A novel approach to prioritizing health technology investments using integrated AI-based ranking model

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Abstract

Purpose – Health technologies are an issue that directly affects the sustainability and quality of health services. Due to budget constraints, it is not financially possible for businesses to apply comprehensive improvement strategies to all these criteria. In this case, it is possible for businesses to implement more priority strategies. Accordingly, the main purpose of this study is to evaluate the important performance indicators of health technology investments.

Design/methodology/approach – Firstly, with the help of the artificial intelligence system, a decision matrix is established. Secondly, spherical fuzzy total order of preference decision-making trial and evaluation laboratory methodology is taken into consideration for weighting the criteria. Thirdly, emerging seven countries are ranked by using spherical fuzzy MultiAtributive Ideal-Real Comparative Analysis (MAIRCA).

Findings – The findings demonstrate that the criteria of health policies and research and development are defined as the most significant factor in this regard. China and Turkey are also found to be the most successful emerging countries with respect to the performance of health technology investments.

Originality/value – The main contribution of this study is that a novel decision-making model is generated by integrating artificial methodology into the spherical fuzzy sets.

Keywords Health technologies, Sustainability, Health investments, Strategy development, Decision making

Paper type Research paper

1. Introduction

Investments made to improve health services and ensure that patients receive better care can be considered within the scope of health technology investments. Investments in areas such as medical devices, health information technologies and remote health services are the main ones (Istepanian, 2022). These investments make significant contributions to improving the quality of health care and the sustainability of the health sector. Health technologies make it possible to make fast and effective diagnosis. Apart from this, remote monitoring of patients becomes easier. In this way, chronic diseases can be monitored more easily (Panda *et al.*, 2022). In addition, thanks to health technologies, accurate information about the history of diseases makes it possible to share data between health professionals (El Khatib *et al.*, 2022). Apart from these, one of the most important factors needed for the success of drug development processes is health technologies (Awad *et al.*, 2022). The need for health technologies is increasing day by day to reduce the cost of health services and ensure the sustainability of health services. If the correct and advanced technologies are not used, a decrease in the quality of the service provided can be observed. Additionally, patients' access to treatment and patient monitoring processes will be disrupted. Therefore, it will be difficult to ensure patient satisfaction.

It is essential to increase the effectiveness of health technologies, which have a significant impact on the health sector (McAlister *et al.*, 2022). Therefore, increasing investments in this

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area is important for sustainability (Groos, 2023). There are many factors that affect investments in the field of health technologies. To increase these investments, the demographic structure and health needs in the region where the investment will be made must be well defined (Yang *et al.*, 2022). If you are not successful in this regard, it is inevitable that it will remain an investment that the target audience will not be interested in. It is also important that the policy and legal framework implemented by decision-makers is at a level that will encourage investments (Goijaerts *et al.*, 2023). One of the most important topics of discussion, especially in electronic health records, is the storage and sale of data for commercial purposes. Drawing a legal framework to protect patients who are concerned about this issue will increase interest in health technologies. In addition, due to high investment costs, a large amount of funds is needed to realize technology investments (Henderson, 2023). Therefore, if investments are to be increased, tax reductions, exemptions or incentives should be widespread. Apart from these, the potential return of the project (Shao and Dou, 2022), the presence of qualified personnel (Kiplagat *et al.*, 2022) and the wide scope of insurance (Zhang *et al.*, 2022) are also important factors that will increase health technology investments.

Health technologies are an issue that directly affects the sustainability and quality of health services. For this reason, there are many studies in the literature investigating health technologies. However, these studies mostly emphasize the importance of health technologies or investigate the efficiency/effectiveness of a technological device. On the other hand, very few studies have been found on increasing investments in the field of health technologies. In this context, the health needs and characteristics of the demographic structure of the region to be invested in, the scope of existing policies and legal regulations, the level of existing technology, the size of R&D costs, the scope of health insurance, the potential return of the market and the availability of qualified personnel are important factors affecting the performance of these investments. Due to budget constraints, it is not financially possible for businesses to apply comprehensive improvement strategies to all these criteria. To solve this problem effectively, priority analysis for the variables needs to be done. In this way, it is possible to determine the most important factors affecting the performance of health technology investments. In this case, it is possible for businesses to implement more priority strategies. In this way, it is possible to make the right applications without incurring very high costs.

Accordingly, the main purpose of this study is to evaluate the important performance indicators of health technology investments. The main research question of this study is which factors should be prioritized while defining appropriate policies regarding health technology projects. In this context, a three-stage fuzzy decision-making model is generated. Firstly, with the help of the artificial intelligence system, decision matrix is established. Secondly, Spherical fuzzy total order of preference decision-making trial and evaluation laboratory (TOP-DEMATEL) methodology is taken into consideration for weighting the criteria. Thirdly, emerging seven countries are ranked by using Spherical fuzzy MAIRCA. The main motivation to make this study is that a novel decision-making model is needed. The main reason behind this situation is that existing decision-making models in the literature are criticized for some reasons. Hence, novel models should be generated by proposing new techniques. For instance, currently existing weighting methods are criticized because of inappropriate weight calculations in some cases. Thus, in this study, a novel fuzzy decision-making model is generated. In this model, TOP-DEMATEL technique is created by the authors to handle these criticisms.

The main contributions of this study are given below.

(1) A novel decision-making model is generated by integrating artificial methodology to the Spherical fuzzy sets. Most of the criticisms related to the fuzzy decision-making methodology is that the evaluations of all experts are considered with equal weights. However, because of some issues, such as demographic factors, the quality of these experts may be different. Hence, in this study, artificial methodology is taken into

consideration to create decision matrix. In this process, working experience of the experts are considered for the generation of this matrix. This situation has a positive influence on both appropriateness and originality of the proposed model.

(2) The generation of TOP-DEMATEL technique is another important contribution of this study. For the symmetrical evaluations, DEMATEL is criticized to provide inappropriate findings. To handle these problems, the steps of TOPSIS are combined to the classical DEMATEL approach. By making this integration, TOP-DEMATEL methodology is proposed. With the help of this new technique, more accurate evaluations can be made. Hence, more effective strategies can be identified for the investors to improve health technology investments.

