SCIENTIFIC OASIS

Journal of Soft Computing and Decision Analytics

Journal homepage: www.jscda-journal.org
ISSN: 3009-3481

JOURNAL OF SOFT COMPUTING AND DECISION ANALYTICS

Application of Pythagorean Fuzzy Analytic Hierarchy Process for Assessing Driver Behavior Criteria Associated to Road Safety

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ARTICLE INFO

Article history:
Received 6 January 2024
Received in revised form 2 February 2024
Accepted 15 February 2024
Available online 19 February 2024

Keywords:
Driver behavior criteria; Road safety; Multi Criteria Decision Making; Pythagorean Fuzzy Analytic Hierarchy Process; Prioritizing.

ABSTRACT

The investigation of road safety issues has long posed a formidable challenge because of intricate and unpredictable practice of human behavior. To address this complexity, experts in the field have turned to linguistic terms for evaluation, capitalizing on recent advancements in ordinary fuzzy sets. A promising way in Multi-criteria decision-making (MCDM) is the utilization of Pythagorean fuzzy sets (PFSs), which provide an extra flexible representation of membership tasks. This study introduces an innovative approach, the Pythagorean Fuzzy Analytic Hierarchy Process (PF-AHP), to measure and rank essential driver behavior criteria in a hierarchical model tailored for diverse driver groups in Budapest city. Our method effectively ranks the model criteria and sub-criteria based on their weighted scores. Consequently, we determine that criteria 'lapses' and 'errors' are the most pivotal factors based on the aggregated weights as compared to all other considerations. In contrast, the criterion 'disobeying speed limits' emerges as the least critical one, followed by 'disobeying overtaking rules' as the second least criterion. Our research highlights that the proposed approach yields robust and useful outcomes, well accommodating the inherent ambiguity in decision-making processes. The resilience of our findings is further affirmed through one-at-a-time sensitivity analysis.

1. Introduction

The Global Road Safety Status Report has brought to light the staggering toll of an estimated 1.35 million annual road traffic accident fatalities [1]. While Europe has made commendable strides in road safety, boasting a remarkable 19% decrease in road deaths over the past six years, the formidable planned goal of halving road crash fatalities between 2010 and 2020 remains an arduous endeavour [2]. Each individual life saved remains a noble pursuit. However, Hungary's road safety performance paints a less optimistic picture, falling lower the EU average with 64 fatalities per million people in 2018, marking a 1% increase from the previous year [3]. An in-depth examination of the Road Safety Action Program unveils that human-related problems stand out as the primary causes of road collisions, emphasizing their pivotal role in the dominion of road safety efforts [4]. Prior research underscores that human factors take center stage as the leading contributors in around 90% of road

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https://doi.org/10.31181/jscda21202439

traffic crashes [5-7]. Within this context, driving behavior emerges as a critical focal point in road safety discussions, influencing numerous facets of road safety, including intentional rule violations, errors stemming from inexperience, inattention, momentary lapses, and age-related factors [8-10]. The assessment of driving behavior assumes a paramount role within traffic studies, offering valuable insights for road safety investigation, microscopic traffic model, and intelligent transportation systems (ITS) [11].

Multi-Criteria Decision Making (MCDM) stands as a pivotal discipline in the realm of operational research, finding particular significance in reckonable assessment of hazardous situations [12]. MCDM grants a diverse spectrum of methodologies tailored to decision-makers and specialists grappling with intricate decision-making dilemmas that hinge on human judgments and involvement [13]. Its fundamental components encompass alternatives, criteria, scores allotted to these alternatives in terms of the criteria, and the criteria weights, representing their comparative significance [14]. In the realm of risk assessment, researchers frequently deploy methodologies such as the Analytic Hierarchy Process (AHP) to prioritize the constraints or advance measures pertaining to complex systems [15-17]. Created by Saaty [18], the AHP serves as a hierarchical MCDM approach encompassing objectives, criteria, and alternatives. It furnishes a well-structured representation of the decision quandary, relying on pairwise comparisons made by evaluators through linguistic expressions. These expressions are then transformed into numerical values through the utilization of fuzzy sets, effectively managing the element of uncertainty [14]. Previous investigations have harnessed the capabilities of the Fuzzy Analytic Hierarchy Process (FAHP) to evaluate and highlight driver behavior criteria entwined with road safety concerns [19, 20]. A triangular fuzzy methodology was seamlessly incorporated with the Best Worst Method (F-BWM) to enhance the precision in estimating driver behavior criteria, facilitating reliable decision-making on the multifaceted landscape of road safety issues [21].

In pursuit of greater flexibility and adaptability within fuzzy Multi-Criteria Decision Making (MCDM) methodologies, the advent of Pythagorean fuzzy sets (PFSs) has ushered in a new era. PFSs, an modification of intuitionistic fuzzy sets, have emerged as a formidable tool, empowering evaluators to express their decisions in a manner that accommodates the nuances of imprecision and vagueness [22]. Unlike their fuzzy counterparts, PFSs offer a departure from the conventional requirement of allocating membership and non-membership scores that collectively sum to 1. Instead, their distinctive feature lies in the focus on the squares of these degrees, which collectively sum to 1. This innovative approach expands the horizons of membership and non-standard membership grades, furnishing professionals with a more extensive toolkit to grapple with and effectively manage the intricate landscape of uncertainty [23]. The main emphasis of this study is to employ the PF-AHP method in estimating and ranking the key factors affecting road safety. To achieve this, a comprehensive questionnaire survey is conducted, utilizing a fuzzy scale to gather responses from different driver groups. These responses are then used to assign weights to the factors in a structured three-level hierarchy, allowing for a systematic prioritization. The ultimate goal is to pinpoint the driver behavior factors that hold the highest ranks, signifying their substantial influence on road safety. By employing the PF-AHP method, this study endeavors to provide valuable insights into enhancing road safety and reducing accidents.

