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A unified theory of acceptance and use of technology and fuzzy artificial intelligence model for electric vehicle demand analysis

Ahmet Faruk Aysan [a,*], Serhat Yüksel [b,g], Serkan Eti [c], Hasan Dinçer [b,h,*], Mahmut Selami Akin [d], Hakan Kalkavan [e], Alexey Mikhaylov [f]

[a] Non-Resident Fellow Middle East Council for Global Affairs (MECGA), Hamad Bin Khalifa University, Qatar Foundation, Doha, P.O. Box 34110, Qatar
[b] School of Business, Istanbul Medipol University, Istanbul, 34810, Turkey
[c] IMU Vocational School, Istanbul Medipol University, Istanbul, 34810, Turkey
[d] Vocational School of Social Sciences, İstanbul Medipol University, Turkey, Istanbul, 34810, Turkey
[e] Faculty of Political Sciences, Department of Economics, Istanbul Medeniyet University, Turkey
[f] Financial Faculty, Financial University Under the Government of the Russian Federation, Moscow, Russia
[g] Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon
[h] Clinic of Economics, Azerbaijan State University of Economics (UNEC), Istiqlaliyyat Str. 6, Baku, AZ 1141, Azerbaijan

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ABSTRACT

This study aims to reveal consumers' intention to purchase Electric Vehicles (EVs) based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model. A hybrid fuzzy decision-making model with three stages is proposed. First, the experts' weights are computed using an artificial intelligence methodology. Second, eight UTAUT-based indicators are examined using a T-Spherical TOPSIS-based DEMATEL (TOP-DEMATEL) methodology. The criteria are weighted by using multi-SWARA (M-SWARA) methodology. Third, an evaluation is conducted for the seven emerging countries by considering a Spherical Fuzzy (SF) Additive Ratio Assessment (ARAS) technique. The main contribution of this study is that a new decision-making methodology can identify more significant determinants of intention to use EVs. The methodological contribution of this study is integrating artificial intelligence methodology with fuzzy decision-making theory. The findings demonstrate that environmental factors play the most significant role in the intention to use EVs. Additionally, performance expectancy is also another critical determinant. We also find environmental issues should also be given importance in the production process of EVs. Using fossil fuels while producing these vehicles will significantly reduce users' confidence. This phenomenon will cause consumers with environmental awareness not to purchase these vehicles.

1. Introduction

Electric vehicles (EVs) are recognized as an environmentally friendly transportation solution. The main reason for this is that these vehicles do not cause carbon emissions. This contributes significantly to countries' reaching their carbon footprint reduction targets [1]. In addition, these instruments produce a very low amount of noise when operating [2]. This contributes significantly to the solution of the sound pollution problem. In addition, EVs can accelerate and slow down very quickly compared to others which also helps to increase the ease of use. On the other hand, they have a much lower cost compared to gasoline-powered vehicles [3]. In summary, EVs have a great importance in terms of reducing dependency on fossil fuels and protecting the environment.

To increase the use of electric vehicles, it should be preferred by users. In this context, investors should pay attention to the issues that will increase customer satisfaction. First, electric vehicles must provide customers with financial advantages [4]. In this framework, fuel and maintenance costs should be decreased by comparing the costs of the classical vehicles. Similarly, there should be enough charging stations throughout the country. Otherwise, users will not be able to recharge their vehicles easily, which will lead to customer dissatisfaction [5]. Ease of use is also an important issue for electric vehicles to be preferred by customers. Otherwise, people who are not happy with their use will not prefer electric vehicles, even if they are environmentally friendly [6,7].

To increase the use of electric vehicles, necessary actions should be taken to improve these issues. However, each of these improvement steps leads to increased costs. Therefore, it is not financially possible for investors to improve on all these factors [8]. Otherwise, the profitability of electric vehicles will decrease significantly because of excessively

* Corresponding authors.
E-mail addresses: aaysan@hbku.edu.qa (A.F. Aysan), serhatyuksel@medipol.edu.tr (S. Yüksel), seti@medipol.edu.tr (S. Eti), hdincer@medipol.edu.tr (H. Dinçer), selamiakin@medipol.edu.tr (M.S. Akin), hakan.kalkavan@medeniyet.edu.tr (H. Kalkavan), alexeyfa@ya.ru (A. Mikhaylov).

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increased costs [9]. It is not very possible for a product that does not increase in profitability to be financially sustainable. Therefore, it is necessary to determine the factors that will most affect the users' decision to purchase electric vehicles. In this way, it will be possible to present more priority strategies to investors [10]. Thus, investors will be able to take actions to ensure customer satisfaction without increasing costs excessively.

Accordingly, it is aimed to identify the most essential factors that affect consumers' intention to purchase EVs based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model in this study. Within this scope, a hybrid fuzzy decision-making model is created that has two stages. First, the experts' weights are computed using an artificial intelligence methodology. Secondly, eight different UTAUT-based determinants are weighted by T-Spherical TOPSIS-based DEMATEL (TOP-DEMATEL) methodology. The criteria are also weighted by using M-SWARA methodology. Finally, an analysis is also performed for emerging seven countries by considering Spherical fuzzy (SF) additive ratio assessment (ARAS) technique. The main motivation of this study is the need for a novel decision-making model with respect to the consumers' intention to purchase EVs. In most of the decision-making models in the literature, the weights of the experts are assumed as equal. However, these people can have different qualifications because of demographic characteristics. Due to this situation, in this model, the weights of the decision makers are computed by using artificial intelligence approach.

The main contributions of this manuscript are underlined below.

(i) Priority strategies will be presented to investors so that customers prefer electric vehicles more. Electric vehicles play a vital role in reducing environmental pollution and fossil fuel dependence. Therefore, it is necessary to take actions to increase customer satisfaction and to ensure that these tools are preferred more [11]. On the other hand, it is not financially reasonable to focus on many different issues together since the improvements to be made increase the costs [6,7]. Therefore, investors need to manage this process by prioritizing more important issues. This study contributes to this process by calculating the importance weights of UTAUT-based criteria.

(ii) Artificial intelligence methodology is integrated to the fuzzy decision-making evaluation. With the help of this issue, the weights of the experts can be calculated. In other words, with this application, the opinions of more qualified experts can be taken into account with a higher weight of importance. This allows analysis processes to be carried out more effectively.

(iii) One of the most important methodological originalities of this study is that a new model called TOP-DEMATEL is developed. It is possible to talk about many advantages of the classical DEMATEL technique, such as the determination of causality analysis. On the other hand, DEMATEL technique can be criticized due to some issues. For example, when there is symmetrical evaluation, the criteria weights become equal incorrectly. To overcome this problem, the final steps of TOPSIS technique are adopted to the classical DEMATEL and a new methodology is introduced by the name of TOP-DEMATEL (Eti et al. 2022). Hence, more appropriate and accurate results can be achieved [12].

(iv) Considering T-SFs also provides some advantages. While making analysis for different t values, it becomes possible to understand the results for different conditions. In other words, a comparative evaluation can be performed so that the consistency of the findings can be checked [13]. Similarly, using SFs also helps to overcome uncertainty problems in a more effective manner because it considers hesitancy conditions [14].

(v) Another important superiority of this manuscript is that a comparative evaluation has been conducted by using M-SWARA technique. This methodology is newly created by making some improvements to the classical SWARA technique. With the help of these improvements, the causal directions between the items can be identified. Hence, by making a comparative analysis with this technique, it can be possible to check the consistency and reliability of the proposed model.

