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***Research paper***

# Advancing Greenwashing Audits: An Innovative Fuzzy Decision-Making Framework Integrating Koch Snowflake Sets and Euclidean Distance-Based Expert Weighting

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**Abstract**

This study aims to identify the priority criteria that should be considered for establishing more effective audit processes to prevent greenwashing. To achieve this objective, a novel fuzzy multi-criteria decision-making model is developed. Euclidean distance-based expert weighting technique is employed to determine the importance weights of six experts based on their demographic characteristics, thereby reducing subjectivity in expert judgments. CIMAS is applied to compute the importance weights of the criteria. Furthermore, the newly developed Koch Snowflake fuzzy sets are integrated into the model to represent uncertainties more precisely, thereby minimizing information loss and increasing the robustness of the results. The originality of the study lies in combining these advanced methods to create a more reliable and effective analytical framework that fills a significant methodological gap in the literature on greenwashing audit processes. The findings reveal that compliance with assurance standards is the most significant factor for enhancing audit effectiveness, followed by corporate transparency and the risk level of greenwashing practices. These results not only contribute to the theoretical literature by offering a new methodological approach but also provide practical implications for policymakers and auditors in designing strategies to strengthen audit mechanisms, improve accountability, and reduce the proliferation of greenwashing practices.

***Keywords***: *Euclidean distance; expert weighting; Koch Snowflake fuzzy sets; CIMAS; greenwashing; audit*

## 1. Introduction

Greenwashing is a misleading strategy that occurs when businesses portray themselves as far more environmentally friendly than they are, to create the impression that they contribute to environmental sustainability. This phenomenon manipulates the decisive role of environmental awareness in consumer choices in today's global economy, leading companies to disregard long-term social and ecological benefits in favor of short-term image gains. The negative effects of greenwashing practices are multifaceted: on the one hand, it erodes consumer trust in businesses and their sustainability narratives, and on the other, it creates unfair competition within the market by diminishing the visibility of initiatives that genuinely provide environmental benefits (Forliano et al., 2025). Furthermore, when individuals seeking environmentally friendly products and services are misled, they may make choices that do not actually contribute to reducing their carbon footprint or preserving natural resources, undermining the effectiveness of efforts to address global environmental problems. Therefore, addressing greenwashing is critical not only from an ethical perspective but also for the success of environmental sustainability policies. This requires transparent and comprehensive oversight of company claims by independent institutions, proper disclosure processes, and the provision of reliable environmental certification mechanisms to consumers (Lublóy et al., 2025). However, the current serious shortcomings in oversight of this process are paving the way for increased greenwashing and the undermining of environmental awareness within society, necessitating stricter controls and sanctions at both the academic and political levels.

To effectively prevent the problem of greenwashing, audit processes must be strengthened not only quantitatively but also qualitatively. In this context, data verifiability is a critical element in preventing misleading statements by providing independent sources to verify environmental performance information provided by businesses. Compliance with audit standards enhances the comparability and reliability of audits by ensuring the use of common criteria across sectors and regions. Corporate transparency, by requiring businesses to provide clear and understandable information in their reporting processes, strengthens the trust of both the public and stakeholders. Furthermore, the level of greenwashing risk requires risk analysis within the framework of companies' fields of activity, business models, and communication strategies, enabling audit prioritization (Huang et al., 2025). Auditor independence prevents conflicts of interest, ensuring the impartiality of audit results. Sustainability audit experience directly impacts audit quality by enhancing auditors' understanding of environmental, social, and governance dimensions. Furthermore, data quality and accessibility contribute to the solid foundation of assessments by ensuring that the information used in the audit process is up-to-date, accurate, and accessible. Finally, impact-focused governance ensures that audits serve sustainable development goals by focusing not only on reporting processes but also on actual environmental and social outcomes (Bai et al., 2025). All these criteria form the foundation for increasing audit effectiveness in combating greenwashing and ensure that audit mechanisms are not merely formal processes but also functional tools for strengthening environmental accountability.

While numerous criteria exist to increase audit effectiveness in combating greenwashing, identifying the most critical factors among these is crucial for the success of the process. Because it's impossible to prioritize all factors equally, it's essential to identify the priority elements for the proper allocation of resources, the efficiency of audit processes, and the effectiveness of policy designs. If the most important criteria aren't clearly defined, audit mechanisms remain superficial, insufficient focus is provided on areas that reveal companies' true environmental performance, thus increasing audit costs and overlooked greenwashing risks due to inaccurate prioritization. These problems undermine the credibility of sustainability policies in the long term, leading to a loss of public trust, inadequate environmental outcomes, and delays in compliance with international standards. The limited number of studies in the literature focusing on which factors are most critical among these criteria presents a significant research gap. This gap both hinders the conceptual clarity of academic debates and creates uncertainty in the decision-making processes of policymakers and audit authorities. Furthermore, this gap, coupled with the inability to develop applicable and comparable prioritization frameworks across sectors, exacerbates the global standardization problem. Therefore, developing a new priority analysis approach will systematically identify the most critical factors by weighting audit criteria. This will contribute to the theoretical literature and pave the way for the construction of a more reliable, effective, and sustainable audit mechanism in practice.

While Nemes et al. (2022) propose an integrated framework to assess greenwashing, their approach remains largely conceptual and lacks the ability to model uncertainty in a mathematically rigorous way. Specifically, their framework relies on qualitative interpretations, which are prone to subjectivity and ambiguity. By contrast, this study introduces Koch Snowflake fuzzy sets, which provide a more precise representation of uncertainty and reduce information loss in the decision-making process. This methodological advancement enables a more reliable assessment of greenwashing risks compared to the conceptual frameworks in the existing literature. Previous studies have commonly employed multi-criteria decision-making methods such as DEMATEL or ANP to evaluate sustainability-related problems (Huang et al., 2025; Ruggeri et al., 2025). Although these methods are effective for analyzing inter-criteria relationships, they suffer from high computational complexity and require a large amount of expert input, which limits their practical applicability. In contrast, the CIMAS technique used in this study offers lower data requirements and a systematic interaction analysis, making it more efficient and scalable across diverse audit contexts. Another limitation of prior frameworks is the assumption of equal weighting for expert opinions, which fails to account for differences in professional background, experience, and expertise. This simplification introduces bias into the evaluation process. To address this gap, the present study applies a Euclidean distance-based expert weighting approach, which objectively determines expert weights by measuring their distance from an anti-ideal profile. This ensures that expert evaluations are incorporated in a more balanced and less subjective manner, thereby enhancing the robustness of the results.

