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A NEW RISK ASSESSMENT METHOD FOR AUTONOMOUS VEHICLE DRIVING SYSTEMS: FERMATEAN FUZZY AHP APPROACH

OTONOM ARAÇ SÜRÜŞ SİSTEMLERİ İÇİN YENİ BİR RİSK DEĞERLENDİRME YÖNTEMİ: FERMATEAN FUZZY AHP YÖNTEMİ

Necip ŞİMŞEK[1] **Murat KİRİŞÇİ**[2]

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Corresponding Author / Sorumlu Yazar
necipsimsek@hotmail.com

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Abstract

The autonomous vehicle driving systems' decision-making processes are distinct from those of the users, enabling them to supervise and control the operations of automobiles in both anticipated and unforeseen situations. Although utilizing this technology has several benefits, including fewer accidents brought on by human error and more effective energy usage, it is also clear that there are significant risks associated. Therefore, it will be useful to design a risk assessment application for these systems given the risks connected with autonomous vehicles and/or driving systems that must be assessed and addressed. This article presents a multi-criteria decision-making strategy to evaluate the risk probabilities of autonomous vehicle driving systems by combining the AHP technique with interval-valued Fermatean fuzzy sets. Interval-valued Fuzzy Fermat presents six options for autonomous driving systems for vehicles, which have been evaluated in the application based on six main criteria and fifteen sub-criteria criteria. The findings of this study have demonstrated that the threat posed by cyberattacks is being addressed and given priority to improve the success of the introduction of autonomous vehicle driving systems.

Keywords: AHP, autonomous vehicle driving systems, decision-making, Fermatean fuzzy environment, risk assessment.

Öz

Otonom araç sürüş sistemlerinin karar verme süreçleri, kullanıcılarınkinden farklıdır ve hem öngörülen hem de öngörülemeyen durumlarda otomobillerin işleyişini denetleme ve kontrol etme olanağı sağlar. Bu teknolojiyi kullanmanın insan hatasından kaynaklanan daha az kaza ve daha verimli enerji kullanımı gibi bir dizi faydası olsa da, bununla ilgili önemli riskler olduğu da açıktır. Bu nedenle, değerlendirilmesi ve ele alınması gereken otonom araçlar ve/veya sürüş sistemleri ile bağlantılı riskler göz önüne alındığında, bu sistemler için bir risk değerlendirme uygulaması tasarlamak faydalı olacaktır. Bu makalede, AHP tekniğini aralık değerli Fermatean bulanık kümelerle birleştirerek otonom araç sürüş sistemlerinin risk olasılıklarını değerlendirileceği çok kriterli bir karar verme stratejisi sunulmaktadır. Aralık değerli Fermatean bulanık kümeler, uygulamada altı ana kriter ve on beş destekleyici kriter temelinde değerlendirilen araçlar için otonom sürüş sistemleri için altı seçenek sunar. Bu çalışmanın bulguları, otonom araç sürüş sistemlerinin tanıtılmasının başarısını artırmak için siber saldırıların oluşturduğu tehdidin ele alındığını ve öncelik verildiğini göstermiştir.

Anahtar Kelimeler: AHP, Fermatean bulanık çevresi, karar verme, otonom araç sürüş sistemi, risk değerlendirme.

[1]İstanbul Commerce University, Department of Mathematics, İstanbul, Türkiye.
necipsimsek@hotmail.com, Orcid.org/0000-0003-3061-5770.

[2]Istanbul University-Cerrahpaşa, Cerrahpaşa Medicine Faculty, Department of Biostatistics and Medical Informatics, İstanbul, Türkiye.
mkirisci@hotmail.com, Orcid.org/0000-0003-4938-5207.

1. INTRODUCTION

Autonomous vehicle driving systems (AVDS) aim to swiftly and effectively provide viable, safe, and human-like driving regulations. The conventional method often involves planning based on search or optimization, followed by a model-based controller. Due to disturbances, uncertainties, and a lack of computing time, this may not be sufficient in some driving conditions.

Recently, both corporate and academic researchers have become much more interested in AV technology. In general, hierarchical building pieces like perception, planning, and control may be used to categorize autonomous driving systems (Son et al., 2019). Segmentation and object categorization help with perception. Graph search, quickly exploring random trees, or optimization-based methods are the foundations of motion planning algorithms. Additionally, feedback controllers that control the steering, throttle, and braking actuators are used in the trajectory-tracking architecture. The safety and computing effectiveness of this tiered strategy may suffer.

Recent years have seen a lot of studies on automating the driving process, but because AV driving control systems are such complicated systems, creating and modeling them is difficult. Many engineers and educators have struggled to predict the outcomes of autonomous car driving control systems over the last few decades, but in recent years, computers have been incredibly useful in modeling such systems.

A self-driving vehicle (SDV) is a vehicle that can navigate on its own and comprehend its environment. A human passenger is not required to drive or even be inside the car at any time. An SDV can do every task that a qualified human driver can and travel wherever a normal vehicle can.

SDVs need sensors, actuators, challenging algorithms, machine learning systems, and robust processors to operate the software. SDVs create and maintain a map of their surroundings using a variety of sensors that are strategically placed all around the vehicle. Radar sensors are used to locate other vehicles. Video cameras can identify people, other cars, traffic signals, and road signs. By reflecting light pulses off the environment surrounding the automobile, lidar (light detection and ranging) sensors measure distances, locate road limitations, and recognize lane markings. Ultrasonic sensors on the wheels identify other vehicles and objects when parking.

There may be some advantages when comparing autonomous vehicle (AV) technology to human-driven vehicles. They might perhaps increase traffic safety, which would be one advantage. Many people lose their lives in automobile accidents every year, but autonomous cars may cause fewer deaths since their software is predicted to be less error-prone than that of human drivers. A decrease in traffic congestion brought on by fewer accidents is another potential advantage of AVs. By eliminating human acts that congest the road, notably stop-and-go traffic, autonomous driving can also achieve this. The possibility of more convenient transportation for individuals who are unable to drive due to age or other circumstances is another advantage of autonomous driving. Other advantages of AVs include the absence of driver fatigue and the opportunity to sleep during nocturnal excursions.

