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A Fuzzy Decision-Making Support Model for Traffic Safety Analysis

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ABSTRACT

Our study delves into the crucial issue of road safety by examining the intricate dynamics of driver behaviour, often resulting in tragic accidents. The importance of comprehending these behaviours is acknowledged, leading us to propose an innovative decision-making support model that integrates the analytic hierarchy process (AHP) with the best worst method (BWM) in a fuzzy context. Our objective is to effectively evaluate the overall influence of driver behaviour on road safety while reducing ambiguity in assessments. In a practical case study involving skilled drivers in Budapest, Hungary, a thorough survey was conducted to prioritise key driving behaviour factors that impact road safety. Our findings reveal 'errors' as the most vital aspect, followed by specific behaviours like 'colliding when reversing without observation' and 'driving under the influence of alcohol'. By simplifying the survey procedure and offering practical insights, our unified model improves decision-making for policymakers striving to tackle road safety issues efficiently. To conclude, our research showcases the effectiveness of merging AHP and BWM methodologies in a fuzzy setting to obtain valuable perspectives on road safety concerns, ultimately aiding in the advancement of sustainable transportation systems.

1 | Introduction

The Global Status Report on Road Safety 2023 indicates that despite a slight decrease in road traffic deaths to 1.19 million/year, efforts to enhance road safety are making an impact. However, the toll of mobility-related fatalities stays unacceptably high, with about 1.35 million persons, equivalent to 18.2 per 100,000 people, losing their lives in roadway collisions in 2016. This averages nearly 3700 deaths per day, with an additional 20–50 million individuals sustaining injuries or disabilities. The goal of halving road traffic deaths and injuries by 2030 requires urgent action (World Health Organization (WHO) 2023). The European Union began creating road safety guidelines in 2010 to reduce road fatalities by 50% by 2020 compared to 2010. The European Commission is working on the target that fatalities and severe injuries should be halved on European roads by 2030, on the approach to 'Vision Zero'—zero fatalities and severe injuries by 2050. In the meantime, the numbers were adjusted to decrease road accident incidence by 2030 (European Commission 2019) substantially. Nevertheless, Hungary (Janstrup 2017) had a significant increase in the fatality ratio compared to recent accident data, underscoring the need for prevention and the relevance of figuring out the underlying causes of accidents. Figure 1 demonstrates the statistical data about fatalities and injuries that transpired within the preceding 20 years.

The Road Safety Action Programme report on situation analysis has observed that human factors contribute to most road accidents. Therefore, addressing these factors is crucial in accomplishing the primary intention of highway safety targets (OECD/ITF 2016). Human errors, also called human factors, significantly contribute to traffic collisions (Yılmaz and Çelik 2006; Varmazyar et al. 2013). Traffic injuries are significantly impacted by risky driving, a human mistake attributed to the driver (Atombo et al. 2017; Sabaté-Tomas et al. 2014). Recent and previous research indicates that around 95% of traffic collisions can be attributed to dangerous behaviours shown by drivers (Bazzaz et al. 2015). There exists a multitude of potential causal elements that contribute to the likelihood of traffic collisions. Using all potential variables in estimating traffic collision projecting models undercuts the precision of the constraint evaluations to a definite range (Nagendra and Khare 2003).

Besides the frequently utilised traffic crash investigation techniques such as negative binomial regression, Poisson models, and logistic regression (Lord and Mannering 2010; Savolainen et al. 2011; Mannering and Bhat 2014; Kassu and Anderson 2019), the use of tree-based data evaluation methods such as hierarchical tree-based regression (HTBR) (Karlaftis and Golias 2002) and classification and regression tree (CART) (Chang and Chen 2005; Chang and Wang 2006; Scheetz et al. 2009; Xu et al. 2014) is considered to be appropriate methods in sorting and prediction of traffic collisions. Despite their widespread use in various fields, traffic safety studies rarely employ tree-based models. Several studies (Scheetz et al. 2009; Xu et al. 2014) say that graphical display alternatives in these models give more information about how crash parameters are related and make it easier to understand the results than the odds ratios utilised in logistic regression methods.

The analytic hierarchy process (AHP) method was created by Saaty (1977), and it is adopted in many works for estimating sustainable decision-making solutions (Moslem et al. 2023). Recently, it has been adopted to estimate the transportation complex issues, such as evaluating the park and ride problem (Ortega et al. 2023; Ortega and Moslem 2023), ameliorating the urban transport system (Gündoğdu et al. 2021; Moslem and Çelikbilek 2020; Moslem 2024), modelling travel modes (Duleba et al. 2022), and estimating the critical factors connected to road safety (Farooq and Moslem 2022). AHP's popularity has significantly increased after combining it with fuzzy logic, and it has been applied in many recent research studies, including transportation (Dos Santos et al. 2019). This integration presents complex issues and risks in the various modes, levels, and approaches. The combined method generates data from risk assessments, which inconsistent models can then implement. The models generated from the risk assessments are used in various areas, such as floor water incursion in coal mines, hazardous transportation substances, and information technology development (Wang et al. 2014). Recently, the best worst method (BWM) has been widely employed in solving complex issues (Mi et al. 2019), where the advantages of BWM over AHP are the smaller number of evaluated pairwise comparisons (PCs), taking into consideration the same problem with the same number of factors and alternatives, and the ability to generate better consistency (Rezaei 2015; Moslem 2023). However, taking advantage of both AHP and BWM is more convenient; recent studies have demonstrated the integration of AHP and BWM for estimating complex problems. In the transport field, Çelikbilek et al. (2022) proposed AHP-BWM in a grey condition to shed light on the most critical factor for enhancing the urban transport system. The integrated model significantly reduced the number of PCs in estimation. Moslem et al. (2020) deconstructed how the integrated AHP-BWM can efficiently evaluate the riskiest driver behaviour elements regarding road safety issues. Farooq et al. (Farooq et al. 2021) employed the AHP-BWM model to detect the riskiest factor influencing frequent lane-changing and its impact on road safety. However, the AHP-BWM model has also been applied in other research fields (Bathrinath et al. 2021; Sharma et al. 2022; Badi et al. 2023).

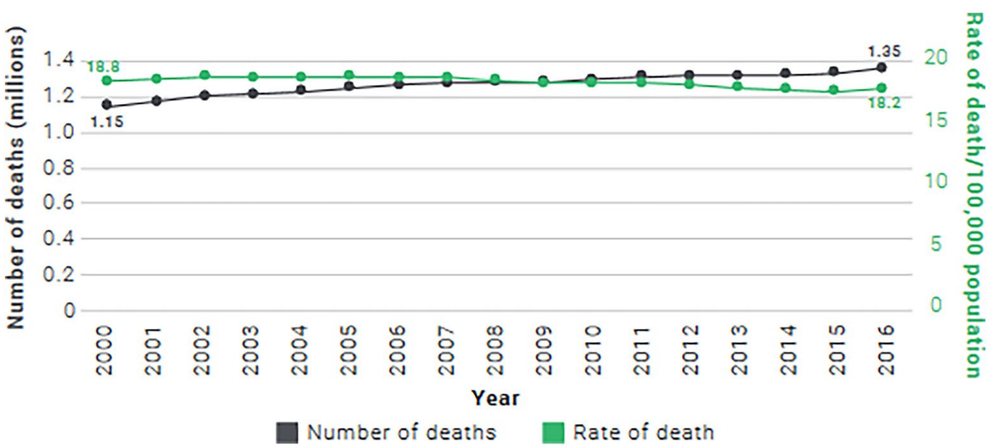

FIGURE 1 | Number and rate of road traffic deaths per 100,000 population; 2000–2016 (World Health Organization (WHO) 2023).

These techniques deploy fuzzy set theory to depict contradictory and imprecise data in the process of making decisions, demonstrating its utility in managing subjective assessments. This study explores the beneficial effects and potency of fuzzy AHP and fuzzy BWM as multiple criteria decision-making (MCDM) techniques for resolving intricate and ever-changing decision-making challenges comprising subjective assessments. The primary emphasis lies in the selection process, wherein decision-makers must assess alternate options by considering several criteria and sub-criteria (Gul et al. 2019; Omidi et al. 2023). Fuzzy logic in the MCDM technique is crucial as it allows decision-makers to successfully navigate the vagueness and unpredictability that commonly emerge when assessing options using numerous criteria. It offers a versatile and instinctive method for representing intricate decision problems, enabling decision-makers to articulate their preferences more organically. The literature has comprehensively investigated using MCDM techniques to address DC selection difficulties in diverse supply chains. However, more research needs to specifically address the problem in uncertain decision-making contexts by implementing fuzzy theory into established MCDM methods. It enables decision-makers to articulate what they consider using language and offers a versatile and instinctive approach to modelling complex decision problems.

A fuzzy-based intelligent decision support model was implemented by Bouraima et al. (2024) for the purpose of determining the issues associated with urban mobility. In their study, Moslem, Gündoğdu, et al. (2024) pointed out a new approach called decomposed fuzzy combinative distance-based assessment (CODAS) and decomposed fuzzy AHP. The primary goal of the proposed method is its ability to enhance the accuracy of parcel locker locating in the context of last-mile delivery. In their study, Moslem and Pilla (2024) introduced a new approach called the parsimonious spherical fuzzy analytic hierarchy method, which targets assessing and enhancing urban transport services. The Fermatean fuzzy Archimedean Heronian Mean-Based Model was implemented by Kakati et al. (2024) in order to enhance and develop a more sustainable urban transport system.

