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MULTICRITERIA DECISION MAKING APPROACH TO SUPPORT ADOPTION OF CONNECTED AND AUTONOMOUS VEHICLES

Siham Farrag

Transportation Research Institute (IMOB)
Universiteit Hasselt, Hasselt 3590, Belgium
&
Middle East College
Knowledge Oasis Muscat, Sultanate of Oman
e-mail: siham.farrag@uhasselt.be

Nabil Sahli

German University of Technology in Oman
Muscat, Sultanate of Oman
e-mail: nabil.sahli@gutech.edu.om

Ansar Yasar, Davy Janssens

Transportation Research Institute (IMOB)
Universiteit Hasselt, Hasselt 3590, Belgium
e-mail: {ansar.yasar, davy.janssens}@uhasselt.be

Abstract. Connected and autonomous vehicles (CAV) have recently attracted policymakers, manufacturers, and customers' attention. Despite their numerous benefits, CAVs still have to overcome many challenges related to the implementation and market penetration. When not dominated by financial constraints, the CAV adoption heavily depends on how policymakers and the government address the other challenges, including public perception, rules, and regulations. This study aims at formulating recommendations to support decision-makers in choosing the most appropriate and sustainable strategy to implement CAV technology. To do so, key barriers were first identified based on the literature review and discussions with decision-makers. Moreover, long-term adoption of CAV technologies in alternative future scenarios is developed. Multicriteria decision-making analysis was conducted to weigh these barriers and rank different strategies of CAV implementation. The transportation system of the Sultanate of Oman was used as a study case. It was found that the lack of technical skills and policies/regulations are the main barriers to the adoption of CAV technologies. To overcome these barriers, suggested strategies include establishing low-cost and short-term solutions, providing training to transportation professionals, and investing in statewide radio communications/IoT for emergency responses.

Keywords: Connected and autonomous vehicles, multicriteria decision making, PROMETHEE, AHP

1 INTRODUCTION

Connected and automated vehicles (CAVs) technologies are fast developing and have recently been introduced to develop and deploy fully connected transport systems. Such systems may enhance road safety, mobility, and environmental wellness [1, 2].

The term "connected" refers to its wireless communication capability. This communication ensures connectivity within the vehicle itself and with the external environment, including other vehicles (vehicle-to-vehicle (V2V) communication) and road infrastructure (vehicle-to-infrastructure (V2I) communication) [3]. More specifically, Automated Vehicle (AV) is defined as a new generation of vehicles equipped with advanced sensors such as radar, LIDAR (light detection and ranging), controllers, actuators, and communication technologies to accomplish driving tasks efficiently and safely instead of human drivers [4]. Combining vehicle connectivity and automation helps get the most out of AVs and Connected Vehicles (CVs) [3, 5]. Such vehicles can recognize potential threats and react accordingly while sharing valuable data with other vehicles, drivers, and traffic management agencies [5, 6, 7, 8]. Several studies have discussed the benefits of CAVs [9, 10, 11, 12] and in particular the decreased number of vehicle crashes [9, 13]. In addition, CAV usage may lead to a more efficient parking system [14]. Other noticeable benefits include lower transportation cost [6], reduced traffic congestion [8, 9, 13, 15], reduced driving stress [16], smoother traffic circulation [6, 15], and improved mobility for elderly and disabled people and those who are under-served by public transportation [17, 18, 19]. Regarding environmental benefits, Wadud et al. [20] stated that automation might reduce gas emissions by almost 50 %. According to the same research, even partial automation may lead to energy consumption reduction [20]. Other research works confirmed a lowered fuel consumption [9, 18, 20].

Despite all the benefits that CAVs may bring, experts are still uncertain about the future of CAVs' implementation [21], especially in undeveloped countries. Indeed, implementing this technology is still facing several barriers and challenges [12, 17, 22]. Cost, safety, security, privacy, liability, infrastructure requirements, and sustainability have been the main challenges [12]. It is worth mentioning here that the impact of these barriers is country-dependent. For instance, Kröger et al. [23] predicted a higher CAV penetration in Germany than in the U.S. as German drivers use more luxury cars and change vehicles more often [23]. A more recent study [2] reviewed the rules and policies on safety and liability related to CAVs. It formulated recommendations based on the best practices observed in some particular countries.

In general, the barriers that have been raised by different studies can be categorized into the seven main following groups [12, 17, 22, 23, 2]:

1. Cost of CAV platforms for large-scale market adoption. The technology needed for a CAV includes new infrastructure such as sensors, communication and guidance technology, and software for each automobile.
2. CAV certification: safety standards for acceptance across different levels.
3. Litigation, liability, and perception: many new insurance and liability issues arise, including persuading insurance providers that the technology will work correctly in all driving environments. Even with near-perfect autonomous driving, there may be instances where a crash is unavoidable.
4. Security: Transportation policymakers, auto manufacturers, and future AV drivers often worry about electronic security. Computer hackers, disgruntled employees, terrorist organizations, and/or hostile nations may more generally target AVs and intelligent transportation systems, causing collisions and traffic disruptions. As one of the worst-case scenarios, a two-stage computer virus could be programmed to first disseminate a dormant program across vehicles over a week-long period, for example.
5. Privacy: AVs are likely to store a large amount of personal data (such as trip patterns and users). This gives rise to five data-related questions: Who should own or control the vehicle's data? What types of data will be stored? With whom will these data sets be shared? In what ways will such data be made available? And, for what ends will they be used?
6. Lack of research: this is due to the uncertainty inherent in new contexts. It is useful to identify the critical gaps in existing investigations to better prepare for AVs' arrival. One of the most pressing needs is a comprehensive market penetration evaluation.
7. Lack of technical skills: the technology is complicated and lacks skilled and trained staff to manage it.

Considerable work is actually needed to provide decision-makers with the required knowledge to support their decisions regarding which scenario to deploy and how to sequence the implementation process so that everything would work best to fulfill their own local transportation system requirements.

The present study aims to formulate recommendations that may support decision-makers to select the most appropriate CAV technology implementation scenario depending on the local context. This is achieved through identifying and ranking key barriers to CAV adoption and evaluating different potential strategies. When isolated measures are taking in a complex system such as the transportation system, the chances that unexpected side-effects occur are relatively high [24, 25]. Experts employ decision-making approaches to prioritize the essential criteria or parameters, reduce uncertainty, and enhance the quality of their decisions. The Multi Criteria Decision Analysis (MCDA) has been successfully used to evaluate transportation policies as it can deal with complex parameters and involve the stakeholders in making better decisions [24, 25, 26, 27].

For our research, we use a combination of two MCDA methods, namely, Analytic Hierarchy Process (AHP) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE).

The contribution of this study is threefold. First, it identifies the key barriers to CAV adoption and suggests a method to rank them. Second, it proposes different CAV deployment scenarios while considering all the barriers in different time domains (short-term and long-term). Third, it recommends and ranks strategies to overcome these barriers when implementing CAV plan.

1.1 Multiple Criteria Decision-Making Techniques

Decision-makers utilize different decision-making approaches to reduce risk, improve the quality of their decisions, and address different criteria or parameters according to their importance. Multiple Criteria Decision-Making (MCDM) is one of the most popular decision-making techniques. Indeed, MCDM is extensively used by many governments, experts, and researchers to evaluate transportation systems [25, 26, 27, 28, 29]. MCDM methods use an analytical or numerical model to find the alternative that best fits a large set of criteria by transforming quantitative and qualitative measures into a single objective value [30]. Several MCDM techniques and approaches have been proposed which take into account the different requirements of the stakeholders. They include AHP, TOPSIS, ELECTRE, PROMETHEE, and their variations [25, 30].

