
REWARDING	7	7	5	8	6
IGNORING	8	9	4	9	6
PUNISHING	8	6	3	8	6
MANIPULATING	7	5	2	5	4
FORGIVING	6	3	1	7	4
		DM3			
Codes	ETHSTA	LEGINF	CORGOV	ORGCUL	SUSRPOL
REWARDING	8	8	8	7	3
IGNORING	8	4	3	4	2
PUNISHING	9	4	9	8	4
MANIPULATING	8	8	8	7	5
FORGIVING	6	3	4	6	2

The Fermatean fuzzy equivalents of the academicians' evaluations are multiplied by the expert weights in Figure 1 and then summed to construct the expert-weighted decision matrix. Before applying the MEREC procedure, the individual evaluations provided by the three experts were aggregated into a single expert weighted decision matrix. First, each linguistic assessment was transformed into its corresponding Fermatean fuzzy representation. Subsequently, the transformed evaluations were multiplied by the expert importance coefficients obtained through the dimension reduction based weighting procedure. Finally, the weighted Fermatean fuzzy evaluations of all experts were aggregated using a weighted averaging approach to generate a single collective decision matrix. This aggregated matrix was then used as the input for the subsequent criterion weighting and alternative ranking analyses. The expert-weighted decision matrix is displayed in Table 10.

Decision Making Advances
Volume 4, Issue 1 (2026) 191-211

Table 10
The Expert-Weighted Decision Matrix

Codes	ETHSTA		LEGINF		CORGOV		ORGCUL		SUSRPOL	
REWARDING	0.832	0.123	0.832	0.123	0.673	0.229	0.774	0.125	0.596	0.320
IGNORING	0.768	0.131	0.756	0.219	0.365	0.530	0.842	0.168	0.534	0.403
PUNISHING	0.818	0.131	0.512	0.395	0.702	0.368	0.800	0.100	0.512	0.395
MANIPULATING	0.712	0.187	0.634	0.279	0.591	0.421	0.566	0.349	0.404	0.499
FORGIVING	0.567	0.335	0.250	0.600	0.301	0.637	0.635	0.266	0.354	0.570

The normalization of the expert-weighted decision matrix is applied and then crisped. The crisped elements are depicted in Table 11.

Table 11
Crisped Elements

Codes	ETHSTA	LEGINF	CORGOV	ORGCUL	SUSRPOL
REWARDING	0.787	0.787	0.646	0.731	0.590
IGNORING	0.725	0.711	0.450	0.796	0.544
PUNISHING	0.772	0.536	0.648	0.756	0.536
MANIPULATING	0.677	0.617	0.566	0.569	0.471
FORGIVING	0.572	0.400	0.384	0.618	0.430

Then, the overall performance (S) of the alternatives is calculated. Additionally, the performance of the alternative is derived by removing each criterion are. The results are presented in Table 12.

Table 12
The Overall Performance and The Performance

Codes	S'					S
	ETHSTA	LEGINF	CORGOV	ORGCUL	SUSRPOL	
REWARDING	0.265	0.265	0.234	0.254	0.220	0.301268
IGNORING	0.333	0.330	0.262	0.347	0.291	0.378311
PUNISHING	0.331	0.277	0.305	0.328	0.277	0.367271
MANIPULATING	0.388	0.375	0.363	0.364	0.337	0.439531
FORGIVING	0.495	0.450	0.445	0.504	0.459	0.560403

Finally, the summation of absolute deviations is calculated. Next, these values are normalized, and the weight vector of the criteria is estimated. The weight vector is illustrated in Figure 2.