Recent research created a fuzzy decision-support system considered to help road safety policymakers in creating informed decisions concerning safety planning (Behnood et al. 2017). In the Fuzzy Inference System-based study, a model was generated that can show a real-time risk assessment model to the drivers. The model included parameters such as car speed, weather conditions, accident frequency, tire tread depth and fatigue (Koçar and Dizdar 2021). Another paper proposed a deep reinforcement learning traffic control strategy integrated with Type-2 fuzzy control. The output action of the Type-2 fuzzy control system substituted the action of choosing the maximum output Q-value of the aim network in the DQN algorithm, decreasing the error produced by the usage of the max operation of the target system. This approach improved the online learning rate of the agent and surged the reward value of the signal control action (Bi et al. 2024). A paper generated a causal reasoning model to characterise drivers' decision-making procedures while driving intelligent vehicles. A unified inference model is created to predict drivers' responses in a supportive driving environment based on fuzzy logic and causal inference. The model can detect the causal relationship of the intelligent driving environment and develop the use of linguistic driving perceptions (Chen et al. 2024). In a recent research, Fuzzy Logic, which contains linguistic terms and uncertainty, was merged with the Cellular Automata model to simulate the decision-making process of right-turn filtering movement at signalised intersections. The study helped to offer a novel approach to linguistically assess cognitions and imitate decision-making actions of the individual driver (Chai et al. 2017). In a study, fuzzy logic was utilised to analyse the safety and quality of roads, and fuzzy logic has suitable flexibility and the capability to define and model phenomena. It also proposed good accuracy for measuring the parameters recognised in this study (Shourideh Ziabari and Kaboodvand 2023). Considering the fuzziness, dependence and interaction of evaluating indices, the fuzzy method was utilised to measure traffic safety, and the evaluation and grading criteria for different indices were determined (Zhao et al. 2010). In our study, considering numerous parameters essential to control the vehicle safety, a fuzzy logic model was created for automatic speed alert, brake alert with sensors and cameras in vehicles. For intelligent transport, the fuzzy interface system (FIS) was created to support drivers' decision-making and make them aware of controlling speed and braking so as to avoid accidents. The Rule-Based System was produced using several linguistic rules (Gupta and Chaudhari 2020).

In their study, Moslem, Deveci, and Pilla (2024) brought forward an innovative methodology combining the BWM and Kendall model to determine the most effective digital voting equipment for strengthening public participation in urban transport decision-making processes. Haseli et al. (2024) examined the sustainability of urban mobility by using the fuzzy ZE-numbers framework in group decision-making, incorporating the BCM and CoCoSo methodologies. Aytekin et al. (2024) investigated the elements influencing transport demand management by utilising a decision-making model grounded in the Q-ROFsets. The novel Fermatean Fuzzy Operational Competitiveness Rating model was introduced by Deveci et al. (2024). This model integrates the Fermatean Fuzzy Distance Measure and Relative Closeness Coefficient techniques to assess the multiple possibilities regarding implementing intelligent transport systems in the metaverse.

The study demonstrates a first-time application of a real-life problem of the novel AHP-BWM in a fuzzy environment to evaluate the riskiest driving behaviour factors that are related to road safety. Despite sample research accessible in other regions globally, there is a lack of suitable studies in Hungary to support policy frameworks on a range of determinant features that expedite risky driving attitudes. Hence, this research was designed to examine the risk (road safety) connected with risky driving behaviours among competent vehicle drivers in Budapest.

The primary contribution of this research lies in the reduction of survey duration and resources through the integration of AHP with BWM; the subsequent contribution involves the mitigation of ambiguity and imprecision among assessors in the assessment phase. Finally, a significant contribution is made through the application of a practical case study in the domain of road safety to authenticate the developed framework.

The authors posit a novel technique to tackle various constraints and obstacles found in current methodologies. These constraints encompass the necessity for a more streamlined decision-making procedure, the mitigation of uncertainties and ambiguities among evaluators, and the aspiration to offer a framework applicable to real-world situations. The integration of AHP with BWM within a fuzzy context presents an innovative strategy for decision-making assistance, particularly in the assessment of the impact of driver behaviour on road safety. This amalgamated approach not only diminishes the time and energy expended on surveys but also amplifies the precision and dependability of the evaluation process through the inclusion of fuzzy logic to address subjective assessments. Through the proposition of this fresh technique, the authors aimed to equip decision-makers with a pragmatic and efficient instrument for addressing intricate road safety concerns and fostering sustainable transportation systems.

1.1 | The Contribution of the Work

The paper contributes to the field in several ways:

- It introduces a novel approach by integrating AHP and BWM with fuzzy logic, enhancing the decision-making process for evaluating drivers' behaviour on road safety. This methodological innovation allows for representing subjective judgements and uncertainty, leading to more nuanced and reliable results.
- The developed model offers practical utility by providing a quicker and less expensive survey process for assessing driver behaviour. This is particularly valuable for transportation authorities and researchers seeking efficient methods to evaluate road safety factors.
- The proposed model reduces estimation time and improves expert perception by utilising rarer comparisons and stable PCs. This contributes to enhanced efficiency in evaluating driver behaviour factors and streamlining road safety interventions and policies.
- The integrated model's flexibility allows for easy modification of survey configurations, accommodating evolving road safety needs and research requirements. This adaptability enhances the model's usability in various contexts and facilitates integration into existing road safety frameworks.

The manuscript is structured in a particular sequence: Section 1 consists of an extensive examination of the existing literature on traffic accidents, decision-making processes and tools utilised for analysing driver behaviour and its influence on road safety. Section 2 outlines the methodology employed in the present study, encompassing the evaluation of risk perception, crucial driving behaviours, road conditions and their association with traffic congestion, violations and injuries. Section 3 summarises the outcomes and key findings from the categorical analysis and factorial prioritisation. Section 4 provides a detailed exposition of the findings, conclusions, study specifics and potential recommendations for future research.

2 | Methodology for the Proposed Research

2.1 | Driver Behaviour Survey

The present work attempts to use a decision-making model with fuzzy logic to estimate the consequences of crucial driver behaviour elements on road safety. The key factors are organised in a hierarchical set with three levels, as depicted in Figure 2. The degrees of violations in this study offer a thorough examination of multiple aspects contributing to road safety hazards. This analysis provides valuable insights into the complex dynamics of driver behaviour and its consequences.

At Level 1, the focus is on fundamental road traffic violations (RTVs), lapses, and errors, shedding light on their significant roles in exacerbating road safety risks. At Level 2, we emphasise the significant impact of ordinary and aggressive violations on crash involvement despite their perceived differences in severity. Moreover, drivers' inattention and specific driving behaviours, such as pulling away from traffic lights in the wrong gear and hitting unseen obstacles when reversing, underscore the critical need to address these nuanced aspects of driver behaviour for comprehensive road safety strategies. Finally, at Level 3, failures related to personal intelligence, maintaining safe gaps, and adherence to traffic rules further elucidate the multifaceted nature of road safety challenges and the diverse array of factors contributing to accidents. By delving into these distinct levels of violations, the discussion offers a nuanced understanding of the complex interplay between driver behaviour and road safety outcomes, paving the way for targeted interventions and evidence-based policy decisions to enhance overall road safety. Here, we briefly discuss the driver behaviour criteria hierarchical structure that affects road safety:

- *Violations*: RTVs such as speeding and running red lights pose an essential threat to road safety, affecting all road users by increasing the risk of accidents and injuries.
- *Lapses*: Lapses in driver behaviour, like inattentiveness and momentary distractions, are critical predictors of accident involvement, emphasising the importance of addressing these behaviours to enhance road safety.
- *Errors*: Cognitive failures, including errors in judgement and slips in performance, contribute to an elevated risk of road accidents, highlighting the need to mitigate these factors to improve road safety.
- *Ordinary violations*: Despite their perceived minorness, ordinary violations significantly increase the risk of crashes, underscoring the need to address these behaviours to improve road safety.
- *Aggressive violations*: Blatant disregard for traffic rules and safety norms through aggressive violations significantly contributes to heightened crash risk, necessitating targeted interventions to curb these behaviours and improve road safety.
- *Drivers' inattention*: Driver inattention, a significant factor in traffic conflicts, underscores the pervasive nature of this problem and its implications for road safety, highlighting the need for interventions to address inattentive driving behaviours.

