Risk Evaluation of Autonomous Vehicle Integration in Traffic Environments

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***Abstract*—The integration of Autonomous Vehicles (AV) into existing transportation systems presents significant challenges, including safety, infrastructure adaptation, and public acceptance. To address these issues, a structured risk assessment framework is essential for guiding decision-making processes. This paper studies the application of the Analytic Hierarchy Process (AHP) as a decision-support tool for evaluating the risk associated with AV integration. Focusing on three critical risk categories - hazard, vulnerability, and exposure - this study uses AHP to assess and prioritize risks. A case study based on the IN2CCAM European project is presented to evaluate the potential impact of AVs in both urban and extra-urban traffic environments. Key Performance Indicators are identified, and the relative weights of various risk factors are determined. The results indicate that the hazard category has the greatest impact on the integration of AVs, with the probability of accidents being the most critical factor. However, social acceptance, production costs and charging infrastructure limitations also play an important role in determining the feasibility of AV adoption.**

***Index Terms*—Autonomous Vehicles, Analytic Hierarchy Process, Key Performance Indicator, Global Traffic Indicator**

I. Introduction

The Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty in 1980 [1], is a widely recognized decision-support method that simplifies complex decision-making scenarios, particularly in the context of Autonomous Vehicles (AVs). As research and development of AVs continues to evolve, their integration into transportation system presents critical challenges, including safety, infrastructure adaptation, and public acceptance. Addressing these challenges requires robust decision-making frameworks capable of handling multiple risk factors simultaneously. In this context, it is crucial to adopt structured methods such as AHP to assess risk factors. AHP facilitates this by decomposing complex problems into a hierarchy of simpler criteria, helping decision-makers manage uncertainty and conflicting factors effectively.

This approach combines subjective assessments and mathematical analysis to derive priorities and support informed decisions. Unlike other decision-support methods, AHP is particularly advantageous for AVs as it allows for a systematic evaluation of both qualitative and quantitative factors, ensuring a comprehensive risk assessment.

AHP method stands out for its flexibility, ease of use, and ability to integrate multiple criteria. It has been adopted in areas such as risk management, strategic planning, and the evaluation of technological alternatives.

One of the key aspects of this research is the use of AHP to compare standard vehicles and AVs. By establishing a structured evaluation framework, this method enables a systematic comparison of risk factors, helping to identify the critical differences between these two transportation paradigms.

In particular, this study applies AHP within the European IN2CCAM project, which focuses on the full integration of Connected, Cooperative, and Automated Mobility (CCAM) services into transport systems. A key element is the use of this method to determine the relative weights of different sub-criteria or Key Performance Indicators (KPIs), ensuring a uniform and comparable impact assessment across different Living Labs (LLs). These KPIs contribute to the evaluation of the Global Traffic Indicator (GTI), a comprehensive metric used to assess the overall impact of AVs deployment on urban traffic. By incorporating AHP into the IN2CCAM methodology, a structured prioritization of risks and performance measures can be achieved, facilitating better decision-making for AVs integration.

This paper aims to explore the application of AHP focusing on three critical risks factors: hazard, vulnerability, and exposure. Understanding these factors is essential to assess the risks associated with the integration of AVs into existing transportation systems. The objective is to establish a priority scale for these risks, ultimately aiding in decision-making regarding AV deployment.

The remainder of this paper is structured as follows: Section II provides a review of related work on risk assessment and decision-support methods for AVs, Section III presents the case study focusing on the European IN2CCAM project, Section IV presents the results, Section V makes a comparison between standard vehicles and AVs, and Section VI discusses key findings and future research directions.

Research supported by the IN2CCAM project (EU Horizon 2020 Research and Innovation Programme Grant Agreement No. 101076791). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

II. Risk Assessment and Decision-Support Methods for AVs

To integrate AVs into today's transportation systems, several challenges need to be addressed. Safety concerns, infrastructure adaptation, and public acceptance require a structured approach to assess multiple factors simultaneously. Several methods, such as fuzzy logic ([2] and [3]) and Parsimonious AHP [4] have been explored for the assessment of risk of AVs. In this context, the AHP stands out as a decision support tool that allows for a structured multi-criteria assessment, making it suitable for risk analysis in the context of AVs.

