Heliyon 9 (2023) e15975

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Barriers to the sustainable adoption of autonomous vehicles in developing countries: A multi-criteria decision-making approach

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ARTICLE INFO

Keywords:
Autonomous vehicles
Adoption barriers
Sustainability
Rough BWM
IR-MABAC

ABSTRACT

The acceptance of AI-based intelligent transportation systems requires addressing the existing barriers and the adoption of macro-decisions and policies by policymakers and governments. This study evaluates the potential barriers to the adoption of Autonomous Vehicles (AVs) in developing countries by considering the sustainability dimensions. The barriers are identified by conducting a comprehensive literature review and studying the academic experts' opinions in related industries. By identifying the main barriers to the sustainable adoption of AVs, a synthesized approach of the Rough Best-Worst Method (RBWM) and Interval-Rough Multi-Attributive Border Approximation Area Comparison (IR-MABAC) is utilized for weighting and evaluating each barrier in this context. According to the results of this study, the "inflation rate", "lack of internet connection quality", and "learning challenges and difficulties to use the AVs" are the top challenges and barriers to the AV adoption which need to be considered by policymakers. As the main contribution of this research, we provide efficient insights on a macro policy scale for decision-makers with respect to the main barriers to the implementation of AVs technology. From the AVs literature and to the best of our knowledge, this is the first study of its kind that considers the barriers to the AV technology implementation through the sustainability concept.

1. Introduction

Road fatalities and injuries are the worst type of casualties which may occur at any time and as many times since the development of high-speed vehicles. According to the WHO (World Health Organization), one fatality happens every 23 seconds on the world's roads [50]. In order to decrease road accidents and fatalities, the autonomous vehicles (AVs) industry is improving day by day. This innovative technology was initiated and deployed by the utilization of computers in the control function of the vehicles [18]. On the other hand, with the growth and influence of artificial intelligence in all scientific fields, AV technology has also taken a continuous upward development. Therefore, the attention of governmental and non-governmental organizations has been fascinated by the context of autonomous driving.

AVs can lead to a revolution in traveling and transportation modes. In this regard, the occurrences of fatal crashes such as in the Tesla autopilot system, and Uber self-driving systems have raised further safety concerns [48,47]. Therefore, the development of relevant legislation for automakers and customers is a requirement to assure safety concerns. Transportation autonomy has also

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https://doi.org/10.1016/j.heliyon.2023.e15975
Received 7 April 2023; Received in revised form 27 April 2023; Accepted 28 April 2023

Available online 9 May 2023

entered cargo transportation, initially. It was claimed level 3 of autonomous trucks can be rolled around 2020 [13] followed by level 4 and level 5 autonomy by 2025 and 2027, respectively.

This context of modern technology is capable to transform the lifestyle of all people who are exposed to this equipment, particularly the elders and disabled people who are not able to drive [17,25]. Additionally, lowering traffic congestion [41] can be emerged by the AVs connection capabilities and a sustainable society could be expected along with decreasing the emissions and consumption of energy and fossil fuels [10,23]. To boost these advantages, the leading automobile companies and technology pioneers are cooperating through AI-based products to make self-driving cars purchasable for all people. However, liability, security, privacy, and regulation are the main concerns of this technology [2].

The adaptation of consumers' behavior against emerging AV technologies has been a crucial concern so far. By different social and infrastructural restrictions toward the diverse features of self-driving cars, the proposed innovative technology has barriers to being implemented, particularly in developing countries. For example, by the initial phase of the transitional period and the coexistence of both autonomous and ordinary vehicles, there is an urgent need to develop strategies for the traffic network and management policies. In addition, barriers related to the infrastructural restrictions and psychological constraints toward AVs are among the main concerns that need to be taken into consideration [5]. Furthermore, people in developing countries may have further limitations such as purchasing power and financial affordability.

Several studies have considered the barriers to AVs adoption [22,24,46]. Prior studies in this field have presented a descriptive investigation on the relationship between the individuals' characteristics and their beliefs about intelligent vehicles [28,37]. A few years later, the researchers conducted an analysis to find the manner of associations among the people's characteristics, social and traveling attributes, and the environmental effects on their opinions about AVs [24,29,16,14].

Many studies showed that sustainability denotes the commitment of the 3 dimensions including economic, environmental, and social issues. Many studies considered the environmental consequences of the AVs by decreasing the congestion of traffic and accidents [4] as well as optimizing fuel efficiency with better driving performance [32]; although from the environmental point of view, a full assessment of AVs is beyond the fuel consumption and the life cycle of the vehicle.

Additionally, the main challenges in manufacturing and recycling electric vehicles must be taken into account [20,49]. The reduction of congestion, less time loss in traffic, lower rate of accidents, and hence more productivity, are among the economic benefits and positive aspects of AVs [42].

On the other hand, AVs can eliminate the labor market by exchanging human drivers with technology. This occurrence can affect many businesses which are interrelated with transportation and logistics [38]. AVs can bring economic advantages by increasing the safety of roads and highways.

According to the NHTSA report, the U.S. encountered roughly faces an annual cost of $242 billion loss due to vehicle crashes including the damages occurred by the accidents, the medical costs, the productivity losses, and the congestion expenses (i.e. the amount of wasted fuel during the traffic time) [1].

From a social standpoint, traffic safety for AVs can also be considered as a social issue. According to [45], 94 percent of road crashes can be assigned to human errors. These errors are related to alcohol use, distractions, high speed of vehicles, low reaction time, etc. So, with the assistance of artificial intelligence in AVs [41], human errors can be eliminated. The accessibility of the elderly and disabled population of society has always been a huge concern that can be improved as a social responsibility of AVs implications. Additionally, people with low income can also benefit from the AVs using the sharing capability of such vehicles which is more convenient and cheaper than the other public transport vehicles [8,33].

As the main contribution of this study, the potential barriers to adopting AVs are evaluated and analyzed on the basis of the sustainability aspect issues as follows: 1) The barriers are investigated and obtained according to the related literature and collecting the experts' opinions in the field. 2) The identified barriers (as the main challenges of the implementation of AVs technology) are weighted using Rough Best-Worst Method (RBWM). 3) The results have been then evaluated by the Interval Rough Multi Attributive Border Approximation Area Comparison (IR-MABAC) approach to obtain the rank of each barrier, and finally, by obtaining the ranked barriers, rational insights are taken to deliver to the policymakers and governments for their consideration. By taking the best action in macro policies, the best decision can be made to provide the situation of AVs technology implementation for globalizing sustainability and fostering sustainable development in developing countries. The outcome of the proposed methodology is presented and discussed.

The rest of the article is arranged as follows: the next section presents the related literature. Section 3 explains the problem statement. The proposed methodology for weighting and evaluating the barriers is described in section 4. The explanation of the case study and the implementation of the proposed methodology are clarified in section 5. In section 6 the verification approach is presented and the outcome of the solutions is discussed, the sensitivity analysis and discussion about the performance of the models are described in section 7, and finally, this work ends up with a conclusion and suggestions for future related investigation.

2. Literature review

According to the definition of the Society of Automotive Engineers (SAE) and accepted by the National Highway Traffic Safety Administration [15], six levels of autonomy have been assigned for AVs which are started from level 0 (with no autonomy) to level 5 (with full autonomy). Generally, autonomous vehicles with levels 4 and 5 are named self-driving cars. This technology is going to bring safe transportation on the basis of eliminating human error [11]. On the other hand, one of the main factors for smart cities to boost the quality of life and sustainability is the smart transportation system [3].

Self-driving vehicles have been the main topic in recent investigations in this area, and recent studies considered the expectation of challenges and opportunities of the AVs' popularity and the changes in the way of transport [31,17,5] and also the topics related to the willingness of the consumers to pay and use the AVs, and risk perception [14,9,6,27,51]. In another way, many other researchers have analyzed the impact of AVs on infrastructures such as parking facilities [35,52] and fossil fuel consumption [12].

Gkartzonikas and Gkritza [22] had an investigation that relied on stated preferences (SP) and used the adult population over 18 years old for its research sample as the experts and product owners. Some of the recent research have forecasted the AVs technologies adaption in the future [6] and travel behavior caused by AVs introduction [27] adaption dependencies of AVs in a real case study [34]. Fagnant and Kockelman [17] had a survey on policy recommendations, opportunities, and barriers. They found out that the parking benefits and fuel efficiency as well as crash savings and reduction of traveling time are the main opportunities in their study. They also estimated the privacy concerns, standards for liability, cost, and licensing as the barriers. Kyriakidis et al. [28] prepared a survey on the acceptance of the users and willingness to buy the AVs. Due to their study, the reduction of traffic crashes and pollution are the positive points, and safety, legal, and privacy issues were the negative points in this field. Daziano et al. [14] explored the early response to the ownership of self-driving cars and the willingness to pay for autonomous vehicles. Their approach was based on microdata and logit models. They found the failure of systems and equipment was the main barrier in this context. Buckley et al. [9] explored the perceptions and responses to the AVs. They used experiments based on a simulator and they found hacking and privacy as a barrier, and stress reduction for drivers as an opportunity in their study.