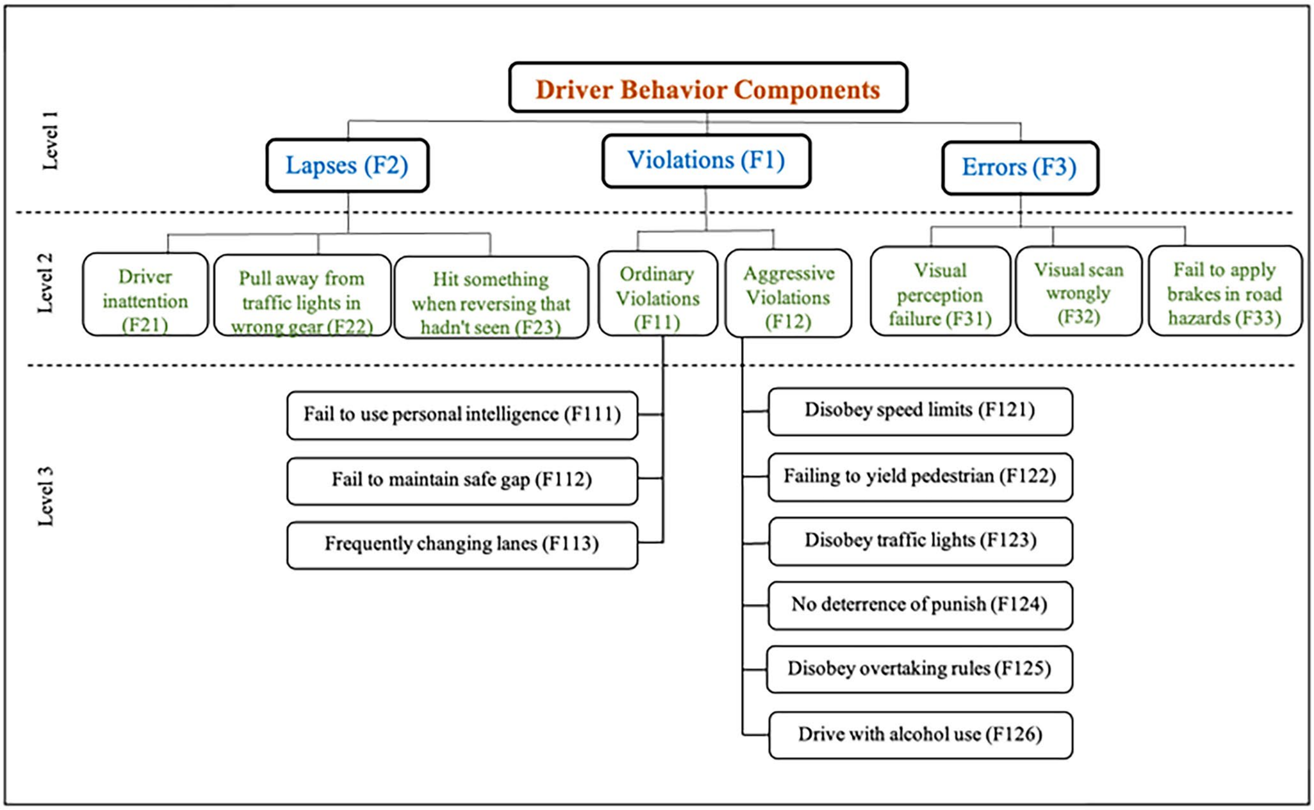

FIGURE 2 | Driver behaviour structure that affects road safety (Farooq et al. 2019).

- *Pulling away from traffic lights in the wrong gear*: Engaging vehicles in inappropriate gear when starting from traffic lights poses safety hazards, emphasising the importance of proper driving habits to mitigate risks on the road.
- Insufficient visual scanning: Insufficient visual scanning undermines the ability to perceive road hazards, underscoring the need for thorough visual scanning in identifying potential risks and mitigating accidents.
- *Neglecting to uphold the safe gap*: It is crucial to keep acceptable distances between vehicles at crossroads to prevent accidents, highlighting the need to accept gaps to ensure traffic safety.
- *Frequent lane changes*: Evaluating the risks associated with changing lanes is crucial for comprehending safety dynamics and devising efficient safety measures, underscoring the need to study lane change behaviours and their impact on road safety.
- *Violating speed limits*: Exceeding the speed limit presents substantial hazards to the safety of the general public, requiring actions to minimise its negative consequences and decrease the likelihood of accidents, injuries, and deaths.
- *Failure to discourage through punishment*: The imposition of significant penalties can serve as a deterrent against illegal driving behaviours, indicating the potential efficacy of punitive measures in diminishing traffic rule infractions and improving road safety.
- *Driving under alcohol influence*: Alcohol-connected impaired driving continues to pose a significant risk to road safety, underscoring the need to tackle this problem in order to improve safety for all individuals on the road.

The questionnaire was disseminated to a cohort of 70 participants (motorists possessing valid driving permits and significant expertise in the field of Transportation engineering) affiliated with the Budapest University of Technology and Economics in Hungary. Participants were reached through email correspondence and provided with a link to the survey hosted on Google Forms. Merely 70% of the population engaged in the study, and an evaluation of the response rate of these contributors was conducted. Solomon (2006) stressed in his study 'Wisdom of Crowds' that state, 20 respondents in a survey can facilitate great judgement. In order to gather pertinent data, the survey was split into two parts. The first part includes vital information of the participants, including their gender, age, level of education (at least a bachelor's degree), and length of driver's licences (most participants had held their licences for over 10 years). These details suggest that the participants have appropriate education and research experience related to the study. The descriptive statistics of the socio-demographic variables are depicted in Table 1. The second section is projected to collect data related to the influence of specified factors on road safety as the outcomes are depicted. The findings derived from this section are elaborated upon in subsequent sections, supported by our integrated AHP-BWM fuzzy decision-making model.

2.2 | The Conventional AHP

The conventional AHP approach utilises hierarchical decision assembly, which is built from decision components of

TABLE 1 | Demographic statistics of evaluators.

Variable details	Frequency	Percentage (%)
Number (N)	70	100
Age (years)		
18–30	14	20
31–50	34	48.5
51 above	22	31.5
Gender		
Male	63	90
Female	07	10
Time of driving licence (years)		
1–5	11	15.71
6–15	37	52.85
16–25	22	31.42
Education		
BS	33	47.14
MSC/PhD	37	52.86

multifaceted decision subjects and is being utilised comprehensively in numerous decision fields (Guo et al. 2023; Abrahamsen et al. 2020).

The main advantages of AHP for hierarchically structured problems include its ability to facilitate complex decision-making by breaking down the problem into manageable components, its flexibility in handling subjective judgements and diverse criteria, and its capability to provide a structured framework for comparing alternatives and prioritising criteria based on their relative importance. Additionally, AHP allows for sensitivity analysis to assess decision robustness.

The hierarchical model usually comprises multi-part components in which the primary criteria and sub-criteria are set, and the significance of relationships among criteria in distinct levels governs the total weight scores for the related factors in the latter level. The critical phases of conventional AHP are depicted in Figure 3:

In AHP, positive square matrix A represents the PCM, where $x_{ij} > 0$ is designated as the subjective ratio among w_i and w_j, and w_x is the measurable weight score from the matrix. The defined eigenvector system of Saaty for the PCMs can be measured by Equation (1):

$$A.w_x = \lambda_{\max}.w_x \Longleftrightarrow w_x\left(A - \lambda_{\max}.I\right) \tag{1}$$

where $\lambda_{\max}$ represents the maximum eigenvalue of a positive square matrix. An example of a PC matrix with six elements is depicted in Table 2.

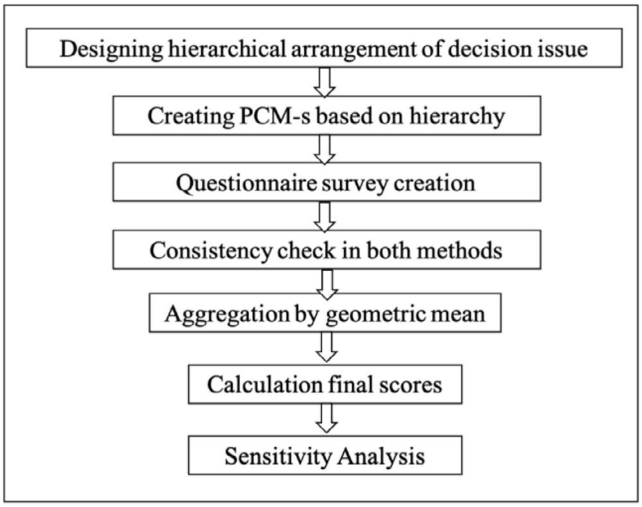

FIGURE 3 | The framework of AHP model.

TABLE 2 | An example of a PC matrix with a structure of six elements.

w_1/w_1	w_1/w_2	w_1/w_3	w_1/w_4	w_1/w_5	w_1/w_6
w_2/w_1	w_2/w_2	w_2/w_3	w_2/w_4	w_2/w_5	w_2/w_6
w_3/w_1	w_3/w_2	w_3/w_3	w_3/w_4	w_3/w_5	w_3/w_6
w_4/w_1	w_4/w_2	w_4/w_3	w_4/w_4	w_4/w_5	w_4/w_6
w_5/w_1	w_5/w_2	w_5/w_3	w_5/w_4	w_5/w_5	w_5/w_6
w_6/w_1	w_6/w_2	w_6/w_3	w_6/w_4	w_6/w_5	w_6/w_6

For empirical PCMs, the interchange is certainly attained for each PCM, $x_{ji} = 1/xij$, where $x_{ii} = 1$. However, consistency is likely not attained for empirical matrices. Consistency factor:

$$x_{ik} = x_{ij}.\mathrm{xjk} \tag{2}$$

Evaluators, in general, use the Saaty scale to estimate the PCs generated by considering the problem's hierarchical arrangement (Saaty 1977).

