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Article

Integrating SIWEC and Koch snowflake fuzzy sets to prioritize trust factors in an artificial intelligence-based audit system

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ABSTRACT

This study aims to identify effective strategies to increase confidence in AI-based audits. A novel decision-making model is being developed to identify these strategies. In this process, seven criteria are identified through a literature review. Furthermore, opinions on these criteria are obtained from 10 different subject-matter experts. The significance ratio for these people is computed based on their work experience. In this process, an artificial intelligence-based approach is taken into consideration. Furthermore, the weights of the selected criteria are determined using the SIWEC methodology. On the other hand, Koch snowflake fuzzy sets are introduced in this study to address uncertainty in decision-making analysis. Perceived change in audit quality (PCAQ) is the most important indicator, with a weight of 0.181. In addition to this issue, stakeholders' acceptance and resistance to technology (SART) play a crucial role in this process, with a weight of 0.166. This study contributes to the literature by creating a novel model to identify prior strategies to improve trust in the AI-based audit systems. These findings pave the way to take appropriate actions to increase the effectiveness of this process.

1. Introduction

Artificial intelligence (AI)-based audit activities have become increasingly popular. The most important goal of this process is to enable more comprehensive, faster auditing. Additionally, it minimizes subjective human resource implications. In non-AI-based audits, auditors perform these activities manually. During this process, some critical issues can be overlooked. Similarly, to save time, auditors must select a sample for their work [1]. This can lead to some important issues being overlooked. AI-based audits aim to minimize these problems. These audits involve continuous auditing and monitoring [2]. Within this framework, all transactions in the process are examined, not just the sampled items. However, there are also some barriers to improving the AI-based audit system in companies. Firstly, people think they will lose their jobs due to the integration of AI techniques into operational processes. In this context, it is thought that because AI can handle many tasks, there will be no need to employ these people. Moreover, people may also think that AI systems cannot perform qualified audit work like human auditors. In other words, they consider that human interaction is necessary to identify key audit findings. These criticisms have a negative impact on the effectiveness of AI-based audit work. Necessary actions should be taken to address these criticisms of AI-based audit work. Otherwise, these systems cannot be implemented effectively in companies. In this process, the main reasons behind these situations should be identified. To achieve this objective, a comprehensive evaluation should be conducted. Within this framework, multi-criteria decision-making models can be generated. These models help to find the most essential items in the process. In the literature, there are also many studies that have considered these models for different purposes, such as banking and energy. Some studies also considered these models for audit work. However, few studies in the literature prioritize analyses to identify the most effective criteria for improving trust in AI-based audit work [3]. This situation creates a significant research gap in the audit literature. On the other hand, most decision-making models use triangular and trapezoidal fuzzy sets in their modeling. Nevertheless, the subject of trust in AI-based audit work is quite complex. This situation creates many uncertainties because there are lots of different determinants of this system. Hence, a new fuzzy set should be generated to handle this process. To satisfy these gaps, the research aims to (1) determine the main criteria that affect trust formation in AI-driven auditing, (2) evaluate the relative importance of these criteria based on expert assessments, (3) examine whether expert demographic characteristics influence the perceived importance of trust factors, and (4) propose and validate an extended SIWEC model integrated with Koch Snowflake Fuzzy Numbers (KSFNs) to enhance the robustness and interpretability of decision-making under uncertainty. By achieving these objectives, the study seeks to provide a scientifically grounded framework for improving stakeholder confidence and audit reliability in technology-enhanced environments.

This study contributes to the literature by filling a gap in the literature on prioritizing critical factors for solving trust problems in artificial intelligence-assisted internal control audits with an original decision-making model integrating machine learning, the SIWEC technique, and Koch snowflake fuzzy sets. The proposed model has many advantages over the decision-making models previously developed in the literature. Firstly, the use of machine learning techniques in calculating the importance weights of experts stands out as a significant innovation. This approach determines expert contributions more objectively by accounting for their demographic characteristics, thereby eliminating the problem of "not taking expert weights into account" observed in most models in the literature. Therefore, this machine learning-based calculation method increases the reliability and originality of the model. Secondly, the Koch snowflake fuzzy sets developed in the study constitute a new fuzzy set approach introduced to the literature and offer significant advantages over other fuzzy sets. These new sets based on fractal numbers can model the uncertainty and variability in expert opinions in a more flexible and detailed way; Thus, they provide a more accurate representation of uncertainties in the decision-making process and increase the reliability of the results. In this respect, Koch snowflake fuzzy sets not only contribute to the current study but also introduce a permanent innovation to the literature on fuzzy logic-based decision-making. Third, calculating the criterion importance weights using the SIWEC technique is another advantage of the model. While many different criteria weighting methods exist in the literature, the SIWEC technique stands out as a more suitable approach than others for multi-dimensional and uncertain issues, such as trust in artificial intelligence-supported internal control audits. This is because SIWEC can evaluate the interrelationships between criteria and the different perspectives of experts in a more holistic way, enabling the model to produce more reliable and effective results for both academic and practical applications.