The second part makes literature evaluation. The third part includes the details about the methodology. The fourth section highlights the results of the proposed model. The discussions and conclusions are explained in the final sections.

2. Literature review

This section presents a comprehensive literature review.

2.1 Health policies and regulations

One of the important issues affecting investments in the field of health technologies is the scope of health policies and regulations (Priyan *et al.*, 2024). It is possible to prevent this problem with the policies and regulations implemented. Apart from this, the implementation of incentive policies will increase the pace of investments in this field (Liu *et al.*, 2022a, b). How the new technologies to be developed will be integrated into the existing health system is also an important question mark. It is important that policies and regulations draw a good road map to resolve this issue. Wei and Huang (2022) examined tax regulations and supply chain coordination in green technology investments. It is stated that policies such as taxation affect investment. Chen *et al.* (2022) investigated the promotion of technology investments. It is underlined that there is a direct relationship between legal regulations and technology investments. Lyu *et al.* (2023) examined the impact of regulatory intervention on an automobile manufacturer’s investment in technology and innovation. It is emphasized that as the subsidy rate increases, innovation and technology investments increase.

2.2 High R&D costs

High R&D costs are another important factor affecting investments in the field of health technologies (Yoon *et al.*, 2023). These high costs can make it difficult to develop health technologies. Indirectly, the improvement that would be achieved through the technology to be developed in healthcare services would be deprived. In addition, high costs can increase the risk of projects by prolonging the time to develop health technologies (Shahzad *et al.*, 2023). Apart from these, investors will avoid investing in high-cost and risky projects. Yang and Chen (2022) conducted a study on increasing green technology investments to reduce carbon emissions. It is emphasized that the high technology investment costs affect the interest in these projects. Fuglie *et al.* (2022) investigated how efficiency policies in the form of higher agricultural R&D expenditures can affect greenhouse gas emissions from agriculture. In the study analyzed using simulations from a global economic model, it is stated that R&D costs affect investments in a negative way.

2.3 Demographic and epidemiological trends

The demographic structure and health needs in the region where the investment will be made affect the health technology investments to be made. Since the use of technological devices will be less in regions where the elderly population is concentrated, investing in technology in these regions will not be an optimal option (Li *et al.*, 2022). Apart from this, epidemiological trends also affect the use of health technologies. Infectious disease frequency, vaccines, and diagnostic tools may determine the level of use of these technologies (Wu, 2023). In addition, chronic disease status also significantly affects this process. In societies where chronic diseases are common, the need for health technologies for diagnosis and treatment may be greater. Brhlikova *et al.* (2023) examined health technology assessment approaches for prioritizing medicines. It states that a technology to be developed should cover all processes related to medicines and should be oriented to health needs. Jansky *et al.* (2023) evaluated open source digital health technologies for Type-1 diabetes care. It is recommended that the concept of patient-centered innovation be brought to the agenda and practices that encourage it be developed.

2.4 Market size and return potential

Another important issue affecting investment decisions in the field of health technologies is the market size and the size of the potential return (Fang *et al.*, 2022). A large market will increase the potential earnings of investments. In this way, more investors will be involved in the process. Moreover, a large market will also increase the growth potential of health technologies. Therefore, a growing market will attract investors' attention (Song, 2023). Castello Esquerdo (2023) aimed to examine the determinants of foreign direct investment of Chinese technology into Latin America. According to the study, which states that the determinants of technology investments are diverse, market size is also an important factor. Zhang *et al.* (2023a, b) examined the impact of green technology investments on supply chain integration decisions. It is determined that investment decisions are significantly affected by competition and market size.

2.5 Gaps in the literature and contribution of the study

The results obtained as a result of the literature review are important for the future of healthcare enterprises. Technology has an active role in both the delivery and sustainability of health services. Accordingly, technology has a great place in carrying out diagnosis and treatment processes. Apart from this, technology is needed to develop drugs, medical devices, and new treatment methods. In addition, storing the big data obtained and guiding policies is possible with technology. Therefore, the importance of health technology investments for the sustainability of health services is undeniable. However, when the studies in the literature are examined, it is seen that the analysis of health technologies or the cost analysis of a specific technological device is generally made. No study aimed at increasing investments in health technologies could be found. However, there are many factors that affect increasing health technology investments. It may not be possible to intervene in all of these factors at the same time. For this reason, the aim of this study is to create a list of criteria affecting health technology investments, add them to the literature, and develop a strategy by weighting these criteria according to their importance. In this study, a new model is developed by integrating artificial intelligence and fuzzy decision-making methodology. Owing to this model, the most important factors affecting the performance of health technology investments are determined. In this way, it is aimed to contribute to eliminating this deficiency stated in the literature.

3. Methodology

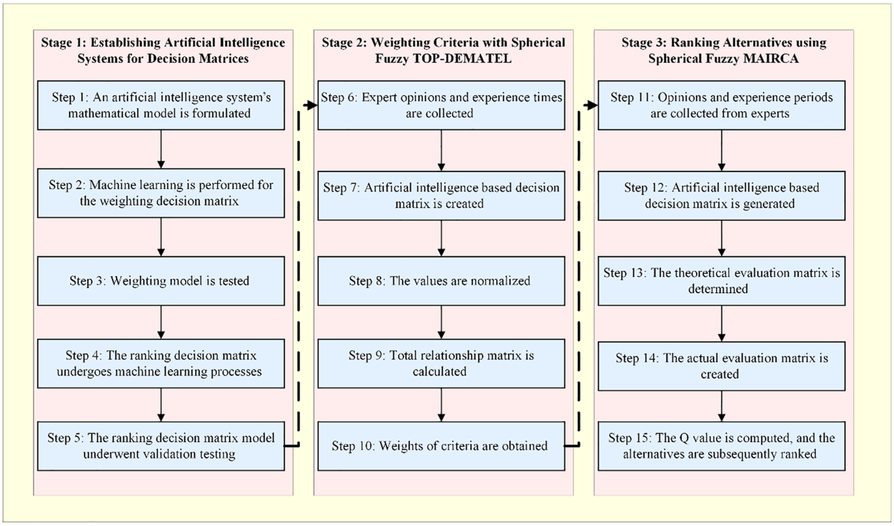
In this study, a methodology is introduced for identifying the paramount criterion and the most suitable country in the context of health technology investments. A hybrid multi-criteria decision-making approach is employed to assess these objectives. The TOP-DEMATEL method is applied to determine the utmost important criterion, while the MAIRCA method is utilized to identify the optimal alternative. In both methodologies, Spherical fuzzy numbers, a current fuzzy number version, are integrated to accommodate uncertainty. Furthermore, an artificial intelligence system is deployed to construct the decision matrices for these methods. The procedural steps of this proposed hybrid method are succinctly outlined in Figure 1.