The impact that autonomous vehicles (AVs), sometimes referred to as self-driving, driverless, or robotic cars, will have on future travel and, subsequently, the need for parking spaces, roadways, and public transit systems They also want to know what government regulations may be put in place to reduce these problems and maximize the benefits of this new technology. Optimists predict that by 2030, AVs will replace the majority of driving, saving significant amounts of money and providing other advantages. However, there are good grounds for skepticism. There is much uncertainty around the advancement of AVs, their benefits and drawbacks, the impact they will have on travel, and customer demand. A lot of work has to be done before AVs can operate securely in crowded metropolitan areas with bad weather, unpaved and unmapped roads, and locations with erratic Wi-Fi access. It is almost guaranteed that the first commercially accessible AVs will be expensive and of poor performance. They will come with added expenses and dangers. Sales will be capped by these limitations. Many drivers won't want to pay extra for vehicles that might not be able to get where they're going because of bad weather or unmapped routes.

The fuzzy set (FS) idea proposed by Zadeh (1965) was used to highlight the ambiguity and irrationality of a membership degree (MD). The intuitionistic fuzzy set (IFS), which Atanassov (1986) later discovered, may express assessment information more thoroughly by tying the non-membership degree (ND) of an element to a given item. IFSs, however, have a design that makes it challenging for judgment specialists to make the right assessments because of their considerable limitations in providing preference information. Yager (2013; 2014) invented the Pythagorean fuzzy set (PFS) to address the aforementioned IFS flaw by extending the range of MD and ND so that MD+ND=1. As a result, PFS provides specialists with more evaluation options to provide their opinions on a range of goals. It is getting harder for professionals to give more accurate assessment information as the decision environment becomes more complex. The ideas of IFS and PFS have been advocated to reduce the ambiguity and uncertainty brought on by the complex subjectivity of human cognition. Therefore, a larger information space is required to meet their evaluation expectations for various goals and take into account the professionals' decision-making process and knowledge base to make more suitable judgments. The Fermatean fuzzy set (FFS) was the first to broaden the range of information expression since it included the cubic sum of MD and ND in the interval. Therefore, compared to IFS and PFS, FFS is a more effective and practical approach for addressing the indeterminacy of choice difficulties. Due to their superiority in presenting confusing information and providing more options for specialists, researchers have pushed for the development of a variety of decision-making methodologies to address real-world choice and assessment challenges.

The FFS has been developed by Senepati and Yager (2020). FFS is better at explaining uncertainties than IFSs and PFSs. This work was continued by Senapati and Yager (2019a), who looked at a variety of new operations and arithmetic mean procedures over FFSs. To solve MCDM difficulties, they also applied the FF-weighted product model. FFS-related new aggregation operators have been defined, and (2019b) has examined the properties that go along with them. In a short time, many studies on FFS have entered the literature (Alkan & Kahraman, 2023; Garg et al., 2020; Jeevaraj, 2021; Kirişci et al., 2022; Kirişci, 2022a, 2022b, 2023; Mary et al., 2023; Senapati & Yager, 2019a, 2019b).

AVs come with a significant amount of risk, which must be properly evaluated by decision-makers. AV issues must be handled carefully given the significant risks associated with autonomous driving technology and how it will interact with the mobility system. This study aims to rank the risks associated with SDVs. In a multi-criteria decision-making (MCDM) dilemma, prioritizing risks requires taking into account a variety of viable solutions as well as conflicting tangible and intangible elements. An integrated MCDM approach according to FFSs is provided to address this MCDM challenge. This suggested solution addresses the prioritization of AV threats by offering cutting-edge integrated MCDM methodologies by the AHP, TOPSIS, and MABAC in a Fermatean fuzzy environment. Studies on sensitivity and comparability will be carried out to show the efficacy and usability of the recommended approach. To determine how the alternative rankings change as the criterion weights change, a sensitivity analysis (SA) will also be carried out. Planners and policymakers will be able to make judgments on SDVs with the aid of this study's findings.

The effect of criteria weights on the DM operation is specified using SA. It is also used to verify the suggested approach. In this analysis, various scenarios are developed that can alter the priorities of the alternatives, and it is demonstrated that the results are variable depending on the shifting weights of the criteria when the priorities of the alternatives are changed by raising or lowering the importance levels of the criteria. The outcome is therefore delicate but typically reliable. When discussing an unknown object's weight, this approach is useful. SA aims to identify the most critical criteria and how the weighting of the criteria affects the prioritization of AV threats. The possible risks are gathered by ISO 26262 standards (ISO, 2011) and literature review.

1.1. Originality

Risks according to SDVs are prioritized using an MCDM approach. The fuzzy approach employed in this work captures the erroneous information that distinguishes decision-makers' assessments. As a result, this study offers further insight into the specific risk environment for AVs in the future and, more broadly, offers policy measures for sustainable urban transportation. The strategy put forward in this study offers a sophisticated and enhanced manner of managing uncertainty in risk prioritization. For MCDM, a technique based on the IVFF-AHP procedure has been suggested to give planners more dependable options. The suggested approach is a helpful tool that may be used to solve various complicated choice issues with many competing criteria because of its adaptable structure. FFSs, as opposed to the IFS and PFS, express the ambiguity of erroneous info through MD and ND better. The professional team is requested to appraise the requirements, and they evaluate potential choices in light of the requirements. The IVFF-AHP is employed to compute the weights of the assessment criteria according to the opinions of professionals. As a result, an analysis is done on how criterion weights affect risk prioritization. To assess the dangers associated with SDVs, the efficacy of the suggested hybrid approach with an FFS is compared to that of another hybrid MCDM technique with a conventional FS.