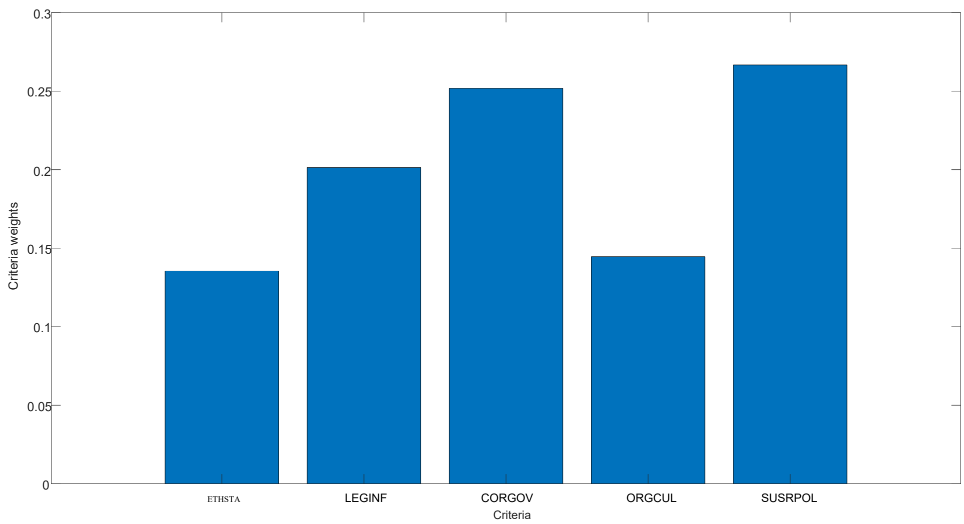

Fig. 2. The Weight Vector of the Criteria

According to Figure 2, the most important issues in unethical pro-organizational behavior are sustainable risk policies and corporate governance. The importance weight values of these criteria are 0.2667 and 0.2518.

4.3. Ranking of the Policy Alternatives using Fermatean Fuzzy WASPAS

Policy alternatives are ranked using the WASPAS method with Fermatean fuzzy numbers. In the analysis, the expert-weighted decision values in Table 10 and the criterion weight vector in Figure 2 are used. First, the normalization values are performed. Afterwards, Qs and Qp are defined. The results of the weighted sum and product models are shown in Table 13.

Table 13
The Qs and Qp

Codes	QS		Qp	
REWARDING	0.745	0.186	0.714	0.234
IGNORING	0.683	0.289	0.584	0.391
PUNISHING	0.684	0.274	0.630	0.348
MANIPULATING	0.586	0.354	0.552	0.401
FORGIVING	0.445	0.494	0.367	0.554

Q values are calculated with various v numbers range 0 to 1. Finally, these values are crisped. The results are displayed in Figure 3.

As can be seen in Figure 3, according to the Q value calculated according to different v values, rewarding is the most appropriate policy alternative for leaders' responses to employees. Moreover, the ranking of the alternatives is the same for all values of v.