2. Pythagorean Fuzzy Analytic Hierarchy approach and its application in Transportation Field

A comprehensive literature review was initiated to gain a deep understanding of applied method and its practice in studied area. Numerous adaptations of the Analytic Hierarchy Process (AHP) have been successfully introduced in the literature [15-20], particularly in the framework of fuzzy and intuitionistic fuzzy environments. However, there are inherent limitations in traditional fuzzy set (FS) and intuitionistic fuzzy set (IFS) theories [24], which hinder their applicability in certain situations. In case, when a decision-maker assigns a membership grade of 0.8 and a non-membership grade of 0.5, the sum exceeds one, presenting a significant challenge. In response to this limitation, Yager presented Pythagorean fuzzy sets (PFSs) [23], which effectively describe uncertainty by ensuring that the sum of squares of membership and non-membership grades is lower than or equal to one, i.e., 〖0.8〗 ^2+ 〖0.5〗 ^2≤1, and they fall within the interval [0,1]. Following the successful extension of PFSs, Zhang and Xu [25] introduced Pythagorean fuzzy numbers (PFNs), which have proven to be flexible in addressing decision-making problems, finding application in various real-world scenarios [25, 26].

Besides, in the research area of transportation management, numerous selection procedures are introduced with fuzzy data. An AHP method was recently utilized, aiming at transport planning experts, to measure which constraints are considered for park and ride facility location [27]. A fuzzy-analytic hierarchy process (AHP) model was also applied to address the challenge of sustainable urban transport development, involving citizen participation to gather predilections for increasing specific features of the public bus system. The research focuses on establishing a robust framework for transportation development tenders, concentrating solely on measuring the weights of the specified factors without implementing an alternative level [28]. The aim of this study is to develop a decision support system (applying the modern MCDM methods; Fuzzy and Interval AHP) which is capable of examining and producing consent among different stakeholders in a transport growth subject [29]. A fuzzy decision system linking analytic hierarchy process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS) methods with intuitionistic fuzzy sets is utilized in implementing autonomous vehicles as a public transport vehicle and choosing an appropriate road for functioning them [30]. A recent study developed a new hybrid system based on picture fuzzy AHP algorithms and linear assignment and its initial real-world utilization on a public transport development project [31].

In 2015, Kazan and colleagues employed fuzzy logic to identify the optimal transportation form and the best transportation company [32]. Traditional selection techniques primarily rely on FS theoretic approaches, which utilize membership values exclusively to evaluate transportation company preferences across various criteria. Recognizing the limitations of this approach, Büyüközkan and team, in 2018 [33], introduced the concept of non-preference, involving non-membership values, by incorporating Intuitionistic Fuzzy Sets (IFSs) as introduced by Atanassov in 1986 [34]. They developed a methodology to choose sustainable urban transportation alternatives by utilizing the Intuitionistic Fuzzy Choquet integral.

A recent study tackles the prioritization of risks associated with self-driving vehicles by introducing novel hybrid MCDM (Multi-Criteria Decision-Making) methods based on the Analytic Hierarchy Process (AHP), the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), and Vlse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) within the framework of Pythagorean fuzzy sets. The validity of the proposed model is confirmed through sensitivity analysis [26].

Ghorbanzadeh *et al.,* [35] applied an Analytical Hierarchical Process (AHP) and Interval Analytic Hierarchy Process (IAHP) methodology to assess passenger satisfaction using surveys conducted in major cities. They evaluated various public transportation systems, including metro, taxi, regular bus (RB), bus rapid transit (BRT), rail rapid transit (RRT), and van, ultimately providing recommendations for improving public transportation service quality. Perez-Dominguez *et al.,* [36] employed Pythagorean Fuzzy combinative distance-based assessment (CODAS) to evaluate the performance of a large city's public transportation network. Additionally, fuzzy sets were utilized in the assessment of transportation systems, as seen in the work of Wang *et al.,* [37], who incorporated polygonal fuzzy sets for assessing logistics transportation. In addition, the Pythagorean Fuzzy DEMATEL method was employed to establish relationships between driver behavior criteria and sub-criteria relevant to road safety. Utilizing these relationships, a criteria network was constructed, and the Pythagorean Fuzzy Analytic Network Process (ANP) was executed to interpret the results [38].

3. Methodology

In this section, the fundamentals of the Pythagorean fuzzy sets (PFS) and the applied methodology is presented with all its details in the following sub-sections.

2.1 Pythagorean Fuzzy Sets

PFS were created by Yager [23] by considering intuitionistic type-2 fuzzy (IFS2) sets firstly introduced by [29]. In PFSs, the total of membership degree and non-membership degree allocated by evaluators can be more than one but the total squares of these are lower than or equivalent to 1 [39]. The mathematical procuration of a PFS is described in [39].

2.2 *Interval Valued Pythagorean Fuzzy Sets*

Zhang [40] develops interval-valued PFSs (IV PFSs). The mathematical incorporation of an IV-PFS is revealed in details in [40].