Fraedrich et al. [19] investigated the AVs' impacts on the infrastructures of the built environment. Their observation was based on online surveys and qualitative interviews. The infrastructural planning and adaptation of AVs and current transport facilities were recognized as the barriers to AVs' implications. They also introduced safety, reduction in parking space, and emission as opportunities in their investigation. Li et al. [30] considered insights and research frontiers in a highly automated vehicles policy context. They reviewed the background works and figured out the opportunities as decreasing the emissions and making mobility for elderly and disabled people possible independently, and reducing the fatalities. They also achieved the main barriers of this area such as the government's role, licensing and testing standards, reliability, public health, legal challenges, and preventive or helpful policies. Litman [31] addressed the impacts on transportation planning. Social equity, increasing the cost of infrastructures, the security and policy issues were the main negative points in the AVs implementation. Nourinejad et al. [35] presented a mixed-integer non-linear mathematical model to design AV's car parks. They solved their proposed model with two approaches: The Benders decomposition approach for exact solutions and a heuristic algorithm. Shladover and Nowakowski [44] had a survey on the regulatory challenges in California for AVs and they concluded that due to lack of clear standards and testing procedures, it is difficult for regulatory agencies, developers, or third parties to certify the safety of AVs. According to a survey by [51], autonomous vehicles are positively viewed in China and 42.35% and 45.28% of the participants expect a lower risk and lower insurance premiums for AVs, respectively.

Raj et al. [39] studied the barriers to the adoption of AVs. They utilized Gray-DEMATEL to analyze the relationship between the barriers which resulted in the lack of customer acceptance as the most important barrier with the highest priority among the others. Shabanpour et al. [43] modeled the adoption behavior of self-driving cars by using the Best-Worst scaling approach. Their study demonstrated that the purchase price and incentive policies are sensitive factors for people. They also found that high-income people and those who experienced an accident are more interested in adopting this technology. Huang et al. [26] considered the intentions toward the AVs adaptation in China. They also analyzed how people's attitudes are affected by the reasoning process. They initiated the behavioral reasoning theory to present the role of psychological traits in the relationship between attitudes, reasoning, and consumers' intention of adoption. Bezai et al. [7] had a survey on the AVs' barriers which can promote their adoption. They found the main barriers to AVs were related to safety, user acceptance, and behavior issues. Other factors such as distrust feeling and perception, also affect the consumers' adoption of AV technology.

By considering the reviewed related works, it can be seen that none of the presented articles have considered the main barriers of the AVs adoption by the sustainability aspect issues in a developing country. To the best of our knowledge, in this study, we contribute to identifying and ranking the main barriers and challenges to AV adoption in developing countries, for the first time. This work considered the sustainable issues to take the best macro policy decisions and actions to provide the ways of implementing AV technology and making people's lives more comfortable all around the world.

3. Problem statement

As a consequence of implementing the advantages of intelligent transport, the consideration of the barriers to the adoption of this concept in developing countries is not negligible. Although many criticisms exist toward this technology, the large-scale reduction of road fatalities and the comfort usage of transport facilities for elderly and disabled people could be the main definite reasons to implement this AI-based technology all over the world.

In this study, a set of critical barriers to the adoption of autonomous vehicles are obtained based on the literature, previous studies, and the opinions of the experts from the Ministry of Roads and Urban Development and the Ministry of Information and Communications in Iran as a developing country. The selected experts have solid academic backgrounds, are highly qualified in the transportation field, and are also engaged with the executive transportation organizations as they can affect the policies for eliminating the barriers to the adoption of AVs. Hence the number of experts is limited. These barriers are associated with sustainable development and the sustainability dimensions are considered in the selection of the adoption of AV barriers. The experts are aware of the infrastructures and legislation which has caused the barriers to implementing the technology; however, they have not had the opportunity of analyzing the challenges scientifically. The data was collected via questionnaires.

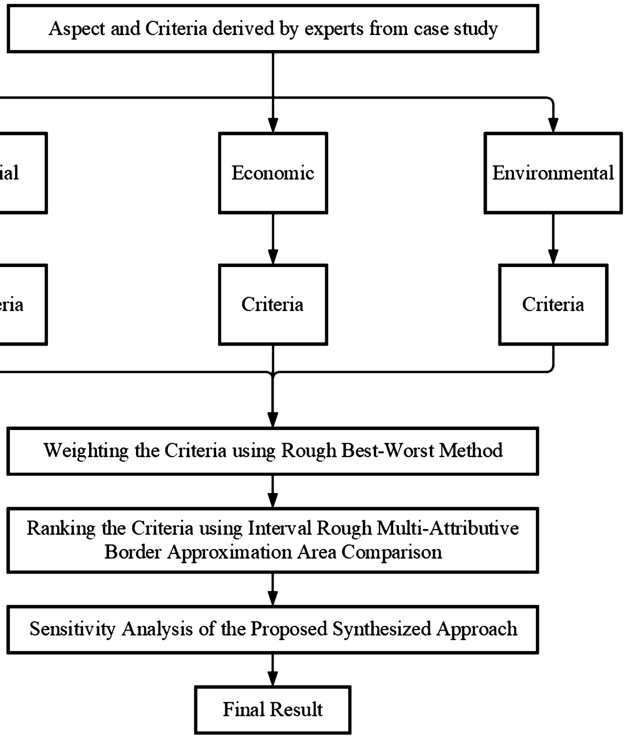

Fig. 1. The overall steps and structure of the proposed methodology.

We summarize the benefits of this work by analyzing and evaluating the barriers to the adoption of AVs in developing countries. The synthesized approaches of RBWM and IRMABAC are presented to obtain the weight of barriers and evaluate the rank of proposed barriers. The proposed approaches are relatively new, yet very popular methods in the discipline of multi-attribute decision-making.

4. Methodology

In this research, we utilize new approaches to obtain the weight of each barrier and evaluate them. In the first step, the main barriers of the AVs' technology adoption are gathered from past related works and the academic experts' opinions by considering the sustainability aspects. The raw data gathered from the experts' opinions are weighted and evaluated using RBWM and IRMABAC. The results of the two multi-criteria decision-making approaches made excellent insights to make the best decisions and utilize the best policies for implementing the AVs technology. Fig. 1 represents the overall structure of the proposed methodology.

4.1. Rough Best-Worst Method (RBWM)

Best-Worst Method is a new approach for solving the multi-criteria decision-making problems introduced by [40] in 2015. In this approach, the best and the worst criteria are distinguished by the decision-maker. After performing a pairwise comparison between each of the best and worst criteria with the other ones, a maximum problem would be formulated to obtain the weight of different criteria. By using rough numbers (RN), the Best-Worst method (BWM) can be modified as RBWM which is helpful in order to consider the imprecision much more comprehensively, which might appear in the group decision-making process. By using the concepts of rough numbers, there is no need for more information to recognize the uncertainty which exists in the intervals of the numbers. In this way, existing data can be maintained in quality in group decision making and the experts' perceptions can be represented as the best-to-others (BO) and others-to-worst (OW). The proposed RBWM is more feasible for experts to consider the causes of conjecture in the criteria assessment. The RBWM, by using a new approach in dealing with imprecision which is based on RN, causes to overcome the existing gap in the BWM approach. So, the application of this approach by considering rough numbers is more beneficial in strategic decision-making contexts which leads to making macro-policies. The algorithm for RBWM consists of the following steps:

Step 1: Specifies a set of assessment criteria and the decision-making process will begin with the m experts. In this step, the criteria (the barriers in this context) are evaluated by experts' opinions, and also the last version of the criteria set means, $C = \{c_1, c_2, ..., c_n\}$ is selected by them, where n identifies the whole number of criteria.

Step 2: In this step, the best and worst criteria are determined according to $C = \{c_1, c_2, ..., c_n\}$, in terms of importance and remarkability based on the expert suggestion. In this case, two or more criteria may be the best or worst candidate from the expert's point of view. In this case, the selected criteria are selected from the candidates.

Step 3: The preference of the utmost influential (most significant) criteria (B) among other remaining criteria from set C should be established based on experts' points of view. Regarding the set of m experts and n criteria, the influential effect of the best criterion B on the other criteria by the set index $j \in \{j = 1, 2, ..., n\}$ should be established by each of the experts. The term a^e_{Bj} $(j = 1, 2, ..., n; 1 \le e \le m)$ illustrates the superiority of criterion B compared to the j-th criterion which is distinguished by the e-th expert. Each conjugate interval of a^e_{Bj} contains a value of interval $a^e_{Bj} \in \{1, 9\}$ which has comparative values already defined. Therefore, the Best vector can be obtained in this way:

$$A^e_B = (a^e_{B1}, a^e_{B2}, ..., a^e_{Bn}); 1 \le e \le m \tag{1}$$

The priority of B to other criterion j represents by a^e_{Bj} in which $(a_{BB})^e = 1$. So, the BO matrices $A^1_B, A^2_B, ..., A^m_B$ are represented for each expert.

Step 4: The preference of the worst criterion among other remaining criteria from set C should be determined based on experts' points of view. The term $a^e_{jw}(j = 1, 2, ..., n; 1 \le e \le m)$ denotes the e-th expert definition to the preference of criterion j in association with criterion W. Similar to B vector, each conjugate interval of a^e_{jw} contains a value of the predefined interval values. Therefore, the worst vector can be gained in this way:

$$A^e_W = (a^e_{1W}, a^e_{2W}, ..., a^e_{nW}); 1 \le e \le m \tag{2}$$

That the priority of criterion j in relation to criterion W is represented by a^e_{jw}, whereby $a^e_{WW} = 1$. This is how the OW matrices $A^1_W, A^2_W, ..., A^m_W$ are obtained for each expert.