(vi) Defining the criteria set based on the UTAUT model also increases the quality of the research. Owing to this technique, many factors can be taken into consideration. Therefore, this technique is considered to have high explanatory power. This situation also supports the process of developing effective strategies.

(vii) For the process of ranking the alternatives, ARAS technique is preferred. This method also offers some advantages compared to its counterparts. First, it is an easy calculation method that does not require complex operations. In addition, it is considered as another advantage that it provides fast solution finding. Moreover, the distance to the optimal is not used like TOPSIS. However, in this process, ratio is taken into consideration instead of distance. This allows the obtained results to reflect more reality.

(viii) Analyzing E7 countries in this study also has some advantages. These countries have developing economies. Countries with developed economies are increasing their investments very quickly to be included in the class. To achieve this goal, there is a possibility that these countries may ignore some risks. As a result, while investments are increased, electricity obtained from fossil fuels will be preferred more. This situation causes the carbon emission problem to increase significantly. Therefore, increasing the use of electric vehicles is of vital importance, especially for these countries.

The literature review part focuses on the details of similar previous studies. The methodology part explains the approaches considered in the evaluations. The analysis result part includes the details of the findings. The discussion part explains the similarities and differences about the findings of this study with the previous ones. The conclusion part summarizes the details of the manuscript.

2. Literature review

The core components of the UTAUT built and identified by Venkatesh et al. [15] are performance expectancy (PE), effort expectancy (EE), social influence (SOI), and facilitating conditions (FAC) that determine behavioral intention. Performance expectancy signifies the degree of belief that using novel technologies increases an individual's performance or provides an advantage [16]. Effort expectancy represents the level of convenience consequent on using innovation. On the other hand, social influence is defined as the degree of importance of utilizing a new tech considered by others, reference groups, or cultural environment [17]. Moreover, facilitating conditions imply the belief in accessing organizational and technical infrastructure support during the latest technology usage process [18]. The social environment is essential to comprehend consumer decision-making since it provides a basis for directly and indirectly interacting with others. Users' peers or others in the social context may influence their behavioral tendency [19]. It clarified as SOI in UTAUT denoting the grade to which users consider how substantial other individuals in society assume the usage of a new technological product [20,21]. Previous research highlights the role of SOI on green purchase intention in various contexts. The influence of society is convincing when consumers online shopping experience for green products [22]. Similarly, Krishnan and Koshy [23] ascertain the perspective of others in users' social environment could shape their preference for high-tech vehicles.

Corporations and governments can facilitate the requirements for innovative green products that represent a strategic tool to foster technological development in a sustainable market and social well-being [24]. Facilitating conditions are individuals' credence about the accessibility of infrastructural support when consuming a new technology [25]. It contains legal regulations, government policies, and technical or organizational support provided by manufacturers to pave the way for the acceptance or adoption of hi-tech products [26]. Lashari et al. [27] offer that offering purchase subsidies or applying tax exemption for eco-friendly vehicles promotes the intention to buy EVs. It indicates favorable legal regulations should encourage green vehicle purchase intention more than other industries. The mentioned constructs of UTAUT constitute extrinsic motivations that drive individuals externally to intend green consumption. However, it should be extended to improve explaining the intention to adopt and use new technologies since the intrinsic stimulus also steers consumer behavior [28] and technology usage [15]. Consumers could assess the trade-off between costs and benefits when buying green products in the economic context [29]. They compare the monetary sacrifices and efficiency in making purchase decisions. The notion is defined as price value representing an intrinsic motivation that shapes attitudes toward buying green products [30] and EVs [31]. Authors suggest that when individuals perceive lower monetary barriers, they favorably intend sustainable consumption [32] and smart device adoption [33].

Personal innovativeness is another component added to UTAUT that acts as a personality trait. Regarding the diffusion of innovation theory, innovator consumers embrace novel products or services faster than others [34]. They could also be defined as early adopters who consider green products and volunteer to protect the environment during shopping [35]. Past studies investigated the relationship between consumer innovativeness and green purchase intention in several aspects. Chauhan et al. [22] validated that personal innovativeness favorably predicts the purchase intention of green products in the digital world in Indian consumers. On the other hand, Li et al. [36] found a significant association between innovativeness and sustainable product purchase intention in China. Hedonic motivation is integrated into the UTAUT model by Venkatesh et al. [15] to comprehend consumers' intrinsic drives shaping behavioral tendencies toward technological products. They revealed that past research has frequently utilized hedonic motivation in the UTAUT model in the last decade. Kumar and Yadav [37] showed that shopping motivations, including hedonic drive, impact sustainable consumption in green apparel. Therefore, based on previous attempts, hedonic motivation should be a substantial component of green purchase intention [38].

Environmental concern is the final element and a novel extension of UTAUT in the context of the behavioral tendency toward EVs. Nevertheless, it reflects individuals' anxiety about potential environmental harm during their consuming process [39]. Previous studies distinguish the role of environmental concern in sustainable consumption in several cultures [40]. Thus, regional diversity should be examined to reveal the relationship between environmental concerns and behavioral tendencies. On the other hand, Dai et al. [41] demonstrated that ecological concern is a substantial driver of green purchase intention. Authors also emphasize environmental concern distinctively shapes the intention to buy EVs. He et al. [42] assert environmental concern should not promote behavioral tendency toward EVs since focusing on green consumers to reduce their environmental concerns might neglect traditional buyers [43].

As a result of the literature review, some important points can be highlighted below.

(i) Though previous attempts heavily concentrated on which components should be more beneficial to explain green purchase intention, how organizational resources could effectively allocate needs to be addressed.

(ii) However, each of these improvement steps leads to increased costs. Therefore, it is not financially possible for investors to improve on all these factors. Otherwise, the profitability of electric vehicles will decrease significantly because of excessively increased costs.

(iii) As a result, it is necessary to identify the factors that will most affect the customers' decision to purchase electric vehicles. With the help of this issue, it can be possible to present more priority strategies to investors. Hence, investors can take actions to ensure customer satisfaction without increasing costs excessively.

To satisfy these underlined issues, in this study, it is aimed to determine the most critical indicators that have an influence on the consumers' intention to purchase EVs based on the UTAUT model. In this context, a hybrid fuzzy decision-making model is proposed.

3. Methodology

This study aims to determine the critical items that affect the consumers' intention to purchase EVs. In this context, a new model is proposed based on the T-SF TOP-DEMATEL and SF ARAS. This section includes the details of these approaches.

3.1. Artificial intelligence systems

In decision-making methods based on expert opinion, giving equal weight to experts is criticized. The basis of this criticism is the differentiation of experts' knowledge due to the difference in their experience. However, it is obvious that not every year of experience adds equal knowledge. Therefore, a non-linear model is needed between experience times, expert opinions and the decision matrix. Artificial intelligence systems are used to model non-linear relationships between input–output layers. Artificial intelligence systems are network structures established by control learning between inputs and output variables. Details regarding the creation of artificial intelligence systems are summarized below.

First, the artificial intelligence system needs to be mathematically coded. During the coding process, layers, neurons, activation functions and loss functions of the artificial intelligence system are defined using Keras and TensorFlow libraries in Python [44]. The system is built by creating 5 hidden layers, excluding the input–output layers. 64 neurons are added to each layer. As for the activation function in neurons, the Sigmoid function given in Eq. (1) is preferred so that it fits the definition range of fuzzy numbers. The main reason for this is that other activation functions such as Relu and linear can produce values outside the range of 0 and 1.

