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ASSESSING PUBLIC ACCEPTANCE OF AUTONOMOUS VEHICLES USING A NOVEL IRN PIPRECIA – IRN AROMAN MODEL

Meijing Song[1,2], Željko Stević[3,4], Ibrahim Badi[5], Dragan Marinković[6], Yifei Lv[7], Kaiyang Zhong[8]

[1]Hainan Vocational University of Science and Technology, Haikou, Hainan, China
[2]Universiti Sains Malaysia, Penang, Malaysia
[3]Department of Mobile Machinery and Railway Transport,
Vilnius Gediminas Technical University, Vilnius, Lithuania
[4]Department of Industrial Management Engineering, Korea University, Seoul, Korea
[5]Department of Mechanical Engineering, Libyan Academy, Misurata, Libya
[6]Institute of Mechanical Science, Vilnius Gediminas Technical University, Vilnius, Lithuania
[7]Faculty of Economics and Management, ALFA University College, Selangor, Malaysia
[8]College of Information Science & Electronic Engineering, Zhejiang University,
Hangzhou, China

ORCID iDs: Meijing Song https://orcid.org/0009-0009-0355-239X
Željko Stević https://orcid.org/0000-0003-4452-5768
Ibrahim Badi https://orcid.org/0000-0002-1193-1578
Dragan Marinković https://orcid.org/0000-0002-3583-9434
Yifei Lv https://orcid.org/0009-0002-3593-2820
Kaiyang Zhong https://orcid.org/0000-0002-5575-0306

Abstract. *Autonomous vehicles (AVs) have become a tangible presence on roads, indicating the emergence of a promising transportation technology for the future, possibly arriving sooner than anticipated. Nevertheless, the extensive integration of this technology is contingent on various factors, with the foremost being the level of public acceptance and adjustment to this advanced technology. Several factors, including safety, privacy, and cost, play crucial roles in fostering acceptance. Consequently, this research delves into the key determinants shaping individuals' willingness to embrace AVs. In this paper, a novel model, which consists of two methods: PIPRECIA and AROMAN with Interval Rough Numbers (IRNs) has been developed. The IRN PIPRECIA serves to define criterion weights, while the most significant contribution of the paper is the extension of the AROMAN method with IRNs for evaluating the public acceptance of autonomous vehicles and adapting all the necessary conditions for their use. The results show that a rapid implementation with extensive testing strategy represents the best solution.*

Key words: *Autonomous Vehicles, IRN PIPRECIA, IRN AROMAN, MCDM*

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Corresponding author: Željko Stević
Department of Mobile Machinery and Railway Transport, Vilnius Gediminas Technical University, Vilnius, Lithuania and Department of Industrial Management Engineering, Korea University, Seoul, Korea
E-mail: zeljko.stevic@vilnius.lt; 172317@korea.ac.kr

1. INTRODUCTION

In recent years, interest in Autonomous vehicles (AVs) has begun to grow [1,2]. We can therefore expect them to spread and expand further and faster, as their popularity increases globally [3]. Consequently, research is increasing to understand the extent to which people accept this technology and their willingness to make it an important transportation option [4,5]. A thorough examination of prior studies on popular acceptance levels unmistakably reveals this divergence in individuals' perceptions worldwide regarding the concept of AVs and, consequently, their openness to embracing this technology [6,7]. In Arab countries, the experimentation with AVs remains constrained, with limited initiatives in place [8,9]. These experiments specifically focus on users of this technology, as indicated by previous research [10].

Beyond potential safety implications, legal and financial considerations are also taken into account [11-13]. Other aspects that are of additional concern can also be identified. The exploration of these considerations involves soliciting individuals' opinions to gauge their willingness and capacity to adopt this technology [14,15]. For instance, despite AVs exhibiting elevated safety levels in comparison to human drivers, safety remains a predominant apprehension for many individuals [16,17]. The heightened safety levels are attributed to the capacity of these vehicles to make intelligent decisions in anticipated traffic scenarios [18]. The heightened focus on safety may stem from the potential impacts on both individuals and transportation infrastructure [19,20].

The capability to make intelligent decisions arises from the advanced technologies integrated into these cars, empowering them with intelligent behavior. These technologies encompass image processing tools that enhance their perceptual capabilities. This provides them with a notable advantage in terms of heightened confidence [21]. However, the utilization of intelligent sensing technologies may have adverse implications for the car owner in case of an accident. Furthermore, the restricted coverage of intelligent sensors could result in a failure to comprehensively grasp the entire environment, potentially resulting in erroneous decisions. This challenge can be effectively addressed through the incorporation of thermal imaging cameras capable of recognizing humans and animals, especially during nighttime driving [22].

Users also voice concerns regarding privacy protection. These worries revolve around the type of data that AVs can store and the potential for unauthorized access or hacking. There is a fear of losing control over their vehicles due to security breaches and the illicit use of the vehicles [23]. This could lead to data loss and misuse [24,25]. Apart from safety and privacy concerns, the financial viability of adopting AVs significantly influences the decision-making process. The substantial expenses associated with these vehicles may lead individuals to hesitate in embracing them [12,26].

The factors outlined above will inevitably impact public trust and approval of AVs to varying degrees. Anticipated resistance is understandable, given the novelty of this technology and the associated information gap. Addressing this issue requires additional research and inquiry. Consequently, this study seeks to delve into the determinants influencing the acceptance of AVs within Libyan society. Its significance lies in providing policymakers, researchers, and specialists with insights to formulate strategies and plans for the future.

Numerous prior studies have aimed to comprehend the public acceptance of AVs. These studies, primarily relying on stated preference surveys and employing descriptive analysis [27], have served various objectives. Some focus on forecasting the future adoption of AVs technology [28], while others investigate its potential repercussions on public health [29]. Moreover, numerous investigations have delved into the advantages of AVs, encompassing reduced logistics costs [30], diminished accident rates [7, 31], lowered fuel consumption [31], and simplified parking [32]. These advantages contribute to the increasing public acceptance of AVs. Conversely, various studies have underscored the existence of potential obstacles that should be addressed to expedite the implementation of AVs [27].

Many prior investigations have examined individuals' attitudes toward the incorporation of AVs. These studies have encompassed assessments of driver confidence, perceptions of AVs capabilities, and confidence in the reliability of the systems, considering their likeness to human drivers. Alongside the potential advantages of AVs, apprehensions about privacy, identity, and societal norms have also been raised [33]. These vehicles have the potential to decrease travel durations and exhibit high fuel and parking efficiency. Nonetheless, several obstacles may impede widespread acceptance of AVs as a global alternative. These barriers encompass substantial initial expenses, irregularities in licensing standards, poorly defined liability, security vulnerabilities, and apprehensions regarding privacy [21].