Similar approaches have been used in smart city logistics, where MILP-based models address Electric Vehicle Routing for Postal Delivery and Waste Collection under energy and charging constraints [5]. A related optimization-based model also addresses EV routing with Smart-Charging strategies, incorporating grid-level constraints to prevent energy peaks at both charging station and district levels [6].

AHP is a multi-criteria decision-making framework that allows for systematic evaluation of alternatives based on multiple criteria. The method involves several key steps [7]:

- Problem Decomposition: the first step break down the main problem into smaller, structured sub-problems. This hierarchy consists of five fundamental levels: the general objective, sub-goals, criteria, sub-criteria or KPIs, and the stakeholders involved [8]. This structured approach ensures a clear and systematic evaluation.
- Pairwise comparison: once the hierarchical structure has been defined, each criterion and sub-criterion must be evaluated to determine its relative importance in AVs risk assessment. In this step, each element is compared against another to assess its priority.

  The comparisons are expressed using the Saaty 1-9 numerical scale [9], to determine the relative weight of each factor. The resulting comparison matrix forms the basis for calculating the weights of the elements in the analysis. The pairwise comparison matrix is a square matrix of size nn, where n is the number of criteria. Each entry a_{ij} represents the relative importance of criterion i over criterion j. Diagonal elements are equal to 1, as a criterion is equally important to itself, and the matrix is reciprocal, meaning $a_{ji} = \frac{1}{a_{ij}}$.

  The values a_{ij} are determined based on a semantic scale ranging from 1/9 to 9, where 1 indicates equal importance, values above 1 indicate greater importance of i over j, and values below 1 indicate the opposite.
- Synthesis of priorities: once the pairwise comparison matrices have been constructed, the decision-maker derives the local weights of the factors at each hierarchical level and aggregates them to obtain global priorities.

The AHP method also allows testing the coherence of the judgments provided. The results are considered coherent if all the relationships between the criteria are correctly respected.

The strength of AHP lies in its ability to incorporate both qualitative and quantitative aspects [10] into the decision-making process, which makes it particularly suitable for evaluating AVs where various criteria are involved.

A related optimization approach has been used to improve last-mile delivery via Hub-and-Robot routing strategies, leveraging park-and-ride infrastructures to minimize delivery distances in urban areas [11].

As pointed out by Bakioglu and Atahan [12], prioritizing risks associated with AVs requires a method that can address complex multi-criteria decision-making problems involving both tangible and intangible criteria.

The study carried out by Raj et al. [13] explores the challenges of AVs adoption, using the Grey-DEMATEL method to analyze the interrelations between public acceptance, infrastructure, and regulatory barriers, complementing multi-criteria decision-making approaches. The study highlights that the AVs adoption involves addressing these interconnected challenges, which is crucial for effective risk assessment and prioritization in the integration of AVs.

Similarly, optimization and simulation tools have been combined to address Electric Vehicle Routing Problems, integrating cost minimization with traffic-aware validation through SUMO [14].

The study conducted by Zhang and Tak [15] explores a variant of the AHP method, providing a different perspective on improving the reliability of risk evaluations in AV-related scenarios by optimizing the correlation between performance metrics and the risk of the test scenarios.

A case study will be presented that illustrates how these tools are used in practice to prioritize risks in the development and integration of AVs.

A. Contribution

The contribution of this research is based on the comprehensive assessment of the three main risk factors related to AVs: hazard, vulnerability and exposure.

Based on the review of the studies cited above, it can be concluded that many works focus on a single aspect of AV risk, but not on the combination of the three risk factors in a single analysis.

The approach of this paper introduces a multi-criteria model that integrates the three risk elements, allowing a more complete and realistic assessment of the impact of AVs on urban mobility. This methodology offers a broader picture for decision makers, allowing them to manage risk effectively.

III. Case Study

A specific methodology has been developed to assess the impact of AVs integration into transportation systems. This evaluation includes key steps and identification of 16 KPI, grouped according to their impact areas.

The adoption of the AHP method to determine the relative weights of different KPI ensures a uniform and comparable assessment of impact. Additionally, this approach incorporates stakeholder consultation and the conduction of specific surveys to better understand the associated risk factors.

A. *Methodology and application*

This subsection presents the methodology and application of the AHP method to the case study. The main objective is to evaluate the risks associated with AV integration in urban and extra-urban traffic.