Velasquez and Hester reviewed 11 standard Multi-Criteria Decision-Making methods that combine different techniques. They concluded that combining different methods can minimize deficiencies that may be seen in certain methods. Such a combination has become a common approach in MCDA [25, 31].

For the purpose of our study, we combine AHP and PROMETHEE. AHP is used to structure the decision problem and to attribute weights to the evaluation criteria. In contrast, PROMETHEE is used to obtain a final ranking of the proposed alternative scenarios and perform sensitivity analysis.

AHP, which was developed by Saaty (1982, 1988, 1995) [32], is probably the most widely applied MCMA for the evaluation of various transport projects related to organizational, technological, environmental, and infrastructural decision subjects [33]. AHP is especially advantageous due to its ability to decompose a complex problem into parts and its usability [25, 30, 31, 32, 33]. AHP is "a theory of measurement through pair-wise comparisons and relies on experts' judgments to derive priority scales" [34]. Its use of pair-wise comparisons allows decision-makers to weight coefficients and easily compare alternatives [29, 30, 31]. AHP is scalable thanks to its hierarchical structure. In order to perform pair-wise comparisons, AHP obviously needs some data. However, it is not as data-intensive as other methods such as Multiple Attribute Utility Theory [35].

The AHP method is performed over three steps [34]:

1. Calculating the Vector of Criteria Weights;
2. Calculating the Alternatives Scores matrix;
3. Ranking the Alternatives.

The AHP method is performed over three steps [34], as described below.

Step 1: Calculating the Vector of Criteria Weights.

First, a pair-wise comparison matrix $A(m * m)$ is created where m is the number of evaluation criteria. The value of each element a_{ij} of A corresponds to the i^{th} criterion's importance compared to the j^{th} criterion. In other words, if $a_{ij} > 1$ then criterion i is more important than criterion j. In this case, values range between 1 to 9. However, when the second criterion is more important, the reciprocals values $(1/2, 1/3, \ldots, 1/8, 1/9)$ are used. Once matrix A created, a normalized pair-wise matrix is generated such as each element of the matrix is calculated according to Equation (1).

$$\overline{\mathrm{a_{i.j}}} = \frac{a_{i.j}}{\sum_{i=1}^{m} a_{ij}}. \tag{1}$$

Equation (2) is then used to calculate each criterion's weight w_j by taking the average of the elements of each row of the normalized matrix.

$$w_j = \frac{\sum_{i=1}^{m} a_{ij}}{m}. \tag{2}$$

Step 2: Calculating the Alternatives Scores matrix.

The score matrix S is a $n * m$ matrix where m is the number of criteria and n is the number of alternatives. To calculate the matrix S, a pair-wise matrix $B^{(i)}$ has to be generated for each of the m criterion $(i = 1, \ldots, m)$. Matrix $B^{(i)}$ is a $n * n$ matrix where each element $a_k h^i$ indicates the importance of the k^{th} alternative in comparison to the h^{th} alternative concerning the i^{th} criterion. If $a_k h^i > 1$ then k^{th} alternative is better than h^{th} alternative with respect to the i^{th} criterion. The same procedure which was applied to matrix A is then applied to each matrix $B^{(i)}$. Each element of the matrix is divided by the sum of entries in the same column and then the average of the elements belonging to the same row is processed to calculate the score vectors $S^{(1)}$, $i = 1, \ldots, m$. In other words, $S^{(1)}$ represents the costs of the scores of different alternatives with respect to the i^{th} criterion as in Equation (3).

$$S = [S^{(1)}, \ldots, S^{(m)}]. \tag{3}$$

Step 3: Ranking the Alternatives.

In this final step, the global score v for each alternative is calculated by simple multiplication, as shown by Equation (4).

$$v = s.w. \tag{4}$$

In order to make sure that the rankings given by different decision-makers and used as inputs to the AHP application are consistent, a consistency ratio (CR) is calculated using Equation (5).

$$CR = \frac{CI}{RI} \tag{5}$$

where CI is Consistency Index (Equation (6)) and RI is the Random Index.

$$CI = \frac{\lambda_{max}^{-n}}{n-1}. \tag{6}$$

PROMETHEE was first developed by Brans (1982) and belongs to the outranking methods family. The weights expressed as a ratio scale represent trade-offs between the criteria. The method is also relatively easy to apply in practice. PROMETHEE method is conducted over 3 steps [36, 37] as described below.

Step 1: A preference index $P_j(a_i, a_j)$ is constructed for each criterion (g_i) and for each pair of actions (a_i, a_j) separately.

Step 2: An appropriate preference functions shape is selected for the decision-maker. Brans and Vincke [36] have proposed six shapes of preference functions based on the type of the data in use, namely, usual shape, U-shape, V-shape, level, linear, and Gaussian.

Step 3: The overall preference index, $(a_i.a_j)$, is calculated for each pair of actions $(a_i.a_j)$ while taking into account all criteria. The outgoing flow $\varphi^+(a_i)$ measures the outranking character of alternative a_i and indicates the degree to which a_i dominates the other alternatives. While the incoming flow $\varphi^{-(a_i)}$ measures the weakness of (a_i) with regards to the other action (a_j). The difference of these measured flows is called the net flow, $\varphi(a)$, which is to be understood as a value function. The higher the net flow is, the better will be the studied action (a_i).

In cases there are group-level decisions (different stakeholders), these flows can also be calculated for each stakeholder $k(k = 1, \ldots, K)$ separately as follows:

$$\pi^K(a_i, b_j), \varphi^{+K}(a_i), \varphi^{-K}(a_i), \text{ and } \varphi^K(a_i).$$

The global net flow $\varphi^G(a_i)$ is calculated as a weighted average of the individual net flows, as shown in Equation (7).

$$\varphi^G(a_i) = \sum_{K=1}^{K} \sum_{j=1}^{m} \pi_j^K(a_i) w_j w_k \tag{7}$$

$$i = 1, 2, \ldots, n$$

where w_K is a weight representing the relative importance of the stakeholder K. For each decision-maker has a decision power given by a non-negative weight w and w_r, $r = (1, 2, \ldots, R)$ in Equation (8).

$$\sum_{r=1}^{R} w_r = 1 \tag{8}$$

1.2 Materials and Methods

Although Connected and Automation has been considered as an emerging technology, the adoption rate of Connected and Autonomous Vehicles (CAV) will depend on how policymakers and governments are addressing various challenges such as infrastructure development, public acceptance, and rules and regulations. Our study intends to identify the barriers to implementing CAV and assess the strategies that can be used to overcome these challenges from different perspectives. We further intend to rank the most appropriate scenarios for a future plan of implementing CAV while considering a specific time domain (e.g., 2020–2030). To do so, we propose to conduct the MCDA following a three-stage approach. Figure 1 depicts an activity diagram that shows the various steps of the approach. In the remainder of this section, the various stages are explained. Although the approach is generic and can be applied to different countries, we use the context of the Sultanate of Oman to illustrate how our approach can be applied.

1.3 Study Case: Sultanate of Oman

The sultanate of Oman is a Gulf country and a member of the Gulf Cooperative Council (GCC) along with UAE, Bahrain, Kuwait, Saudi Arabia, and Qatar. With the discovery of oil reserves, Oman has become a high-income nation and has seen a rapid development of its infrastructure [38]. All GCC countries, including Oman, have common characteristics regarding the transport sector, such as low age of the national vehicle fleet, similar modes of traffic management, limited public awareness of appropriate traffic procedures, and limited penetration of public transport [39]. Besides, the most frequently used mode of transport in the GCC countries are private cars. Technical standards for imported vehicles, whether new or used, are high [39].