The details of the mathematical steps of the methods used in the study are presented under subtitles.

3.1 Artificial intelligence-based decision matrices

In multi-criteria decision-making methods, one of the initial steps involves the generation of decision matrices. In systems reliant on expert opinions, the conventional practice of creating a decision matrix through the aggregate of evaluations has faced criticism in the literature (Hentout *et al.*, 2023). Numerous studies posit that assigning equal importance to experts with varying levels of experience is not methodologically sound. In response to these critiques, the study proposes an artificial intelligence model designed to factor in the expertise periods of experts (Kushwaha *et al.*, 2023). The essential steps of this model are detailed and outlined below.

In *Step 1*, the mathematical model of the artificial intelligence system is formulated. Artificial intelligence systems consist of three fundamental elements: the number of layers, activation function, and parameter calculation algorithm. The number of layers contributes to the system's capacity to learn complex patterns and establish non-linear connections between input and output variables. The activation function transforms the cumulative value in neurons before transmitting it to the subsequent neuron. In the proposed artificial intelligence model, a total of 9 layers are utilized, with 7 designated as hidden layers. The input layer is structured with two variables: experts' opinions and years of experience. The output layer is defined to represent the components of the Spherical fuzzy number. The sigmoid function as the activation function in the layers is preferred by its compatibility with the domain of fuzzy numbers. In contrast to other activation functions such as ReLu and Linear, the Sigmoid function's output range between 0 and 1 (Souayeh and Sabir, 2023). The Sigmoid function is expressed by Equation (1), where the variable *e* represents the Euler number.



Source(s): Authors'

Figure 1. Flowchart

$$S(x) = \frac{1}{1 + e^{-ax}} \quad (1)$$

Optimization algorithms are employed to compute connection values between neurons, minimizing errors. The Adam algorithm, one of the optimization algorithms, are favored for their ability to perform efficient calculations with small datasets (Reyad *et al.*, 2023). The mathematical details of the algorithm are given in Equations (2–6).

$$W_{t+1} = W_t - \frac{a}{\sqrt{\widehat{S}_t + \epsilon}} \widehat{V}_t \quad (2)$$

$$\widehat{V}_t = \frac{V_t}{1 - \beta_1^t} \quad (3)$$

$$\widehat{S}_t = \frac{S_t}{1 - \beta_2^t} \quad (4)$$

$$V_t = \beta_1 V_{t-1} + (1 - \beta_1) \frac{\partial L}{\partial w_t} \quad (5)$$

$$S_t = \beta_2 S_{t-1} + (1 - \beta_2) \left[\frac{\partial L}{\partial w_t} \right]^2 \quad (6)$$

In this context, a demonstrates learning coefficient, w gives information about the weight, β indicates the degree to which past gradients are involved in the process and $\frac{\partial L}{\partial w_t}$ refers to the gradient. *S* and *V* are also randomly determined initial values.

Step 2 is associated with the machine learning phase of the artificial intelligence model. The model undergoes training to acquire the decision matrix utilized in the SF TOP-DEMATEL method for criterion weighting. The machine learning dataset is generated through simulation technique. The expert opinions are represented in a manner using Spherical Fuzzy numbers, as detailed in Table 1.

Subsequently, the output variable is computed employing Equations (7) and (8).

$$SWAM = \left\{ \left[1 - \prod_{i=1}^{n} \left(1 - \mu_i^2\right)^{w_i} \right]^{\frac{1}{2}}, \prod_{i=1}^{n} v_i^{w_i}, \left[\prod_{i=1}^{n} \left(1 - \mu_i^2\right)^{w_i} - \prod_{i=1}^{n} \left(1 - \mu_i^2 - \pi_i^2\right)^{w_i} \right]^{\frac{1}{2}} \right\} \quad (7)$$

Table 1. Linguistic variable for weighting

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

Source(s): Yüksel *et al.* (2024)

$$w_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{8}$$

In Equations (7) and (8), the variable *d* represents the expert's years of experience, while μ, *v*, and *π* values signify the membership degree, non-membership degree, and hesitancy degree of the Spherical fuzzy number, respectively.

In *Step 3,* the artificial intelligence model is tested, where error terms are considered to evaluate the success of the machine learning process. The Mean Squared Error (MSE) value is computed by mean the squares of the error terms, as illustrated in Equation (9) (Blair and Bar-Shalom, 2023).

$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left(Y_i - \widehat{Y}_i\right)^2 \tag{9}$$

Where, *Y* represents the actual value and $\widehat{Y}$ is the output value of the model. *m* is number of data. A *MSE* value close to zero signifies a high learning success for the model. A lower *MSE* indicates a higher accuracy of the machine learning model.

Step 4 is similar Step 2, employing Equations (7) and (8). The distinction lies in the fact that, in this step, the output value is configured as a decision matrix intended for ranking purposes. The Spherical Fuzzy number equivalents of expert opinions in Table 2 are considered.

In *Step 5*, the validity of the artificial intelligence model, trained for ranking, is evaluated by considering the *MSE* value given in Equation (9). Similarly, for the validity of the model, this value should be close to 0.

3.2 Spherical fuzzy TOP-DEMATEL

The DEMATEL method is employed to assess the importance weights of factors influencing a given objective, considering the effect among these factors (Özdemirci *et al.*, 2023). However, the subsequent step of weight calculation following the assessment of effects has faced criticism in the literature (Oflaz *et al.*, 2023). Because of these critiques, the TOP-DEMATEL method is utilized. The procedural steps of this model are outlined as follows (Eti *et al.*, 2023).