2.3 *Pythagorean Fuzzy AHP Method*

The pseudo program for implementing the Pythagorean Fuzzy Analytic Hierarchy Process (PF-AHP) system is provided in Algorithm 1, outlined below [22]:

Algorithm 1. Pseudo illustration of PF-AHP [22]

Algorithm 1: Pythagorean Fuzzy Analytic Hierarchy Process (PF-AHP)

Input:
- Hierarchy structure with criteria and sub-criteria
- Pairwise comparison matrices (PCMs) for each criterion
- Fuzzy scale data collected from experts

Output:
- Aggregated weights for criteria and sub-criteria

1. Initialize all matrices and variables.
2. Create the pairwise comparison matrices (PCMs) based on expert decisions.
3. Normalize the PCMs to ensure consistency.
4. Calculate the geometric mean of the standardized PCMs for each criterion.
5. Compute the fuzzy synthesis matrix based on the geometric mean values.
6. Apply the power mean operator to aggregate the fuzzy synthesis matrix.
7. Normalize the aggregated result to attain the final weights.
8. Return the aggregated weights for criteria and sub-criteria.

End of Algorithm 1.

The applied scale for linguistic expressions is described in [22].

3. Application

Within this section, the Pythagorean Fuzzy Analytic Hierarchy Process (PF-AHP) has been implemented as a robust tool to evaluate the factors intricately linked to driver behavior, factors whose ramifications reverberate directly through the domain of road safety. In the forthcoming discussion, we will delve into the meticulous process of data collection, unfurl the structural framework underpinning the problem at hand, and elucidate the procedural steps that the methodology meticulously follows. This comprehensive exploration promises to shed light on the inner workings of the PF-AHP approach in the context of scrutinizing driver behavior's role in shaping road safety outcomes.

3.1 Questionnaire survey

Diligent endeavors have been relentlessly undertaken to discern and mitigate behaviors that cast shadows of risk over driving safety. In this pursuit, an array of tools has emerged, each wielding its unique strengths. However, among these, the Driver Behavior Questionnaire (DBQ) has distinguished itself through its longevity and extensive adoption within the field [41, 42]. Originating in the early 1990s, the DBQ was meticulously crafted to serve as a compass for navigating the intricate landscape of problematic driving behavior within research [43, 44]. Its enduring relevance and sustained prevalence mark it as a cornerstone in the ongoing quest to unveil and address behaviors that intersect with road safety.

Within the present research undertaking, a meticulously designed questionnaire survey, founded upon the application of a fuzzy scale [45], has been harnessed as a means to accord precedence to pivotal determinants pertaining to driver behavior and their bearing upon road safety. The Pythagorean Fuzzy Analytic Hierarchy Process (PF-AHP) framework has been diligently employed in this context. Notably, the survey encompasses individuals from three distinct cohorts of automobile operators, all hailing from Budapest, Hungary. The first constituent of this study, denoted as Group 1, is characterized by foreign drivers possessing Hungarian driver's licenses and an extensive history of driving. It is imperative to acknowledge that the issuance of driver's licenses to non-native individuals is contingent upon a residency of no less than six months within the confines of Hungary. Extant scholarship has underscored regional disparities in driving inclinations with regard to issues of road safety, a facet of considerable import for the delineation of road safety strategies and promotional initiatives [20, 46]. Moreover, empirical investigations have illuminated the intricate interplay between self-reported driving comportment and the incidence of road traffic mishaps, encompassing both active and passive incidents, across divergent nations [47]. In a parallel vein, Group 2 comprises seasoned drivers, characterized by their substantial accumulated driving experience, while Group 3 encompasses nascent drivers, defined by their relatively limited exposure to the realm of motoring. Each of these assemblages comprises 35 randomly selected participants, whose contribution to the study assumes the form of providing nuanced linguistic appraisals through the medium of the Analytic Hierarchy Process (AHP) questionnaire.

The questionnaire investigation consisted of two sections: the first section designed to gather demographic information about the participants. The second section was designed to assess the specified driver behavior criteria that impact road safety, as discussed in the subsequent sections.

The key demographic and driver-related characteristics for three distinct groups, namely Group G1, Group G2, and Group G3, each consisting of 35 participants.

i. Age: The mean age for Group G1 is approximately 32.25 years, with a standard deviation (SD) of 5.64. In contrast, Group G2 has a slightly higher mean age of around 38.27 years, with a lower SD of 3.67. Group G3, consisting of younger individuals, exhibits a mean age of approximately 21.64 years, with a SD of 2.74. These statistics highlight the variations in age distribution among the groups, with Group G2 being the oldest and Group G3 the youngest.
ii. Sex: In terms of gender distribution, Group G1 primarily comprises male participants, as indicated by a mean of 1.0 and a SD of 0.0. Group G2 has a predominantly male composition but with some female participants, reflected by a mean of 0.883 and a SD of 0.353. In contrast, Group G3 consists of a more balanced gender mix, with a mean of 0.785 and a SD of 0.317. These values elucidate the gender diversity within each group.

iii. Driving Experience: Group G1 has the highest mean driving experience of approximately 3.52 years, with a SD of 2.72, indicating a relatively moderate level of experience. In contrast, Group G2 displays a substantially higher mean driving experience of approximately 17.33 years, with a SD of 2.71, implying a group with significantly more experienced drivers. Group G3, characterized by its younger age, exhibits a much lower mean driving experience of approximately 1.85 years, with a SD of 1.04, highlighting their limited exposure to driving. These statistics emphasize the considerable disparities in driving experience among the groups.
iv. Driver Occupation: The mean values for driver occupation reflect the employment status of participants. Group G1, with a mean of 0.912 and a SD of 0.542, primarily comprises individuals who are employed in some occupation. Group G2, with a mean of 1.0 and a SD of 0.0, consists entirely of employed individuals. In contrast, Group G3, with a mean of 0.361 and a SD of 0.648, predominantly consists of students. These data underline the variation in occupational status among the three groups, with Group G3 being mostly composed of students and Group G2 comprising solely employed individuals.