Step 5: Experts' answers would be vary, so due to the average of these answers, the rough BO matrix is determined. The matrices of the accumulated sequences of experts A^{*e}_B are formed according to the BO matrix of the experts' answers $A^e_B = [a^e_{Bj}]_{1\times mn}$.

$$A^{*e}_B = [a^1_{B1}, ..., a^m_{B1}; a^1_{B2}, ..., a^m_{B2}; ...; a^1_{Bn}, ..., a^m_{Bn}]_{1\times mn} \tag{3}$$

Where $a^e_{Bj} = \left\{a^1_{Bj}, a^2_{Bj}, \dots, a^m_{Bn}\right\}$ denotes the sequences in which the comparative importance of criterion B is defined with respect to criterion j. Each sequence a^e_{Bj} is converted into rough sequence $RN\left(a^e_{Bj}\right) = \left[\underline{Lim}\left(a^e_{Bj}\right), \overline{Lim}\left(a^e_{Bj}\right)\right]$ by using the equations (1) - (6), where $\underline{Lim}\left(a^e_{Bj}\right)$ shows the minimum amount and $\overline{Lim}\left(a^e_{Bj}\right)$ illustrates the maximum amount of the rough sequence $RN\left(a^e_{Bj}\right)$.

Therefore, the BO matrices $A^{*1}_B, A^{*2}_B, \dots, A^{*m}_B$ are calculated for sequence $RN\left(a^e_{Bj}\right)$. For BO matrix, the average rough sequence is calculated as follows:

$$RN\left(\overline{a}_{Bj}\right) = RN\left(a^1_{Bj}, \dots, a^e_{Bj}\right) = \begin{cases} a^{-L}_{Bj} = \frac{1}{m}\sum_{e=1}^m a^{eL}_{Bj} \\ a^{-U}_{Bj} = \frac{1}{m}\sum_{e=1}^m a^{eU}_{Bj} \end{cases} \tag{4}$$

where $a^{-L}_{Bj} = \frac{1}{m}\sum_{e=1}^m a^{eL}_{Bj}$ and $a^{-U}_{Bj} = \frac{1}{m}\sum_{e=1}^m a^{eU}_{Bj}$, and also e shows the e-th expert $(e = 1, 2, \dots, m)$, $RN\left(a^e_{Bj}\right)$ illustrates the rough sequence. The averaged rough BO matrix is obtained from the average of answers $\overline{A}_B$:

$$\overline{A}_B = \left[\overline{a}_{B1}, \overline{a}_{B2}, \dots, a^m_{Bn}\right]_{1\times n} \tag{5}$$

Step 6: The matrices of the accumulated sequences of the experts (A^{*e}_W) are formed based on the OW matrix of the average answers of the experts $A^e_W = \left[a^e_{jW}\right]_{1\times n'}$ as with the rough BO matrices, for each element a^e_{jW}.

$$A^{*e}_W = \left[a^1_{1W}, \dots, a^m_{1W};\ a^1_{2W}, \dots, a^m_{2W}; \dots;\ a^1_{nW}, \dots, a^m_{nW}\right] \tag{6}$$

$a^e_{jW} = \left\{a^1_{jw}, a^2_{jw}, \dots, a^m_{nw}\right\}$ demonstrates the sequence that the comparative importance of criterion j is qualified in proportion to criterion W. The sequences a^e_{jW} are converted to rough sequences $RN\left(a^e_{jw}\right) = \left[\underline{Lim}\left(a^e_{jw}\right),\ \overline{Lim}\left(a^e_{jw}\right)\right]$, as it is shown in step 5. Thus, a rough BO matrix is configured for any of the rough sequences of expert e $(1 \le e \le m)$. So, to calculate the matrix of an averaged rough OW, the equation (7) is applied to the experts' average opinions for the rough sequences of the OW matrix.

$$RN\left(\overline{a}_{jw}\right) = RN\left(a^1_{jw}, a^2_{jw}, \dots, a^e_{jw}\right) = \begin{cases} a^{-L}_{jw} = \frac{1}{m}\sum_{e=1}^m a^{eL}_{jw} \\ a^{-U}_{jw} = \frac{1}{m}\sum_{e=1}^m a^{eU}_{jw} \end{cases} \tag{7}$$

The e^{th} expert's suggestion is shown by e, and the rough sequence demonstrated by $RN\left(a_{jw}\right)$. So, the averaged rough OW matrix of the expert's average responses $\overline{A}_W$ is acquired as follows:

$$\overline{A}_W = \left[\overline{a}_{1w}, \overline{a}_{2w}, \dots, \overline{a}_{nw}\right]_{1\times n} \tag{8}$$

Step 7: The main objective of this step is to calculate the optimized amount of rough values for the weight coefficients related to each criterion $\left[RN\left(W_1\right),\ RN\left(W_2\right), \dots, RN\left(W_n\right)\right]$ from the set C. To comply with this the maximum difference of $\left|\frac{RN(W_B)}{RN(W_j)} - RN\left(a_{Bj}\right)\right|$ and $\left|\frac{RN(W_j)}{RN(W_w)} - RN\left(W_{jw}\right)\right|$ should be minimized.

For all the interval rough weight coefficient values of the criteria $RN\left(W_j\right)=\left[\underline{Lim}\left(W_j\right),\ \overline{Lim}\left(W_j\right)\right]=\left[W_j^L,\ W_j^U\right]$ the condition is satisfied that $0\le W_j^L\le W_j^U\le 1$ for each evaluation criterion $c_j\in C$. The weight coefficient W_j is a subset of interval $\left[W_j^L,\ W_j^U\right]$, that is, $W_j^L\le W_j^U$ for each of the j values $(j=1,2,\dots,n)$. Based on this, for the rough values of weight coefficients of the criteria, $\sum_{j=1}^n W_j^U\ge 1$ would be concluded. As of this, the weight coefficients exist in the interval $W_j\in[0,1]$, $(j=1,2,\dots,n)$ and $\sum_{j=1}^n W_j=1$. The limits which have been defined previously were expressed in the following min-max model:

$$
\begin{aligned}
& minmax_j \left|\frac{RN(W_B)}{RN(W_j)}-RN(a_{Bj})\right|,\left|\frac{RN(W_j)}{RN(W_w)}-RN(W_{jw})\right| \\
& s.t. \\
& \sum_{j=1}^n W_j^L\le 1; \\
& \sum_{j=1}^n W_j^U\ge 1; \\
& W_j^L\le\ W_j^U,\ \forall j=1,2,\dots,n; \\
& W_j^L,\ W_j^U\ge 0,\ \forall j=1,2,\dots,n
\end{aligned}
\tag{9}
$$

The rough weight coefficient of a criterion is $RN\left(W_j\right)=\left[\underline{Lim}\left(W_j\right),\ \overline{Lim}\left(W_j\right)\right]=\left[W_j^L,\ W_j^U\right]$. So the following model (expression (10)) is equivalent to the previous model (expression (9)).

$$
\begin{aligned}
& min\zeta \\
& s.t. \\
& \left|\frac{W_B^L}{W_j^U}-a_{Bj}^{-U}\right|\le\zeta;\left|\frac{W_B^U}{W_j^L}-a_{Bj}^{-L}\right|\le\zeta; \\
& \left|\frac{W_j^L}{W_w^U}-a_{jw}^{-U}\right|\le\zeta;\left|\frac{W_j^U}{W_w^L}-a_{jw}^{-L}\right|\le\zeta; \\
& \sum_{j=1}^n W_j^L\le 1;\sum_{j=1}^n W_j^U\ge 1; \\
& W_j^L\le\ W_j^U,\ \forall j=1,2,\dots,n; \\
& W_j^L,\ W_j^U\ge 0,\ \forall j=1,2,\dots,n
\end{aligned}
\tag{10}
$$

Where the optimal values are illustrated by $RN\left(W_j\right)=\left[W_j^L,\ W_j^U\right]$ for the weight coefficients, also $RN\left(W_B\right)=\left[W_B^L,\ W_B^U\right]$ shows the weight coefficients for the best criterion and $RN\left(W_w\right)=\left[W_w^L,\ W_w^U\right]$ shows that of the worst. $RN\left(\overline{a}_{jw}\right)=\left[a_j^L,\ a_j^U\right]$ is the values of average rough OW matrix and $RN\left(\overline{a}_{Bj}\right)=\left[a_{Bj}^L,\ a_{Bj}^U\right]$ is the values of average rough BO matrix (see equations (5) and (8)). The optimal values of the weight coefficients are obtained by solving model (10) for evaluating criteria $\left[RN\left(w_1\right),RN\left(w_2\right),\dots,RN\left(w_n\right)\right]$ and ζ.

4.2. Interval Rough Multi-Attributive Border Approximation Area Comparison (IR-MABAC)

One of the newest approaches as multi-attribute decision-making is the MABAC method [21]. The main structure of the MABAC method is demonstrated in the definition of the distance of the criterion function from any observed alternative border approximation zones. This approach is also justifiable for the MCDM problems which would be led to macro-policy making. In this work, the MABAC method was modified to use interval rough numbers. The main steps of utilizing the interval rough MABAC method (IR-MABAC) are described as follows:

Step 1: The initial matrix (X) for decision-making should be configured. In this step, the m number of alternatives are evaluated by n criteria. The vector A_i determines as follows:

$A_i=\left(IRN\left(x_{i1}\right),\ IRN\left(x_{i2}\right),\dots,\ IRN\left(x_{im}\right)\right)$ where the value of the i number of alternatives and j number of criteria ($i=1,2,\dots,m$; $j=1,2,\dots,n$) shown as $IRN\left(x_{ij}\right)=\left[RN\left(x_{ij}^L\right),\ RN\left(x'^U_{ij}\right)\right]=\left(\left[x_{ij}^L,\ x_{ij}^U\right],\ \left[x'^L_{ij},\ x'^U_{ij}\right]\right)$.

$$
X=\begin{bmatrix}
 & C_1 & C_2 & \dots & C_n \\
A_1 & IRN\left(x_{11}\right) & IRN\left(x_{12}\right) & \cdots & IRN\left(x_{1n}\right) \\
A_2 & IRN\left(x_{21}\right) & IRN\left(x_{22}\right) & \cdots & IRN\left(x_{2n}\right) \\
 & \dots & \dots & & \dots \\
A_m & IRN\left(x_{m1}\right) & IRN\left(x_{m2}\right) & \cdots & IRN\left(x_{mn}\right)
\end{bmatrix}_{mn}
\tag{11}
$$

where m and n represent the total number of alternatives and the total criteria number, respectively.