In *Step 6*, expert opinions and experience times are collected. Utilizing the linguistic expressions provided in Table 1, experts engage in pairwise comparisons of the criteria. In

Table 2. Linguistic variables for ranking

Terms	μ	*v*	*π*
Absolutely low importance	0.1	0.9	0
Very low importance	0.2	0.8	0.1
Low importance	0.3	0.7	0.2
Slightly low importance	0.4	0.6	0.3
Equal importance	0.5	0.5	0.4
Slightly more importance	0.6	0.4	0.3
More importance	0.7	0.3	0.2
Very more importance	0.8	0.2	0.1
Absolutely more importance	0.9	0.1	0

Source(s): Pamucar *et al.* (2024)

Step 7, the assessments and experience durations acquired from the expert team are used as input for the artificial intelligence model designed for weighting. By leveraging these two input variables, a Spherical Fuzzy decision matrix is generated through the artificial intelligence model. The direct relationship matrix (D) derived from artificial intelligence is expressed in Equation (10).

$$D = \begin{bmatrix} 0 & \cdots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ \vdots & \ddots & \vdots \\ (\mu_{n1}, v_{n1}, \pi_{n1}) & \cdots & 0 \end{bmatrix} \tag{10}$$

Step 8 involves normalization of the values. Initially, the D matrix is partitioned into three sub-matrices based on the components of the Spherical Fuzzy number. Subsequently, these three sub-matrices undergo normalization using Equations (11) and (12).

$$X = sD \tag{11}$$

$$s = \min\left[\frac{1}{\max\limits_{i} \sum\limits_{j=1}^{n} |d_{ij}|}, \frac{1}{\max\limits_{j} \sum\limits_{i=1}^{n} |d_{ij}|}\right] \tag{12}$$

Step 9 is the computation of the Total Relationship Matrix. The Total Relationship Matrix (T) is determined by applying Equation (13) to each normalized matrix (X).

$$T = X * (1 - X)^{-1} \tag{13}$$

For the resulting T matrix with the definition of a spherical fuzzy set, Euclidean normalization is applied. Subsequently, the obtained values are defuzzied stationary through the utilization of Equation (14).

$$Score = \mu^t - \eta^t - \nu^t \tag{14}$$

Here, μ^t, η^t and ν^t, represent the components of the Spherical fuzzy total relationship matrix, respectively.

In *Step 10*, criterion weights are obtained using Equations (15–22).

$$C_j^* = \sqrt{\sum_{i=1}^{n} \left(t_i - \max_j t_i\right)^2} \; j = 1, 2, ..n \tag{15}$$

$$C_j^- = \sqrt{\sum_{i=1}^{n} \left(t_i - \min_j t_i\right)^2} \; j = 1, 2, ..n \tag{16}$$

$$R_i^* = \sqrt{\sum_{j=1}^{n} \left(t_j - \max_i t_j\right)^2} \; i = 1, 2, ..n \tag{17}$$

$$R_i^- = \sqrt{\sum_{j=1}^{n}\left(t_j - \max_i t_j\right)^2}\ i = 1, 2, ..n \tag{18}$$

$$S_i^* = C_i^* + R_i^* \tag{19}$$

$$S_i^- = C_i^- + R_i^- \tag{20}$$

$$w_i = \frac{S_i^-}{S_i^- + S_i^*} \tag{21}$$

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{22}$$

3.3 Spherical fuzzy MAIRCA

MAIRCA is a multi-criteria decision-making technique employed for ranking alternatives. In this approach, the total gap between expert evaluations and theoretical evaluations is quantified (Hezam *et al.*, 2023). The procedural steps of the model, integrated with Spherical Fuzzy numbers, are delineated below.

In *Step 11*, a team of experts is formed, tasked with evaluating the alternatives based on criteria. During the evaluation process, the scores presented in Table 2 are considered, along with the collection of the experts' experience periods.

In *Step 12*, the decision matrix is generated from the ranking artificial intelligence model. The experts' evaluation scores and experience periods serve as input to the model, resulting in the generation of the spherical fuzzy decision matrix (Z) in Equation (23).

$$Z = \begin{bmatrix} (\mu_{11}, v_{11}, \pi_{11}) & \cdots & (\mu_{1n}, v_{1n}, \pi_{1n}) \\ \vdots & \ddots & \vdots \\ (\mu_{m1}, v_{m1}, \pi_{m1}) & \cdots & (\mu_{mn}, v_{mn}, \pi_{mn}) \end{bmatrix} \tag{23}$$

In *Step 13*, the theoretical evaluation matrix (K_p) is determined. Utilizing the uniform probability distribution, the theoretical evaluation matrix is calculated through the application of Equations (24) and (25).

$$P_{Bi} = \frac{1}{m} \tag{24}$$

$$K_p = \begin{bmatrix} k_{p11} & \cdots & k_{p1n} \\ \vdots & \ddots & \vdots \\ k_{pm1} & \cdots & k_{pmn} \end{bmatrix} = \begin{bmatrix} P_{B1}w_1 & \cdots & P_{B1}w_n \\ \vdots & \ddots & \vdots \\ P_{Bm}w_1 & \cdots & P_{Bm}w_n \end{bmatrix} \tag{25}$$

Here, P_{Bi} denotes the probability of preference, and w represents the weights of criteria.

Step 14 is concerned with creating the actual evaluation matrix (K_r). Initially, the Z matrix is defuzzied with the help of Equation (14) and normalized, followed by multiplication with the values of the theoretical evaluation matrix in this step. These operations are conducted using Equations (26) and (27).

$$k_{rij} = k_{pij}\left(\frac{S\left(\widetilde{z}_{ij}\right) - \min\left(S\left(\widetilde{z}_{ij}\right)\right)}{\max\left(S\left(\widetilde{z}_{ij}\right)\right) - min\left(S\left(\widetilde{z}_{ij}\right)\right)}\right) \text{ if benefit criteria} \tag{26}$$

$$k_{rij} = k_{pij}\left(\frac{S\left(\widetilde{z}_{ij}\right) - \max\left(S\left(\widetilde{z}_{ij}\right)\right)}{\min\left(S\left(\widetilde{z}_{ij}\right)\right) - max\left(S\left(\widetilde{z}_{ij}\right)\right)}\right) \text{ if cost criteria} \tag{27}$$

S(Z) function is the score value of spherical fuzzy *z* number.