2. Literature review

Technological advancements are needed to increase trust in AI-based audits. Thanks to technological advances, businesses can now have a comprehensive operational infrastructure. This infrastructure enables much better coordination among departments within businesses. This increases employee trust in technology [4]. This can also be very effective in AI-based audits. Thanks to developing technology, it has been shown that audit activities performed by AI are very comprehensive. In this context, AI studies can perform much more comprehensive analyses than a human auditor during audits [5]. This increases employee trust in AI-based audits. Furthermore, advanced technologies can also share numerical and visual representations of AI-based audits [6]. This increases employee confidence in the success of audits. Furthermore, thanks to technological advancements, employees can share written documentation or videos detailing how audits are conducted. This increases the transparency of AI audit activities [7]. This practice also helps increase employee trust in these audits. Employing qualified personnel is also crucial for improving the performance of AI-based auditing activities. Advanced technology is required for effective AI auditing. The use of this comprehensive technology within a company can also have some disadvantages. Systemic problems can arise during the process of adapting these technologies to the company. If these problems are not addressed, employee motivation to use AI decreases [8]. Employing qualified personnel is vital to this process. Personnel with comprehensive knowledge of the subject can quickly resolve these problems. This helps prevent problems from escalating. Otherwise, the negative effects of these problems will grow, and user confidence in AI auditing will decrease [9]. In summary, qualified personnel are needed to effectively adopt and implement technology within the company. Thanks to the work of these personnel, long-term problems in AI-based auditing activities will not arise [10]. This also allows for the smooth operation of auditing activities. In this way, audit activities will be carried out successfully, and employees' confidence in artificial intelligence-based audit activities will increase.

Senior management support also plays a significant role in increasing trust in AI-based auditing. Auditing activities are crucial for improving a company's performance. In this context, the successful execution of auditing activities is crucial. However, some issues can negatively impact audit performance [11]. Chaos between auditors and audited personnel is a prime example. During audits, auditors may find deficiencies in departments [12]. Departmental personnel may also be unhappy with their own shortcomings [13]. Consequently, they may resist this process. This situation is more common in AI-based audits. Departmental personnel may not accept AI-generated findings. This significantly hinders the continuity of auditing activities [14]. Senior management support is crucial to minimizing these problems. Both the audit team and the audited department personnel are organizationally subordinate to senior management [15]. Therefore, decisions made by senior management are binding on both teams. In this context, if the top management gives its opinion on the implementation of artificial intelligence-based audits, these problems will be significantly reduced [16].

This literature review yields several key insights. Firstly, AI-based audits have become increasingly popular, particularly in recent years. This suggests that businesses will increasingly implement these activities in the coming years. However, there are some concerns about new intelligence-based auditing efforts [17]. In this context, specific actions are needed to increase confidence in these auditing activities. However, few studies examine which factors are most important [18]. This creates a significant gap in the auditing literature. Ignorance of the most critical factors increases uncertainty surrounding the process. Therefore, a new study is needed to analyze the priorities of variables in this process. Fuzzy logic-based multi-criteria decision-making analyses can be considered in this process.

Over the past two decades, various multi-criteria decision-making approaches such as the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Decision-Making Trial and Evaluation Laboratory (DEMATEL) have been extensively applied to prioritization problems in management and auditing research. More recently, fuzzy-based extensions of these models (e.g., Fuzzy AHP, Fuzzy TOPSIS, and Fuzzy DEMATEL) have been introduced to capture uncertainty in expert evaluations. However, these conventional models still face limitations when dealing with multidimensional, interrelated trust factors in AI-driven audit environments, particularly in integrating demographic variability and fractal uncertainty into expert opinions. To address these gaps, this study develops an advanced hybrid framework that integrates the SIWEC weighting method with the newly proposed Koch snowflake fuzzy sets, offering enhanced reliability and interpretability in the prioritization of trust-related criteria. Therefore, there is a clear research gap concerning the systematic evaluation and prioritization of determinants that shape the quality of AI-driven audits [19].