Step 2: The value of the elements in the initial matrix (X) is normalized as follows:

$$N = \begin{array}{c} \\ \end{array}\begin{bmatrix} & C_1 & C_2 & \dots & C_n \\ A_1 & IRN\left(t_{11}\right) & IRN\left(t_{12}\right) & \cdots & IRN\left(t_{1n}\right) \\ A_2 & IRN\left(t_{21}\right) & IRN\left(t_{22}\right) & \cdots & IRN\left(t_{2n}\right) \\ & \dots & \dots & & \dots \\ A_m & IRN\left(t_{m1}\right) & IRN\left(t_{m2}\right) & \cdots & IRN\left(t_{mn}\right) \end{bmatrix}_{mn} \tag{12}$$

The following expression determines the values of $IRN\left(t_{ij}\right)$ in matrix (N) which is normalized:

a) For the benefits' criteria (bigger value is desirable)

$$\begin{aligned} IRN\left(t_{ij}\right) &= \left(\left[t_{ij}^L,\ t_{ij}^U\right],\ \left[t'^L_{ij},\ t'^U_{ij}\right]\right) \\ &= \left(\left[\frac{x_{ij}^L - x_j^-}{x_j^+ - x_j^-},\ \frac{x_{ij}^U - x_j^-}{x_j^+ - x_j^-}\right],\ \left[\frac{x'^L_j - x_j^-}{x_j^+ - x_j^-},\ \frac{x'^U_j - x_j^-}{x_j^+ - x_j^-}\right]\right) \end{aligned} \tag{13}$$

b) For the costs' criteria (smaller value is desirable)

$$\begin{aligned} IRN\left(t_{ij}\right) &= \left(\left[t_{ij}^L,\ t_{ij}^U\right],\ \left[t'^L_{ij},\ t'^U_{ij}\right]\right) \\ &= \left(\left[\frac{x'^U_j - x_j^+}{x_j^- - x_j^+},\ \frac{x'^L_j - x_j^+}{x_j^- - x_j^+}\right],\ \left[\frac{x_j^U - x_j^+}{x_j^- - x_j^+},\ \frac{x_j^L - x_j^+}{x_j^- - x_j^+}\right]\right) \end{aligned} \tag{14}$$

The x_j^+ and x_j^- represent the maximum and minimum amount of the rough boundary interval for the considered criteria.

$$x_j^- = \min_j \left\{ x_{ij}^L,\ x'^L_{ij} \right\} \tag{15}$$

$$x_j^+ = \max_j \left\{ x_{ij}^U,\ x'^U_{ij} \right\} \tag{16}$$

Step 3: In this step, the weighted matrix $V = \left[IRN\left(x_{ij}\right)\right]_{m\times n}$ is calculated, where each element of the matrix can be defined as follows:

$$IRN\left(v_{ij}\right) = IRN\left(w_i\right).\ IRN\left(t_{ij}\right) + IRN\left(w_i\right) \tag{17}$$

In the normalized matrix (N), the elements are represented by $IRN\left(t_{ij}\right)$, and the weights coefficients of criteria are shown by $IRN\left(w_j\right)$. By utilizing the equation (17), we define the weighted matrix (V) as follows:

$$V = \begin{bmatrix} \left(\left[v_{11}^L, v_{11}^U\right], \left[v\prime_{11}^L, v\prime_{11}^U\right]\right) & \dots & \left(\left[v_{1n}^L, v_{1n}^U\right], \left[v\prime_{1n}^L, v\prime_{1n}^U\right]\right) \\ \left(\left[v_{21}^L, v_{21}^U\right], \left[v\prime_{21}^L, v\prime_{21}^U\right]\right) & \dots & \left(\left[v_{2n}^L, v_{2n}^U\right], \left[v\prime_{2n}^L, v\prime_{2n}^U\right]\right) \\ \dots & \dots & \dots \\ \left(\left[v_{m1}^L, v_{m1}^U\right], \left[v\prime_{m1}^L, v\prime_{m1}^U\right]\right) & \dots & \left(\left[v_{mn}^L, v_{mn}^U\right], \left[v\prime_{mn}^L, v\prime_{mn}^U\right]\right) \end{bmatrix}_{m\times n} \tag{18}$$

where n is the number of criteria and m is the number of alternatives.

Step 4: In this step, the border approximation area matrix (G) would be determined. This matrix (G) is determined according to the following expression:

$$IRN\left(g_i\right) = (\prod_{j=1}^{m} IRN\left(v_{ij}\right))^{1/m} = \left(\left[\left\{\prod_{j=1}^{m} v_{ij}^L\right\}^{\frac{1}{m}},\ \left\{\prod_{j=1}^{m} v_{ij}^U\right\}^{\frac{1}{m}}\right],\ \left[\left\{\prod_{j=1}^{m} v'^L_{ij}\right\}^{\frac{1}{m}},\ \left\{\prod_{j=1}^{m} v'^U_{ij}\right\}^{\frac{1}{m}}\right]\right) \tag{19}$$

where $IRN\left(v_{ij}\right)$ represents the elements of the weighted matrix (V). The $(1 \times n)$ matrix of border approximation area (G) is formed after calculation of the $IRN\left(g_{ij}\right)$ value as follows:

$$G = \begin{array}{cccc} C_1 & C_2 & \dots & C_n \\ \left[IRN\left(g_1\right)\right. & IRN\left(g_2\right) & \dots & \left.IRN\left(g_n\right)\right] \end{array} \tag{20}$$

Step 5: The elements of the matrix of the alternatives distance are calculated according to the border approximation area (Q). The subtraction result of the weighted matrix (V) elements and the value of border approximation area (G) is the alternatives distance from the border approximation area $IRN\left(q_{ij}\right)$

$$Q = V - G = \begin{bmatrix} IRN(v_{11}) & IRN(v_{12}) & \dots & IRN(v_{1n}) \\ IRN(v_{21}) & IRN(v_{22}) & \dots & IRN(v_{2n}) \\ \dots & \dots & \dots & \dots \\ IRN(v_{m1}) & IRN(v_{m1}) & \dots & IRN(v_{mn}) \end{bmatrix}_{m\times n} - \begin{bmatrix} IRN(g_1) & IRN(g_2) & \dots & IRN(g_n) \end{bmatrix}_{1\times n} \tag{21}$$

$$Q = \begin{bmatrix} IRN(v_{11}) - IRN(g_1) & \dots & IRN(v_{1n}) - IRN(g_n) \\ IRN(v_{21}) - IRN(g_1) & \dots & IRN(v_{2n}) - IRN(g_n) \\ \dots & \dots & \dots \\ IRN(v_{m1}) - IRN(g_1) & \dots & IRN(v_{mn}) - IRN(g_n) \end{bmatrix}_{m\times n} \tag{22}$$

where $IRN(g_j)$ shows the border approximation area for criterion C_i and $IRN(v_{ij})$ represents the elements of the weighted matrix (V). Also, m shows the number of alternatives and n shows the number of criteria. Alternative A_i can be part of the border approximation area (G) which included the upper (G^+) and the lower (G^-) approximation area ($A_i \in \{G \vee G^+ \vee G^-\}$). The upper approximation area (G^+) is represented by the ideal alternative (A^+), whereas the lower approximation area (G^-) contains the anti-ideal alternative (A^-). The alternative A_i is close to or equal to ideal alternative if the $IRN(q_{ij}) > IRN(g_j)$ in which $IRN(q_{ij}) \in G^+$. It is necessary that the alternative A_i is a subset of the upper approximation area (G^+) in order to choose as the best of the set.

Step 6: Alternatives are ranked in this step. The value of criteria functions can be obtained as follows:

$$IRN(S_i) = \sum_{J=1}^{N} IRN(q_j), j = 1,2,...,n,\ i = 1,2,...,m \tag{23}$$

as the cumulative value of the alternative distance from the border approximate areas $IRN(q_i)$. The final values of criteria functions of alternatives are calculated by summation of the elements of the matrix Q by row. The ranking of the alternatives is performed by implementing the rules for the ranking of interval rough numbers or rough interval numbers transformation to real numbers. Transforming the interval rough number $IRN(S_i) = ([S_i^L,\ S_i^U],\ [S{\prime}_i^L,\ S{\prime}_i^U])$ into a real number S_i is done by utilizing the equations (24) and (25). It can be used to the intervals of both object classes to determine indicators $\mu_i (0 \le \mu_i \le 1)$.

$$\mu_i = \frac{RB(S_{ui})}{RB(S_{ui}) + RB(S_{li})}; RB(S_{ui}) = S{\prime}_i^U - S{\prime}_i^L; RB(S_{li}) = S_i^U - S_i^L \tag{24}$$

$$S_i = \mu_i . S_i^L + (1 - \mu_i) . S{\prime}_i^U \tag{25}$$

5. Case study

As a case study, the developed model was implemented for the barriers analysis of AVs adoption in Iran as a developing country. In the following, there are the selected indicators and their quantities for AVs barriers from the Social, Economic, and Environmental standpoints separately. It should be noted that provided indicators are not widely accepted. The geographic diversity of the natural and human environment requires that appropriate indicators for the local situation and research field should be selected which have the following three features: (1) Be able to cover the needs of different groups (including managers, designers, and users), (2) Adequate and accurate information about them be available and (3) Be able to consider three aspects of sustainable development (economic, environmental and social). Indicators are selected based on the third set of indicators of sustainable development which was approved by the Commission on Sustainable Development (CSD) and considering the mentioned features. The related experts are senior executive managers in the transportation organizations and automotive industry with solid academic backgrounds, from the main research centers of transportation organizations, and universities, with ministerial positions in Iran. The related data was gathered through the questionnaires filled out by the experts. These 8 experts' opinions were used as an input parameter for RBWM, and Table 1 shows the aspects and criteria which are obtained in the automotive Industry. In this table, all the barriers are categorized according to sustainability dimensions. Most of the important barriers are mentioned and counted as 23 in total. The questionnaire form is provided as supplementary materials.