1) Problem Decomposition: based on the analysis, hazard, vulnerability, and exposure are identified as the main categories of risk. Each category has been broken down into the following KPI:

- Accident rate: percentage of accidents involving AVs, normalized directly.
- Accident severity: the percentage of accidents resulting in injuries or fatalities.
- Traffic queue length: assessed between 0 meters (no queue) and 50 meters (equivalent to 10 vehicles).
- Waiting time at traffic lights: range from 0 minutes (no waiting) to 20 minutes.
- Sudden decelerations: percentage of decelerations in relation to kilometers traveled.
- Technical failures: failure rates in sensors, mechanical systems and software.
- Environmental factors: presence or absence of adverse weather conditions.
- Production, charging and parking costs: normalized according to defined ranges.
- Social acceptance: percentage of negative responses in questionnaires.
- Pollutant production: comparative values of CO_2 and NO_x emissions between scenarios.

Hazard has been evaluated through accident rates, traffic efficiency indicators (as queue lengths, signal wait times), decelerations, and potential failures in mechanical, electronic, and software components. Tools like SUMO simulations and Python algorithms have been used to assess these risks.

The vulnerability risk focuses on adverse environmental factors such as weather conditions affecting AV sensors, and Internet connection disruptions, both of which are critical for real-time decision-making and safe operations.

Finally, exposure risk addressed economic (production, charging, and parking costs), environmental (pollutants generated during charging), and social acceptance factors. User surveys highlighted key preferences and concerns, revealing that cost, safety, accessibility, and efficiency are pivotal for acceptance, particularly among diverse demographics such as commuters, individuals with disabilities, and high-income travelers.

2) Pairwise comparison: in the evaluation process, surveys have been conducted with experts in the transportation sector, using the Saaty scale (1-9) [17] to compare criteria and KPI. The data has been organized into comparison matrices and relative weights have been derived.

After defining the 16 KPI considered in the evaluation of the GTI, comparison matrices have been developed to collect decision-maker's assessments. Specifically, two types of pairwise comparison analyses have been conducted following two distinct hierarchies:

- In the first hierarchy, all 16 comparison criteria have been assessed at the same level, resulting in a 16x16 evaluation matrix. Relative weights have been assigned based on subjective judgments, occasionally supplemented by findings from previous analyses addressing similar issues. For each pair of criteria, a question has been formulated as follows: "*For the evaluation of the GTI, how much more important is criterion A compared to criterion B?*". Verbal assessments (e.g., equally important, more important, less important, etc.) have been translated into numerical values. The evaluation scale ranged from 1 to 4. Therefore, it has been determined which KPI weighs more and which weighs less, and that is why it has not been necessary to normalize the values.
  Table I shows the weight evaluation related to the first hierarchy.
- In the second hierarchy, three separate matrices have been constructed to evaluate the KPI associated with three primary categories: hazard, vulnerability, and exposure. This resulted in three comparison matrices of dimensions 8x8, 2x2, and 6x6, respectively. The number of pairwise comparison has been significantly lower than in the first analysis. The numerical assignment procedure for each comparison follows the same methodology as in the first hierarchy, using the same evaluation scale.

3) Synthesis of priorities: starting from the complete matrices, the overall weight of each KPI in contributing to the GTI has been calculated. In particular, the priority synthesis phase has been performed using a Python library to simplify and lighten the strictly algebraic component of matrix calculation. The chosen library has been *pyDecision* [18], which includes the resolution of many of the most widely used MCDA methods in the literature.

Each of these three criteria has been assigned the same weight in the GTI evaluation. Therefore, it is necessary to divide each result obtained from the algorithm by three to calculate the weight of each KPI for the GTI.

B. *Results*

In this subsection, the results are presented. In Fig. 1 and Fig. 2, two graphs are represented that highlight the importance of each criterion and the differences in the two types of analysis conducted.

In detail, as can be seen in Fig. 1, the risk criteria that have been found to be the most critical are decelerations, sensor and electronic failures and software failures.

The criterion related to the social acceptance of AVs has also been found to be of primary importance. This aspect has been strongly underlined by previous studies in which it was assessed that the lack of acceptance by consumers is among the main obstacles to the adoption of AVs.