In this paper, a novel model which consists of two methods: PIPRECIA (PIvot Pair-wise Relative Criteria Importance Assessment method) and AROMAN (Alternative Ranking Order Method Accounting for Two-Step Normalization) and Interval Rough Numbers (IRNs) has been developed. The emphasis is on the novelty of the work through the development of the novel Interval Rough AROMAN method. The previously developed IRN PIPRECIA serves to define criterion weights, while the most significant contribution of the paper is the extension of the AROMAN method with IRNs for evaluating the public acceptance of autonomous vehicles and adapting all the necessary conditions for their use.

2. Methods

In this section, the work methodology is presented with a focus on the algorithms of the applied, i.e. developed method. The emphasis is on the novelty of the work through the development of the novel Interval Rough AROMAN method. The flow of the research and the steps of the approaches used are presented in more detail below.

2.1. Interval Rough PIPRECIA Method

PIPRECIA is a method frequently used to determine the significance of criteria, which can be seen by its application in various areas [34-36] and by numerous extensions of the method [37-39]. The paper [40] introduces the extension of the method with IRNs and its steps are given below.

In order to obtain the value functions of the criteria, two linguistic scales converted into IRNs are used. The scales differ depending on whether criteria have greater significance (Table 1) or less significance (Table 2).

Table 1 Scale for assessing the criteria with greater significance

Linguistic term	Abbr.		IRN		
Almost equal value	AE	Scale 1-2	1	[1.00, 1.05]	[1.10, 1.10]
Slightly more significant	SM		2	[1.10, 1.20]	[1.20, 1.25]
Moderately more significant	MMS		3	[1.20, 1.35]	[1.30, 1.40]
More significant	M		4	[1.30, 1.50]	[1.40, 1.55]
Much more significant	MM		5	[1.40, 1.65]	[1.50, 1.70]
Dominantly more significant	DM		6	[1.50, 1.80]	[1.60, 1.85]
Absolutely more significant	AM		7	[1.60, 1.90]	[1.70, 1.95]

Table 2 Scale for assessing the criteria with less significance

Linguistic term	Abbr.		IRN		
Weakly less significant	WL		1	[0.80, 0.90]	[0.85, 0.95]
Moderately less significant	MLS		1/2	[0.70, 0.80]	[0.75, 0.85]
Less significant	L		1/3	[0.60, 0.70]	[0.65, 0.75]
Really less significant	RL	Scale 0-1	1/4	[0.50, 0.60]	[0.55, 0.65]
Much less significant	ML		1/5	[0.40, 0.50]	[0.45, 0.55]
Dominantly less significant	DL		1/6	[0.30, 0.40]	[0.35, 0.45]
Absolutely less significant	AL		1/7	[0.20, 0.30]	[0.25, 0.35]

Step 1. Assess the criteria by experts using the scales given above. With the IRN PIPRECIA method, experts first assess the significance of the second criterion in relation to the previous criterion.

$$IRN\left[s_j^r\right] = \begin{cases} > \left[1,1\right], \left[1,1\right] & \text{if} \quad C_j > C_{j-1} \\ = \left[1,1\right], \left[1,1\right] & \text{if} \quad C_j = C_{j-1} \\ < \left[1,1\right], \left[1,1\right] & \text{if} \quad C_j < C_{j-1} \end{cases} \tag{1}$$

IRN [s^r_j] denotes the assessment of the criteria by each expert r.

Step 2. Since it is a group decision-making, the initial IRN matrix is obtained by aggregating experts' estimates using one of available aggregators.

$$IRNDWGA\left\{IRN(\varphi_1), IRN(\varphi_2), .., IRN(\varphi_n)\right\} = \left(\begin{array}{c} \left[\dfrac{\sum_{j=1}^{n} \underline{\varphi}_{lj}}{1+\left\{\sum\limits_{j=1}^{n} w_j \left(\dfrac{1-f(\underline{\varphi}_{lj})}{f(\underline{\varphi}_{lj})}\right)^{\rho}\right\}^{1/\rho}}, \dfrac{\sum_{j=1}^{n} \overline{\varphi}_{lj}}{1+\left\{\sum\limits_{j=1}^{n} w_j \left(\dfrac{1-f(\overline{\varphi}_{lj})}{f(\overline{\varphi}_{lj})}\right)^{\rho}\right\}^{1/\rho}} \right], \\ \left[\dfrac{\sum_{j=1}^{n} \underline{\varphi}_{uj}}{1+\left\{\sum\limits_{j=1}^{n} w_j \left(\dfrac{1-f(\underline{\varphi}_{uj})}{f(\underline{\varphi}_{uj})}\right)^{\rho}\right\}^{1/\rho}}, \dfrac{\sum_{j=1}^{n} \overline{\varphi}_{uj}}{1+\left\{\sum\limits_{j=1}^{n} w_j \left(\dfrac{1-f(\overline{\varphi}_{uj})}{f(\overline{\varphi}_{uj})}\right)^{\rho}\right\}^{1/\rho}} \right] \end{array} \right) \tag{2}$$

Here, the aggregation is conducted using the IRN Dombi weighted geometric averaging aggregator, which is an operator frequently used for averaging values [41-44].

Step 3. Calculate the coefficient IRN [k_j].

$$IRN[k_j] = \begin{cases} = [1,1],[1,1] & \text{if} \quad j = 1 \\ 2 - [s_j] & \text{if} \quad j > 1 \end{cases} \tag{3}$$

Step 4. Calculate the interval rough weight IRN $[q_j]$.

$$RN[q_j] = \begin{cases} = [1,1],[1,1] & \text{if} \quad j = 1 \\ \dfrac{[q_{j-1}]}{[k_j]} & \text{if} \quad j > 1 \end{cases} \tag{4}$$

Step 5. Calculate the relative interval rough weight *IRN* $[w_j]$.

$$IRN[w_j] = \frac{[q_j]}{\sum_{j=1}^{n}[q_j]} \tag{5}$$

The inverse IRN PIPRECIA method is used in the following steps.
Step 6. Reassess the criteria by experts, starting from the penultimate criterion.

$$IRN[s_j^{r'}] = \begin{cases} > [1,1],[1,1] & \text{if} \quad C_j > C_{j+1} \\ = [1,1],[1,1] & \text{if} \quad C_j = C_{j+1} \\ < [1,1],[1,1] & \text{if} \quad C_j < C_{j+1} \end{cases} \tag{6}$$

IRN $[s^r_j{}']$ denotes the assessment of criteria by expert *r*.
Then, it is required to aggregate all experts' estimates.
Step 7. Calculate the coefficient *IRN* $[k_j']$.

$$IRN[k_j'] = \begin{cases} = [1,1],[1,1] & \text{if} \quad j = n \\ 2 - [s_j'] & \text{if} \quad j > n \end{cases} \tag{7}$$

Step 8. Calculate the interval rough weight *IRN* $[q_j']$.

$$\overline{q_j}' = \begin{cases} = [1,1],[1,1] & \text{if} \quad j = n \\ \dfrac{\overline{q_{j+1}}'}{\overline{k_j}'} & \text{if} \quad j > n \end{cases} \tag{8}$$

Step 9. Calculate the relative interval rough weight *IRN* $[w_j']$.

$$IRN[w_j'] = \frac{[q_j']}{\sum_{j=1}^{n}[q_j']} \tag{9}$$

Step 10. Calculate the final values.

$$[w_j''] = \frac{1}{2}\left(IRN[w_j] + IRN[w_j']\right) \tag{10}$$

Step 11. Test the results by applying Spearman and Pearson correlation coefficients.