The purpose of this study is to identify the priority criteria that should be considered for establishing more effective audit processes that will contribute to the prevention of greenwashing. The motivation for this study is that, despite the increasing need for transparency in sustainability reporting, the effectiveness of audit mechanisms remains limited, paving the way for the proliferation of greenwashing practices. To this end, a comprehensive literature review was conducted, and eight different criteria that directly impact audit effectiveness are identified. To determine which of these criteria are most critical, a unique fuzzy multi-criteria decision-making model is developed. In the first stage of the proposed model, the Euclidean distance-based expert weighting technique is used to determine importance weights based on the demographic characteristics of six different experts, aiming to reduce subjectivity in expert opinions. In the second stage, the CIMAS technique is applied to determine the importance levels of the criteria. Additionally, Koch Snowflake fuzzy sets, a new addition to the literature, are integrated into this method to more accurately model uncertainties. Criterion weights are also calculated using the AHP technique. Due to this issue, the consistency of the results can be tested. This methodological approach allows for both consideration of differences in expert opinions and minimizing uncertainty in the decision-making process. The research questions addressed in this study are as follows: (1) Which criteria should be considered in audit processes aimed at resolving the greenwashing problem? (2) How should prioritization be implemented to identify the most critical criteria? (3) How can differences in expert opinions and process uncertainties be managed more reliably with a unique fuzzy decision-making model? The answers to these research questions both fill the existing gap in the literature and provide a concrete roadmap for improving audit effectiveness in practice.

This study fills the methodological gap in the literature by presenting a novel decision-making model augmented with Koch Snowflake fuzzy sets for determining priority criteria for greenwashing audit processes. The proposed model possesses several advantages over existing methods in the literature and offers a unique contribution in these respects. (1) First, the use of the newly developed Koch Snowflake fuzzy sets in the model is a significant methodological innovation. Compared to triangular, q-rung orthopair (q-ROF), and spherical fuzzy sets, it represents uncertainties more precisely and reduces information loss in the decision-making process. This constitutes a significant novelty both in theoretical literature and in applied analyses. (2) Another advantage of the model is the determination of the importance weights of the experts using the Euclidean distance-based expert weighting technique. While most studies assume equal weighting for experts, this approach more realistically reflects the contribution of each expert by considering their different demographic characteristics. This increases the reliability of the model's outputs and minimizes subjectivity. (3) Finally, the CIMAS technique, preferred for calculating criteria importance levels, offers advantages over other multi-criteria methods such as DEMATEL and ANP, such as lower computational complexity, a more systematic interaction analysis, and a reduced data requirement from experts. This not only increases ease of implementation but also allows for more consistent identification of inter-criteria relationships. All these advantages demonstrate that the proposed model offers a more reliable, original, and effective analytical framework for solving the greenwashing problem.

Section 2 underlines the steps of the proposed model. The results of this model are explained in Section 3. On the other side, Section 4 makes a discussion and Section 5 demonstrates the main concluding issues.

## 2. Methods

This section includes the identify of Koch Snowflake Fuzzy Sets (KSFSs), Euclidean distances-based experts' weighting, and CIMAS. KSFSs are used for measuring the uncertainty and Euclidean distances are used for computing the important of experts' evaluations. Moreover, the criteria are weighted with CIMAS.

## 2.1 Koch Snowflake fuzzy sets (KSFSs)

Assume that $\mathbb{S}$ be a finite discourse universe. A KSFS $(\mathcal{K})$ is an item having the form in Equation (1) (Kou et al., 2025).

$$\mathcal{K} = \{\mathfrak{x}, (\mathfrak{m}_{\mathcal{K}}(\mathfrak{x}), \mathfrak{n}_{\mathcal{K}}(\mathfrak{x})) | \mathfrak{x} \in \mathbb{S}\} \tag{1}$$

Wherein the function $\mathfrak{m}_{\mathcal{K}}(\mathfrak{x}), t_{\mathcal{K}}(\mathfrak{x})$ and $0 \leq (\mathfrak{m}_{\mathcal{K}}(\mathfrak{x}))^{k} + (\mathfrak{m}_{\mathcal{K}}(\mathfrak{x}))^{k} \leq 1$ are the degrees of membership and non-membership of $\mathfrak{x}$ to $\mathcal{K}$, respectively. The indeterminacy degree is identified in Equation (2).

$$\gamma_{\mathcal{K}}(\mathfrak{x}) = \sqrt{1 - (\mathfrak{m}_{\mathcal{K}}(\mathfrak{x}))^{k} - (\mathfrak{n}_{\mathcal{K}}(\mathfrak{x}))^{k}} \tag{2}$$

Consider that $\mathcal{F}$ and $\mathcal{G}$ be two FFNs and $\varphi$ is a positive real number. Then, some operations are descripted by Equations (3) – (6).

$$\mathcal{F} \oplus \mathcal{G} = \left( \sqrt[k]{\frac{\mathfrak{m}_{\mathcal{F}}^{k} + \mathfrak{m}_{\mathcal{G}}^{k} - \mathfrak{m}_{\mathcal{F}}^{k}\mathfrak{m}_{\mathcal{G}}^{k} - (1-a)\mathfrak{m}_{\mathcal{F}}^{k}\mathfrak{m}_{\mathcal{G}}^{k}}{1-(1-a)\mathfrak{m}_{\mathcal{F}}^{k}\mathfrak{m}_{\mathcal{G}}^{k}}}, \frac{\mathfrak{n}_{\mathcal{F}}^{k}\mathfrak{n}_{\mathcal{G}}^{k}}{\sqrt[k]{a+(1-a)\left(\mathfrak{n}_{\mathcal{F}}^{k} + \mathfrak{n}_{\mathcal{G}}^{k} - \mathfrak{n}_{\mathcal{F}}^{k}\mathfrak{n}_{\mathcal{G}}^{k}\right)}} \right) \tag{3}$$