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

While a in Eq. (1) defines the slope of the function, the e value is the Euler number. Calculating the parameters of the artificial intelligence system is an optimization problem and is solved by iteration. Among many optimization methods, the Adam algorithm is preferred due to its high performance with small data. The mathematical equations of the Adam algorithm are given in Eqs. (2)–(6).

$$W_{t+1} = W_t - \frac{a}{\sqrt{\hat{S}_t + \epsilon}} \hat{V}_t \tag{2}$$

$$\hat{V}_t = \frac{V_t}{1 - \beta_1^t} \tag{3}$$

$$\hat{S}_t = \frac{S_t}{1 - \beta_2^t} \tag{4}$$

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

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

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. The calculations between Eqs. (2)–(6) are repeated to improve the parameters. Therefore, epoch is set to 100. The reason for this is that although the number of repetitions increases, there is no marginal improvement in the model. During the recovery process of the parameters, the considered value is calculated through the loss function. At the same time, this function is also used to show the learning success of the artificial intelligence system. Different loss functions have been defined in the literature. One of the frequently used loss functions for continuous variables is the Mean Squared Error (MSE) function given in Eq. (7).

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (Y_i - \hat{Y}_i)^2 \tag{7}$$

Table 1
Fuzzy sets.

Scales	S	U	d
4	.85	.15	.45
3	.6	.2	.35
2	.35	.25	.25
1	0	.3	.15
0	0	0	0

Where, Y is the actual value of the model and $\hat{Y}$ represents the output value. m is amount of data. A low *MSE* value indicates that the learning success of the artificial intelligence system is high, and the parameters are close to the fit value. The artificial intelligence system needs a training data set to learn. Train dataset is obtained by simulation in this study. A thousand data sets are produced, including expert opinion and years of experience. This data set forms the input of the system. The output variable is created through the linguistic expressions of the relevant method. In this process, experts' years of experience are normalized by Eq. (8) and used as expert weights. These expert importance values are used to obtain the relevant decision matrix.

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

In Eq. (8), the variable d represents the expert's years of experience.

3.2. T-SF TOP-DEMATEL

DEMATEL method is mainly used to compute the weights of different determinants that have an impact on a subject. The main difference of this approach by comparing with the similar ones is that the causal directions of the factors can be defined [45]. Because of this superiority, this approach was preferred by many scholars for various purposes. However, this technique is also criticized by different researchers for many issues. For example, regarding the symmetrical evaluation, the weights of the items are computed as equal incorrectly although the experts do not think like this. To overcome this problem, final steps of TOPSIS are integrated into the classical DEMATEL and a new methodology (TOP-DEMATEL) is created. In this model, this new approach is considered with T-SF sets. The combination of three functions refers to the T-SF number. The details are demonstrated in Eq. (9) in which d, s and u explain hesitancy, membership, and non-membership (Özdemirci et al. 2023).

$$0 \le s^t + u^t + d^t \le 1 \tag{9}$$

Based on the values of these items, different fuzzy systems can be generated. The following factors can be obtained from a T-SF set.

- t = 2" refers to the SF set.
- "t = 1" shows picture fuzzy set.
- "u = 0" means q-ROFSs.
- "t = 2" and "d = 0" indicate Pythagorean fuzzy set.
- "t = 1" and "d = 0" denote Intuitionistic fuzzy set.

The steps of T-SF TOP-DEMATEL are explained below.

Firstly, the evaluations are provided from the experts. While converting these values into the fuzzy numbers, the scales in Table 1 are used.

Zi matrix is generated by Eq. (10).

$$Z^i = \begin{bmatrix} 0 & \cdots & \left(s^i_{1n}, u^i_{1n}, d^i_{1n}\right) \\ \vdots & \ddots & \vdots \\ \left(s^i_{n1}, u^i_{n1}, d^i_{n1}\right) & \cdots & 0 \end{bmatrix} \tag{10}$$

Secondly, decision matrix is constructed with Eqs. (11) and (12) using artificial intelligence system.

$$TSFWAM_W\left(\tilde{A}_{S1}, \tilde{A}_{S1}, \dots \tilde{A}_{Sn}\right) = \left\{ \begin{array}{c} \left[1 - \prod_{i=1}^{n}\left(1 - s^t_{\tilde{A}_{Si}}\right)^{w_i}\right]^{\frac{1}{t}}, \\ \prod_{i=1}^{n} u^{w_i}_{\tilde{A}_{Si}}, \\ \prod_{i=1}^{n} d^{w_i}_{\tilde{A}_{Si}} \end{array} \right\} \tag{11}$$

$$Z = \begin{bmatrix} 0 & \cdots & \left(s^d_{1n}, u^d_{1n}, d^d_{1n}\right) \\ \vdots & \ddots & \vdots \\ \left(s^d_{n1}, u^d_{n1}, d^d_{n1}\right) & \cdots & 0 \end{bmatrix} \tag{12}$$

Thirdly, sub-matrices (Xs, Xu and Xd) are identified and normalized by Eqs. (13) and (14).

$$X = sZ \tag{13}$$

$$s = \min\left[\frac{1}{\max_i \sum_{j=1}^{n}\left|z_{ij}\right|}, \frac{1}{\max_j \sum_{i=1}^{n}\left|z_{ij}\right|}\right] \tag{14}$$

Eq. (15) denotes these three submatrices.

$$X^s = \begin{bmatrix} 0 & \cdots & s_{1n} \\ \vdots & \ddots & \vdots \\ s_{n1} & \cdots & 0 \end{bmatrix} X^u = \begin{bmatrix} 0 & \cdots & u_{1n} \\ \vdots & \ddots & \vdots \\ u_{n1} & \cdots & 0 \end{bmatrix} X^d = \begin{bmatrix} 0 & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{n1} & \cdots & 0 \end{bmatrix} \tag{15}$$

Fourthly, total relationship matrix (T) is created as in Eq. (16).

$$T = \begin{bmatrix} s^T_{11}, u^T_{11}, d^T_{11} & \cdots & \left(s^T_{1n}, u^T_{1n}, d^T_{1n}\right) \\ \vdots & \ddots & \vdots \\ \left(s^T_{n1}, u^T_{n1}, d^T_{n1}\right) & \cdots & s^T_{nn}, u^T_{nn}, d^T_{nn} \end{bmatrix} \tag{16}$$

Fifthly, by using Eq. (17), defuzzification is made.

$$Scorex = s^T - u^T - d^T \tag{17}$$

Eqs. (18)–(24) are used to compute the weights of the items.

$$C^*_j = \sqrt{\sum_{i=1}^{n}\left(t_i - \max_j t_i\right)^2} \tag{18}$$

$$C^-_j = \sqrt{\sum_{i=1}^{n}\left(t_i - \min_j t_i\right)^2} \tag{19}$$

$$R^*_i = \sqrt{\sum_{j=1}^{n}\left(t_j - \max_i t_j\right)^2} \tag{20}$$

$$R^-_i = \sqrt{\sum_{j=1}^{n}\left(t_j - \max_i t_j\right)^2} \tag{21}$$

$$S^*_i = C^*_i + R^*_i \tag{22}$$

$$S^-_i = C^-_i + R^-_i \tag{23}$$

$$W_i = \frac{S^-_i}{S^-_i + S^*_i} \tag{24}$$

3.3. M-SWARA

Classical SWARA technique is considered to calculate the significance weights of the determinants. However, in this framework, the causal directions between the factors are not taken into consideration. By focusing on this issue, some improvements are implemented to this technique in this study [46]. As a result, a new methodology by the name of M-SWARA is created. This approach provides an opportunity to consider causal relationships in the analysis process. By using Eq. (25), relation matrix is created from expert evaluations [47].