3. Proposed methodology

In this study, Koch Snowflake is being developed as a new type of fuzzy number. This process draws inspiration from various geometric shapes found in fractal geometry. These shapes are used to calculate degrees in fuzzy logic processes. This offers a significant solution to the issue of uncertainty management, a frequently criticized issue in fuzzy multi-criteria decision-making analyses. This new application not only adds methodological originality to the study but also enables more successful analysis. Computationally, this approach provides smoother defuzzification convergence and greater sensitivity to subtle differences in expert evaluations. Therefore, KSFNs offer a more realistic and robust framework for capturing ambiguity and variability in human judgment compared to standard fuzzy numbers.

Extended SIWEC is the updated version of SIWEC. While the classical method only considers the prevalence of decision-makers' assessments, this version also includes a score calculated from experts' demographic information [20]. The calculation steps are as follows. Firstly, the criteria and demographic information are defined and collected from decision makers. The demographic information matrix is symbolized by X, and the initial decision-making matrix is formed as Y [21]. In other words, two matrices are created. The first matrix relates information about decision makers as Eq (1).

$$X = [x_{ij}]_{a\times b} \tag{1}$$

Wherein a and b refer to the number of decision makers and demographic variables, respectively. The second matrix includes the evaluations of criteria as Eq (2).

$$Y = [\tilde{y}_{ij}]_{a\times c} \tag{2}$$

Wherein c is the number of criteria. Thus, $\tilde{y}_{ij}$ is the Koch Snowflake fuzzy numbers. Then, this number's components are the membership ($\mathcal{s}$) and non-membership ($\mathcal{t}$) degrees and these degrees have the condition in Eq (3).

$$0 \le \mathcal{s}^{\frac{\log(4)}{\log(3)}} + \mathcal{t}^{\frac{\log(4)}{\log(3)}} \le 1 \tag{3}$$

After creating two matrices, the second matrix's values are defuzzified using Eq (4).

$$y_{ij} = \frac{1+\mathcal{s}_{\tilde{y}_{ij}}^{\frac{\log(4)}{\log(3)}} - \mathcal{t}_{\tilde{y}_{ij}}^{\frac{\log(4)}{\log(3)}}}{2} \tag{4}$$

Next, defuzzified values are normalized via Eq (5).

$$z_{ij} = \frac{y_{ij}}{\max y_{ij}} \tag{5}$$

Afterward, the weights of normalized evaluations are calculated. For this, two values are computed from the standard deviation and demographic information. The first value is estimated with the help of Eq (6).

$$f_i = \sqrt{\frac{1}{c}\sum_{j=1}^{c}\left(z_{ij} - \sum_{j=1}^{c}\frac{z_{ij}}{c}\right)^2} \tag{6}$$

Another value is obtained with a machine learning algorithm. For this, the X matrix is used. The X matrix is standardized via Eqs (7) and (8).

$$c_{ij} = x_{ij} - \bar{x}_j \tag{7}$$

$$\mathcal{r}_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{d} c_{ij}^2}} \tag{8}$$

Then, the covariance matrix ($\mathcal{C}$) is constructed and the elements of this matrix are calculated by Eq (9).

$$cov_{ij} = \frac{\sum_{t=1}^{d}(\mathcal{r}_{ti} - \bar{\mathcal{r}}_i)(\mathcal{r}_{tj} - \bar{\mathcal{r}}_j)}{a} \tag{9}$$

Next, eigenvalues are found via Eq (10), and then the eigenvector is determined with Eq (11).

$$\det(\mathcal{C} - \mathrm{I}\lambda) = 0 \tag{10}$$

$$\big(\mathcal{C} - \mathrm{I}(\max\lambda)\big)v = 0 \tag{11}$$

Thus, the second evaluation weighting value is defined using Eqs. (12) and (13).

$$A = Xv \tag{12}$$

$$s_i = \frac{A}{\sum A} \tag{13}$$

By summing two values and multiplying by normalized evaluations, a weighted matrix is created. This procedure is shown in Eq (14).