3.2 Driver behavior model

The study of driver attitudes and behaviors plays a pivotal role in advancing road safety. A multitude of factors directly impact road safety, including driving attitudes, driving experience, and a driver's perception of traffic risks [48]. Reason *et al.,* [44] categorize driving behaviors into three fundamental categories: lapses, errors, and violations, and explore their correlation with accidents. Lapses and errors usually occur during routine tasks that demand minimal conscious attention and are unintentional in nature, while violations involve deliberate misconduct. To evaluate deviant driving behaviors, an extended form of the Driver Behavior Questionnaire (DBQ) was employed, which includes categories for aggressive and ordinary violations, as well as lapses and errors [49, 50]. Aggressive violation attitudes reflect a negative disposition toward fellow road users and are associated with specific types of aggressive traffic violations [50]. In the present study, we utilized a well-established driver behavior model [45], comprising twenty-one driver behavior items organized within a hierarchical structure comprising of three levels, as illustrated in Fig. 1. At the first level, three primary driver behavior factors are identified: 'violations,' 'lapses,' and 'errors.' These core driver attitude factors are further subdivided into associated sub-factors at the second level. The second level, in turn, dissects the sub-criteria of habitual and aggressive violations into their respective lower-level sub-criteria.

This hierarchical model offers a comprehensive framework for assessing driver behavior and allows us to investigate the nuanced aspects of driving attitudes and behaviors with a high level of granularity. It provides a structured foundation for our analysis, enabling a high in-depth consideration of the factors influencing road safety.

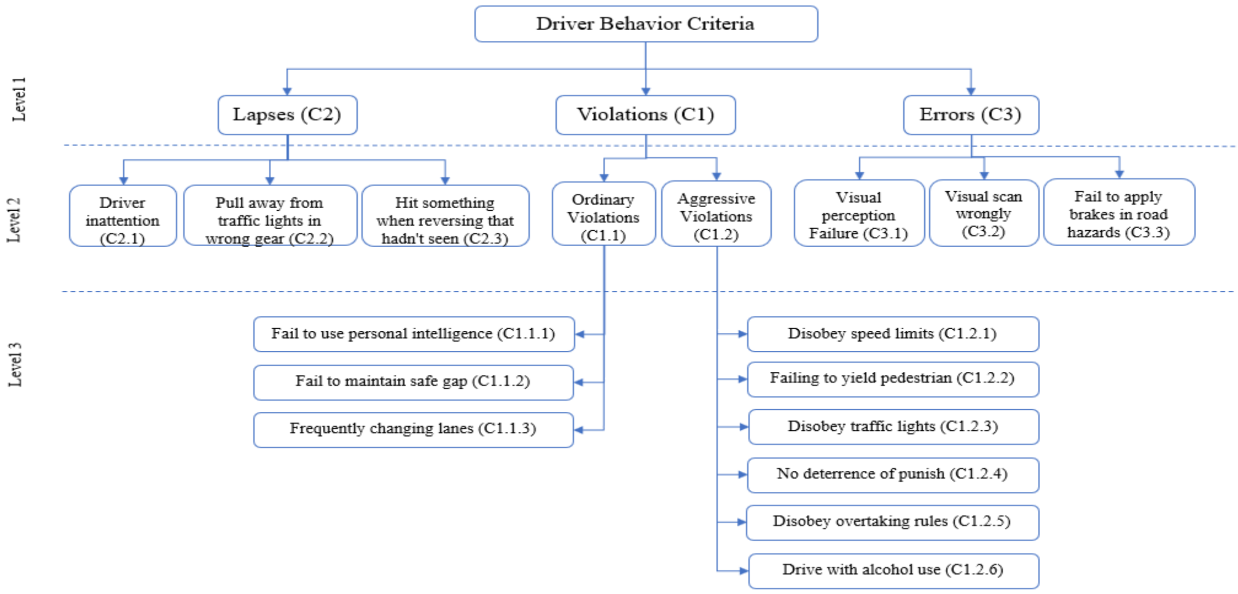

Fig. 1. Driver behavior model [45]

3.3 Steps of the Application

The application process initiates with the development of Pairwise Comparison Matrices (PCMs) by considering the hierarchical structure, as presented in Figure 1. Following the construction of PCMs in Step 1, the methodology proceeds to the evaluation of main criteria in relation to the overarching Goal, relying on judgments from Group 1 participants. This assessment encompasses several key steps, which are outlined below:

Step 2 involves the implementation of a consistency method founded on Saaty's scale to verify the consistency ratio (CR) of the PCM. The resulting matrix by the application of the algorithm is delineated in Table 1. This step is pivotal in ensuring the reliability of the decision-making procedure, which is an essential aspect of the applied methodology. It enables the assessment of the degree of consistency within the PCM and facilitates the identification of any potential inconsistencies that may require further attention and adjustment.

Table 1
Converted PCM for consistency procedure

wrt Goal	C1	C2	C3
C1	1	3	0.33
C2	0.33	1	0.2
C3	3	5	1

Since CR is estimated as 0.0334, we proceed with the subsequent step.