6. Results

Evaluation of the barriers was done according to the scale where 9 denotes exceptional domination, and 1 denotes insignificant domination which is shown in Table 2. Table 3 represents the expert comparison through BO and OW vectors. This table is obtained from the data which was gathered from the experts.

According to the equations (1) to (6), the crisp expert evaluations are shown in BO and OW vectors. The vectors are transformed into RN numbers which are represented in Table 11 in Appendix A. The concept of rough numbers helped us to consider more precise data from experts. This concept is demonstrated in Table 11.

Table 4 shows the aggregated RBO (Rough Best-to-Others) and ROW (Rough Others-to-Worst) vectors which are derived by the transformation of BO and OW vectors by using the equation (6).

Table 1
Defined barriers of the AV's adoption.

Aspects	Sub-theme	AV barriers	(Ci)
Social	Equality and Justice / welfare	The increasing number of unemployed drivers	C1
		Social inequity	C2
		The lack of internet connection quality	C3
	Education and Literacy	Weak distribution of educational and promotional publications to promote public awareness with the advantage of AV's	C4
		Learning challenges and difficulties to use the AVs	C5
	Security, Safety, and Crimes	The number of driving offenders	C6
		AV's system failure	C7
		The fear of unsafe interaction with pedestrians	C8
		Lack of functionality in unexpected emergency situation	C9
		The fear of unsafe interaction with other popular vehicles	C10
Economic	Macro-economic Performance	The effect of AVs' technologies implementation on the Gross domestic product (GDP) per capita	C11
		Inflation rate	C12
		The investment made in the AVs from the public budget (the investment catches from the private sector)	C13
		High cost of consuming the huge amount of internet data for each AV	C14
	Trade	The challenges of trading with international markets due to the political conditions (e.g. sanctions)	C15
		The higher price of AVs than the non-AVs for customers	C16
	Financial	High cost of establishing the related infrastructures	C17
		High cost of importing the components	C18
		The cost of new product development for the car manufacturer	C19
Environmental	Atmosphere	The harmful effects of 5G internet waves for residential areas	C20
	Recycling	The technology of recycling and remanufacturing of AVs perception sensors (e.g., LIDAR, RADAR, etc.) and electronic chips	C21
	Climate Change	Induced traveling of non-AVs (culminated in consuming more fossil fuel due to more traveling distances of non-AVs)	C22
		Increasing the emissions of greenhouse gases by easier and faster traveling	C23

Table 2
The importance factor (priority) among alternative criteria (barriers).

Importance	Extremely Low	Very Low	Low	M-low	Moderate	M-high	High	Very High	Extremely High
Value	1	2	3	4	5	6	7	8	9

The calculation of optimal rough weight coefficient values of criteria performed based on the RBO and ROW vectors. According to Table 4 and model (10), the optimal rough weight coefficient values of criteria were obtained and represented in Table 12 in Appendix A. By analysis of the derived weights from Table 12, it is found that the following conditions are satisfied:

1. $\sum_{j=1}^{n} W_j^L \leq 1$ and $\sum_{j=1}^{n} W_j^U \geq 1$.
2. The coefficient weights of the criteria should be in the interval that is $0 \leq W_j^L \leq W_j^U \leq 1,\ W_j \in [0,\ 1],\ (j = 1, 2, \ldots, 23)$.

6.1. Ranking of criteria by utilization of IR-MABAC

According to the expressions (1) to (13) of the [36], an initial decision matrix is formed which is shown in Table 5.

The normalized form of Table 5 is represented as Table 6. The normalization process is done based on the equations (13) to (16).

After the normalization of the initial decision matrix, the weighted matrix V is formed using the obtained weight matrix and based on the equations (17) and (18). This is shown in Table 7.

The border approximation area matrix is derived from the equation (19) and is shown in Table 8.

Table 9 represents the matrix elements of alternatives distance (Q) which is obtained by the equation (22).

Finally, the barriers are ranked according to the equation (23) as shown in Table 10.

The ranking shown in Table 10 can be utilized as a policy guideline and decision-making for the implementation of AVs technology in a real-world case. The table prioritizes the barriers to be eliminated based on their ranks. According to Fig. 2, by proper planning, policymakers can adopt suitable strategies for utilizing the AVs technology considering sustainability dimensions in its industry. For example, the first three indicators according to the above ranking are as follows:

Rank 1 (Indicator 12): Inflation rate.

Rank 2 (Indicator 3): The lack of internet connection quality

Rank 3 (Indicator 5): Learning challenges and difficulties to use the AVs.

In order to achieve sustainability goals, managers can focus on the important indicators derived from the expression (22).

Table 3
BO and OW vectors of expert judgment.

Criteria	Expert															
	BO								OW							
	E1	E2	E3	E4	E5	E6	E7	E8	E1	E2	E3	E4	E5	E6	E7	E8
C1	5	3	3	4	2	3	4	5	3	3	5	4	5	3	4	5
C2	2	2	3	2	3	2	4	2	1	1	1	1	1	1	1	1
C3	6	3	4	5	6	2	3	3	4	3	7	5	4	5	3	7
C4	3	5	4	2	3	4	5	3	5	2	8	4	5	2	6	5
C5	4	5	2	3	2	3	5	3	3	5	8	4	5	3	6	7
C6	3	5	2	3	4	5	2	3	5	5	2	4	3	6	4	5
C7	1	2	2	1	2	1	2	1	6	4	9	6	9	5	4	7
C8	2	2	3	3	2	3	2	2	5	8	7	4	6	5	7	6
C9	2	3	2	3	3	2	2	3	6	8	7	5	8	7	8	6
C10	3	4	3	2	3	2	2	4	6	6	7	8	6	7	5	9
C11	2	2	2	3	3	2	2	3	8	7	8	7	6	9	5	8
C12	1	1	1	1	1	1	1	1	5	7	7	6	5	8	8	7
C13	2	5	4	2	3	2	5	3	7	6	6	5	6	7	6	7
C14	2	3	3	2	2	3	2	2	7	7	8	7	6	5	6	7
C15	2	2	3	2	3	2	3	3	7	6	6	7	5	6	8	9
C16	2	4	4	2	3	2	4	3	7	6	5	5	7	5	6	6
C17	3	5	3	5	3	5	4	2	5	8	5	8	8	6	5	5
C18	4	3	2	3	5	3	3	4	5	8	7	5	8	6	7	5
C19	2	4	2	3	3	2	2	4	7	6	6	7	5	6	7	8
C20	2	3	2	3	4	2	3	1	7	8	8	5	8	6	6	7
C21	4	5	2	3	2	3	4	3	6	8	8	5	6	8	7	8
C22	2	3	4	5	6	3	4	2	5	7	7	8	8	5	6	7
C23	4	3	5	2	2	1	2	5	6	6	5	4	8	7	8	6

Table 4
Aggregated RBO and ROW vectors.

Criteria	Aggregated RBO Best: C12		Criteria	Aggregated ROW Worst: C2	
C1	2.979	4.275	C1	3.558	4.525
C2	2.134	2.896	C3	3.813	5.771
C3	3.073	4.972	C4	3.679	5.894
C4	3.260	4.275	C5	3.863	6.373
C5	3.048	4.115	C6	3.299	5.030
C6	2.881	4.115	C7	4.771	7.579
C7	1.563	1.750	C8	4.692	6.855
C8	2.416	2.609	C9	5.623	7.545
C9	2.438	2.750	C10	5.626	7.594
C10	2.635	3.353	C11	5.938	8.030
C11	2.344	2.609	C12	5.240	7.327
C13	2.746	4.052	C13	5.619	6.621
C14	2.466	2.609	C14	5.566	7.142
C15	2.438	2.750	C15	5.564	7.594
C16	2.725	3.525	C16	5.115	6.353
C17	3.313	4.438	C17	5.181	7.063
C18	2.936	3.916	C18	5.208	7.166
C19	2.521	3.250	C19	5.576	7.049
C20	2.138	3.049	C20	5.623	7.545
C21	3.006	3.896	C21	5.823	7.671
C22	2.78571	4.57292	C22	5.489	7.327
C23	2.35417	3.97173	C23	5.158	7.123

7. Sensitivity analysis and discussion

In this section, sensitivity analysis is fulfilled to identify the effects of weight fluctuations on the process of decision. However, by this method, the robustness of the applied proposed model is evaluated by experimenting with rational scenarios. This analysis contains the increasing weight parameters which may change the priority of alternatives that can affect the rank of the criteria. When the ranking of alternatives fluctuates as a result of weight changes, the results obtained are sensitive by using the methods described. But if these do not have a lot of fluctuations and changes, the results will be robust.

This analysis is illustrated in Fig. 3, Table 13, and Table 14 (in Appendix A) to show the variation of the weights of the barriers and the robustness of the criteria ranking. The sensitivity analysis of the synthesized RBWM-IRMABAC model for evaluating the adoption of AVs barriers in developing countries has been done through 23 scenarios for each existing criterion. The authors focused

Table 5
Initial decision matrix values.