$$\varsigma_k = \begin{bmatrix} 0 & \varsigma_{12} & \cdots & \cdots & \varsigma_{1n} \\ \varsigma_{21} & 0 & \cdots & \cdots & \varsigma_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varsigma_{n1} & \varsigma_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{25}$$

Aggregated values are generated by Eq. (26).

$$\varsigma = \left\{ \begin{array}{c} \left[1-\prod_{i=1}^{k}\left(1-\varsigma_{\mu_i}^2\right)^{\frac{1}{k}}\right]^{\frac{1}{2}} e^{2\pi\cdot\left[1-\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^2\right)^{\frac{1}{k}}\right]^{\frac{1}{2}}}, \\ \prod_{i=1}^{k}\varsigma_{v_i}^{\frac{1}{k}} e^{2\pi\cdot\prod_{i=1}^{k}\left(\frac{\gamma_i}{2\pi}\right)^{\frac{1}{k}}}, \\ \left[\begin{array}{c}\prod_{i=1}^{k}\left(1-\varsigma_{\mu_i}^2\right)^{\frac{1}{k}} \\ -\prod_{i=1}^{k}\left(1-\varsigma_{\mu_i}^2-\varsigma_{h_i}^2\right)^{\frac{1}{k}}\end{array}\right]^{\frac{1}{2}} e^{2\pi\cdot\left[\begin{array}{c}\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^2\right)^{\frac{1}{k}} \\ -\prod_{i=1}^{k}\left(1-\left(\frac{\alpha_i}{2\pi}\right)^2-\left(\frac{\beta_i}{2\pi}\right)^2\right)^{\frac{1}{k}}\end{array}\right]^{\frac{1}{2}}} \end{array} \right\} \tag{26}$$

Eq. (27) is considered to generate defuzzified values.

$$\boldsymbol{Def}\,\varsigma_i = \varsigma_{\mu_i} + \left(\frac{\varsigma_{\mu_i}}{\varsigma_{\mu_i}+\varsigma_{h_i}+\varsigma_{v_i}}\right) + \left(\frac{\alpha_i}{2\pi}\right) + \left(\frac{\left(\frac{\alpha_i}{2\pi}\right)}{\left(\frac{\alpha_i}{2\pi}\right)+\left(\frac{\gamma_i}{2\pi}\right)+\left(\frac{\beta_i}{2\pi}\right)}\right) \tag{27}$$

After that, s_j (importance rate), k_j (coefficient), q_j (recalculated weight), and w_j (weight) values are calculated by Eqs. (28)–(30).

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases} \tag{28}$$

$$q_j = \begin{cases} 1 & j = 1 \\ \frac{q_{j-1}}{k_j} & j > 1 \end{cases} \tag{29}$$

$$If\, s_{j-1} = s_j,\ q_{j-1} = q_j;\ If\, s_j = 0,\ k_{j-1} = k_j$$

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{30}$$

In the final step, weights are calculated while transposing and limiting the matrix to the power of 2t+1.

3.4. SF ARAS

The ARAS method is a multi-criteria decision-making method in which the alternatives are evaluated by experts and compares the scores of the selected alternatives with the ideal best alternative [48]. Since ARAS is a very effective method that can solve different decision-making problems, it has advantages over other methods. This method is very efficient in determining the most suitable candidate among many alternatives. The main benefit of using the ARAS approach is that the degree of alternative utility is calculated by comparing the variable with what is ideally best [49]. The steps of the ARAS method with SF sets are as follows.

Step 1: Expert Opinions are collected with scales in Table 2 and converted into fuzzy numbers.

Table 2
Scales.

Scales	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

Step 2: The decision matrix (A) is formed by averaging the expert opinions. The average of n spherical fuzzy numbers is calculated with the help of Eqs. (31) and (32).

$$SWAM\left(A_{s1},\ldots,A_{Sn}\right) = \left\{ \begin{array}{c} \left[1-\prod_{i=1}^{n}\left(\begin{array}{c}1\\-\mu_{A_{si}}^2\end{array}\right)^{\frac{1}{n}}\right]^{\frac{1}{2}}, \\ \prod_{i=1}^{n} v_{A_{si}}^{\frac{1}{n}}, \\ \left[\begin{array}{c}\prod_{i=1}^{n}\left(1-\mu_{A_{si}}^2\right)^{\frac{1}{n}} \\ -\prod_{i=1}^{n}\left(\begin{array}{c}1-\mu_{A_{si}}^2\\-\pi_{A_{si}}^2\end{array}\right)^{1/n}\end{array}\right]^{1/2} \end{array} \right\} \tag{31}$$

$$A = \begin{bmatrix} \left(\mu_{11}, v_{11}\pi_{11}\right) & \cdots & \left(\mu_{m1}, v_{m1}, \pi_{m1}\right) \\ \vdots & \ddots & \vdots \\ \left(\mu_{1n}, v_{1n}, \pi_{1n}\right) & \cdots & \left(\mu_{mn}, v_{mn}, \pi_{1mn}\right) \end{bmatrix} \tag{32}$$

Step 3: The decision matrix is multiplied by the criterion weights (w) to obtain the weighted decision matrix (X). Eqs. (33) and (34) are used to multiply a real number and SF number.

$$X = w.A \tag{33}$$

$$\lambda\tilde{A}_s = \left\{ \begin{array}{c} \left(1-\left(1-\mu_{\tilde{A}_s}^2\right)^{\lambda}\right)^{\frac{1}{2}}, \\ v_{\tilde{A}_s}^{\lambda}, \\ \left(\begin{array}{c}\left(1-\mu_{\tilde{A}_s}^2\right)^{\lambda} \\ -\left(1-\mu_{\tilde{A}_s}^2-\pi_{\tilde{A}_s}^2\right)^{\lambda}\end{array}\right)^{2} \end{array} \right\} \tag{34}$$

Step 4: Optimal values are calculated for each criterion. For the Benefit criteria, the highest value is accepted as the optimal value, while for the cost criteria, the smallest value is the optimal value. In SF numbers, the larger of the two numbers is determined over the score and accuracy values. A number with a higher score is also considered larger. If the score values are equal, the number with the greater accuracy value is considered large. The details of this process are denoted in Eqs. (35) and (36).

$$Score = (\mu - \pi)^2 - (v - \pi)^2 \tag{35}$$

$$Accuracy = \mu^2 + v^2 + \pi^2 \tag{36}$$

Step 5: Optimal values and alternatives are summed on the basis of criteria and SF optimality function ($\tilde{S}_{Si}$) is calculated with the help of Eq. (37).

$$\tilde{S}_{Si} = \sum_{i=1}^{m}\left(\begin{array}{c}\left(\mu_1, v_1, \pi_1\right) \\ +\left(\mu_2, v_2, \pi_2\right) \\ +\cdots+\left(\mu_m, v_m, \pi_m\right)\end{array}\right) \tag{37}$$

Step 6: Using score and accuracy functions in Eqs. Eq. (35)–(36), $\tilde{S}_{Si}$ values are defuzzified and Si values are calculated. S_0 is the defuzzified value of the sum of the optimal values.