In the second type of analysis conducted, as shown in Fig. 2, the most important criteria are those related to the risk of vulnerability of the AVs: environmental factors, in

TABLE I
WEIGHT EVALUATION BY COMPARING ALL CRITERIA WITH EACH OTHER

				GTI															
				Hazard								Vulnerability		Exposure					
				Acc. rate	Acc. severity	Traffic		Dec.	Failures			Env. Factors	Internet dis.	Cost			S. Acc.	Pollutant Prod.	
						Queue	T. lights		Sensors Electronics	Mechanical	Software			Prod.	Ch.	Park.		Co_2	No_H
GTI	H	Acc. rate		1	3	1/2	2	1/4	1/3	1/3	1/3	1/2	1/3	1/2	1/2	1/2	1/2	1/3	1/3
		Acc. severity		1/3	1	1/4	1/3	1/4	1/4	1/4	1/4	1/3	1/4	1/3	1/3	1/4	1/3	1/4	1/4
		Traffic	Queue	2	4	1	3	1/3	1/2	1/2	1/2	1/2	1/4	2	2	4	1/3	3	3
			T. lights	1/2	3	1/3	1	1/2	1/4	1/4	1/4	1/3	1/3	1/4	2	1/2	1/3	1	1
		Decelerations		4	4	3	2	1	2	2	2	2	4	2	4	4	2	4	4
		Failures	Sensors Elec.	3	4	2	4	1/2	1	3	2	3	4	4	3	4	2	3	3
			Mech.	3	4	2	4	1/2	1/3	1	1/2	2	3	3	3	3	1	2	2
			Soft.	3	4	2	4	1/2	1/2	2	1	4	4	4	3	4	2	3	3
	V	Env. Factors		2	3	2	3	1/2	1/3	1/2	1/4	1	2	2	1/2	4	1/3	2	2
		Internet disruptions		3	4	4	3	1/4	1/4	1/3	1/4	1/2	1	1/4	1/2	1	1/3	1/2	1/2
	E	Cost	Prod.	2	3	1/2	4	1/2	1/4	1/3	1/4	1/2	4	1	1/2	3	2	4	4
			Ch.	2	3	1/2	1/2	1/4	1/3	1/3	1/3	2	2	2	1	2	1/3	3	3
			Park.	2	4	1/4	2	1/4	1/4	1/3	1/4	1/4	1	1/3	1/2	1	1/4	1/2	1/4
		S. Acc.		2	3	3	3	1/2	1/2	1	1/2	3	3	1/2	3	4	1	3	3
		Pollutant Prod.	Co_2	3	4	1/3	1	1/4	1/3	1/2	1/3	1/2	2	1/4	1/3	4	1/3	1	2
			No_H	3	4	1/3	1	1/4	1/3	1/2	1/3	1/2	2	1/4	1/3	4	1/3	1/2	1

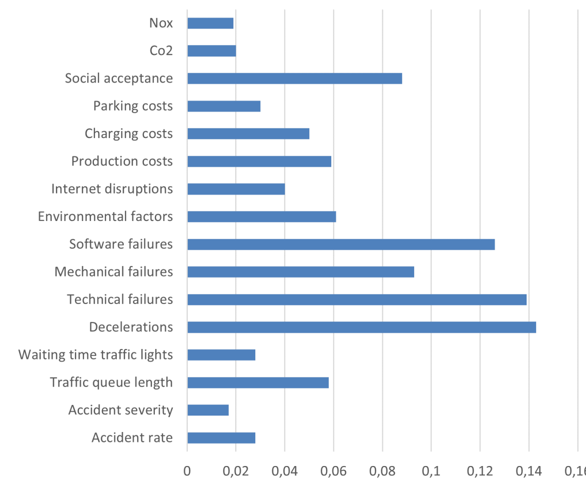

Fig. 1. Weights obtained from first hierarchical process

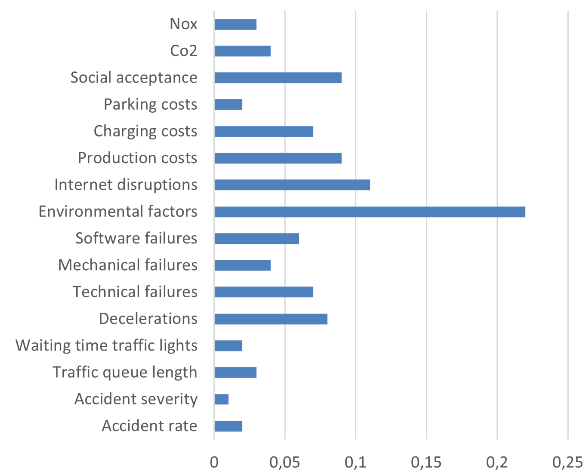

Fig. 2. Weights obtained from second hierarchical process

detail adverse climatic factors, and the possibility of internet interruption.

