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A Security-by-Design Decision-Making Model for Risk Management in Autonomous Vehicles

MOHAMED ABDEL-BASSET[1], (Senior Member, IEEE), ABDUALLAH GAMAL[1], NOUR MOUSTAFA[2], (Senior Member, IEEE), AHMED ABDEL-MONEM[1], AND NISSREEN EL-SABER[1]

[1]Faculty of Computers and Informatics, Zagazig University, Zagazig 44519, Egypt
[2]School of Engineering and Information Technology, University of New South Wales at ADFA, Canberra, ACT 2612, Australia

Corresponding author: Abduallah Gamal (abduallahgamal@zu.edu.eg)

ABSTRACT Autonomous/self-driving vehicles have gained significant attention these days, as one of the intelligent transportation systems. However, those vehicles have risks related to their physical implementation and security against cyber threats. Therefore, this study proposes a new security-by-design model for estimating the uncertainty of autonomous vehicles and measuring cyber risks; thus it assists decision-makers in addressing the risks of the physical design and their attack surfaces. The proposed model is developed using neutrosophic sets that efficiently tackle multi-criteria decision-making (MCDM) problems with extensive conflicting criteria and alternatives. The proposed model integrates MCDM, Analytic Hierarchy Process (AHP), Multi-Attributive Border Approximation Area Comparison (MABAC), and Preference Ranking Organization Method for Enrichment Evaluations II (PROMETHEE II), along with single-valued neutrosophic sets (SVNSs). An illustrative case considering ten risks in self-driving vehicles is used to validate the feasibility of the proposed model. Compared to the state-of-the-art methods, the proposed model is considered consistent and reliable to deal with and represent uncertainty and incomplete risk information using neutrosophic sets.

INDEX TERMS Autonomous vehicles, attack surfaces, cyber threat, MCDM, AHP, MABAC, PROMETHEE II, ranking risks.

I. INTRODUCTION

Intelligent Transportation Systems (ITS), especially autonomous/self-driving vehicles, have become real in our era. Autonomous vehicles are one of the major categories of ITS that could result in reducing the requirements of drivers, decreasing transportation expenditures, and improving traffic flows. Those vehicles can be connected with other ones, where they are connected using communication techniques and tools which are known as vehicles to everything (V2X) [1]. V2X can be represented in various technological forms, including vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V), vehicle-to-pedestrian (V2P and vehicle-to-network (V2N) systems. In this essence, ITS contains an intelligent system, robotic, and computerized driving technology combined coherently. It is expected that autonomous vehicles are going to be used in countries, cities, and streets [2].

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Previous studies have introduced various features, advantages, and benefits of these driverless vehicles. These benefits include increased mobility for older adults and incapacities, enhancing motorists' and walkers' safety, reducing pollution, and crashes [3]. In this context, this automated technology can have manufacturing and cyber risks [4]. The risks of manufacturing are interaction among the electronic infrastructure, user, and utonomous technology that can cause troubles for the user, walkers, and anything on the road [5]. In California, rear-end crashes are considered common crashes of driverless vehicles [6]. The risks of cybersecurity include attack surfaces and vectors, where various vulnerabilities in the physical implementation of the vehicles would be exploited using various attacking techniques such as denial of service (DoS) and Distributed DoS (DDoS) attacks [7].

In 2040, autonomous vehicles are expected to be 40% of vehicles [8]. This would help recognize how people use and adapt these vehicles for achieving safety on roads [9]. The safety of the vehicles is a vital issue due to usage in different areas like transportation operations and terrorist intervention [10]. Being technology-dependent, driverless vehicles could imply risks. Moreover, these vehicles have a complex system that contains various risks like vehicles to infrastructure and V2V systems [11]. Consequently, there is no full security in a system that does not contain attack surfaces or vectors. When systems have interactions with humans, this would produce vulnerabilities [12]. These risks contain uncertainty and incomplete information which make it a decision problem. To do so, fuzzy sets have been developed to address the uncertainty of incomplete information and model uncertainty of cyberattacks. Fuzzy sets work with true and false (T, F) situations but cannot deal with indeterminate (I). The generalization of fuzzy sets introduces an intuitionistic fuzzy set and interval value intuitionistic fuzzy set. The interval value intuitionistic fuzzy set cannot express the inconsistency and indeterminacy information. Another drawback of the interval value intuitionistic fuzzy set that the range of membership and non-membership degrees must gratify the sum of membership and non-membership degrees within a closed interval value [0, 1] [13]. To overcome these drawbacks, the neutrosophic set is introduced with truth, falsity and indeterminacy (T, I, F) membership [13]. This can deal with inconsistency and indeterminacy of risk information. Single-valued neutrosophic sets (SVNSs) are considered a subclass of neutrosophic sets. This can be used in vague, incomplete, uncertain vagueness, and inconsistent information, and cyberattack information.

In this paper, the ranking of driverless vehicle risks is introduced as an MCDM problem with the neutrosophic sets, including AHP, MABAC, and PROMETHEE II. The main objective is to introduce our hybrid framework for ranking driverless vehicles' associated risks in uncertain circumstances. This hybridization introduces a better collective alternative than a single technique; i.e. one technique can complement the other [14]. The use of the three methods can perfectly rank the risks of autonomous vehicles.

By capturing risk information, AHP introduces the best decision by setting importance to decision-makers [15]. AHP is applied to many problems such as manufacturing processes, education, modeling attack surfaces, and their vectors [16]. Additionally, its hierarchical structure can accommodate decision-making problems in various dimensions.

MABAC is a powerful MCDM technique that is simple and precise with a systematic and straightforward computation approach. However, all criteria are assumed compensatory [17]–[18]. PROMETHEE II is constructed on non-compensatory standards. The outranking results of PROMETHEE II are calculated from pairwise judgments of alternatives in contradiction of each attribution in fewer, uncomplicated, and simple calculations [19]. The main contributions of this study can be summarized as follows:

- We employ an MCDM with a hybrid framework model of neutrosophic sets, involving AHP, MABAC and PROMETHEE II, to effectively model and rank risks associated with autonomous vehicles and accomplish high safety and security to drivers and pedestrians.
- We autonomously evaluate the risks of driverless vehicles concerning each criterion. Then, we apply the AHP method to determine the weights of criteria and apply the MABAC and PROMETHEE II methods to rank risks.
- We provide a comparative analysis with Pythagorean fuzzy AHP, TOPSIS, VIKOR to determine the proposed model's effectiveness for ranking risks of driverless vehicles.
- We introduce a sensitivity analysis to examine the credibility of the proposed model via changing the weights of criteria under ten risk scenarios for measuring the ranking of driverless vehicles constrained to these changes.

The remainder of this paper is organized as follows. Section II introduces the literature review. Section III provides the definitions of the problem. Section IV presents the methodology of this study. Section V presents the application of the proposed methodology. Section VI provides a comparative analysis of previous studies. Section VII shows the sensitivity analysis. Section VIII presents managerial implications. Section IX concludes the study.

II. LITERATURE REVIEW

This section reviews the main evaluation criteria, and then the sub-criteria for each main criterion.

Transport plays a vital role in developing social and economic nationalism—transport costs enormous money to be safe and healthy for passengers and walkers [20]. Transport roads face many risks that threaten walkers and drivers [21]. Many injure and approximately 1.2 million death worldwide that cause by motor vehicle crashes on the roads [22]. Reasons for accidents vary from driver's experience in different situations, driver's awareness of road emergencies, weather conditions, traffic conditions, failure of the brake, and high speed [23], [24]. To reduce these causalities, and reducing human errors, driverless vehicles can be used in improved safe routes [25]. That is, driverless vehicles have the potential to introduce more safe roads.

There are some recent studies in the field of ITS that have been applied under many scenarios. For instance, Li *et al.* [26] proposed a combined trajectory planning and tracking algorithm for vehicle control under the effects of the traffic environments and human driving styles. Chen *et al.*, [27] suggested two techniques to improve the stability of the policy model training with as little manual data as possible on end-to-end autonomous driving. Chen *et al.* [28] developed a deep Monte Carlo Tree Search (deep-MCTS) control method for vision-based autonomous driving for predicting driving maneuvers to assist in enhancing the stability and performance of driving control. Amini [29] introduced a data-driven simulation and training engine capable of learning end-to-end autonomous vehicle control policies using only sparse rewards for allowing virtual agents to drive along a continuum of new local trajectories.

Some studies focus on software and hardware risks in self-driving vehicles [30]. The related software/hardware risks could be internet crashes, failures in a Global Position System (GPS), failure in sensors, and losses in signals that could be occurred via cyberattacks [4], [31]. As a result, Bhavsar *et al.* [32] presented that 14% of sequential failure in the vehicle component and consequences found 158 per one million mi of travel failure of the infrastructure of a piece. Lee and Kolodge [33] introduced driverless vehicles' attitudes and their motivation factors. Cyber-attacks, such as DoS and DDoS, could exploit the vulnerabilities of autonomous vehicles which would corrupt the infrastructure, causing failures and harming the economy of these vehicles [34].

These risks contain uncertainty and incomplete information. Michelmore *et al.* [25] suggested assessment techniques for uncertainty to predict crashes in autonomous driving. Huang *et al.* [35] proposed a model to assess uncertainty in testing data-driven self-driving. Sener and Zmud [36] treated uncertainty in using self-driving vehicles. La Torre and Mendivil [37] made a model risk aversion of average investors and their desire to maximize the expected return with the least risk; they used the probability multi-measure to overcome uncertainty and incomplete information.

Moreover, to overcome this uncertainty and incomplete information, researchers use fuzzy sets in their studies. Zolfaghari and Mousavi [38] used the hesitant fuzzy sets and VIKOR method to rank and ordered risks of projects under uncertainty of conditions. Faizi *et al.* [39] used hesitant fuzzy sets as well. Hesitant fuzzy sets are a generalization of the fuzzy set to deal with the delay in decision making to rank reversal paradox and using imperfect information. The fuzzy sets can deal correctly with uncertainty. Still, they cannot deal with indeterminate values, so the researchers introduce the intuitionistic fuzzy sets and interval-valued intuitionistic fuzzy sets that deal with uncertainty. These improvements introduce the non-membership and membership degree, unlike classical fuzzy sets [40]. The neutrosophic set is a generalization of fuzzy sets and can handle uncertainty and incomplete information as it represents the truth, indeterminate and falsity (T, I, and F). They handle problems with uncertainty, ambiguity, vague, and inconsistency. The application of neutrosophic sets has been applied in many fields, such as medical diagnoses, machine learning, optimization design, image processing, algebraic system, and computational intelligence [41]–[45]. SVN is a subclass of neutrosophic sets that can be used in the engineering field giving the ability and potential to represent inconsistent, vague, ambiguous, imperfect, incomplete, and uncertain information. Yang *et al.* [46] introduced the SVNSs with the rough systems and produced a hybrid model. The neutrosophic sets for conflicting criteria and alternatives are named MCDM. Yang *et al.* [46] introduced SVNSs with MCDM to measure the values between options and ideal choices. The neutrosophic sets use MCDM techniques to deal with uncertainty, such as AHP, VIKOR, TOPSIS, MABAC and PROMETHEE [47], [48].

Saaty developed the AHP method that can be utilized for weighting criteria and ranking alternatives in MCDM activities [49]. AHP method is applying in many fields to assess the conflicting criteria. Lyu *et al.* [50] used the AHP method to rank the risk of construction shield tunnels in Jinan. Ilbahar *et al.* [51] applied the AHP to rank the risk assessment for occupational health and safety. Bakioglu and Atahan [52] proposed a model consisting of Pythagorean fuzzy AHP, TOPSIS, and VIKOR to rank driverless vehicles' risks. They used seven main criteria and ten criteria with eight risks. The main limitation of their study that it does not take into consideration the indeterminacy value. Also, Karasan *et al.* [10] proposed the Pythagorean fuzzy AHP to analyze driverless vehicles' risks. They used four main criteria and twenty sub-criteria main limitations of their study used the fuzzy sets and did not handle indeterminacy.

MABAC is an MCDM method proposed by Pamučar and Ćirović in 2015 [17]. MABAC is a consistent and reliable method. It stands for multi-attributive border approximation area comparison. Pamučar and Ćirović [17] used the MABAC to select the transport and handle resources. Wang *et al.* [53] applied the MABAC method with q-rung orthopedic. Wei *et al.* [54] applied the MABAC method for green supplier selection.

Brans and Vincke suggested the PROMETHEE-I and PROMETHEE-II techniques which received much attention, for their reliance on the principle of partial and total arrangement [55]. Debbarma *et al.* [56] applied the PROMETHEE II method to determining the optimal performance-emission trade-off vantage in a hydrogen-biohol dual fuel endeavor. Sianturi *et al.* [57] explored the use of the Extended PROMETHEE II method in solving the problem of determining the best students and generate more efficient decisions. They used four criteria in the determination of best student and policy makers can add other criteria. Each methodology has drawbacks in which policymakers should take into consideration [58]. A single model or technique cannot introduce a better solution for many problems [59]. Therefore, a hybrid model can effectively deal with issues than a single one. To conclude the literature review, and to the best of our knowledge, no study of ranking the risks of driverless vehicles considering different criteria and risks handling the indeterminacy value at the same time.