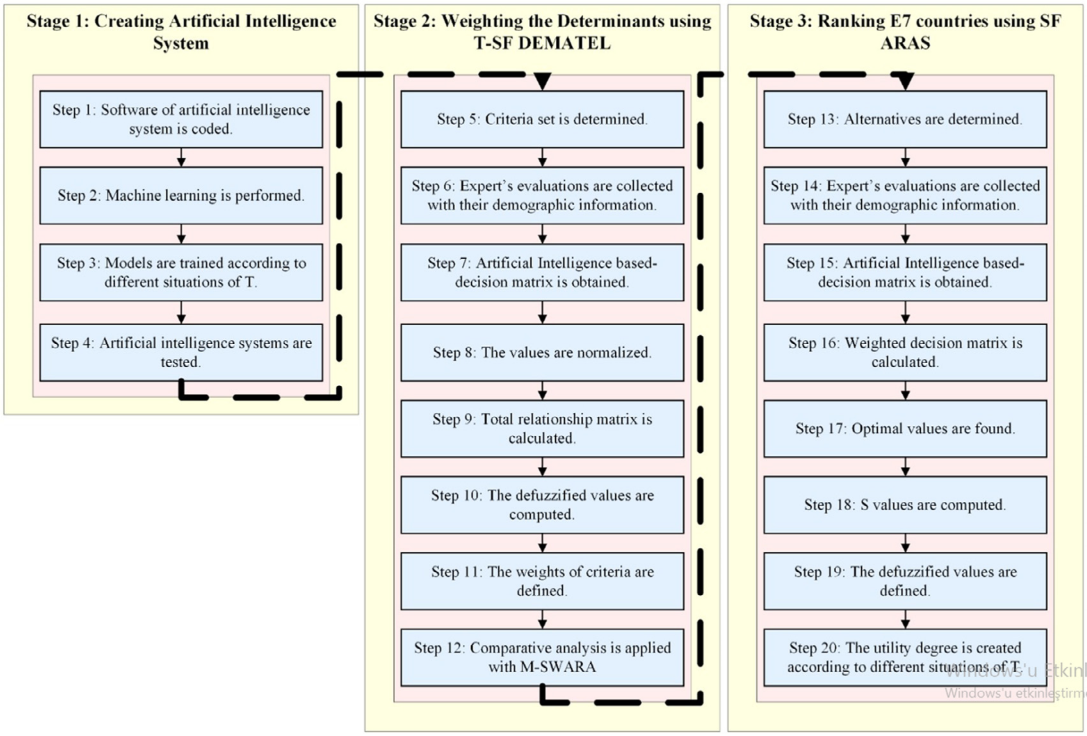

Fig. 1. Flowchart.

Table 3
MSE values.

Systems	Values
T = 2	.0058
T = 1	.0065
U = 0 T = Golden Ratio	.0071
d = 0 T = 2	.0053
d = 0 T = 1	.0056

Table 4
UTAUT-based determinants.

UTAUT-based determinants
Performance expectancy (PXPCT)
Effort expectancy (EXPCT)
Social influence (SNFLC)
Facilitating conditions (FCDTN)
Personal innovativeness (PRNVT)
Environmental concern (EVCNC)
Hedonic motivation (HMVTN)
Price value (PCVAL)

Step 7: The utility degree (Ki) is calculated by dividing the sums of the alternatives by the sum of the optimal value using Eq. (38). The alternative with a high Ki value is accepted as the best alternative.

$$K_i = \frac{S_i}{S_0} \tag{38}$$

4. Analysis results

In this study, a new model is proposed to understand which factors play more essential role on the consumers' intention to purchase EVs. The flowchart of this model is defined in Fig. 1.

The results are presented in the following sub sections.

4.1. Creating artificial intelligence systems

Using Eqs. (1)–(8), an artificial intelligence model is created. By definition of the T-SF cluster, machine learning is performed separately for each situation. In other words, a single mathematical artificial intelligence system with 7 layers, sigmoid activation function and Adam optimization is built. However, the learning process is carried out differently due to the difference in the output variable. MSE values of the learning success of these five artificial intelligence systems are given in Table 3.

According to the values in Table 3, the MSE values of the 5 different models established are very close to zero. Therefore, it can be stated that the models are successful.

4.2. Weighting the determinants

In the analysis process, firstly, the criteria list is created. For this purpose, the factors are selected based on the parameters of UTAUT technique. Table 4 explains these factors.

T-SF TOP-DEMATEL technique is considered for the evaluation of these eight determinants. Firstly, evaluations are provided from the expert team that consists of three different decision makers. One of these people is a professor in the university and he does detailed research on the customer intention, clean energy projects and strategic management. He has more than 24 years of working experience in this area. On the other side, the other two decision-makers are the top managers in the renewable energy companies that operate internationally. These people have a minimum of 26 years of experience, and they have managed many projects on renewable energy, new product development and customer satisfaction. The criteria are evaluated by experts using 5 different scales, the details of which are given in Table 1. Experts' evaluations of criteria and alternatives are presented in Table A.1. Expert opinions and experience periods are given as input to the created artificial intelligence models. The decision matrices obtained from the five models are given in Table A.2 in Appendix. The analysis results are explained below for the conditions where t = 2. The decision matrix (Z) is constructed. Firstly, the evaluations of the experts are converted into fuzzy numbers as detailed in Table 1. For this purpose, Eq. (10) is taken

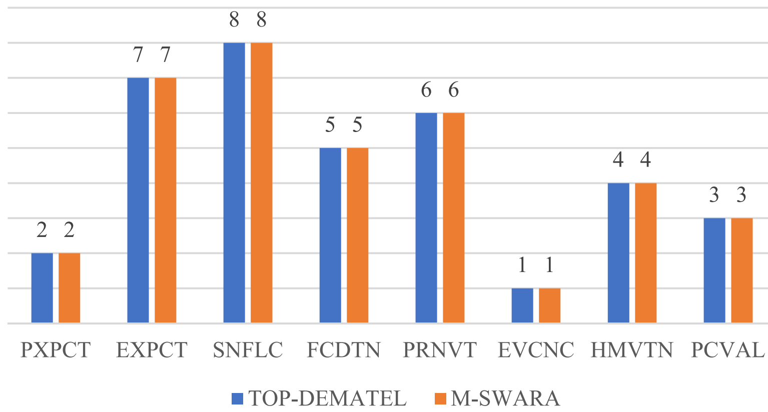

Fig. 2. Comparative weights.

Table 5
Weights of the determinants.

Determinants	C*	C-	S*	S-	Weights
PXPCT	.35076	.46524	1.57852	1.13344	.134556576
EXPCT	.15909	.17190	1.25378	.74274	.119771731
SNFLC	1.11741	.46344	2.54328	1.25148	.106176895
FCDTN	.13009	.16424	1.15702	.71172	.122616393
PRNVT	.18383	.17310	1.11370	.68148	.122218367
EVCNC	.46142	.61811	1.65917	1.31000	.142045301
HMVTN	.50759	.35200	1.43520	.91696	.125508339
PCVAL	.19625	.21577	1.17545	.76680	.127106399

into consideration. After that, Eqs. (11) and (12) are implemented so that the final form of this matrix is obtained. In the following stage, sub-matrices (X^s, X^u and X^d) are identified and normalized by Eqs. (13) and (14). Also, for the construction of submatrices, Eq. (15) is taken into consideration. After that, total relationship matrix (T) is generated with Eq. (16). Next, defuzzification is performed by Eq. (17). Eqs. (18)–(24) are considered for the identification of the weights of the factors. The results are indicated in Table 5.