$$t_{ij} = z_{ij}(f_i + s_i) \tag{14}$$

Finally, the total values of criteria are obtained with Eq (15), and then, the weights of criteria are defined as Eqs (16).

$$g_j = \sum_{i=1}^{a} t_{ij} \tag{15}$$

$$w_j = g_j / \sum_{j=1}^{c} g_j \tag{16}$$

4. Results' analysis

Firstly, the criteria are defined as explainability of AI decisions (EID), impact on auditor trust (IAT), error detection accuracy (EDA), perception of data privacy violation (PDPV), compliance with regulatory standards (CRS), perceived change in audit quality (PCAQ), and stakeholders' acceptance and resistance to technology (SART). The seven criteria defined in this study demonstrate how trust can be increased in AI-based audits. Compliance with regulatory standards relates to whether the work performed violates legal regulations. This is critical for increasing trust in AI audits. Perceived change in audit quality is also essential for increasing trust. Finally, stakeholders' acceptance and resistance to technology reflect the influence of cultural factors. These factors demonstrate the decisive role in trust formation. Similarly, demographic information is defined as age, global experience, and manager experience. The first matrix formed in Eq (1) is shown in Table 1.

Table 1 demonstrates that there are 10 different experts. Ten decision makers' evaluations are collected. Table 1 presents the demographic characteristics of the experts participating in the study. These factors constitute the data used in the analysis process. The expert group comprises diverse age groups and experience levels. The opinions of younger experts can contribute to adapting to technological innovations. Consequently, more comprehensive expert opinions are obtained through diverse perspectives. Next, the evaluations are transformed into KSFNs. The second matrix formed in Eq (2) is given in Table 2.

Table 1. Expert demographic data matrix

Decision Makers	Age	Global Experience	Manager Experience
DM-1	59	35	10
DM-2	44	23	8
DM-3	42	20	7
DM-4	59	39	10
DM-5	50	26	9
DM-6	40	19	5
DM-7	48	25	6
DM-8	46	23	6
DM-9	39	18	4
DM-10	56	35	9

There are two distinct processes for obtaining expert opinions. First, the experts are provided with a detailed explanation of the study's purpose and criteria definitions. This allows them to gain knowledge of the topic. In the second stage, experts are asked to evaluate each criterion. Questions related to the criteria are prepared, and experts are expected to respond. After gathering expert opinions, these values are converted into Koch Snowflake fuzzy numbers. After creating two matrices, the second matrix's values are defuzzified using Eq (4). The defuzzified matrix is shared in Table 3.

Table 4 shows the normalized values of the evaluations for the seven criteria. During the normalization process, the values of each criterion are rescaled to a specific scale. The scores provided by each expert may have different scales. The primary goal of normalization in this process is to minimize biases that may arise. Higher values in this table indicate that experts consider that criterion more effective. The values in Table 4 prepare the data for the next step, weighting. Afterward, the weights of normalized evaluations are calculated. For this, two values are computed from the standard deviation and demographic information. The first value is estimated employing Eq (6). The standard deviations are summarized in Table 5.

The values in Table 5 indicate the degree of consistency among experts regarding the criteria. Standard deviation is a statistical indicator of variability within a distribution. Low values in this process indicate that experts are nearing consensus. Conversely, high standard deviation values indicate that experts offer varying assessments of the criterion. Therefore, Table 5 represents an important intermediate step in the model's reliability analysis. These values establish statistical robustness for the weighting calculations used in the next stage of the model. Another value is obtained with a machine learning algorithm. For this, the X matrix is used. The X matrix is standardized via Eqs (7) and (8). The standardized matrix is expressed in Table 6.

Table 6 is obtained by transforming the variables to a form that is statistically comparable. Each variable has different units of measurement. The standardization process aims to minimize scale differences resulting from it. Positive values in the table indicate that the expert is above average in the demographic variable. Conversely, negative values indicate below average. Table 6 also provides data for the machine learning-based component of the model. This allows individual experience differences to be taken into account in the assessment of trust factors. Then, the covariance matrix (C) is constructed, and the elements of this matrix are calculated by Eq (9). The covariance matrix is displayed in Table 7.

