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Innovative financial solutions for sustainable investments using artificial intelligence-based hybrid fuzzy decision-making approach in carbon capture technologies

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Abstract
High costs, technical difficulties, and policy uncertainties are the main challenges in carbon capture technology investments. Therefore, innovative financial products are required to develop projects that overcome these difficulties. Some issues must be considered when developing innovative financial products. An important problem in this process is that these features cannot possibly exist together in the new financial product, because each of these features incurs some costs. Therefore, identifying the most important features of innovative financial products is necessary. Accordingly, this study develops a new and innovative financial product to increase the effectiveness of investments in carbon capture technologies. For this purpose, a novel artificial intelligence (AI)-based fuzzy decision-making model is constructed. First, the weights of the experts were calculated by considering AI methodology. Second, the factors affecting investment in carbon capture technologies were weighted using a spherical fuzzy DEMATEL. Finally, the financial features required for investments were ranked using the spherical fuzzy ARAS method. This study's main contribution is its creation of a novel fuzzy decision-making model by integrating AI methodology with fuzzy decision-making theory. In this process, the weights of the experts are calculated using an AI approach. It is concluded that cost-effectiveness must be prioritized in the development of new financial products. Technological competence is another aspect that should be considered in this process. However, innovative financial products should include risk management and flexible financing.

Keywords: Innovative financial product, Flexible payments, Risk management, Carbon capture technologies, Artificial intelligence, Spherical fuzzy sets

Introduction

Investments in low-carbon technology development are aligned with the net-zero emission target by 2050, as committed to by countries in parallel with the Kyoto Protocol and Paris Agreement to combat climate change (Wang et al. 2023a, b, c). According to the United Nations (2024), global investment in renewable energy production doubled from \$331 billion in 2015 to \$658 billion in 2023. Investments in energy transition

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technologies, such as renewable energy, energy efficiency, electric transportation, heat, energy storage, hydrogen, and carbon capture and storage, increased by 70% in 2022 compared with the pre-pandemic period, reaching USD 1.3 trillion. However, investments in renewable energy sources have not met expectations (IRENA & CPI, 2023:10; United Nations 2024:22). Carbon capture technology captures carbon from the waste gases emitted by power plants and other industrial facilities. Its purpose is to reduce emissions or remove existing carbon from the atmosphere by storing it in the ocean or underground. According to Wang et al. (2023a, b, c), China, which has the highest carbon emissions, is projected to reduce carbon emissions by 3.8% by 2040 through the implementation of CCS technology. Despite the widespread adoption of carbon capture technologies by governments, traditional companies are hesitant to invest in them owing to their high costs and financing difficulties. However, achieving carbon neutrality by 2060 is possible with the necessary investments (Chu et al. 2024a, b). However, carbon capture technologies are expensive. According to Pratama and Mac Dowell (2022) and Sievert, Cameron, and Carter (2023), the cost of carbon capture projects in Canada is close to the upper limit of the costs estimated in the literature. Additionally, this cost's rate of decline over the years has been slow (Sievert et al. 2023). However, studies have shown that achieving higher capture rates with carbon capture technology at low marginal costs is economically feasible for transitioning to net zero (Brandl et al. 2021).

It is vital to have sufficient financial resources to develop carbon-capture technologies. These projects involved comprehensive engineering applications. Therefore, advanced technological applications are required to develop such projects. Therefore, research and development efforts should be undertaken to develop such technologies. Businesses must possess sufficient financial resources to achieve these goals. Additionally, various risks are associated with carbon capture technologies. To effectively manage these risks, businesses must have sufficient financial resources (Saqib et al. 2023). Otherwise, these risks cannot be managed correctly and businesses may face financial losses. However, finding sufficient financial resources is critical for reducing the cost of carbon capture technologies. As the initial investment costs of these projects are very high, providing low-cost financing is critical in improving their financial performance. Innovative financial products are necessary to provide adequate financing for carbon-capture technologies. These products offer investors various options. Owing to these innovative products, investors may diversify their portfolios (Shang et al. 2023). This situation contributes to providing sufficient financing for carbon capture technologies. Moreover, carbon capture technologies often require long-term investment. Innovative financial products enable the identification of long-term financing sources. Additionally, innovative financial products are necessary for effective risk management processes in carbon capture projects. These innovative products can be designed to manage different risks more successfully (Mehmood et al. 2024).

Some issues must be considered in the development of innovative financial products for carbon capture technology investments. First, the new financial products must be suitable for different investor profiles. Otherwise, these products will not attract the attention of investors (Du et al. 2023). Therefore, new financial products must be developed to meet the expectations of different customer types. However, the new financial products must possess flexible financing characteristics. In carbon capture technologies, the initial cost is very high and the payback period is very long (Huo et al. 2023). Therefore, traditional financing methods such as bank loans cannot meet the needs of these projects. This issue should be considered when developing innovative financial products. Additionally, new financial products must provide many financing opportunities (Ai et al. 2023). One of the most important reasons for this is the high investment costs of carbon capture projects. In traditional financing products, financial institutions are reluctant to provide large loans (Brahmi et al. 2023). Therefore, currently available products are insufficient to finance carbon capture technology projects. In this context, attention should be paid to eliminating this deficiency by developing new and innovative financing methods. An important problem is that it is not possible for all these features to exist together in a new financial product (Moiseev et al. 2023). The most important reason is that each of these features incurs a cost. Therefore, combining too many features in a financial product is not feasible (Najam 2023). Therefore, determining the most important features is important. Thus, it is possible to develop more effective and preferred financial products. However, few studies have focused on the critical indicators of this process. Hence, this situation can be regarded as the main gap in the literature on carbon capture investment projects. In summary, it is vital to determine the most important features required for innovative financial products to be developed specifically for carbon capture technology investments.

Accordingly, this study identifies a new and innovative financial product to increase the effectiveness of investments in carbon capture technologies. In this framework, the main research question is to determine which innovative financial products are more appropriate for improving project performance. For this purpose, a novel artificial intelligence (AI)-based fuzzy decision-making model is constructed. First, the weights of the experts were calculated by considering artificial intelligence methodology. Second, the factors affecting investments in carbon capture technologies were weighted using a spherical fuzzy DEMATEL. Finally, we ranked the financial features required for investments. Thus, the features of new and innovative financial products to be developed were determined. The spherical fuzzy ARAS method was used to rank the features. The main motivation for this study is the strong need for a novel model. Most decision-making models in the literature have been criticized for some situations. In these models, the weights of the experts were assumed to be equal (Kou et al. 2023a,b,c). However, the qualifications of the experts can differ because of demographic factors. Consequently, a new model that weights the experts during the analysis process is required. To address this problem in the proposed model, AI methodology was used to compute the weights of these people. With this issue, a more appropriate evaluation can be conducted.

The main contributions of this study are as follows. (i) A novel fuzzy decision-making model was created by integrating an artificial intelligence methodology with the fuzzy decision-making theory. In this process, the weights of the experts are calculated using an AI approach. For this purpose, the different demographic factors of these experts, such as salary, working experience, and education, were considered. Thus, the opinions of experts can be considered with different weights depending on their qualifications. In other words, experts with better knowledge and experience may have higher importance in the analysis process. Thus, more realistic results were obtained. (ii) Using the DEMATEL methodology to weight the criteria also provides some advantages. The main criteria that improve the performance of newly generated innovative financial products can influence each other. Because of this situation, causal directions should be considered to understand the most critical indicators. The main advantage of DEMATEL over similar methods is its focus on the causality analysis among the determinants. Hence, this technique is preferred in the proposed model for evaluating the impact relation map of these items. This significantly contributed to the effectiveness of the findings.

The remainder of the paper is organized as follows. "Literature review" section includes a review of the literature. "Methodology" section provides information about the proposed model. "Analysis results" section consists of the analysis results. "Discussion" and "Conclusion" section presents the discussion and conclusions.