It is concluded that environmental factors have the highest weight (.142045301). Moreover, performance expectancy is also found as another critical issue with the weight of (.134556576). Hence, with the aim of attracting the attention of the customers for the selection of EVs, the companies should give priorities to environmental issues. In this context, the whole process should be designed as environmentally friendly, such as production of the raw materials of the vehicles. The results are also defined for different conditions to check the appropriateness of the findings. Comparative results are denoted in Table 6.

Table 6 explains that the results are very similar for different conditions. For instance, the most important factor (environmental issues) is the same for all situations. It is understood that the findings of the proposed model are reliable and consistent. The criteria are also weighted by using M-SWARA methodology. Comparative weights are indicated in Fig. 2.

Fig. 2 indicates that the weights of both TOP-DEMATEL and M-SWARA are the same. Hence, it is understood that the proposed model provides coherent and reliable results.

4.3. Ranking E7 countries

In the final stage of the proposed model, E7 countries (Brazil, China, India, Indonesia, Mexico, Russia and Turkey) are examined. For this purpose, SF ARAS methodology is considered. Evaluations are obtained from the expert team by considering the scales in Table 2. The decision matrix (A) is created by averaging the expert opinions in Table A.1 with the help of Eqs. (31) and (32). In the following stage, optimal values are computed for each item with the help of Eqs. (35) and (36). Moreover, $\tilde{S}_{Si}$ values are defuzzified by using score and accuracy functions. In the following stage, the utility degree (Ki) is calculated by dividing the sums of the alternatives by the sum of the optimal value using Eq. (38). The alternative with a high Ki value is accepted as the best alternative. Ranking results of the countries are shown in Table 7.

The ranking results are also illustrated in Fig. 3.

Table 6 and Fig. 3 indicate that Russia in the most successful E7 country regarding the actions taken for attracting the customers to prefer EVs. Turkey and Mexico have also high performance in this respect. However, China, Brazil and Indonesia are on the last ranks. The findings of this study are especially important for these countries that have lower performance. These countries can improve their performance while considering the important points stated in this study. Finally, the ranking of these countries is computed by using different weights. With the help of this comparative evaluation, the consistency of the ranking results can be measured. Comparative ranking solutions are demonstrated in Table 8.

Fig. 4 gives also significant information with respect to the ranking results.

Table 8 and Fig. 4 show that the ranking results are similar for all different conditions. This situation gives information that the findings are reliable and consistent.

5. Discussions

According to the results obtained in this study, environmental concern is the most important factor for consumers' approval of using electric vehicles. If automobile manufacturing companies are producing electric vehicles as an investment, they need to convince the customers, and the essential manner is to comply with environmental issues. Otherwise, the customer's credibility will decrease, and brand trust will not be established. Even if there are many benefits at the end of electric vehicle production, there will not be enough demand because it will be against the purpose of exit, but it will mean a loss of investment. Apart from environmental awareness, customers will also consider the performance of the electric vehicle, which creates confidence in consumers regarding both economic efficiency and innovative satisfaction. In this respect, ensuring environmental awareness by integrating performance is critical for eco-friendly consumers' choices.

Regardless, electric vehicles should not emit carbon emissions and harm the environment. On that note, not only the use but also the process of electric generation is crucial. Accordingly, it is necessary to provide transparency about where and how electricity is produced [50]. In the renewable energy production context, Kul et al. [51] drew attention to the increase in greenhouse gas emissions from biomass

Table 6
Comparative results.

Determinants	t = 2		t = 1		u = 0, t = g*		u = 0, t = 2		u = 0, t = 1		u = 0, d = 0, t = 1	
	WG	RK	WG	RK	WG	RK	WG	RK	WG	RK	WG	RK
PXPCT	.135	2	.133604	2	.137	2	.128	2	.133	2	.135	2
EXPCT	.120	7	.110955	7	.119	7	.119	7	.112	7	.120	7
SNFLC	.106	8	.109075	8	.107	8	.107	8	.109	8	.106	8
FCDTN	.123	5	.124281	5	.125	5	.125	5	.124	5	.123	5
PRNVT	.122	6	.11333	6	.121	6	.124	6	.115	6	.122	6
EVCNC	.142	1	.152498	1	.142	1	.142	1	.149	1	.142	1
HMVTN	.126	4	.125868	4	.125	4	.126	4	.128	4	.126	4
PCVAL	.127	3	.13039	3	.125	3	.128	3	.130	3	.127	3

g*: calculated by golden ratio; WG: weights; RK: ranking.

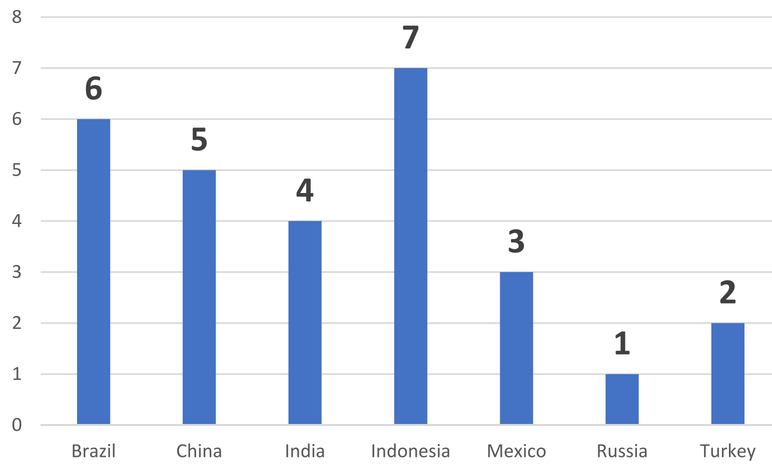

Fig. 3. Ranking results of E7 countries.

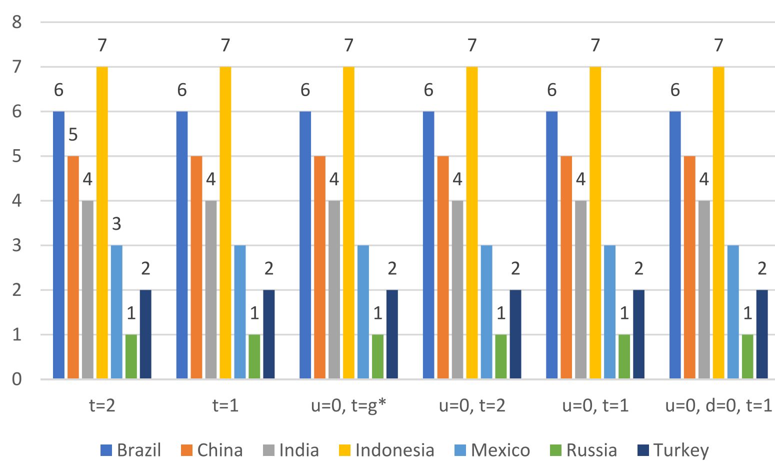

Fig. 4. Comparative ranking results.

Table 7
Ranking results of the countries.