III. PROBLEM DEFINITION

This section explains the main evaluation criteria in determining the risks that would affect self-driving vehicles, and then the sub-criteria for each major criterion. Risks of self-driving vehicles are assessed through nine sets of criteria: legislation criterion, unregulated industry criterion, financial aspects criterion, increased exposure to radiation criterion, hardware criterion, traffic criterion, accidents criterion, malfunctions criterion, and remote control and hacking criterion. The legislation criterion includes one sub-criterion, namely legislation and data protection. The unregulated industry criterion is divided into two sub-criterion, namely limited information on technology, and safety standards. The financial aspects criterion includes three sub-criterion, namely operating cost, revenue potential, and the number of passengers.

The increased exposure to radiation criterion includes one sub-criterion, namely serious health problem. The hardware criterion contains three sub-criterions: IT infrastructure, hardware integration and requirements, and robustness. The traffic criterion includes one sub-criterion, namely Traffic crowding. The accidents criterion comprises three sub-criterions: road accidents, weather conditions, and the false security of sense to passengers. The malfunctions criterion contains three sub-criterions: human errors, software malfunctions, and mechanical malfunctions. Last, the remote control and hacking criterion includes three sub-criterions: theft of private data, hacking, and computer viruses. The main criteria and their sub-criteria are listed as follows:

A. LEGISLATIONS S_1

Consider S_1 the main criterion refers to legislation and data protection.

1) LEGISLATION AND DATA PROTECTION S_{11}

For driverless vehicles, responsibility is an important issue. Responsibilities are defined in situations of when malfunction, injure of walkers, damage the drivers or manufacturers [60].

B. UNREGULATED INDUSTRY S_2

Consider S_2 as the main criterion refers to unregulated industry and limited information of technology. The industry of driverless vehicles is unregulated which is good for developers, companies, and manufacturers but not for users and customers. With an unregulated industry, there is reduced quality, high cost, and a decrease in profit [61].

1) LIMITED INFORMATION ON TECHNOLOGY S_{21}

Risks can result from limited information on technology. That is, many manufacturing errors are due to a lack of driverless vehicle technology.

2) SAFETY STANDARD S_{22}

Many new companies in the driverless vehicles market with no formal announced safety standards. Users must check all information about driverless vehicles.

C. FINANCIAL ASPECTS S_3

Consider S_3 as the main criterion for financial aspects such as the operating cost, the number of passengers, and profit [62].

1) OPERATING COST S_{31}

Risks related to the operating cost of driverless vehicles result in developers cannot add some features due to the high operation costs.

2) REVENUE POTENTIAL S_{32}

Risks of driverless vehicles can occur due to expected and actual revenue. When less revenue than expected is gained, it is always harder to make upgrade decisions as it may double the chances of risks in the driverless vehicles market.

3) NUMBER OF PASSENGERS S_{33}

The increased number of passengers of driverless vehicles can increase awareness of the project and attract more revenue to the project.

D. INCREASED EXPOSURE TO RADIATION S_4

Consider S_4 as the main criterion for risks caused by exposure to radiation.

1) SERIOUS HEALTH PROBLEM S_{41}

Driverless vehicle components, such as GPS, sensor, Bluetooth, Wi-Fi can produce harmful radiation risks for users and customers with prolonged usage. Outcomes of electronic radiation can cause health problems like eye issues, headaches, and so on.

E. HARDWARE S_5

The hardware components of driverless vehicles may fail. So that driverless companies produce more robust components such as sensors.

1) IT INFRASTRUCTURE S_{51}

Failure risks can occur when infrastructure components fail. The infrastructure robustness depends on the technical capacity and the associated effective operations. [62].

2) HARDWARE INTEGRATION AND REQUIREMENTS S_{52}

Risks can occur due to problems in hardware safety requirements, worst-case testing, functional testing under normal conditions, and incorrect specifications of the hardware. Hardware should contain the safety requirements, safety lifecycle of hardware, and testing of hardware.

3) ROBUSTNESS S_{53}

Risks can occur in driverless vehicles due to the less robustness of hardware. Risks come from when the hardware of driverless vehicles is broken down.

F. TRAFFIC S_6

Consider S_6 as the main criteria regarding traffic. The system of driverless vehicles should be tested on many roads and cars. With mixed traffic, driverless vehicles can be risky and confused due to having various levels of automation [63].

1) TRAFFIC CROWDING S_{61}

Traffic crowing can cause many risks for driverless vehicles.

G. ACCIDENTS S_7

Many accidents of driverless vehicles can be caused by roads, so developers should take into account all types of roads and possible problems to avoid accidents.

1) ROAD ACCIDENTS S_{71}
Accidents can occur due to problems with roads. This makes it an important risk to consider.

2) WEATHER CONDITIONS S_{72}
Driverless vehicles cannot be programmed for high weather conditions consequences which may cause many accidents. Weather conditions can affect sensors and their connectivity to other devices. That is a possible risk that comes from decreasing the visible area of a driverless vehicle.

3) THE FALSE SECURITY OF SENSE TO PASSENGER S_{73}
Risks can occur due to false security of sense to passengers from driverless vehicles.

H. MALFUNCTIONS S_8
Consider S_8 as the main criterion that refers to components failure in driverless vehicles.

1) HUMAN ERRORS S_{81}
Malfunctions can be caused by human errors or component failure.

2) SOFTWARE MALFUNCTIONS S_{82}
Driverless vehicles have the risk of software failure due to bugs by developers or due to the complexity of the developed program.

3) MECHANICAL MALFUNCTIONS S_{83}
Risks related to malfunctions of mechanical parts of vehicles may result in real accidents. Malfunctions can occur in self-driving vehicles more than conventional vehicles [64].

I. REMOTE CONTROL AND HACKING S_9
Consider S_9 as the main criterion for remote control and hacking of driverless vehicles. Hackers may get into systems to change how the driverless vehicle system operates [63].

1) THEFT OF PRIVATE DATA S_{91}
Data privacy is still an issue in such systems.

2) HACKING S_{92}
Malicious hacking is one of the serious remote-control attacks which may cause many problems with driverless vehicles [52].

3) COMPUTER VIRUSES S_{93}
Due to connected computer systems in driverless vehicles, a possibility of injecting viruses and other harmful programs into driverless vehicle systems.

IV. METHODOLOGY
A. NEUTROSOPHIC LINGUISTIC INFORMATION
In a quantitative form, it cannot evaluate many problems because it contains incomplete, vague, ambiguous, inconsistent, and uncertain information to assess information in qualitative form. Neutrosophic linguistic information can be used in different fields. Table 1 presents the linguistic terms that experts used to make decision matrices. The extremely bad term was expressed to the least term, and the extremely good described the highest term. Each linguistic term has the SVNSs. That includes the truth, indeterminacy, and falsity. These SVNSs convert to one crisp value to be used in the proposed model easily and smoothly.

TABLE 1. Single valued neutrosophic scale.

Linguistic term	Abbreviation	SVNNs		
		T	I	F
Extremely Bad	EB	0.00	1.00	1.00
Very Very Bad	VVB	0.10	0.90	0.90
Very Bad	VB	0.20	0.85	0.80
Bad	B	0.30	0.75	0.70
Medium Bad	MB	0.40	0.65	0.60
Medium	M	0.50	0.50	0.50
Medium Good	MG	0.60	0.35	0.40
Good	G	0.70	0.25	0.30
Very Good	VG	0.80	0.15	0.20
Very Very Good	VVG	0.90	0.10	0.10
Extremely Good	EG	1.00	0.00	0.00

B. SUGGESTED HYBRID MCDM APPROACH
MCDM handles the composite decision problems which include various conflicting criteria. MCDM procedures compute an ideal alternative or rank alternatives in which the maximum ranked is measured as the best alternative to the experts. One of the main characteristics of self-driving vehicles is their imprecision in various fields. Since the problem of ranking driverless vehicle risks has a set of selected alternatives with conflicting criteria, MCDM procedures may be efficiently applied to deal with this problem. They rank the risks involved in driverless vehicles in four primary phases by suggested methodology.

In the first phase, the objective, criteria, and risks are determined. In this field and survey of the literature, the criteria and alternatives are collected and described, making pairwise comparisons through the group of consulting experts. In the first three steps, the hierarchy tree that shows the objective from study, criteria, and alternatives is built. Then, from steps 4 to 7, the neutrosophic set steps are calculated, and a matrix of the decision matrix's opinions.

In the second phase, the AHP method is used to determine the weights of criteria from steps 8 to 11.

In the third and fourth phases, MABAC and PROMETHEE II are applied using selected criteria and risks. The rest of the steps show the suggested hybrid MCDM procedure. The proposed methodology is represented in Fig. 1.

In this work, the following MCDM procedures are implemented to rank the risks of the driverless vehicle:

- ✓ The MABAC method
- ✓ The PROMETHEE II method

The steps of the decision-making algorithm are briefly defined as follows:

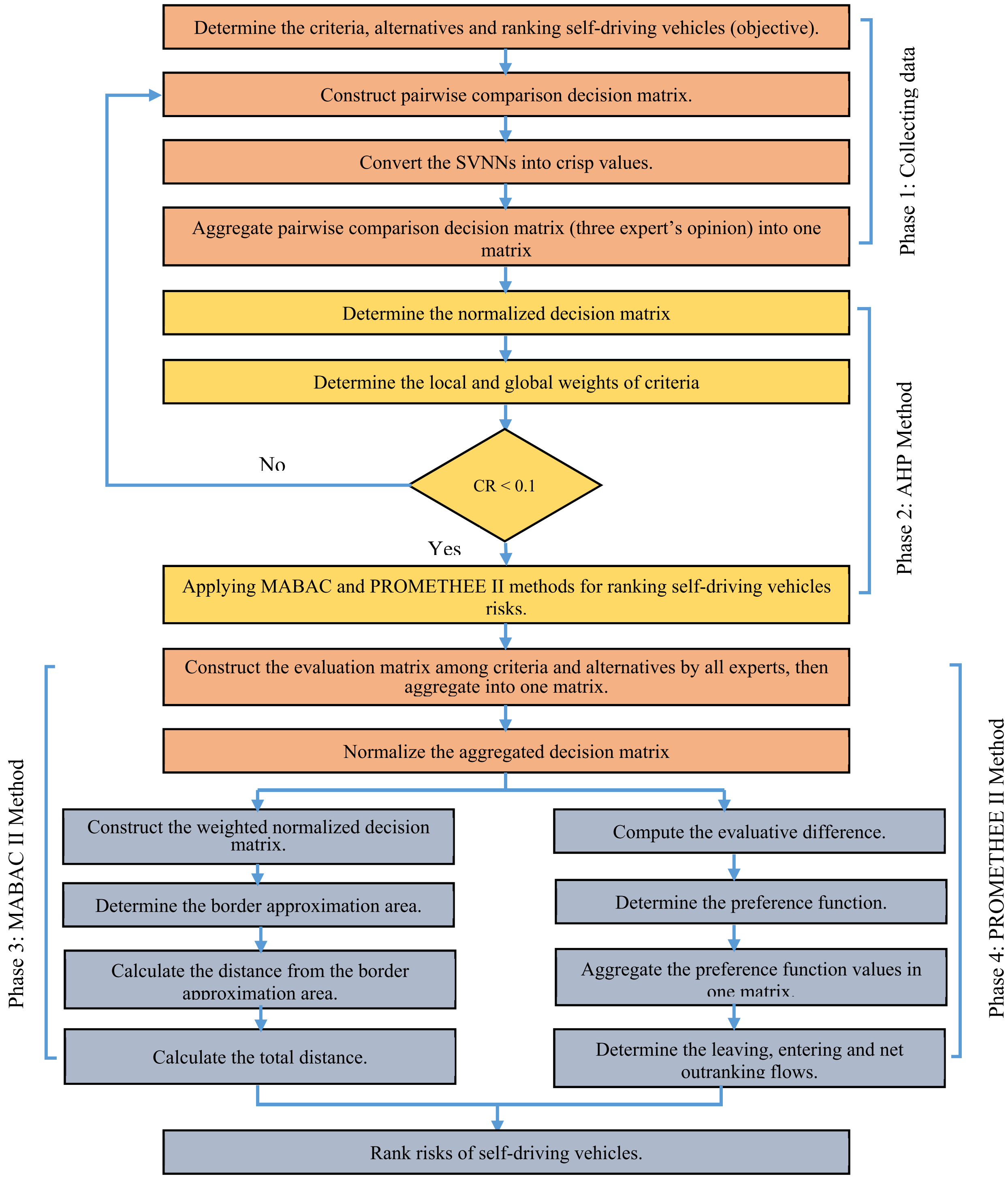

FIGURE 1. **The framework of suggested methodology.**

Step 1. Applying the neutrosophic sets the first step is to determine the goal from this study that ranking risks of self-driving vehicles.

Step 2. Collecting the main criteria and sub-criteria risks of self-driving vehicles, where x refers to criterion $(x = 1, 2, 3, \ldots\ldots.a)$.

Step 3. collecting alternatives risks of self-driving vehicles; where y refers to alternative (y = 1, 2, 3, ...b) and o refers to several criteria and p refers to the number of alternatives and build a hierarchy tree to show the objective, main and sub-criteria, and alternatives.