The organization of this paper is as follows: Section 2 provides essential information that will be used throughout the paper. In Section 3, the newly proposed method, algorithm and the equations to be used in this algorithm are given. Again in this section, the risk assessment problem of AVs was defined and analyzed by making calculations with the given algorithm. The results obtained with the application of the method proposed in Section 4 are evaluated.

2. PRELIMINARIES

Let X be a non-empty set.

Definition 2.1. An IFS A in X is $A=\{(x,\zeta_A(x),\eta_A(x)): x\in X\}$, where the functions $\zeta_A,\eta_A: X\to[0,1]$ defined the MD and ND of an element to the sets A with the condition that $0\leq\zeta_A(x)+\eta_A(x)\leq 1$, for $\forall x\in X$.

The hesitancy degree(HD) $\theta_A(x)=1-\zeta_A(x)-\eta_A(x)$.

Definition 2.2. A PFS B in X is $B=\{(x,\zeta_B(x),\eta_B(x)): x\in X\}$, where the functions $\zeta_B,\eta_B: X\to[0,1]$ defined the MD and ND of an element to the sets B for $0\leq{\zeta_B}^2(x)+{\eta_B}^2(x)\leq 1$, for $\forall x\in X$.

The HD $\theta_B(x)=\sqrt{1-\left({\zeta_B}^2(x)+{\eta_B}^2(x)\right)}$.

Definition 2.3. An FFS C in X is $C = \{(x, \zeta_C(x), \eta_C(x)): x \in X\}$, where the functions $\zeta_C, \eta_C: X \to [0,1]$ defined the MD and ND of an element to the sets C for $0 \le {\zeta_C}^3(x) + {\eta_C}^3(x) \le 1$, for $\forall x \in X$.

The HD $\theta_C(x) = \sqrt[3]{1 - \left({\zeta_C}^3(x) + {\eta_C}^3(x)\right)}$.

Definition 2.4. An IVFFS D in X is $D = \{(x, \zeta_D(x), \eta_D(x)): x \in X\}$, where the functions $\zeta_D, \eta_D \subseteq [0,1]$ defined the MD and ND of an element to the sets D.

For every $x \in X, \zeta_D(x)$ and $\eta_D(x)$ are closed intervals, and their lower and upper bounds are denoted by $\zeta_D^L(x), \zeta_D^U(x), \eta_D^L(x), \eta_D^U(x)$, respectively. Hence, D can also be given $\zeta_D(x) = [\zeta_D^L(x), \zeta_D^U(x)] \subseteq [0,1]$, $\eta_D(x) = [\eta_D^L(x), \eta_D^U(x)] \subseteq [0,1]$, where the expression is subject to the condition $0 \le \left(\zeta_D^U(x)\right)^3 + \left(\eta_D^U(x)\right)^3 \le 1$.

For each $x \in X$, $\theta_D(x) = [\theta_D^L(x), \theta_D^U(x)]$ is called the HD in IVFFSs, where

$$\theta_D^L(x) = \sqrt[3]{1 - \left[\left(\zeta_D^L(x)\right)^3 + \left(\eta_D^L(x)\right)^3\right]}; \qquad \theta_D^U(x) = \sqrt[3]{1 - \left[\left(\zeta_D^U(x)\right)^3 + \left(\eta_D^U(x)\right)^3\right]}.$$

Consider the three IVFFNs

$$D = ([\zeta_D^L(x), \zeta_D^U(x)], [\eta_D^L(x), \eta_D^U(x)]),$$
$$D_1 = \left(\left[\zeta_{D_1}^L(x), \zeta_{D_1}^U(x)\right], \left[\eta_{D_1}^L(x), \eta_{D_2}^U(x)\right]\right),$$
$$D_2 = \left(\left[\zeta_{D_2}^L(x), \zeta_{D_2}^U(x)\right], \left[\eta_{D_2}^L(x), \eta_{D_2}^U(x)\right]\right).$$

Then, the arithmetical operations of IVFFNs are defined as:

$$D_1 \boxplus D_2 = \left(\begin{bmatrix} \sqrt[3]{\left(\zeta_{D_1}^L\right)^3 + \left(\zeta_{D_2}^L\right)^3 - \left(\zeta_{D_1}^L\right)^3 . \left(\zeta_{D_2}^L\right)^3}, \\ \sqrt[3]{\left(\zeta_{D_1}^U\right)^3 + \left(\zeta_{D_2}^U\right)^3 - \left(\zeta_{D_1}^U\right)^3 . \left(\zeta_{D_2}^U\right)^3} \end{bmatrix}, \left[\eta_{D_1}^L . \eta_{D_2}^l, \eta_{D_1}^u . \eta_{D_2}^U\right] \right),$$

$$D_1 \boxtimes D_2 = \left(\left[\zeta_{D_1}^L . \zeta_{D_2}^l, \zeta_{D_1}^u . \zeta_{D_2}^U\right], \begin{bmatrix} \sqrt[3]{\left(\eta_{D_1}^L\right)^3 + \left(\eta_{D_2}^L\right)^3 - \left(\eta_{D_1}^L\right)^3 . \left(\eta_{D_2}^L\right)^3}, \\ \sqrt[3]{\left(\eta_{D_1}^U\right)^3 + \left(\eta_{D_2}^U\right)^3 - \left(\eta_{D_1}^U\right)^3 . \left(\eta_{D_2}^U\right)^3} \end{bmatrix}, \right),$$

$$\lambda D = \left(\left[\sqrt[3]{1 - (1 - (\zeta_D^L)^3)^\lambda}, \sqrt[3]{1 - (1 - (\zeta_D^U)^3)^\lambda}, \right], \left[(\eta_D^L)^\lambda, (\eta_D^U)^\lambda\right]\right),$$

$$D^\lambda = \left(\left[(\zeta_D^L)^\lambda, (\zeta_D^U)^\lambda\right], \left[\sqrt[3]{1 - (1 - (\eta_D^L)^3)^\lambda}, \sqrt[3]{1 - (1 - (\eta_D^U)^3)^\lambda}, \right]\right).$$