In *Step 15*, *Q* values are computed. In this stage, the difference between the theoretical evaluation and the actual evaluation values (*G*) is calculated and aggregated. A smaller total gap (*Q*) signifies that the alternative is more suitable. *Q* value is calculated by Equation (28) and (29).

$$G = K_p - K_r = \begin{bmatrix} g_{11} & \cdots & g_{1n} \\ \vdots & \ddots & \vdots \\ g_{m1} & \cdots & g_{mn} \end{bmatrix} = \begin{bmatrix} k_{p11} - k_{r11} & \cdots & k_{p1n} - k_{r1n} \\ \vdots & \ddots & \vdots \\ k_{pm1} - k_{rm1} & \cdots & k_{pmn} - k_{rmn} \end{bmatrix} \tag{28}$$

$$Q = \sum g_{ij} \tag{29}$$

4. Analysis results

The objective is to identify the factors influencing health technology investments and rank the E7 countries accordingly. The step-by-step analysis results aligned with this goal are presented below.

4.1 Establishing artificial intelligence systems for decision matrices (stage 1)

In *Stage 1*, decision matrices, to be utilized in multi-criteria decision-making techniques, are established through artificial intelligence systems. These two matrices are created, involving a sequence of 5 steps.

Step 1: An artificial intelligence system's mathematical model is formulated.

In *Step 1*, an artificial intelligence model comprising 9 layers is established. The layer structure included 128, 64, 32, 16, 8, 4, and 2 neurons, respectively. The Sigmoid function, as defined in Equation (1), is employed as the activation function for each layer. Parameter calculations between layers are computed using the Adam algorithm described in Equations (2–6). The output layer is configured with a three-component structure. The model's software is implemented using the Keras and TensorFlow libraries in Python.

Step 2: Machine learning is performed for the weighting decision matrix

In *Step 2*, machine learning is performed through simulation using a dataset encompassing 3,000 expert opinions and experience periods. The values from Table 1 are considered in formulating the output variable, which is generated with the help of Equations (7) and (8). Artificial intelligence machine learning has epoch 100 iterations with this dataset. The iterative and the specified number of iterations aim to minimize the error.

Step 3: Weighting model is tested.

In *Step 3*, the weighting model is subjected to testing, utilizing Equation (9) as a metric for assessing success. *MSE* value for the model, implemented with a 3,000-train dataset, is calculated as 0.0041. The proximity of this value to zero suggests the success of the model.

Step 4: The ranking decision matrix undergoes machine learning processes.

In *Step 4*, the machine learning process for the ranking decision matrix is undergone. The artificial intelligence model is trained with 1,000 simulation data, considering the values in Table 2. In the training process, 100 epochs are utilized to enhance the learning success of the model.

Step 5: The ranking decision matrix model underwent validation testing.

Step 5 is executed to assess the success of the ranking decision matrix. Equation (9) is employed for testing the validity of the ranking artificial intelligence model, yielding a calculated *MSE* value of 0.0028, which is in close to zero.

4.2 Weighting criteria with spherical fuzzy TOP-DEMATEL (stage 2)

In *Stage 2*, indicators of health technology investments, as identified in the literature, undergo a weighting process. This stage is included 5 steps.

Step 6: Expert opinions and experience times are collected.

In *Step 6*, a team of experts, comprising individuals with academic expertise or holding managerial positions in the field, is formed. The experience periods for these experts are 15, 23, and 17. Table 3 gives information about the selected criteria.

The details of the opinions gathered from these experts are outlined in Table A1.

Step 7: Artificial intelligence-based decision matrix is created.

In *Step 7*, the opinions in Table A1 and experience periods of the experts are inputted into the weighting artificial intelligence model. Following the evaluation of the artificial intelligence model, the initial direct matrix is created. The representation of the initial direct matrix (D) is shown in Table 4.

Step 8: The values are normalized.

In *Step 8*, the D matrix is partitioned into 3 submatrices, which are subsequently normalized using Equations (11) and (12). The normalized submatrices are presented in Table A2.

Step 9: Total relationship matrix is calculated.

In *Step 9*, total relationship matrix (T) is calculated with the help of Equation (13). Then, Euclidean normalization is applied to the values of T. Finally, the spherical fuzzy T matrix is defuzzied using Equation (14). Total relationship matrix is figured in Table A3.

Step 10: Weights of criteria are obtained.

Step 10 involves the weighting of criteria (w), using Equations (15–22) for calculating the criterion weights. The outcomes of the criterion weights are presented in Table 5.

Table 3. Criteria list

Selected criteria	Codes
Scope of health policies and regulations	SHPR
Size of R&D costs	SRDC
Health needs and demographics	HND
Level of available technology	LAT
Coverage of health insurance and financing	CHIF
Size of the market and potential returns	SMPR
Qualification of personnel	QP

Source(s): Authors'