Step 4. According to SVNNs in Table 1 [58], [65] the pairwise comparisons decision matrix that collects opinions of experts is built as:

$$\mathrm{K^M} = \begin{bmatrix} \mathrm{k_{11}^M} & \cdots & \mathrm{k_{1x}^M} \\ \vdots & \ddots & \vdots \\ \mathrm{k_{y1}^M} & \cdots & \mathrm{k_{xy}^M} \end{bmatrix} \tag{1}$$

where M indicates the number of experts.

Step 5. Applying the score function to convert SVNNs to crisp values as [18].

$$\mathrm{S}\left(\mathrm{k_{xy}^M}\right) = \frac{2 + \mathrm{T_{xy}^M} - \mathrm{I_{xy}^M} - \mathrm{F_{xy}^M}}{3} \tag{2}$$

$\mathrm{T_{xy}^M}, \mathrm{I_{xy}^M}, \mathrm{F_{xy}^M}$, present truth, indeterminacy, and falsity of the SVNNs.

Step 6. Combine the pairwise comparison matrix to make one matrix that aggregates the expert's opinions as:

$$k_{ab} = \frac{\sum_{M=1}^{M} k_{xy}}{M} \tag{3}$$

Step 7. The aggregation of the pairwise comparison matrix that contains the judgments of decision-makers is built as:

$$\mathrm{K} = \begin{bmatrix} \mathrm{k_{11}} & \cdots & \mathrm{k_{1a}} \\ \vdots & \ddots & \vdots \\ \mathrm{k_{b1}} & \cdots & \mathrm{k_{xy}} \end{bmatrix} \tag{4}$$

Step 8. Applying the AHP method the first step is to compute the normalize matrix from the aggregation pairwise judgments as:

$$\mathrm{w_y^b} = \frac{\mathrm{w_y}}{\sum_{\mathrm{y}=1}^{\mathrm{b}} \mathrm{w_y}}; \quad \mathrm{y} = 1, 2, 3, \ldots\ldots.\mathrm{b} \tag{5}$$

Step 9. From the normalized matrix determine the row average weights (priorities) of main and sub-criteria (local weights) as:

$$\mathrm{w}_x = \frac{\sum_{\mathrm{x}=1}^{\mathrm{a}} \left(\mathrm{k_{xy}}\right)}{\mathrm{b}}; \quad \mathrm{x} = 1, 2, 3, \ldots\ldots.\mathrm{a}; \quad \mathrm{y} = 1, 2, 3, \ldots\ldots.\mathrm{b}; \tag{6}$$

Step 10. Compute global weights of sub-criteria by multiply main criteria weights by sub-criteria (local) weights

Step 11. Check the consistency ratio (CR) to validate the opinions of experts are consistent or not by first calculate the $lambda_{max}$(compute the weighted columns by multiply the weights of criteria by the value of aggregation pairwise matrix, then sum the value row of weighted columns this results in the weighted sum, finally divide the weighted sum by weights of criteria) then compute the consistency index and finally calculate the CR as.

$$CR = \frac{CI}{RI} \text{ And } CI = \frac{lambda_{max} - o}{o - 1} \tag{7}$$

where o refers to the number of criteria. $lambda_{max}$ is the maximum eigenvalue. CI is a consistency index and RI is a random index. If the CR is less or equal to 0.1 the opinion of experts is accepted otherwise the value of opinion experts not consistent then reevaluate the matrix.

Step 12. Starting from this step, the MABAC method is applied. Equations (1-4) are applied to construct the aggregated pairwise comparison matrix between criteria and alternatives.

Step 13. From the aggregation matrix between criteria and alternatives, the normalized matrix of the decision matrix is constructed as:

$$\mathrm{Z_{xy}} = \frac{\mathrm{k_{xy}} - \mathrm{k_y^-}}{\mathrm{k_y^+} - \mathrm{k_y^-}}; \quad \mathrm{x} = 1, 2, 3, \ldots \mathrm{a}, \quad \mathrm{y} = 1, 2, 3, \ldots.\mathrm{b} \text{ for Beneficial criteria} \tag{8}$$

$$\mathrm{Z_{xy}} = \frac{\mathrm{k_{xy}} - \mathrm{k_y^+}}{\mathrm{k_y^-} - \mathrm{k_y^+}}; \quad \mathrm{x} = 1, 2, 3, \ldots \mathrm{a}, \quad \mathrm{y} = 1, 2, 3, \ldots.\mathrm{b} \text{ for Non} - \text{Beneficial criteria} \tag{9}$$

where $\mathrm{k_y^-} = \min(k_y)$ and $\mathrm{k_y^+} = \max(k_y)$, also Z_{xy} is normalized value. Where the beneficial criteria refers to positive criteria and the non-beneficial criteria refers to negative criteria (cost criteria)

Step 14. From the normalized decision matrix, the weighted normalized of the decision matrix is computed as:

$$\hat{Z}_{xy} = W_y + W_y * \mathrm{X_{xy}}; \quad \mathrm{x} = 1, 2, 3, \ldots a, \quad \mathrm{y} = 1, 2, 3, \ldots.\mathrm{b} \tag{10}$$

Step 15. From the weighted normalized matrix, the border approximation area matrix is determined as:

$$R_y = (\Pi_{y=1}^{a} \hat{Z}_{xy})^{1/a}; \quad y = 1, 2, 3, \ldots.b \tag{11}$$

Step 16. Calculate the distance from the border approximation area as:

$$D_{xy} = \hat{Z}_{xy} - R_y; \quad \mathrm{x} = 1, 2, 3, \ldots \mathrm{a}, \ \mathrm{y} = 1, 2, 3..\mathrm{b} \tag{12}$$

Step 17. The total distance from the border approximation area is determined as:

$$T_x = \sum_{y=1}^{b} D_{xy}; \quad \mathrm{x} = 1, 2, 3, \ldots \mathrm{a}; \ \mathrm{y} = 1, 2, 3, ..\mathrm{b} \tag{13}$$

Step 18. The risks are ranked according to the total distance value to order the risks of self-driving vehicles.

Step 19. Applying the PROMETHEE II method is started. The first step is to apply Eqs (1-4) to construct the aggregation pairwise comparison between criteria and alternatives.

Step 20. From the aggregation, the pairwise comparison matrix normalizes the decision matrix.

$$\mathrm{E_{xy}} = \frac{\mathrm{k_{xy}} - \mathrm{k_y^-}}{\mathrm{k_y^+} - \mathrm{k_y^-}}; \quad \mathrm{x} = 1, 2, 3, \ldots \mathrm{a}, \quad \mathrm{y} = 1, 2, 3, \ldots.\mathrm{b} \text{ for Beneficial criteria} \tag{14}$$

$$\mathrm{E_{xy}} = \frac{\mathrm{k_y^+} - \mathrm{k_{xy}}}{\mathrm{k_y^+} - \mathrm{k_y^-}}; \quad \mathrm{x} = 1, 2, 3, \ldots \mathrm{a}, \quad \mathrm{y} = 1, 2, 3, \ldots.\mathrm{b} \text{ for Non} - \text{Beneficial criteria} \tag{15}$$

where $\mathrm{k_y^-} = \min(k_y)$ *and* $\mathrm{k_y^+} = \max(k_y)$.

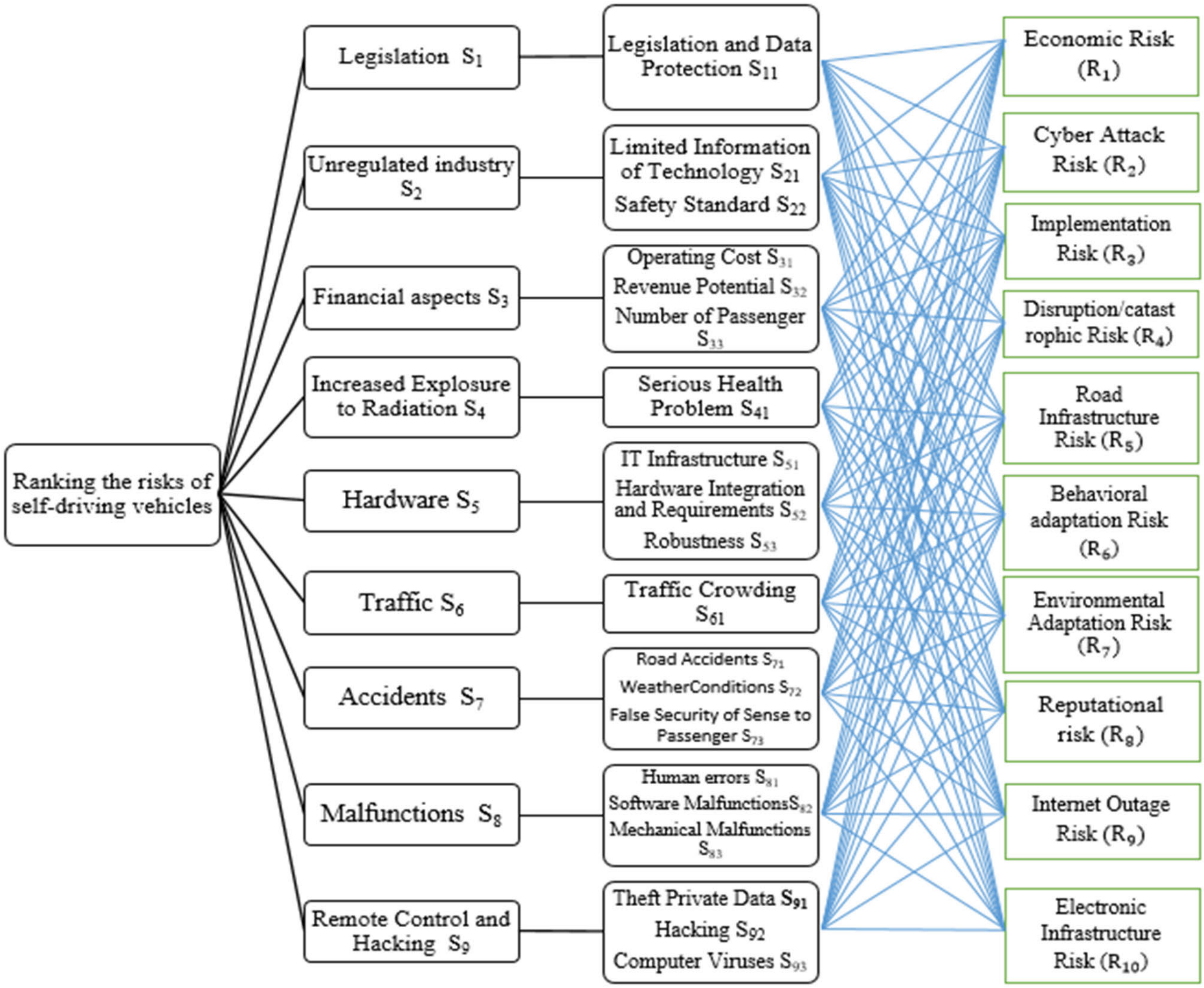

FIGURE 2. **The objective, main criteria, and sub-criteria and risks hierarchy tree.**

TABLE 2. **The aggregated value of decision matrices between the main criteria.**

Criteria	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
S_1	0.5	0.4611	0.2833	0.71113	0.7167	0.2833	0.5	0.8317	0.7167
S_2	2.51134	0.5	0.7167	0.75003	0.2833	0.7167	0.60556	0.8167	0.2833
S_3	3.529827	1.395284	0.5	0.7167	0.750033	0.5	0.2833	0.8167	0.7167
S_4	1.48296	1.33833	1.39528	0.5	0.75003	0.75003	0.35553	0.7167	0.8167
S_5	1.39528	3.52982	1.33833	1.33833	0.5	0.7167	0.8167	0.2833	0.6778
S_6	3.52982	1.39528	2	1.3383	1.39528	0.5	0.75003	0.7167	0.5
S_7	2	1.74148	3.52982	3.0198	1.22444	1.33833	0.5	0.5	0.78336
S_8	1.203125	1.22444	1.22444	1.39528	3.52982	1.39528	2	0.5	0.7167
S_9	1.39528	3.52982	1.39528	1.22444	1.53990	2.30837	1.28138	1.39528	0.5

Step 21. Use the normalized matrix to compute the evaluative difference of y^{th} alternatives concerning other alternatives.

Step 22. Determine the preference function $f_y(a, b)$ as.

$$f_y(a,b) = 0 \; if \; \mathrm{E_{ay}} \leq \mathrm{E_{by}} \tag{16}$$

$$f_y(a,b) = \mathrm{E_{ay}} - \mathrm{E_{by}} \; if \; \mathrm{E_{ay}} \geq \mathrm{E_{by}} \tag{17}$$

Step 23. Then aggregate preference functions value in one matrix as:

$$G(a,b) = \frac{\left[\sum_{y=1}^{o} W_y f_y(a,b)\right]}{\sum_{y=1}^{o} W_y} \tag{18}$$

Step 24. Determine the leaving (Positive) and entering (Negative) outranking flows.

TABLE 3. Final weights for the nine main criteria and twenty sub-criteria.