2.2. A Novel Interval Rough AROMAN Method

AROMAN is a method created in [45] for evaluating and ranking alternative solutions. In this section, for the first time in the literature, the extension of the AROMAN method with IRN has been presented, and it is explained in detail throughout the following several steps.

Step 1. Define the initial interval rough matrix (Ш).

$$Ш = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} IRN(ш_{11}) & IRN(ш_{12}) & \dots & IRN(ш_{1n}) \\ IRN(ш_{21}) & IRN(ш_{22}) & & IRN(ш_{2n}) \\ \dots & \dots & \dots & \dots \\ IRN(ш_{m1}) & IRN(ш_{m2}) & \dots & IRN(ш_{mn}) \end{bmatrix}_{m\times n} \end{array} \tag{11}$$

where alternatives are denoted by *m*, and criteria by *n*.

Step 2. Normalize the initial interval rough group matrix.

$$H = \begin{array}{c} \\ A_1 \\ A_2 \\ \dots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} IRN(н_{11}*) & IRN(н_{12}*) & \dots & IRN(н_{1n}*) \\ IRN(н_{21}*) & IRN(н_{22}*) & & IRN(н_{2n}*) \\ \dots & \dots & \dots & \dots \\ IRN(н_{m1}*) & IRN(н_{m2}*) & \dots & IRN(н_{mn}*) \end{bmatrix}_{m\times n} \end{array} \tag{12}$$

where *IRN* $(н_{ij})$ denotes the values of the interval rough normalized matrix *(H)*.

Step 2.1. a1) For "*benefit* type" criteria (linear)

$$IRN(н_{ij}) = \left([н_{ij}^L, н_{ij}^U],[н_{ij}^{'L}, н_{ij}^{'U}]\right) = \left(\left[\frac{ш_{ij}^L - ш_{ij}^-}{ш_{ij}^+ - ш_{ij}^-}, \frac{ш_{ij}^U - ш_{ij}^-}{ш_{ij}^+ - ш_{ij}^-}\right], \left[\frac{ш_{ij}^{'L} - ш_{ij}^-}{ш_{ij}^+ - ш_{ij}^-}, \frac{ш_{ij}^{'U} - ш_{ij}^-}{ш_{ij}^+ - ш_{ij}^-}\right]\right) \tag{13}$$

b1) For "*cost* type" criteria (linear)

$$IRN(н_{ij}) = \left([н_{ij}^L, н_{ij}^U],[н_{ij}^{'L}, н_{ij}^{'U}]\right) = \left(\left[\frac{ш_{ij}^{'U} - ш_{ij}^+}{ш_{ij}^- - ш_{ij}^+}, \frac{ш_{ij}^{'L} - ш_{ij}^+}{ш_{ij}^- - ш_{ij}^+}\right], \left[\frac{ш_{ij}^U - ш_{ij}^+}{ш_{ij}^- - ш_{ij}^+}, \frac{ш_{ij}^L - ш_{ij}^+}{ш_{ij}^- - ш_{ij}^+}\right]\right) \tag{14}$$

where $ш_{ij}^-$ and $ш_{ij}^+$ denotes minimum and maximum values of the rough boundary interval of the criteria, respectively:

$$ш_{ij}^- = \min_i \{ш_{ij}^L, ш_{ij}^{'L}\} \tag{15}$$

$$ш_{ij}^+ = \max_i \{ш_{ij}^U, ш_{ij}^{'U}\} \tag{16}$$

Step 2.2. a2) For "*benefit* type" criteria (vector)

$$IRN(в_{ij}) = \left([в_{ij}^L, в_{ij}^U],[в_{ij}^{'L}, в_{ij}^{'U}]\right) = \left(\left[\frac{ш_{ij}^L}{г_{ij}^{U'}}, \frac{ш_{ij}^U}{г_{ij}^{L'}}\right], \left[\frac{ш_{ij}^{L'}}{г_{ij}^U}, \frac{ш_{ij}^{U'}}{г_{ij}^L}\right]\right) \tag{17}$$

b2) For "*cost* type" criteria (vector)

$$IRN(в_{ij}) = \left([в_{ij}^L, в_{ij}^U],[в_{ij}^{'L}, в_{ij}^{'U}]\right) = 1 - \left(\left[\frac{ш_{ij}^L}{г_{ij}^{U'}}, \frac{ш_{ij}^U}{г_{ij}^{L'}}\right], \left[\frac{ш_{ij}^{L'}}{г_{ij}^U}, \frac{ш_{ij}^{U'}}{г_{ij}^L}\right]\right) \tag{18}$$

where

$$IRN(г_j) = \left([г_j^L, г_j^U],[г_j^{'L}, г_j^{'U}]\right) = \sqrt{\sum_{i=1}^m (ш_{ij})^2} \tag{19}$$

Step 2.3. Perform aggregated averaged normalization

The aggregated averaged normalization is performed by the following Equation**:**

$$IRN(н_{ij}*) = \frac{(н_{ij} \otimes \alpha) + (в_{ij} \otimes \alpha)}{2} \tag{20}$$

where $н_{ij}^*$ is the aggregated averaged normalization and α is a weighting factor varying from 0 to 1. In this specific case, α is 0.5.

Step 3. Compute the weighted matrix:

$$IRN(Б_{ij}) = \left([б_{ij}^{L}, б_{ij}^{U}, б_{ij}^{'L}, б_{ij}^{'U}]\right)_{m\times n} = \left([n_{ij}^{L*} \times \mathrm{w}_{ij}^{L}, n_{ij}^{U*} \times \mathrm{w}_{ij}^{U}, n_{ij}^{'L*} \times \mathrm{w}_{ij}^{'L}, n_{ij}^{'U*} \times \mathrm{w}_{ij}^{'U}]\right) \tag{21}$$

IRN (*wj*) denotes criteria weights.