Table 7 shows the covariance relationships between experts' demographic characteristics. This analysis reveals how closely the experts' demographic profiles align. A positive value highlights a direct relationship between the two variables. However, a negative covariance indicates an inverse relationship. For example, the covariance value between age and international experience of 0.098 indicates that international experience tends to increase with age. These calculations allow us to identify the indirect impact of demographic variables on trust factors. Next, eigenvalues are found via Eq (10), and then the eigenvector is determined with Eq (11).

Table 2. Expert fuzzy evaluations (KSFNs)

Experts	EID	IAT	EDA	PDPV	CRS	PCAQ	SART
DM-1	(.5,.4)	(.6,.3)	(.5,.4)	(.6,.3)	(.6,.3)	(.9,.1)	(.8,.1)
DM-2	(.5,.4)	(.5,.4)	(.6,.3)	(.7,.2)	(.7,.2)	(.8,.1)	(.8,.1)
DM-3	(.5,.4)	(.6,.3)	(.7,.2)	(.7,.2)	(.5,.4)	(.9,.1)	(.7,.2)
DM-4	(.6,.3)	(.7,.2)	(.4,.5)	(.6,.3)	(.6,.3)	(.9,.1)	(.7,.2)
DM-5	(.5,.4)	(.5,.4)	(.5,.4)	(.6,.3)	(.7,.2)	(.8,.1)	(.8,.1)
DM-6	(.6,.3)	(.6,.3)	(.6,.3)	(.6,.3)	(.7,.2)	(.7,.2)	(.6,.3)
DM-7	(.7,.2)	(.7,.2)	(.5,.4)	(.7,.2)	(.6,.3)	(.8,.1)	(.7,.2)
DM-8	(.8,.1)	(.8,.1)	(.6,.3)	(.5,.4)	(.5,.4)	(.9,.1)	(.8,.1)
DM-9	(.4,.5)	(.7,.2)	(.6,.3)	(.6,.3)	(.6,.3)	(.9,.1)	(.8,.1)
DM-10	(.5,.4)	(.6,.3)	(.4,.5)	(.4,.5)	(.7,.2)	(.9,.1)	(.8,.1)

Table 3. Defuzzified expert evaluations

Experts	EID	IAT	EDA	PDPV	CRS	PCAQ	SART
DM-1	.551	.653	.551	.653	.653	.910	.850
DM-2	.551	.551	.653	.753	.753	.850	.850
DM-3	.551	.653	.753	.753	.551	.910	.753
DM-4	.653	.753	.449	.653	.653	.910	.753
DM-5	.551	.551	.551	.653	.753	.850	.850
DM-6	.653	.653	.653	.653	.753	.753	.653
DM-7	.753	.753	.551	.753	.653	.850	.753
DM-8	.850	.850	.653	.551	.551	.910	.850
DM-9	.449	.753	.653	.653	.653	.910	.850
DM-10	.551	.653	.449	.449	.753	.910	.850

Table 4. Normalized evaluation matrix

Experts	EID	IAT	EDA	PDPV	CRS	PCAQ	SART
DM-1	.605	.717	.605	.717	.717	1.000	.934
DM-2	.605	.605	.717	.827	.827	.934	.934
DM-3	.605	.717	.827	.827	.605	1.000	.827
DM-4	.717	.827	.493	.717	.717	1.000	.827
DM-5	.605	.605	.605	.717	.827	.934	.934
DM-6	.717	.717	.717	.717	.827	.827	.717
DM-7	.827	.827	.605	.827	.717	.934	.827
DM-8	.934	.934	.717	.605	.605	1.000	.934
DM-9	.493	.827	.717	.717	.717	1.000	.934
DM-10	.605	.717	.493	.493	.827	1.000	.934

Table 5. Standard deviations of criteria

Experts	Standard Deviation
DM-1	.142
DM-2	.129
DM-3	.131
DM-4	.143
DM-5	.140
DM-6	.050
DM-7	.097
DM-8	.158
DM-9	.155
DM-10	.190

Table 6. Standardized demographic matrix

Experts	Age	Global Experience	Manager Experience
DM-1	.474	.390	.409
DM-2	-.190	-.148	.094
DM-3	-.279	-.282	-.063
DM-4	.474	.569	.409
DM-5	.075	-.013	.252
DM-6	-.367	-.327	-.378
DM-7	-.013	-.058	-.220
DM-8	-.102	-.148	-.220
DM-9	-.412	-.372	-.535
DM-10	.341	.390	.252