The IVFF weighted average operator is a mapping $IVFFWA: D^n \to D$, where

$$IVFFWA(D_1, D_2, \ldots, D_n) = \left(\left[\sqrt[3]{\left(1 - \prod_{i=1}^{n}\left(1 - \left(\zeta_{D_i}^{L}\right)^3\right)^{\omega_i}\right)}, \sqrt[3]{\left(1 - \prod_{i=1}^{n}\left(1 - \left(\zeta_{D_i}^{U}\right)^3\right)^{\omega_i}\right)}\right] \left[\prod_{i=1}^{n}\left(\eta_{D_i}^{L}\right)^{\omega_i}, \prod_{i=1}^{n}\left(\eta_{D_i}^{U}\right)^{\omega_i}\right]\right).$$

The IVFF weighted geometric operator is a mapping $IVFFWG: D^n \rightarrow D$, where

$$IVFFWG(D_1, D_2, \ldots, D_n) = \left(\left[\prod_{i=1}^{n}\left(\zeta_{D_i}^{L}\right)^{\omega_i}, \prod_{i=1}^{n}\left(\zeta_{D_i}^{U}\right)^{\omega_i}\right] \left[\sqrt[3]{\left(1 - \prod_{i=1}^{n}\left(1 - \left(\eta_{D_i}^{L}\right)^3\right)^{\omega_i}\right)}, \sqrt[3]{\left(1 - \prod_{i=1}^{n}\left(1 - \left(\eta_{D_i}^{U}\right)^3\right)^{\omega_i}\right)}\right]\right).$$

3. NEW METHOD BASED ON IVFF-AHP

3.1 AHP Method

In 1980, Saaty (2008) introduced AHP, one of the most widely used MCDM strategies in the literature. In difficult MCDM scenarios, the approach has a structured form that is utilized to balance criteria and reach judgments. As a result, employing the usual AHP approach to express the decision-judgment makers in ambiguous situations is difficult. A fuzzy AHP has been added to the original AHP to mimic the ambiguity involved in human decision-making and judgment. Fuzzy-AHP was utilized to handle several MCDM issues in published papers, and the approach has subsequently altered as a result of new fuzzy set expansions. The first fuzzy-AHP modification by calculating fuzzy weights and fuzzy alternative scores using triangular fuzzy integers has been given by (Van Laarhoven & Pedrand, 1983). Buckley (1985) employed the geometric mean approach according to trapezoidal fuzzy numbers to compute the fuzzy weights and fuzzy alternative scores. CA's unique method for obtaining the synthetic extent values of the fuzzy AHP pairwise comparison scale utilizing triangular fuzzy numbers is introduced by (Chang, 1986). The interval-valued type-2 fuzzy AHP approach and a unique ranking mechanism according to type-2 fuzzy sets have been established (Kahraman et al., 2016). An intuitionistic fuzzy AHP was created by Sadiq and Tesfamariam (Sadiq & Tesfamariam, 2009) to deal with ambiguity and uncertainty in DM. The score function based on IVIFNs is given and suggests an original IVIF-AHP solution (Wu et al., 2013). The ordered weighted averaging (OWA) operator is employed to merge expert ideas in the hesitant fuzzy AHP, which was created by Oztaysi et al. (2015). In Gul's (2018) special method for risk assessment in the area of occupational health and safety, fuzzy VIKOR and PF-AHP were combined. The PF-AHP has been employed to weigh the risk features. Fuzzy VIKOR was then utilized to rank the threats. The unique method that merged AHP with COPRAS based on PFSs to investigate the choice of digital supply chain partners is proposed (Büyüközkan & Göçer, 2021). The method yields accurate answers that better capture the ambiguity of the DM environment, according to Karasan et al. (2019), who developed and compared a revolutionary Pythagorean fuzzy AHP methodology to a conventional fuzzy AHP. For each option in a paired comparison, a neutrosophic AHP technique using triangular neutrosophic numbers is presented by Abdel-Basset et al. (2017). A unique IV-neutrosophic AHP technique with cosine similarity measurements and interval-valued neutrosophic AHP was developed by Bolturk and Kahraman (2018). Complex IV-q-rung orthopair FSs were built by Garg et al. (2021) and then utilized to build both geometric and averaging aggregation operators. They suggested the CIVq-ROFS-based AHP and TOPSIS techniques. A unique hybrid fuzzy AHP and linear assignment model was created by (Gündoğdu et al., 2021). For integrating AHP with TOPSIS, Mathew et al. (2020) presented a new technique with spherical fuzzy sets. The IVFF-AHP was developed by Alkan and Karaman (2023). In this work, the major criteria and sub-criteria, the criteria weights, and the alternative rankings were all determined using the IVFF-AHP technique.

3.2. Proposed Method

The set $A_i = \{A_1, A_2, \dots, A_n\}$, having $i = 1,2,\dots,n$ alternatives, is evaluated by m decision criteria of set $C_j = \{C_1, C_2, \dots, C_m\}$, with $j = 1,2,\dots,m$. Let $\omega_j = (\omega_1, \omega_2, \dots, \omega_m)$ be vector set used for defining the criteria weights, where $\omega_j > 0$ and $\sum_{j=1}^{n} \omega_j = 1$. Table 1 presents linguistic terms and their corresponding IVFNs. The steps of the IVFF-AHP method are:

Step 1: Build the hierarchical structure by determining the criteria and alternatives.