Literature review

One solution to global warming is the use of carbon capture and storage technologies (Gautam and Mondal 2023). This is essential for the sustainability of projects in which these technologies provide cost efficiency. Chen et al. (2023a, b) stated in their research that calcium cycle technology integrated with chemical cycle combustion, which is a carbon capture technology, is efficient and cost-effective. However, they emphasized that their evaluations needed to be made sufficiently. Conversely, Qiao et al. (2023) compared the efficiency of integrated carbon capture and utilization (ICCU) Technology in a coal-fired power plant with Carbon Capture Utilization technology. These results indicate that the ICCU is cost-efficient. Nie et al. (2023) and Kwakwa et al. (2023) suggested carbon trading due to its effectiveness in reducing unit costs because of their research. Moreover, membrane-based carbon capture technologies provide cost savings of 38–42% compared to liquid absorption, indicating that it is a technology that should be considered in terms of efficiency (Olabi et al. 2023). The success of carbon capture technologies, a solution to global warming, is directly related to customer satisfaction. Byrd and Cooperman (2018) showed that investors' decisions regarding carbon capture technologies in the coal industry are directly related to developments and their returns. Referring to the results of research and development activities in carbon capture technologies, Naims and Eppinger (2022) and Chang et al. (2023) emphasized that increases in customer satisfaction are among the critical elements of this innovation. For example, Xiang et al. (2023) developed a product and service system model based on a low-carbon production design. This model aims to simultaneously optimize customer satisfaction, profit, and carbon footprint. Meng et al. (2023) proposed a two-level game optimization planning model that considers customer satisfaction in the energy sector and provides low-carbon operations. Similarly, Wang et al. (2023a, b, c) developed a low-carbon system that increased the satisfaction of energy users with an optimal energy distribution model for multiple energy stations.

Combating global climate change is a policy issue, and legal regulations must be implemented to make progress (Lu et al. 2022). Carbon capture technologies and legal infrastructure that are compatible with legal regulations are important factors that affect the success of carbon-emission targets. Policymakers' sensitivity to environmental concerns and the implementation of relevant legal regulations will also increase carbon emission activities by accessing financial resources (Kim et al. 2022). For example, Lefvert et al. (2022) touched upon the importance of the subject by emphasizing that adopting the policy needed for the development of bioenergy, and carbon capture and storage technology will soon enable the development of projects. Nurdiawatia and Urbana (2022), discussing the development of green hydrogen and carbon capture technology, emphasized the need for more policy instruments for such niche markets in Switzerland. Chen et al. (2022) and Gowd et al. (2023) suggested that introducing an internationally valid regulatory framework would increase the efficiency of carbon capture technologies. Supporting the efficiency of carbon capture activities through laws and procedures also increases technological efficiency. Traditional technologies have disadvantages in terms of reducing carbon emissions (Nandhini et al. 2023). Research on the development and use of various carbon capture technologies in different sectors is available in literature. Perpiñán et al. (2023) focused on integrating the carbon capture technology into steel production. Conversely, Zhou et al. (2023) evaluated technological developments by comparing the effects of different CO_2 capture technologies on methanol production process performance. Chen et al. (2023a, b) developed a new system design by combining water-based carbon capture technology with adiabatic compressed air energy storage. Ding et al. (2023) presented an innovative proposal for carbon capture, utilization, and storage technology using supersonic decarburization.

Providing the financial resources required to disseminate carbon capture technology projects at high investment costs is essential in the fight against environmental pollution. In addition to state policies, institutional actors in capital markets have begun to attach greater importance to these investments (Wu et al. 2023). Developing financial resources requires considering the expectations of different investor profiles. This literature review includes studies aimed at understanding the financial product preferences of individual investors. For example, Faradynawati and Söderberg (2022) conducted a three-country study of the different profiles of individual investors using digital financial advisors. Similarly, Ventre et al. (2023) and Dziejarski et al. (2023) analyzed investors' financial product preferences. In their research, in which they explained investor profiles using behavioral finance, they tried to reveal the decision-making process based on the levels of knowledge, cognitive limitations, and patience. In their research on green financial investment products, Gáspár et al. (2023) revealed that young women tended to make these investments. Studies have also been conducted to understand the profiles of individual investors. However, no studies have been conducted based on the investor profile for the development of financial products required by innovative technology projects that require significant investments. In addition to financing sources, research on blockchain and crowdfunding opportunities has emerged in recent years (Alvi and Ulrich 2023). Flexible financial product financing facilitates long-term investments. Shen et al. (2023) stated that the promotion of green development in agricultural production could be financed with flexible and suitable products through digital financial participation. Similarly, Mapanje et al. (2023) stated that fintech could increase the financing efficiency of sustainable agricultural practices. The digital transformation that emerges with fintech delivers financial services and products in more agile, flexible, economical, and transparent ways (Irimia-Diéguez et al. 2023). Lyu et al. (2023) and Khan et al. (2023) state that digital technology helps create functional, efficient, and personalized financial products. Thus, rich and flexible financing conditions can be provided to businesses. Zhang and Umair (2023) contributed to the literature by approaching financial products from a different perspective, revealing the interdependence of financial instruments and their roles in sustainable development.

The scale of projects and minimizing risks are other notable issues in developing appropriate financial products that support the development of carbon capture technologies. Green financing provides environmental financing for environment-friendly enterprise projects (Jiakui et al. 2023). Furthermore, Zhang et al. (2023) revealed that green financing accelerates the improvement of the industrial structure. Liu and Wang (2023) touched on the importance of establishing pilot regions where intensive research and development studies were conducted to ensure green finance reform. Additionally, traditional banking products are based on credit and debt. This situation cannot support the risk and limited liquidity of large-scale projects developed for environmental impacts (Li et al. 2023; Fikru and Azure 2023). Conversely, Ren et al. (2023a, b) investigated the impact of financial inclusion on corporate innovation. The research revealed that traditional financial participation is more damaging than digital financial participation, and that both participation models restrict innovation efficiency. Finally, they emphasized that both types of financial inclusion work differently for businesses of different sizes. In this respect, it is essential to minimize the risks of developing financial products that enable the implementation of large-scale and long-term projects on carbon capture technologies. Jing (2023) points out that digital financial risk management should be implemented to develop digital financial products. Moreover, Le et al. (2020) revealed in their research the necessity of advanced financing products that can address the complex risks associated with renewable energy investments. Murugan and Sree Kala (2023) contributed to this field by proposing machine learning strategies for large-scale data-driven financial risk management and analysis. Du and Shu (2023) and Tan et al. (2023a, b) contributed to the field of financial risk by proposing a method for detecting financial risk behaviors and financial risk management, in which they proposed a risk pre-alarm model based on deep learning. Conversely, Kaur et al. (2023), in their research on the risks of decentralized finance (DeFi), stated that financial risks are at the highest level in the sub-criteria and offered a suggestion perspective for future developments of relevant applications.

Various cost-efficient carbon capture technologies are being developed. Ensuring customer satisfaction in developed projects is essential for environmental impact and technological advancement. Obtaining concrete outcomes regarding global climate change requires the implementation of appropriate state policies. One way to access the required financial resources is by ensuring legal regulations. Providing a legal infrastructure also trigger innovative technology efficiency. Different carbon capture technology models designed for different sectors have been found in the literature. However, corporate actors in capital markets are increasingly interested in innovative and environmentally friendly technologies. There is a need to develop different financial products to increase investments in large-scale projects. Thus, identifying different investor profiles and supporting them with products that provide flexible financing is essential. Additionally, the diversity of project scales is an essential issue in the development of financial products. The issue of minimizing risk in financial products offered to investors is also frequently mentioned in the literature. The development of digital financial products and integration of applications, such as deep learning and artificial intelligence, into financial products have been among the most frequently researched topics in recent years. One limitation of the literature is that a model for financial products to be developed based on the aforementioned criteria and issues needs to be mentioned. In other words, determining the most important features is necessary. Thus, developing more effective and preferred financial products is possible. In summary, it is vital to determine the most important features required to develop innovative financial products, specifically for carbon capture technology investments. To address this gap in the literature, this study proposes a new model to identify the most critical factors while generating a new and innovative financial product for carbon capture technology investments.