Main criteria	Sub-criteria	Weights of main criteria	Weights of sub-criteria	Global weights
Legislation S_1	Legislation and data protection S_{11}	0.062	0.062	0.062
Unregulated industry S_2	Limited information on technology S_{21}	0.074	0.033	0.033
	Safety Standard S_{22}		0.040	0.041
Financial aspects S_3	Operating cost S_{31}	0.091	0.014	0.014
	Revenue potential S_{32}		0.030	0.031
	Number of passengers S_{33}		0.046	0.046
Increased exposure to radiation S_4	Serious Health Problem S_{41}	0.088	0.088	0.088
Hardware S_5	IT infrastructure S_{51}	0.106	0.025	0.026
	Hardware integration and Requirements S_{52}		0.036	0.036
	Robustness S_{53}		0.043	0.044
Traffic S_6	Traffic crowding S_{61}	0.119	0.119	0.119
Accidents S_7	Road accidents S_{71}	0.149	0.045	0.046
	Weather conditions S_{72}		0.049	0.049
	False security of sense to passenger S_{73}		0.054	0.054
Malfunctions S_8	Human errors S_{81}	0.152	0.030	0.031
	Software malfunctions S_{82}		0.051	0.051
	Mechanical malfunctions S_{83}		0.069	0.069
Remote control and hacking S_9	Theft private data S_{91}	0.159	0.044	0.045
	Hacking S_{92}		0.052	0.053
	Computer viruses S_{93}		0.061	0.062

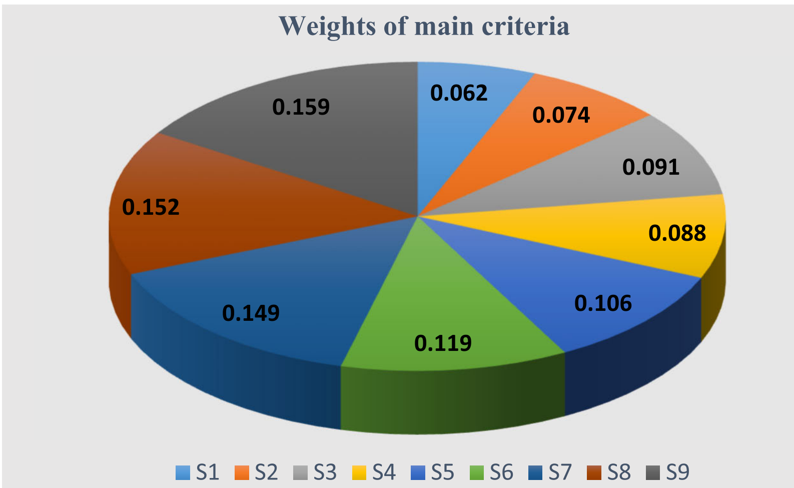

FIGURE 3. Final weights of main criteria.

The leaving flow Ψ^+ is determined [59], [66] as

$$\Psi^+ = \frac{1}{p-1}\sum\nolimits_{b=1}^{p} G(b,a)b = 1, 2, ..p(a \neq b) \quad (19)$$

The negative flow Ψ^+ is determined as.

$$\Psi^- = \frac{1}{p-1}\sum\nolimits_{b=1}^{p} G(b,a)b = 1, 2, \ldots .p(a \neq b) \quad (20)$$

Step 25. The net outranking flow for each risk is determined [52], [66] as:

$$\Psi = \Psi^+ - \Psi^- \quad (21)$$

Step 26. The risks are ranked according to net outranking flow Ψ.

V. APPLICATION

To assess the associated risks, the nine main criteria, twenty sub-criteria, and ten alternatives are proposed based on the ones introduced in [52]. Fig. 2 shows the objective, main and sub-criteria, and risks. With three experts, using Eq (1) and using the scale in Table 1, the opinion of experts are gathered in a pairwise comparison listed in Tables (10-12). The comparison matrix of nine main criteria is proposed for the first, second, and third experts demonstrated in Table 13 to Table 18. The score function is calculated using Eq (2) to obtain the crisp values. The pairwise judgment for three experts is aggregated using Eq (3) and the aggregated decision is estimated using the (4) matrix in Table 2 for the main criteria. The normalized decision matrix is determined using Eq (5) as demonstrated in Table 19, and the row average

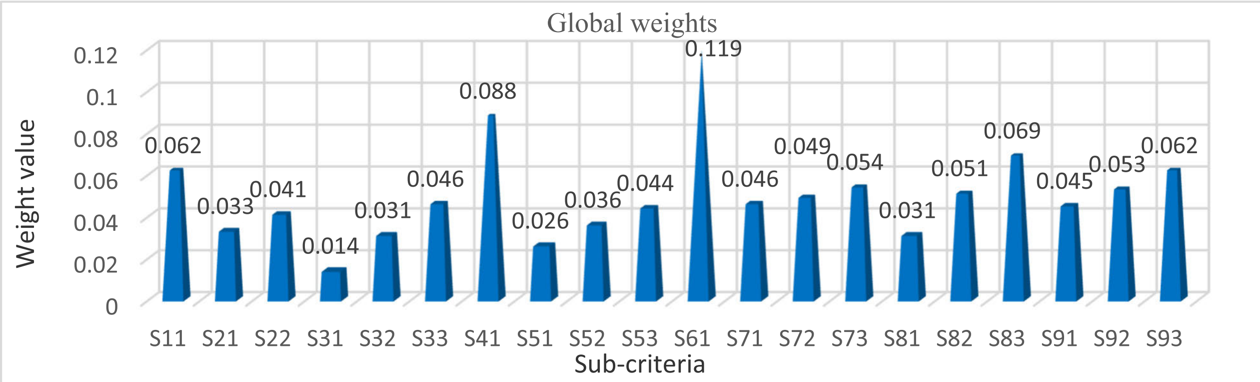

FIGURE 4. The global weights of sub-criteria.

TABLE 4. The aggregated pairwise comparison matrix of three experts for MABAC and PROMETHEE II methods.

Criteria/Risks	S_{11}	S_{21}	S_{22}	S_{31}	S_{32}	S_{33}	S_{41}	S_{51}	S_{52}	S_{53}
R_1	0.4277	0.3611	0.4277	0.7833	0.6778	0.4277	0.3944	0.6444	0.4666	0.3944
R_2	0.6833	0.7500	0.7500	0.7167	0.2833	0.5	0.7500	0.8167	0.7500	0.8167
R_3	0.2833	0.7500	0.5	0.4611	0.7833	0.2833	0.7833	0.7167	0.7500	0.2499
R_4	0.3277	0.7833	0.3555	0.8167	0.6055	0.2499	0.4277	0.7500	0.7167	0.2833
R_5	0.2833	0.7167	0.2833	0.7833	0.5389	0.7167	0.3944	0.3222	0.8167	0.538
R_6	0.7833	0.2499	0.6778	0.7167	0.2833	0.7833	0.7833	0.2833	0.5722	0.7500
R_7	0.7500	0.2166	0.6444	0.8167	0.7500	0.7500	0.7833	0.3611	0.3555	0.7833
R_8	0.2833	0.5	0.3555	0.2499	0.8167	0.2833	0.4277	0.7833	0.6444	0.5389
R_9	0.2833	0.5	0.2833	0.5	0.4277	0.5389	0.7833	0.7167	0.7167	0.1833
R_{10}	0.816	0.8167	0.7167	0.3555	0.4277	0.8167	0.3555	0.7833	0.8167	0.7500

Criteria/Risks	S_{61}	S_{71}	S_{72}	S_{73}	S_{81}	S_{82}	S_{83}	S_{91}	S_{92}	S_{93}
R_1	0.2499	0.7500	0.7167	0.7111	0.7833	0.4277	0.2888	0.5722	0.7500	0.6055
R_2	0.7500	0.8167	0.7500	0.6055	0.8167	0.5778	0.7833	0.2833	0.2166	0.8167
R_3	0.7500	0.1833	0.1833	0.7167	0.6167	0.2833	0.7500	0.5	0.3944	0.4277
R_4	0.2833	0.3944	0.4611	0.7500	0.5722	0.6167	0.8167	0.6167	0.7833	0.2833
R_5	0.8167	0.2833	0.7167	0.5	0.2888	0.5	0.8167	0.1833	0.5	0.7833
R_6	0.7500	0.5722	0.3611	0.1833	0.5055	0.8167	0.5389	0.4277	0.3222	0.7167
R_7	0.1833	0.7500	0.4611	0.6722	0.8167	0.1833	0.3166	0.7167	0.8167	0.5
R_8	0.7833	0.8167	0.6778	0.2888	0.7833	0.6055	0.4611	0.8167	0.5389	0.2833
R_9	0.3611	0.7500	0.1833	0.2833	0.5722	0.7167	0.3555	0.4277	0.6167	0.8167
R_{10}	0.2166	0.5	0.7500	0.7833	0.7167	0.2833	0.8167	0.6167	0.2833	0.6778

TABLE 5. The border approximation matrix for MABAC method.

Border approximation R	S_{11}	S_{21}	S_{22}	S_{31}	S_{32}	S_{33}	S_{41}	S_{51}	S_{52}	S_{53}
	0.985	0.933	0.950	0.847	0.927	0.963	1.03	0.917	0.949	0.962

Border approximation R	S_{61}	S_{71}	S_{72}	S_{73}	S_{81}	S_{82}	S_{83}	S_{91}	S_{92}	S_{93}
	1.06	0.971	0.976	0.986	0.936	0.973	1.008	0.963	0.977	0.997

TABLE 6. The total distance from the border approximation area.

Total distance	$\mathbf{R_1}$	$\mathbf{R_2}$	$\mathbf{R_3}$	$\mathbf{R_4}$	$\mathbf{R_5}$
T	-17.8834	-17.5799	-17.8047	-17.8966	-17.833
Total distance	$\mathbf{R_6}$	$\mathbf{R_7}$	$\mathbf{R_8}$	$\mathbf{R_9}$	$\mathbf{R_{10}}$
T	-17.731	-17.775	-17.8106	-17.8606	-17.7662

is determined using Eq (6), then the weights of main and sub-criteria are illustrated in Table 3.

Fig. 3 shows the final weights of the main criteria and the relationship between the main criteria of the proposed model on the vertical axis and the values of the weights on the horizontal axis for each criterion. Fig. 4 depicted the global weights of sub-criteria, as it reveals the relationship between the sub-criteria of the proposed model on the vertical line and the values of the weights on the horizontal line for each criterion. The consistency is tested. CR is estimated

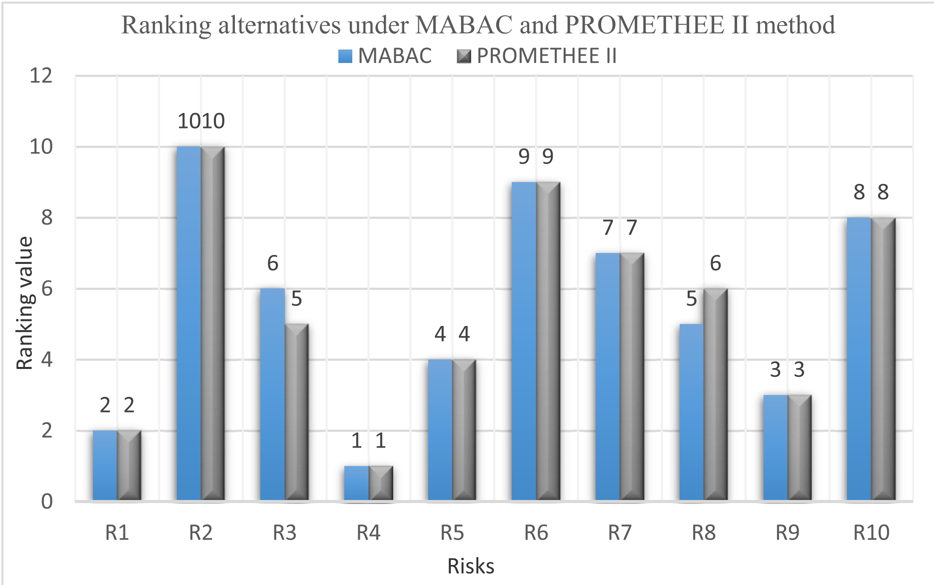

FIGURE 5. Ranking of MABAC and PROMETHEE II.

TABLE 7. The leaving, entering and net outranking flows.

Risks	Leaving outranking flows	Entering outranking flows	Net outranking flows
R_1	0.161594	0.253349	-0.09175
R_2	0.300929	0.102792	0.198137
R_3	0.216493	0.22853	-0.01204
R_4	0.162914	0.266289	-0.10338
R_5	0.210857	0.245701	-0.03484
R_6	0.273292	0.203068	0.070223
R_7	0.25494	0.232378	0.022562
R_8	0.214574	0.22617	-0.0116
R_9	0.187804	0.261852	-0.07405
R_{10}	0.257034	0.220301	0.036733

TABLE 8. The proposed and compared study ranking with different MCDM methods.