Criteria	$IRN(X_j)$	
	$RN(X_j^L)$	$RN(X_j^U)$
C1	1.295387	0.966667
C2	0.761905	0.038
C3	1.89881	1.958333
C4	1.014137	2.214435
C5	1.066667	2.509673
C6	1.233333	1.730655
C7	0.1875	2.808333
C8	0.19375	2.162649
C9	0.3125	1.922173
C10	0.717708	1.967262
C11	0.265625	2.092262
C12	0	2.0875
C13	1.30625	1.001786
C14	0.14375	1.57619
C15	0.3125	2.029762
C16	0.8	1.238542
C17	1.125	1.88125
C18	0.980208	1.957292
C19	0.729167	1.473214
C20	0.910714	1.922173
C21	0.889583	1.848512
C22	1.787202	1.8375
C23	1.61756	1.965179

Table 6
Normalized initial decision matrix values.

Criteria	$IRN(t_j)$	
	$RN(t_j^L)$	$RN(t_j^U)$
X1	0.461265	0.344214
X2	0.271301	0.013531
X3	0.676134	0.697329
X4	0.361117	0.788523
X5	0.379822	0.893652
X6	0.439169	0.616257
X7	0.066766	1
X8	0.068991	0.770083
X9	0.111276	0.684453
X10	0.255564	0.700509
X11	0.094585	0.745019
X12	0	0.743323
X13	0.465134	0.356719
X14	0.051187	0.561255
X15	0.111276	0.722764
X16	0.284866	0.441024
X17	0.400593	0.669881
X18	0.349036	0.696958
X19	0.259644	0.524587
X20	0.32429	0.684453
X21	0.316766	0.658224
X22	0.636393	0.654303
X23	0.575986	0.699767

on one criterion for each scenario in which the weight coefficient increased by 30 percent, whereas the weight of the other remaining scenarios was decreased by 30 percent. For scenarios 1 to 23, the focus was on a criterion. Finally, the rank of the barriers considered in this work was demonstrated in Table 13, and Table 14.

As it is clear in Fig. 3, the results of ranking the barriers of AVs for each scenario did not change the ranking of the alternatives. So, the sensitivity analysis shows the high degree of robustness of the results of using the RBWM-IRMABAC models by valid output data in terms of the expert's opinion. In this case, it can be concluded that the priority of the barriers to AV's adoption in the case study is reasonable to be invested in. The RBWM and IR-MABAC approaches performed well in prioritizing the barriers. This indicates that the solution approaches for each type of decision-making problem would be important to obtain the best results. The ultimate goal is long-term (strategic) planning considering macro policies which require a huge amount of budget for eliminating the existing

Table 7
Values of the weighted matrix V.

Criteria	$IRN(v_j) = IRN(w_j).IRN(t_j) + IRN(w_j)$	
	$IRN(v_j^L)$	$IRN(v_j^U)$
V1	0.008607	0.034412
V2	0.003115	0.001581
V3	0.141633	0.091656
V4	0.033443	0.151488
V5	0.046914	0.181412
V6	0.11355	0.072247
V7	0.026136	0.065
V8	0.06756	0.015046
V9	0.055675	0.076643
V10	0.00452	0.116825
V11	0.010727	0.172233
V12	0.125	0.310312
V13	0.135378	0.112879
V14	0.034164	0.066978
V15	0.027226	0.249801
V16	0.141335	0.052886
V17	0.138239	0.043083
V18	0.033051	0.01663
V19	0.02217	0.079431
V20	0.033902	0.051376
V21	0.062941	0.025537
V22	0.007364	0.02101
V23	0.012293	0.016148

Table 8
Values of the border approximation area matrix.

Criteria	$IRN\left(g_j\right) = (\prod_{j=1}^{m} IRN(v_j))^{1/m}$	
	$RN(g_j^L)$	$RN(g_j^U)$
g1	0.008607	0.034412
g2	0.005178	0.007376
g3	0.015601	0.017085
g4	0.018877	0.029482
g5	0.022647	0.042401
g6	0.029628	0.046339
g7	0.029102	0.048634
g8	0.032333	0.042
g9	0.034345	0.044903
g10	0.028041	0.049409
g11	0.025695	0.055348
g12	0.029316	0.063899
g13	0.032978	0.066758
g14	0.033061	0.066774
g15	0.032636	0.072913
g16	0.035767	0.071464
g17	0.038727	0.069368
g18	0.038388	0.064077
g19	0.037295	0.064805
g20	0.037117	0.064057
g21	0.038062	0.061312
g22	0.037781	0.059889
g23	0.040333	0.066896

barriers. So, the more powerful solution approaches for strategic decision-making problems, the more efficient and cost-efficient solutions would be obtained.

On the other hand, this research encountered a few limitations, particularly regarding the number of experts, which indicates the importance of international data-gathering approaches, the requirements of international joint research, collaborations, and data sharing to generalize the model for a wider geographic area of developing countries. Despite the restrictions imposed in this study, our sensitivity analysis demonstrated the robustness of the proposed model. So, the results may be generalized to other developing countries. In other words, policymakers can reach a good estimation of the challenges and solutions to deal with the implementation of autonomous vehicle infrastructures in other developing countries.

Table 9
The matrix elements of alternatives distance.

Criteria	Q = V-G	Criteria	Q = V-G
Q1	0	Q13	0.112307677
Q2	-0.006151357	Q14	0.001121208
Q3	0.146441375	Q15	-0.176970441
Q4	-0.1228726	Q16	0.107190843
Q5	-0.141113272	Q17	0.102924186
Q6	0.087830353	Q18	0.047745788
Q7	-0.016632231	Q19	0.021039686
Q8	-0.044356784	Q20	-0.013082679
Q9	-0.0382407	Q21	0.043576093
Q10	0.071401723	Q22	0.049363651
Q11	-0.117839711	Q23	0.057979648
Q12	-0.264337754		

Table 10
Ranking of criteria (barriers).

Criteria	$IRN(C_i) = \sum_{j=1}^{N} IRN(q_j)$, $j = 1, 2, \ldots, n$, $i = 1, 2, \ldots, m$	Rank
C1	0	18
C2	-0.00615	19
C3	0.146441	2
C4	-0.12287	22
C5	0.141113	3
C6	0.08783	7
C7	-0.01663	20
C8	0.044357	12
C9	-0.03824	14
C10	0.071402	8
C11	-0.11784	21
C12	0.264338	1
C13	0.112308	4
C14	0.001121	17
C15	-0.17697	23
C16	0.107191	5
C17	0.102924	6
C18	0.047746	11
C19	0.02104	15
C20	0.013083	16
C21	0.043576	13
C22	0.049364	10
C23	0.05798	9

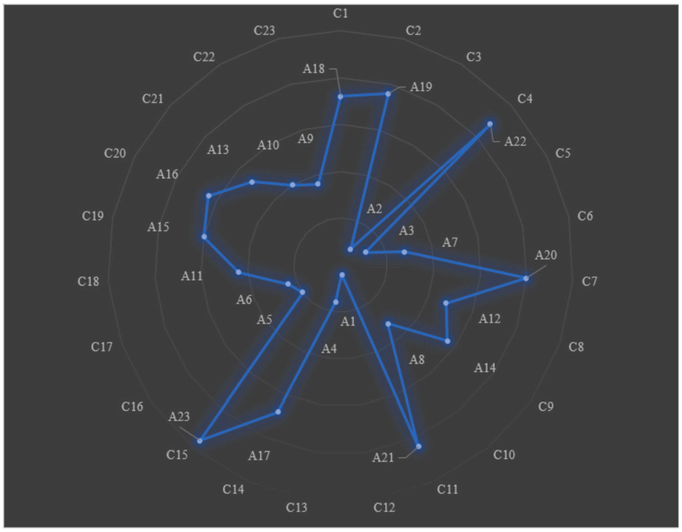

Fig. 2. Spider graph of the criteria ranking in sustainable adoption of AVs problem.

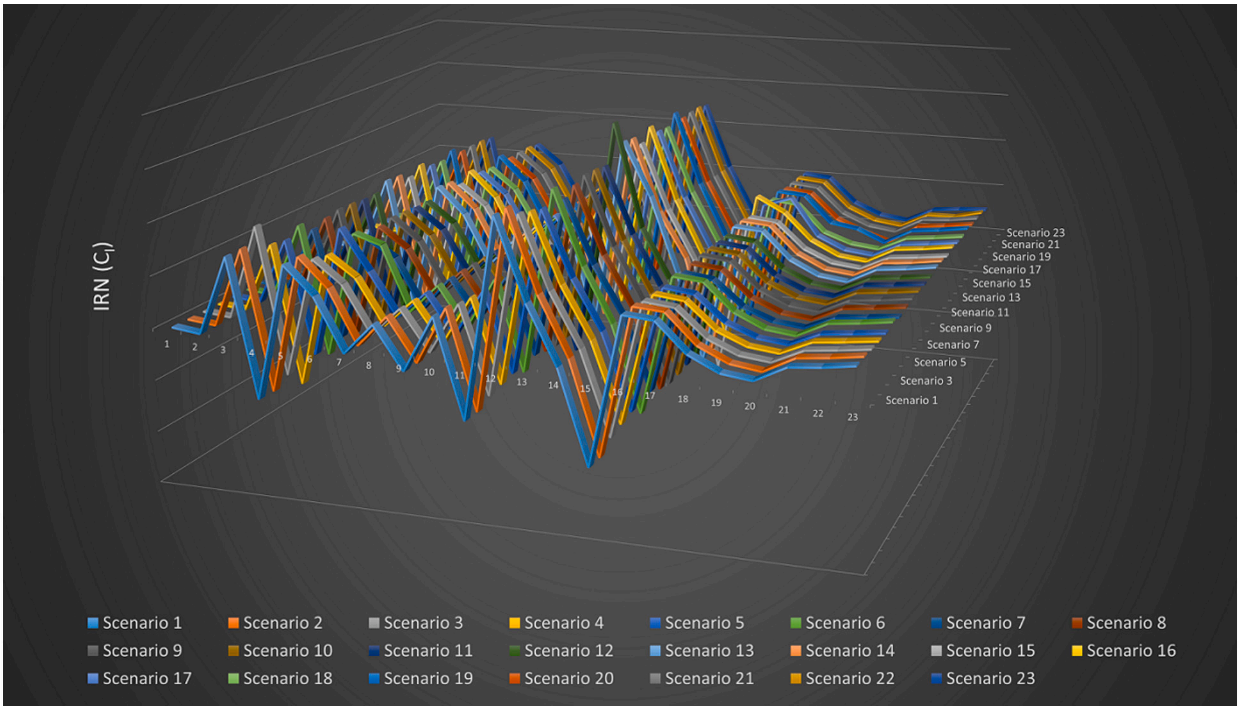

Fig. 3. The variation of the barriers in each scenario.