Methodology

This study identifies a new and innovative financial product to increase the effectiveness of investments in carbon capture technologies. In this context, a novel model is proposed by integrating an artificial intelligence technique and fuzzy decision-making methodology. DEMATEL is a weighting method that considers the interaction between criteria. The greatest advantage of this method is that it can calculate the total effect by considering the effects between criteria. Because weighting methods such as AHP do not consider the relationship or effect between criteria, the DEMATEL method was preferred in this study. Additionally, the ARAS method was used to rank the alternatives. One of the greatest advantages of the ARAS is its computational simplicity. Additionally, methods such as TOPSIS and VIKOR, which consider the metric distance, have been criticized in the literature. The main reason for this is because metric calculations on ordinal scales do not reflect the truth. The ARAS method is superior to other methods because it considers the total ratio of the optimal value instead of the distance to the optimal value. The integration of the artificial intelligence approach with the fuzzy decision-making theory is another advantage of the proposed model when compared with previously generated models. Most existing models do not consider the weights of the experts. However, these individuals may have different qualifications based on their demographic factors. Therefore, taking the average of these evaluations have been criticized by many scholars. To overcome this problem, the decision matrix in the proposed model was created using an artificial intelligence methodology. With the help of this issue, the weights of the experts can be computed by considering their qualifications.

Machine learning is a sub-branch of artificial intelligence. One machine-learning method is dimension reduction. In this study, a dimension reduction algorithm, which is a sub-branch method of artificial intelligence, is preferred. In artificial intelligence modeling, an mxn-dimensional feature matrix obtained from n features belonging to m experts is converted into an mx1-dimensional matrix. The new matrix obtained from artificial intelligence, which contains the information of the feature matrix at the maximum level, is considered the weight of the experts. In other words, an expert weight score from n features is provided by artificial intelligence. In this process, the dimension-reduction model used was based on a principal component analysis. The feature matrix is reduced to a one-dimensional matrix by changing its axis. The new axes were derived from the basic components. The details of the methods used in this study to increase the effectiveness of investments in carbon capture technologies are summarized in Fig. 1.

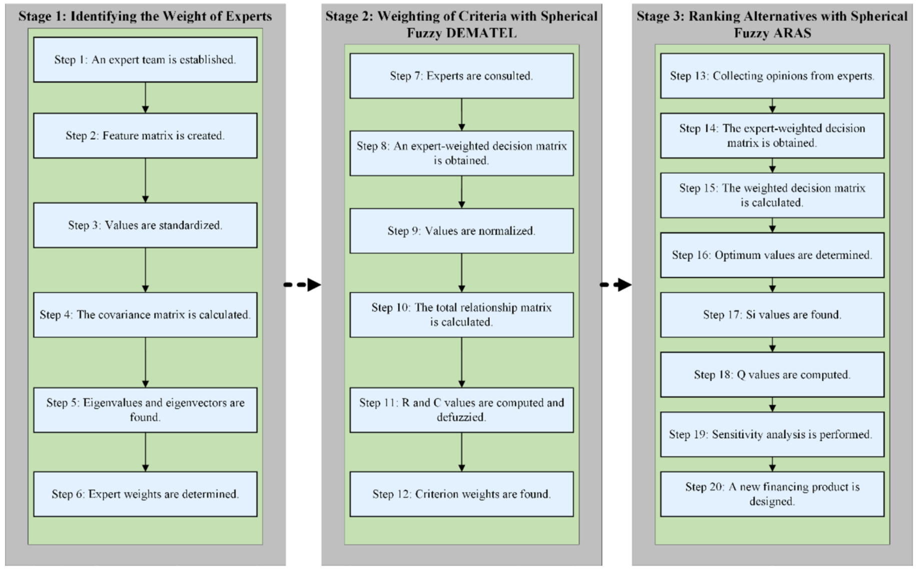

Fig. 1 Flowchart

Step 1 involves creating a team of experts. In this step, an expert team consisting of academics who have conducted studies on the subject or managers who have experience in the field is brought together. The purpose of establishing this team is to obtain expert opinions for multi-criteria decision-making methods. In *Step 2*, demographic information about the members of the expert team, such as education, experience and age, is collected. A matrix is created showing the different characteristics of each demographic information expert. The feature matrix (F) is shown in Eq. (1). f_{ij} represents the i^{th} feature knowledge of the j^{th} expert.

$$F = \begin{bmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots \\ f_{m1} & \cdots & f_{mn} \end{bmatrix} \tag{1}$$

The details and mathematical processes of the methods, the steps of which are shown in Fig. 1, are presented under subtitles.

Dimension reduction

Dimensional reduction analysis is a machine learning technique used to extract p features from k features. In other words, the aim of the method is to reduce the number of variables in a high-dimensional dataset while minimizing the variance loss. Projections of the dataset were used for this purpose. It is difficult to analyze large amounts of data and extract information. Therefore, dimension-reduction analysis aims to obtain similar information with less data (Bansal et al. 2023). In the process of obtaining the decision matrix, expert opinions were assigned equal weights. In this case, multi-criteria decision-making methods are often criticized. The basis of these criticisms is that there is a difference in knowledge because experts have different demographic information such as experience and education. In this study, a weight calculation method that considers demographic information was developed using the dimensionality reduction method of an artificial intelligence model.

In this process, the importance weights of the experts were obtained using the information in the feature matrix formed by the demographic information of the experts, such as age, experience period, and education. At this stage, a dimensionality-reduction algorithm is applied to the feature matrix. The new dimension represents the new scores that contain expert knowledge. In this study, it is recommended that the new scores be used as expert weights. Therefore, different degrees of importance can be assigned to the opinions of experts with varying levels of demographic information. The most important benefit of this method is that expert weights can be objectively determined through machine learning. A possible disadvantage of this method is that the analysis cannot be performed in the absence of missing demographic information. Another disadvantage is that it requires knowledge of expert features. The linear dimension reduction steps for the weights of the experts are summarized below.

In the selection of experts, their experience, academic studies/publications, and seniority were considered. The designated experts were contacted via e-mail and the purpose of the study was explained. After obtaining interview approval, face-to-face meetings were held with experts who were geographically close. Online meetings were held for experts who could not meet face to face. Demographic information and expert opinions were collected during these interviews. A feature matrix was constructed that accepts the demographic information of experts as an element. A dimension reduction algorithm was used to obtain the weights of the experts using the feature matrix.

In *Step 3*, the values of the matrix are standardized. In the standardization process, the values were centralized using Eqs. (2) and (3). The normalized matrix (*N*) is given by Eq. (4). The centralized values (*c*) are normalized using Eq. (5).

$$c_{ij} = f_{ij} - \overline{f}_j \tag{2}$$

$$\overline{f}_j = \frac{\sum_{i=1}^{m} f_{ij}}{m} \tag{3}$$

$$N = \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \tag{4}$$

$$n_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{m} c_{ij}^2}} \tag{5}$$

Step 4 involves the calculation of the covariance matrix. The covariance matrix (*CM*) of the *N* matrix is calculated using Eqs. (6)-(9).

$$CM = \begin{bmatrix} cov(n_1, n_1) & \cdots & cov(n_1, n_n) \\ \vdots & \ddots & \vdots \\ cov(n_n, n_1) & \cdots & cov(n_n, n_n) \end{bmatrix} \tag{6}$$

$$cov(x,y) = \frac{\sum_{i=i}^{m}(x_i - \overline{x})(y_i - \overline{y})}{n} \tag{7}$$

$$\overline{x}_j = \frac{\sum_{i=1}^{m} x_{ij}}{m} \tag{8}$$

$$\overline{y}_j = \frac{\sum_{i=1}^{m} y_{ij}}{m} \tag{9}$$

A covariance matrix is a concept used in statistics and linear algebra. Covariance is a statistical measure of the relationship between two random variables. The covariance matrix is important because it represents the relationship between the features in the dataset. Measuring the relationship of each variable with other variables helps understand the structure of the dataset owing to the covariance matrix. The eigenvalues and eigenvectors required for the dimension reduction were then calculated.

Step 5 includes finding values of the eigenvalue (λ) and eigenvector (V). The eigenvalues of the covariance matrix were determined using the following Eq. (10). I in the equation represents the identity matrix. The eigenvalues represent the rotation or expansion factors of the matrix and reflect its characteristic properties.

$$Det(CM - \lambda I) = 0 \tag{10}$$

An eigenvalue–eigenvector analysis of matrices is used to understand the basic properties and behavior of a matrix. The calculation of eigenvalues and eigenvectors is used in applications such as finding the components of the matrix that represent important structures in high-dimensional data, understanding the behavior of the matrix, and dimensionality reduction (Qi et al. 2023). The determinant is a numerical value associated with a square matrix. The determinant usually provides information about the properties of the matrix and its solvability states. This determinant is used in the eigenvalue calculations. The eigenvalues are the roots of the characteristic polynomial of the matrix. The coefficients of the polynomial are expressed as determinants. A value of zero indicates that the characteristic polynomial has roots that satisfy the eigenvalues of the matrix. In this case, the eigenvalues (λ) are the roots of the characteristic polynomial of the matrix. These roots were observed when the determinant was zero. Each component has a corresponding eigenvalue.