$$\mathcal{F} \otimes \mathcal{G} = \left( \frac{\mathfrak{m}_{\mathcal{F}}^{k}\mathfrak{m}_{\mathcal{G}}^{k}}{\sqrt[k]{a+(1-a)\left(\mathfrak{m}_{\mathcal{F}}^{k} + \mathfrak{m}_{\mathcal{G}}^{k} - \mathfrak{m}_{\mathcal{F}}^{k}\mathfrak{m}_{\mathcal{G}}^{k}\right)}}, \sqrt[k]{\frac{\mathfrak{n}_{\mathcal{F}}^{k} + \mathfrak{n}_{\mathcal{G}}^{k} - \mathfrak{n}_{\mathcal{F}}^{k}\mathfrak{n}_{\mathcal{G}}^{k} - (1-a)\mathfrak{n}_{\mathcal{F}}^{k}\mathfrak{n}_{\mathcal{G}}^{k}}{1-(1-a)\mathfrak{n}_{\mathcal{F}}^{k}\mathfrak{n}_{\mathcal{G}}^{k}}} \right) \tag{4}$$

$$\varphi \odot \mathcal{F} = \left( \sqrt[k]{\frac{[1+(a-1)\mathfrak{m}_{\mathcal{F}}^{k}]^{\varphi} - (1-\mathfrak{m}_{\mathcal{F}}^{k})^{\varphi}}{[1+(a-1)\mathfrak{m}_{\mathcal{F}}^{k}]^{\varphi} - (a-1)(1-\mathfrak{m}_{\mathcal{F}}^{k})^{\varphi}}}, \frac{\sqrt[k]{a}\,\mathfrak{n}_{\mathcal{F}}^{\varphi}}{\sqrt[k]{[1+(a-1)(1-\mathfrak{n}_{\mathcal{F}}^{k})]^{\varphi} + (a-1)\mathfrak{n}_{\mathcal{F}}^{\varphi k}}} \right) \tag{5}$$

$$\mathcal{F}^{\varphi} = \left( \frac{\sqrt[k]{a}\,\mathfrak{m}_{\mathcal{F}}^{\varphi}}{\sqrt[k]{[1+(a-1)(1-\mathfrak{m}_{\mathcal{F}}^{k})]^{\varphi} + (a-1)\mathfrak{m}_{\mathcal{F}}^{\varphi k}}}, \sqrt[k]{\frac{[1+(a-1)\mathfrak{n}_{\mathcal{F}}^{k}]^{\varphi} - (1-\mathfrak{n}_{\mathcal{F}}^{k})^{\varphi}}{[1+(a-1)\mathfrak{n}_{\mathcal{F}}^{k}]^{\varphi} - (a-1)(1-\mathfrak{n}_{\mathcal{F}}^{k})^{\varphi}}} \right) \tag{6}$$

Let's suppose KSFN is $\mathcal{F} = (\mathfrak{m}_{\mathcal{F}}, \mathfrak{n}_{\mathcal{F}})$. Equations (7) and (8) obtain the score and accuracy functions, respectively.

$$sc(\mathcal{F}) = \frac{\mathfrak{m}_{\mathcal{F}}{}^{k} - \mathfrak{n}_{\mathcal{F}}{}^{k} + 1}{2} \tag{7}$$

$$ac(\mathcal{F}) = \mathfrak{m}_{\mathcal{F}}{}^{k} + \mathfrak{n}_{\mathcal{F}}{}^{k} \tag{8}$$

## 2.2 Euclidean distance-based experts' weighting

Giving equal weight to expert evaluations has been criticized on several grounds. The most fundamental reason is the unequal expertise of experts. This manuscript explores an objective approach to address this. This approach considers the relative distance of experts from an anti-ideal expert, based on their professional knowledge. In other words, the further an expert is from the anti-ideal, the more expert they are. Consequently, the more weight their evaluations carry. The steps in the calculation process are outlined below (Han et al., 2025).
A matrix $(\mathcal{M} = [m_{ij}])$ is formed. The matrix includes professional characteristics of experts such as age, experience, income and certificate, etc. Then, the objects of matrix are standardized by Equations (10) – (12).

$$\bar{m}_j = \frac{\sum_{i=1}^{\varsigma} m_{ij}}{\varsigma} \tag{9}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{\varsigma} (m_{ij} - \bar{m}_j)^2}{\varsigma}} \tag{10}$$

$$z_{ij} = \frac{m_{ij} - \bar{m}_j}{\sigma_j} \tag{11}$$

Wherein $\varsigma$ is the number of experts. Later, the anti-ideal expert is defined using the minimum objects. In other words, the standardized objects of anti-ideal expert are selected with the help of Equation (12).

$$\psi_j = \min_i z_{ij} \tag{12}$$

Afterwards, the Euclidean distances among the experts and anti-ideal expert are obtained via Equation (13).

$$\Delta_i = \sqrt{\sum_{j=1}^{v} (z_{ij} - \psi_j)^2} \tag{13}$$

Wherein $v$ refers to the number of columns of the matrix. Finally, the normalized distances of experts are estimated by Equation (14).

$$\Gamma_i = \frac{\Delta_i}{\sum_{i=1}^{\varsigma}\Delta_i} \tag{14}$$

### 2.3 CIMAS

The purpose of CIMAS is to weight criteria. This method collects evaluations in two different ways. The first is rating. The second is distributing 100 points to criteria according to their importance. By comparing the results of these two evaluations, the reliability of the results can be tested. One of the greatest advantages of this method is the applicability of this reliability test. The calculation steps are summarized below (Yalçın et al., 2025).
Firstly, the criteria are identified and evaluated by experts. Then, the evaluations are converted to KSFNs, and the input-data matrix is formed as Equation (15).

$$\mathcal{D} = [d_{ij}];\, i = 1,2,\dots,\varsigma\; j = 1,2,\dots,\not{f} \tag{15}$$

Wherein $\not{f}$ is the criteria's number. Later, numbers of this matrix are crisped using Equation (16).

$$x_{ij} = sc(d_{ij}) \tag{16}$$

Wherein $sc$ is defined in Equation (7). Next, the normalized input-data matrix is created. The numbers of the normalized input-data matrix are calculated by Equation (17).