Step 2: Build the pairwise comparison matrix $Z = \left(z_{ij}\right)_{m \times m}$ according to the ideas of professionals. For $z_{ij} = \left(\left[\zeta_{ij}^L, \zeta_{ij}^U\right], \left[\eta_{ij}^L, \eta_{ij}^U\right]\right)$,

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1m} \\ z_{21} & z_{22} & \cdots & z_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ z_{m1} & z_{m2} & \cdots & z_{mm} \end{bmatrix}.$$

Step 3: Check for the consistency of each pairwise comparison matrix (Z). Here, to measure the consistency of professional judgments, match the crisp numbers obtained after defuzzifying to IVFFNs given in Table 2 based on Saaty's scale. Then, apply Saaty's classical consistency process.

Step 4: Aggregate the judgments of professionals.

The pairwise comparison matrix constituted for each professional is aggregated by using the IVFFWG aggregation operator. Let $E_k = \{E_1, E_2, \dots, E_K\}$, with $k = 1,2,\dots,K$, denote the set of professionals having influence weights ω_k for each E_k; $\sum_{k=1}^{K} \omega_k = 1$.

$$IVFFWG(z_1, z_2, \dots, z_k) = \left(\left[\prod_{k=1}^{K} (\zeta_k^L)^{\omega_k}, \prod_{k=1}^{K} (\zeta_k^U)^{\omega_k} \right], \left[\sqrt[3]{\left(1 - \prod_{k=1}^{K} (1 - (\eta_k^L)^3)^{\omega_k}\right)}, \sqrt[3]{\left(1 - \prod_{k=1}^{K} (1 - (\eta_k^U)^3)^{\omega_k}\right)} \right] \right). \tag{1}$$

Step 5: Find the differences matrix $D = \left(d_{ij}\right)_{m \times m}$ between the lower and upper points of the membership and non-membership functions using Equations (2) and (3).

$$d_{ij}^L = \left(\zeta_{ij}^L\right)^3 - \left(\eta_{ij}^U\right)^3, \tag{2}$$

$$d_{ij}^L = \left(\zeta_{ij}^U\right)^3 - \left(\eta_{ij}^L\right)^3. \tag{3}$$

Step 6: Find the interval multiplicative matrix $S = \left(s_{ij}\right)_{m \times m}$ with Equations (4) and (5).

$$s_{ij}^{L} = \sqrt[3]{1000^{d_{ij}^{L}}}, \tag{4}$$

$$s_{ij}^{U} = \sqrt[3]{1000^{d_{ij}^{U}}}. \tag{5}$$

Step 7: Obtain the indeterminacy value $T = \left(t_{ij}\right)_{m \times m}$ of z_{ij} using Equation (6).

$$t_{ij} = 1 - \left(\zeta_{ijU}^{3} - \zeta_{ijL}^{3}\right) - \left(\eta_{ijU}^{3} - \eta_{ijL}^{3}\right). \tag{6}$$

Step 8: Multiply the indeterminacy degrees with $S = \left(s_{ij}\right)_{m \times m}$ matrix to obtain the matrix of un-normalized weights $R = \left(r_{ij}\right)_{m \times m}$ using Equation (7).

$$r_{ij} = \left(\frac{s_{ij}^{L} + s_{ij}^{U}}{2}\right) t_{ij}. \tag{7}$$

Step 9: Obtain the normalized priority weights ω_i by using Equation (8).

$$\omega_i = \frac{\sum_{j=1}^{m} r_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{m} r_{ij}}. \tag{8}$$

Step 10: Rank the alternatives based on the normalized priority weights obtained in Step 9.

Consistency: The equation

$$CRT = \frac{CIX}{PIX} \tag{9}$$

is called the consistency ratio, where $CIX = \frac{\lambda_{max}}{n-1}$, RIX is the consistency index, and λ_{max} the random index, and principal eigenvalue for CRT, respectively.

Table 1. Linguistic Terms Scale with IVFFN equivalents

Linguistic Terms	**IVFFNs**			
	ζ_L	ζ_U	η_L	η_U
Certainly High Importance(CH)	0,95	1	0	0
Very High Importance(VH)	0,8	0,9	0,1	0,2
High Importance(H)	0,7	0,8	0,2	0,3
Slightly More Importance(SM)	0,6	0,65	0,35	0,4
Equally Importance(EI)	0,5	0,5	0,5	0,5
Slightly Less Importance(SL)	0,35	0,4	0,6	0,65
Low Importance(L)	0,2	0,3	0,7	0,8
Very Low Importance(VL)	0,1	0,2	0,8	0,9
Certainly Low Importance(CL)	0	0	0,95	1

3.3. Algorithm

Algorithm 1 IVFF-AHP

Input: Numbers of evaluation criteria and pairwise comparison matrices.
Output: Normalized priority weights.
Begin
    For j=1; m **do**
        1. Input: Pairwise comparison matrix using the Table 1.
        2. Convert the linguistic terms into corresponding IVFFNs.
        3. Check the consistency analysis.
           For all Z **do**
               CRT using Equation 9.
           End for
        4. **If** CRT>0.1
               Return to Step 1.
           Else
               Go to Step 5.
           End if
        5. Compute the IVFFWG using the Equation 1.
    End for
        6. Calculate the difference matrix using Equations 2, 3.
        7. Compute the multiplicative matrix using Equations 4, 5.
        8. Obtain the indeterminacy value of the t_{ij} using Equation 6.
        9. Obtain the matrix of un-normalized weights using Equation 7.
        10. Determine the normalized priority weights using Equation 8.
        11. Rank the alternatives based on the normalized priority weights.
End

3.4. Problem Structure

A plan is necessary for the security prioritization of AVDS technologies. The possible risks have been identified using a literature review and the ISO 26262 standards (ISO, 2011). The testing revealed several risk variables, and their weights and priorities were calculated. Therefore, the agreement aims to offer a roadmap for selecting the riskiest component and taking the required precautions to reduce its risk for further research.