The consistency test in AHP is applied to ensure that all PCMs have a consistency factor of agreeable inconsistency (Saaty 1977). The consistency ratio (CR) has to be less than 10%, and it is computed from Equation (3):

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \tag{3}$$

Where RI is a typical CI value of the same size randomly created PCM. Consistency Index (CI) is computed from Equation (4):

$$\mathrm{CI} = \frac{\lambda_{\max} - m}{m - 1} \tag{4}$$

2.3 | Fuzzy AHP

The fundamental model of driver behaviour factors was utilised in the context of Budapest; nonetheless, in order to mitigate the ambiguity of respondents, the AHP technique was implemented within a fuzzy environment. Throughout the computational procedure, fuzzy numbers enable assessors to express their subjective assessments in PCs, facilitating the derivation of more accurate results. Consequently, the survey was structured based on hierarchies and PCs pertaining to the primary factors, along with the development of sub-factors. Following the adoption of the Fuzzy AHP (F-AHP) principles, estimations of PCs, determination of final weights, and assessment of consistency were conducted. Sun (2010) used the concept of a mathematical model. However, the questionnaire was created with triangular fuzzy numbers (TFNs).

S fuzzy number abbreviated $\widetilde{S}$ on $\mathbb{R}$ as a TFN if its membership function $\mu S(x): \mathbb{R} \rightarrow [0, 1]$ is similar in value to Equation (5):

$$\mu\, \widetilde{S}(x) = \begin{cases} \dfrac{x-1}{m-1}, & l \le x \le m \\ \dfrac{u-x}{u-m}, & m \le x \le u \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

From the previous equation (Equation 1), l and u express lower and higher limits of fuzzy number $\widetilde{S}$, and m is the modal value for $\widetilde{S}$. TFN can be depicted by $\widetilde{S} = (l, m, u)$. Operational rules of TFN $\widetilde{S}_1 = (l_1, m_1, u_1)$ and $\widetilde{S}_2 = (l_2, m_2, u_2)$ are demonstrated as resulting Formulas (6–10).

Lower and higher limits of the accumulation of a fuzzy number $\bigoplus$

$$S_1 \bigoplus \widetilde{S}_2 = (l_1, m_1, u_1) \bigoplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{6}$$

Lower and higher bounds of the multiplication of a fuzzy number $\otimes$

$$\begin{aligned} \widetilde{S}_1 \bigotimes \widetilde{S}_2 &= (l_1, m_1, u_1) \bigotimes (l_2, m_2, u_2) \\ &= (l_1 l_2, m_1 m_2, u_1 u_2) \\ &\quad \text{for } l_1, l_2 > 0; m_1, m_2 > 0; u_1 u_2 > 0 \end{aligned} \tag{7}$$

The lower and higher limits subtraction of the fuzzy number $\ominus$

$$\widetilde{S}_1 \ominus \widetilde{S}_2 = (l_1, m_1, u_1) \ominus (l_2, m_2, u_2) = (l_1 - u_2, m_1 -, m_2, u_1 - l_2) \tag{8}$$

The lower and higher limits division of a fuzzy number $\emptyset$

$$\begin{aligned} \widetilde{S}_1 \emptyset \widetilde{S}_2 &= (l_1, m_1, u_1) \emptyset (l_2, m_2, u_2) \\ &= \left(\frac{l_1}{u_2}, \frac{m_1}{, m_2}, \frac{u_1}{l_2} \right) \text{for } l_1, l_2 > 0; m_1, m_2 > 0; u_1 u_2 > 0 \end{aligned} \tag{9}$$

Reciprocal of fuzzy number

$$\widetilde{S}^{-1} = (l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right) \text{ for } l_1, l_2 > 0; m_1, m_2 > 0; u_1 u_2 > 0 \tag{10}$$

Gumus (2009) and Sun (2010) proposed Table 3 to evaluate PCs.

Linguistic conditions were employed to estimate PCs by examining which factor is the most significant, as $S(5 \times 5)$ is the most considerable matrix in our work.

where

$$\widetilde{S} = \begin{bmatrix} 1 & \widetilde{S}_{12} & \widetilde{S}_{13} & \widetilde{S}_{14} & \widetilde{S}_{15} \\ \widetilde{S}_{21} & 1 & \widetilde{S}_{23} & \widetilde{S}_{24} & \widetilde{S}_{25} \\ \widetilde{S}_{31} & \widetilde{S}_{32} & 1 & \widetilde{S}_{34} & \widetilde{S}_{35} \\ \widetilde{S}_{41} & \widetilde{S}_{42} & \widetilde{S}_{43} & 1 & \widetilde{S}_{45} \\ \widetilde{S}_{51} & \widetilde{S}_{52} & \widetilde{S}_{53} & \widetilde{S}_{54} & 1 \end{bmatrix} = \begin{bmatrix} 1 & \widetilde{S}_{12} & \widetilde{S}_{13} & \widetilde{S}_{14} & \widetilde{S}_{15} \\ 1/\widetilde{S}_{12} & 1 & \widetilde{S}_{23} & \widetilde{S}_{24} & \widetilde{S}_{25} \\ 1/\widetilde{S}_{13} & 1/\widetilde{S}_{23} & 1 & \widetilde{S}_{34} & \widetilde{S}_{35} \\ 1/\widetilde{S}_{14} & 1/\widetilde{S}_{14} & 1/\widetilde{S}_{34} & 1 & \widetilde{S}_{45} \\ 1/\widetilde{S}_{15} & 1/\widetilde{S}_{25} & 1/\widetilde{S}_{35} & 1/\widetilde{S}_{45} & 1 \end{bmatrix} \tag{11}$$

$$S_{ij} = \begin{cases} \widetilde{9}^{-1}, \widetilde{8}^{-1}, \widetilde{7}^{-1}, \widetilde{6}^{-1}, \widetilde{5}^{-1}, \widetilde{4}^{-1}, \widetilde{3}^{-1}, \widetilde{2}^{-1}, \widetilde{1}, \widetilde{2}, \widetilde{3}, \widetilde{4}, \widetilde{5}, \widetilde{6}, \widetilde{7}, \widetilde{8}, \widetilde{9}, 1, & i \ne j \\ 1 & i = j \end{cases}$$

The fuzzy geometric mean was employed to accumulate the fuzzy scores.

2.4 | The Conventional BWM

Rezaei (2015) found that BWM may effectively address intricate problems using the PC approach, reducing time and effort. BWM independently derives the weights, which can be integrated with other MCDM methods (Mahdiraji et al. 2018; Kumar et al. 2019; Omrani et al. 2020). BWM is a method that has been recently proposed. In this approach, the user decides the criterion that holds the most significance and the criterion that holds the lowest significance. After collecting the criteria as mentioned earlier, a comparative analysis has been implemented to determine the most significant criterion in relation to other criteria and the least significant criterion in relation to other criteria. Significance values are employed to compute the weights assigned to the criteria.

Nevertheless, human qualitative judgments, such as the paired comparisons based on a 1–9 scale by decision-makers in BWM, sometimes exhibit ambiguity and intangibility.

TABLE 3 | Fuzzy scale based on TFN.

Number	Linguistic	TFN
9	Perfect	(8, 9, 10)
8	Absolute	(7, 8, 9)
7	Very good	(6, 7, 8)
6	Fairly good	(5, 6, 7)
5	Good	(4, 5, 6)
4	Preferable	(3, 4, 5)
3	Not bad	(2, 3, 4)
2	Weak advantage	(1, 2, 3)
1	Equal	(1, 1, 1)

Additionally, information regarding criteria in the real world is often ambiguous and uncertain (Gündoğdu et al. 2021; Bathrinath et al. 2021; Sharma et al. 2022). Hence, in particular practical scenarios, the utilisation of fuzzy numbers instead of crisp values can be employed to conduct reference comparisons of BWM. This approach may align more closely with real-world situations and yield more persuasive ranking outcomes. This study presents an extension of BWM to the fuzzy environment, introducing a fuzzy-based BWM. Reference comparisons are performed using fuzzy comparing judgements, as described by Guo and Zhao (2017). The subsequent procedures outline the fundamental steps involved in the processing of BWM (Moslem 2023):

- identifying decision problems and related elements
- determining the most essential and least essential element
- establishing preference for the most essential element over other elements
- establishing preference for the least essential element over other elements
- conducting consistency test
- scaling weights

2.5 | Fuzzy BWM

Different fuzzy systems have been recommended as intuitionistic fuzzy systems, such as TFNs (Guo and Zhao 2017), dominance degree, Z-numbers (Li et al. 2019), interval type-2 (Wu et al. 2019), Fermatean fuzzy sets (Senapati and Yager 2020) and Decomposed Fuzzy sets (Cebi et al. 2023). Mi et al. (2019) presented several BWM applications and extensions that interested readers and researchers can analyse in detail.

In BWM, there are n factors, and fuzzy PCs on these n factors can be accomplished by utilising linguistic terms, as discussed in Table 3. After that, linguistic assessments are altered to TFNs. Then, the fuzzy comparison matrix is attained as follows,

$$A^{\%} = \begin{array}{c} \\ c_1 \\ c_2 \\ \mathrm{M} \\ c_n \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & \mathrm{L} & c_n \end{array} \\ \begin{bmatrix} a_{11}^{\%} & a_{12}^{\%} & \mathrm{L} & a_{1n}^{\%} \\ a_{21}^{\%} & a_{22}^{\%} & \mathrm{L} & a_{2n}^{\%} \\ \mathrm{M} & \mathrm{M} & \mathrm{O} & M \\ a_{n1}^{\%} & a_{n2}^{\%} & \mathrm{L} & a_{nn}^{\%} \end{bmatrix} \end{array}$$

where a_{ij} denotes relative fuzzy partiality of factor i to factor j, which is a TFN; $a_{ij} = (1, 1, 1)$ when $i = j$.