GCC countries have agreed on a joint initiative that aims at enhancing the efficiency of transport services through smart and sustainable transportation [40].

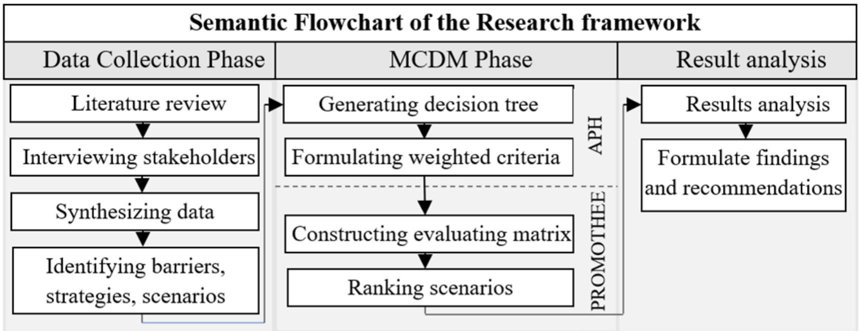


Figure 1. Schematic flow-chart of the research framework

This has raised the need to build an intelligent transportation system that can cope with the growing needs. With regards to Oman, we interviewed experts from Muscat Municipality, the Directorate General of Traffic (DGT), and Royal Oman Police (ROP) (DGT and ROP are the two organizations that are responsible for traffic management in Oman). These experts confirmed that they are seeking to develop the transportation system by implementing an intelligent transport network and a better integration of ITS's different technology in the main cities.

1.4 Data Collection Stage

The first stage aims to identify the potential causes for the slow diffusion of CAVs and the various strategies that can be used to overcome these barriers. At least two sources of data may be used, namely, literature review and stakeholder interviews. As barriers and strategies are highly influenced by the context of the country in which CAV technology is to be implemented, a context-related literature review is needed in addition to the general overview. In particular, if the targeted country is A, reviewed studies should focus on countries similar to A. In this regard, countries similar to A are countries that have similar road infrastructure, similar financial resources, similar social culture, and/or similar administration and politics.

A second and valuable data source is the stakeholders of the targeted country's transportation system (or region). Indeed, they are the most familiar with the local context and may thus highly contribute to understanding the situation. In particular, they can help to set up the framework for the faced barriers, the strategies which may work, and the best scenarios which can be implemented. Moreover, when stakeholders are involved at an early stage, it may push discussions deeper, help decision-makers understand all aspects of the problem better, and increase acceptance of the final solution [41, 42]. Stakeholders should include representatives from both policy decision-makers and transportation experts/academics. In our case, the following stakeholders have been involved: six policymakers, two experts from academia, and four traffic experts from governmental and private agencies. Stakeholders' opinions can be gauged via questionnaires and/or interviews. Our research jointly developed a detailed questionnaire with a few local traffic experts to ensure that the questions are more targeted and focus on the local context.

The questionnaire is composed of three parts: the first part performs a pair-wise comparison of the barriers using the symmetrical structure of a 9-point scale [34, 43] to weigh the various potential barriers. The second and third parts perform a 5-point qualitative assessment with a scale ranging from 1 (very low impact) to 5 (very high impact) [44] to rank the strategies and scenarios. These last two parts aim at selecting the most suitable scenario to implement CAV technologies. This selection should be based on the reference years of implementation (e.g., 2030–2050) and the priority level of the factors/strategies that may help overcome the identified barriers.

The literature review outcome is combined with stakeholders' input and synthesized to identify barriers and strategies for the targeted context and potential scenarios. For our study case, four main barriers were identified: Financial Feasibility, Policies and Regulation, Technical Feasibility, and Social Perception. In order to evaluate the impact of these barriers, it is necessary to describe them with measurable criteria. For this reason, each barrier has been thus refined with criteria that can be used to measure the impact of the barrier on the implementation of CAV. These criteria are depicted as follows:

1. Financial Feasibility defined by
   (a) Infrastructure Cost (e.g., sensors, detectors, signs, communication system), which is required to make CAV viable on the road;
   (b) Operation Cost including maintenance, administrative work, and technology cost.
2. Policies and Regulation is defined by
   (a) Security and Privacy Concerns which may include issues related to the responsibilities of stored personal data of road users;
   (b) Regulation and Certification related to safety standard.
3. Technical Feasibility defined by
   (a) Lack of Research;
   (b) Lack of Technical Skills.
4. Social Perception defined by
   (a) Social inequity;
   (b) Social acceptance.

Regarding the potential strategies, the followings were identified:

1. Providing ongoing training to transportation professionals;
2. Improving public awareness for connected and autonomous vehicles;
3. Improving public transportation system by making it a connected system;
4. Developing initiatives in cooperation with local academic institutions and private sector to develop researches in CAV field;
5. Investing in statewide radio communications/IoT for emergency response;
6. Establishing a central traffic management organization to ensure the implementation of new technologies;
7. Prioritizing short-term and low-cost solutions when large-scale solutions are not feasible in the short-term;
8. Developing a strategy towards increasing the number of electric cars;
9. Investing in capital mobility improvements and traffic management technologies;
10. Encouraging public sector to invest in connected infrastructure to encourage CAV adoption.

In order to assess the barriers, it is essential to set up their evaluation criteria. For our study case, we identify eight criteria related to the barriers previously identified.

Finally, and in terms of scenarios, a framework composed of two scenarios was proposed for future CAV implementation planning, as shown in Table 1. The first scenario, named Advancing Technology, is a slow and incremental implementation of CAV. In contrast, named Connected Infrastructure, the second one is an optimistic scenario where a fleet of automated vehicles operates in a more connected infrastructure. Each of these proposed scenarios assumes varied levels of automation, connectivity, and electrification.

1.4.1 Multiple Criteria Decision Making (MCDM) Stage

This second stage aims to weigh the criteria we identified in the previous stage and to rank the strategies and scenarios according to their suitability in overcoming the identified barriers. Two MCDM techniques were used to increase the analysis's effectiveness and increase the accuracy of evaluation by collecting the advantages of different approaches and avoiding one single technique's limitation. In particular, we combine the outranking method PROMETHEE with the AHP method. PROMETHEE method is better suited to perform exhaustive sensitivity analyses and avoid inconstancies between scores on criteria, which is likely to happen in AHP. On the other hand, PROMETHEE cannot construct the required decision tree or the guidelines to determine the weights. Therefore, AHP is used to structure the decision-making problem and to determine the weights of the criteria.

In contrast, PROMETHEE is used to perform the criteria' aggregation, the ranking of the alternatives, and the sensitivity analyses. The conduction of each of

	Connectivity[1]	Automation[2]	Electrification[3]
Scenario 1: Advancing Technology	Medium Connectivity Less than 25 % of vehicles communicate with other vehicles, infrastructure, and other devices (smartphones). 25–50 % of public transportation communicates with other vehicles and the infrastructure.	Low Automation Less than 25 % of vehicles will be partially automated	Low Electrification 25 % of the vehicle are electric
Scenario 2: Connected Infrastructure	High Connectivity 50–75 % of vehicles communicate with other vehicles, infrastructure, and other devices. All public transportation can communicate with other vehicles, roadside infrastructure.	Medium Automation 25–50 % of vehicles will be partially automated	Medium Electrification 25–50 % of the vehicle are electric

[1] Degree of communication with other vehicles (V2V), infrastructure (V2I), and other devices (V2X).