8. Conclusion

Autonomous and Intelligent Vehicles are trends in governing policies and need to be considered more precisely to manage and set laws and legislations. Also, this concept has been captured increasingly in academic topics and many investigations which have considered the managerial insights to manipulate the AVs legislations which are published through scientific journals. The current work discussed the main barriers to the implementation and adoption of AVs' technology in developing countries which need to be considered to prioritize the relevant policies to fade them out. To hit this aim, the potential barriers to AVs adoption in developing countries (e.g., Iran) have been obtained through the related literature and experts' opinions and to evaluate their priority, a synthesized method of Rough BWM and Interval Rough MABAC was applied. The authors implemented a new approach to consider the real-world uncertainty in the decision-making process on the basis of the interval rough numbers, and the concept of IRN and the related algorithms for their computational operations were described. The RBWM method was applied to determine the weight of the criteria and the IRMABAC approach was utilized to evaluate and rank the barriers. The sensitivity analysis was performed through 23 scenarios in order to assess the robustness of the proposed model. There will be several practical implications for government and policymakers which resulted in this study. The evaluation showed that the "Inflation rate" is the 1st rank among the barriers to implementing the AVs' technology in Iran. To overcome this barrier, governmental policies need to be taken into consideration for lowering and controlling the value of the currency. On the other hand, "The lack of internet connection quality" is the 2nd rank barrier that needs to be invested to expand and develop the internet connection infrastructures by establishing the 5G or 6G cellular technology and also holding the proper data centers. According to the mentioned ranked barriers in this work, the insights which lead to making the suitable policies, in this case, improve the sustainable development as the criteria were categorized through the main three sustainability dimensions, and overcoming these barriers would omit the obstacles from the way of sustainable development.

This study relied on only 8 experts' opinions and these experts mainly have academic characteristics and have executive positions in the automotive industry and transportation organizations in Iran. Although the number of experts might be low, the sensitivity analysis demonstrated the robustness of our results, and the decision on the basis of these 8 experts' opinions would be rational and remarkable.

It would be interesting to consider the risk evaluation of implementing AVs in developing countries by the Multi-Attribute Decision-Making approaches for future research. It is also applicable to consider the resilient dimensions in the AVs implementation.

Data availability

All data is included in the article, supplementary material, or referenced in the article. The direct link to the Supplementary material: https://www.cell.com/cms/10.1016/j.heliyon.2023.e15975/attachment/765ded26-d7ab-4a7b-97fc-6442bd4e3093/mmc1.pdf.

Table 11
Rough BO and OW vectors of expert judgment.

Criteria	Expert															
	BO															
	E1		E2		E3		E4		E5		E6		E7		E8	
C1	3.6	5.0	2.8	3.9	2.8	3.9	3.2	4.5	2.0	3.6	2.8	3.9	3.2	4.5	3.6	5.0
C2	2.0	2.5	2.0	2.5	2.3	3.3	2.0	2.5	2.3	3.3	2.0	2.5	2.5	4.0	2.0	2.5
C3	4.0	6.0	2.8	4.3	3.0	5.3	3.3	5.7	4.0	6.0	2.0	4.0	2.8	4.3	2.8	4.3
C4	2.8	3.9	3.6	5.0	3.2	4.5	2.0	3.6	5.0	3.9	3.2	4.5	3.6	5.0	2.8	3.9
C5	2.8	4.7	3.4	5.0	2.0	3.4	2.6	3.8	5.0	3.4	2.6	3.8	3.4	5.0	2.6	3.8
C6	2.6	3.8	3.4	5.0	2.0	3.4	2.6	3.8	4.5	4.7	3.4	5.0	2.0	3.4	2.6	3.8
C7	1.0	1.5	1.5	2.0	1.5	2.0	1.0	1.5	4.0	2.0	1.0	1.5	1.5	2.0	1.0	1.5
C8	2.0	2.4	2.0	2.4	2.4	3.0	2.4	3.0	4.2	2.4	2.4	3.0	2.0	2.4	2.0	2.4
C9	2.0	2.5	2.5	3.0	2.0	2.5	2.5	3.0	4.0	3.0	2.0	2.5	2.0	2.5	2.5	3.0
C10	2.5	3.4	2.9	4.0	2.5	3.4	2.0	2.9	4.3	3.4	2.0	2.9	2.0	2.9	2.9	4.0
C11	2.0	2.4	2.0	2.4	2.0	2.4	2.4	3.0	4.0	3.0	2.0	2.4	2.0	2.4	2.4	3.0
C12	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
C13	2.0	3.3	3.3	5.0	2.7	4.7	2.0	3.3	4.4	4.0	2.0	3.3	3.3	5.0	2.4	4.0
C14	2.0	2.4	2.4	3.0	2.4	3.0	2.0	2.4	4.6	2.4	2.4	3.0	2.0	2.4	2.0	2.4
C15	2.0	2.5	2.0	2.5	2.5	3.0	2.0	2.5	4.0	3.0	2.0	2.5	2.5	3.0	2.5	3.0
C16	2.0	3.0	3.0	4.0	3.0	4.0	2.0	3.0	4.4	3.6	2.0	3.0	3.0	4.0	2.4	3.6
C17	2.8	4.0	3.8	5.0	2.8	4.0	3.8	5.0	4.8	4.0	3.8	5.0	3.0	4.8	2.0	3.8
C18	3.1	4.3	2.8	3.6	2.0	3.4	2.8	3.6	4.0	5.0	2.8	3.6	2.8	3.6	3.1	4.3
C19	2.0	2.8	2.8	4.0	2.0	2.8	2.3	3.5	4.3	3.5	2.0	2.8	2.0	2.8	2.8	4.0
C20	1.8	2.7	2.3	3.3	1.8	2.7	2.3	3.3	4.0	4.0	1.8	2.7	2.3	3.3	1.0	2.5
C21	3.0	4.3	3.3	5.0	2.0	3.3	2.6	3.7	5.0	3.3	2.6	3.7	3.0	4.3	2.6	3.7
C22	2.0	3.6	2.5	4.2	3.0	4.8	3.3	5.5	4.0	6.0	2.5	4.2	3.0	4.8	2.0	3.6
C23	2.3	4.7	2.0	4.3	3.0	5.0	1.8	3.3	4.0	3.3	1.0	3.0	1.8	3.3	3.0	5.0

Criteria	Expert															
	OW															
	E1		E2		E3		E4		E5		E6		E7		E8	
C1	3.0	4.0	3.7	4.0	4.0	5.0	3.4	4.6	4.0	5.0	3.0	4.0	3.4	4.6	4.0	5.0
C2	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
C3	3.5	5.3	3.0	4.8	4.8	7.0	4.0	6.0	3.5	5.3	4.0	6.0	3.0	4.8	4.8	7.0
C4	3.8	5.8	4.5	4.6	4.6	8.0	2.7	5.5	3.8	5.8	2.0	4.6	4.1	7.0	3.8	5.8
C5	3.0	5.1	3.4	6.2	5.1	8.0	3.3	5.8	4.0	6.2	3.0	5.1	4.3	7.0	4.7	7.5
C6	4.0	5.3	3.1	5.3	2.0	4.3	3.3	4.8	2.5	4.6	4.3	6.0	3.3	4.8	4.0	5.3
C7	5.0	7.4	2.0	6.3	6.3	9.0	5.0	7.4	6.3	9.0	4.3	7.0	4.0	6.3	5.3	8.3
C8	4.7	6.3	2.4	8.0	5.7	7.3	4.0	6.0	5.2	6.8	4.7	6.3	5.7	7.3	5.2	6.8
C9	5.7	7.1	2.5	8.0	6.2	7.6	5.0	6.9	6.9	8.0	6.2	7.6	6.9	8.0	5.7	7.1
C10	5.8	7.0	3.0	7.0	6.2	7.8	6.4	8.5	5.8	7.0	6.2	7.8	5.0	6.8	6.8	9.0
C11	7.0	8.3	2.5	7.8	7.0	8.3	6.3	7.8	5.5	7.6	7.3	9.0	5.0	7.3	7.0	8.3
C12	5.0	6.6	1.0	7.4	6.2	7.4	5.3	7.2	5.0	6.6	6.6	8.0	6.6	8.0	6.2	7.4
C13	6.3	7.0	3.8	6.4	5.8	6.4	5.0	6.3	5.8	6.4	6.3	7.0	5.8	6.4	6.3	7.0
C14	6.4	7.2	2.3	7.2	6.6	8.0	6.4	7.2	5.7	6.9	5.0	6.6	5.7	6.9	6.4	7.2
C15	6.2	7.8	2.5	7.0	5.8	7.0	6.2	7.8	5.0	6.8	5.8	7.0	6.4	8.5	6.8	9.0
C16	5.9	7.0	3.2	6.4	5.0	5.9	5.0	5.9	5.9	7.0	5.0	5.9	5.5	6.4	5.5	6.4
C17	5.0	6.3	3.8	8.0	5.0	6.3	6.3	8.0	6.3	8.0	5.2	7.5	5.0	6.3	5.0	6.3
C18	5.0	6.4	3.4	8.0	5.8	7.5	5.0	6.4	6.4	8.0	5.3	7.2	5.8	7.5	5.0	6.4
C19	6.3	7.3	2.8	6.7	5.8	6.7	6.3	7.3	5.0	6.5	5.8	6.7	6.3	7.3	6.5	8.0
C20	6.2	7.6	2.5	8.0	6.9	8.0	5.0	6.9	6.9	8.0	5.7	7.1	5.7	7.1	6.2	7.6
C21	5.7	7.3	3.3	8.0	7.0	8.0	5.0	7.0	5.7	7.3	7.0	8.0	6.0	7.8	7.0	8.0
C22	5.0	6.6	3.0	7.4	6.2	7.4	6.6	8.0	6.6	8.0	5.0	6.6	5.3	7.2	6.2	7.4
C23	5.4	6.8	3.8	6.8	4.5	6.6	4.0	6.3	6.3	8.0	5.7	7.7	6.3	8.0	5.4	6.8