The eigenvectors represent the directions corresponding to the eigenvalues of the matrix. Eigenvectors are used for dimensionality reduction, matrix multiplier analysis, and many other applications. A new space is obtained when the eigenvectors corresponding to the eigenvalues of the covariance matrix represent the components of a new dataset. Thus, the variance in the dataset was preserved. The eigenvector of a matrix is the vector proportional to itself as a result of multiplying the matrix by a single scalar. Eigenvector analysis is used in many artificial intelligence and machine learning applications such as feature selection, data compression, and recursive learning. Particularly, eigenvalues and eigenvectors play an important role in representing and modeling datasets. The largest among n eigenvalues is considered using Eq. (11). This is because the largest eigenvalue constructs the eigenvector that accounts for the largest proportion of variance in matrix F. That is, the largest eigenvalue creates the largest eigenvector, and the largest eigenvector creates the largest explanatory score. Thus, the aim was to preserve the highest variance in the dataset or maximize the total variance in the new matrix. In other words, focusing on the largest eigenvalues minimizes the information loss during dimension reduction. As the eigenvectors corresponding to the largest eigenvalues represent the highest variance in the dataset, the basic information is preserved.

$$\lambda_{max} = \max_{i} \lambda_i \tag{11}$$

Eigenvectors express the directions that do not change under the influence of a linear transformation. That is, the eigenvector is the transformation matrix used to transform a dataset into a new space. Eigenvectors refer to the principal components of a dataset. In other words, the eigenvectors show the relationships between interdependent variables in the covariance matrix. In dimensionality reduction, the eigenvectors express how the relationships between the original features are distributed among the principal components. The eigenvector is calculated with Eq. (12).

$$(CM - \lambda_{max} I) * V = 0 \tag{12}$$

In *Step 6*, the weights are calculated. For this purpose, a transformation is applied by multiplying the F matrix by the eigenvector using Eq. (13). The resulting new space matrix (H) is then normalized using Eq. (14). These normalized values are used as expert weights (ew).

$$H = F * V \tag{13}$$

$$ew_i = \frac{h_i}{\sum_{i=1}^{m} h_i} \tag{14}$$

Spherical Fuzzy DEMATEL

DEMATEL is a multi-criteria decision-making method that calculates criterion weights by including the interactions between criteria in the analysis. In the literature on multicriteria decision-making, the DEMATEL method is used for two purposes. The first is to examine the cross-criterion effects (Khan et al. 2024; Bagherian et al. 2024), while the second was to weight the criterion by considering its effects (Zhan et al., 2024; Fidan et al. 2024). The steps of the DEMATEL method integrated with spherical fuzzy numbers are presented below (Özdemirci et al. 2023).

In *Step 7*, experts are consulted to determine the importance of the criteria. Using the scores in Table 1, expert team members compared the criteria. The expert opinions were converted into fuzzy numbers. μ is the membership degree, ν is the non-membership degree, and π is the hesitancy degree.

In *Step 8*, an expert-weighted decision matrix is obtained from the expert opinions. Using Eq. (15), the weighted mean of the spherical fuzzy expert opinions is computed,

Table 1 Linguistic score

Terms	μ	v	π
Strong	0.85	0.15	0.45
Moderate	0.6	0.2	0.35
Weak	0.35	0.25	0.25
No Influence	0	0.3	0.15

and the expert-weighted decision matrix (DM) is calculated. The ew values in the equation represent the importance levels of the experts.

$$SWAM = \left\{ \left[1 - \prod_{i=1}^{n} \left(1 - \mu_i^2\right)^{ew_i} \right]^{\frac{1}{2}}, \prod_{i=1}^{n} v_i^{ew_i}, \left[\prod_{i=1}^{n} \left(1 - \mu_i^2\right)^{ew_i} - \prod_{i=1}^{n} \left(1 - \mu_i^2 - \pi_i^2\right)^{ew_i} \right]^{\frac{1}{2}} \right\} \tag{15}$$

$$DM = \begin{bmatrix} 0 & \cdots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ \vdots & \ddots & \vdots \\ (\mu_{n1}, v_{n1}, \pi_{n1}) & \cdots & 0 \end{bmatrix} \tag{16}$$

In *Step 9*, the values are normalized. First, DM is divided into three submatrices based on the components of the spherical fuzzy number. Then, all three submatrices are normalized using Eqs. (17) and (18).

$$X = sDM \tag{17}$$

$$s = \min \left[\frac{1}{\max\limits_{i} \sum_{j=1}^{n} |dm_{ij}|}, \frac{1}{\max\limits_{j} \sum_{i=1}^{n} |dm_{ij}|} \right] \tag{18}$$

Step 10 involves the calculation of the total relationship matrix. Using Eq. (19), the components of the total relationship matrix (T) are calculated from each normalized submatrix (X). Subsequently, the Euclidean normalization process is applied to define the spherical fuzzy set.

$$T = X * (1 - X)^{-1} \tag{19}$$

Step 11 involves computing the R and C values. The spherical fuzzy R and C values are calculated using Eqs. (20)-(22). Afterwards, these values are defuzzied with the help of Eq. (23).

$$r_i = \sum_{i=1}^{n} < \mu_{ij}^T, v_{ij}^T, \pi_{ij}^T > \tag{20}$$

$$c_j = \sum_{j=1}^{n} < \mu_{ij}^T, v_{ij}^T, \pi_{ij}^T > \tag{21}$$

$$e.g. < \mu_{11}^T, v_{11}^T, \pi_{11}^T > + < \mu_{12}^T, v_{12}^T, \pi_{12}^T > \\ = \left\langle \left(\left(\mu_{11}^T\right)^2 + \left(\mu_{12}^T\right)^2 - \left(\mu_{11}^T\right)^2 \left(\mu_{12}^T\right)^2 \right)^{0,5}, v_{11}^T v_{12}^T \right. \\ \left. \left(\left(1 - \left(\mu_{11}^T\right)^2\right) \left(\pi_{11}^T\right)^2 + \left(1 - \left(\mu_{12}^T\right)^2\right) \left(\pi_{11}^T\right)^2 - \left(\pi_{11}^T\right)^2 \left(\pi_{12}^T\right)^2 \right)^{0,5} \right\rangle \tag{22}$$

$$Score = (2\mu - \pi)^2 - (v - \pi)^2 \tag{23}$$

With *Step 12*, the weights of the criteria (w) are found, using Eq. (24).

$$w_i = \frac{R_i + C_i}{\sum_{i=1}^{n} (R_i + C_i)} \tag{24}$$

Spherical fuzzy ARAS

ARAS method is a multi-criteria decision-making method in which alternatives are ranked in terms of criteria. The steps of the ARAS method with spherical fuzzy numbers are given below (Wang et al. 2024).

In *Step 13*, the opinions of the experts are collected. These opinions are converted into fuzzy numbers corresponding to the score values in Table 2.