$$nx_{ij} = \frac{x_{ij}}{\sum_{i=1}^{\varsigma} x_{ij}} \tag{17}$$

After creating the normalized input-data matrix, the expert-weighted matrix is constructed. However, unlike classical CIMAS, it is suggested in this manuscript to use normalized distances instead of using only years of experience. Thus, the objects of the expert weighted matrix are obtained by Equation (18).

$$\mathfrak{w}_{ij} = \Gamma_i nx_{ij} \tag{18}$$

Afterwards, the maximum object of each criterion is identified via Equation (19). Similarly, the minimum object of each criterion is defined by Equation (20).

$$\mathcal{R}_j^+ = \max_i \mathfrak{w}_{ij} \tag{19}$$

$$\mathcal{R}_j^- = \min_i \mathfrak{w}_{ij} \tag{20}$$

Next, the difference among the minimum and maximum objects of each criterion is estimated with the help of Equation (21).

$$\delta_j = \mathcal{R}_j^+ - \mathcal{R}_j^- \tag{21}$$

The criteria's importances are defined by normalizing the differences. For this, Equation (22) is used.

$$\mathfrak{I}_j = \frac{\delta_j}{\sum_{j=1}^{\not{f}}\delta_j} \tag{22}$$

Finally, since this method is a subjective method, its reliability needs to be tested. In other words, a second evaluation is collected from the same experts, and the reliability index is calculated. In the second evaluation, the criteria are evaluated from experts on a scale from 0 to 100. The average score in second evaluation for each criterion ($AS_j$) is computed. After that, reliability index among two evaluations is estimated via Equation (23).

$$RI = \frac{\sum_{j=1}^{\not{f}}|100\mathfrak{I}_j - AS_j|}{100} \tag{23}$$

If this index value is greater than 0.1, the evaluation process is repeated from the beginning.

## 3. Results

This section shares the results of prioritizing criteria to make greenwashing audits more effective. First, the expert weights are obtained. Then, the calculation of the criteria weights is presented. Finally, the results are compared using AHP.

### 3.1 Obtaining the experts' weights

Professional characteristics such as age, experience, income and certificate of six experts are collected, and the matrix is formed. In this study, four demographic attributes—age, professional experience (years), income level, and professional certification—were selected to reflect the heterogeneity of expert profiles. Age and experience capture seniority and accumulated knowledge, while income serves as a proxy for professional position, and certification represents formal qualifications. Each variable was collected in its natural scale (years for age and experience, income in monetary units, and certification on an ordinal scale from 1 to 3). To ensure comparability across attributes, all data were standardized prior to distance calculation. This procedure allows the Euclidean distance-based expert weighting to be replicated in other contexts with different expert groups. The matrix containing these four characteristics of experts is summarized in Table 1.

**Table 1:** Professional Characteristics

| | Age | Experience | Income | Certificate |
|---|---|---|---|---|
| Expert1 | 40 | 18 | 3000 | 2 |
| Expert2 | 45 | 23 | 3500 | 1 |
| Expert3 | 43 | 20 | 3300 | 3 |
| Expert4 | 47 | 25 | 3600 | 2 |
| Expert5 | 46 | 25 | 3500 | 3 |
| Expert6 | 44 | 20 | 3300 | 1 |

As can be seen from professional characteristics of six experts in Table 1, the average age, experience, income and certificates are estimated using Equation (9). The average characteristics equal to 44.167, 21.833, 3366.667, and 2, respectively. Next, the standard deviations of these characteristics are computed via Equation (10). The standard deviation values of characteristics are 2.27, 2.67, 197.2, and .82, respectively. Then, the standardized object is obtained via Equation (11). The standardized objects are presented in Table 2.

**Table 2:** Standardized Objects

| | Age | Experience | Income | Certificate |
|---|---|---|---|---|
| Expert1 | -1.838 | -1.435 | -1.859 | .000 |
| Expert2 | .368 | .437 | .676 | -1.225 |
| Expert3 | -.515 | -.686 | -.338 | 1.225 |
| Expert4 | 1.250 | 1.185 | 1.183 | .000 |
| Expert5 | .809 | 1.185 | .676 | 1.225 |
| Expert6 | -.074 | -.686 | -.338 | -1.225 |

Later, the anti-ideal expert is defined using the minimum objects. In other words, the standardized objects of anti-ideal expert are selected with the help of Equation (12). In this situation, the standardized age, experience, income and certificate of anti-ideal expert are -1.838, -1.435, -1.859 and -1.225, respectively. Next, the Euclidean distance among six experts and anti-ideal expert is computed with Equation (13). Finally, normalized distances are defined via Equation (15). The distances and coefficients are illustrated in Table 3.

**Table 3:** Euclidean Distance and Coefficients

| | Distance | Coefficient |
|---|---|---|
| Expert1 | 1.225 | .058 |
| Expert2 | 3.846 | .182 |
| Expert3 | 3.260 | .154 |
| Expert4 | 5.211 | .247 |
| Expert5 | 5.128 | .243 |
| Expert6 | 2.447 | .116 |

## 3.2 Calculating the weights of criteria

The eight criteria included in this study were derived from a comprehensive literature review and selected because they directly affect the effectiveness of audit processes (e.g., assurance standards, transparency, auditor independence). Although factors such as consumer perception or regulatory enforcement are also relevant for addressing greenwashing, they represent external contextual drivers rather than internal audit process criteria. Therefore, they were excluded from the present framework to maintain methodological focus and internal consistency. The criteria affecting the audit in greenwashing audits are verifiability of sustainability claims (VRFCS), compliance with assurance standards (CPASD), level of corporate transparency (LVCTS), risk of greenwashing practices (RGWPS), auditor independence and objectivity (AIDPO), auditor's experience in ESG auditing (ADESG), ESG data quality and accessibility (EDQAC), and materiality and stakeholder relevance (MTSKR). These criteria are evaluated by six experts using evaluation numbers. The evaluation numbers of six experts are displayed in Table 4.