[2] Degree to which vehicles are automated. The range between Level 0 (no automation) and Level 5 (full automation). Partially automation: include simple driver assistance functions such as cruise control, ABS, auto emergency braking, automated parking, and lane-keeping.

[3] The growth of electric vehicles.

Table 1. Overview of the policy packages

these two methods constitutes a separate step in our approach. These two steps are detailed in what follows.

AHP Step. Based on the data collection data (first stage), a hierarchical decision tree (Figure 2) is generated. This tree highlights the multiple criteria and sub-criteria on which each identified scenario will be evaluated. In our case, we aim at evaluating two scenarios: Advancing Technology and Connected Infrastructure.

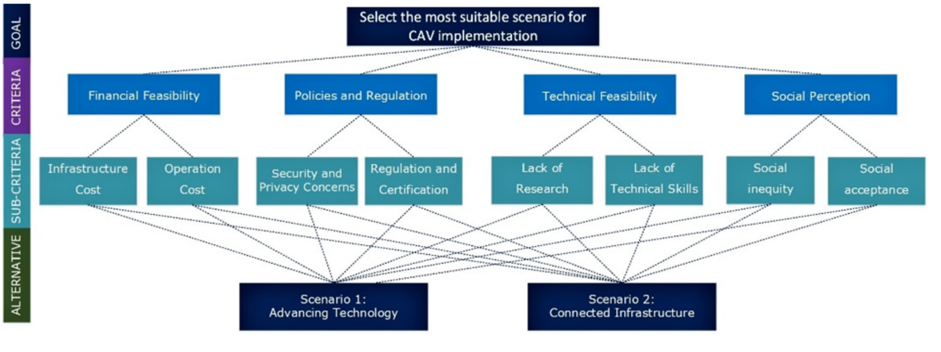


Figure 2. The hierarchical decision tree

In the previous stage, a 9-point qualitative scale questionnaire was used to weigh the various potential barriers. AHP method is applied at this second stage to calculate the weight of each criterion and sub-criteria. These weights will be used in the next step to rank the barriers/strategies using PROMETHEE. Our study case used the software Expert Choice [45] to accomplish this task.

PROMETHEE Step. In this step the identified potential scenarios are evaluated in terms of their weights by constructing the evaluation matrix. In our study case, we used PROMETHEE Visual as a PROMETHEE decision-making software. In the previous stage, the stakeholders evaluated each criterion with a 5-point qualitative scale ranging from 1 to 5, which represent "very low impact" and "very high impact", respectively. To calculate the degree of preference associated with the best alternative in the pair-wise comparison process, specific preference functions for each criterion and parameter values (min./max.) were identified [37].

To achieve a quantitative assessment, the Usual Shape or the Level Type Preference function can be used (according to PROMETHEE guidelines [45]). In our study case, the Usual Shape Preference function was applied. Indeed, according to the PROMETHEE guidelines, this function is preferred for a small number of levels on the criteria scale, which is the case for our studied example.

The stakeholders who are involved in the decision process may have different priorities and objectives. They may even evaluate differently according to subjective criteria. Since these criteria are measured qualitatively, it is essential to consider this parameter while applying PROMOTHEE method. This can be achieved by defining several scenarios which all share the same lists of actions and criteria, but everything else (evaluations, preference functions, and criteria weights) is different. In our study case, we use Group Decision Support System (GDSS) extension.

Once the evaluation matrix and each stakeholder's preference functions are performed, the scenarios are evaluated and ranked using multi-scenario preference flows. The positive flow ($\Phi+$) and negative flow ($\Phi-$) for Partial Ranking (PROMETHEE I) and the net flow (Φ) values for complete ranking (PROMETHEE II) were calculated.

Additionally, the decision problem is visualized in the GAIA (Geometrical Analysis for Interactive Aid) plane where points and criteria represent scenarios by vectors. The length of the criterion vector is a measure of its power [46]. A scenario that scores high on a particular criterion is drawn, in the graph, in the direction of the corresponding criterion axis [26]. The weights vector's projection corresponds to the decision stick (red line in Figure 3), which indicates the direction of the best [44].

Other tools such as Action Profile (see Figure 4) can be used for a graphical representation of the uni-criterion net flow scores relative to each scenario. According to our proposed approach, a final stage is needed to analyze the results and draw decision-makers' recommendations. This phase is illustrated using our study case (Oman) and presented in the next section.

2 RESULTS AND DISCUSSION

This final phase may help authorities and other stakeholders improve the way they plan to implement CAV in the transportation system.

In the previous stage, and based on the AHP procedure, the weight of each criterion and sub-criteria of the barriers was calculated. These results are related to our study case (Oman) and may differ for other countries. Nevertheless, the same approach can be applied to different countries.

Preferences	IC	OC	S&P	R&C	LoR	LoTS	SI	SA
Active	Yes	Yes	Yes	yes	yes	yes	yes	yes
Min/Max	Max	Max	Max	max	max	max	max	max
Weight	4,40	13,30	13,40	13,40	12,10	36,30	5,30	1,80
Preference function	Usual	Usual	Usual	Usual	Usual	Usual	Usual	Usual
Thresholds	Abs.	Abs.	Abs.	Abs.	Abs.	Abs.	Abs.	Abs.
Q	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
P	2,00	2,00	2,00	2,00	2,00	2,00	2,00	2,00
S	3,00	3,00	3,00	3,00	3,00	3,00	3,00	3,00
Scenario 1 2020-2030	2,00	2,00	1,00	1,00	1,00	4,00	2,00	3,00
Scenario 2 2020-2030	4,00	3,00	5,00	4,00	3,00	4,00	3,00	4,00
Scenario1 2030-2050	1,00	2,00	2,00	3,00	2,00	3,00	2,00	3,00
Scenario2 2030-2050	3,00	3,00	2,00	3,00	2,00	3,00	2,00	3,00

Table 2. PROMETHEE I/II scores

Overall, the Technical Feasibility criteria, which includes Lack of Technical Skills and Lack of Research, get the highest preference rate (39.7 %), followed by Polices and Regulation (38 %), Social Perception (21.1 %), and finally the Financial Feasibility (11.4 %). These results may be explained by the fact that the implementation or development in Oman's transportation system is considered high-level decision-making and that the economic factor does not dominate the decision-making process, as may be the case in other countries. The suggested scenarios were evaluated using Visual PROMETHEE software. Using PROMETHEE II ranking (Table 2), and based on the net preference flow of the analyzed alternatives for both reference years (2020–2030 and 2030–2050). The studied barriers would highly affect the second scenario's implementation (Connected Infrastructure) in 2020–2030, followed by the first scenario (Advancing Technology) within the same period 2020–2030. In contrast, these same barriers would have a low impact if the second scenario (Connected Infrastructure) has to be implemented in 2030–2050 and even lower impact if scenario 1 (Advancing Technology) has to be implemented in 2030–2050.

The decision problem and alternative scenarios are visualized in the GAIA plane, as shown in Figure 3. In this plane, each studied scenario is represented by a small square (e.g., scenario 1 within 2020–2030 is represented in the upper right quarter), and a vector represents each criterion. The square representing each scenario is placed on the graph depending on its net flow score pointed by the criteria that impact this scenario [37].