Here, we elaborated on the comprehensive phases of fuzzy BWM for outlining fuzzy weights of factors. However, this detailed phase can also be applied to the fuzzy weight estimation of alternatives (Guo and Zhao 2017).

Step 1. Create a decision system. Assume n factor $(c_1, c_2, \ldots c_n)$.

Step 2. Identify the best and worst factors; the best factor is cB, and the worst is c_W.

Step 3. Conduct comparisons for the best factor.

Step 4. Conduct comparisons for the worst factor.

Step 5. Compute fuzzy weights. In this paper, we utilised Equation (12) for converting TFNs to crisp numbers as follows:

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \left| \frac{w_j}{w_W} - a_{jW} \right| \right| \right\}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} R(w_i) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \ldots, n \end{cases} \tag{12}$$

where $w_B = (l_B^w,\ m_B^w,\ u_B^w)$, $w_j = \left(l_j^w \le m_j^w \le u_j^w\right)$, $w_W = (l_W^w \le m_W^w \le u_W^w)$, $w_{Bj} = \left(l_{Bj}^w \le m_{Bj}^w \le u_{Bj}^w\right)$ and $w_{jW} = \left(l_{jW}^w \le m_{jW}^w \le u_{jW}^w\right)$, and Equation (12) can be transmitted to the subsequent nonlinearly controlled optimisation problem.

$$\min \xi$$

$$s.t. \begin{cases} \left| \frac{w_B}{w_j} - a_{Bj} \right| \le \xi \\ \left| \frac{w_j}{w_W} - a_{jW} \right| \le \xi \\ \sum_{j=1}^{n} R(w_i) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \ldots, n \end{cases} \tag{13}$$

where $\xi = \left(l^\xi, m^\xi, u^\xi\right)$.

Taking into consideration $l^\xi \le m^\xi \le u^\xi$, it is assumed that $\xi^* = (k^*, k^*, k^*)$, $k^* \le l^\xi$, then Equation (13) can be converted as

$$\min \xi$$

$$s.t. \begin{cases} \frac{(l_B^w,\ m_B^w,\ u_B^w)}{\left(l_j^w, m_j^w, u_j^w\right)} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right) \le (k^*, k^*, k^*) \\ \frac{\left(l_j^w, m_j^w, u_j^w\right)}{(l_W^w, m_W^w, u_W^w)} - \left(l_{Bj} \le m_{Bj} \le u_{Bj}\right) \le (k^*, k^*, k^*) \\ \sum_{j=1}^{n} R(w_i) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \ldots, n \end{cases} \tag{14}$$

Step 6. Determine CR. CR is evaluated in the same way as conventional BWM. The CI for fuzzy BWM employed is depicted in Table 6.

2.6 | The Proposed Fuzzy-AHP-BWM

The literature review was not considered in addressing this issue mainly due to the prevalent use of deterministic models in existing studies (Moslem et al. 2020; Farooq et al. 2021), which are inadequate in handling uncertainties and subjective assessments inherent in decision-making. Conversely, our novel framework goes beyond traditional methods by incorporating fuzzy sets, enhancing the AHP and BWM with fuzzy logic to create a more sophisticated and adaptable decision-making structure for expressing preferences more intuitively. This enhancement allows our model to address the inherent ambiguity and vagueness in decision-making contexts, particularly when evaluating complex issues like the impact of driver behaviour on road safety. Therefore, by integrating fuzzy sets into the decision-making process, our model surpasses the constraints of current methodologies and presents a more holistic resolution to the issue at hand.

Let us consider a decision problem involving n factors arranged into m levels. Let $k=1$, ..., m represent the levels in the decision. For any given level j, let there be h factors denoted as $j=1$, ..., h, and let J be a combination of all decision factors, such that $J=1$, ..., n. Thus, J represents the first factor on the first level, and so on for all factors in the decision.

The initial step in this model is to select levels or levels within the decision-making process where the Parsimonious AHP will be applied. Choosing the level(s) that contain a sufficient number of factors (denoted by 'h') is suggested, which can alleviate the burden of multiple PCs for evaluators. Additionally, it is advised (in line with Saaty's 7 ± 2 rule for a PCM) to choose the level(s) where equal to 5×5 PC matrices or larger are to be estimated (Saaty 1977). From our experience, the PCs for a 5×5 matrix may be challenging for non-experts.

In the conventional AHP method, to get a fully formed matrix for n factors, it is necessary to assess $n(n-1)/2$ PCs. Conversely, for BWM, only $2n-3$ PCs are needed. This demonstrates that BWM is an effective technique that can save time and energy for both assessors and analysts. For instance, if there are only 10 factors, the conventional AHP method would require 45 comparisons, whereas using BWM for the same PCM would only require 17 comparisons.

For Level 1 of the set hierarchical models, the different assessor groups occupied the elements of f12, f13, and f23 to compare F1, F2 and F3.

In conventional AHP, 28 comparisons have to be estimated. However, in the F-AHP-BWM model, only 20 comparisons have to be estimated. Figure 4 depicts the initial phases of the model.

The paper's novelty lies in the integration of fuzzy logic into the AHP-BWM model for assessing driver behaviour's impact on road safety, which enhances decision-making processes and results in more accurate evaluations compared to traditional approaches.

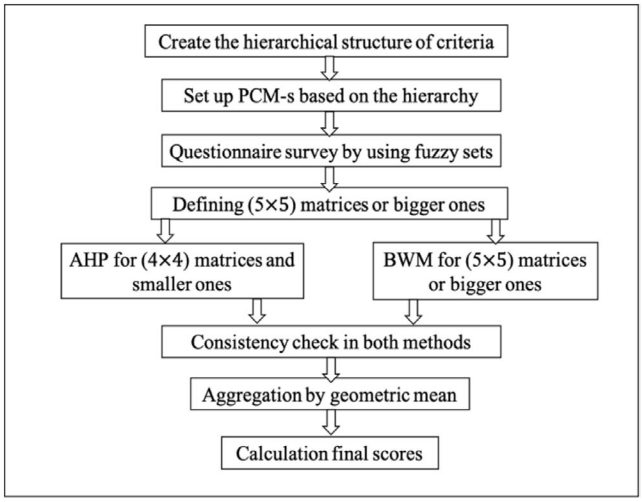

FIGURE 4 | Framework of fuzzy-BWM-AHP model.

3 | A Case Study for Road Traffic Analysis

The integrated fuzzy AHP-BWM model, built on matrix magnitude, efficiently evaluated driver behaviour parameters linked to traffic safety. First, the analytical hierarchy procedure was used to analyse a hierarchical structure comprising four (3×3) matrices and one (2×2) matrix (Table 4). In the final stage, the weight scores for a (6×6) matrix were computed using the fuzzy best-worst approach (Table 5), which needed just nine comparisons as opposed to the fuzzy AHP method's 15 comparisons.

Based on surveyor replies to the DBQ, the integrated model results for the initial layer indicated that 'errors' (F3) are the most significant component and 'violations' (F1) are the second most significant factor related to the behaviour of driver road safety. Driving mistakes are a foremost contributing element in road accidents; thus, considering their origins and effects is important when making decisions about road safety (Papantoniou et al. 2019). However, as indicated in Table 6, 'lapses' (F2) are the least important component.

The integrated model results for the next phase revealed that the most vital driving behaviour element connected to highway shelter is 'Hit something when reversing that had not seen (F23)'. Meanwhile, 'Aggressive violations' (F12) are seen as the most crucial element compared to other mentioned criteria. Those drivers who are comparatively high on trait aggressiveness are stated to commit higher traffic violations than those with lower scores (Zeshui and Cuiping 1999). However, (F22) is detected as the least significant factor in the second level. Meanwhile, 'Ordinary violations' (F11) are seen as the most crucial element compared to other mentioned criteria. The factors' rank in Level 2 (Table 7).

In Level 3, the integrated model was conducted due to one (6×6) matrix (BWM) and one (3×3) matrix (AHP). The (F-126) was the most significant factor in Level 3. Because Hungary has a zero-tolerance policy for driving while inebriated, the findings

TABLE 4 | The generated normalised weight scores from the fuzzy AHP for all matrices that are smaller than (6×6).

Level 1		Level 2		Level 3	
Factor	**Weight**	**Factor**	**Weight**	**Factor**	**Weight**
Driver behaviour factors		F1		F-11	
F1	0.416	F-11	0.123	F-111	0.399
F2	0.161	F-12	0.877	F-112	0.466
F3	0.447	F2		F-113	0.157
		F-21	0.484		
		F-22	0.096		
		F-23	0.439		
		F3			
		F-31	0.153		
		F-32	0.242		
		F-33	0.627		

TABLE 5 | The generated normalised weight scores from the fuzzy BWM for the (6×6) matrix.

Factor	F-121	F-122	F-123	F-124	F-125	F-126
Score weight	0.152	0.236	0.152	0.076	0.095	0.289

TABLE 6 | The factors' weights in Level 1.

Factor	F1	F2	F3
Weight	0.416	0.161	0.447

can be explained (World Health Organization (WHO) 2023). Subsequently, the model results detected (F-122) as the second most significant factor. However, the results detected (F-113) as the least significant factor, as shown in Table 8. The final rank of factors is in Level 2.

3.1 | Sensitivity Analysis

In this section, sensitivity studies are conducted for Levels 1–3 to validate the outcomes of the proposed methodology. The present study examines the impact of alterations in weights assigned to criteria on the outcomes of the rating process.