Table 4. Initial direct matrix

	Scope of health policies and regulations (SHPR)			Size of R&D costs (SRDC)			Health needs and demographics (HND)			Level of available technology (LAT)			Coverage of health insurance and financing (CHIF)			Size of the market and potential returns (SMPR)			Qualification of personnel (QP)		
Scope of health policies and regulations (SHPR)	0.00	0.00	0.00	0.44	0.25	0.34	0.67	0.20	0.44	0.77	0.17	0.48	0.63	0.21	0.43	0.34	0.26	0.28	0.72	0.18	0.46
Size of R&D costs (SRDC)	0.72	0.18	0.46	0.00	0.00	0.00	0.67	0.20	0.44	0.15	0.30	0.16	0.52	0.24	0.39	0.52	0.24	0.39	0.77	0.17	0.48
Health Needs And Demographics (HND)	0.77	0.17	0.48	0.67	0.20	0.44	0.00	0.00	0.00	0.77	0.17	0.48	0.67	0.20	0.44	0.77	0.17	0.48	0.42	0.25	0.33
Level of available technology (LAT)	0.60	0.22	0.42	0.67	0.20	0.44	0.15	0.30	0.16	0.00	0.00	0.00	0.52	0.24	0.39	0.67	0.20	0.44	0.52	0.24	0.39
Coverage of health insurance and financing (CHIF)	0.15	0.30	0.16	0.77	0.17	0.48	0.52	0.24	0.39	0.15	0.30	0.16	0.00	0.00	0.00	0.67	0.20	0.44	0.52	0.24	0.39
Size of the market and potential returns (SMPR)	0.77	0.17	0.48	0.52	0.24	0.39	0.77	0.17	0.48	0.77	0.17	0.48	0.77	0.17	0.48	0.00	0.00	0.00	0.77	0.17	0.48
Qualification of personnel (QP)	0.74	0.18	0.47	0.74	0.18	0.47	0.42	0.25	0.33	0.77	0.17	0.48	0.52	0.24	0.39	0.77	0.17	0.48	0.00	0.00	0.00

Source(s): Authors'

Table 5. Weighting results

Indicators	Weights
SHPR	0.1546
SRDC	0.1485
HND	0.1429
LAT	0.1458
CHIF	0.1275
SMPR	0.1387
QP	0.1420

Source(s): Authors'

According to the results of the SF TOP-DEMATEL analysis, the criteria of health policies and R&D have been identified as the most significant, given their higher weight values. Conversely, the criterion of insurance is determined to be the least important.

4.3 Ranking alternatives using spherical fuzzy MAIRCA (stage 3)

In *Stage 3*, E7 countries are ranked in 5 steps using the Spherical Fuzzy MAIRCA method.

Step 11: Opinions and experiences periods are collected from experts.

In *Step 11*, the assembled expert team evaluates the alternatives using the linguistic variables outlined in Table 2. The expert evaluations are shared in Table A4.

Step 12: Artificial intelligence-based decision matrix is generated.

In *Step 12*, the opinions in Table A4 and experience periods of the experts are inputted into the ranking artificial intelligence model. Following the evaluation of the artificial intelligence model, the decision matrix is created. The representation of decision matrix (Z) is shown in Table 6.

Step 13: The theoretical evaluation matrix is determined.

With the help of Equations (24) and (25), the theoretical evaluation matrix is computed in *Step 13*. In this calculation, the value of m is set to 7, and the values in Table 4 are employed as w values. The theoretical evaluation matrix is given in Table A5.

Step 14: The actual evaluation matrix is created.

In *Step 14*, the actual evaluation matrix is created using Equations (26) and (27). The actual evaluation matrix is presented in Table A6.

Step 15: The Q value is computed, and the alternatives are subsequently ranked.

In *Step 15*, the ranking of countries is executed, wherein Q values are computed using Equations (28) and (29). The Q values are provided in Table 7.

The rankings of the countries, based on their Q values, are illustrated in Figure 2.

According to Figure 2, the best countries in terms of health technology investments are China and Turkey. Indonesia and Russia are other successful countries emerging countries in this context. However, the performance of Mexico and Brazil is lower in comparison with other countries. In order to test the consistency of the results, an analysis is also performed with the AHP method. The results of this analysis are presented in Table 8.

AHP analysis results are similar to MAIRCA analysis results. It can be said that the analysis results are consistent.

Table 6. Decision matrix

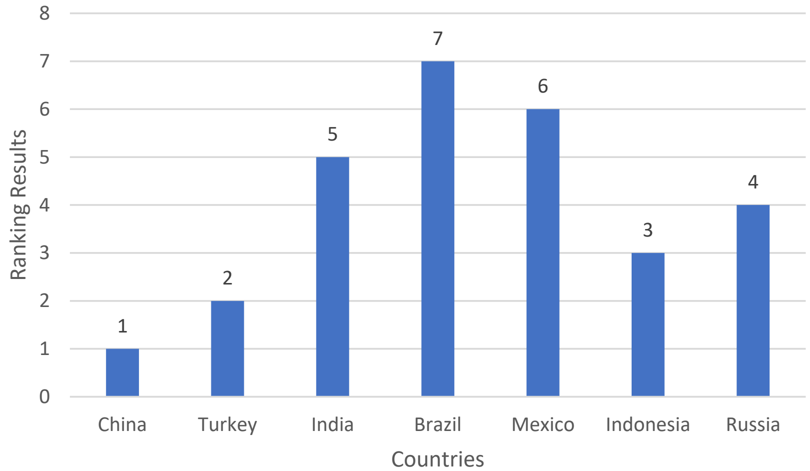
	SHPR			SRDC			HND			LAT			CHIF			SMPR			QP		
China	0.63	0.39	0.19	0.78	0.23	0.17	0.59	0.44	0.20	0.81	0.20	0.17	0.53	0.50	0.20	0.59	0.44	0.20	0.73	0.28	0.18
Turkey	0.48	0.55	0.21	0.27	0.76	0.24	0.84	0.18	0.16	0.73	0.28	0.18	0.18	0.84	0.25	0.59	0.44	0.20	0.69	0.33	0.18
India	0.46	0.57	0.21	0.18	0.84	0.25	0.57	0.46	0.20	0.37	0.66	0.22	0.37	0.66	0.22	0.18	0.84	0.25	0.48	0.55	0.21
Brazil	0.27	0.76	0.24	0.18	0.84	0.25	0.28	0.75	0.23	0.27	0.76	0.24	0.28	0.75	0.23	0.27	0.76	0.24	0.78	0.24	0.17
Mexico	0.18	0.84	0.25	0.69	0.33	0.18	0.27	0.76	0.24	0.27	0.76	0.24	0.69	0.33	0.18	0.18	0.84	0.25	0.27	0.76	0.24
Indonesia	0.33	0.70	0.23	0.19	0.83	0.25	0.85	0.16	0.16	0.45	0.58	0.21	0.59	0.44	0.20	0.59	0.44	0.20	0.18	0.84	0.25
Russia	0.70	0.32	0.18	0.64	0.39	0.19	0.19	0.83	0.25	0.73	0.28	0.18	0.27	0.76	0.24	0.18	0.84	0.25	0.43	0.60	0.21