CRediT authorship contribution statement

Alireza Shahedi: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Iman Dadashpour: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Mahdi Rezaei: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Table 12
Optimal rough weight coefficients of the criteria values.

Weights of criteria	$RN(W_j^L)$	$RN(W_j^U)$	Criteria
RN(W1)	0.00589	0.0256	The increasing number of unemployed drivers (C1)
RN(W2)	0.00245	0.00156	Social inequity (C2)
RN(W3)	0.0845	0.054	The lack of internet connection quality (C3)
RN(W4)	0.02457	0.0847	Weak distribution of educational and promotional publications to promote public awareness with the advantage of AVs (C4)
RN(W5)	0.034	0.0958	Learning challenges and difficulties to use the AVs (C5)
RN(W6)	0.0789	0.0447	The number of driving offenders (C6)
RN(W7)	0.0245	0.0325	AV's system failure (C7)
RN(W8)	0.0632	0.0085	The fear of unsafe interaction with pedestrian (C8)
RN(W9)	0.0501	0.0455	Lack of functionality in unexpected emergency situation (C9)
RN(W10)	0.0036	0.0687	The fear of unsafe interaction with other popular vehicles (C10)
RN(W11)	0.0098	0.0987	The effect of AVs' technologies implementation on the Gross domestic product (GDP) per capita (C11)
RN(W12)	0.125	0.178	Inflation rate (C12)
RN(W13)	0.0924	0.0832	The investment made in the AVs from the public budget (the investment catches from the private sector) (C13)
RN(W14)	0.0325	0.0429	High cost of consuming the huge amount of internet data for each AV (C14)
RN(W15)	0.0245	0.145	The challenges of trading with international markets due to the political conditions (e.g. sanctions) (C15)
RN(W16)	0.11	0.0367	Higher price of AVs than the non-AVs for customer (C16)
RN(W17)	0.0987	0.0258	High cost of establishing the related infrastructures (C17)
RN(W18)	0.0245	0.0098	High cost of importing the components (C18)
RN(W19)	0.0176	0.0521	The cost of new product development for the car manufacturer (C19)
RN(W20)	0.0256	0.0305	The harmful effects of 5G internet waves for residential areas (C20)
RN(W21)	0.0478	0.0154	The technology of recycling and remanufacturing of AVs perception sensors (e.g., LIDAR, RADAR, etc.) and electronic chips (C21)
RN(W22)	0.0045	0.0127	Induced traveling of non-AVs (culminated in consuming more fossil fuel due to more traveling distances of non-AVs) (C22)
RN(W23)	0.0078	0.0095	Increasing the emissions of greenhouse gases by easier and faster traveling (C23)
	$\sum_{j=1}^{23} RN(W_j^L) = 0.99241$	$\sum_{j=1}^{23} RN(W_j^U) = 1.20186$	

Table 13
The variation of the rank for each of the barriers in Scenarios 1 to 12.

Criteria	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Rank Sign
C1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	A18
C2	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	A19
C3	0.14	0.15	0.18	0.13	0.12	0.14	0.12	0.13	0.13	0.13	0.13	0.13	A2
C4	-0.12	-0.12	-0.11	-0.14	-0.10	-0.12	-0.10	-0.11	-0.11	-0.11	-0.11	-0.11	A22
C5	0.14	0.14	0.12	0.12	0.16	0.13	0.11	0.12	0.13	0.12	0.12	0.12	A3
C6	0.09	0.09	0.08	0.08	0.08	0.11	0.07	0.08	0.08	0.08	0.08	0.08	A7
C7	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01	A20
C8	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	A12
C9	-0.04	-0.04	-0.03	-0.03	-0.03	-0.04	-0.03	-0.03	-0.05	-0.04	-0.04	-0.04	A14
C10	0.07	0.07	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.09	0.06	0.06	A8
C11	-0.12	-0.12	-0.10	-0.10	-0.10	-0.11	-0.09	-0.10	-0.11	-0.10	-0.15	-0.10	A21
C12	0.26	0.26	0.24	0.23	0.22	0.25	0.22	0.23	0.24	0.24	0.24	0.31	A1
C13	0.11	0.11	0.10	0.10	0.10	0.11	0.10	0.10	0.10	0.10	0.10	0.10	A4
C14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	A17
C15	-0.18	-0.18	-0.16	-0.15	-0.15	-0.17	-0.14	-0.15	-0.16	-0.16	-0.15	-0.15	A23
C16	0.11	0.11	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	A5
C17	0.10	0.10	0.10	0.09	0.09	0.10	0.09	0.09	0.10	0.10	0.09	0.09	A6
C18	0.05	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.04	A11
C19	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	A15
C20	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	A16
C21	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	A13
C22	0.05	0.05	0.05	0.05	0.04	0.05	0.04	0.05	0.05	0.05	0.05	0.05	A10
C23	0.06	0.06	0.05	0.05	0.05	0.06	0.05	0.05	0.05	0.05	0.05	0.05	A9

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.

Table 14
The variation of the rank for each of the barriers in Scenarios 13 to 23.

Criteria	Scenario 13	Scenario 14	Scenario 15	Scenario 16	Scenario 17	Scenario 18	Scenario 19	Scenario 20	Scenario 21	Scenario 22	Scenario 23	Rank Sign
C1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	A18
C2	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	A19
C3	0.15	0.14	0.13	0.15	0.13	0.13	0.15	0.13	0.14	0.14	0.13	A2
C4	-0.12	-0.12	-0.11	-0.12	-0.11	-0.11	-0.12	-0.11	-0.11	-0.11	-0.11	A22
C5	0.14	0.14	0.12	0.14	0.13	0.12	0.14	0.13	0.13	0.13	0.12	A3
C6	0.09	0.09	0.08	0.09	0.08	0.08	0.09	0.08	0.08	0.08	0.08	A7
C7	-0.02	-0.02	-0.01	-0.02	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	A20
C8	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	A12
C9	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	-0.04	A14
C10	0.07	0.07	0.06	0.07	0.07	0.06	0.07	0.07	0.07	0.07	0.06	A8
C11	-0.12	-0.12	-0.10	-0.12	-0.11	-0.11	-0.12	-0.11	-0.11	-0.11	-0.11	A21
C12	0.26	0.26	0.24	0.26	0.25	0.24	0.26	0.24	0.25	0.25	0.24	A1
C13	0.16	0.11	0.10	0.11	0.11	0.10	0.11	0.10	0.11	0.11	0.10	A4
C14	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	A17
C15	-0.18	-0.17	-0.22	-0.18	-0.16	-0.16	-0.18	-0.16	-0.16	-0.16	-0.16	A23
C16	0.11	0.11	0.10	0.13	0.10	0.10	0.11	0.10	0.10	0.10	0.10	A5
C17	0.10	0.10	0.09	0.10	0.12	0.10	0.10	0.10	0.10	0.10	0.10	A6
C18	0.05	0.05	0.04	0.05	0.05	0.04	0.05	0.04	0.04	0.04	0.04	A11
C19	0.02	0.02	0.02	0.02	0.02	0.02	0.04	0.02	0.02	0.02	0.02	A15
C20	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01	A16
C21	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04	A13
C22	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.05	A10
C23	0.06	0.06	0.05	0.06	0.05	0.05	0.06	0.05	0.06	0.06	0.05	A9

Acknowledgements

The authors would like to thank all partners within the Hi-Drive project for their cooperation and valuable contribution. This research has received funding from the European Union's Horizon 2020 research and innovation programme, under grant agreement No. 101006664. The article reflects only the authors' view and neither European Commission nor CINEA is responsible for any use that may be made of the information this document contains.

Appendix A

In this section, Table 11, Table 12, Table 13, and Table 14 are demonstrated. Table 11 shows the rough values for BO and OW vectors which are obtained by the experts' judgment. Table 12 shows the optimal rough weight coefficient of the criteria values. Table 13, and Table 14 show the results of the rank variation for each criterion in the sensitivity analysis.

Appendix B. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e15975.

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