Countries	Ki values	Ranking
Brazil	.86019	6
China	.86246	5
India	.87227	4
Indonesia	.84470	7
Mexico	.87623	3
Russia	1.36118	1
Turkey	.90195	2

combustion and its adverse effects on health, environmental problems caused by Hydroelectric Power Plants, and the pollution of geothermal waters. Furthermore, in a study of developing countries, Bamisile et al. [52] and Springer et al. [38] found that integrating plug-in battery electric vehicles and hydrogen generation is encouraging to maximize electricity generated from renewable energy systems and reduce greenhouse gas emissions.

Moreover, the working conditions and personal rights of people working in the electric vehicle production process will be legally supervised by governments and, beyond that, ethically controlled by potential customers. Ensuring environmentally friendly vehicle production requires employees to work in accordance with decent work

Table 8
Comparison of ranking results.

Countries	t = 2	t = 1	u = 0, t = g*	u = 0, t = 2	u = 0, t = 1	u = 0, d = 0, t = 1
Brazil	6	6	6	6	6	6
China	5	5	5	5	5	5
India	4	4	4	4	4	4
Indonesia	7	7	7	7	7	7
Mexico	3	3	3	3	3	3
Russia	1	1	1	1	1	1
Turkey	2	2	2	2	2	2

g*: calculated by golden ratio.

criteria [53]. Otherwise, there will be an ethical inconsistency, damaging brand trust and ceasing to be a sustainable business model. In this respect, Kalkavan et al. [54] investigated the role of moral values in the sustainable economic development of developing countries and highlighted the significance of institutions' compliance with human rights and laws both ethically and religiously in the producing and consuming processes. In one regard, Sovacool [55] emphasized that ethical concerns such as law, justice, and social cohesion are as crucial as technological advancement in the transformation process in energy systems; meanwhile.

In conclusion, the earlier approach, which considered the business only as an economic structure, has evolved into a business model with a value-oriented sustainability perspective focusing on the human-society-environment balance. However, high renewable energy prices and insufficient production capacity to meet energy needs prevent countries from abandoning traditional fossil fuels entirely. In this respect, they continue to produce electricity from coal and natural gas. At this point, it should be aimed to minimize environmental damage if it is unavoidable in the energy transition process. Lastly, innovative technological developments such as electric vehicles can contribute to the environment and social welfare both in terms of the production method it uses and the purpose it wants to achieve. In this connection, establishing definite legal rules in the transition to electric vehicle use will also lead companies to meet socio-economic and environmental standards.

Performance expectation of electric vehicles is another issue that has an impact on customers' preferences. In this context, individuals need to increase their performance by using these tools. Otherwise, there is a risk that users will not prefer these vehicles. In this context, it would be appropriate to integrate many features that users will be satisfied with the performance of these vehicles. Therefore, actions should be taken to increase comfort in the use of electric vehicles. In this direction, the serial speed change will be a feature that will increase the satisfaction of the users. Similarly, the ability of electric vehicles to travel long distances is another performance indicator that can have an impact on customer satisfaction. This will contribute to the preference of these vehicles more.

6. Conclusions

The purpose of this study is to find the expectations of the consumers to purchase EVs based on the UTAUT model. Within this framework, a hybrid fuzzy decision-making model is created that includes three stages. In the first stage, artificial intelligence methodology is taken into consideration to compute the weights of the experts. Secondly, eight different UTAUT-based indicators are analyzed by using T-SF TOP-DEMATEL methodology. The criteria are also weighted by using M-SWARA methodology. Secondly, an evaluation is also made for emerging seven countries by considering SF ARAS technique. Because both the results of TOP-DEMATEL and M-SWARA are the same, it is understood that the proposed model provides coherent and reliable findings. It is identified that environmental factors play the most significant role in the intention to use EVs. Additionally, performance expectancy is also another critical determinant for this situation. Based on these findings, it is recommended that companies should give significance mainly not to use fossil fuels in the production process of these vehicles. This situation causes consumers with environmental awareness to prefer these vehicles.

The main contribution of this manuscript is the generation of a novel fuzzy decision-making model by integrating M-SWARA, TOP-DEMATEL and ARAS. With the help of this comprehensive model, uncertainty in the decision-making process can be reduced in a significant manner. Hence, this novel model can be taken into consideration to solve very complex problem in the real life. In other words, owing to this novel model, investors can identify appropriate investment strategies in their industries. The main limitation of this study is that the criteria list is created based on the parameters of UTAUT model. Thus, for future studies, different methodologies can be taken into consideration. Another significant limitation is that for the purposes of ranking alternatives, only ARAS methodology is used. Therefore, in the following studies, another evaluation can also be performed to make a comparative evaluation. Finally, focusing on only E7 countries is also accepted as another limitation of this manuscript. The subject of this study is also important for other countries. Owing to this issue, different country groups, such as G7 economies can be examined. The proposed model has also some limitations. In this model, facial expressions of the decision makers are not taken into consideration. However, emotions of these people while making evaluations can provide significant information to reach more effective analysis results. Hence, in the future studies, facial expressions can be considered in the decision-making model. Similarly, experts could not leave the evaluations regarding some questions blank. However, these people may not have clear information on some issues. Therefore, in future studies, the collaborative filtering technique should be included in the proposed new decision-making model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix

See Tables A.1 and A.2.

Table A.1
Expert opinions.

	Expert 1								Expert 2								Expert 3							
	PXPCT	EXPCT	SNFLC	FCDTN	PRNVT	EVCNC	HMVTN	PCVAL	PXPCT	EXPCT	SNFLC	FCDTN	PRNVT	EVCNC	HMVTN	PCVAL	PXPCT	EXPCT	SNFLC	FCDTN	PRNVT	EVCNC	HMVTN	PCVAL
PXPCT	0	3	3	3	3	1	4	3	0	3	2	2	3	1	3	2	0	4	3	3	3	1	3	4
EXPCT	2	0	1	2	2	1	1	2	1	0	1	2	2	1	1	1	2	0	2	1	1	1	2	2
SNFLC	1	1	0	2	2	2	2	3	2	1	0	2	1	1	1	2	2	2	0	1	2	1	3	2
FCDTN	2	1	2	0	2	1	3	1	2	3	2	0	2	2	1	1	1	2	1	0	1	1	2	2
PRNVT	1	2	1	2	0	1	3	2	1	2	2	3	0	1	2	1	1	1	1	1	0	1	2	2
EVCNC	4	4	4	4	4	0	4	4	4	3	3	4	3	0	3	4	4	4	3	3	3	0	3	3
HMVTN	2	1	1	2	2	1	0	2	2	3	2	1	2	1	0	1	2	3	1	1	3	2	0	1
PCVAL	2	1	1	2	3	1	2	0	2	2	1	1	2	2	1	0	1	2	1	2	3	1	2	0
	PXPCT	EXPCT	SNFLC	FCDTN	PRNVT	EVCNC	HMVTN	PCVAL	PXPCT	EXPCT	SNFLC	FCDTN	PRNVT	EVCNC	HMVTN	PCVAL	PXPCT	EXPCT	SNFLC	FCDTN	PRNVT	EVCNC	HMVTN	PCVAL
Brazil	1	5	7	6	8	9	1	2	2	4	6	7	7	8	3	4	2	6	6	7	6	8	3	4
China	1	2	5	7	3	5	4	3	3	3	4	7	3	5	5	4	3	3	6	8	3	6	5	3
India	3	6	4	1	8	9	5	7	2	5	5	2	7	7	4	8	2	7	3	2	9	9	5	7
Indonesia	4	5	3	8	7	5	6	9	3	6	4	7	6	6	5	8	5	4	2	7	8	4	7	8
Mexico	4	8	6	3	6	5	9	7	5	7	6	3	7	6	8	8	5	9	5	4	7	5	9	7
Russia	4	5	2	7	4	6	1	4	4	5	3	6	5	7	3	5	5	7	3	8	5	7	2	4
Turkey	5	8	3	9	9	8	1	5	5	8	2	8	8	6	1	5	6	9	4	8	8	9	3	6

Table A.2
Decision matrices.