In this study, we examined the impact of modifying the weight assigned to the primary criterion at Level 1 on the outcomes of the ranking process. Initially, 20 novel weight coefficient vectors were produced and categorised into 20 distinct situations. New weight coefficient vectors were generated in each instance by decreasing the weight coefficient by 15%. Equations (15) and (16) were utilised for this objective (Deveci et al. 2024; Demir et al. 2024).

$$w_{n\beta} = (1 - w_{n\alpha})\left(\frac{w_\beta}{1 - w_n}\right) \quad (15)$$

$$w_{n\beta} + w_{n\alpha} = 1 \quad (16)$$

The variable $w_{n\beta}$ represents the fresh weight values computed for the criteria. The lowered value of the criterion is denoted as $w_{n\alpha}$. The criterion's original value is marked as w_β, whereas the criterion's original value with a lowered value is represented as w_n.

Consequently, the range of variation for w_3 at Level 1 is generated within the interval $w_3 \in [0.0169, 0.3708]$. In the present scenario, the weighting value in Scenario 1 (S1) is denoted as $w_3 = 0.3708$, while in Scenario 20 (S20), the weighted value is represented as $w_3 = 0.0169$. Equation (1) is employed subsequent to each modification of w_3 to compute the weights of the remaining criteria. Figure 5 displays updated weight values of criteria obtained from 20 scenarios for Level 1.

The range of variation for w_{23} at Level 2 is generated within the interval $w_{23} \in [0.0121, 0.2657]$. In the present scenario, the weighting value in S1 is denoted as $w_{23} = 0.2657$, whereas in S20, the weighted value is represented as $w_{23} = 0.0169$. Equation (1) is employed after each modification of w_{23} to compute the weights of the remaining criteria. Figure 6 displays the updated weight values of criteria obtained from 20 scenarios for Level 2.

In turn, the range of variation for w_{126} at Level 3 is produced within the interval $w_{126} \in [0.0152, 0.3329]$. In the given scenario, the weighting value in S1 is denoted as $w_{126} = 0.3329$, whereas the weighted value in S20 is indicated by $w_{23} = 0.0152$. Equation (1) is employed after each modification of w_{126} to compute the weights of the remaining criteria. Figure 7 displays updated weight values of criteria obtained from 20 scenarios for Level 3.

These findings indicate the dynamic nature of the F-AHP-BWM model, wherein the weighting values of criteria are subject to change based on different scenarios. This sensitivity analysis provides insights into the robustness and adaptability of the model, allowing decision makers to assess the implications of various scenarios on the final decision outcomes.

TABLE 7 | Final weight for Level 2 sub-factors.

Factor	F-11	F-12	F-21	F-22	F-23	F-31	F-32	F-33
Weight	0.051	0.365	0.078	0.015	0.439	0.068	0.108	0.280

TABLE 8 | The final weighted average scores for the third-level factors.

Factor	F111	F112	F113	F121	F122	F123	F124	F125	F126
Weight	0.020	0.024	0.008	0.024	0.058	0.057	0.022	0.045	0.166

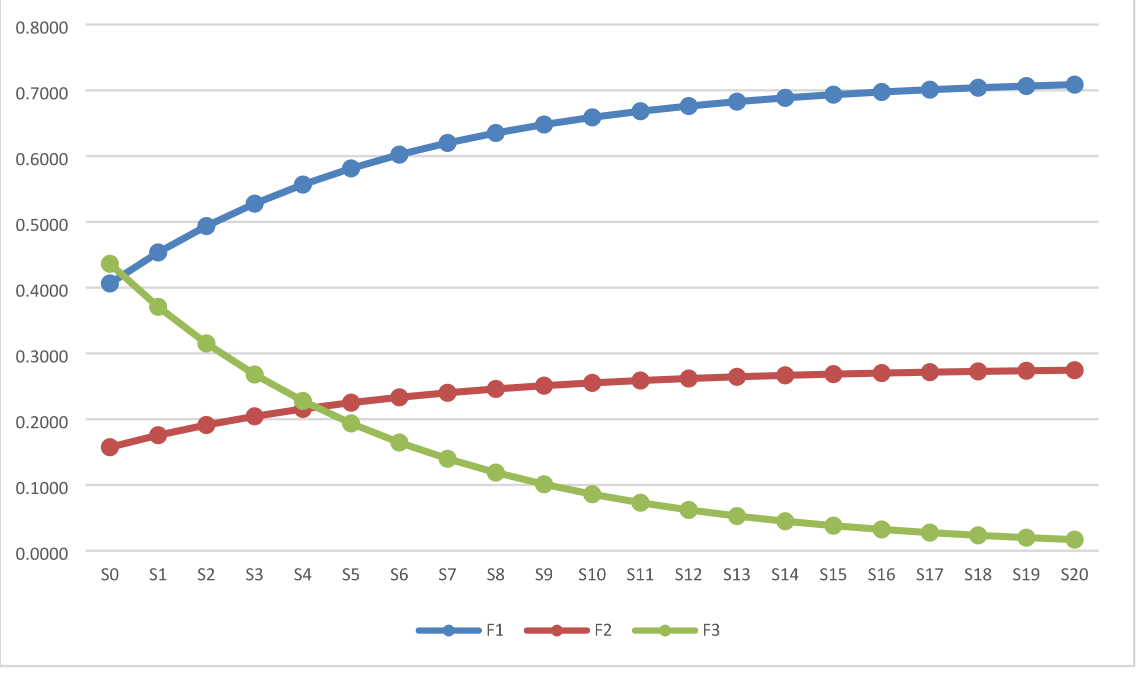

FIGURE 5 | Changes in criteria weights according to various scenarios for Level 1.

3.2 | Comparative Analysis

In this section, we compare the factor weights obtained from two different decision-making methods, where we considered only the (6×6 matrix) because it is the spotted matrix to apply the FBWM: FAHP and F-AHP-BWM. From Figure 8, it is evident that there are variations in the factor weights between the two methods for each factor. For instance, in factor F121, FAHP assigns a weight of 0.0237, whereas F-AHP-BWM assigns a higher weight of 0.0482. Similarly, for factor F126, FAHP assigns a weight of 0.1662, whereas F-AHP-BWM assigns a lower weight of 0.0916. These discrepancies highlight the differences in how the two methods prioritise and evaluate the factors. It is essential to analyse these variations to understand their impact on the overall decision-making process and the resulting outcomes. Additionally, further investigation may be needed to determine which method provides more accurate or reliable results based on specific contexts and requirements of decision-making problems.

Minor discrepancies imply a degree of coherence or congruence between the two approaches, prompting the need to determine if these deviations fall within an acceptable threshold, a critical consideration contingent upon the specific demands and intricacy of the decision-making context. Variables such as the scale of measurement, the characteristics of decision criteria, and the inclinations of decision-makers can impact the understanding of these distinctions. Nevertheless, an analysis of sensitivity was executed on the F-AHP-BWM model, accompanied by a comparative assessment to gauge its efficacy in relation to alternative methodologies. This comparative scrutiny scrutinised the fluctuations in the weighting of criteria across 20 different scenarios. Significantly, the outcomes unveiled notable variances in the criteria weights, underscoring the dynamic nature of the model. These findings underscore the resilience and flexibility of the F-AHP-BWM model in addressing diverse situations and furnishing valuable perspectives for the decision-making process.

4 | Concluding Remarks

Evaluation and prioritisation of driver behaviour play a pivotal role in tackling road safety concerns, given the extensive driver behaviour data and its diverse nature. Preceding the construction of our advanced AHP-BWM framework, we examined

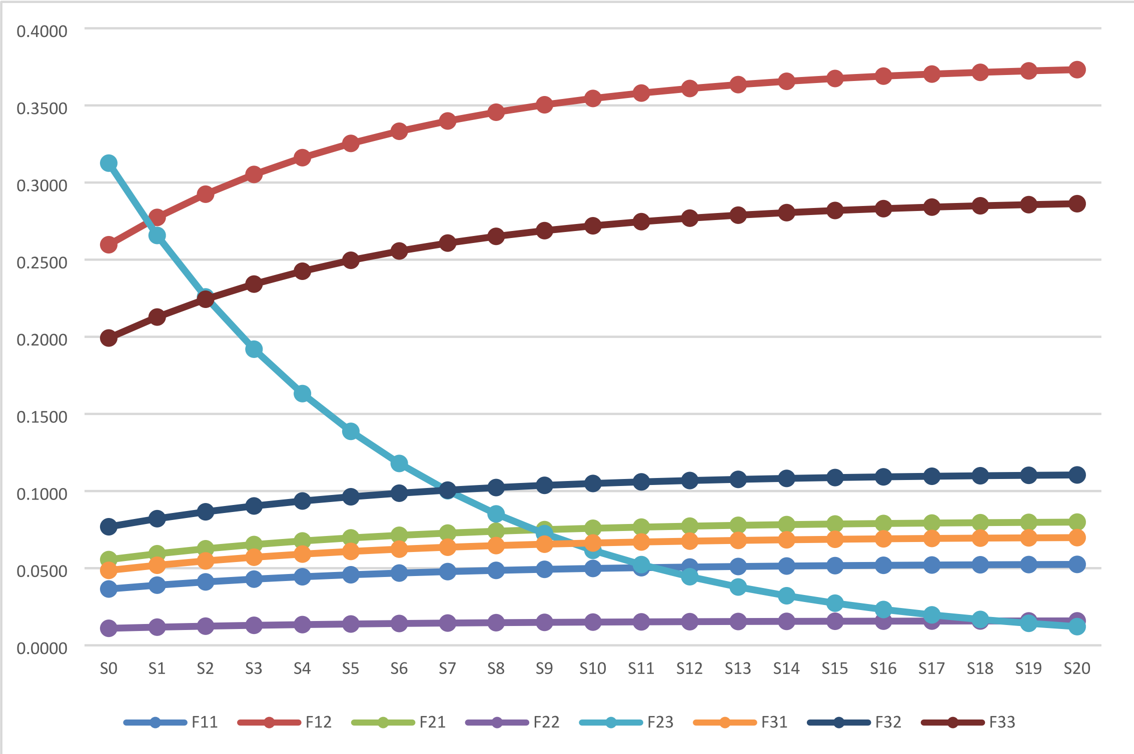

FIGURE 6 | Changes in criteria weights according to various scenarios for Level 2.