Source(s): Authors’

Table 7. Ranking results

Countries	*Q*
China	0.0184
Turkey	0.0526
India	0.0997
Brazil	0.1090
Mexico	0.1015
Indonesia	0.0748
Russia	0.0757

Source(s): Authors'



Source(s): Authors'

Figure 2. Alternatives results

Table 8. Comparative analysis

Countries	MAIRCA	AHP
China	1	1
Turkey	2	2
India	5	5
Brazil	7	7
Mexico	6	6
Indonesia	3	3
Russia	4	4

Source(s): Authors'

5. Discussion

According to the analysis results, the factor that most affects investments in the field of health technologies is the scope of health policies and regulations. Health policies and regulations are the basic elements that direct the health system of a country. Financial regulations and incentives may affect investments in health technologies. In addition, effective competition and market regulations can increase investments. Apart from this, individuals are sensitive about their health data. Health technologies are also important because they process health data. Regulations to be made in this regard also have the potential to increase investments. Therefore, ensuring that policies and regulations are fair, sustainable, and balanced can increase investments in health technologies. Zhang and Ren (2023) aimed to create a new governance model to promote environmentally friendly technology transfer between China and other countries. It is underlined that there are legal gaps in the field of technology transfer and technology investment. Lyu *et al.* (2023) investigated how regulatory intervention affects an automaker's investments in green technology and innovation. It is emphasized that the regulations are effective in directing the investments to be made. Liu *et al.* (2022a, b) and Meckling and Strecker (2023) stated that regulations have an important place in technology investments.

Another important factor affecting investments in the field of health technologies is R&D costs. R&D plays a key role in the development of innovative products and services, such as new treatment methods, diagnostic tools or digital health solutions. Accordingly, the size of the budget that businesses will allocate for R&D is of great importance. The fact that the costs are at reasonable levels will also affect the price of the new service or vehicle to be launched on the market. This will provide a competitive advantage to the business. Therefore, it can be said that R&D costs significantly affect investments in the field of health technologies. Zhang *et al.* (2023a, b) stated that R&D costs are an obstacle to investing and this can be prevented with incentives. Henderson *et al.* (2023) focused on the costs of bringing precision oncology drugs from research and development to market. It is stated that reducing R&D costs is very beneficial for the sector. Feng and Liu (2022) examined the impact of green R&D cost on prices, green levels and operating profits. It is defined in the results of the study that R&D costs affect many issues, including prices.

E7 countries play an important role in the global arena due to their economic growth, strategic location, and population size. For this reason, it is possible to develop new products and initiatives through investments in the field of health technologies in E7 countries. In this way, it can contribute to the growth of the domestic economy. Furthermore, having a strong infrastructure in the field of health technologies can make E7 countries more competitive in the global arena. Therefore, health technologies developed for export may enable us to have a greater say in the global market. Accordingly, greater investment in health technologies can provide economic and social advantages as well as improving the quality of health services. Shahzad *et al.* (2023) examined the impact of corporate ownership on the moral hazards of technology investment in China. Ji *et al.* (2022) evaluated the impact of information technology investment on firm innovation performance. It is understood from the study that China is in a good position in technology investments. Hamid and Wang (2023) studied green innovation efficiency in BRICS countries. It is understood that Turkey is successful in terms of green innovation efficiency.

6. Conclusion

This study examines the essential performance indicators of health technology investments. For this purpose, a three-stage fuzzy decision-making model is generated. Firstly, with the help of the artificial intelligence system, decision matrix is established. Secondly, Spherical fuzzy TOP-DEMATEL methodology is taken into consideration for weighting the criteria. Thirdly, emerging seven countries are ranked by using Spherical fuzzy MAIRCA. The findings demonstrate that the criteria of health policies and R&D are defined as the most significant factor in this regard. On the other side, the criterion of insurance is determined as the least important. China and Turkey are also found as the most successful emerging countries with respect to the performance of health technology investments. Indonesia and Russia are other successful countries emerging countries in this context. However, the performance of Mexico and Brazil is lower in comparison with other countries.

The theoretical contribution of this study is that it provides a model for evaluating complex processes such as health policies and investment strategies. In addition, it is possible to compare the health technology investment performances of countries with the spherical fuzzy MAIRCA method. An important practical implication is that health policies play a fundamental role in health technology investments. Policymakers should know that they need to consider this if they aim for an improvement in this area. In addition, the impact of R&D on investments should not be ignored by authorities. The roadmap that emerging countries such as China and Turkey should follow is indicated. In addition, investors considering investing in the health technology field can act more consciously by taking the criteria list presented in this study as a guide.

The main contribution of this study is that a novel decision-making model is generated by integrating artificial methodology to the Spherical fuzzy sets. In this process, working experience of the experts are considered for the generation of this matrix. The generation of TOP-DEMATEL technique is another important contribution of this study. The main limitation of this study is that the analysis is performed for only emerging countries. Nevertheless, health technology investments play also a crucial role for developed countries. Hence, in the following evaluations, developed countries can be taken into consideration. Moreover, the limitation of the proposed model is that only working experience is considered to differentiate the experts. However, the quality of the experts may depend on some other factors, such as educational level. Therefore, for future research direction, many different factors can also be considered to weight the experts.