In particular, we highlight the evident usefulness, ease of use, clarity of the results, and the relative interpretation that the application of the AHP method allows for the study and evaluation of various aspects concerning the problem of the integration of AVs. The results obtained offer a clear and universally understandable hierarchy of risks priorities, so that in research, development and production frontiers it will be possible to place particular emphasis on these priority risk factors.

The results show that the hazard criterion has obtained the highest weight (0.45), followed by vulnerability (0.35) and exposure (0.20). Among the KPI, the probability of accidents has been the most relevant, indicating the need to focus efforts on detection and response technologies.

IV. AHP FOR COMPARISON STANDARD VEHICLE VS. AUTONOMOUS VEHICLE

The last phase of this research is conducted within the framework of the IN2CCAM European project (full title: *Enhancing Integration and Interoperability of CCAM ecosystem*), an Innovation Action funded under the Horizon Europe program [16]. The project aims to integrate CCAM services into fleet and traffic management systems as part of the CCAM Partnership, with the goal of accelerating the deployment of automated, cooperative, and connected mobility technologies and systems. The consortium's objective is to design and implement innovative solutions for connected and automated vehicles, infrastructure, and users, catering to both passenger and freight transport needs.

The study involves modeling a hypothetical scenario in which GTI values are calculated using the previously determined weights for two cases: one with AVs integrated into traffic and another with only traditional vehicles. The main objective is to determine in which of the two scenarios the GTI has a lower value, since a lower GTI reflects a lower negative impact on traffic conditions and management.

For the analysis, the KPI values obtained from simulations or usage statistics have been normalized to a range of 0 to 1, according to the characteristics of the scenario evaluated. This is because each KPI has different units and, to avoid one KPI having an advantage over another just because of the unit in which it has been measured, the values have been normalized to be able to compare two different scenarios.

The GTI is defined as the weighted sum of all considered KPIs. Each normalized KPI is multiplied by its previously determined weight, with the results derived from the initial AHP application. These evaluations, detailed in Table I, provide a structured approach to assess the actual contribution of each KPI to the GTI.

In the worst-case scenario, the GTI reaches a maximum value of 1, indicating that all risk factors correspond to the most critical possible conditions.

A. First scenario: exclusive use of traditional vehicles

The first scenario considers the exclusive use of traditional vehicles. In this case, some KPIs had to be excluded as no data could be obtained on them, and therefore they did not represent a source of risk for a traditional vehicle. In fact, software failures and Internet interruptions were assigned a value of 0.

The evaluated KPI are shown in Table II.

TABLE II
EXCLUSIVE USE OF TRADITIONAL VEHICLES KPI

KPI	**Weight**	**KPI Value**	**Normalized Value**	**Contrib. to GTI**
Accident rate	0.020	22%	0.22	0.00484
Accident severity	0.010	5%	0.05	0.00055
Traffic queue length	0.030	20 m	0.40	0.013733
Waiting time at traffic lights	0.020	6 min	0.30	0.0052
Decelerations	0.080	7%	0.07	0.005507
Technical failures	0.070	1%	0.01	0.000348
Mechanical failures	0.040	5%	0.05	0.002233
Software failures	0.060	no	0	0
Environmental factors	0.22	0	0	0
Internet disruptions	0.11	no	0	0
Production costs	0.090	€ 35000	0.03	0.002618
Charging costs	0.070	€ 1.80	0.20	0.014133
Parking costs	0.02	€ 0.50	0.25	0.004333
Social acceptance	0.090	20%	0.20	0.018200
CO_2	0.040	100%	1.00	0.036333
NO_x	0.030	100%	1.00	0.029000

B. Second scenario: integration of AVs

The second scenario examines the integration of AVs, incorporating specific KPIs related to AVs (Table III).