The dangers that affect SDVs are described using risk analysis. International standards and problems raised in the literature have helped establish criteria for the safety of SDVs. The hazards associated with SDVs are first described. The prioritization of these hazards was then studied using the novel methodology suggested in this study.

The risks are given as:
A_1 – Economic Risks,
A_2 – Cyber Attack Risks,
A_3 – Implementation Risks,
A_4 – Disruption/Catastrophic Risks,
A_5 – Road Infrastructure Risks,
A_6 – Behavioral Adaptation Risks,
A_7 – Environmental Adaptation Risks,
A_8 – Reputational Risks,
A_9 – Internet Outage Risks,
A_{10} – Electronic Infrastructure Risks.

The determined main and sub-criteria are:

K_1 - Information Security;
- K_{11} – Hacking-Cyber Security
- K_{12} – Data Protection
- K_{13} - Legislation

K_2 - Problems of Components
- K_{21} - Human errors
- K_{22} - Hardware malfunctions
- K_{23} - Mechanical malfunctions
- K_{24} - Software malfunctions

K_3 – Accidents
- K_{31} - Road accidents
- K_{32} - Weather conditions
- K_{33} - Infrastructure conditions

K_4 - Traffic
- K_{41} - Traffic crowding

K_5 - Availability of Required Information
- K_{51} - Correct mapping
- K_{52} - Real-time updating of information

K_6 - Social Development
- K_{61} - Social acceptance
- K_{62} - Reliability

3.5. Computations

The Hierarchy Tree of risks is given in Figure 1.

In the initial stage, pairwise comparisons and fuzzy linguistic variables must be taken into account while computing the weights of the criterion using the IVFF-AHP method. The decision-making process can tolerate significant fuzziness, ambiguity, and imprecision. Additionally, an FFS is chosen to evaluate the risks related to SDVs utilizing AHP. The primary aim of utilizing an FFS is to improve the ranking of SDV threats in hybrid MCDM techniques while reducing computation complexity and calculation execution time.

Three professionals will utilize the rating scales indicated in Table 2 to examine their pairwise judgments of the dangers. For the primary criteria given in Table 3 and the sub-criteria listed in Table 2, the professional team constructed 6X6 comparison matrices and presented them. The consistency check is used to judge how impartial the professional opinions are in the pairwise comparison matrix. The CRTs of each matrix are calculated using Equation 9, and the results are determined to be less than 0.1, which is suitable. The weights are also reliable enough to be applied to assessments.

In Table 8, the IVFFSs are indicated for the key criteria that correspond to the language terms in Table 1. The major criterion between the higher and lower values of the MF and NF is then computed using Equations 2 and 3 and is indicated in Table 9. To create the interval multiplicative matrix in Table 10, Equations 4 and 5 are used.

Table 11 shows the weights before normalization, which were determined using Equation 7. Table 12 shows the final priority weights for the primary and secondary criteria after the outcomes of all these calculations were applied to the sub-criteria. The results indicate that information security needs are the most important, with a weight of 0.338. However, the social development criteria are the least important, with a weight of 0.04.

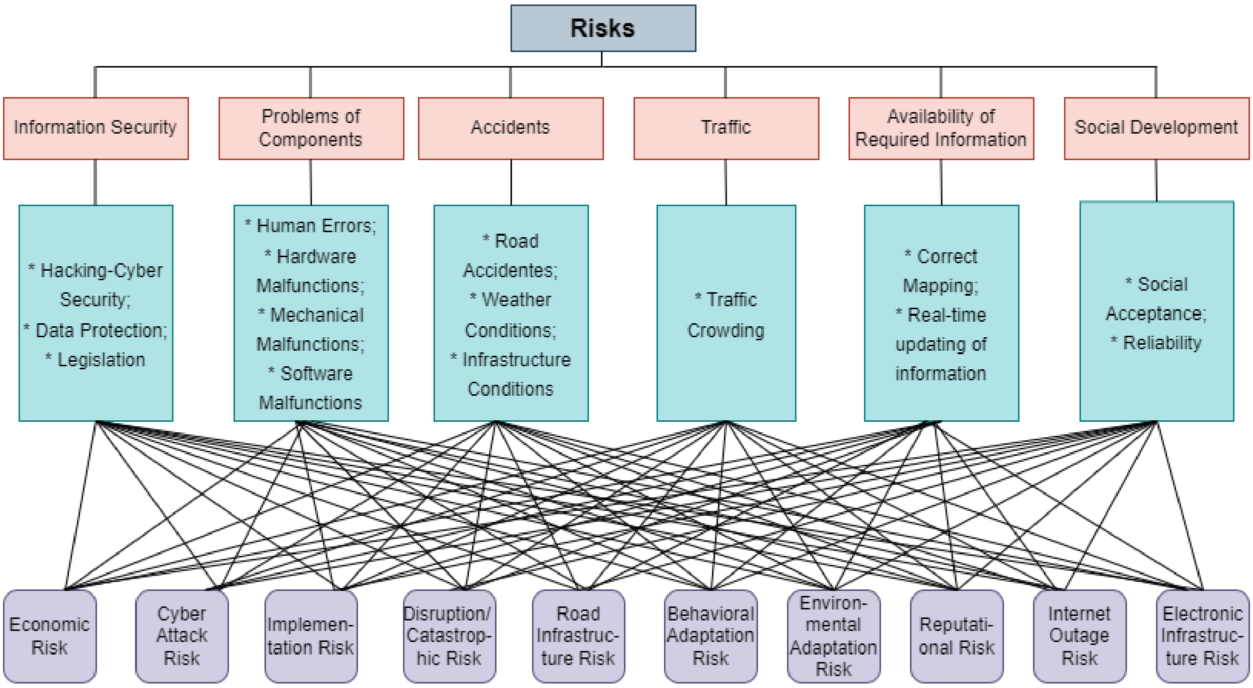

Figure 1. Hierarchy Tree of Risk Factors

Table 2. Pairwise Comparison Matrix of Main Criteria

	K_1	K_2	K_3	K_4	K_5	K_6
K_1	EI	SM	SM	VH	H	H
K_2	SL	EI	SM	VH	SM	H
K_3	SL	SL	EI	H	SM	SM
K_4	VL	VL	L	EI	L	SM
K_5	L	SL	SM	H	EI	H
K_6	L	L	SL	SL	L	EI

In Table 2, IVFFNs in Table 1 have been used in the pairwise comparison matrix given for the main criteria. In obtaining the values of the diagonal elements in the pairwise comparisons matrix, the EI value is given based on the principle that the comparison of any alternative with itself is equal to itself.