For Step 3, linguistic expressions are transformed and for Step 4, difference matrix $\left(D = \left(d_{ij}\right)_{3\times3}\right)$ is calculated, then for Step 5, interval multiplicative matrix (IMM) $\left(S = \left(s_{ij}\right)_{3\times3}\right)$ is achieved after the measurements as in Table 2.

Table 2
IMM of the difference matrix

wrt Goal	C1	C2	C3
C1	(0.611, 1.636)	(1.178, 3.153)	(0.317, 0.849)
C2	(0.317, 0.849)	(0.611, 1.636)	(0.165, 0.44)
C3	(1.178, 3.153)	(2.271, 6.078)	(0.611, 1.636)

After measuring the indeterminacy grades in Step 6, the matrix of weights $\left(T = \left(t_{ij}\right)_{3\times3}\right)$ is created which is specified in Table 3.

Table 3
Matrix of weights

Criterion	Weight
C1	2.77
C2	1.44
C3	5.34
Sum	9.54

For the last stage of the PF AHP, the weights attained in Step 7 are normalized and the local weights are measured. The results are presented in Table 4.

Table 4
Weights of the main-criteria based on Group 1 judgments

Criterion	Weight
C1	0.29
C2	0.15
C3	0.56

4. Conducted Outcomes and Discussion

Fig. 2. presents a comprehensive overview of the weight assignment process for different criteria within three distinct driver groups (G1, G2, and G3), along with the aggregated final weights. These weights are integral to the decision-making process and offer insights into the relative importance of each criterion within the hierarchical structure.

Key observations from the adopted results include:

i. Local and Global Weights: The local weights represent the significance of each criterion within their respective groups, while the global weights reflect their overall importance across all groups. It is evident that the same criterion can have varying local and global weights depending on the group's perspective.
ii. Aggregated Weight: The aggregated weight for each criterion is computed by considering the local weights across all three groups. This final weight provides a comprehensive assessment of the criterion's significance, incorporating diverse viewpoints.
iii. Variability Among Groups: The figure highlights the potential disparities in how different driver groups perceive the importance of specific criteria. These variations are essential for understanding the divergent attitudes and priorities among groups.
iv. Hierarchical Structure: The criteria are organized hierarchically, with main criteria (C1, C2, C3) broken down into sub-criteria (C11, C12, C111, etc.). This structured approach allows for a more detailed evaluation of various aspects related to road safety.

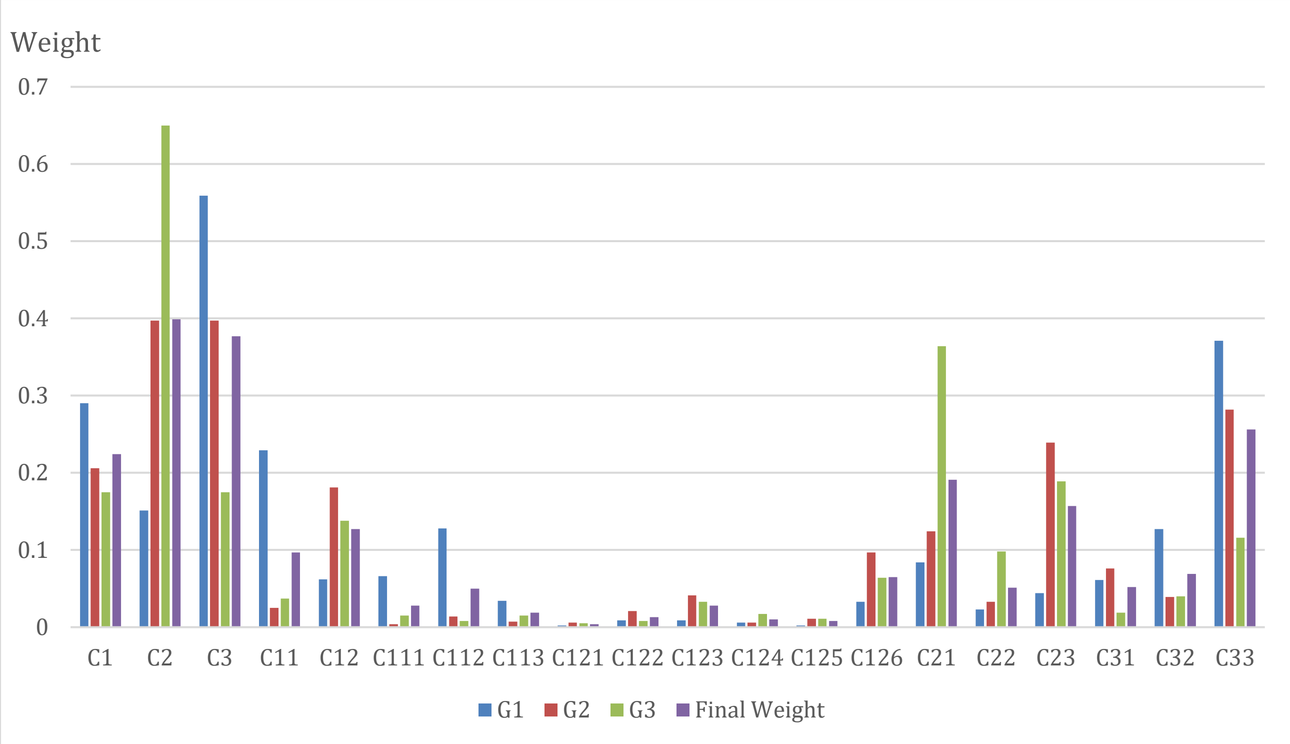

Fig. 2. Outcomes of the application

For a more comprehensive analysis of driver Group 1, the results indicate that, at the first level of the hierarchy, the criterion (C3) is identified as the highest critical factor related to road safety. Conversely, (C2) is examined to be the least impactful factor among the other criteria for this specific group. However, when considering all the groups together, (C2) attains the highest rank as the most influential criterion, emphasizing its significance in the overall evaluation of road safety. The assessment of all groups collectively confirms (C2) as the most critical level-1 criterion, underscoring its universal importance in the framework of road safety.