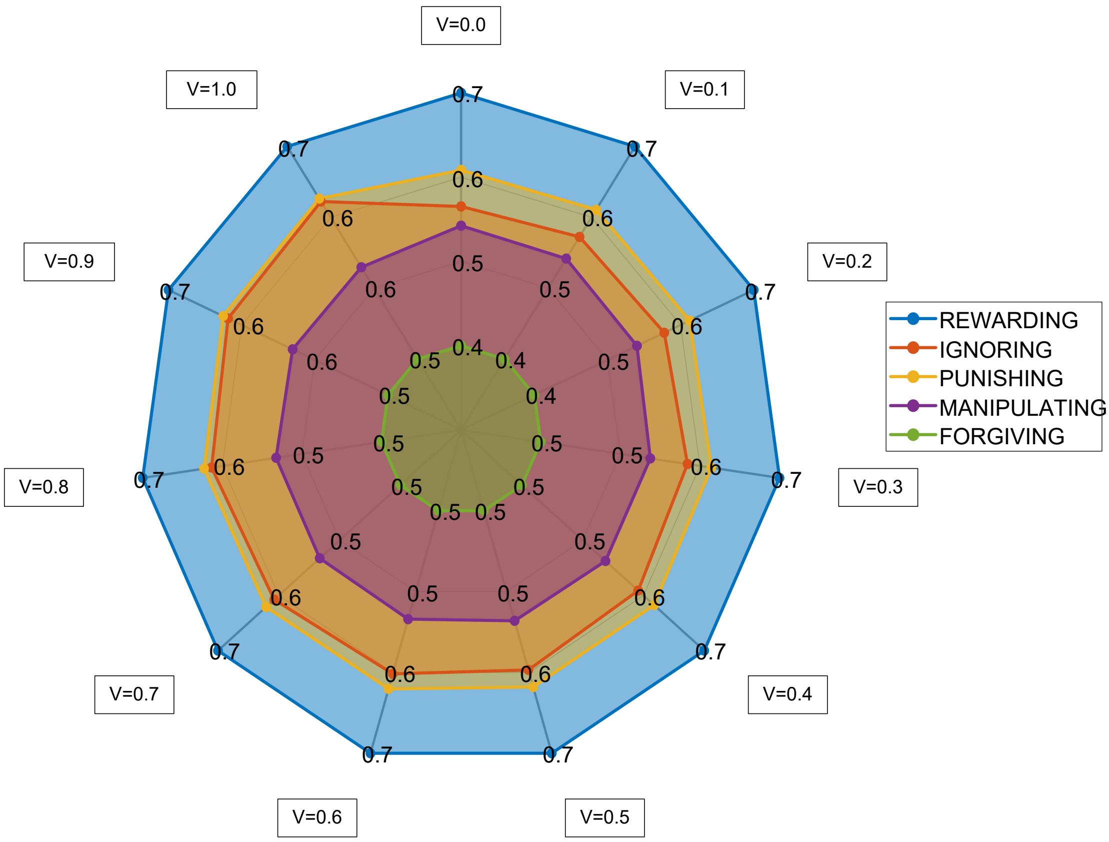

Fig. 3. The Defuzzified Values for Different Values

4.4. Comparative Analysis

The results of WASPAS are compared with Ranking Technique by Geometric Mean of Similarity Ratio to Optimal Solution (RATGOS). These analyses are repeatedly performed with four different weights. The numerical values presented in Figure 4 represent the final performance scores obtained for each alternative under the respective comparative evaluation scenarios. These scores are directly generated by the corresponding MCDM methods and are used to determine the relative ranking of the alternatives. Higher values indicate better overall performance according to the evaluation criteria and expert assessments. The primary objective of presenting these values is to examine whether the relative ordering of the alternatives remains consistent across different comparative analyses. The details of comparative analysis are visualized in Figure 4.