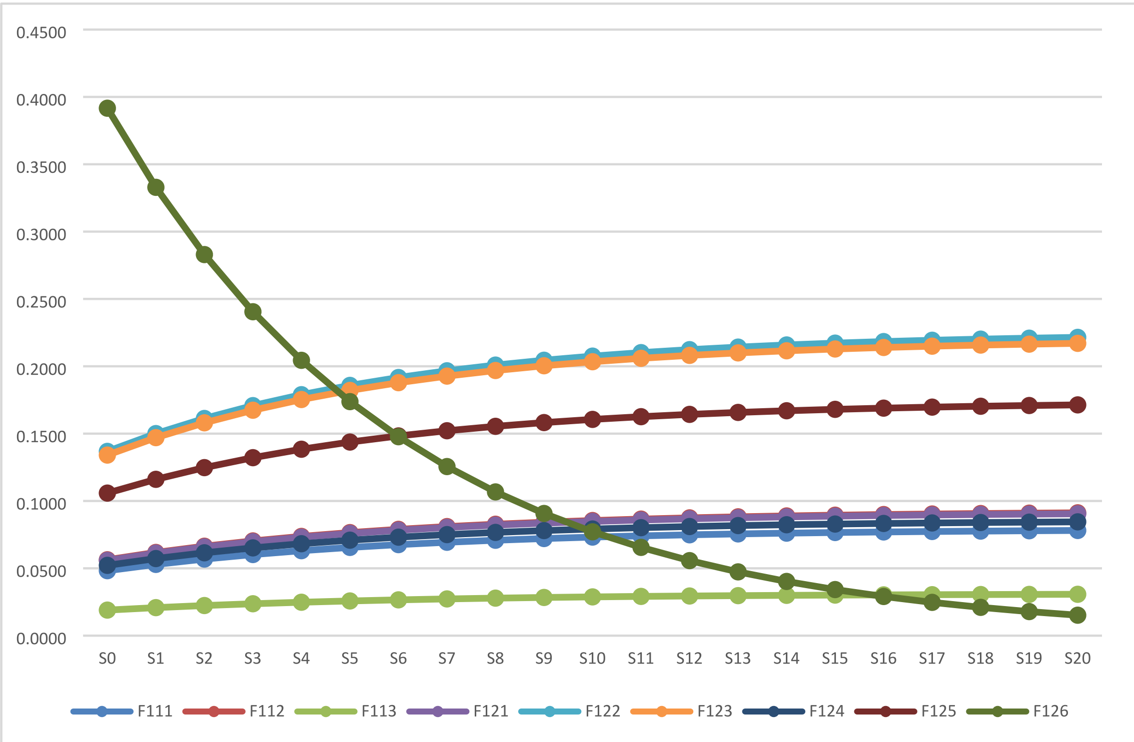

FIGURE 7 | Changes in criteria weights according to various scenarios for Level 3.

numerous complex challenges linked with AHP. Through the engagement of resident drivers possessing valid licences, we gathered driver behaviour data utilising a questionnaire structured around a 'fuzzy scale'.

Our improvement over the baseline method involved integrating AHP and BWM with fuzzy logic to accommodate subjective judgements and uncertainty. This enhancement facilitates a more refined decision-making process, resulting in more

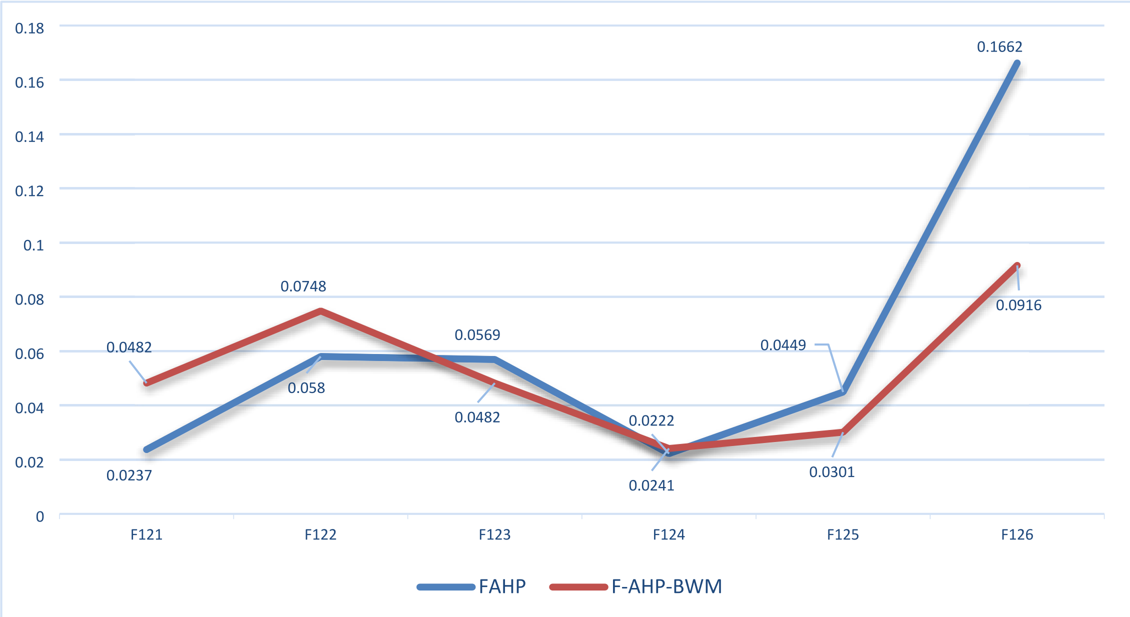

FIGURE 8 | Comparative analysis.

consistent and reliable evaluations of the impact of driver behaviour's on road safety. With its rarer comparisons than the traditional AHP approach, the proposed model efficiently estimates three-level structure driver behaviour factors, reducing estimation time and enhancing expert perception. The model yields more accurate results with supplementary stable PCs than standard approaches. The integrated model offers faster and more cost-effective survey processes while providing flexibility in survey configuration adjustments, unlike traditional AHP and comprehensive PC questionnaires.

The model's findings indicated that, at the initial level of the hierarchical structure, 'errors' with a final weight score of (0.447) have the most significant influence on road safety, next to 'violations' (0.416). According to the model results for the subsequent level, 'aggressive violations' (0.365) and 'hitting something when reversing that you had not observed' (0.439) are the two most critical driving behaviour factors associated with traffic safety. The driver behaviour element 'pull away from traffic lights in wrong gear' has the least substantial impact on road safety, with a final weight score of (0.015). Compared to other specified characteristics, the third-level model findings showed that 'drive with alcohol use' had the highest final weight score (0.166), followed by 'frequently changing lanes' (0.058). In contrast, the model's findings indicated that 'failing to use personal intelligence' was the driver behaviour element with the lowest final weight score (0.020) regarding road safety. In future words, recent fuzzy sets, such as q-rung orthopair fuzzy sets, pythagorean fuzzy and aggregation operators, such as Schweizer–Sklar operations, can be used (Ecer and Pamucar 2022; Kou et al. 2023; Gayen et al. 2023; Akram et al. 2023; Tian 2024; Kara et al. 2024; Wang, Yang, and Han 2024; Lo et al. 2024; Wang, Zhao, and Zheng 2024).

However, the scope of the research is geographically limited to a case study involving professional drivers in Budapest, Hungary. As such, the findings may not be fully generalisable to wider populations or different cultural and traffic frameworks. Also, the study focused mainly on professional or skilled drivers, possibly neglecting key behavioural differences present in non-professional or younger drivers. The selected set of behavioural factors, while comprehensive, may not capture emerging behaviours influenced by modern technology, such as distracted driving due to mobile device usage. Future research could address these limitations by expanding the geographical scope and integrating a more diverse sample of drivers across different regions and demographic groups. Comparative studies involving varying levels of driver expertise and cultural backgrounds could increase the robustness and applicability of the model. Furthermore, integrating real-time behavioural data, such as telematics or sensor-based driving patterns, with the AHP-BWM framework could deliver more objective and dynamic insights. Future work might also explore the application of machine learning techniques alongside multi-criteria decision-making methods to improve the predictive capabilities of road safety models.

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Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

References

Abrahamsen, E. B., M. F. Milazzo, J. T. Selvik, F. Asche, and H. B. Abrahamsen. 2020. "Prioritising Investments in Safety Measures in the Chemical Industry by Using the Analytic Hierarchy Process." *Reliability Engineering & System Safety* 198: 106811.