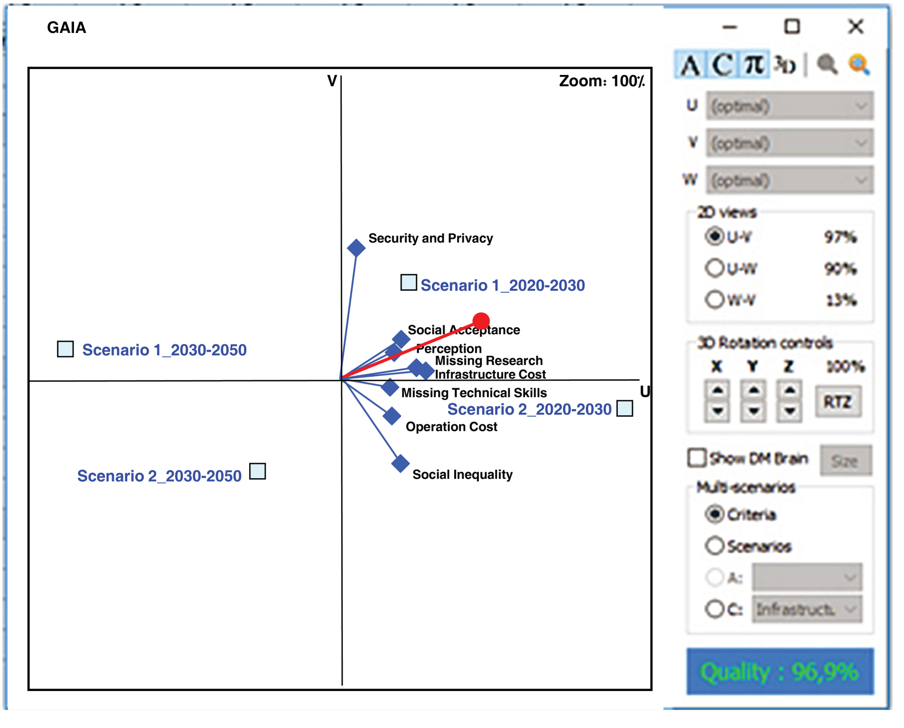
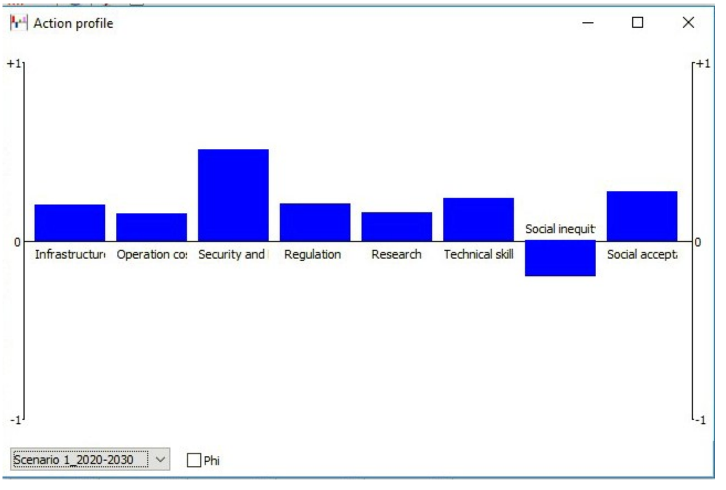
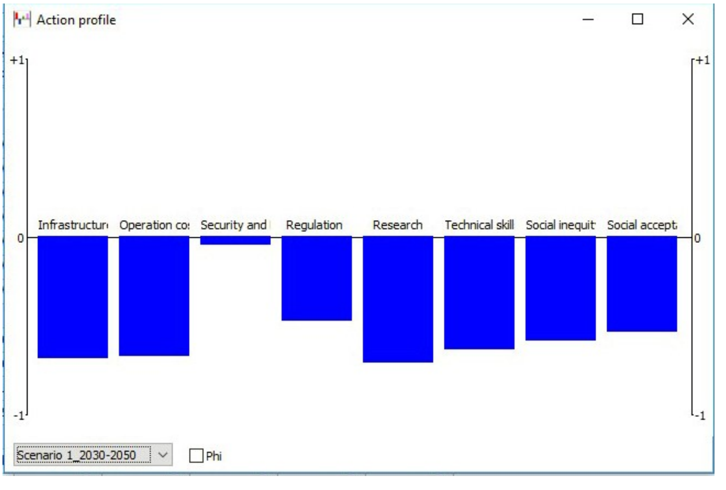


Figure 3. GAIA plane for reference years 2020–2030 and 2030–2050

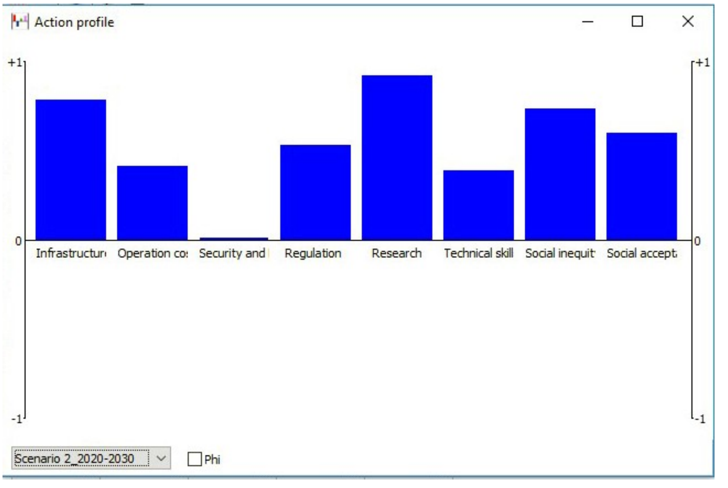
The length (or size) of a vector reflects the impact power of its corresponding criterion [46]. The weights vector projection in the GAIA plane corresponds to another axis, i.e., the decision stick (red line), which indicates the best scenario's direction, given the weights allocated to the considered criteria [44]. According to Figure 3, the identified barriers affect the implementation of both studied scenarios in the early plan (2020–2030). Criterion Security and Privacy has the highest differentiating power and represents indifferent preferences compared to the other criteria influencing the implementation of scenario 1 in 2020–2030. Moreover, criterion Social Inequity has the highest impact of implementing the second scenario over the short-term timeline (2020–2030). The decision axis reveals that for 2030, scenario 1 (Advancing Technology) is clearly the best compromise. While, for the long-term timeline (reference years 2030–2050), scenario 2 may be a more viable option.



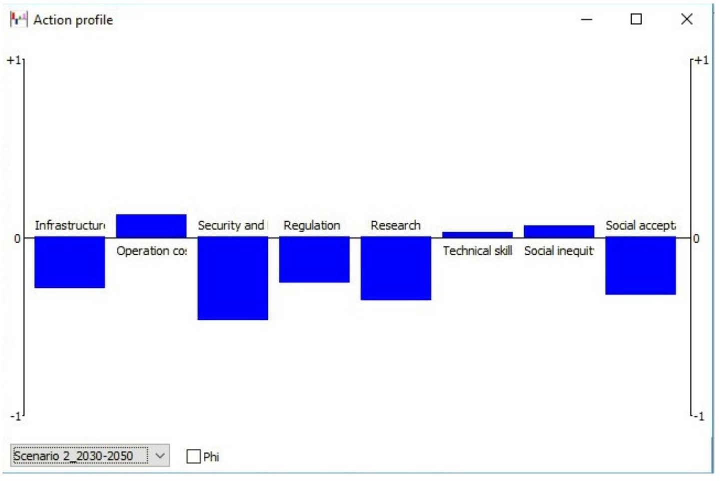
a) Scenario 1 (2020–2030)



b) Scenario 1 (2030–2050)



c) Scenario 2 (2000–2030)



d) Scenario 2 (2030–2050)

Figure 4. The action profiles of scenarios

Figure 4 shows a graphical representation of the uni-criterion net flow scores for each given scenario and displays a specific action profile. Positive scores (upward bars) correspond to criteria that impact the studied scenario, while negative scores (downward bars) correspond to those that have no impact. The size of the bars refers to the weight of the criteria. For instance, in scenario 1 (2020–2030) (Figure 4 a)), the criterion Security and Privacy has a positive score, and the bar has the most significant size. This means that Security and Privacy would have the highest impact if the scenario has to be implemented in 2020–2030.