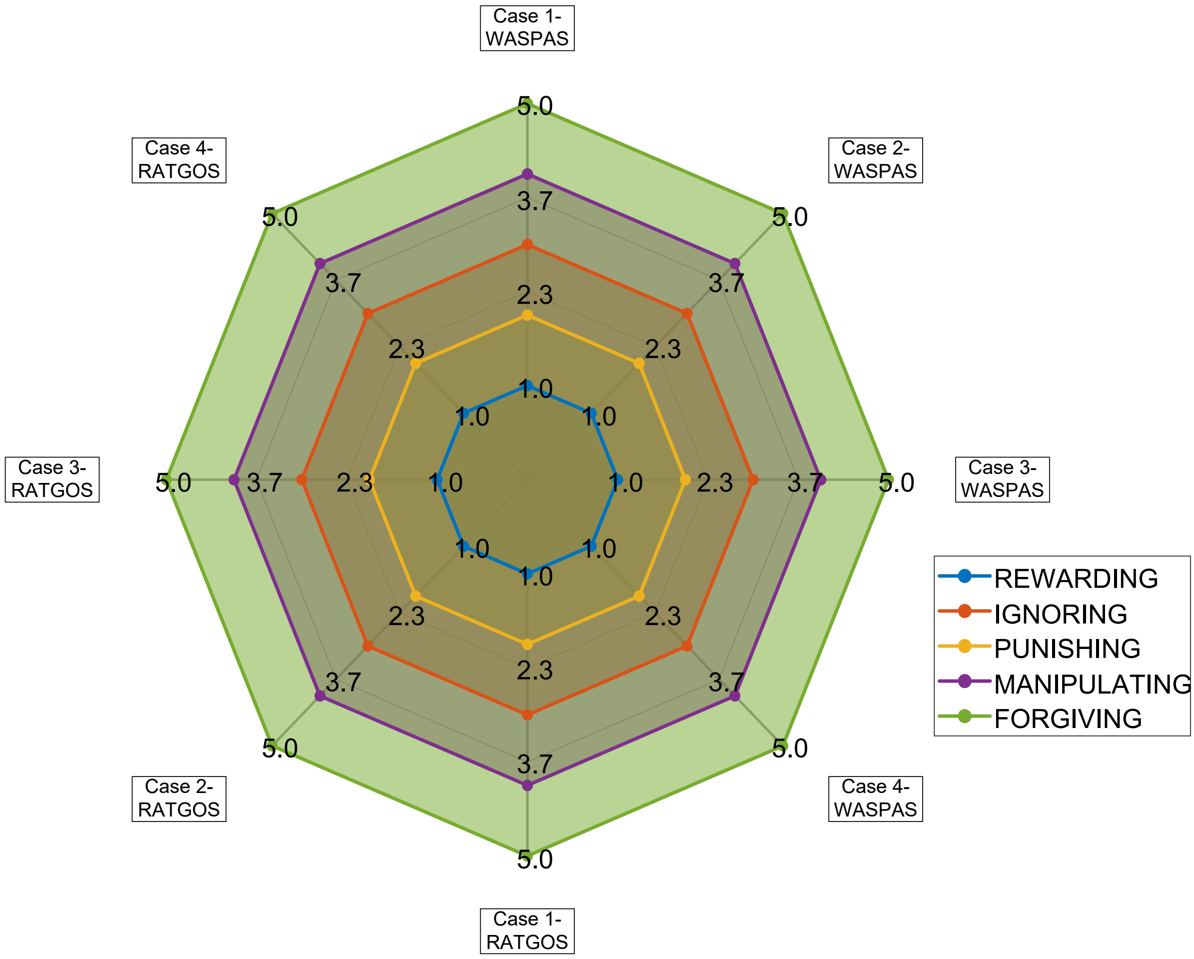

Fig. 4. Results of Comparative Analysis

According to Figure 4, the rankings of policy alternatives are similar. Thus, the results of analysis are validated. The results of this study should be interpreted as structured expert-based prioritizations rather than empirical validations of leadership effectiveness. The identification of sustainable risk policies as the most influential criterion suggests that experts perceive ethical leadership responses as closely linked to long-term organizational resilience rather than short-term behavioral control. This emphasis differs from parts of the ethical leadership literature that primarily focus on individual moral traits or leader–follower interactions, indicating a more systemic and policy-oriented interpretation of ethical leadership effectiveness.

Similarly, the prioritization of rewarding as the most favorable leadership response reflects a normative judgment regarding motivational alignment rather than a causal claim about behavioral outcomes. While prior studies have reported both positive and negative consequences of reward-based responses to unethical pro-organizational behavior, the present findings highlight how experts weigh ethical ambiguity, organizational goals, and leadership responsibility when evaluating response strategies under uncertainty. Rather than reiterating existing findings, the present study extends the discussion by illustrating how ethical leadership concepts can be translated into a comparative decision structure. The divergence and convergence between the expert-based rankings and prior behavioral studies provide insight into how normative managerial reasoning may differ from empirically observed behavior, thereby opening avenues for future empirical validation.

5. Discussion

To increase the performance of the ethical leadership response model, sustainable risk policies are determined as the most important criterion. Thanks to the effective implementation of these policies, it is possible to manage the risks of the business more successfully. This makes it easier for businesses to increase their long-term performance. Lin *et al.,* [34] identified that sustainable risk policies also positively enhance the popularity of businesses. It is possible to reduce ethical problems in businesses that manage their risks more successfully [35]. This increases investors' and customers' confidence in the business. According to Xu and Ju [36], another advantage of sustainable risk policies is that they increase employee satisfaction. The likelihood of more motivated personnel committing ethical violations decreases significantly. Chien and Lin [37] determined that sustainable risk policies help organizations comply with legal regulations and standards. Thus, the possibility of the business being penalized as a result of violation of the law is reduced.

It has been concluded that rewarding employees to increase the performance of the ethical leadership model is the best policy alternative. Reward policies are a very important tool to increase employee motivation. Similarly, thanks to this system, positive behaviors are also encouraged. Employees show higher performance when they see that they are rewarded by their managers. Moreover, Xie *et al.,* [38] concluded that another important advantage of the reward system is that it increases employees' commitment to the institution. This situation encourages employees to exhibit positive behavior. In other words, if employees receive rewards for behaving in accordance with ethical principles, they are more willing to continue such behavior [39]. In addition to them, Tetteh *et al.,* [40] discussed that the reward system offers employees the opportunity to provide regular feedback. This enables businesses to implement the performance management process more effectively. On the other hand, Jin *et al.,* [41] mentioned that reward policies reinforce the ethical values and culture of the organization. This situation contributes significantly to increasing the competitiveness of businesses.