In *Step 14*, the expert-weighted spherical fuzzy decision matrix (A) is obtained from the experts' spherical fuzzy opinions using Eq. (15). The expert-weighted spherical fuzzy decision matrix is given by Eq. (25).

$$A = \begin{bmatrix} (\mu_{11}, v_{11}\pi_{11}) & \cdots & (\mu_{m1}, v_{m1}, \pi_{m1}) \\ \vdots & \ddots & \vdots \\ (\mu_{1n}, v_{1n}, \pi_{1n}) & \cdots & (\mu_{mn}, v_{mn}, \pi_{mn}) \end{bmatrix} \tag{25}$$

Step 15 involves the calculation of the weighted decision matrix. Using Eqs. (26) and (27), the weighted decision matrix *(X)* is calculated. w represents the weight of the criteria.

$$X = w.A \tag{26}$$

Table 2 Linguistic scoring for ranking

	μ	v	π
1	0.5	0.4	0.4
2	0.1	0.9	0
3	0.2	0.8	0.1
4	0.3	0.7	0.2
5	0.4	0.6	0.3
6	0.6	0.4	0.3
7	0.7	0.3	0.3
8	0.8	0.2	0.1
9	0.9	0.1	0

$$\lambda\widetilde{A}_s = \left\{ \left(1-\left(1-\mu_{\widetilde{A}_s}^2\right)^{\lambda}\right)^{1/2}, \nu_{\widetilde{A}_s}^{\lambda}, \left(\left(1-\mu_{\widetilde{A}_s}^2\right)^{\lambda} - \left(1-\mu_{\widetilde{A}_s}^2 - \pi_{\widetilde{A}_s}^2\right)^{\lambda}\right)^2 \right\} \quad (27)$$

Step 16 involves determining optimal values. While the maximum value is considered the optimal value for the benefit criteria, the minimum value is the optimal value for the cost criteria. To calculate the optimal values, the score values in Eq. (23) were used to compare the spherical fuzzy numbers. In *Step 17*, S_i values are found. The row totals (S) for the alternatives and optimal case are calculated using Eq. (28).

$$\widetilde{S}_i = \sum_{i=1}^{m} \left(\mu_{ij}, \nu_{ij}, \pi_{ij}\right) \quad (28)$$

Next, the row totals are defuzzied with Eq. (23). In *Step 18*, the Q values are computed with Eq. (29).

$$\mathrm{Q_i} = \frac{\mathrm{S_i}}{\mathrm{S_0}} \quad (29)$$

The alternative with a higher Q_i value is considered the best. Q_o is the row total of the optimal values.

Sensitivity analysis is performed in *Step 19*. To demonstrate the consistency of the results, the ARAS analysis is performed with different weights, and the results are compared. In *Step 20,* a new financial product is designed.

Analysis results

This study aims to develop a new and innovative financial product to increase carbon capture technology investments. To develop new products, the importance weights of the factors affecting carbon capture technologies were first determined using the spherical fuzzy DEMATEL method. Subsequently, the features of new and innovative financial products are ranked using the spherical fuzzy ARAS method. A sensitivity analysis was performed to ensure the consistency of the analysis results. Finally, based on the results, the ideal, new, and innovative financial product was recommended. The results of these stages of the analysis are shared under the subheadings in this section.

Determining of criteria and alternatives for new and innovative financial product

From the literature review, effective criteria for carbon capture technology investments were determined. The criteria used in the study are listed in Table 3, along with the analysis codes.

Table 3 Indicators for carbon capture technology investments

Indicators	Code
Cost effectiveness	COST
Customer satisfaction	CSAT
Legal effectiveness	LEGL
Qualification of Personnel	QUOP
Market condition	MRKT
Technological improvement	TECH

Ensuring cost-effectiveness is vital in increasing the effectiveness of carbon capture technology investments. Lower-cost solutions reduce investors' risks and increase returns on investments. This has significantly contributed to increasing business competitiveness. Conversely, lower-cost solutions make it easier to obtain financing by increasing the returns on investment. Ensuring customer satisfaction is another factor that can improve project performance. Customer satisfaction can increase the demand for carbon capture technologies. This would allow businesses to increase their sales volumes. Customer satisfaction is the desire to comply with environmental and social responsibilities. This situation supports businesses that pay more attention to environmental issues. It is also necessary to ensure the effectiveness of legal processes to increase the effectiveness of carbon capture technology investments. Effective legal processes ensure that carbon capture projects are monitored and audited. This contributes significantly to increasing market reliability. Moreover, competent personnel should be employed to increase the effectiveness of carbon capture technology investments. This allows for a more accurate application of carbon capture technologies. Market conditions and technological improvements are also critical factors that affect the performance of these projects. Additionally, the features considered in determining the new and innovative financial products are listed in Table 4.

While the indicators in Table 3 constitute the criteria for the DEMATEL method, the features in Table 4 are considered as the alternatives listed in the ARAS method.

Identifying the weights of experts

The DEMATEL and ARAS methods are multicriteria decision-making methods based on expert opinions. The decision matrices created for these methods were based on expert opinions. The decision matrix based on expert opinions is typically created using an average operator. When performing average processing, expert assessments are assumed to be of equal importance. This assumption has often been criticized in the literature. The basis of this criticism is that factors such as the duration of experience and level of education affect the importance of experts. In other words, the opinions of experts with more experience are more important. A similar situation is expressed in the literature that the opinions of experts with higher academic education should be given importance. In this study, considering these criticisms, a new expert-weighting method was proposed. For this purpose, the dimensionality reduction method, which is a machine learning method, was applied to obtain the decision matrix.

Table 4 Features of new and innovative financial product

Alternatives	Code
Suitability for investor profiles	PROF
Sustainability	SUST
Time of projects	TOPR
Flexibility finance	FLEX
Scale of project	SCAL
Effective risk management	RISK

Table 5 Features matrix

	Experience (year)	Education	Salary (€)
Expert 1	25	Master's Degree	3000
Expert 2	30	PhD	3500
Expert 3	15	Master's Degree	2500

Table 6 Weights of experts

	ew
Expert 1	0.333
Expert 2	0.389
Expert 3	0.278

Step 1 involved creating a team of experts. Three different experts were selected based on their experiences and academic studies in the field. The experts comprised the team members. In *Step 2*, the demographic information of the team members was obtained. A feature matrix that included expert experience, education, and salary was created. The feature matrices are listed in Table 5.

Step 3 involves the standardization of the feature matrix. The main purpose is to remove the unit size of the features. With Eqs. (2) and (3), the feature matrix is centralized. Afterwards, the values are standardized by normalizing them with the help of Eqs. (4) and (5). The standardized feature matrix is presented in Table 11 in the Appendix. In *Step 4*, the covariance matrix of the features is calculated. The covariance coefficient between the two features is computed using Eqs. (7)-(9). The covariance matrix given in Eq. (6) is listed in Table 12 *Step 5* involves determining the eigenvalues and eigenvectors. Three eigenvalues are obtained using Eq. (10). The reason there are three is that there are three features of experts. The largest eigenvalue is obtained using Eq. (11). The largest eigenvalue was considered because it formed an eigenvector that contained the maximum variance of the feature matrix. Finally, by Eq. (12), the eigenvector is calculated. The calculated eigenvalues and eigenvectors are listed in Tables 13 and 14, respectively. In *Step 6*, the importance weights of the experts are calculated. Space transformation is performed by multiplying the feature matrix and eigenvector using Eq. (13). That is, the projection of the feature matrix is computed. Finally, the obtained values are normalized using Eq. (14). These normalized values are used to express the importance weights of the experts. The importance weights of the experts are listed in Table 6.

As shown in Table 6, Expert 2 is the team member with the most important opinion. The importance level of Expert 2 was 38.9% as they had the highest level of education, experience, and salary.

Weighing the criteria using spherical fuzzy DEMATEL

The indicators listed in Table 3 are weighted using the spherical fuzzy DEMATEL. In *Step 7,* experts are consulted. The experts performed the evaluations using the terms listed in Table 1. The experts' evaluations are presented in Table 7.

In *Step 8*, an expert-weighted decision matrix is obtained. After converting the expert opinions in Table 7 into fuzzy numbers using Eq. (15), the decision matrix is obtained.

Table 7 Experts' evaluations for weighting

	COST	CSAT	LEGL	QUOP	MRKT	TECH
Expert 1						
COST	–	3	3	3	2	3
CSAT	1	–	0	2	2	3
LEGL	1	2	–	3	3	2
QUOP	3	1	1	–	0	0
MRKT	2	3	3	1	–	0
TECH	3	3	2	2	2	–
Expert 2						
COST	–	3	3	2	2	3
CSAT	2	–	1	2	2	2
LEGL	1	2	–	3	2	2
QUOP	3	1	1	–	1	1
MRKT	2	3	3	1	–	1
TECH	3	3	3	2	2	–
Expert 3						
COST	–	3	3	3	3	2
CSAT	0	–	1	2	3	3
LEGL	1	1	–	1	2	2
QUOP	2	2	2	–	1	1
MRKT	1	2	2	0	–	0
TECH	3	2	3	3	3	–

Table 8 Weights, R and C values

Criteria	R	C	w
COST	1.050	1.870	0.232
CSAT	1.056	0.777	0.146
LEGL	1.058	0.842	0.151
QUOP	1.056	0.395	0.115
MRKT	1.056	0.617	0.133
TECH	1.055	1.738	0.222

The *ews* values used in Eq. (15) are listed in Table 6. The decision matrix is presented in Table 15. *Step 9* describes the normalization of the values. First, matrix is divided into three components, and the normalized decision matrix is obtained using Eqs. (17) and (18). The normalized submatrices are listed in Table 16. In *Step 10*, the total relationship matrix is calculated. Using Eq. (19), the components of the total relationship matrix were obtained from each of the three normalized submatrices. Subsequently, Euclidean normalization was applied to the Spherical fuzzy set definition. The total relationship matrix is presented in Table 17. In *Step 11*, *R* and *C* values are calculated using Eqs. (20)–(22), and defuzzified using Eqs. (23). *Step 12* contains criterion weights. *R, C* values and criterion weights calculated with Eq. (24) are listed in Table 8.