**Table 4:** Evaluation Numbers

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| Expert1 | 7 | 1 | 5 | 6 | 4 | 9 | 7 | 3 |
| Expert2 | 4 | 1 | 4 | 5 | 7 | 1 | 2 | 8 |
| Expert3 | 6 | 8 | 1 | 2 | 5 | 2 | 5 | 4 |
| Expert4 | 5 | 8 | 5 | 7 | 3 | 7 | 9 | 6 |
| Expert5 | 3 | 4 | 2 | 7 | 1 | 7 | 7 | 5 |
| Expert6 | 6 | 6 | 1 | 1 | 1 | 6 | 6 | 2 |

The evaluation numbers are converted to KSFNs. An input-data matrix is constructed that accepts these KSFNs as elements. This input-data matrix is expressed in Table 5.

**Table 5:** Input-data Matrix

| | VRFCS | | CPASD | | LVCTS | | RGWPS | | AIDPO | | ADESG | | EDQAC | | MTSKR | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Expert1 | .7 | .2 | .1 | .9 | .5 | .4 | .6 | .3 | .4 | .5 | .9 | .1 | .7 | .2 | .25 | .6 |
| Expert2 | .4 | .5 | .1 | .9 | .4 | .5 | .5 | .4 | .7 | .2 | .1 | .9 | .1 | .75 | .8 | .1 |
| Expert3 | .6 | .3 | .8 | .1 | .1 | .9 | .1 | .75 | .5 | .4 | .1 | .75 | .5 | .4 | .4 | .5 |
| Expert4 | .5 | .4 | .8 | .1 | .5 | .4 | .7 | .2 | .25 | .6 | .7 | .2 | .9 | .1 | .6 | .3 |
| Expert5 | .25 | .6 | .4 | .5 | .1 | .75 | .7 | .2 | .1 | .9 | .7 | .2 | .7 | .2 | .5 | .4 |
| Expert6 | .6 | .3 | .6 | .3 | .1 | .9 | .1 | .9 | .1 | .9 | .6 | .3 | .6 | .3 | .1 | .75 |

Later, numbers of this matrix are crisped using Equation (16). In other words, the score function of each object in Table 5 is obtained. The crisped matrix exhibited in Table 6.

**Table 6:** Crisped Matrix

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| Expert1 | .753 | .090 | .551 | .653 | .449 | .910 | .753 | .325 |
| Expert2 | .449 | .090 | .449 | .551 | .753 | .090 | .180 | .850 |
| Expert3 | .653 | .850 | .090 | .180 | .551 | .180 | .551 | .449 |
| Expert4 | .551 | .850 | .551 | .753 | .325 | .753 | .910 | .653 |
| Expert5 | .325 | .449 | .180 | .753 | .090 | .753 | .753 | .551 |
| Expert6 | .653 | .653 | .090 | .090 | .090 | .653 | .653 | .180 |

Next, the normalized matrix is created. The numbers of the normalized matrix are calculated by Equation (17). In other words, the objects are divided by the sum of criterion. The normalized matrix is illustrated in Table 7.

**Table 7:** Normalized Matrix

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| Expert1 | .223 | .030 | .289 | .219 | .199 | .273 | .198 | .108 |
| Expert2 | .133 | .030 | .235 | .185 | .334 | .027 | .047 | .283 |
| Expert3 | .193 | .285 | .047 | .060 | .244 | .054 | .145 | .149 |
| Expert4 | .163 | .285 | .289 | .253 | .144 | .226 | .240 | .217 |
| Expert5 | .096 | .151 | .094 | .253 | .040 | .226 | .198 | .183 |
| Expert6 | .193 | .219 | .047 | .030 | .040 | .196 | .172 | .060 |

After creating the normalized input-data matrix, the expert-weighted matrix is constructed. In other words, the objects in Table 7 are multiplied by the coefficients in Table 3. Equation (18) is used for this. The expert-weighted matrix is summarized in Table 8.

**Table 8:** Expert-weighted Matrix

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| Expert1 | .013 | .002 | .017 | .013 | .012 | .016 | .011 | .006 |
| Expert2 | .024 | .005 | .043 | .034 | .061 | .005 | .009 | .051 |
| Expert3 | .030 | .044 | .007 | .009 | .038 | .008 | .022 | .023 |
| Expert4 | .040 | .070 | .071 | .062 | .035 | .056 | .059 | .054 |
| Expert5 | .023 | .037 | .023 | .061 | .010 | .055 | .048 | .045 |
| Expert6 | .022 | .025 | .005 | .003 | .005 | .023 | .020 | .007 |

Afterwards, the maximum object of each criterion is identified via Equation (19). Similarly, the minimum object of each criterion is defined by Equation (20). In other words, the maximum and minimum objects are selected according to criteria. The results are shared in Table 9.

**Table 9:** Maximum and Minimum Objects

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| Max | .040 | .070 | .071 | .062 | .061 | .056 | .059 | .054 |
| Min | .013 | .002 | .005 | .003 | .005 | .005 | .009 | .006 |

Next, the difference among the minimum and maximum objects of each criterion is estimated with the help of Equation (21). The criteria's importances are defined by normalizing the differences. For this, Equation (22) is used. The weight vector is displayed in Table 10.

**Table 10:** Differences and Weights

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| Difference | .027 | .069 | .066 | .059 | .056 | .051 | .051 | .047 |
| Weight | .064 | .161 | .155 | .138 | .132 | .119 | .119 | .111 |

According to weight values in Table 10, the order of importance of the criteria are CPASD, LVCTS, RGWPS, AIDPO, ADESG, EDQAC, MTSKR, and VRFCS. In other words, the most important criterion is compliance with assurance standards with .161. The second important criterion is level of corporate transparency with .155. Finally, the reliability index is tested. For this, the second evaluations are collected on the scale 0 to 100 from six experts. Then, these evaluations are averaged. Next, Equation (23) is computed. The results are expressed in Table 11.