T = 1	PXPCT			EXPCT			SNFLC			FCDTN			PRNVT			EVCNC			HMVTN			PCVAL		
PXPCT	.00	.00	.00	.73	.18	.18	.62	.20	.20	.62	.20	.20	.62	.20	.20	.02	.30	.29	.78	.17	.17	.73	.18	.18
EXPCT	.32	.25	.25	.00	.00	.00	.13	.28	.28	.23	.26	.26	.23	.26	.26	.02	.30	.29	.13	.28	.28	.32	.25	.25
SNFLC	.13	.28	.28	.13	.28	.28	.00	.00	.00	.23	.26	.26	.32	.25	.25	.23	.26	.26	.44	.23	.23	.52	.22	.22
FCDTN	.23	.26	.26	.13	.28	.28	.23	.26	.26	.00	.00	.00	.23	.26	.26	.02	.30	.29	.52	.22	.22	.13	.28	.28
PRNVT	.02	.30	.29	.23	.26	.26	.02	.30	.29	.23	.26	.26	.00	.00	.00	.02	.30	.29	.52	.22	.22	.32	.25	.25
EVCNC	.83	.15	.15	.83	.15	.15	.78	.17	.17	.78	.17	.17	.78	.17	.17	.00	.00	.00	.78	.17	.17	.78	.17	.17
HMVTN	.32	.25	.25	.27	.26	.26	.02	.30	.29	.23	.26	.26	.44	.23	.23	.13	.28	.28	.00	.00	.00	.23	.26	.26
PCVAL	.23	.26	.26	.13	.28	.28	.02	.30	.29	.32	.25	.25	.62	.20	.20	.02	.30	.29	.32	.25	.25	.00	.00	.00
T = 2	PXPCT			EXPCT			SNFLC			FCDTN			PRNVT			EVCNC			HMVTN			PCVAL		
PXPCT	.00	.00	.00	.87	.18	.18	.80	.20	.20	.80	.20	.20	.80	.20	.20	.01	.30	.30	.89	.16	.16	.87	.18	.18
EXPCT	.57	.25	.25	.00	.00	.00	.36	.28	.28	.48	.27	.27	.48	.27	.27	.01	.30	.30	.36	.28	.28	.57	.25	.25
SNFLC	.36	.28	.28	.36	.28	.28	.00	.00	.00	.48	.27	.27	.57	.25	.25	.48	.27	.27	.67	.23	.23	.73	.22	.22
FCDTN	.48	.27	.27	.36	.28	.28	.48	.27	.27	.00	.00	.00	.48	.27	.27	.01	.30	.30	.73	.22	.22	.36	.28	.28
PRNVT	.01	.30	.30	.48	.27	.27	.01	.30	.30	.48	.27	.27	.00	.00	.00	.01	.30	.30	.73	.22	.22	.57	.25	.25
EVCNC	.91	.15	.16	.91	.15	.16	.89	.16	.16	.89	.16	.16	.89	.16	.16	.00	.00	.00	.89	.16	.16	.89	.16	.16
HMVTN	.57	.25	.25	.54	.26	.26	.01	.30	.30	.48	.27	.27	.67	.23	.23	.36	.28	.28	.00	.00	.00	.48	.27	.27
PCVAL	.48	.27	.27	.36	.28	.28	.01	.30	.30	.57	.25	.25	.80	.20	.20	.01	.30	.30	.57	.25	.25	.00	.00	.00

u = 0 T = q	PXPCT		EXPCT		SNFLC		FCDTN		PRNVT		EVCNC		HMVTN		PCVAL	
PXPCT	.00	.00	.83	.18	.76	.20	.76	.20	.76	.20	.00	.31	.87	.16	.83	.18
EXPCT	.52	.25	.00	.00	.31	.28	.43	.26	.43	.26	.00	.31	.31	.28	.52	.25
SNFLC	.31	.28	.31	.28	.00	.00	.43	.26	.52	.25	.43	.26	.62	.23	.70	.21
FCDTN	.43	.26	.31	.28	.43	.26	.00	.00	.43	.26	.00	.31	.70	.21	.31	.28
PRNVT	.00	.31	.43	.26	.00	.31	.43	.26	.00	.00	.00	.31	.70	.21	.52	.25
EVCNC	.88	.16	.88	.16	.87	.16	.87	.16	.87	.16	.00	.00	.87	.16	.87	.16
HMVTN	.52	.25	.49	.25	.00	.31	.43	.26	.62	.23	.31	.28	.00	.00	.43	.26
PCVAL	.43	.26	.31	.28	.00	.31	.52	.25	.76	.20	.00	.31	.52	.25	.00	.00
d = 0 T = 1	PXPCT		EXPCT		SNFLC		FCDTN		PRNVT		EVCNC		HMVTN		PCVAL	
PXPCT	.00	.00	.75	.18	.63	.21	.63	.21	.63	.21	.01	.31	.80	.17	.75	.18
EXPCT	.36	.25	.00	.00	.16	.28	.26	.27	.26	.27	.01	.31	.16	.28	.36	.25
SNFLC	.16	.28	.16	.28	.00	.00	.26	.27	.36	.25	.26	.27	.46	.23	.54	.22
FCDTN	.26	.27	.16	.28	.26	.27	.00	.00	.26	.27	.01	.31	.54	.22	.16	.28
PRNVT	.01	.31	.26	.27	.01	.31	.26	.27	.00	.00	.01	.31	.54	.22	.36	.25
EVCNC	.84	.15	.84	.15	.80	.17	.80	.17	.80	.17	.00	.00	.80	.17	.80	.17
HMVTN	.36	.25	.32	.26	.01	.31	.26	.27	.46	.23	.16	.28	.00	.00	.26	.27
PCVAL	.26	.27	.16	.28	.01	.31	.36	.25	.63	.21	.01	.31	.36	.25	.00	.00
d = 0 T = 2	PXPCT		EXPCT		SNFLC		FCDTN		PRNVT		EVCNC		HMVTN		PCVAL	
PXPCT	.00	.30	.86	.17	.80	.20	.80	.20	.80	.20	.04	.30	.89	.16	.86	.17
EXPCT	.57	.25	.00	.30	.40	.28	.48	.27	.48	.27	.04	.30	.40	.28	.57	.25
SNFLC	.40	.28	.40	.28	.00	.30	.48	.27	.57	.25	.48	.27	.68	.23	.73	.22
FCDTN	.48	.27	.40	.28	.48	.27	.00	.30	.48	.27	.04	.30	.73	.22	.40	.28
PRNVT	.04	.30	.48	.27	.04	.30	.48	.27	.00	.30	.04	.30	.73	.22	.57	.25
EVCNC	.90	.16	.90	.16	.89	.16	.89	.16	.89	.16	.00	.30	.89	.16	.89	.16
HMVTN	.57	.25	.55	.26	.04	.30	.48	.27	.68	.23	.40	.28	.00	.30	.48	.27
PCVAL	.48	.27	.40	.28	.04	.30	.57	.25	.80	.20	.04	.30	.57	.25	.00	.30

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