Table 3. Pairwise Matrix for K_1

	K_{11}	K_{12}	K_{13}
K_{11}	EI	SM	H
K_{12}	SM	EI	H
K_{13}	H	H	EI

Table 4. Pairwise Matrix for K_2

	K_{21}	K_{22}	K_{23}	K_{24}
K_{21}	EI	H	L	L
K_{22}	H	EI	VH	L
K_{23}	SL	VH	EI	L
K_{24}	VH	SL	SL	EI

Table 5. Pairwise Matrix for K_3

	K_{31}	K_{32}	K_{33}
K_{31}	EI	H	CH
K_{32}	VH	EI	VH
K_{33}	CH	L	EI

Table 6. Pairwise Matrix for K_5

	K_{51}	K_{52}
K_{51}	EI	VH
K_{52}	CH	EI

Table 7. Pairwise Matrix for K_6

	K_{61}	K_{62}
K_{61}	EI	SM
K_{62}	SL	EI

In Tables 3-7, pairwise comparison matrices were obtained for the sub-criteria of the main criteria. After linguistic expressions in the pairwise comparison, matrices are converted to IVFFNs using the relevant scale. IVFFN equivalents of the main criteria are given in Table 8. When CRTs are obtained from the main criteria, the results are $CRT_{K1} = 0{,}0268$, $CRT_{K2} = 0{,}0392$, $CRT_{K3} = 0{,}0301$, $CRT_{K4} = 0{,}0122$, $CRT_{K5} = 0{,}0337$, $CRT_{K6} = 0{,}0937$. As can be seen from these results, all CRTs of the main criteria were less than 0,1.

Table 8. IVFF Values for Main Criteria

	K_1	K_2	K_3	K_4	K_5	K_6
K_1	([0,5, 0,5], [0,5, 0,5])	([0,5, 0,65], [0,35, 0,4])	([0,5, 0,65], [0,35, 0,4])	([0,8, 0,9], [0,1, 0,2])	([0,65, 0,8], [0,2, 0,35])	([0,65, 0,8], [0,2, 0,35])
K_2	([0,35, 0,4], [0,5, 0,65])	([0,5, 0,5], [0,5, 0,5])	([0,5, 0,65], [0,35, 0,4])	([0,8, 0,9], [0,1, 0,2])	([0,5, 0,65], [0,35, 0,4])	([0,65, 0,8], [0,2, 0,35])
K_3	([0,35, 0,4], [0,5, 0,65])	([0,35, 0,4], [0,5, 0,65])	([0,5, 0,5], [0,5, 0,5])	([0,65, 0,8], [0,2, 0,35])	([0,4, 0,5], [0,4, 0,5])	([0,5, 0,65], [0,35, 0,4])
K_4	([0,1, 0,2], [0,8, 0,9])	([0,1, 0,2], [0,8, 0,9])	([0,2, 0,35], [0,65, 0,8])	([0,5, 0,5], [0,5, 0,5])	([0,2, 0,35], [0,65, 0,8])	([0,5, 0,65], [0,35, 0,4])
K_5	([0,2, 0,35], [0,65, 0,8])	([0,35, 0,4], [0,5, 0,65])	([0,4, 0,5], [0,4, 0,5])	([0,65, 0,8], [0,2, 0,35])	([0,5, 0,5], [0,5, 0,5])	([0,65, 0,8], [0,2, 0,35])
K_6	([0,2, 0,35], [0,65, 0,8])	([0,2, 0,35], [0,65, 0,8])	([0,35, 0,4], [0,5, 0,65])	([0,35, 0,4], [0,5, 0,65])	([0,2, 0,35], [0,65, 0,8])	([0,5, 0,5], [0,5, 0,5])

After linguistic expressions in the pairwise comparison, matrices are converted to IVFFNs using the relevant scale(Table 1), and each expert's assessment is aggregated with the IVFFWG operator(Equation 1). Equations 2 and 3 are employed to compute the difference matrix D of the primary criterion between the higher and lower values of the MF and NF, which is denoted in Table 9. Equations 4 and 5 are employed to build the interval multiplicative matrix in Table 10.

Table 9. The Matrix D for The Main Criteria

	K_1	K_2	K_3	K_4	K_5	K_6
K_1	(0,0, 0,0)	(0,061, 0,222)	(0,061, 0,222)	(0,504, 0,728)	(0,232, 0,504)	(0,232, 0,504)
K_2	(-0,232, 0,061)	(0,0, 0,0)	(0,061, 0,232)	(0,504, 0,728)	(0,061, 0,232)	(0,232, 0,504)
K_3	(-0,232, -0,061)	(-0,232, -0,061)	(0,0, 0,0)	(0,232, 0,504)	(-0,061, -0,061)	(0,061, 0,232)
K_4	(-0,728, -0,504)	(-0,728, -0,504)	(-0,504, -0,232)	(0,0, 0,0)	(-0,504, -0,232)	(0,061, 0,232)
K_5	(-0,504, -0,232)	(-0,504, -0,232)	(-0,061, -0,061)	(-0,232, -0,061)	(0,0, 0,0)	(0,232, 0,504)
K_6	(-0,504, -0,232)	(-0,504, -0,232)	(-0,232, -0,061)	(-0,232, -0,061)	(-0,504, -0,232)	(0,0, 0,0)