**Table 11:** RI

| | Weight | Expert1 | Expert2 | Expert3 | Expert4 | Expert5 | Expert6 | Second | RI |
|---|---|---|---|---|---|---|---|---|---|
| VRFCS | .064 | 6 | 8 | 5 | 6 | 4 | 7 | 6.00 | |
| CPASD | .161 | 16 | 19 | 20 | 16 | 20 | 17 | 18.00 | |
| LVCTS | .155 | 16 | 17 | 20 | 15 | 19 | 15 | 17.00 | |
| RGWPS | .138 | 13 | 15 | 15 | 14 | 16 | 13 | 14.33 | .083 |
| AIDPO | .132 | 13 | 13 | 15 | 13 | 15 | 13 | 13.67 | |
| ADESG | .119 | 12 | 9 | 10 | 12 | 10 | 12 | 1.83 | |
| EDQAC | .119 | 12 | 13 | 10 | 12 | 11 | 12 | 11.67 | |
| MTSKR | .111 | 12 | 6 | 5 | 12 | 5 | 11 | 8.50 | |

As can be seen from RI in Table 11, this index value is 0.083 and lower than 0.1. In other words, the results of CIMAS are reliability. To better explain the CIMAS calculation process, a step-by-step example is provided for the CPASD (Compliance with Assurance Standards) criterion. First, the experts' evaluations for this criterion are presented in Table 5 as KSFN (Koch Snowflake Fuzzy Number) values. These values were converted to individual scores using the score function (Equation 16) and are shown in Table 6. For example, the 0.09 value obtained by Expert2 for CPASD indicates that it rated this criterion relatively low. The scores obtained for each criterion are then normalized and presented in Table 7. These scores are multiplied by the expert weights (Table 3) to obtain the expert-weighted matrix in Table 8. At this stage, Expert4 produced the highest weighted value for the CPASD criterion. The minimum and maximum values were then determined (Table 9), and the relative importance levels of the criteria were calculated by calculating their differences (Table 10). As a result, the CPASD criterion emerged as the most important criterion, with a weight of 0.161. This example demonstrates the step-by-step operation of the CIMAS method and how expert opinions are systematically translated into the final weights.

### 3.3 Comparing using AHP

The same six experts evaluate these criteria according to AHP. In other words, criteria are compared in pairs by experts. Next, the average of each expert's comparison is calculated. Thus, the pairwise comparison matrix is constructed. The pairwise comparison matrix is exhibited in Table 12.

**Table 12:** Pairwise Comparison Matrix

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| VRFCS | 1.000 | .113 | .125 | .143 | .172 | .208 | .264 | .361 |
| CPASD | 8.833 | 1.000 | 2.667 | 3.667 | 4.667 | 5.667 | 6.667 | 7.500 |
| LVCTS | 8.000 | .422 | 1.000 | 2.167 | 3.167 | 4.167 | 5.167 | 6.167 |
| RGWPS | 7.000 | .292 | .472 | 1.000 | 2.333 | 3.333 | 4.333 | 5.333 |
| AIDPO | 5.833 | .224 | .319 | .458 | 1.000 | 2.833 | 3.833 | 4.833 |
| ADESG | 4.833 | .182 | .242 | .311 | .440 | 1.000 | 2.333 | 3.500 |
| EDQAC | 3.833 | .153 | .194 | .236 | .299 | .458 | 1.000 | 2.667 |
| MTSKR | 2.833 | .135 | .163 | .190 | .227 | .297 | .492 | 1.000 |

Afterwards, the objects of pairwise comparison matrix are normalized by dividing the sum of criteria. The normalized pairwise comparison matrix is shown in Table 13.

**Table 13:** Normalized Pairwise Comparison Matrix

| | VRFCS | CPASD | LVCTS | RGWPS | AIDPO | ADESG | EDQAC | MTSKR |
|---|---|---|---|---|---|---|---|---|
| VRFCS | .0237 | .045 | .0241 | .0175 | .014 | .0116 | .011 | .0115 |
| CPASD | .2095 | .3967 | .5146 | .4487 | .3793 | .3154 | .2768 | .2391 |
| LVCTS | .1897 | .1675 | .193 | .2651 | .2574 | .2319 | .2145 | .1966 |
| RGWPS | .166 | .1157 | .0911 | .1224 | .1896 | .1856 | .1799 | .1701 |
| AIDPO | .1383 | .0888 | .0616 | .0561 | .0813 | .1577 | .1591 | .1541 |
| ADESG | .1146 | .0722 | .0466 | .0381 | .0358 | .0557 | .0969 | .1116 |
| EDQAC | .0909 | .0609 | .0375 | .0289 | .0243 | .0255 | .0415 | .085 |
| MTSKR | .0672 | .0534 | .0314 | .0233 | .0184 | .0165 | .0204 | .0319 |

Finally, the average of the row is obtained for computing the weights of criteria. The weight vector of AHP is given in Table 14. Moreover, the RI for AHP is estimated. The RI equals .07. Since this value is less than 0.1, the results are consistent.

**Table 14:** Weights

| | Weight |
|---|---|
| VRFCS | .020 |
| CPASD | .348 |
| LVCTS | .214 |
| RGWPS | .153 |
| AIDPO | .112 |
| ADESG | .071 |
| EDQAC | .049 |
| MTSKR | .033 |

When the results in Table 14 are examined, the priority order of the criteria affecting the audit in greenwashing audits is exactly the same as the priority order of CIMAS. According to both methods, the most effective criterion affecting the audit in greenwashing audits is compliance with assurance standards.