When the criterion weights were examined, the highest value belonged to the COST criterion of 0.232. The second criterion is the TECH criterion. The importance weight of this criterion is 0.222. The importance levels of these criteria are shown in Fig. 2.

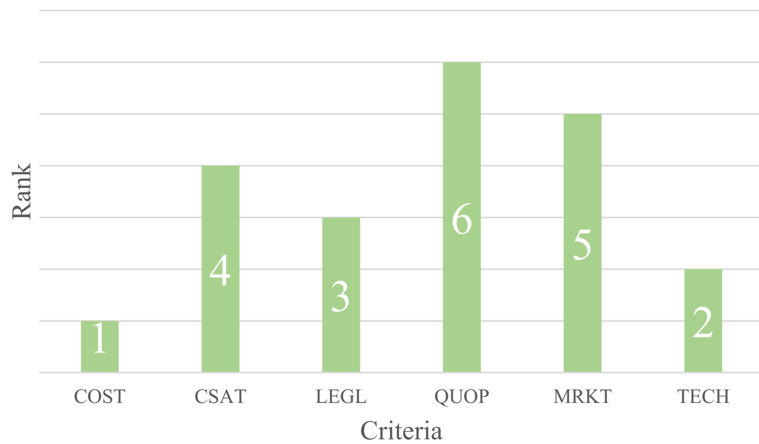

Fig. 2 Important level of criteria

According to Fig. 2, the most important criteria are "Cost Effectiveness" and "Technological Improvement". Carbon capture technologies are crucial in reducing greenhouse gas emissions. However, cost-effectiveness must be ensured to successfully implement these technologies. Otherwise, the return on investment significantly decreases. This negatively affects project development. However, ensuring cost-effectiveness of carbon capture technologies significantly increases business competitiveness. Government incentives play a key role in achieving these goals. Moreover, ensuring technological development is vitally important to this process. Technological advances can also increase the efficiency of carbon capture technologies. Owing to these new applications, the energy consumption can be reduced. Thus, it is possible to reduce costs and increase efficiency.

Ranking the alternatives using spherical fuzzy ARAS

The features in Table 4 were ranked using the spherical fuzzy ARAS. In *Step 13*, opinions from team members were collected. Team members evaluated the alternatives using the scale shown in Table 2. The expert evaluations are presented in Table 9.

Step 14 involves obtaining the expert-weighted decision matrix using Eqs. (15) and (25). The importance weights of the experts are listed in Table 6. The decision matrices used for the spherical fuzzy ARAS method are listed in Table 18. *Step 15* presents the calculation of the weighted decision matrix. The criterion weights in Table 8 and the decision matrix in Table 18 are multiplied by Eqs. (26) and (27). The multiplication results of the weighted decision matrix are listed in Table 19. In *Step 16*, the optimal values are determined. For each criterion, the score in Eq. (23) was considered. Because the criteria considered in the study were benefits, the value with the highest score was determined as the optimal value. The optimal values are given Table 20. In *Step 17*, S_i values were calculated using Eq. (28). The S_i values were then defuzzified using Eq. (23). The S_i values of the alternatives and optimal values are listed in Table 21. In *Step 18*, Q values are computed by Eq. (29). Q values are listed in Table 10.

Table 9 Evaluation of the Team

	COST	CSAT	LEGL	QUOP	MRKT	TECH
Expert 1						
PROF	1	2	3	4	4	3
SUST	5	4	3	2	5	6
TOPR	7	4	3	2	8	8
FLEX	8	9	9	8	8	9
SCAL	6	7	6	8	7	7
RISK	9	9	9	9	8	9
Expert 2						
PROF	2	2	3	5	4	4
SUST	4	4	3	2	4	7
TOPR	6	5	5	3	8	7
FLEX	8	8	9	9	9	8
SCAL	5	5	5	9	6	7
RISK	9	9	9	9	8	8
Expert 3						
PROF	2	2	4	5	5	5
SUST	3	3	4	1	3	9
TOPR	5	5	5	4	6	7
FLEX	9	9	9	8	8	8
SCAL	6	7	6	8	7	6
RISK	8	8	9	9	9	9

Table 10 Q values

Alternatives	Q
PROF	− 0.0414
SUST	0.1510
TOPR	0.3081
FLEX	0.9241
SCAL	0.3854
RISK	0.9956

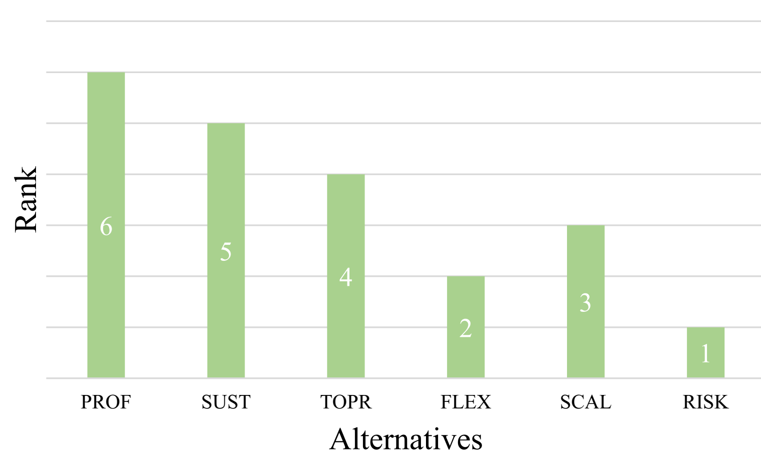

Fig. 3 Ranking of features of financial product

The highest value in Table 10 is 0.9956. This value belongs to the RISK. FLEX is the second most important feature with a value of 0.9241. The ranking of the features of carbon capture technology investments is shown in Fig. 3.

As shown in Fig. 3, the most important features of financing products in carbon capture technology investments are "Effective Risk Management" and "Flexible Finance". Effective risk management is important for the success of newly developed innovative financial products. Potential risks must first be correctly identified to ensure effective risk management. Conversely, successful implementation of risk management ensures the determination of correct strategies to reduce, and control identified risks. This contributes to minimizing financial losses caused by risks. Additionally, effective risk management allows a clearer understanding of the benefits provided by financial products. Furthermore, investor confidence must be ensured for innovative financial products to succeed. The successful implementation of risk management provides an important opportunity to achieve this goal.

Sensitivity analysis

Step 19 demonstrates the consistency of the analysis of financial product features in carbon capture technology investment. By changing the criterion weights, the alternatives listed in Table 4 are ranked for 20 different cases. The weights used in this study were obtained from scenarios created by considering different situations. The results of the sensitivity analysis are shown in Fig. 4.

According to the sensitivity analysis results, there was no change in the ranking of the alternatives, and the results were consistent.

Definition of new and innovative financial product

In *Step 20*, a new and innovative financial product is designed for carbon capture technology investment projects. In this context, cost-effectiveness must be prioritized in the development of new financial products. Technological competence is another aspect that should be considered in this process. However, such innovative financial products should include both risk management and flexible financing. This new financial product primarily provides investors with cost advantages. Additionally, this product should be developed to minimize the risks associated with carbon capture projects. Additionally, the product should offer flexible repayment opportunities.