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Appendix

Table A1. Experts opinions for weighting

	SHPR	SRDC	HND	LAT	CHIF	SMPR	QP
Expert 1							
SHPR	0	3	3	4	2	2	4
SRDC	4	0	3	1	2	2	4
HND	4	3	0	4	3	4	1
LAT	3	3	1	0	2	3	2
CHIF	1	4	2	1	0	3	2
SMPR	4	2	4	4	4	0	4
QP	3	3	1	4	2	4	0
Expert 2							
SHPR	0	1	3	4	3	1	3
SRDC	3	0	3	1	2	2	4
HND	4	3	0	4	3	4	2
LAT	2	3	1	0	2	3	2
CHIF	1	4	2	1	0	3	2
SMPR	4	2	4	4	4	0	4
QP	4	4	2	4	2	4	0
Expert 3							
SHPR	0	2	3	4	3	2	4
SRDC	4	0	3	1	2	2	4
HND	4	3	0	4	3	4	2
LAT	3	3	1	0	2	3	2
CHIF	1	4	2	1	0	3	2
SMPR	4	2	4	4	4	0	4
QP	4	4	2	4	2	4	0

Source(s): Authors'

Table A2. Normalized submatrices

	SHPR	SRDC	HND	LAT	CHIF	SMPR	QP
SHPR	0.0000	0.1016	0.1524	0.1760	0.1445	0.0787	0.1661
SRDC	0.1661	0.0000	0.1524	0.0351	0.1198	0.1198	0.1760
HND	0.1760	0.1524	0.0000	0.1760	0.1524	0.1760	0.0963
LAT	0.1381	0.1524	0.0351	0.0000	0.1198	0.1524	0.1198
CHIF	0.0351	0.1760	0.1198	0.0351	0.0000	0.1524	0.1198
SMPR	0.1760	0.1198	0.1760	0.1760	0.1760	0.0000	0.1760
QP	0.1702	0.1702	0.0963	0.1760	0.1198	0.1760	0.0000
SHPR	0.0000	0.1708	0.1386	0.1199	0.1445	0.1812	0.1281
SRDC	0.1281	0.0000	0.1386	0.2077	0.1630	0.1630	0.1199
HND	0.1199	0.1386	0.0000	0.1199	0.1386	0.1199	0.1731
LAT	0.1493	0.1386	0.2077	0.0000	0.1630	0.1386	0.1630
CHIF	0.2077	0.1199	0.1630	0.2077	0.0000	0.1386	0.1630
SMPR	0.1199	0.1630	0.1199	0.1199	0.1199	0.0000	0.1199
QP	0.1248	0.1248	0.1731	0.1199	0.1630	0.1199	0.0000
SHPR	0.0000	0.1224	0.1570	0.1720	0.1526	0.1010	0.1652
SRDC	0.1652	0.0000	0.1570	0.0568	0.1400	0.1400	0.1720
HND	0.1720	0.1570	0.0000	0.1720	0.1570	0.1720	0.1174
LAT	0.1492	0.1570	0.0568	0.0000	0.1400	0.1570	0.1400
CHIF	0.0568	0.1720	0.1400	0.0568	0.0000	0.1570	0.1400
SMPR	0.1720	0.1400	0.1720	0.1720	0.1720	0.0000	0.1720
QP	0.1679	0.1679	0.1174	0.1720	0.1400	0.1720	0.0000

Source(s): Authors'

Table A3. Total relationship matrix

	SHPR	SRDC	HND	LAT	CHIF	SMPR	QP
SHPR	−0.1267	−0.1608	−0.1400	−0.1365	−0.1472	−0.1639	−0.1402
SRDC	−0.1544	−0.1373	−0.1505	−0.1859	−0.1681	−0.1685	−0.1485
HND	−0.1119	−0.1187	−0.1034	−0.1092	−0.1163	−0.1084	−0.1337
LAT	−0.1795	−0.1739	−0.1960	−0.1502	−0.1832	−0.1723	−0.1831
CHIF	−0.2128	−0.1771	−0.1891	−0.2114	−0.1592	−0.1832	−0.1945
SMPR	−0.0949	−0.1133	−0.0851	−0.0914	−0.0907	−0.0886	−0.0916
QP	−0.1198	−0.1189	−0.1358	−0.1154	−0.1353	−0.1151	−0.1085

Source(s): Authors'

Table A4. Expert opinions for ranking

	SHPR	SRDC	HND	LAT	CHIF	SMPR	QP
Expert 1							
China	5	5	2	3	1	4	8
Turkey	9	3	1	1	7	2	7
India	6	8	5	4	3	9	2
Brazil	7	8	4	3	3	4	8
Mexico	6	1	4	4	7	6	3
Indonesia	6	6	1	3	1	6	1
Russia	8	7	5	8	3	1	5
Expert 2							
China	7	5	6	3	2	3	6
Turkey	7	3	1	1	7	2	6
India	6	9	6	2	3	9	2
Brazil	9	7	4	3	3	5	7
Mexico	5	1	4	2	7	6	3
Indonesia	6	6	1	3	1	6	1
Russia	7	7	5	8	3	1	4
Expert 3							
China	6	5	4	3	2	4	7
Turkey	8	3	1	1	7	2	7
India	6	9	6	3	3	9	2
Brazil	8	8	4	3	3	5	8
Mexico	6	1	4	3	7	6	3
Indonesia	6	6	1	3	1	6	1
Russia	8	7	5	8	3	1	5

Source(s): Authors’

Table A5. Theoretical evaluation matrix

	SHPR	SRDC	HND	LAT	CHIF	SMPR	QP
China	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203
Turkey	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203
India	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203
Brazil	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203
Mexico	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203
Indonesia	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203
Russia	0.0221	0.0212	0.0204	0.0208	0.0182	0.0198	0.0203

Source(s): Authors’

Table A6. Actual evaluation matrix

	SHPR	SRDC	HND	LAT	CHIF	SMPR	QP
China	0.0191	0.0212	0.0123	0.0208	0.0124	0.0198	0.0188
Turkey	0.0123	0.0029	0.0201	0.0179	0.0000	0.0198	0.0173
India	0.0116	0.0000	0.0116	0.0037	0.0064	0.0000	0.0098
Brazil	0.0035	0.0000	0.0027	0.0000	0.0033	0.0040	0.0203
Mexico	0.0000	0.0180	0.0024	0.0000	0.0182	0.0000	0.0028
Indonesia	0.0062	0.0002	0.0204	0.0071	0.0144	0.0198	0.0000
Russia	0.0221	0.0160	0.0000	0.0179	0.0029	0.0000	0.0082

Source(s): Authors’

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