## 4. Discussion

In contemporary society, environmental concerns have emerged as a central issue worldwide. Businesses, as key players in economic activities, are receiving significant scrutiny regarding their environmental practices. Some companies proudly highlight their environmental investments and successes in their annual or corporate social responsibility reports, while conveniently leaving out any negative details about the pollution they have caused. This practice not only misleads consumers, causing them to make purchasing choices that go against their values and eroding consumer trust, but it also disturbs fair competition in the market (Zhang, 2025). Corporations face pressure from investors, regulatory bodies, and consumers to adopt ESG principles, driven by increased awareness of climate change, social inequalities, and ethical governance. ESG reporting and compliance have become crucial for companies aiming to maintain their competitive edge. He increased emphasis on ESG has led to a rising demand for reliable data and accountability, making forensic auditing a vital tool for verifying ESG claims and detecting potential fraud. Auditing in the ESG realm goes beyond traditional financial audits by examining non-financial disclosures related to environmental practices, labor standards, and governance policies (Hossain, 2025). The issues surrounding the relevance and comparability of ESG data lead to conceptual confusion, while the growing fragmentation of regulations represents a substantial research gap that affects both academic insights and the practical application of responsible business practices. In practice, interpretations of ESG vary widely. Some consider ESG, sustainable investing, and responsible investing to be overlapping concepts while others perceive ESG more narrowly, seeing it as a structured framework for implementing and assessing sustainability performance (Ketterling, 2025). Audit companies' participation in ESG assurance differs across various ESG domains, industries, and levels of organizational maturity. Internal auditors are increasingly taking on roles as assurance providers, consultants, and advisors in ESG reporting, risk management, and accountability, while also playing a crucial part in sustainability and environmental strategy. Furthermore, their involvement is influenced by regulatory and market pressures, stakeholder expectations, governance practices, and support from leadership. Audit committees, regulatory bodies, and corporate entities aim to enhance ESG assurance systems by providing actionable insights and practical recommendations (Sheta et al., 2025) The effective influence of government regulations on corporate sustainability practices, the necessity for enhanced corporate governance, and the theoretical connection between governance and environmental performance is needed for the compliance of ESG reports (Hashed et al., 2025). ESG assurance practices are anticipated to influence the generalizability of ESG compliance auditing. There is a need for a cohesive legal framework, strong quality infrastructure, and unified standard-setting mechanisms to facilitate effective and credible ESG implementation across all sectors. In the existing literature, authors propose future research directions that are essential for enhancing internal audit capabilities and for guiding policy, practice, and the wider conversation on ESG assurance. Varied regulations and public awareness contribute to a gap between ESG compliance standards and auditors' engagement with non-financial data analysis. The auditors' responsibilities and qualifications need to be clarified based on the expectations from ESG compliance and regulative framework. The effectiveness of ESG regulations in attaining the overarching objectives of sustainability and social responsibility should be examined.

The growing popularity of environmental, social, and governance (ESG) investing, also known as socially responsible investing, is driving the private sector to enhance its ESG performance. Numerous factors influence ESG disclosures, including natural disasters, political and legal frameworks, ownership structures, board attributes, and the characteristics of the CEO (Seow, 2024). The current complexities of the geopolitical landscape, which have intensified various economic, environmental, and social issues, not only maintain the significance of the ESG agenda at both global and microeconomic levels but also necessitate its reevaluation considering new challenges and threats. Auditors enhance the quality of ESG disclosures by emphasizing the presence, type, and execution of the audit, which significantly boosts the credibility, visibility, stakeholder confidence, and utility of sustainability reporting. The assurance offered by external auditors significantly improves the accuracy of the claims made in ESG reports, underscoring the vital role that external management plays in ensuring the reported information is reliable. It is usually agreed that audits deliver an external, independent assessment of the disclosed information, potentially lowering the likelihood of organizations presenting biased or erroneous data. Thus, the external auditor is expected to be more successful in enhancing transparency and building stakeholder trust compared to the internal auditor (Nuraini and Amrulloh, 2024). Sustainability reporting and its assurance are increasingly being mandated worldwide, accompanied by the establishment of international standards for sustainability assurance. These measures aim to enhance the confidence and trust of investors, regulators, and other stakeholders in sustainability-related disclosures (Hajaya et.al.,2025). Consequently, the foundation of reliable, consistent, and relevant ESG data now underpins high-quality reporting for both private and public sector organizations. External ESG auditors play a crucial role in ensuring that data is accurately reported and not misrepresented in ESG reporting (Rosing et al., 2025). There are studies examined the utility of external auditing for ESG reporting that mostly concluded that it is a useful tool for providing corporate transparency. However, the measurement standards and training options of external auditors are not discussed in different perspectives. Industry stakeholders are urged to focus on training external auditors in ESG-specific risks to improve their detection capabilities of complexities. By adopting new measures, stakeholders can work together to strengthen the accountability and accuracy of ESG reporting, promoting a more transparent and sustainable corporate environment.

Greenwashing involves intricate, multifaceted features and dynamic elements that span various disciplines and dimensions. Recognizing and measuring greenwashing is a highly complex endeavor due to its deceptive characteristics, which obstruct straightforward observations (Lublay et al., 2025). There is no single definition of greenwashing or a standardized set of behaviors that could aid in identifying it. The conceptualization and understanding of greenwashing have been shaped by various fields, including business (such as advertising, ethics, and marketing), media and communications, environmental studies and management, production engineering, law, and the social sciences (encompassing economics, geography, political science, psychology, and sociology), among others. Given the wide range of viewpoints involved in this discussion, it's not surprising that there is no universally accepted definition of the concept. Additionally, as greenwashing gains significance and draws more attention, definitions continue to change, creating a dynamic challenge for policymakers, practitioners, and scholars who are engaged with the topic. Consequently, greenwashing can manifest in various ways and encompass different elements of interest, revealing both objective and subjective realities. The literature indicates that, similar to corporations, even governments can participate in greenwashing. In fact, they frequently collaborate as partners in corporate greenwashing efforts (Nemes et al., 2022) The environmental and socioeconomic effects of products and processes must be evaluated and measured in a scientifically rigorous way, utilizing standardized methods to ensure that the findings can be substantiated and validated for the industry and the region (Ruggeri et.al., 2025) When standards are inadequate or poorly enforced, third-party certification can unintentionally encourage greenwashing practices. Besides, numerous certified companies have been implicated in greenwashing scandals (Wen and Wang, 2025).