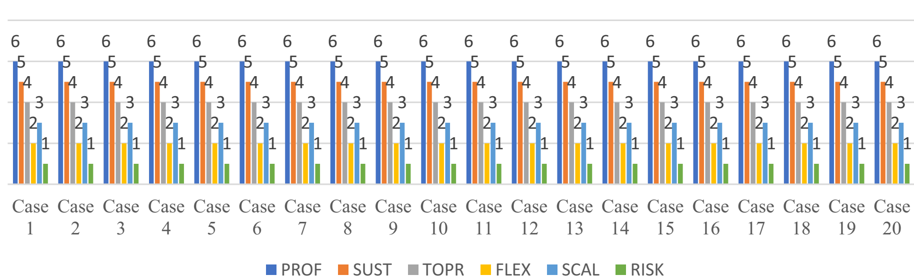

Fig. 4 Result of sensitivity analysis

Discussion

As a result of the analysis, cost-effectiveness was found to be the most important factor affecting investments in carbon capture technologies. However, carbon capture technologies are expensive (Goren et al. 2024; Chu et al. 2024a, b). Additionally, ensuring cost-effectiveness provides a competitive advantage for businesses (Tan et al. 2023a, b; Goren et al. 2024). Cost-effectiveness is an important factor for a business that aims to ensure its sustainability. Moreover, the cost-effectiveness of carbon capture technologies makes such investments more attractive. Mun et al. (2023), Wu et al. (2024a, b), and Yin et al. (2024) developed a carbon-techno-economic methodology that combines carbon tax and process costs. Cost-effectiveness has been stated to be important for improving carbon capture processes. Ren et al. (2023a, b) aimed to reduce the carbon emissions from China's cement industry. Technological investment costs play an important role in this process. Xu et al. (2023) examined electricity generation from coal by using carbon capture and storage technologies in China, and it was emphasized that attention should be paid to the technology costs to achieve the desired success.

The results show that technological development is the second most important factor affecting investment in carbon capture technologies. Carbon capture technologies are developing rapidly. Accordingly, keeping up with advancing technologies affects business efficiency (Kobayashi 2023; Foorginezhad et al. 2024). Moreover, new technologies make production processes more economical and attract more investors (Xin-gang et al. 2023; Kindred et al. 2024). Technological improvements have also increased the reliability of carbon capture technologies by reducing errors (Kuen et al. 2023; Migo-Sumagang et al. 2024). Jiang and Liu (2023) examined the methods for achieving carbon neutrality while maintaining economic vitality. This study, which compares BRICS and G7 countries, states that technological innovation maintains economic vitality and achieves carbon neutrality. Wang et al. (2023a, b, c) analyzed the impact of foreign direct investment on carbon emissions in China. The results of this study, using data from 2006 to 2019, address the impact of technological development on carbon emissions.

However, other studies have highlighted the importance of certain environmental factors. It is important that legal factors are sufficient for the success of newly developed innovative financial products (Haruna et al. 2024). In this context, new products must comply with the country's laws (Abdulai and Issahaku 2024). Therefore, if the product to be developed is expected to be used in many different countries, it must comply with all the rules of these different countries. Otherwise, businesses may face serious financial losses (Weng and Li 2024). Similarly, legally sound and reliable financial products gain investors' trust. This is vitally important to the successful development of financial products. Moreover, a strong legal framework reduces the risks associated with financial products. This ensures the trust of investors and financial institutions. Conversely, market conditions are important for the success of the newly developed innovative financial products (Abbas et al. 2024). For innovative financial products to be successful, it is important to understand and meet market demands and needs correctly. Thus, it is possible to meet customer expectations more accurately (Ahmed et al. 2024).

The World Energy Outlook Report (IEA 2023) states that worldwide investments in carbon capture and storage projects have reached a record level of $3 billion. The main driving forces behind these investments are tax reductions and grant financing programs in North America. Furthermore, investments in Canada and China, as well as regulations in Denmark, Indonesia, Japan, and Malaysia, have enabled other countries to make progress in this area. The European Commission established one of the largest financing programs in the world to provide funding for innovative and low-carbon technologies. The program includes a large innovation fund that supports technologies such as renewable energy; energy-intensive industries; energy storage; and carbon capture, usage, and storage. The NER 300 program, which is part of this fund, provides approximately €2 billion (European Commission 2024a, b).

Although there is a widespread belief that carbon capture technologies require substantial public financing (Chu et al. 2024a, b), some experts suggest that the most successful projects should be conducted through public–private partnerships (Wang et al. 2021). According to the sustainable development scenario of the International Energy Agency, the construction of 70–100 carbon capture plants would require a total capital investment of between \$655 billion and \$1280 billion per year. Promoting private-sector investment is recommended to secure funding for carbon capture (Rassool 2021:3). Increasing the inflow of private capital into this technology is necessary because public capital currently accounts for over 60% of the total financing of carbon capture projects (Chen, et al. 2022). According to the Climate Change AR6 Synthesis Report (IPCC 2023:86), policy instruments, increased public support, and technological innovation can help reduce barriers to carbon capture deployment, including technological, economic, institutional, ecological, environmental, and socio-cultural factors. Similarly, the Global Status of CCS Report (2023) suggests that increased policy support can encourage private sector investment. The report predicts an increase in financing opportunities for carbon capture projects and a decrease in the associated risks. Overcoming financial barriers is crucial for increasing investment in carbon capture technology. Therefore, developing innovative financing strategies is important.

Risk management of innovative financial products is critical for carbon capture technology investment. Many risks are associated with the implementation processes of these projects. One of the biggest risks associated with carbon capture technologies is liquidity risk (Wu et al. 2024a, b). The main reason for this is that, although the initial investment costs of the project are very high, the payback period is long. This situation increases the project liquidity risk. Yang et al. (2023) argued that innovative financial products must be capable of managing this risk. In this context, liquidity risk should be managed more effectively owing to this financial product with its flexible repayment feature. Lermyte (2023) indicated that exchange rate risk is another type of risk important for carbon capture technology investments. Investors may have to import raw materials for these projects from abroad (Kabir et al. 2024; Bhatia et al. 2024). Therefore, they must pay for imported products in the foreign currency. He et al. (2023) stated that possible fluctuations in exchange rates may also make these products more expensive. This situation can cause business costs to increase radically. In this context, innovative financial products must contribute to the effective management of risk. In this process, foreign exchange risk insurance is offered as a new financial product (Aizenman et al. 2024). This product also protects investors from exchange rate fluctuations.

Conclusion

This study identifies a new and innovative financial product to increase the effectiveness of investments in carbon capture technologies. Within this framework, a novel AI-based fuzzy decision-making model is constructed. First, the weights of the experts were calculated by considering artificial intelligence methodology. Second, the factors affecting investment in carbon capture technologies were weighted using a spherical fuzzy DEMATEL. Finally, the financial features required for investments were ranked using the spherical fuzzy ARAS method. It is concluded that cost-effectiveness must be prioritized in the development of new financial products. Technological competence is another aspect that should be considered in this process. However, innovative financial products should include risk management and flexible financing.

It is possible to offer policy recommendations for an effective cost analysis when developing a new financial product. In this context, detailed planning should be conducted first. This allows the project management process to be conducted effectively. Based on this analysis, costs can be predicted in advance. Evaluation of alternative cost scenarios is another policy suggestion that should be considered. A more comprehensive perspective can be obtained by considering scenarios based on various assumptions. However, the possible risks of each cost item should be evaluated, and a risk analysis should be performed. Additionally, strategies can be developed to ensure high technological competence when developing new financial products. In this context, a company should create a culture that encourages innovation. This will contribute significantly to the development and implementation of more effective technologies. Similarly, companies can seek support from other businesses with expertise in this field to increase their technological competencies. Furthermore, continuous training and development opportunities should be provided for employees to maintain their technological skills.

The main contribution of this study is the creation of a novel fuzzy decision-making model by integrating artificial intelligence methodology with fuzzy decision-making theory. In this process, the weights of the experts are calculated using an artificial intelligence approach. For this purpose, the different demographic factors of these experts, such as salary, working experience, and education, were considered. This significantly contributed to the effectiveness of the findings. The main limitation of this study is that a country-specific evaluation was not conducted. Nonetheless, the analysis results can vary according to the specifications of this study. Hence, future studies should evaluate both developing and developed economies. However, the proposed model has some limitations. The ARAS methodology was considered when ranking the alternatives. Most ranking models, including ARAS, have been criticized by scholars for several reasons. Therefore, in future studies, a novel ranking technique can be introduced to overcome these limitations. This will positively contribute to the effectiveness of the analysis results.