For scenario 1 (2020–2030), all barriers, except Social Inequity, have a positive score (Figure 4 a)), which indicates a positive impact on the implemented of this scenario in reference years (2020–2030), while these barriers show a negative impact on the implantation of this same scenario in 2030–2050 (Figure 4 b)).

Figure 4 c) shows that the studied barriers highly affect the implementation of scenario 2 in reference years 2020–2030, while Figure 4 d) shows that for reference years 2030–2050, most barriers would not impact the implementation of the scenario. This can be explained by the fact that by 2030–2050 most of these barriers are expected to be mitigated or even resolved.

As discussed in the previous phase, and to rank strategies, the net flows have to be calculated. The positive flow ($\Phi+$), negative flow($\Phi-$) (PROMETHEE I), and the net flow (Φ) values (PROMETHEE II) were obtained using the PROMETHEE Diamond which, is an alternative two-dimensional joint representation of both PROMETHEE I and II rankings (see Figure 5).

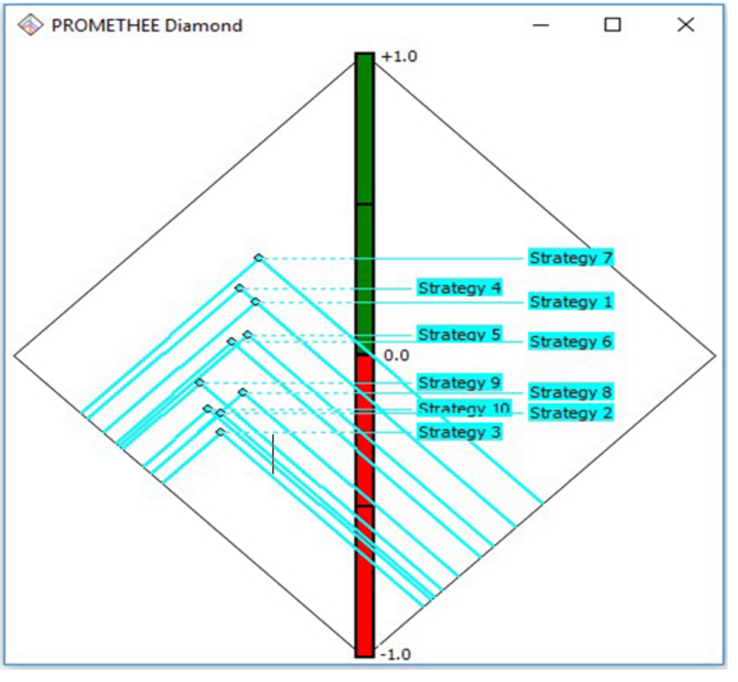


Figure 5. The PROMETHEE Diamond for ranking the strategies

The square (in Figure 5) represents the ($\Phi+$, $\Phi-$) plane where a point indicates each action. The plane makes a 45° angle. The vertical dimension gives then the Φ net flow. $\Phi+$ scores increase from the left to the top corner, while $\Phi-$ scores increase from the left to the bottom corner. Based on the analyzed alternatives' net preference flow, the complete ranking of the strategies shows that strategy 7, "Prioritizing short-term and low-cost solutions when large-scale solutions are not feasible in the short-term," has the highest impact. Followed by strategy 4, "Developing/supporting programs in cooperation with community colleges and private sector to develop research in the CAV field," and then strategy 1, "Provide ongoing training to transportation professionals." On the opposite, strategy 3, "Improving public transportation system to be a connected system," has the lowest impact.

3 CONCLUSIONS AND RECOMMENDATIONS

Although there has been an increasing interest in connected and automated vehicles (CAVs), this technology is still to be considered under development. The proper deployment of CAVs requires that legal, financial feasibility, social, and technical challenges are addressed. This paper aims to formulate recommendations that may help decision-makers select the most appropriate policy package to implement CAV technology. When the cost factor cannot dominate the decision-making outcomes, one needs to study the other factors that may affect the CAV adoption. To address this challenge, we propose a three-phase approach that takes as input the stakeholders' opinions and expectations and comes up with recommendations on the best strategy/scenario to implement CAV technology. The core of this approach is based on Multi-Criteria Decision Analysis (MCDA) techniques. In particular, it combines two popular methods, namely, AHP and PROMETHEE. This combination aims to get the most of each method, which provides higher performance analysis and increases the evaluation's accuracy.

As a case study, we used the context of the Sultanate of Oman. We identified two potential policy scenarios. We identified the evaluation criteria and set two-time domains (short-term and long-term) for implementing these scenarios. We recommended the most appropriate scenario and strategy to implement CAV technology in Oman for various time references by applying our approach. Nevertheless, our study has some limitations. Our data collection phase relies on only twelve stakeholders' opinions, although they are all experts in traffic systems and traffic management. While a sensitivity analysis supports the robustness of the obtained results, involving more experts would have revealed finer aspects and outcomes. Second, our approach has been only tested in the context of the Sultanate of Oman. Conducting similar studies on other countries with different profiles and contexts would contribute to improving the approach and the accuracy of its outcomes.

Nevertheless, based on the case study, we identified concrete actions to support CAV adoption in the Gulf countries in general and in Oman. These actions were validated by the experts as well as by MCDA analysis. They include:

1. Expanding the research funding for the autonomous vehicle;
2. Setting standards for liability, security, and data privacy, which is suitable for the Gulf countries;

3. Prioritizing short-term and low-cost solutions when large-scale solutions are not feasible in the short-term;
4. Developing initiatives in cooperation with local academic institutions and the private sector to develop researches in the CAV field;
5. Providing ongoing training to transportation professionals;
6. Establish a central traffic management organization to ensure the implementation of new technologies.

Finally, this study provides a framework for a strategic plan to adopt CAV technology by transportation infrastructures. It may also support the Gulf Transportation Systems Strategic Plan to implement the best initiatives to improve safety, mobility, economic competitiveness, and sustainability.

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REFERENCES

[1] Kuang, X.—Zhao, F.—Hao, H.—Liu, Z.: Assessing the Socioeconomic Impacts of Intelligent Connected Vehicles in China: A Cost-Benefit Analysis. Sustainability, Vol. 11, 2019, No. 12, Art. No. 3273, doi: 10.3390/su11123273.

[2] Lee, D.—Hess, D. J.: Regulations for On-Road Testing of Connected and Automated Vehicles: Assessing the Potential for Global Safety Harmonization. Transportation Research Part A: Policy and Practice, Vol. 136, 2020, pp. 85–98, doi: 10.1016/j.tra.2020.03.026.

[3] Dopart, K.: U.S. DOT Automated Research Program. U.S. Department of Transportation, Intelligent Transportation Systems Joint Program Office. Presented at Automated Vehicle Symposium 2014, Burlingame, CA, 2014.

[4] (SAC) The Strategic Advisory Committee of Technology Roadmap for Energy Saving and New Energy Vehicles, SAE-China: Technology Roadmap for Energy Saving and New Energy Vehicles. China Machine Press, Beijing, China, 2016.