Table 10. The Matrix S

	K_1	K_2	K_3	K_4	K_5	K_6
K_1	(1,0, 1,0)	(1,235, 2,228)	(1,235, 2,228)	(5,702, 12,36)	(2,228, 5,702)	(2,228, 5,702)
K_2	(-0,232, 0,061)	(1,0, 1,0)	(1,235, 2,228)	(5,702, 12,36)	(1,235, 2,228)	(2,228, 5,702)
K_3	(-0,232, -0,061)	(0,45, 0,81)	(1,0, 1,0)	(2,228, 5,702)	(0,45, 0,45)	(1,235, 2,228)
K_4	(-0,728, -0,504)	(0,081, 0,1754)	(0,1754, 0,45)	(1,0, 1,0)	(0,1754, 0,45)	(1,235, 2,228)
K_5	(-0,504, -0,232)	(0,1754, 0,45)	(1,235, 2,228)	(0,45, 1,235)	(1,0, 1,0)	(2,228, 5,702)
K_6	(-0,504, -0,232)	(0,1754, 0,45)	(0,45, 1,235))	(0,45, 1,235)	(0,1754, 0,45)	(1,0, 1,0)

Table 11. Weights

	K_1	K_2	K_3	K_4	K_5	K_6
K_1	1,0	1,96	1,94	9,32	4,55	4,55
K_2	0,52	1,0	1,94	9,32	1,96	4,55
K_3	0,52	0,52	1,0	4,55	1,02	1,96
K_4	0,09	0,09	0,22	1,0	0,22	1,96
K_5	0,22	0,52	1,02	4,55	1,0	4,55
K_6	0,22	0,22	0,52	0,52	0,22	1,0

Table 12. Priority Weights

Criteria	Sub-Criteria	Main Criteria Weight	Criteria Weight
Information Security	Hacking-Cyber Security	0,338	0,14
	Data Protection		0,14
	Legislation		0,08
Problems of Components	Human Errors	0,252	0,10
	Hardware Malfunctions		0,07
	Mechanical Malfunctions		0,05
	Software Malfunctions		0,07
Accidents	Road Accidents	0,147	0,05
	Weather Conditions		0,03
	Infrastructure Conditions		0,03
Traffic		0,064	0,03
Availability of Required Information	Correct Mapping	0,140	0,05
	Real-Time Updating of information		0,07
Social Development	Social Acceptance	0,059	0,04
	Reliability		0,05

4. DISCUSSION

These risks may be taken into account by businesses that are interested in producing these vehicles. Interaction between AVs and the environment can lead to several dangers. This research offers a hybrid method for ranking these hazards. As a result, disruption and major disasters are the least dangerous hazards, whereas cyberattacks are the deadliest. Because hackers may steal both the operating system of vehicles and the personal information of passengers, developers working on driverless cars can develop incredible ways to prevent them from committing both crimes.

The market for AVs will suffer if these aren't produced by developers. The cyberattack may be defended via artificial intelligence. Deep learning and machine learning are examples of artificial intelligence technologies that can give a system more robust security features. Automated technology can identify and prevent hacking offenses. Internet outages, electronic system failures, interruptions, natural catastrophes, implementations, transportation infrastructure, and environmental adaption are all major concerns. Before adopting autonomous automobiles, businesses should consider functional testing throughout the production phase. The criteria and standards for AVs should be specified by the decision-makers. This article highlights the risks connected to AVs for managers, enterprises, and decision-makers. This research rates the risk that AVs pose.

Another aspect of the use of the AV risk assessment approach heavily relies on the policy implications. In addition to creating an effective system that results in advancements, governments must see the idea of AVs as a milestone that benefits society in terms of transportation and cost-effective operations.

4.1. Limitations

Although the proposed decision system works efficiently and effectively, it is still unclear how to make the right decisions under complex scenarios. Additionally, the perception and comprehension of human behaviors including posture, voice, and motion will be important for AV safety. AVs will need to electronically connect with road infrastructure, satellites, and other cars (such as vehicular clouds) as autonomous technology advances. How do you make sure cybersecurity is one of the biggest concerns for AVs? Safety is the most important concern that can have a big impact on how the public feels about new AV technology. Other main concerns preventing the commercialization of AVs include cost and public interest.

5. CONCLUSION

Although AVs provide a variety of benefits, like efficient energy consumption, a decrease in harmful gas emissions, and a safer driving environment, there may also be several safety-related risks. To conduct a risk evaluation, it will be beneficial to use analytical methods like MCDM procedures. To draw more accurate and helpful findings from this risk assessment process, the FS theory may be used with MCDM methodologies. This study set out to fill a crucial knowledge gap in the literature by illuminating the methods for identifying and prioritizing the risks connected to SDVs. To rank and prioritize processes within the IVFF environment, IVFF-AHP was applied. The AHP, methodology has been rebuilt for this purpose using the IVFF environment.

It is essential to examine the dangers posed by these vehicles to lessen their negative impacts and boost industrial profitability. The findings of this work will assist decision-makers by reducing the uncertainty of professional judgments and enabling them to consider elements including interruption, implementation, environmental factors, acceptance, and responsibility, in addition to hacking and malfunction factors and internet outages. People who use and operate self-driving technology may find the study beneficial. The results of this research show that the threat of cyberattacks is being prioritized and targeted to increase the effectiveness of the deployment of SDVs.

It is conceivable to propose that various integrated fuzzy-based MCDM approaches can be used for this problem as a suggestion for future research, and the outcomes can be compared in this paper. The proposed methodology can also be used to analyze the roadmap for AVDS technology enhancement in addition to risk assessment.

Authorship Contributions
All authors equally contributed to the design and implementation of the research, the analysis of the results, and the writing of the manuscript.

Conflict of Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Statement of Research and Publication Ethics
Research and publication ethics were complied with in the study.

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