Step 4. Summarize the normalized weighted values of the criteria type min (*Mi*) and the normalized weighted values of the max type (*Цi*) individually. It can be done using Eqs. (22) and (23):

$$IRN(M_i) = \left([м_i^{L}, м_i^{U}, м_i^{'L}, м_i^{'U}]\right)_{1\times m} = \sum_{j=1}^{n} (Б_{ij}) \quad \text{for} \quad C \tag{22}$$

$$IRN(Ц_i) = \left([ц_i^{L}, ц_i^{U}, ц_i^{'L}, ц_i^{'U}]\right)_{1\times m} = \sum_{j=1}^{n} (Б_{ij}) \quad \text{for} \quad B \tag{23}$$

Step 5. Compute the final ranking of the alternatives. The final ranking of the alternatives (*Чi*) is obtained by Eq. (24):

$$IRN(Ч_i) = \left([ч_i^{L}, ч_i^{U}, ч_i^{'L}, ч_i^{'U}]\right)_{1\times m} = (M_i)^{\gamma} + (Ц_i)^{(1-\gamma)} \tag{24}$$

where γ is the coefficient in interval 0.1-0.9.

3. CASE STUDY

This case study aims to analyze the level of acceptability of AVs in Libya. With the ongoing development of the automotive industry, the potential for AVs to be implemented on Libyan roads generates interesting inquiries regarding their reception and integration within the local environment. AVs possess the capacity to fundamentally transform transportation, boost road safety [46], and optimize mobility efficiency. Yet, the effective incorporation of AVs into the transportation system of Libya hinges on comprehending the attitudes, views, and apprehensions of the local populace towards this nascent technology.

Libya's transportation infrastructure [47], like to those in many developing nations, mainly depends on private car usage and lacks a significant presence of public transportation. Libya has one of the highest rates of road traffic fatalities globally [48]. This is a hurdle in terms of public adoption of autonomous mobility. Hence, the objective of this study is to investigate the pivotal factors that impact the public's willingness to embrace AVs in Libya. Consequently, this will offer vital knowledge to steer decision-making procedures about the implementation of AVs. It will establish the foundation for future efforts to encourage popular approval and facilitate the shift towards a more autonomous transportation system.

3.1. Forming the MCDM Model

In this section, the formation of the MCDM model is shown, that is, the description of the strategies of public acceptance of AVs (Table 3) and nine evaluation criteria that have been used for evaluation (Table 4).

Table 3 Description of suitable strategies for evaluation

	Strategy	Description
S1	Gradual Adoption with Limited Use Cases	In this scenario, AVs are phased in for limited use cases like controlled settings (e.g., dedicated lanes, closed campuses) or specific applications. Before widespread adoption, AV technology must gain public trust.
S2	Geographically Targeted Deployment	Deploying AVs in certain cities is another option. Deployment in certain places allows localised testing, infrastructure development, and public participation. This method allows for context-specific public acceptance assessments.
S3	Piloted AV Programs	Piloted AV programs involve AV developers and local transportation authorities conducting small-scale real-world experiments. This option permits controlled testing and data collecting with public input. It seeks transparency, communication, and engagement to address public problems.
S4	Rapid Deployment with Extensive Testing	This scenario aggressively deploys AVs into the transport system after significant testing and validation. This scenario targets efficiency, congestion, and transportation system improvements with better technical readiness and public acceptance.

Table 4 Description of used criteria

	Criterion	Description
C1	Safety	Safety is a key public acceptance factor. Compare AV safety to human-driven vehicles. This covers accident rates, reliability, and AV technology robustness.
C2	Trust and Reliability	Assess public trust in AV technology. Take into account system transparency, AV performance, and autonomous system reliability.
C3	Privacy and Data Security	Examine AV privacy and data security issues. Assess public opinion on data collecting, storage, and unauthorized access. Consider how privacy measures affect public approval.
C4	Job Displacement and Economic Impact	Assess public opinion on AV deployment's effects on jobs and the economy. Assess job displacement problems in transportation and delivery. Assess the perceived economic benefits and drawbacks of AVs.
C5	Environmental Impact	Assess public opinion of AVs' environmental impact. Consider energy efficiency, greenhouse gas reduction, and AVs' potential for sustainable transportation. Assess how environmental benefits or concerns affect public acceptance.
C6	Accessibility and Inclusivity	Assess public opinion on AV accessibility and inclusion. Consider how AVs can carry disabled or limited-mobility people. Evaluate public opinion on AVs' transportation equity and accessibility potential.
C7	Legal and Regulatory Framework	Assess public opinion on AV law and regulation. Assess if people think current safety and liability regulations are enough. Assess public trust in AV deployment laws and regulations.
C8	Social and Cultural Acceptance	Consider the social and cultural adoption of AVs. Examine cultural norms, technology attitudes, and public acceptability of AVs on roads.
C9	User Experience and Comfort	Assess public opinion on AV comfort and user experience. Consider ride quality, convenience, and usability.

3.2. Determining Criteria Weights using the IRN PIPRECIA Method

Determining the criteria weights is of crucial importance in MCDM [48]. In this approach, their importance has been evaluated by four experts according to the IRN PIPRECIA and Inverse IRN PIPRECIA methodology, which is shown in Table 5. Four experts in the areas of transportation engineering, artificial intelligence, and the psychology of accidents were contacted. All the experts had more than 15 years' worth of expertise in their line of specialization. This provided a comprehensive insight into the various factors that contribute to the assessment of the public perception and safety issues arising from the use of self-driving cars. Then, the experts' estimates are aggregated by the IRN Dombi weighted geometric averaging operator to obtain a matrix *IRN* $[s^r_j]$. The following example represents the aggregation procedure for C4:

$$IRN(C_4^{E1}) = \left([0.80, 0.90], [0.85, 0.95]\right), IRN(C_4^{E2}) = \left([0.70, 0.80], [0.75, 0.85]\right),$$
$$IRN(C_4^{E3}) = \left([0.70, 0.80], [0.75, 0.85]\right), RN(C_2^{E4}) = \left([0.60, 0.70], [0.65, 0.75]\right)$$

In the aggregation process, the weights of experts are w_{DM}=(0.250,0.250,0.250,0.250). The computation procedure is given below:

Table 5 Evaluation of criteria by four experts according to required scales

P	C1	C2	C3	C4	…	C8	C9
E1		[1,1.05], [1.1,1.1]	[0.7,0.8], [0.75,0.85]	[0.8,0.9], [0.85,0.95]		[1.1,1.2] [1.2,1.25]	[0.6,0.7], [0.65,0.75]
E2		[0.7,0.8], [0.75,0.85]	[0.7,0.8], [0.75,0.85]	[0.7,0.8], [0.75,0.85]	…	[1.2,1.35] [1.3,1.4]	[0.7,0.8] [0.75,0.85]
E3		[0.7,0.8], [0.75,0.85]	[0.7,0.8], [0.75,0.85]	[0.7,0.8], [0.75,0.85]		[1.2,1.35] [1.3, 1.4]	[0.7,0.8] [0.75,0.85]
E4		[0.7,0.8], [0.75,0.85]	[0.7,0.8], [0.75,0.85]	[0.6,0.7], [0.65,0.75]		[1,1.2] [1.2,1.25]	[0.8,0.9] [0.85,0.95]
P-I	**C1**	**C2**	**C3**	**C4**	**…**	**C8**	**C9**
E1	[1.1,1.2], [1.2,1.25]	[1.1,1.2], [1.2,1.25]	[1,1.05], [1.1,1.1]	[1,1.05], [1.1,1.1]		[1.2,1.35] [1.3,1.4]	
E2	[1.1,1.2], [1.2,1.25]	[1.1,1.2], [1.2,1.25]	[1.1,1.2], [1.2,1.25]	[1,1.05], [1.1,1.1]	…	[1.1,1.2] [1.2,1.25]	
E3	[1.1,1.2], [1.2,1.25]	[1.1,1.2], [1.2,1.25]	[1.1,1.2], [1.2,1.25]	[1,1.05], [1.1,1.1]		[1.1,1.2] [1.2,1.25]	
E4	[1.1,1.2], [1.2,1.25]	[1.1,1.2], [1.2,1.25]	[1.2,1.35], [1.3,1.4]	[0.7,0.8], [0.75,0.85]		[1,1.05] [1.1,1.1]	

Then, experts' estimates are aggregated by the IRN Dombi weighted geometric averaging operator to obtain a matrix. *IRN* $[s^r_j]$. The following example represents the aggregation procedure for C4:

$$IRN(C_4^{E1}) = \left([0.80, 0.90], [0.85, 0.95]\right), IRN(C_4^{E2}) = \left([0.70, 0.80], [0.75, 0.85]\right),$$
$$IRN(C_4^{E3}) = \left([0.70, 0.80], [0.75, 0.85]\right), RN(C_2^{E4}) = \left([0.60, 0.70], [0.65, 0.75]\right)$$

In the aggregation process, the weights of experts are w_{DM}=(0.250,0.250,0.250,0.250). The computation procedure is given below:

$$IRND(C_4)=\begin{cases} C_{l4}=\dfrac{\sum_{j=1}^{4}\underline{\varphi}_{lj}}{1+\left\{\sum_{j=1}^{4}w_j\left(\dfrac{1-f(\underline{\varphi}_{lj})}{f(\underline{\varphi}_{lj})}\right)^{\rho}\right\}^{1/\rho}}=\dfrac{3.30}{1+\left(0.250\times\left(\dfrac{1-0.242}{0.242}\right)+...+0.250\times\left(\dfrac{1-0.333}{0.333}\right)\right)}=0.797 \\ C_{u4}=\dfrac{\sum_{j=1}^{4}\overline{Lim}(\varphi_j)}{1+\left\{\sum_{j=1}^{4}w_j\left(\dfrac{1-f(\overline{\varphi}_{lj})}{f(\overline{\varphi}_{lj})}\right)^{\rho}\right\}^{1/\rho}}=\dfrac{3.70}{1+\left(0.250\times\left(\dfrac{1-0.243}{0.243}\right)+...+0.250\times\left(\dfrac{1-0.324}{0.324}\right)\right)}=0.900 \\ C_{l4'}=\dfrac{\sum_{j=1}^{4}\underline{\varphi}_{lj}}{1+\left\{\sum_{j=1}^{4}w_j\left(\dfrac{1-f(\underline{\varphi}_{lj})}{f(\underline{\varphi}_{lj})}\right)^{\rho}\right\}^{1/\rho}}=\dfrac{3.55}{1+\left(0.250\times\left(\dfrac{1-0.239}{0.239}\right)+....+0.250\times\left(\dfrac{1-0.338}{0.326}\right)\right)}=0.855 \\ C_{u4'}=\dfrac{\sum_{j=1}^{4}\overline{Lim}(\varphi_j)}{1+\left\{\sum_{j=1}^{4}w_j\left(\dfrac{1-f(\overline{\varphi}_{lj})}{f(\overline{\varphi}_{lj})}\right)^{\rho}\right\}^{1/\rho}}=\dfrac{3.90}{1+\left(0.250\times\left(\dfrac{1-0.244}{0.244}\right)+...+0.250\times\left(\dfrac{1-0.320}{0.320}\right)\right)}=0.951 \end{cases}$$

$$=\left([0.797,0.900],[0.855,0.951]\right)$$

where $f(IRN\ \varphi_4)$ is calculated:

$$f(IRN(\varphi_4))=\begin{cases} f(\underline{Lim}(\varphi_4))=\dfrac{\underline{Lim}(\varphi_1)}{\sum_{i=1}^{4}\underline{Lim}(\varphi_i)}=\dfrac{0.80}{3.30}=0.242 \\ f(\overline{Lim}(\varphi_4))=\dfrac{\overline{Lim}(\varphi_i)}{\sum_{i=1}^{4}\overline{Lim}(\varphi_1)}=\dfrac{0.90}{3.70}=0.243 \\ f(\underline{Lim}'(\varphi_4))=\dfrac{\underline{Lim}(\varphi_1)}{\sum_{i=1}^{4}\underline{Lim}(\varphi_i)}=\dfrac{0.85}{3.55}=0.239 \\ f(\overline{Lim}'(\varphi_4))=\dfrac{\overline{Lim}(\varphi_i)}{\sum_{i=1}^{4}\overline{Lim}(\varphi_1)}=\dfrac{0.95}{3.90}=0.244 \end{cases}$$

After the entire procedure, including the Inverse IRN PIRECIA steps, has been conducted, the final weights (Table 6) are obtained.