Nevertheless, the prioritization of rewarding should not be interpreted as unconditional reinforcement of unethical pro-organizational behavior. Rather, experts appear to favor recognition mechanisms that reinforce ethical intentions while simultaneously discouraging future ethical violations through clear organizational boundaries and accountability. Previous research has demonstrated that inappropriate rewarding of unethical behavior may foster moral disengagement, psychological entitlement, and the normalization of unethical conduct within organizations. Such unintended consequences may weaken ethical culture by creating perceptions that organizational success justifies violations of ethical standards. Therefore, any reward-based leadership response should be accompanied by transparent ethical guidelines, explicit communication regarding acceptable behavior, and appropriate monitoring mechanisms to ensure that recognition supports ethical commitment rather than legitimizing unethical practices.

This study does not claim to empirically validate ethical leadership outcomes through behavioral, survey-based, or organizational data. Instead, its contribution lies in advancing ethical leadership research from a decision-support and normative reasoning perspective. Ethical leadership research has predominantly focused on explaining behavioral antecedents and consequences, while comparatively less attention has been paid to how leaders systematically prioritize response strategies under ethical ambiguity and uncertainty. The proposed framework contributes to ethical leadership theory by formalizing the cognitive and evaluative processes underlying leaders' responses to unethical pro-organizational behavior. By translating theoretically grounded ethical criteria into a structured prioritization model, the study shifts the analytical focus from behavioral measurement to managerial judgment and policy design. Although hybrid fuzzy multi-criteria decision-making frameworks incorporating methods such as MEREC and WASPAS have been employed in prior research, the originality of this study does not rest solely on methodological integration. Rather, novelty emerges from the application of these techniques to the ethical leadership response domain, the explicit modeling of uncertainty through Fermatean fuzzy sets, and the systematic representation of expert reasoning in ethically sensitive decision contexts. The policy implications derived from the model should therefore be interpreted as analytically informed guidance rather than empirically validated prescriptions. The framework offers a transparent and replicable tool to support ethical leadership decision-making, which can be complemented in future research by case studies, surveys, or experimental designs to enhance empirical validation and practical trustworthiness. In this sense, the study extends ethical leadership scholarship by providing a methodological bridge between normative ethical theory and managerial decision-support systems, rather than by introducing a new behavioral model of leadership effectiveness.

6. Conclusion

This study makes an analysis to improve the performance of the ethical leadership response model by constructing a novel fuzzy decision-making model. Firstly, the weights of decision makers are calculated with dimension reduction methodology. After that, the weights of the selected criteria are identified via Fermatean fuzzy MEREC. The final stage is related to the ranking of the policy alternatives using Fermatean fuzzy WASPAS. It is concluded that sustainable risk policies are found as the most important issue to increase the performance of the ethical leadership response model. In addition to this condition, it is also identified that rewarding employees to increase the performance of the ethical leadership model is the best policy alternative.

A number of policy recommendations can be implemented to increase the effectiveness of appropriate risk policies. First, businesses should comprehensively plan possible risks by creating a comprehensive procedure. Similarly, these procedures significantly support taking the necessary precautions against these risks. On the other hand, all employees should be provided regular training on sustainability and risk management. In this way, employees' awareness of sustainable risk can be increased. Moreover, effective communication is also necessary to increase the performance of sustainable risk policies. Thanks to the effective communication of the business, it is possible to detect potential risks early. This allows quick action to be taken to solve possible problems. On the other hand, rewarding employees must be implemented effectively to increase the performance of the ethical leadership model. To achieve this goal, some policy recommendations can be determined. In this context, very different reward systems should be developed. In this context, while financial rewards such as premiums and bonuses can be applied, moral rewards such as plaques can also be used. Similarly, a transparent and fair reward system should be designed. This significantly supports increasing the work motivation of employees.