Table 7. Covariance matrix of demographics

Factors	Age	Global Experience	Manager Experience
Age	.100	.098	.088
Global Experience	.098	.100	.086
Manager Experience	.088	.086	.100

Table 8. Eigenvalue-based expert weights

Experts	EID
DM-1	.127
DM-2	.091
DM-3	.084
DM-4	.132
DM-5	.104
DM-6	.078
DM-7	.096
DM-8	.092
DM-9	.074
DM-10	.122

The eigenvalues are .2813, .0002, and .0170, respectively. The explained variances of these eigenvalues are 93.75%, 00.56%, and 5.69%. So, the maximum variance is the first eigenvalue. In other words, the first eigenvalue is selected, and eigenvector is calculated as .58736, .58381, and .56052. Thus, the second evaluation weighting value is defined using Eqs (12) and (13). The second set of decision-maker values is presented in Table 8.

Table 8 shows expert weights determined based on eigenvalue and eigenvector results. These data are calculated based on the covariance matrix derived from the experts' demographic characteristics. The primary goal here is to objectively determine the expert contribution weights based not only on their assessment scores but also on their demographic profiles. The numerical values in Table 8 represent each expert's demographic contribution. These results demonstrate that the model can differentiate expert contributions by taking demographic variables into account. By summing two values and multiplying by normalized evaluations, a weighted matrix is created. This procedure is shown in Eq (14). The weighted matrix is shown in Table 9.

Table 9 is a composite of expert assessments, considering both statistical consistency (standard deviation) and demographic weights (eigenvalue- and eigenvector-based coefficients). This table reflects the experts' experience levels. At this stage, each expert's assessment scores are first multiplied by their standard deviation values and then by their demographic-based weights. The results show the final normalized and weighted scores for each criterion. Finally, the total values of the criteria are obtained using Eq (15), and the criterion weights are defined using Eq (16). Figure 1 presents the results.

As shown in Figure 1, the most important criteria are Perceived Change in Audit Quality and Stakeholders' Acceptance and Resistance to Technology, with coefficients of .181 and .166, respectively. The results indicate that Perceived Change in Audit Quality (PCAQ) and Stakeholders' Acceptance and Resistance to Technology (SART) are the two most influential factors in fostering trust in AI-based internal control audits. On the other side, the Explainability of AI Decisions (EID) and Error Detection Accuracy (EDA) have lower weights. These results indicate that improving employee perceptions is a priority. In other words, necessary actions should be taken to increase employee trust in AI-based audits. To find an effective solution to this problem, the origin of this negative perception must be determined. Cultural factors can play a crucial role in this process. Due to specific cultural factors, employees may resist AI-based audit activities. To minimize this issue, employees can be provided with comprehensive training on AI-based audit activities.

Table 9. Final weighted decision matrix

Experts	EID	IAT	EDA	PDPV	CRS	PCAQ	SART
DM-1	.163	.193	.163	.193	.193	.269	.251
DM-2	.133	.133	.158	.182	.182	.206	.206
DM-3	.130	.154	.178	.178	.130	.215	.178
DM-4	.197	.227	.135	.197	.197	.275	.227
DM-5	.147	.147	.147	.175	.201	.227	.227
DM-6	.092	.092	.092	.092	.106	.106	.092
DM-7	.160	.160	.117	.160	.138	.180	.160
DM-8	.233	.233	.179	.151	.151	.249	.233
DM-9	.113	.190	.165	.165	.165	.229	.214
DM-10	.189	.223	.154	.154	.258	.312	.291