Table 6 Ranking of the criteria after applying the IRN PIPRECIA method

	IRN PIPRECIA	Inverse IRN PIPRECIA	final wj	Rank
C1	[0.119,0.160],[0.145,0.197]	[0.057,0.167],[0.142,0.346]	[0.088,0.164],[0.143,0.272]	1
C2	[0.093,0.136],[0.118,0.175]	[0.052,0.134],[0.113,0.260]	[0.072,0.135],[0.116,0.217]	3
C3	[0.072,0.113],[0.095,0.152]	[0.046,0.107],[0.091,0.195]	[0.059,0.110],[0.093,0.173]	6
C4	[0.060,0.103],[0.083,0.145]	[0.042,0.086],[0.073,0.148]	[0.051,0.095],[0.078,0.146]	8
C5	[0.052,0.099],[0.076,0.146]	[0.046,0.089],[0.074,0.144]	[0.049,0.094],[0.075,0.145]	9
C6	[0.053,0.108],[0.087,0.169]	[0.058,0.102],[0.089,0.159]	[0.056,0.105],[0.088,0.164]	7
C7	[0.058,0.129],[0.105,0.214]	[0.075,0.123],[0.111,0.183]	[0.066,0.126],[0.108,0.198]	4
C8	[0.054,0.134],[0.106,0.237]	[0.095,0.143],[0.135,0.204]	[0.075,0.139],[0.121,0.220]	2
C9	[0.044,0.120],[0.091,0.222]	[0.086,0.116],[0.109,0.155]	[0.065,0.118],[0.100,0.188]	5

Based on the results obtained and the significance of the criteria, the final ranking is as follows: C1>C8>C2>C7>C9>C3>C6>C4>C5.

3.3. Assessing Strategies using the IRN AROMAN Method

Experts evaluated potential strategies using interval numbers. Since it is a group decision-making when applying the rules for operations with interval numbers, an initial decision matrix, shown in Table 7, is obtained.

The following calculation involves a three-phase normalization procedure depending on the type of criteria. Since the experts use linguistic terms for evaluation, all criteria have been modelled as benefit, so Eqs. (13) and (17) are applied. For example, in order to perform linear normalization for the first alternative according to the first criterion, it is necessary to do the following:

$$IRN(\textit{н}_{11}) = \left([0.043, 0.548], [0.117, 0.617]\right) = \left(\begin{array}{l} \left[\dfrac{5.580-5.500}{7.380-5.500}, \dfrac{6.530-5.500}{7.380-5.500} \right], \\ \left[\dfrac{5.720-5.500}{7.380-5.500}, \dfrac{6.660-5.500}{7.380-5.500} \right] \end{array} \right)$$

$$IRN(\textit{в}_{11}) = \left([0.399, 0.533], [0.427, 0.570]\right) = \left(\left[\frac{5.580}{13.989}, \frac{6.530}{12.247} \right], \left[\frac{5.720}{13.405}, \frac{6.660}{11.679} \right] \right)$$

while:

$$IRN(\textit{г}_{1}) = \left([11.678, 13.405], [12.247, 13.989]\right) = \left(\begin{array}{l} \left[\begin{array}{l} \sqrt{(5.58)^2 + (5.88)^2 + (5.50)^2 + (6.36)^2}, \\ \sqrt{(6.53)^2 + (6.97)^2 + (6.25)^2 + (7.03)^2} \end{array} \right], \\ \left[\begin{array}{l} \sqrt{(5.72)^2 + (6.29)^2 + (5.67)^2 + (6.75)^2}, \\ \sqrt{(6.66)^2 + (7.32)^2 + (6.58)^2 + (7.38)^2} \end{array} \right] \end{array} \right)$$

Table 7 Initial Interval Rough Matrix

	C1	C2	C3	C4	…	C8	C9
A1	[5.58,6.53] [5.72,6.66]	[6.11,6.79] [6.29,7.04]	[3.14,3.86] [3.63,4.47]	[3.59,5.14] [3.91,5.55]		[4.32,4.82] [4.42,4.88]	[2.88,3.97] [3.24,4.35]
A2	[5.88,6.97] [6.29,7.32]	[5.70,6.79] [6.11,7.07]	[4.67,6.15] [4.93,6.34]	[2.88,3.97] [3.50,4.47]		[2.42,3.94] [3.00,4.73]	[4.11,4.79] [4.35,5.29]
A3	[5.50,6.25] [5.67,6.58]	[4.77,6.12] [5.04,6.24]	[3.32,4.60] [3.42,4.75]	[3.54,4.82] [3.76,4.96]	...	[4.83,6.14] [5.25,6.47]	[2.40,3.63] [2.95,4.33]
A4	[6.36,7.03] [6.75,7.38]	[6.62,7.25] [6.93,7.53]	[5.70,6.79] [6.11,7.07]	[4.70,5.79] [5.36,6.50]		[1.73,3.31] [2.22,3.92]	[4.40,5.63] [4.95,6.33]

After that, it is necessary to apply Eq. (20):

$$IRN(\textit{н}_{11}{*}) = \frac{(0.043 \otimes 0.500) + (0.399 \otimes 0.500)}{2} = \left([0.110, 0.270], [0.136, 0.297]\right).$$

In this way, the final normalized interval rough matrix shown in Table 8 is obtained.

Table 8 Normalized Interval Rough Matrix

	C1	C2	C3	C4	...	C8	C9
A1	[0.11,0.27] [0.14,0.30]	[0.23,0.32] [0.25,0.36]	[0.07,0.15] [0.11,0.21]	[0.13,0.31] [0.17,0.37]	...	[0.24,0.32] [0.26,0.34]	[0.10,0.23] [0.14,0.28]
A2	[0.16,0.34] [0.22,0.40]	[0.19,0.32] [0.23,0.36]	[0.20,0.36] [0.23,0.39]	[0.07,0.19] [0.13,0.26]		[0.10,0.24] [0.15,0.32]	[0.21,0.30] [0.24,0.37]
A3	[0.10,0.23] [0.13,0.28]	[0.09,0.25] [0.12,0.27]	[0.08,0.22] [0.10,0.24]	[0.13,0.28] [0.16,0.31]		[0.28,0.43] [0.33,0.48]	[0.06,0.19] [0.12,0.28]
A4	[0.23,0.35] [0.29,0.41]	[0.29,0.37] [0.32,0.41]	[0.29,0.41] [0.33,0.45]	[0.23,0.37] [0.31,0.47]		[0.04,0.19] [0.09,0.25]	[0.23,0.38] [0.30,0.47]

After that, the procedure of weighting the normalized matrix with the criteria weights obtained with the IRN PIPRECIA method is performed. Further, the calculation is performed using Eqs. (23) and (24), so the final results obtained are presented in Table 9.