Ranking	alternatives of compared study				Criteria and risks of compared study (previous study)	
	MABAC	PROMETHEE II	TOPSIS	VICKOR		
1	R_2	R_2	R_2	R_2	Electronic infrastructure risk R_1	Hacking and Privacy Factors (C_1)
2	R_3	R_5	R_4	R_4	Cyber-attack risk R_2	Malicious Hacking (C_{11})
3	R_5	R_3	R_5	R_1	Environmental adaptation risk R_3	Information Security (C_{12})
4	R_7	R_4	R_1	R_5	Reputational risk R_4	Malfunction of AVs components (C_2)
5	R_1	R_1	R_3	R_3	Internet outage risk R_5	Hardware and Software System
6	R_4	R_7	R_7	A6	Behavioral adaptation risk R_6	Failure (C_{21})
7	R_8	R_6	R_6	R_7	Road infrastructure risk R_7	Mechanical failure (C_{22})
						Environmental Factors (C_3)
						Infrastructure condition (C_{31})
						Weather condition (C_{32})
8	R_2	R_8	R_2	R_2	Disruption/catastrophic risk R_8	Traffic Congestion (C_4)
						Availability of Required Information (C_5)
						Social Acceptance (C_6)
						Legislation and Legal Liability (C_7)

using Eq (7). CR is set at 0.079, which is less than 0.1 to be accepted. Consequently, the weights of the criteria are consistent.

The results of MABAC started with the opinion of three experts in a comparison matrix with the scale of SVNNs; after that, this scale is converted to a crisp value and three comparison matrices are aggregated in one matrix using Eqs. (1-4). The comparison matrix between the criteria and alternatives is listed in Table 4. From the aggregated comparison matrix, the normalized matrix

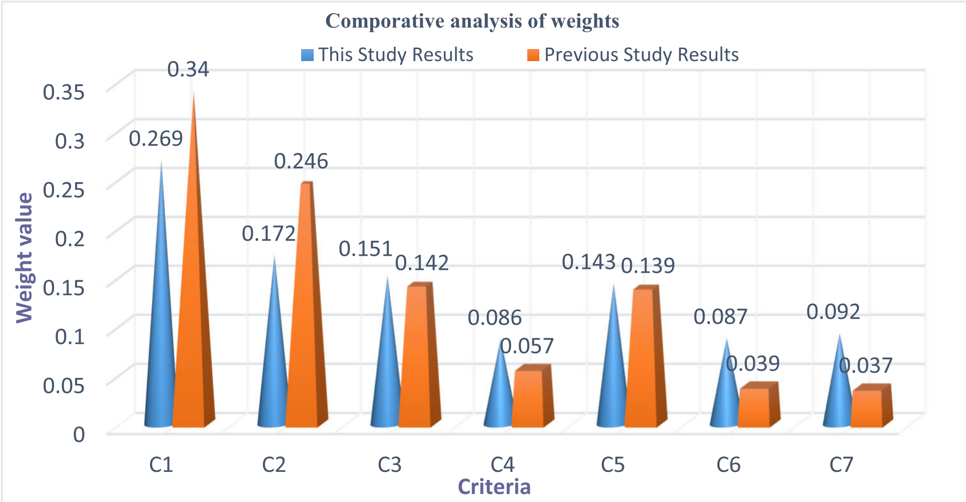

FIGURE 6. The comparative analysis of main criteria weights between pythagorean fuzzy and neutrosophic AHP.

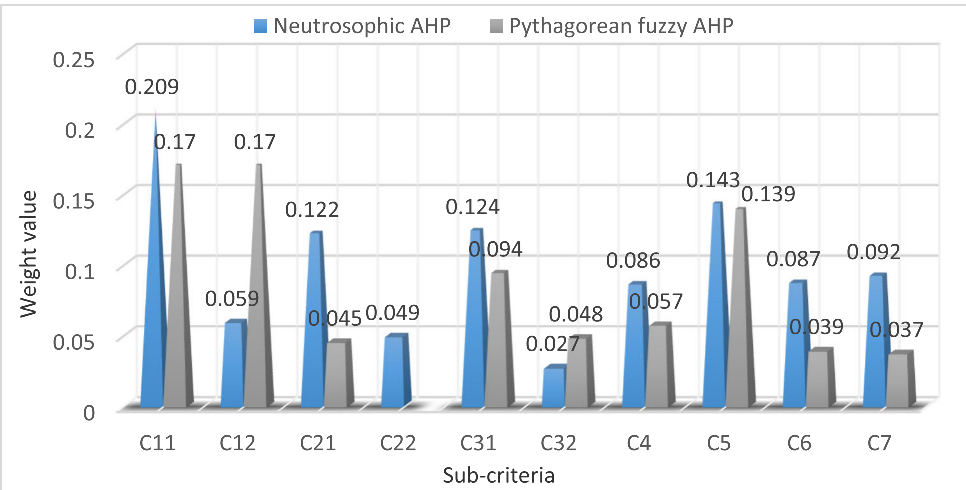

FIGURE 7. Comparative of sub-criteria global weights between pythagorean fuzzy and neutrosophic AHP.

is estimated using Eqs. (8-9). In Table 20, the normalized decision matrix for the MABAC method for positive and negative criteria, where the operating cost S_{31} is negative (non-beneficial) criteria and the rest of criteria positive (beneficial), applying Eq (9) for S_{31} and the rest Eq (8). From the normalized decision matrix, the weighted normalized decision matrix is estimated using Eq (10) as demonstrated in Table 21. The border approximation area matrix is calculated using Eq (11) as illustrated in Table 5.

The distance from the border approximation area is measured using Eq (12), as listed in Table 21. The total distance from the border approximation area is obtained from Eq (13) as demonstrated in Table 6. The ranking of alternatives by total distance is calculated. Fig. 5 shows this ranking, where the cyber-attack R_2 is considered as the best alternative and has a higher ranking than the disruption risk R_4. Fig. 5 shows the relationship between the risks on the vertical axis and the ranking values on the horizontal line for each risk.

The PROMETHEE II results: Eqs. (1-4) is applied to obtain the aggregated pairwise comparison matrix from the opinion of three experts. Then the normalized decision matrix is estimated using Eqs. (14-15), as listed in Table 23. Eq. (15) is used for calculating negative criteria (operating cost S_{31}) and the rest criteria are positive criteria using Eq (14). Then, the evaluative difference is estimated for R_1- R_2, R_1- R_3, R_1- R_4, R_1- R_5, R_1- R_6, etc, to risk 10. Then, using Eqs. (16-17), the preference function is measured if R_1- R_2 is less or equal to 0, and the preference function is zero if R_1- $R_2 > 0$ then the preference function is R_1- R_2. The preference in the preference matrix is calculated using Eq (18), as demonstrated in Table 24. Then, the leaving and entering outranking flows are measured using Eqs. (19-20), as listed in Table 7. The net outranking flows are measured using Eq (21), as listed in Table 7.

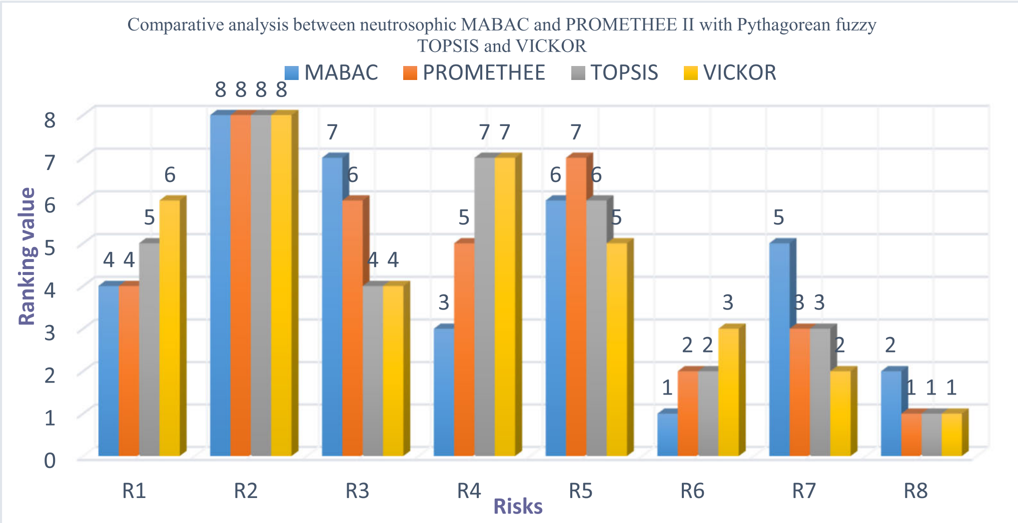

FIGURE 8. Comparative analysis of MCDM methods.

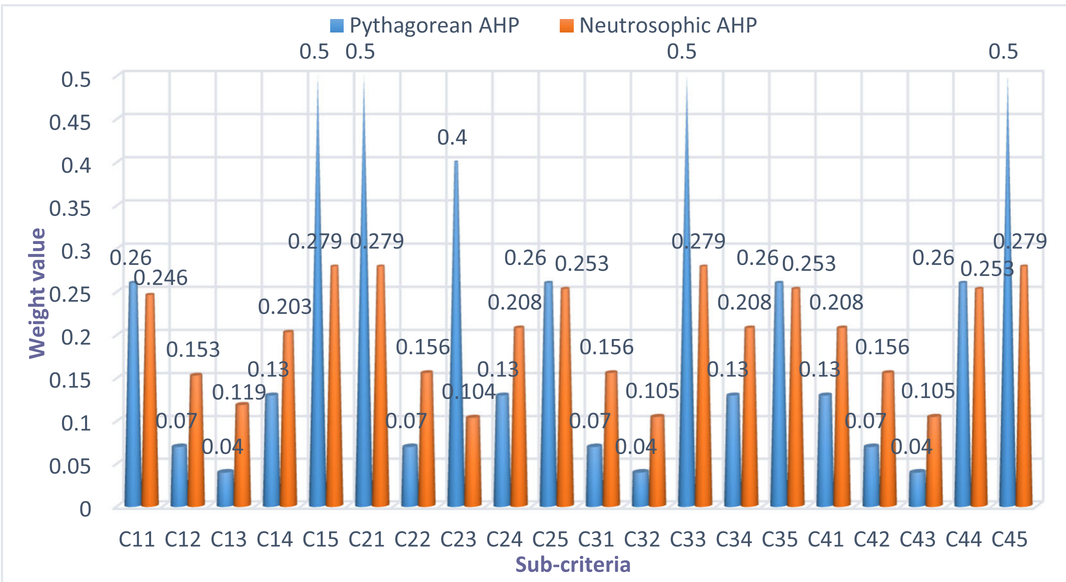

FIGURE 9. Comparative analysis between pythagorean AHP and neutrosophic AHP.

TABLE 9. The aggregation rank in differ scenarios.

Rank	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10
1	R_2	R_6	R_2	R_7	R_7	R_7	R_2	R_2	R_2	R_7
2	R_6	R_2	R_7	R_{10}	R_{10}	R_{10}	R_6	R_6	R_7	R_2
3	R_7	R_{10}	R_3	R_6	R_6	R_6	R_3	R_3	R_6	R_9
4	R_{10}	R_7	R_6	R_2	R_2	R_2	R_5	R_5	R_{10}	R_6
5	R_3	R_1	R_1	R_5	R_5	R_5	R_8	R_8	R_3	R_{10}
6	R_8	R_3	R_9	R_8	R_8	R_8	R_9	R_9	R_8	R_1
7	R_9	R_8	R_4	R_3	R_3	R_3	R_{10}	R_{10}	R_1	R_5
8	R_5	R_4	R_{10}	R_9	R_9	R_9	R_7	R_7	R_9	R_8
9	R_1	R_9	R_8	R_1	R_4	R_4	R_4	R_4	R_4	R_3
10	R_4	R_5	R_5	R_4	R_1	R_1	R_1	R_1	R_5	R_4

A. RESULTS AND DISCUSSION

In this work, three experts were asked to assess the judgment comparison by single-valued neutrosophic scale for main criteria, sub-criteria, and risks for each criterion. Then three judgment comparison matrices were used from the main criteria and each sub-criteria in three comparison

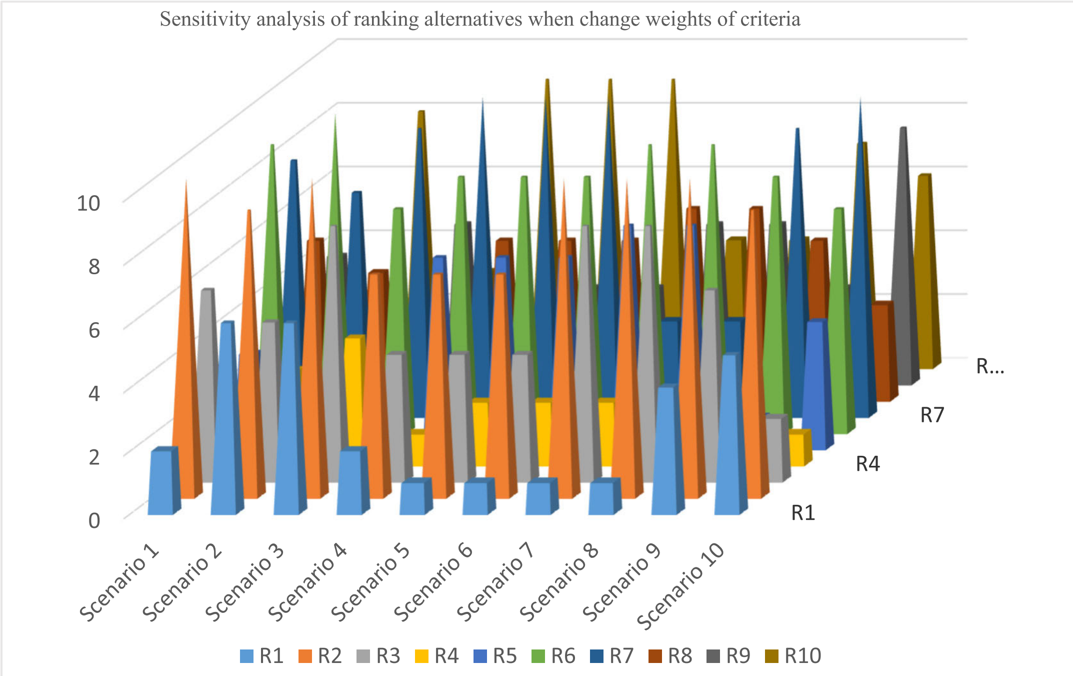

FIGURE 10. Sensitivity analysis of ranking alternatives.