TABLE III
INTEGRATION OF AVS KPIS

KPI	**Weight**	**KPI Value**	**Normalized Value**	**Contrib. to GTI**
Accident rate	0.028	17%	0.17	0.00476
Accident severity	0.017	2.80%	0.03	0.000476
Traffic queue length	0.058	25 m	0.50	0.029
Waiting time at traffic lights	0.028	6 min	0.30	0.0084
Decelerations	0.143	5%	0.05	0.00715
Technical failures	0.139	3%	0.03	0.00417
Mechanical failures	0.093	1.60%	0.02	0.001488
Software failures	0.126	0.90%	0.01	0.001134
Environmental factors	0.061	0	0.00	0
Internet disruptions	0.04	1.20%	0.01	0.000480
Production costs	0.059	€ 95000	0.38	0.022559
Charging costs	0.050	€ 0.50	0.61	0.030263
Parking costs	0.03	€ 0.50	0.25	0.007500
Social acceptance	0.088	55%	0.60	0.0528
CO_2	0.020	70% less	0.20	0.004
NO_x	0.019	75% less	0.15	0.00285

C. Comparison of First and Second scenario results

The results obtained highlight a key insight: the scenario without AV integration produces the lowest GTI and therefore, under current conditions, no AV integration represents the most favorable option. This conclusion underlines the challenges associated with AV integration, particularly in economic and social terms.

In the scenario with full AV integration, the key factors influencing the results are social acceptance, production costs, charging costs and queue length. It should be noted that the criteria identified as most critical in the AHP assessment do not always emerge as the most influential in a real-world scenario. For example, even though the KPI related to decelerations receives the highest weight, its actual impact on GTI remains relatively minor. This discrepancy is justified by the high level of reliability that AV integration entails, which reduces the frequency of severe decelerations caused by software or sensor failures. Consequently, the perceived risk of such events remains low under normal operating conditions.

A particularly result is the significant role of social acceptance in determining the viability of AV integration. Despite not being the highest priority KPI initially, public perception and trust in AVs are decisive factors, suggesting that technological advancement alone is insufficient: broader social acceptance is crucial for widespread adoption.

Similarly, cost factors pose substantial barriers to integration. From the results, it can be deduced that AV adoption will only become viable when production and operation costs decline at a steady pace (e.g. by 15-20% annually), making AVs a competitive alternative to traditional vehicles.

Furthermore, the long-term viability of AV technologies extends beyond private self-driving cars, encompassing shared mobility solutions such as autonomous shuttles and buses [19], which could improve accessibility and efficiency in urban transport.

For the first scenario, with the lowest GTI, pollution-related KPIs had the greatest influence, which was predictable. However, this comparison is inherently limited by the inability to account for certain risk factors unique to human-driven vehicles. In this study, an idealized scenario has been taken as a reference, where human drivers maintain maximum attention and expertise, which does not fully reflect real-world driving conditions.

Finally, trust in AVs (and consequently their social acceptance) can be significantly improved through continued research and development. Projects such as IN2CCAM contribute to optimizing the integration of AVs by addressing critical barriers and refining methodologies to assess their impact.

V. Conclusions

This paper presents the implementation of a multi-criteria approach for the analysis of risks related to the use of AVs. The three risk factors of hazard, vulnerability and exposure and the related KPIs are considered. Through the use of the AHP, it was in fact possible to provide a clear and traceable framework for the assessment of the importance of the various criteria involved and, consequently, for the evaluation of the respective priorities for the decision maker.

The comparison between the exclusive use of traditional vehicles and the full integration of AVs underscores the effectiveness of AHP as a decision-support tool for managing the complexities of AV integration in urban and extra-urban mobility systems. In particular, the analysis highlighted the importance of considering some criteria, such as decelerations, sensor and electronic failures, social acceptance, as priorities compared to others.

Finally, this research contributes to optimizing AV integration strategies by identifying key risk factors and their relative importance. Projects as IN2CCAM and other similar initiatives can leverage these insights to improve policy recommendations, infrastructure planning, and public engagement strategies, ensuring a balanced and well-informed approach to the adoption of autonomous mobility.

Regarding future developments, it would be interesting to expand the study by including new risk factors and increase the opinion of additional experts in the field. Furthermore, the integration of other decision support methodologies could further enrich the analysis and provide even more detailed and useful results to decision makers.

The proposed approach is confirmed to offer a solid basis for future research and practical applications, contributing to the improvement of urban mobility systems and the diffusion of innovative technologies in the field of transport.

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