Table 9 Final results obtained applying the IRN PIPRECIA – IRN AROMAN model

$IRN(Ц_i) = \sum_{j=1}^{n}(Б_{ij})$	$IRN(Ч_i) = (M_i)^{\gamma} + (Ц_i)^{(1-\gamma)}$	AV	Rank	
[0.081,0.286],[0.159,0.532]	[0.729,0.854],[0.924,0.961]	0.867	3	A1
[0.092,0.336],[0.195,0.636]	[0.797,0.893],[0.945,0.972]	0.902	2	A2
[0.062,0.258],[0.134,0.483]	[0.695,0.834],[0.913,0.956]	0.849	4	A3
[0.129,0.388],[0.255,0.729]	[0.854,0.924],[0.961,0.980]	0.930	1	A4

Since decision-making is reduced to only benefit criteria in this case, the matrix *IRN* (M_i) is not calculated, i.e. it is equal to zero, while the calculation example for benefit criteria is as follows:

$$IRN(Ц_1) = ([0.081, 0.286],[0.159, 0.532]) = \left(\begin{bmatrix} 0.010 + 0.017 + 0.044 + ... + 0.007, \\ 0.044 + 0.043 + 0.016 + ... + 0.027 \end{bmatrix} \atop \begin{bmatrix} 0.020 + 0.029 + 0.011 + ... + 0.014, \\ 0.081 + 0.077 + 0.037 + ... + 0.052 \end{bmatrix} \right)$$

In the last step, the matrix is calculated as follows:

$$IRN(Ч_1) = ([0.729, 0.854, 0.924, 0.961]) = (0)^{0.5} + (0.081)^{(1-0.5)}$$

with a value γ = 0.5.

The findings indicate that safety stands out as the foremost criterion, especially in a country with one of the highest road accident death rates globally. Following closely in second place is the cultural acceptance of AVs, underscoring the presence of diverse cultural challenges in this context. Trust and reliability secured the third position in the rankings, primarily attributed to the scarcity of information available about these cars, relying heavily on personal observations and social media. In contrast, environmental factors were deemed the least important, stemming from a lack of environmental awareness among many individuals and the perception that their impact is not considered significant. Job displacement and economic impact were assigned the lowest ranking, primarily because of the significant personal dependence on cars for mobility, which diminishes the anticipated impact of this technology on employment.

The outcomes indicate that the most effective strategy involves rapid implementation coupled with extensive testing. Executing this strategy poses a significant challenge for decision-makers, as they may encounter difficulties in adequately preparing and allocating the required resources. Additionally, there is a need for comprehensive and targeted public awareness campaigns. The strategy of focusing on specific geographical areas, particularly in large urban cities, ranks second in effectiveness. This approach enables the gathering of data and the accumulation of knowledge before broader implementation. It also aids in pinpointing weaknesses and identifying necessary improvements before expanding the application to larger geographical areas.

4. Verification Tests

In this section of the study, several verification tests which should demonstrate the usability of the developed IRN AROMAN method have been created. First, a sensitivity analysis has been carried out with changes in the weights of nine criteria. The second test involves a comparative analysis with four other methods, and the third includes a rank reversal analysis.

4.1. Sensitivity Analysis

Determining the influence of the criteria weights on the final ranking of alternative solutions is practically an indispensable step, which is also confirmed by the following studies [50-54]. It is very important to determine if and how the new simulated values affect the changes in the final values of the alternatives. Figure 1 shows the values of the new criteria weights.

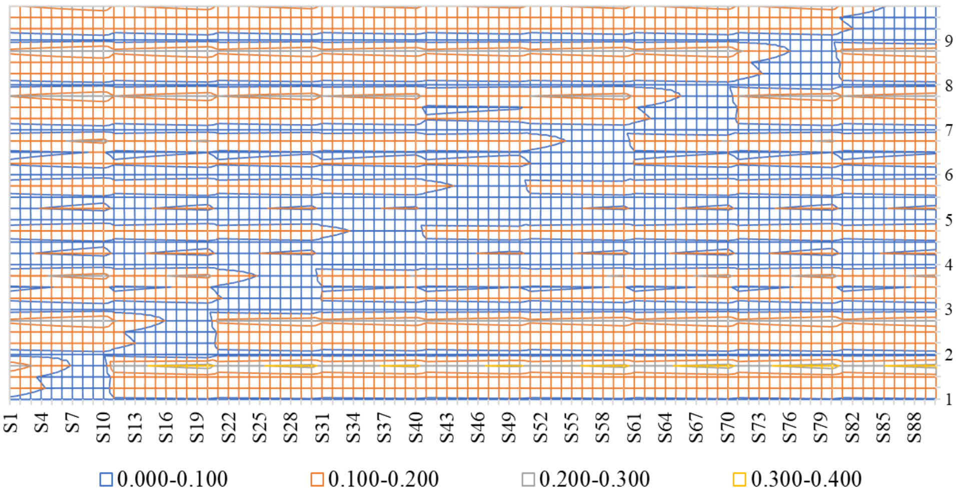

Fig. 1 Criteria weights in new 90 scenarios

In this case, a total of 90 scenarios in which new values are simulated for all criteria in the percentage values of 5-95 have been created, so that each criterion in any of the scenarios tends to zero. After the new criteria values have been set, it is necessary to perform calculations in 90 models using the IRN AROMAN method. The results are presented in Fig. 2.

Although there is a large number of scenarios in which the new weights of the nine criteria have been defined, it is important to note that there are no changes in the ranks of the strategies, so the initial results remain the same throughout the entire sensitivity analysis.

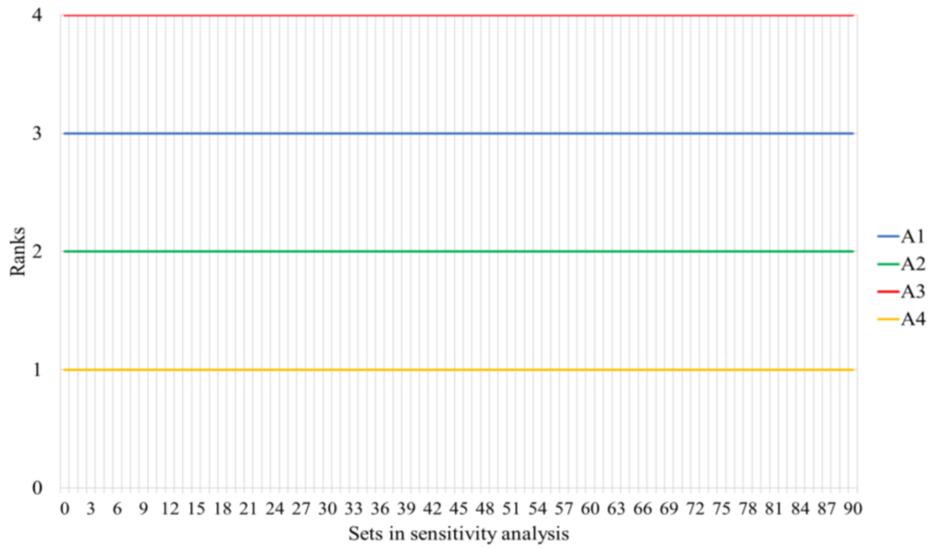

Fig. 2 Results of SA

4.2. Comparative Analysis

A comparative analysis has been conducted with four other MCDM methods: ARAS (additive ratio assessment) [55], COPRAS (Complex Proportional Assessment) [56], SAW (Simple Additive Weighting), [57], CoCoSo (combined compromise solution) [58] with IRNs in order to verify the stability of the developed model, which is shown in Figs. 3 and 4.