TABLE 10. Evaluation pairwise comparison matrix for nine main criteria by first expert.

Criteria	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
S_1	0.5	B	B	VG	G	B	M	VG	G
S_2	1/B	0.5	G	VG	B	G	VG	VG	B
S_3	1/B	1/G	0.5	G	VG	M	B	VG	G
S_4	1/VG	1/VG	1/G	0.5	G	VG	M	G	VG
S_5	1/G	1/B	1/VG	1/G	0.5	G	VG	B	G
S_6	1/B	1/G	1/M	1/VG	1/G	0.5	G	G	M
S_7	1/M	1/VG	1/B	1/M	1/VG	1/G	0.5	M	VG
S_8	1/VG	1/G	1/VG	1/G	1/B	1/G	1/M	0.5	G
S_9	1/G	1/B	1/G	1/VG	1/G	1/M	1/VG	1/G	0.5

TABLE 11. Evaluation pairwise comparison matrix for nine main criteria by second expert.

Criteria	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
S_1	0.5	MB	B	VG	G	B	M	VG	G
S_2	1/MB	0.5	G	G	B	G	M	VG	B
S_3	1/B	1/G	0.5	G	VG	M	B	VG	G
S_4	1/VG	1/G	1/G	0.5	G	G	B	G	VG
S_5	1/G	1/B	1/VG	1/G	0.5	G	VG	B	VG
S_6	1/B	1/G	1/M	1/G	1/G	0.5	G	G	B
S_7	1/M	1/M	1/B	1/B	1/VG	1/G	0.5	M	G
S_8	1/VG	1/VG	1/VG	1/G	1/B	1/G	1/M	0.5	G
S_9	1/G	1/B	1/G	1/VG	1/VG	1/B	1/G	1/G	0.5

matrices. Then the comparison matrices are aggregated in one matrix for main and sub-criteria. After that, the AHP method is applied.

By applying the neutrosophic AHP, the study found that traffic S_6 has the highest weight in the main criteria with a value of 0.119, the legislation S_1 has the least weight in the main criteria with a value equals to 0.062.

In global weights of sub-criteria, the traffic crowding criterion S_{61} has the highest weight with a value equals 0.119 and the operating cost criterion S_{31} is the least weight in global criteria with a value equals 0.014. CR is used to determine the opinions of experts are valid or not. It is found that CR equal to 0.079 which is less than 0.1; hence, we conclude that the experts' opinions are consistent. The three experts are asked to assess in a pairwise comparison matrix

TABLE 12. Evaluation pairwise comparison matrix for nine main criteria by third expert.

Criteria	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
S_1	0.5	G	B	M	G	B	M	G	VG
S_2	1/G	0.5	G	G	B	G	M	VG	B
S_3	1/B	1/G	0.5	G	G	M	B	VG	G
S_4	1/M	1/G	1/G	0.5	VG	G	B	G	VG
S_5	1/G	1/B	1/G	1/VG	0.5	G	VG	B	M
S_6	1/B	1/G	1/M	1/G	1/G	0.5	VG	G	G
S_7	1/M	1/M	1/B	1/B	1/VG	1/VG	0.5	M	VG
S_8	1/G	1/VG	1/VG	1/G	1/B	1/G	1/M	0.5	G
S_9	1/VG	1/B	1/G	1/VG	1/M	1/G	1/VG	1/G	0.5

TABLE 13. Evaluation pairwise comparison matrix for sub-criteria of unregulated industry criterion by all experts.

First expert	S_{21}	S_{22}
S_{21}	0.5	VG
S_{22}	1/VG	0.5
Second expert	S_{21}	S_{22}
S_{21}	0.5	VVG
S_{22}	1/VVG	0.5
Third expert	S_{21}	S_{22}
S_{21}	0.5	VG
S_{22}	1/VG	0.5

TABLE 14. Evaluation pairwise comparison matrix for sub-criteria of financial aspects criterion by all experts.

First expert	S_{31}	S_{32}	S_{33}
S_{31}	0.5	B	M
S_{32}	1/B	0.5	MB
S_{33}	1/M	1/MB	0.5
Second expert	S_{31}	S_{32}	S_{33}
S_{31}	0.5	M	MB
S_{32}	1/M	0.5	M
S_{33}	1/MB	1/M	0.5
Third expert	S_{31}	S_{32}	S_{33}
S_{31}	0.5	MB	B
S_{32}	1/MB	0.4	G
S_{33}	1/B	1/G	0.5

TABLE 15. Evaluation pairwise comparison matrix for sub-criteria of hardware criterion by all experts.

First expert	S_{51}	S_{52}	S_{53}
S_{51}	0.5	VG	M
S_{52}	1/VG	0.5	VVG
S_{53}	1/M	1/VVG	0.5
Second expert	S_{51}	S_{52}	S_{53}
S_{51}	0.5	VVG	VVG
S_{52}	1/VVG	0.5	VG
S_{53}	1/VVG	1/VG	0.5
Third expert	S_{51}	S_{52}	S_{53}
S_{51}	0.5	VG	VVG
S_{52}	1/VG	0.5	VG
S_{53}	1/VVG	1/VG	0.5

between criteria and alternatives. That is we have three pairwise comparison matrices. After that, the three matrices are aggregated into one matrix to allow for the application of MABAC and PROMETHEE II methods to rank risks.

In applying MABAC, start with the aggregated decision matrix. The MABAC results as follows, cyber-attack risk R_2 is the highest-ranking with a total distance value equal to -17.5799 and disruption/catastrophic risk R_4 is the least ranking of alternatives with a total distance value equal to -17.8966.

The PROMETHEE II results are as follows, cyberattack risk R_2 is the highest-ranking with net outranking flow value equal 0.198137 and disruption/catastrophic risk R_4 is the least ranking of alternatives with a net outranking flow value equal to -0.10338.

TABLE 16. Evaluation pairwise comparison matrix for sub-criteria of accidents criterion by all experts.

First expert	S_{71}	S_{72}	S_{73}
S_{71}	0.5	VG	VVG
S_{72}	1/VG	0.5	VVG
S_{73}	1/VVG	1/VVG	0.5
Second expert	S_{71}	S_{72}	S_{73}
S_{71}	0.5	VVG	VVG
S_{72}	1/VVG	0.5	VG
S_{73}	1/VVG	1/VG	0.5
Third expert	S_{71}	S_{72}	S_{73}
S_{71}	0.5	VG	VVG
S_{72}	1/VG	0.5	VG
S_{73}	1/VVG	1/VG	0.5

TABLE 17. Evaluation pairwise comparison matrix for sub-criteria of malfunctions criterion by all experts.

First expert	S_{81}	S_{82}	S_{83}
S_{81}	0.5	G	B
S_{82}	1/G	0.5	VG
S_{83}	1/B	1/VG	0.5
Second expert	S_{81}	S_{82}	S_{83}
S_{81}	0.5	VG	M
S_{82}	1/VG	0.5	G
S_{83}	1/M	1/G	0.5
Third expert	S_{81}	S_{82}	S_{83}
S_{81}	0.5	VB	G
S_{82}	1/VB	0.5	M
S_{83}	1/G	1/M	0.5

TABLE 18. Evaluation pairwise comparison matrix for sub-criteria of remote control and hacking criterion by all experts.

First expert	S_{91}	S_{92}	S_{93}
S_{91}	0.5	VG	G
S_{92}	1/VG	0.5	VG
S_{93}	1/G	1/VG	0.5
Second expert	S_{91}	S_{92}	S_{93}
S_{91}	0.5	VG	G
S_{92}	1/VG	0.5	VG
S_{93}	1/G	1/VG	0.5
Third expert	S_{91}	S_{92}	S_{93}
S_{91}	0.5	VG	VG
S_{92}	1/VG	0.5	VG
S_{93}	1/VG	1/VG	0.5

TABLE 19. The normalized matrix of nine main criteria for AHP method.

Criteria	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
S_1	0.0284	0.0305	0.0228	0.0646	0.0670	0.0332	0.0704	0.1220	0.1305
S_2	0.1431	0.0330	0.0578	0.0682	0.0265	0.0842	0.0853	0.1248	0.0493
S_3	0.2011	0.0923	0.0403	0.0651	0.0701	0.0587	0.0399	0.1248	0.1247
S_4	0.0845	0.0885	0.1126	0.0454	0.0701	0.0881	0.0501	0.1095	0.1421
S_5	0.0795	0.2335	0.1080	0.1217	0.0467	0.0842	0.1151	0.0432	0.1179
S_6	0.2011	0.0923	0.1615	0.1217	0.1305	0.0587	0.1057	0.1095	0.0870
S_7	0.1139	0.1152	0.2850	0.2746	0.1145	0.1572	0.0704	0.0764	0.1363
S_8	0.0718	0.0810	0.0988	0.1269	0.3302	0.1639	0.2819	0.0764	0.1247
S_9	0.0762	0.2335	0.1126	0.1113	0.1440	0.2712	0.1806	0.2132	0.0870

VI. COMPARATIVE ANALYSIS

A. FIRST COMPARATIVE ANALYSIS

The comparative analysis is used to give the proposed hybrid method robustness and effectiveness. To do so, we compared the proposed model under the neutrosophic environment with this study. It produced a model with Pythagorean fuzzy AHP, TOPSIS, and VIKOR. Comparing the previous studies with ours is detailed below. Analysis of (neutrosophic AHP and Pythagorean fuzzy AHP [52], (neutrosophic MABAC and Pythagorean fuzzy TOPSIS),

TABLE 20. The normalized decision matrix by MABAC method.

Criteria/Risks	S_{11}	S_{21}	S_{22}	S_{31}	S_{32}	S_{33}	S_{41}	S_{51}	S_{52}	S_{53}
R_1	0.2708	0.8889	0.3095	0.0624	0.7395	0.3137	0.0909	0.6771	0.2409	0.3333
R_2	0.7500	0.8889	1.000	0.1874	0	0.4411	0.9220	1	0.8554	1
R_3	0	0.9444	0.4642	0.6666	0.9375	0.0588	0.9999	0.8125	0.8554	0.1052
R_4	0.0833	0.8333	0.1547	0	0.6041	0	0.1688	0.8750	0.7831	0.1578
R_5	0	0.0555	0	0.0624	0.4791	0.8235	0.0909	0.0729	1	0.5614
R_6	0.9375	0	0.8452	0.1874	0	0.9411	0.9999	0	0.4698	0.8947
R_7	0.8750	0.4722	0.7738	0	0.8750	0.8823	0.9999	0.1458	0	0.9473
R_8	0	0.4722	0.1547	1.062	1	0.0588	0.1688	0.9375	0.6265	0.5614
R_9	0	1	0	0.5937	0.2708	0.5098	0.9999	0.8125	0.7831	0
R_{10}	1	0.3610	0.9285	0.8645	0.2708	1	0	0.9375	1	0.8947

Criteria/Risks	S_{61}	S_{71}	S_{72}	S_{73}	S_{81}	S_{82}	S_{83}	S_{91}	S_{92}	S_{93}
R_1	0.1052	0.8947	0.9411	0.8796	0.9368	0.3859	0	0.6140	0.8889	0.6041
R_2	0.8947	1	1.000	0.7036	1	0.6228	0.9368	0.1578	0	1
R_3	0.8947	0	0	0.8888	0.6210	0.1578	0.8736	0.5	0.2963	0.2708
R_4	0.1578	0.3333	0.4901	0.9444	0.5368	0.6842	1	0.6842	0.9444	0
R_5	1	0.1578	0.9411	0.5277	0	0.5	1	0	0.4722	0.9375
R_6	0.8947	0.6140	0.3137	0	0.4105	1	0.4736	0.3859	0.1759	0.8125
R_7	0	0.8947	0.4901	0.8147	1	0	0.0525	0.8421	1	0.4062
R_8	0.9473	1	0.8725	0.1759	0.9368	0.6666	0.3262	1	0.5370	0
R_9	0.2807	0.8947	0	0.1666	0.5368	0.8421	0.12629	0.3859	0.6667	1
R_{10}	0.0526	0.5	1.000	0.9999	0.8105	0.1578	1	0.6842	0.1111	0.7395

and (neutrosophic PROMETHEE II and Pythagorean fuzzy VIKOR results are detailed.