To operationalize these findings, organizations should translate ethical leadership priorities into formal governance mechanisms rather than relying solely on managerial discretion. Human resource departments may integrate ethical response criteria into leadership competency frameworks, performance evaluation systems, and executive development programs. Ethics committees should establish standardized decision protocols that distinguish acceptable organizational commitment from unethical pro-organizational behavior, while compliance units should periodically review leadership responses through ethics audits and employee feedback mechanisms. In addition, organizations may define measurable performance indicators, such as ethical climate assessments, whistleblowing resolution rates, and employee trust surveys, to evaluate whether leadership interventions effectively strengthen ethical organizational culture over time.

One important limitation of this study concerns the size and composition of the expert panel. The empirical evaluation is based on the judgments of three academic experts, which may be considered limited in number for drawing broadly generalizable policy conclusions. Although small expert panels are commonly employed in fuzzy multi-criteria decision-making studies—particularly when the focus is on depth of expertise rather than statistical inference—the restricted sample size inevitably constrains the external validity of the findings. In addition, the expert group consists solely of academics, and does not include practitioners such as organizational leaders, ethics officers, compliance specialists, or human resource managers. As a result, the derived rankings should not be interpreted as direct prescriptions for organizational practice, but rather as analytically structured insights reflecting expert-level normative evaluations. Accordingly, the policy implications of this study are positioned as decision-support guidance rather than actionable managerial rules. The proposed model is intended to assist leaders and organizations in systematically prioritizing ethical leadership response strategies under uncertainty, not to substitute for context-specific managerial judgment or empirical behavioral evidence. Future research may enhance the practical relevance and robustness of the model by expanding the expert pool to include practitioners from diverse organizational roles and by comparing expert-based prioritizations with behavioral or survey-based empirical findings. Such extensions would allow for triangulation between normative expert judgment and real-world organizational outcomes.

The selection of evaluation criteria in this study is grounded in a comprehensive review of the ethical leadership and unethical pro-organizational behavior literature, complemented by expert consultation. The identified criteria—ethical standards, legal infrastructure, corporate governance, organizational culture, and sustainable risk policies—represent recurring dimensions emphasized in prior conceptual and empirical studies addressing ethical leadership response mechanisms. Rather than aiming to exhaust all possible ethical dimensions, the study focuses on a parsimonious yet theoretically representative set to ensure analytical tractability within a multi-criteria decision-making framework. The use of a 1–9 linguistic scoring scale follows established practices in fuzzy decision-making literature, where such scales provide sufficient granularity to capture expert judgment while maintaining interpretability and stability during fuzzification. This scale is particularly suitable for Fermatean fuzzy environments, as it allows simultaneous representation of membership, non-membership, and hesitation degrees without imposing excessive cognitive burden on experts. Fermatean fuzzy sets are employed due to their enhanced ability to model uncertainty and hesitation compared to classical fuzzy, intuitionistic fuzzy, and Pythagorean fuzzy frameworks. By allowing a wider admissible space for membership and non-membership degrees, Fermatean fuzzy sets offer greater flexibility in representing ambiguous ethical evaluations, which are inherently subjective and context dependent. Although a comparative analysis comparing alternative fuzzification frameworks or scoring scales could further enrich the robustness assessment, such an extension is beyond the scope of the present study. Instead, robustness is partially addressed through comparative ranking and sensitivity analysis across different aggregation parameters. The proposed evaluation structure should therefore be interpreted as a theoretically informed and methodologically consistent baseline framework rather than a universally optimal configuration. Future research may extend this framework by testing alternative scoring scales, fuzzification methods, and hybrid uncertainty representations to assess the stability and generalizability of the findings across different methodological assumptions.

Although expert-based MCDM studies generally prioritize the quality and depth of expertise over large sample sizes, the present findings should be interpreted as exploratory decision-support outcomes rather than universally generalizable managerial recommendations. The exclusive inclusion of academic experts reflects the theoretical orientation of this study and provides conceptual consistency for evaluating ethical leadership response strategies. Nevertheless, incorporating practitioners such as senior executives, ethics officers, compliance professionals, and human resource managers in future research would strengthen ecological validity, improve practical relevance, and enable comparison between academic and practitioner perspectives on ethical leadership decision making. Future research may compare the proposed framework under alternative fuzzy environments, including Pythagorean, spherical, q-rung orthopair, and interval valued formulations, to investigate the robustness of strategy rankings across different uncertainty representations.

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Conflicts of Interest
The authors declare no conflicts of interest.

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