At the second level (level 2), the outcomes reveal that (C33) is the most critical factor, followed (C11), whereas (C22) is identified as the least critical factor in assessment to the other stated factors. In the third level (level 3), the results highlight (C112) as the most critical factor, followed by (C111). (C121) is found to be the least critical criterion based on the obtained weight scores. For driver Group 2, at the first level, (C2) and (C3) are determined as the most critical factors for road safety, while (C1) has the least impact according to the weight scores. At level 2, (C33) is the most critical factor, followed by 'Hitting something when reversing that had not been seen' (C23). (C11) is observed as the least critical factor among the specified factors. In the third level, (C126) is identified as the most critical factor, followed by (C123), while (C111) is the least critical criterion based on the measured weight scores. For driver Group 3, the outcomes show (C2) as the most critical factor at the first level of the hierarchical structure, with (C1) and (C3) being the least critical factors based on weight scores. At level 2, (C21) is the most critical factor, followed by (C23), while (C31) is detected as the least important factor in comparison to the other stated factors. In the third level, (C126) is the most critical factor, followed by (C123). (C121) is the least critical criterion based on the estimated weight scores.

Taking into account the aggregated weights, (C2) emerges as the most critical factor related to road safety. Preceding factor investigation study examined that 'lapses' items were strongly associated with forming a grouping of 'lapses' and 'errors' and some violation items [50]. The criteria

(C33), (C1), (C21), and (C12) are also identified as substantial risks due to their high weight scores. Conversely, (C121) is measured to be the least critical factor compared to the other factors detected. A previous research revealed that Budapest drivers tend to be less obedient with speed limits [20]. Additionally, (C125) is the second least critical issue in terms of road safety.

a. Sensitivity Analysis

One-at-a-time sensitivity analyses are commenced to monitor changes at all levels, focusing on group dominances. In these analyses, weights are assigned for each group, and subsequent shifts are carefully observed. The initial examination pertains to Level 1, specifically the main criteria. Figure 3 illustrates the changes in response to variations in group weights.

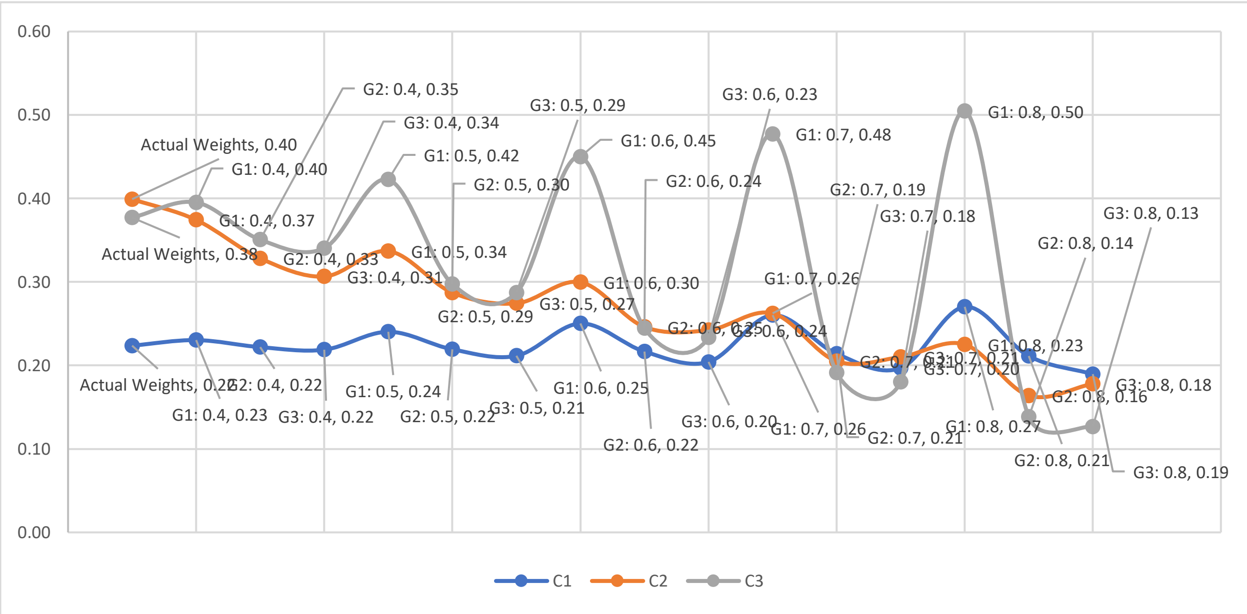

Fig. 3. Weights of Level 1 Criteria with respect to changes

To enhance visualization, the weights of the groups have been multiplied by a factor of 10. As illustrated in Figure 2, it is evident that 'Criterion C1' exhibits minimal variations across the different groups, indicating a high degree of consistency in its weight compared to the other criteria across all dominance groups. In contrast, 'Criterion C2' consistently decreases in weight as the groups' weights increase. 'Criterion C3' is the most variable criterion based on these changes. Notably, when 'Group 1' assumes dominance, 'Criterion C3' carries the maximum weight as compared to the other criteria. Furthermore, across all levels of group weights, 'Group 1' exerts the most significant influence on the criteria. This analysis underscores that 'Criterion C1' enjoys the highest level of consensus, with groups assigning similar values when evaluating it. Conversely, 'Criterion C3' exhibits the most fluctuation in values during evaluations. To further explore this, it is recommended that additional focus groups be engaged to evaluate 'Criterion C3.'