First, the data from the previous study [52] are used to apply our hybrid method. Then, the seven main criteria, ten global criteria, and eight risks are used. Table 8 shows the criteria and alternatives of the compared study. First, the neutrosophic set and the AHP method are applied to obtain the weights of the main criteria. This shows that the hacking and privacy factors (C_1) is the highest importance and the traffic factor C_4 is the least important. And the reaming importance are ordered as $C_1 > C_2 > C_3 > C_5 > C_7 > C_6 > C_4$. Fig. 6 shows the comparative analysis of criteria weights between this study (proposed model) and the previous study [52]. Fig. 6 shows the relationship between the main criteria on the vertical axis and the values of the weights on the horizontal axis. The compared study (Pythagorean fuzzy AHP) finds that S_1 has the importance of the height and C_7 has the worst importance of the remaining criteria importance as $C_1 > C_2 > C_3 > C_5 > C_4 > C_6 > C_7$. Then find the sub-criteria and global criteria. By this model we found that the C_{11} has the largest weight of global criteria, and C_{32} has the least important in global criteria. But in the compared study (Pythagorean fuzzy AHP) C_{22} has the highest importance and S_{71} has the least weight of global criteria. Fig. 7 shows the global weights of sub-criteria of neutrosophic AHP and Pythagorean fuzzy AHP.

Applying the neutrosophic MABAC method to this model, the R_2 (Cyber Attack Risk) has the highest risk, and the R_6 (Behavioral adaptation Risk) has the least risk. When applying the PROMETHEE II method, find that R_2(Cyber Attack Risk) has the best alternative and R_8 (Disruption/catastrophic Risk) has the least risk. But the compared study (Pythagorean fuzzy TOPSIS) find the R_2 (Cyber Attack Risk) has the best alternative and the R_8 (Disruption/catastrophic Risk) has the worst alternative, and the Pythagorean fuzzy VICKOR method find that R_2 (Cyber Attack Risk) has the height risk and R_8 (Disruption/catastrophic Risk) has the least risk. Table 8 shows the proposed and compared study MCDM methods ranking. Fig. 8. Show the ranking risks under comparative methods. We conclude that the suggested hybrid model is a useful approach to deal with MCDM. The neutrosophic sets, AHP, PROMETHEE II and MABAC, are the consistent methods compared with other methods.

B. SECOND COMPARATIVE ANALYSIS

Another comparative analysis has been performed to compare between Pythagorean fuzzy AHP and neutrosophic AHP using the main and sub-criteria from [10]. In Table 25, the main and sub-criteria are presented. The analysis was made by sub-criteria. In Pythagorean fuzzy AHP sub-criteria found in C_1 (Hardware Requirements) that C_{15} (Incorrect specifications of hardware) has the highest weights equal 0.5 and the least weight is C_{13} (Safety lifecycle steps for hardware) with a value of 0.04. In C_2 (Hardware Integration) sub-criteria found C_{21} (Functional testing under) is the highest weight equal to 0.5 and C_{23} (Mechanical endurance test) is the least weight with 0.04. In the C_3 found that C_{35} is the highest weight and C_{32} is the least weight with 0.04. In C_4 found that c_{45} is the highest weight with 0.5 and C_{43} is the least weight with 0.04.

For the neutrosophic AHP results, in C_1, we found that C_{15} has the highest weight 0.279 with and C_{13} has the least weight with 0.119. In C_2 found that C_{21} has the highest weight with 0.279 and C_{23} has the least weight with 0.104. In C_3 (Supporting Processes) found that C_{33} (Qualification of software components) has the highest weight with 0.279 and C_{32} (Qualification of hardware components) has the least weight with 0.104. In C_4 (Others) found that C_{45} (Loss of energy supply or disturbances) has the highest weight

TABLE 21. The weighted normalized decision matrix. For MABAC method.

Criteria/Risks	S_{11}	S_{21}	S_{22}	S_{31}	S_{32}	S_{33}	S_{41}	S_{51}	S_{52}	S_{53}
R_1	0.0787	0.0623	0.0536	0.0148	0.0539	0.0604	0.0960	0.0436	0.0446	0.0586
R_2	0.1085	0.0623	0.082	0.0166	0.031	0.0662	0.1691	0.052	0.0667	0.088
R_3	0.062	0.0641	0.0600	0.0233	0.0600	0.0487	0.1759	0.0471	0.0667	0.0486
R_4	0.0671	0.0605	0.0473	0.014	0.0497	0.046	0.1028	0.048	0.0641	0.0509
R_5	0.062	0.0348	0.041	0.0148	0.0458	0.0838	0.0960	0.0278	0.072	0.0687
R_6	0.1201	0.033	0.0756	0.0166	0.031	0.0892	0.1759	0.026	0.0529	0.0833
R_7	0.1162	0.0485	0.0727	0.014	0.0581	0.0865	0.1759	0.0297	0.036	0.0856
R_8	0.062	0.0485	0.0473	0.0288	0.062	0.0487	0.1028	0.0503	0.0585	0.0687
R_9	0.062	0.066	0.041	0.0223	0.0393	0.0694	0.1759	0.0471	0.0641	0.044
R_{10}	0.124	0.0210	0.0790	0.0261	0.0393	0.092	0.088	0.0503	0.072	0.0833
Criteria/Risks	S_{61}	S_{71}	S_{72}	S_{73}	S_{81}	S_{82}	S_{83}	S_{91}	S_{92}	S_{93}
R_1	0.1315	0.0871	0.0951	0.1014	0.0600	0.0706	0.069	0.0726	0.1001	0.0994
R_2	0.2254	0.092	0.098	0.092	0.062	0.0827	0.1336	0.0521	0.053	0.124
R_3	0.2254	0.046	0.049	0.102	0.0502	0.0590	0.1292	0.0675	0.0687	0.0787
R_4	0.1377	0.0613	0.0730	0.105	0.0476	0.0858	0.138	0.0757	0.1030	0.062
R_5	0.238	0.0532	0.0951	0.0825	0.031	0.0765	0.138	0.045	0.0780	0.1201
R_6	0.2254	0.0742	0.0643	0.054	0.0437	0.102	0.1016	0.0623	0.0623	0.1123
R_7	0.119	0.0871	0.0730	0.0979	0.062	0.051	0.0726	0.0828	0.106	0.0871
R_8	0.2317	0.092	0.0917	0.0635	0.0600	0.085	0.0915	0.09	0.0814	0.062
R_9	0.1524	0.0871	0.049	0.0629	0.0476	0.0939	0.0777	0.0623	0.0883	0.124
R_{10}	0.1252	0.069	0.098	0.108	0.0561	0.0590	0.138	0.0757	0.0588	0.1078

TABLE 22. The distance from the border approximation area.

Criteria/Risks	S_{11}	S_{21}	S_{22}	S_{31}	S_{32}	S_{33}	S_{41}	S_{51}	S_{52}	S_{53}
R_1	-0.906	-0.870	-0.896	-0.848	-0.873	-0.903	-0.935	-0.873	-0.905	-0.903
R_2	-0.876	-0.870	-0.868	-0.847	-0.896	-0.897	-0.86	-0.865	-0.883	-0.874
R_3	-0.923	-0.869	-0.890	-0.840	-0.86	-0.915	-0.855	-0.870	-0.883	-0.913
R_4	-0.918	-0.872	-0.902	-0.849	-0.877	-0.917	-0.928	-0.868	-0.885	-0.911
R_5	-0.923	-0.898	-0.909	-0.848	-0.881	-0.879	-0.935	-0.889	-0.877	-0.893
R_6	-0.865	-0.900	-0.874	-0.847	-0.896	-0.874	-0.855	-0.891	-0.896	-0.878
R_7	-0.869	-0.884	-0.877	-0.849	-0.869	-0.877	-0.855	-0.887	-0.913	-0.876
R_8	-0.923	-0.884	-0.902	-0.834	-0.865	-0.915	-0.928	-0.867	-0.891	-0.893
R_9	-0.923	-0.867	-0.909	-0.841	-0.887	-0.894	-0.855	-0.870	-0.885	-0.918
R_{10}	-0.861	-0.912	-0.871	-0.837	-0.887	-0.871	-0.943	-0.867	-0.877	-0.878
Criteria/Risks	S_{61}	S_{71}	S_{72}	S_{73}	S_{81}	S_{82}	S_{83}	S_{91}	S_{92}	S_{93}
R_1	-0.929	-0.884	-0.881	-0.884	-0.876	-0.903	-0.939	-0.890	-0.877	-0.898
R_2	-0.835	-0.879	-0.878	-0.894	-0.874	-0.890	-0.874	-0.910	-0.924	-0.873
R_3	-0.835	-0.925	-0.927	-0.884	-0.886	-0.914	-0.879	-0.895	-0.909	-0.918
R_4	-0.923	-0.910	-0.903	-0.881	-0.889	-0.887	-0.870	-0.887	-0.874	-0.935
R_5	-0.823	-0.918	-0.881	-0.903	-0.905	-0.897	-0.870	-0.918	-0.899	-0.877
R_6	-0.835	-0.897	-0.911	-0.932	-0.893	-0.871	-0.906	-0.900	-0.915	-0.885
R_7	-0.942	-0.884	-0.903	-0.888	-0.874	-0.922	-0.935	-0.880	-0.871	-0.910
R_8	-0.829	-0.879	-0.884	-0.922	-0.876	-0.888	-0.917	-0.873	-0.896	-0.935
R_9	-0.908	-0.884	-0.927	-0.923	-0.889	-0.879	-0.930	-0.900	-0.889	-0.873
R_{10}	-0.935	-0.902	-0.878	-0.878	-0.880	-0.914	-0.870	-0.887	-0.919	-0.889

with 0.279 and C_{43} (Sufficiency of the resources to support the functionality) has the least value with 0.104. Fig. 9 shows the comparative analysis between Pythagorean AHP and neutrosophic AHP.

VII. SENSITIVITY ANALYSIS

The rank of risks is correlated with the weights of criteria. So, this change should be assessed. In this study, we show the sensitivity of how the rank of alternatives alteration due to change weights of criteria. The weights of criteria will be changed by 5% or 50% increased or decreased. When the criterion weight increased, the remaining will decrease. Table 26 lists the ten scenarios of altering the weights of criteria. When weights increase or decrease the sum of all weights must be equal to 1. In scenario 1, every weight of criteria is treated as equally important. The following nine other scenarios focus on legislation, unregulated industry, financial aspects, increased exposure to radiation, hardware, traffic, accidents, malfunctions, and remote control and hacking.

Ranking alternatives with different scenarios with MABAC and PROMETHEE II methods is shown in Table 27. The ranking of alternatives is different from MABAC and PROMETEE II methods and several scenarios. In scenario 1, R_2 is the best alternative and R_4 is the worst alternative. In scenario 2, R_6 is the best alternative and R_5 is the worst alternative. In scenario 3, R_2 is the best alternative and R_5 is the worst alternative. In scenario 4, R_7 is the best alternative

TABLE 23. The normalized matrix of decision matrix by PROMETHEE II method.

Criteria/Risks	S_{11}	S_{21}	S_{22}	S_{31}	S_{32}	S_{33}	S_{41}	S_{51}	S_{52}	S_{53}
R_1	0.2708	0.8889	0.3095	0.0588	0.7395	0.3137	0.0909	0.6771	0.2409	0.3333
R_2	0.7500	0.8889	1.000	0.1764	0	0.4411	0.9220	1	0.8554	1
R_3	0	0.9444	0.4642	0.6274	0.9375	0.0588	0.9999	0.8125	0.8554	0.1052
R_4	0.0833	0.8333	0.1547	0	0.6041	0	0.1688	0.8750	0.7831	0.1578
R_5	0	0.0555	0	0.0588	0.4791	0.8235	0.0909	0.0729	1	0.5614
R_6	0.9375	0	0.8452	0.1764	0	0.9411	0.9999	0	0.4698	0.8947
R_7	0.8750	0.4722	0.7738	0	0.8750	0.8823	0.9999	0.1458	0	0.9473
R_8	0	0.4722	0.1547	1.0000	1	0.0588	0.1688	0.9375	0.6265	0.5614
R_9	0	1	0	0.5588	0.2708	0.5098	0.9999	0.8125	0.7831	0
R_{10}	1	0.3610	0.9285	0.8137	0.2708	1	0	0.9375	1	0.8947
Criteria/Risks	S_{61}	S_{71}	S_{72}	S_{73}	S_{81}	S_{82}	S_{83}	S_{91}	S_{92}	S_{93}
R_1	0.1052	0.8947	0.9411	0.8796	0.9368	0.3859	0	0.6140	0.8889	0.6041
R_2	0.8947	1	1.000	0.7036	1	0.6228	0.9368	0.1578	0	1
R_3	0.8947	0	0	0.8888	0.6210	0.1578	0.8736	0.5	0.2963	0.2708
R_4	0.1578	0.3333	0.4901	0.9444	0.5368	0.6842	1	0.6842	0.9444	0
R_5	1	0.1578	0.9411	0.5277	0	0.5	1	0	0.4722	0.9375
R_6	0.8947	0.6140	0.3137	0	0.4105	1	0.4736	0.3859	0.1759	0.8125
R_7	0	0.8947	0.4901	0.8147	1	0	0.0525	0.8421	1	0.4062
R_8	0.9473	1	0.8725	0.1759	0.9368	0.6666	0.3262	1	0.5370	0
R_9	0.2807	0.8947	0	0.1666	0.5368	0.8421	0.12629	0.3859	0.6667	1
R_{10}	0.0526	0.5	1.000	0.9999	0.8105	0.1578	1	0.6842	0.1111	0.7395

TABLE 24. The aggregation of the preference function value for PROMETHEE II method.