The effectiveness of ESG assurance depends on having standardized procedures for ESG auditing. By implementing uniform audit protocols, auditors can consistently evaluate ESG claims across different industries and the ESG reporting standards chosen by companies. Corporations are increasingly pursuing assurance for their published environmental, social, and governance (ESG) reports. Some companies rely on their audit firm to provide assurance for these reports, while others prefer to obtain assurance services from a separate firm. Big Four firms that audit financial reports and provide assurance for ESG reports play a vital role in improving the reliability and credibility of corporate ESG reports (Liu et.al., 2025). The rise in the number of sustainability reports has not led to a corresponding increase in public trust, primarily due to inconsistencies and incomplete information. It is believed that the information often highlights only positive aspects and fails to provide a comprehensive view of ESG implementation. As a result, independent assurance has gained significance and has rapidly evolved in numerous countries (Darsono et.al., 2025). The European Union implemented a new regulatory framework that necessitated greater collaboration between the sustainability and audit departments. This collaboration resulted in tensions, as sustainability professionals and financial auditors had differing views on the key issues to address with clients and the changes needed in a company's report. The absence of globalization in reporting and assurance leads to confusion and discrepancies in the assurance process. Auditors face additional challenges as they frequently encounter various reporting frameworks, differing levels of data maturity within organizations, and qualitative data that is difficult to quantify. Moreover, auditing sustainability data requires specialized knowledge related to environmental officers, social impact assessments, and governance structures, which may exceed the expertise of typical financial audit teams (Rawat et al., 2025) Professional auditing is a recognized field of study grounded in evolving global research. Additionally, it involves a craft that requires continuous training and the application of systematic and analytical methodologies. Furthermore, auditing is an art that embraces creativity and innovation in its approach to each engagement, considering the global context of technology, sustainability, and societal issues. Finally, auditors act as advisors throughout the audit process, contributing to the attainment good governance of sustainability (Ridley and Gulko, 2025).

Transparent audit refers to an organization's openness in providing comprehensive, honest, and accountable information to all stakeholders. This concept encompasses not just financial data but also social, environmental, and corporate governance information. In literature conducting multi-case analyses and integrating various quantitative and qualitative methodologies could offer a more thorough understanding of how audit effectiveness and sustainable innovation interact with external factors like regulatory frameworks and stakeholder pressures. For future studies, exploring the relationship between auditor independence and sustainable innovation would enhance our understanding of the ethical challenges in ESG auditing, particularly regarding conflicts of interest, the reliability of assurances, and inconsistencies in regulations. Fraud represents a major and widespread risk in the larger context of cybercrime, fueled by the swift advancement of digital technologies. The effectiveness of external auditors in assessing fraud risks is often scrutinized, particularly in light of numerous legal actions taken against auditors who fail to identify financial statement manipulations, misstatements, misconduct, and deviations from standards. Thus, digital technology skills are essential for auditors. This capability enables the provision of independent assurance that financial statements are free from significant misstatements. This indicates a pressing need for the profession to launch an initiative aimed at helping external auditors enhance and update their skills in fraud risk assessment (Razali et al., 2025) The technologies associated with Audit 4.0, including satellite imaging, sensors and the Internet of Things (IoT), and social media, have the potential to enhance audit evidence and improve the effectiveness of ESG audits. Given that satellites can also be utilized to detect carbon dioxide and other greenhouse gas (GHG) emissions, it presents a potential solution for verifying carbon dioxide disclosures (Gu et.al., 2023). Despite these advantages, firms face challenges such as the high costs associated with technology implementation, vulnerabilities related to cybersecurity, and the necessity for ongoing workforce upskilling. While digital transformation has the potential to significantly change the auditing landscape, a balanced approach that combines technology, regulatory guidance, and human expertise is essential for preserving audit integrity and quality (Syam et al., 2025) The swift progress of audit technology, encompassing data analytics, artificial intelligence (AI), and blockchain, has profoundly changed the auditing profession. These technologies offer the potential to boost audit efficiency and effectiveness by automating repetitive tasks, enhancing data accuracy, and providing more in-depth insights (Taunaumang et al., 2025).

## 5. Conclusion

This study aims to determine which criteria should be prioritized to increase the effectiveness of audit processes aimed at preventing greenwashing. To this end, eight criteria are identified through a comprehensive literature review, and a novel two-stage fuzzy multi-criteria decision-making model is proposed. The method first reduces subjectivity in expert judgments by calculating the demographic weights of six experts using the Euclidean distance-based expert weighting technique. Criterion weights are then obtained using the CIMAS technique. To more precisely represent process uncertainties, a newly introduced Koch Snowflake fuzzy set is integrated into the model. Furthermore, the results are checked for consistency using the weights calculated using AHP. The findings indicate that compliance with assurance standards is the most critical factor in increasing audit effectiveness aimed at preventing greenwashing, followed by institutional transparency and the level of greenwashing risk. The study's contributions to the literature are (i) strengthening conceptual clarity regarding audit criteria by filling the prioritization gap, (ii) proposing a methodological framework combining Koch Snowflake fuzzy sets, CIMAS, and expert weighting, and (iii) providing cross-consistency testing using AHP. However, theoretical limitations include the eight-criteria framework's exclusion of potential additional dimensions, its reliance on judgment-based data, and its inability to fully reflect contextual/temporal changes in a cross-sectional setting. Limitations of the proposed model include the sensitivity of the distance metric used in expert weightings to demographic attribute definitions, the sensitivity of Koch Snowflake membership parameters to the outcome, and the dependence of CIMAS on the consistency of input judgments. To address these limitations, future robustness analyses using different distance metrics, alternative/additional fuzzy sets, and larger, multi-stakeholder expert panels can be conducted. Similarly, cross-sector and cross-country applications, automated extraction of transparency indicators using text mining, time-based updates, and external validation studies using real-world performance data are recommended. From a policy and practice perspective, strengthening regulations that mandate compliance with assurance standards is crucial. Furthermore, standardized reporting templates and audit traceability can be implemented to ensure transparency. Furthermore, the recommendations include expanding risk-based audit programs, developing independent auditor pools and data infrastructure, and integrating findings into sustainability strategies. Thus, the study provides a concrete roadmap for a more reliable, effective, and sustainable audit ecosystem, both theoretically and practically. From a practical perspective, the proposed model can be implemented in audit firms, internal audit departments, or ESG consulting practices with minimal resource requirements. The data inputs are limited to expert demographic profiles and their evaluations of predefined criteria, which can be collected through structured surveys. Standard computational tools (e.g., Excel, MATLAB, Python) are sufficient to conduct the Euclidean distance, Koch Snowflake fuzzy set, and CIMAS calculations. Moreover, the results can be directly integrated into existing ESG reporting frameworks such as GRI, SASB, or CSRD by prioritizing audit focus areas (e.g., compliance with assurance standards, corporate transparency). This demonstrates that the model is not only theoretically innovative but also practically applicable in real-world audit contexts.

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