[5] Stamatiadis, P.—Gartner, N.—Xie, Y.—Chen, D.: Strategic Planning for Connected and Automated Vehicles in Massachusetts. Technical Report. Massachusetts Department of Transportation, MA, 2018.

[6] Bagloee, S. A.—Tavana, M.—Asadi, M.—Oliver, T.: Autonomous Vehicles: Challenges, Opportunities, and Future Implications for Transportation Policies. Journal of Modern Transportation, Vol. 24, 2016, No. 4, pp. 284–303, doi: 10.1007/s40534-016-0117-3.

[7] Elliott, D.—Keen, W.—Miao, L.: Recent Advances in Connected and Automated Vehicles. Journal of Traffic and Transportation Engineering (English Edition), Vol. 6, 2019, No. 2, pp. 109–131, doi: 10.1016/j.jtte.2018.09.005.

[8] Talebpour, A.—Mahmassani, H. S.: Influence of Connected and Autonomous Vehicles on Traffic Flow Stability and Throughput. Transportation Research Part C: Emerging Technologies, Vol. 71, 2016, pp. 143–163, doi: 10.1016/j.trc.2016.07.007.

[9] Farrag, S. G.—Outay, F.—Yasar, A.—Janssens, D.—Kochan, B.—Jabeur, N.: Toward the Improvement of Traffic Incident Management Systems Using Car2X Technologies. Personal and Ubiquitous Computing, Vol. 25, 2021, pp. 163–176, doi: 10.1007/s00779-020-01368-5.

[10] Farrag, S. G.—El-Hansali, M. Y.—Yasar, A.—Shakshuki, E.: Simulation-Based Evaluation of Using Variable Speed Limit in Traffic Incidents. Procedia Computer Science, Vol. 175, 2020, pp. 340–348, doi: 10.1016/j.procs.2020.07.049.

[11] Farrag, S. G.—Outay, F.—Yasar, A. U.—El-Hansali, M. Y.: Evaluating Active Traffic Management (ATM) Strategies Under Non-Recurring Congestion: Simulation-Based with Benefit Cost Analysis Case Study. Sustainability, Vol. 12, 2020, No. 15, Art. No. 6027, doi: 10.3390/su12156027.

[12] Fagnant, D. J.—Kockelman, K.: Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations. Transportation Research Part A: Policy and Practice, Vol. 77, 2015, pp. 167–181, doi: 10.1016/j.tra.2015.04.003.

[13] Li, S.—Sui, P. C.—Xiao, J.—Chahine, R.: Policy Formulation for Highly Automated Vehicles: Emerging Importance, Research Frontiers and Insights. Transportation Research Part A: Policy and Practice, Vol. 124, 2019, pp. 573–586, doi: 10.1016/j.tra.2018.05.010.

[14] Zhang, W.—Guhathakurta, S.—Fang, J.—Zhang, G.: Exploring the Impact of Shared Autonomous Vehicles on Urban Parking Demand: An Agent-Based Simulation Approach. Sustainable Cities and Society, Vol. 19, 2015, pp. 34–45, doi: 10.1016/j.scs.2015.07.006.

[15] Calvert, S. C.—Schakel, W. J.—van Lint, J. W. C.: Will Automated Vehicles Negatively Impact Traffic Flow? Journal of Advanced Transportation, Vol. 2017, 2017, Art. No. 3082781, doi: 10.1155/2017/3082781.

[16] Buckley, L.—Kaye, S. A.—Pradhan, A. K.: A Qualitative Examination of Drivers' Responses to Partially Automated Vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, Vol. 56, 2018, pp. 167–175, doi: 10.1016/j.trf.2018.04.012.

[17] European Commission: A European Strategy on Cooperative Intelligent Transport Systems, a Milestone Towards Cooperative, Connected and Automated Mobility. COM/2016/0766 Final. European Commission, Brussels, Belgium, 2016.

[18] Litman, T.: Autonomous Vehicle Implementation Predictions. Victoria Transport Policy Institute, 2019, Retrieved from: `http://www.vtpi.org/avip.pdf`.

[19] Turcksin, L.—Bernardini, A.—Macharis, C.: A Combined AHP-PROMETHEE Approach for Selecting the Most Appropriate Policy Scenario to Stimulate a Clean Vehicle Fleet. Procedia – Social and Behavioral Sciences, Vol. 20, 2011, pp. 954–965, doi: 10.1016/j.sbspro.2011.08.104.

[20] Wadud, Z.—MacKenzie, D.—Leiby, P.: Help or Hindrance? The Travel, Energy and Carbon Impacts of Highly Automated Vehicles. Transportation Research Part A: Policy and Practice, Vol. 86, 2016, pp. 1–18, doi: 10.1016/j.tra.2015.12.001.

[21] Bansal, P.—Kockelman, K. M.: Forecasting Americans' Long-Term Adoption of Connected and Autonomous Vehicle Technologies. Transportation Research Part A: Policy and Practice, Vol. 95, 2017, pp. 49–63, doi: 10.1016/j.tra.2016.10.013.

[22] Raj, A.—Kumar, A.—Bansal, P.: A Multicriteria Decision Making Approach to Study Barriers to the Adoption of Autonomous Vehicles. Transportation Research Part A: Policy and Practice, Vol. 133, 2020, pp. 122–137, doi: 10.1016/j.tra.2020.01.013.

[23] Kröger, L.—Kuhnimhof, T.—Trommer, S.: Does Context Matter? A Comparative Study Modelling Autonomous Vehicle Impact on Travel Behaviour for Germany and the USA. Transportation Research Part A: Policy and Practice, Vol. 122, 2019, pp. 146–161, doi: 10.1016/j.tra.2018.03.033.

[24] Fraedrich, E.—Heinrichs, D.—Bahamonde-Birke, F. J.—Cyganski, R.: Autonomous Driving, the Built Environment and Policy Implications. Transportation Research Part A: Policy and Practice, Vol. 122, 2019, pp. 162–172, doi: 10.1016/j.tra.2018.02.018.

[25] Mardani, A.—Jusoh, A.—Nor, K.—Khalifah, Z.—Zakwan, N.—Valipour, A.: Multiple Criteria Decision-Making Techniques and Their Applications – A Review of the Literature from 2000 to 2014. Economic Research – Ekonomska Istraživanja, Vol. 28, 2015, No. 1, pp. 516–571, doi: 10.1080/1331677X.2015.1075139.

[26] Macharis, C.—Geudens, T.: Reviewing the Use of Multi-Criteria Decision for the Evaluation of Transport Projects: Time for a Multiactor Approach. 2009, 34 p.

[27] Camargo Pérez, J.—Carrillo, M. H.—Montoya-Torres, J. R.: Multi-Criteria Approaches for Urban Passenger Transport Systems: A Literature Review. Annals of Operations Research, Vol. 226, 2015, pp. 69–87, doi: 10.1007/s10479-014-1681-8.

[28] Xue, Y.—Zhang, Y.—Chen, Y.: An Evaluation Framework for the Planning of Electric Car-Sharing Systems: A Combination Model of AHP-CBA-VD. Sustainability, Vol. 11, 2019, No. 20, Art. No. 5627, doi: 10.3390/su11205627.

[29] Nalmpantis, D.—Roukouni, A.—Genitsaris, E.—Stamelou, A.—Naniopoulos, A.: Evaluation of Innovative Ideas for Public Transport Proposed by Citizens Using Multi-Criteria Decision Analysis (MCDA). European Transport Research Review, Vol. 11, 2019, Art. No. 22, doi: 10.1186/s12544-019-0356-6.