Appendix

See Tables 11, 12, 13, 14, 15, 16, 17, 18, 19, 20 and 21

Table 11 Standardized features matrix

	Experience (year)	Education	Salary (€)
Expert 1	0.154	− 0.408	0.0
Expert 2	0.617	0.816	0.707
Expert 3	− 0.772	− 0.408	− 0.707

Table 12 Covariance matrix

	Experience (year)	Education	Salary (€)
Experience (year)	0.333	0.252	0.327
Education	0.252	0.333	0.289
Salary (€)	0.327	0.289	0.333

Table 13 Eigenvalues

	Values
Eigenvalue 1	0.913
Eigenvalue 2	0.0
Eigenvalue 3	0.087

Table 14 Eigenvector

Values
0.579
0.551
0.601

Table 15 Decision Matrix for DEMATEL

	COST			CSAT			LEGL			QUOP			MRKT			TECH		
COST	0.00	0.00	0.00	0.85	0.15	0.45	0.85	0.15	0.45	0.78	0.17	0.47	0.70	0.18	0.45	0.81	0.16	0.47
CSAT	0.44	0.24	0.29	0.00	0.00	0.00	0.29	0.27	0.23	0.60	0.20	0.35	0.70	0.18	0.45	0.78	0.17	0.47
LEGL	0.35	0.25	0.25	0.55	0.21	0.33	0.00	0.00	0.00	0.79	0.17	0.49	0.72	0.18	0.46	0.60	0.20	0.35
QUOP	0.81	0.16	0.47	0.44	0.23	0.29	0.44	0.23	0.29	0.00	0.00	0.00	0.29	0.27	0.23	0.29	0.27	0.23
MRKT	0.55	0.21	0.33	0.81	0.16	0.47	0.81	0.16	0.47	0.30	0.26	0.23	0.00	0.00	0.00	0.22	0.28	0.20
TECH	0.85	0.15	0.45	0.81	0.16	0.47	0.80	0.17	0.47	0.70	0.18	0.45	0.70	0.18	0.45	0.00	0.00	0.00

Table 16 Normalized sub-matrices

μ	**COST**	**CSAT**	**LEGL**	**QUOP**	**MRKT**	**TECH**
COST	0.000	0.213	0.213	0.197	0.176	0.202
CSAT	0.111	0.000	0.072	0.150	0.176	0.197
LEGL	0.088	0.137	0.000	0.197	0.180	0.150
QUOP	0.202	0.111	0.111	0.000	0.072	0.072
MRKT	0.137	0.202	0.202	0.075	0.000	0.056
TECH	0.213	0.202	0.199	0.176	0.176	0.000
v	**COST**	**CSAT**	**LEGL**	**QUOP**	**MRKT**	**TECH**
COST	0.000	0.129	0.129	0.144	0.159	0.140
CSAT	0.207	0.000	0.228	0.172	0.159	0.144
LEGL	0.215	0.183	0.000	0.149	0.156	0.172
QUOP	0.140	0.202	0.202	0.000	0.228	0.228
MRKT	0.183	0.140	0.140	0.226	0.000	0.240
TECH	0.129	0.140	0.142	0.159	0.159	0.000
π	**COST**	**CSAT**	**LEGL**	**QUOP**	**MRKT**	**TECH**
COST	0.000	0.196	0.196	0.206	0.197	0.205
CSAT	0.128	0.000	0.098	0.152	0.197	0.206
LEGL	0.109	0.145	0.000	0.212	0.201	0.152
QUOP	0.205	0.127	0.127	0.000	0.098	0.098
MRKT	0.145	0.205	0.205	0.100	0.000	0.087
TECH	0.196	0.205	0.206	0.197	0.197	0.000

Table 17 Total relationship matrix

	COST			**CSAT**			**LEGL**			**QUOP**			**MRKT**			**TECH**		
COST	0.40	0.30	0.41	0.51	.35	0.48	0.52	0.35	0.49	0.51	0.35	0.49	0.50	0.36	0.48	0.54	0.35	0.50
CSAT	0.38	0.44	0.39	0.30	0.37	0.33	0.35	0.45	0.38	0.38	0.44	0.39	0.40	0.43	0.41	0.43	0.42	0.42
LEGL	0.37	0.43	0.39	0.38	0.43	0.39	0.30	0.36	0.33	0.42	0.41	0.42	0.41	0.41	0.41	0.41	0.41	0.41
QUOP	0.38	0.46	0.38	0.32	0.48	0.34	0.32	0.48	0.34	0.25	0.41	0.28	0.30	0.49	0.33	0.31	0.48	0.34
MRKT	0.37	0.44	0.38	0.39	0.43	0.39	0.40	0.43	0.40	0.33	0.46	0.35	0.28	0.38	0.31	0.33	0.45	0.36
TECH	0.53	0.36	0.49	0.50	0.37	0.49	0.51	0.36	0.49	0.49	0.37	0.48	0.50	0.37	0.48	0.39	0.31	0.41

Table 18 Decision Matrix for ARAS

	COST			**CSAT**			**LEGL**			**QUOP**			**MRKT**			**TECH**		
PROF	0.31	0.69	0.26	0.10	0.90	0.00	0.23	0.77	0.14	0.37	0.63	0.27	0.33	0.67	0.23	0.31	0.70	0.22
SUST	0.32	0.69	0.23	0.28	0.73	0.18	0.23	0.77	0.14	0.29	0.72	0.24	0.32	0.69	0.23	0.76	0.24	0.18
TOPR	0.60	0.41	0.27	0.37	0.63	0.27	0.35	0.66	0.26	0.21	0.80	0.13	0.76	0.24	0.16	0.74	0.26	0.17
FLEX	0.84	0.16	0.08	0.87	0.13	0.05	0.90	0.10	0.00	0.85	0.15	0.07	0.85	0.15	0.07	0.84	0.16	0.07
SCAL	0.54	0.47	0.30	0.62	0.39	0.24	0.54	0.47	0.30	0.85	0.15	0.07	0.67	0.34	0.24	0.68	0.32	0.23
RISK	0.88	0.12	0.04	0.88	0.12	0.04	0.90	0.10	0.00	0.90	0.10	0.00	0.84	0.16	0.08	0.87	0.13	0.05

Table 19 Weighted decision matrix

	COST			CSAT			LEGL			QUOP			MRKT			TECH		
PROF	0.15	0.92	0.13	0.04	0.98	0.00	0.09	0.96	0.05	0.13	0.95	0.10	0.12	0.95	0.09	0.15	0.92	0.11
SUST	0.16	0.92	0.11	0.11	0.95	0.07	0.09	0.96	0.05	0.10	0.96	0.09	0.12	0.95	0.09	0.42	0.73	0.12
TOPR	0.31	0.81	0.16	0.15	0.94	0.11	0.14	0.94	0.11	0.07	0.97	0.04	0.33	0.83	0.09	0.40	0.74	0.11
FLEX	0.49	0.66	0.06	0.43	0.74	0.04	0.47	0.71	0.00	0.37	0.81	0.04	0.39	0.78	0.04	0.49	0.66	0.06
SCAL	0.28	0.84	0.17	0.26	0.87	0.11	0.22	0.89	0.14	0.37	0.81	0.04	0.27	0.86	0.12	0.36	0.78	0.14
RISK	0.54	0.61	0.04	0.44	0.74	0.03	0.47	0.71	0.00	0.42	0.77	0.00	0.38	0.79	0.05	0.52	0.64	0.04

Table 20 Optimal values

	COST			CSAT			LEGL			QUOP			MRKT			TECH		
Optimal	0.54	0.61	0.04	0.44	0.74	0.03	0.47	0.71	0.00	0.42	0.77	0.00	0.39	0.78	0.04	0.52	0.64	0.04

Table 21 S_i values

	Optimal			PROF			SUST			TOPR			FLEX			SCAL			RISK		
S	0.88	0.12	0.04	0.29	0.72	0.22	0.48	0.56	0.20	0.60	0.43	0.22	0.86	0.14	0.06	0.66	0.35	0.24	0.88	0.12	0.04
Score	2.94			−0.12			0.44			0.91			2.72			1.13			2.93		

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Author contributions
SY conceived of the study and participated in its design and coordination and helped to draft the manuscript. SE participated in the design of the study, performed the statistical analysis and helped to draft the manuscript. HD participated in the design of the study and performed the statistical analysis. YG participated in the design of the study and performed the statistical analysis. GO conceived of the study and participated in its design and coordination and helped to draft the manuscript. NO conceived of the study and participated in its design and coordination and helped to draft the manuscript. All authors read and approved the final manuscript.

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