Next, a similar pattern is implemented to the Level-2 criteria. Figure 4 illustrates the changes in weights as the groups undergo weight changes.

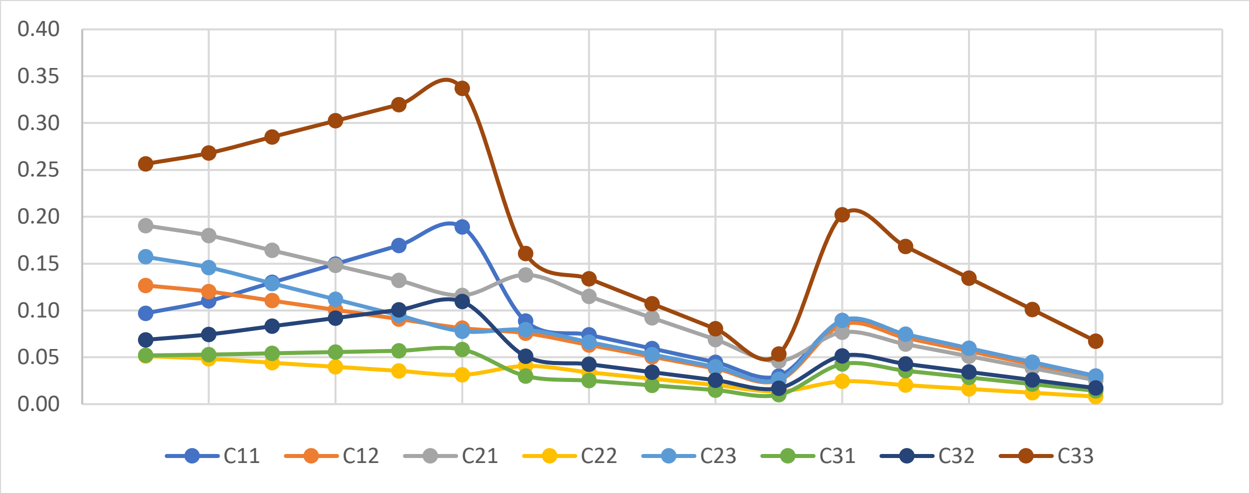

Fig. 4. Weights of Level 2 Criteria with respect to changes

Initially, the application results indicate that 'Criterion C33' carries the maximum weight, while 'Criterion C22' possesses the lowest weight among the criteria. When subject to sensitivity analysis, the ranks remain mostly consistent, with only minor shifts observed. Notably, 'Criterion C33' is the most affected by these shifts compared to the other criteria. Its ultimate influence occurs when the weights of 'Group-2' are set at 0.5 and 0.7. Additionally, 'Criterion C33' and 'Criterion C21' display a high degree of convergence when the weights of 'Group-1' are set at 0.7. Furthermore, they exhibit estimated values under certain circumstances:

i. Group-1: Weight is equal to 0.6, while Group-2 and Group-3 each have a weight of 0.20. This suggests that in this specific decision-making context, Group-1 holds the highest influence, with Groups 2 and 3 being of equal, but lesser, significance.
ii. Group-1: Weight is equal to 0.7, and the others are 0.15. Group-1 is assigned the highest weight in this scenario, indicating its dominant role in the decision. The other groups have lower, but still varying, levels of influence.
iii. Group-2: Weight is equal to 0.6, and the others are 0.20. In this case, Group-2 is the most influential, while the other groups share equal, but less, importance.
iv. Group-3: Weight is equal to 0.5, and the others are 0.25. Group-3 holds the middle ground in terms of influence, with the other groups having relatively higher weights.
v. Group-3: Weight is equal to 0.6, and the others are 0.20. Group-3 takes precedence in this context, while the other groups share similar, lower levels of influence.

In addition to the observations regarding 'Criterion C11,' it's important to highlight the dynamic nature of its ranking as the weight of 'Group-2' varies. When 'Group-2' is assigned a weight of 0.5, 'Criterion C11' secures the second-highest position, emphasizing its increased influence at that specific weight configuration. However, what follows is a noteworthy trend: as the weight of 'Group-2' deviates from this particular value, 'Criterion C11' experiences fluctuations in its rank, indicating its sensitivity to changes in this weight. Conversely, 'Criterion C31' and 'Criterion C22' exhibit a remarkable level of stability within the hierarchy of Level-2 criteria. Regardless of the variations in group weights or the specific weight configurations, these criteria maintain their positions relatively well. This stability underscores their consistent importance in the decision-making process and their resistance to fluctuations induced by changes in group weights. This insight into the behavior of specific criteria and their responses to alterations in group weights provides valuable information for decision-makers. It underscores the nuanced dynamics at play within the decision framework, helping in making informed choices when considering different weight assignments for the involved groups.

To complete the analysis, we also assess the impact of the groups on the Level-3 criteria. The changes in weights with respect to the groups' weight changes are presented in Figure 5.