[30] Dodgson, J.—Spackman, M.—Pearman, A.—Phillips, L.: Multi-Criteria Analysis: A Manual. Communities and Local Government Publications, 2009.

[31] Velasquez, M.—Hester, P. T.: An Analysis of Multi-Criteria Decision-Making Methods. International Journal of Operations Research, Vol. 10, 2013, No. 2, pp. 56–66.

[32] Saaty, T. L.: The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation. McGraw-Hill, New York, 1990.

[33] Baffoe, G.: Exploring the Utility of Analytic Hierarchy Process (AHP) in Rank-

ing Livelihood Activities for Effective and Sustainable Rural Development Interventions in Developing Countries. Evaluation and Program Planning, Vol. 72, 2019, pp. 197–204, doi: 10.1016/j.evalprogplan.2018.10.017.

[34] Saaty, T. L.: Decision Making with the Analytic Hierarchy Process. International Journal of Services Sciences. Vol. 1, 2008, No. 1, pp. 83–98.

[35] Cinelli, M.—Stuart, R.—Kirwan, K.: Analysis of the Potentials of Multi Criteria Decision Analysis Methods to Conduct Sustainability Assessment. Ecological Indicators, Vol. 46, 2014, pp. 138–148, doi: 10.1016/j.ecolind.2014.06.011.

[36] Brans, J. P.—Vincke, P.: Note – A Preference Ranking Organisation Method: The PROMETHEE Method for MCDM. Management Science, Vol. 31, 1985, No. 6, pp. 647–656, doi: 10.1287/mnsc.31.6.647.

[37] Mareschal, P.—Brans, J. P.: The PROMETHEE-GAIA Decision Support System for Multi-Criteria Investigations. Investigation Operativa, Vol. 4, 1994, No. 2, pp. 107–117.

[38] Belwal, R.—Belwal, S.: Public Transportation Services in Oman: A Study of Public Perceptions. Journal of Public Transportation, Vol. 13, 2010, No. 4, doi: 10.5038/2375-0901.13.4.1.

[39] Mabry, R.: Urbanization and Physical Activity in the GCC: A Case Study of Oman. LSE Middle East Centre Paper Series, Vol. 21, 2018.

[40] Leung, H.—El Faouzi, N. E.—Kurian, A.: Guest Editorial: Intelligent Transportation System (ITS). Information Fusion, Vol. 12, 2011, No. 1, pp. 2–3, doi: 10.1016/j.inffus.2010.06.003.

[41] Geldermann, J.—Treitz, M.—Bertsch, V.—Rentz, O.: Moderated Decision Support and Countermeasure Planning for Off-Site Emergency Management. In: Loulou, R., Waaub, J.-P., Zaccour, G. (Eds.): Energy and Environment: Modelling and Analysis. Kluwer, Dordrecht, 2005, pp. 63–80, doi: 10.1007/0-387-25352-1_3.

[42] Aapaoja, A.—Haapasalo, H.—Söderström, P.: Early Stakeholder Involvement in the Project Definition Phase: Case Renovation. ISRN Industrial Engineering, Vol. 2013, 2013, Art. No. 953915, doi: 10.1155/2013/953915.

[43] Vaidya, O. S.—Kumar, S.: Analytic Hierarchy Process: An Overview of Applications. European Journal of Operational Research, Vol. 169, 2006, No. 1, pp. 1–29, doi: 10.1016/j.ejor.2004.04.028.

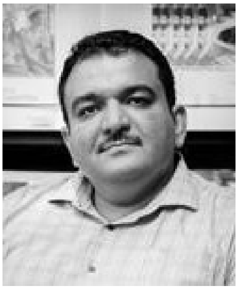
[44] Visual PROMETHEE 1.4 Manual. September 5, 2013, `https://www.promethee-gaia.net`.

[45] Ishizaka, A.—Labib, A: Analytic Hierarchy Process and Expert Choice: Benefits and Limitations. OR Insight, Vol. 22, 2009, No. 4, pp. 201–220, doi: 10.1057/ori.2009.10.

[46] Dağdeviren, M.: Decision Making in Equipment Selection: An Integrated Approach with AHP and PROMETHEE. Journal of Intelligent Manufacturing, Vol. 19, 2008, pp. 397–406, doi: 10.1007/s10845-008-0091-7.

Siham Farrag graduated as Civil Engineer and obtained her Ph.D. in transportation science from the Hasselt University, Belgium, in 2021. She is currently working at Civil Engineering Department at the Middle East College, Oman. She is teaching different courses in the domain of transportation engineering, project management, and other civil engineering domains. Her research interests focus on solving different transportation problems which include but are not limited to the following topics: traffic safety, drivers behavior, traffic management and traffic incident managements, intelligent transportation system (ITS), autonomous vehicles, impact of transportation on environment, and air pollution.

Nabil Sahli holds his Engineer diploma (1999), his Master degree (2001), and his Ph.D. degree (2006) in computer science from the Laval University (Canada). He is currently Head of Department of Computer Science in the German University of Technology in Oman. He received several grants for research projects about agent-based simulation, e-government, sensor networks, trust models, and traffic management. His current research interests include multiagent systems, machine learning, and smart transportation.



Ansar Yasar is Professor at the Transportation Research Institute (IMOB), Hasselt University Belgium, one of the top European institutes focusing on the broader themes of road safety and transport management using new modes of mobility. He is Senior Member of IEEE, Chartered Engineer UK, Fellow BCS and EUR ING (European Engineer). At IMOB, he worked on the European FP7 project DATA SIM (2011–2014), European ERA-NET Smart-PT (2014–2017), H2020 Track & Know (2018–2020) and H2020 iSCAPE (2016-2019) projects. He is currently responsible for the H2020 Search & Rescue project (2020–2023) with a consortium of several international partners. He is responsible for the Intelligent Transport Systems (ITS) and Intelligent Topics in Transportation courses for the masters of transportation sciences students and related research around this topic at UHasselt. Furthermore, he is currently Head of the Business Development Unit at the institute focusing on several applications including Safe Routes to Schools & Safe-Trucking system that resulted in creation of successful spin-off companies. His broader research interests include smart cities and communities, connected and intelligent mobility, drones system management, road safety using smart transport solutions and mobility management. As a part of his basic research, he has expertise in modelling pedestrian flow using various IoT-based techniques and simulations tools such as VisWalk. He has supervised several Master and Ph.D. students in the topics of transport and pedestrian modelling using infused ITS techniques. He received his Ph.D. in engineering from

Katholieke Universiteit Leuven, Belgium, his M.Sc. degree in computer science and engineering from Linkoping University, Sweden and his B.Sc. degree in software engineering from Foundation University Islamabad, Pakistan. He has authored more than 200 research articles in renowned international journals, conferences and workshops. As one of his accomplishments, he has co-edited a book entitled "Data Science and Simulation in Transportation Research" published by IGI Global in December 2013. Furthermore, he has been involved in organization of many international peer-reviewed conferences, summer schools and other scientific events. He is also a technical expert to evaluate project proposals submitted to the European R & D – EUREKA and COST frameworks.

Davy Janssens graduated as Commercial Engineer in management informatics from the Limburg University in 2001. He received his Ph.D. degree in economics from the Hasselt University, Belgium, in 2005. He is currently working as Professor with Hasselt University. He is teaching different courses in the domain of transportation sciences. At the level of scientific research, he is a member of the Transportation Research Institute, Hasselt University, where he is the Programme Leader in the domain of travel behavior research. His interests include the application domain of advanced quantitative modeling (e.g., data mining) and activity-based transportation modeling.