Risks	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
R_1	0	0.1000	0.2044	0.1447	0.2124	0.2253	0.0984	0.1460	0.1777	0.1449
R_2	0.3302	0	0.3103	0.3631	0.2594	0.2314	0.3467	0.2824	0.3651	0.2193
R_3	0.2826	0.0851	0	0.2210	0.2310	0.1951	0.2496	0.2027	0.2192	0.2617
R_4	0.1315	0.1129	0.1296	0	0.1811	0.2342	0.1851	0.1331	0.1848	0.1733
R_5	0.2627	0.0795	0.2031	0.2447	0	0.1692	0.30173	0.1818	0.2648	0.1898
R_6	0.3776	0.0803	0.2692	0.3996	0.2710	0	0.24063	0.2923	0.2724	0.2562
R_7	0.2156	0.1518	0.2798	0.3067	0.3598	0.1968	0	0.2938	0.2750	0.2147
R_8	0.2180	0.1173	0.1964	0.2183	0.2034	0.2121	0.2573	0	0.2443	0.2636
R_9	0.2001	0.0842	0.1634	0.2204	0.2369	0.1426	0.1890	0.1947	0	0.258
R_{10}	0.2614	0.1136	0.3000	0.2777	0.2559	0.2205	0.2228	0.3082	0.3528	0

TABLE 25. The main and sub-criteria of comparative study.

Hardware Requirements C_1	C_{11} - Hardware safety requirements C_{12} - Designing hardware for safety concerns C_{13} - Safety lifecycle steps for hardware C_{14} - Assessment of architectural constraints C_{15} – Incorrect specifications of hardware
Hardware Integration C_2	C_{21} - Functional testing under normal conditions C_{22} - Worst-case testing C_{23} - Mechanical endurance test C_{24} - Accelerated life test C_{25} - Over limit testing
Supporting Processes C_3	C_{31} - Update management C_{32} - Qualification of hardware components C_{33} - Qualification of software components C_{34} - Qualification of software tools C_{35} - Configuration management
Others C_4	C_{41} - Correct implementation of the functionality C_{42} - Robustness C_{43} - Sufficiency of the resources to support the functionality C_{44} – Human errors C_{45} – Loss of energy supply or disturbances

and R_4 is the worst alternative. In scenario 5, R_7 is the best alternative and R_1 is the worst alternative. In scenario 6, R_7 is the best alternative, and R_1 is the worst alternative. In scenario 7, R_2 is the best alternative and R_1 is the worst alternative. In scenario 8, R_2 is the best alternative, and R_1 is the worst alternative. In scenario 9, R_2 is the best alternative, and R_5 is the worst alternative. In scenario 10, R_7 is the best alternative and R_4 is the worst alternative.

TABLE 26. Ten scenarios change of criteria weights.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10
Criteria	Equal weights	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9
S_1	0.111	0.5	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
S_2	0.111	0.0625	0.5	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
S_3	0.111	0.0625	0.0625	0.5	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625
S_4	0.111	0.0625	0.0625	0.0625	0.5	0.0625	0.0625	0.0625	0.0625	0.0625
S_5	0.111	0.0625	0.0625	0.0625	0.0625	0.5	0.0625	0.0625	0.0625	0.0625
S_6	0.111	0.0625	0.0625	0.0625	0.0625	0.0625	0.5	0.0625	0.0625	0.0625
S_7	0.111	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.5	0.0625	0.0625
S_8	0.111	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.5	0.0625
S_9	0.111	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.0625	0.5

TABLE 27. The ranking alternatives (risks) under ten scenario by MABAC, PROMETHEE II methods.

scenarios	Method	Rank									
		1	2	3	4	5	6	7	8	9	10
Scenario 1	MABAC	R_2	R_6	R_7	R_{10}	R_3	R_8	R_9	R_5	R_1	R_4
	PROMETHEE II	R_2	R_{10}	R_8	R_7	R_6	R_3	R_1	R_9	R_4	R_5
Scenario 2	MABAC	R_6	R_2	R_1	R_7	R_1	R_3	R_8	R_4	R_9	R_5
	PROMETHEE II	R_6	R_{10}	R_2	R_7	R_1	R_3	R_8	R_4	R_9	R_5
Scenario 3	MABAC	R_2	R_7	R_3	R_6	R_1	R_9	R_4	R_{10}	R_8	R_5
	PROMETHEE II	R_2	R_7	R_6	R_{10}	R_1	R_3	R_4	R_9	R_8	R_5
Scenario 4	MABAC	R_7	R_{10}	R_6	R_2	R_5	R_8	R_3	R_9	R_1	R_4
	PROMETHEE II	R_{10}	R_7	R_6	R_2	R_1	R_5	R_8	R_3	R_9	R_4
Scenario 5	MABAC	R_7	R_{10}	R_6	R_2	R_5	R_8	R_3	R_9	R_1	R_4
	PROMETHEE II	R_6	R_7	R_2	R_{10}	R_3	R_9	R_1	R_8	R_4	R_5
Scenario 6	MABAC	R_7	R_{10}	R_6	R_2	R_5	R_8	R_3	R_9	R_4	R_1
	PROMETHEE II	R_{10}	R_2	R_6	R_7	R_8	R_3	R_1	R_5	R_4	R_9
Scenario 7	MABAC	R_2	R_6	R_3	R_5	R_8	R_9	R_{10}	R_7	R_4	R_1
	PROMETHEE II	R_6	R_2	R_{10}	R_7	R_5	R_3	R_8	R_1	R_9	R_4
Scenario 8	MABAC	R_2	R_6	R_3	R_5	R_8	R_9	R_{10}	R_7	R_4	R_1
	PROMETHEE II	R_{10}	R_2	R_7	R_6	R_1	R_8	R_4	R_5	R_3	R_9
Scenario 9	MABAC	R_2	R_7	R_6	R_{10}	R_3	R_8	R_{10}	R_9	R_4	R_5
	PROMETHEE II	R_2	R_{10}	R_6	R_7	R_4	R_3	R_5	R_8	R_1	R_9
Scenario 10	MABAC	R_7	R_2	R_9	R_6	R_{10}	R_1	R_5	R_8	R_3	R_4
	PROMETHEE II	R_7	R_{10}	R_6	R_2	R_1	R_9	R_4	R_5	R_8	R_3

The alternatives are aggregated to obtain the best alternatives because MABAC and PROMETHEE II have different ranking of alternatives. The aggregation is applied using Z as the number of alternatives, each alternative takes Z points for being the first choice. Z-1 is the second choice [65]. The best alternative has the highest point, whilst the worst alternative has the least points and so on. Fig. 10 shows the sensitivity analysis when the weights of criteria are changed. In Table 9, the aggregation ranking for ten scenarios is given.

VIII. MANAGERIAL IMPLICATIONS

Interaction environment with driverless vehicles can cause many risks so companies that are interested in producing these vehicles can consider these risks. This work introduces a hybrid methodology to rank these risks. As a result, a cyber-attack is the highest risk, and disruption and catastrophic events are the least important risk. Hackers can theft the private data of passengers as well as the operating system of vehicles, so the developers of driverless vehicles can make rotten systems to prevent hackers to do these crimes.

If developers do not make these, the market of driverless vehicles is going to be negatively affected. Artificial intelligence can introduce a solution to overcome this hacking. Machine learning and deep learning are a subclass of artificial intelligence that can make a system with more security functions. The automated system can block hacking crimes and block hackers. The risks of behavior adaption, infrastructure electronics, environment adaption, and mechanical risks are serious. Before releasing driverless vehicles, companies should consider functional testing in the manufacturing process. The decision-makers should define the certifications and standards of driverless vehicles. This paper helps decision-makers, companies, managers to define the risks of driverless vehicles. This study provides driverless vehicle risks ranking.

IX. CONCLUSION

This study aims to identify and rank various risks of self-driving vehicles and consider the indeterminacy of information, which is the gap in the previous studies. Therefore, in this study, three different MCDM methods that include AHP to obtain the weights of criteria and MABAC and PROMETHEE II for ranking the self-driving vehicle risks, have proposed with SVNSs. The sensitivity analysis suggested the validating of outcomes. The comparative analysis was introduced with Pythagorean fuzzy AHP, TOPSIS, and

VICTOR to test the proposed model's performance. Similar results are obtained from the carrying out of three methods for ranking risks of self-driving vehicles. These approaches can easily be applied to other issues. Analysis and ranking risks of driverless cars to invalidate the impact of risks and make profits of driverless vehicles in the industry are provided.

This study would allow decision-makers to consider various types of risks, including privacy data, hacking, and malfunctions software and hardware, with aggregated comparison judgment of experts and decision-makers. This study can help developers, programmers, and manufacturers that performing operations of self-driving vehicles. This study shows that cyber-attack risk R_2 is the best alternative (means that it is high-risk ranking), and disruption/ catastrophic risk R_4 is the least alternative (means that it is the least risk ranking). The ranking risks of self-driving vehicles can help companies to assign marketing, safety management, and research. The companies that make self-driving vehicles consider these risk factors to produce vehicles better and fewer risks—making this study provide a safer life for passengers and walkers. This study overcame gaps in the limited research, introduced analysis to all types of risks, and considered indeterminacy information.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in the research.

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ETHICAL APPROVAL

This article does not contain any studies with human participants or animals performed by any of the authors.

APPENDIX

See Tables 10–27.

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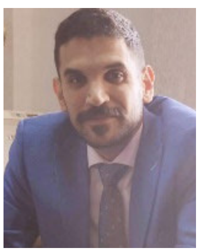
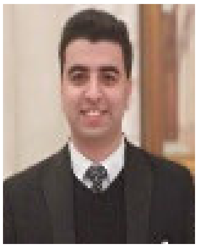


MOHAMED ABDEL-BASSET (Senior Member, IEEE) received the B.Sc., M.Sc., and Ph.D. degrees in operations research from the Faculty of Computers and Informatics, Zagazig University, Egypt. He is currently an Associate Professor at the Faculty of Computers and Informatics, Zagazig University. He has published more than 200 articles in international journals and conference proceedings. His current research interests include optimization, operations research, data mining, computational intelligence, applied statistics, decision support systems, robust optimization, engineering optimization, multi-objective optimization, swarm intelligence, evolutionary algorithms, and artificial neural networks. He is working on the application of multi-objective and robust meta-heuristic optimization techniques. He is also an editor/a reviewer in different international journals and conferences.

ABDUALLAH GAMAL received the B.Sc. and M.Sc. degrees from the Department of Operations Research, Faculty of Computers and Informatics, Zagazig University, Egypt. His research interests include computation intelligence, optimization, swarm intelligence, evolutionary algorithms, and neutrosophic sets and logic.

NOUR MOUSTAFA (Senior Member, IEEE) received the bachelor's and master's degrees in information systems from the Faculty of Computer and Information, Helwan University, Egypt, in 2009 and 2014, respectively, and the Ph.D. degree in cyber security from the University of New South Wales (UNSW), in 2017. He was a Postdoctoral Fellow in cyber security at UNSW Canberra, Australia, from June 2017 to February 2019. He is currently a Postgraduate Discipline Coordinator (Cyber) and a Lecturer in cyber security and computing at the School of Engineering and Information Technology (SEIT), UNSW Canberra. His research interests include cyber security, in particular network security, host-intrusion and network-intrusion detection systems, statistics, deep learning, and machine learning techniques. He is interested in designing and developing threat detection and forensic mechanisms to the Industry 4.0 technology for identifying malicious activities from cloud computing, fog computing, the IoT, and industrial control systems over virtual machines and physical systems.



AHMED ABDEL-MONEM received the B.Sc. degree from the Department of Decision Support, Faculty of Computers and Informatics, Zagazig University, Egypt. He is working on the application of MCDM for solving real problems. His research interests include robust optimization, swarm intelligence, MCDM, neutrosophic sets, fuzzy sets, and data science.

NISSREEN EL-SABER received the B.Sc. degree in information systems from the Faculty of Computers and Informatics, Zagazig University, Egypt, the M.Sc. degree in information systems from the Faculty of Computers and Informatics, Cairo University, Egypt, in 2009, and the Ph.D. degree in computer science from the University of Leicester, U.K., in 2015. She is currently a Lecturer with the Faculty of Computers and Informatics, Zagazig University. Her research interests include analysis, design, modeling, and compliance of processes in real life systems.