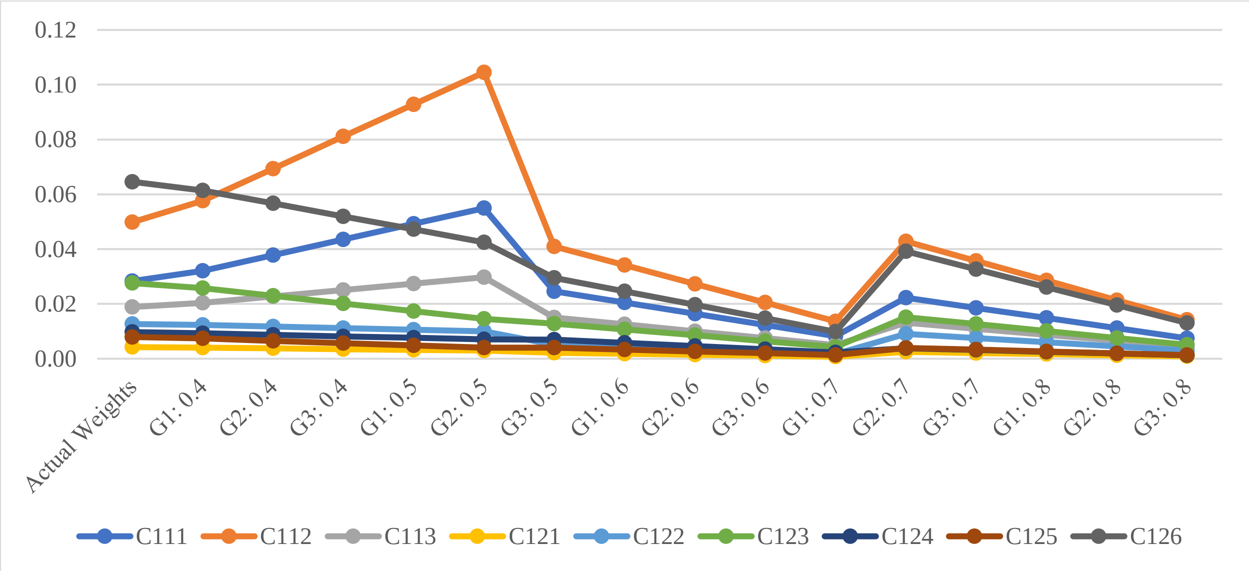

Fig. 5. Weights of Level 3 Criteria with respect to changes

Within the third-level analysis, characterized by group weights generally less than 0.1, the shifts in rankings are subtler compared to the previous levels. However, intriguing patterns emerge as the group weights increase. Notably, 'Criterion C112' rises to the top position and obtains the maximum weight allocation among the Level-3 criteria. What's particularly interesting is that there are two distinctive peak points in this analysis, occurring when the weights of 'Group-2' are set at 0.5 and 0.7. These peaks suggest that 'Criterion C112' is particularly sensitive to variations in the weight of 'Group-2.' This observation highlights the dynamic nature of this criterion's influence within different weight configurations. Furthermore, when the weights of both 'Group-1' and 'Group-2' are equal and set at 0.5, 'Criterion C111' secures the second rank, indicating that it gains prominence under specific weight assignments. This type of insight is valuable for decision-makers as it underlines the intricate relationships between group weights and criterion rankings. It's worth noting that the criteria 'C121,' 'C122,' 'C124,' and 'C125' are associated with relatively small weights in this analysis. As a consequence, the influence of the groups on these criteria remains minimal. This may suggest that these criteria are less sensitive to variations in group weights and maintain consistent positions within the hierarchy.

The analyses reveal that all Pairwise Comparison Matrices (PCMs) exhibit sensitivity to changes in group weights. However, as the ultimate critical criteria remain consistent in most cases, it can be concluded that the application's results demonstrate robustness against fluctuations in the primary criteria weights.

5. Conclusion

The uniformity and potential conflicts in driver behavior criteria influencing crash risk may vary due to diverse driving features. The PF-AHP process presents an effective approach to address the uncertainties associated with driver behavior in managing complex road safety problems. For driver group (G1), the results of our approach reveal that (C3) emerges as the most critical factor associated to road safety at the first level of the hierarchical structure. At the second level, (C33) is identified as the crucial critical factor, followed by (C11). In the third level (C112) is identified as the highest critical factor, followed by (C111). In the case of driver group (G2), the application results indicate that (C2) and (C3) are the most critical factors at the first level of the hierarchical model. At the second level, (C33) is identified as the crucial critical factor, followed by 'Clashing with something when reversing that was not seen' (C23). In the third level, 'Driving with alcohol use' (C126) is the crucial critical factor, followed by (C123). For driver group (G3), the results demonstrate that (C2) is the highest critical factor at the first level of the hierarchical model. At the second level, (C21) is identified as the crucial critical factor, followed by 'Hitting something during reversing that was not seen' (C23). In the third level, (C126) is considered the utmost critical factor, followed by (C123).

Based on the aggregated weights, (C2) is determined to be the most critical factor related to road safety, surpassing all other stated factors. In contrast, (C121) is identified as the least critical factor when compared to the other specified factors. Given the meaningful outcomes generated by our system through the calculations, it can help as an important decision-support tool for handling ambiguous data. Investigators and local policymakers can leverage our model to attain robust results, a fact substantiated by the sensitivity analysis. For future studies, expanding the dataset by including surveys from cities with related social credentials could enhance our work and allow for the development of practical behavioral systems. Additionally, introducing a new questionnaire section to measure indeterminacy could lead to the need for a new uncertainty modeling approach, such as the application of neutrosophic sets, to address this aspect.

Acknowledgement
This research was not funded by any grant

Conflicts of Interest
The authors declare no conflicts of interest.

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