In Fig. 3, we can notice that there are no changes in the ranks of alternative solutions, regardless of which method is applied. It should be noted that this is because of a small number of alternatives considered in this paper, but there would be certain differences in the ranks if the number of alternative solutions increases, which is understandable in one way.

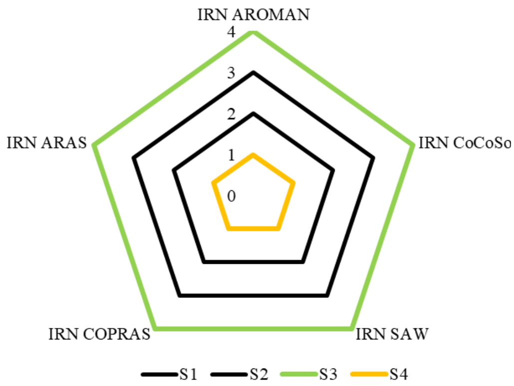

Fig. 3 Ranks in CA

Figure 4 shows the values of the alternatives in the comparative analysis conducted in order to test if some alternatives are similar to each other.

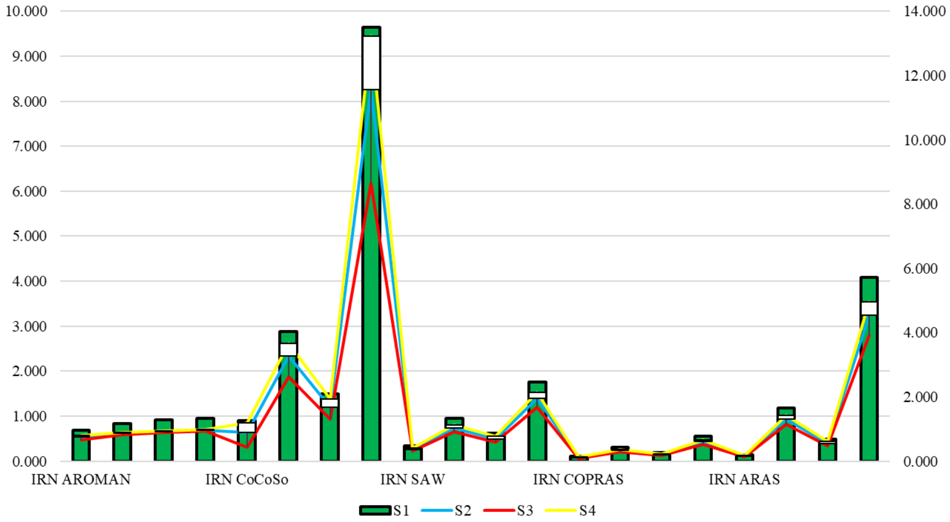

Fig. 4 Values in CA

4.3. Rank reversal analysis

The third verification test involves changing the size of the initial decision matrix, the results of which are shown in Fig. 5.

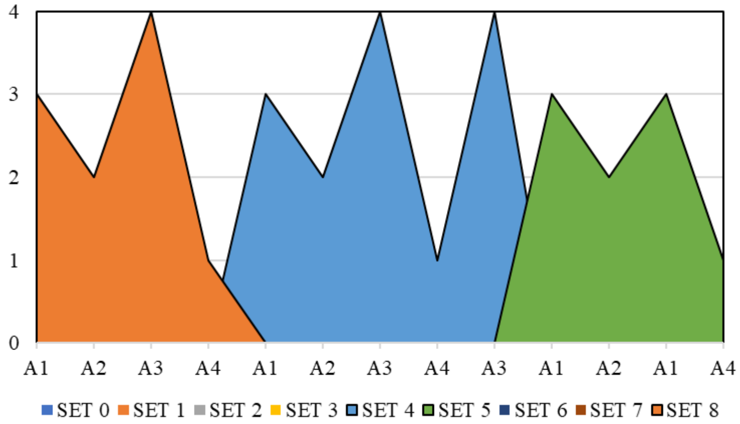

Fig. 5 Results of RRA

A total of eight sets have been formed in this analysis, where there is the elimination of the worst strategy in the first three sets and recalculation is done with the IRN PIPRECIA – IRN AROMAN model. The fourth set includes adding the strategy with the worst characteristics, so that there are five alternatives in total. The fifth set is formed in such a way that the worst alternative is replaced by the second worst alternative. The remaining three sets imply the size of the initial matrix with four alternatives, but with a smaller number of criteria, because one of the criteria is eliminated in each of these three sets, so that there is a 4x6 matrix in the last set. Regardless of the diversity in defining sets in rank reversal analysis, there is no change in ranks, that is, the initial results remain the same.

5. CONCLUSION

In this paper, the evaluation of strategies for the introduction of autonomous vehicles has been carried out creating a novel approach which includes the extension of the AROMAN method with IRNs. In this way, the contribution from the scientific and methodological aspects is presented since the developed model can be applied in different areas.

Transportation holds a crucial role in shaping individuals' engagement in various life activities. This study offers insights into the public acceptance of AVs and the policies aimed at integrating them into diverse transportation modes, marking a new era in the field of transportation. The choice of a specific mode of transport is intertwined with numerous influencing factors. These factors can exhibit variations not only from one country to another but even within different urban areas within the same country. Public acceptance stands out as a pivotal element in the seamless integration of AVs into established transport networks. Decision-makers engaged in the integration of this technology should, therefore, consider these factors diligently to arrive at the most suitable decisions regarding their incorporation into respective communities. To comprehend the implications of these factors, the research employed a MCDM method, which revealed that security, privacy, and trust are the foremost considerations, emphasizing the necessity for a strategy development that incorporates these aspects. These results hold significance for manufacturers as well, urging them to consider these factors in their processes. In terms of strategy, rapid deployment coupled with thorough testing is the most effective approach. This requires a heightened commitment to validating vehicles extensively before their widespread market introduction. Such a proactive measure will substantially reduce potential risks, ultimately enhancing public confidence. Subsequent investigations could expand upon this study by exploring additional factors that might impact people's acceptance of the technology. Future research endeavors could delve deeper into scrutinizing the potential economic and environmental ramifications associated with the integration of the technology. Also, future research activities can be related to developing similar models and applying them for various decisions in the transportation field.

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