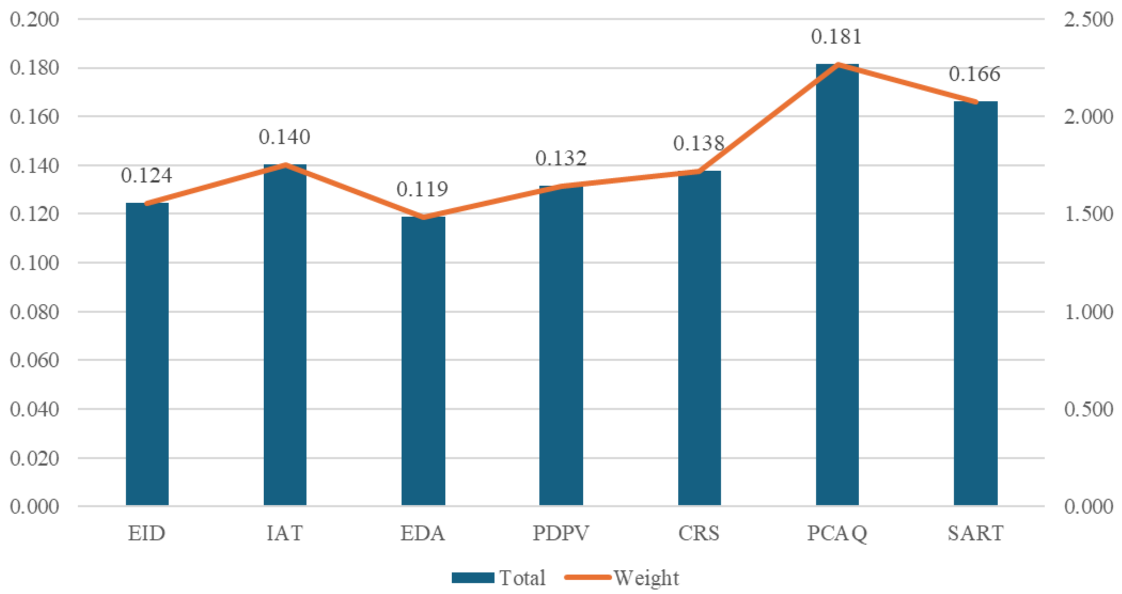

Figure 1. Final criterion weights

This may change some employees' negative perspectives on these activities. On the other hand, the quality of the findings identified by audit activities must be demonstrated. In this context, numerical results and visuals related to these findings can be shared. This significantly reduces this negative opinion. Many other researchers in the literature also support these points. Baporikar [22] states that a comprehensive document describing the processes of these activities should be created to increase trust in AI-based audit activities. In addition to this issue, Koo et al. [23] also state that sharing comprehensive numerical results will increase employees' confidence in AI-based audit results.

5. Conclusion

The purpose of this study is to identify key indicators for improving trust in AI-based audit work. To achieve this objective, a novel decision-making model is recommended by integrating Koch snowflake fuzzy sets, SIWEC, and machine learning. It is concluded that changes in perceived audit quality are the most essential indicator. On the other hand, stakeholder acceptance and resistance to technology should also be considered in this process. As these results show, social factors are at least as important as technological factors in increasing trust in these audit activities. This provides significant guidance for developing strategies. Technological development is crucial for improving the quality of these audits. However, attention must also be paid to how these developments are perceived by personnel. Otherwise, even if technological advancements are made, the staff's disbelief in them will negatively impact the process. In this context, a comprehensive causal analysis is necessary to develop effective strategies. This analysis will help determine what influences people's perception of these audit activities. Cultural factors can be significant in this process. Some people may be resistant to technological advancements due to cultural influences. These individuals may fear losing their jobs due to technological advancements. This situation also increases the negative impact of AI-based audit activities. Minimizing this negative impact is crucial for both the operational and financial performance of the workplace. Several policy recommendations can be developed to achieve this goal. Comprehensive training programs can be conducted to ensure employees have a favorable view of these auditing activities. These training programs can emphasize that AI won't completely replace the process but rather contribute to its improvement. This allows for a significant increase in employee confidence in AI-based audits. This study has several significant methodological and theoretical limitations. Firstly, it does not analyze any specific sector. Instead, it conducts a general analysis of the quality of AI audits. However, the factors affecting this process may vary across sectors. Therefore, future studies could focus on specific sectors such as banking and automotive. The results of these studies could enable the development of more precise strategies to increase the success of AI-based audits in these sectors. Furthermore, the decision-making model proposed in this study has some limitations. This study utilizes a small number of expert opinions. Increasing the number of expert opinions in future studies is also critical for assessing the study's consistency. In this context, two different expert teams could be formed from both academics and industry professionals. This would also allow for comparative analyses. This would allow for differences in perspective between academia and industry on this issue. Another limitation of this model is that it is not designed as a hybrid. In this context, the model provides no ranking of alternatives. In future studies, alternative strategy proposals can be identified. Ranking of these alternatives can be achieved using techniques such as TOPSIS and VIKOR.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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