Akram, M., G. Ali, and J. C. R. Alcantud. 2023. "A New Method of Multi-Attribute Group Decision Making Based on Hesitant Fuzzy Soft Expert Information." *Expert Systems* 40, no. 8: e13357.

Atombo, C., C. Wu, E. O. Tettehfio, and A. A. Agbo. 2017. "Personality, Socioeconomic Status, Attitude, Intention and Risky Driving Behavior." *Cogent Psychology* 4, no. 1: 1376424.

Aytekin, A., S. Korucuk, and Ö. F. Görçün. 2024. "Determining the Factors Affecting Transportation Demand Management and Selecting the Best Strategy: A Case Study." *Transport Policy* 146: 150–166.

Badi, I., D. Pamučar, Ž. Stević, and L. J. Muhammad. 2023. "Wind Farm Site Selection Using BWM-AHP-MARCOS Method: A Case Study of Libya." *Scientific African* 19: e01511.

Bathrinath, S., M. Dhanasekar, B. Dhanorvignesh, et al. 2021. "Modeling Sustainability Risks in Sugar Industry Using AHP-BWM." *Materials Today: Proceedings* 50: 1397–1404.

Bazzaz, M. M., A. Zarifian, M. Emadzadeh, and V. Vakili. 2015. "Driving Behaviors in Iran: A Descriptive Study Among Drivers of Mashhad City in 2014." *Global Journal of Health Science* 7, no. 7: 39–45.

Behnood, H. R., E. Ayati, T. Brijs, M. P. Neghab, and Y. Shen. 2017. "A Fuzzy Decision-Support System in Road Safety Planning." *Proceedings of the Institution of Civil Engineers Transport* 170, no. 5: 305–317.

Bi, Y., Q. Ding, Y. Du, D. Liu, and S. Ren. 2024. "Intelligent Traffic Control Decision-Making Based on Type-2 Fuzzy and Reinforcement Learning." *Electronics* 13: 3894.

Bouraima, M. B., E. Ayyildiz, G. Ozcelik, N. A. Tengecha, and Ž. Stević. 2024. "Alternative Prioritization for Mitigating Urban Transportation Challenges Using a Fermatean Fuzzy-Based Intelligent Decision Support Model." *Neural Computing and Applications* 36, no. 13: 7343–7357.

Cebi, S., F. K. Gündoğdu, and C. Kahraman. 2023. "Consideration of Reciprocal Judgments Through Decomposed Fuzzy Analytical Hierarchy Process: A Case Study in the Pharmaceutical Industry." *Applied Soft Computing* 134: 110000.

Çelikbilek, Y., S. Moslem, and S. Duleba. 2022. "A Combined Grey Multi Criteria Decision Making Model to Evaluate Public Transportation Systems." *Evolving Systems* 14: 1–15.

Chai, C., Y. D. Wong, and X. Wang. 2017. "Safety Evaluation of Driver Cognitive Failures and Driving Errors on Right-Turn Filtering Movement at Signalized Road Intersections Based on Fuzzy Cellular Automata (FCA) Model." *Accident; Analysis and Prevention* 104: 156–164.

Chang, L. Y., and W. C. Chen. 2005. "Data Mining of Tree-Based Models to Analyze Freeway Accident Frequency." *Journal of Safety Research* 36, no. 4: 365–375. https://doi.org/10.1016/j.jsr.2005.06.013.

Chang, L. Y., and H. W. Wang. 2006. "Analysis of Traffic Injury Severity: An Application of Non-Parametric Classification Tree Techniques." *Accident Analysis & Prevention* 38, no. 5: 1019–1027. https://doi.org/10.1016/j.aap.2006.04.009.

Chen, C., J. Wang, and W. Yin. 2024. "Fuzzy Causal Inference Model for Human-Vehicle Cooperative Decision-Making Modeling." In *CHCHI '23: Proceedings of the Eleventh International Symposium of Chinese CHI*. Association for Computing Machinery.

Demir, G., P. Chatterjee, and D. Pamučar. 2024. "Sensitivity Analysis in Multi-Criteria Decision Making: A State-of-the-Art Research Perspective Using Bibliometric Analysis." *Expert Systems with Applications* 237: 121660.

Deveci, M., A. R. Mishra, P. Rani, et al. 2024. "Evaluation of Intelligent Transportation System Implementation Alternatives in Metaverse Using a Fermatean Fuzzy Distance Measure-Based OCRA Model." *Information Sciences* 657: 120008.

Dos Santos, P. H., S. M. Neves, D. O. Sant'Anna, C. H. de Oliveira, and H. D. Carvalho. 2019. "The Analytic Hierarchy Process Supporting Decision Making for Sustainable Development: An Overview of Applications." *Journal of Cleaner Production* 212: 119–138.

Duleba, S., Y. Çelikbilek, S. Moslem, and D. Esztergár-Kiss. 2022. "Application of Grey Analytic Hierarchy Process to Estimate Mode Choice Alternatives: A Case Study From Budapest." *Transportation Research Interdisciplinary Perspectives* 13: 100560.

Ecer, F., and D. Pamucar. 2022. "A Novel LOPCOW-DOBI Multi-Criteria Sustainability Performance Assessment Methodology: An Application in Developing Country Banking Sector." *Omega* 112: 102690.

European Commission. 2019. "EU Road Safety Policy Framework 2021–2030—Next Steps Towards 'Vision Zero'." SWD, 283 Final, Brussels.

Farooq, D., and S. Moslem. 2022. "Estimating Driver Behavior Measures Related to Traffic Safety by Investigating 2-Dimensional Uncertain Linguistic Data—A Pythagorean Fuzzy Analytic Hierarchy Process Approach." *Sustainability* 14, no. 3: 1881.

Farooq, D., S. Moslem, and S. Duleba. 2019. "Evaluation of Driver Behavior Criteria for Evolution of Sustainable Traffic Safety." *Sustainability* 11: 3142.

Farooq, D., S. Moslem, A. Jamal, et al. 2021. "Assessment of Significant Factors Affecting Frequent Lane-Changing Related to Road Safety: An Integrated Approach of the AHP–BWM Model." *International Journal of Environmental Research and Public Health* 18, no. 20: 10628.

Gayen, S., A. Sarkar, and A. Biswas. 2023. "Schweizer-Sklar Operations Based Hybrid Aggregation Operator to Dual Hesitant Q-Rung Orthopair Fuzzy Set and Its Application on MCGDM." *Expert Systems* 40, no. 7: e13257.

Gul, M., M. F. Ak, and A. F. Guneri. 2019. "Pythagorean Fuzzy VIKOR-Based Approach for Safety Risk Assessment in Mine Industry." *Journal of Safety Research* 69: 135–153.

Gumus, A. T. 2009. "Evaluation of HazardousWaste Transportation Firms by Using a Two Step Fuzzy-AHP and TOPSIS Methodology." *Expert Systems with Applications* 36: 4067–4074.

Gündoğdu, F. K., S. Duleba, S. Moslem, and S. Aydın. 2021. "Evaluating Public Transport Service Quality Using Picture Fuzzy Analytic Hierarchy Process and Linear Assignment Model." *Applied Soft Computing* 100: 106920.

Guo, J., C. Luo, and K. Ma. 2023. "Risk Coupling Analysis of Road Transportation Accidents of Hazardous Materials in Complicated Maritime Environment." *Reliability Engineering & System Safety* 229: 108891.

Guo, S., and H. Zhao. 2017. "Fuzzy Best-Worst Multi-Criteria Decision-Making Method and Its Applications." *Knowledge-Based Systems* 121: 23–31.

Gupta, R., and O. Chaudhari. 2020. "Application of Fuzzy Logic in Prevention of Road Accidents Using Multi Criteria Decision Alert." *Current Journal of Applied Science and Technology* 39: 51–61.

Haseli, G., S. R. Bonab, M. Hajiaghaei-Keshteli, S. J. Ghoushchi, and M. Deveci. 2024. "Fuzzy ZE-Numbers Framework in Group Decision-Making Using the BCM and CoCoSo to Address Sustainable Urban Transportation." *Information Sciences* 653: 119809.

Janstrup, K. H. 2017. "Road Safety Annual Report." https://doi.org/10.1787/23124571.

Kakati, P., T. Senapati, S. Moslem, and F. Pilla. 2024. "Fermatean Fuzzy Archimedean Heronian Mean-Based Model for Estimating Sustainable Urban Transport Solutions." *Engineering Applications of Artificial Intelligence* 127: 107349.

Kara, K., G. C. Yalçın, E. G. Kaygısız, and S. Edinsel. 2024. "Assessing the Academic Performance of Turkish Universities in 2023: A MEREC-WEDBA Hybrid Methodology Approach." *Journal of Operations Intelligence* 2, no. 1: 252–272. https://doi.org/10.31181/jopi21202422.

Karlaftis, M. G., and I. Golias. 2002. "Effects of Road Geometry and Traffic Volumes on Rural Roadway Accident Rates." *Accident Analysis & Prevention* 34: 357–365.

Kassu, A., and M. Anderson. 2019. "Analysis of Severe and Nonsevere Traffic Crashes on Wet and Dry Highways." *Transportation Research Interdisciplinary Perspectives* 2: 100043. https://doi.org/10.1016/j.trip.2019.100043.

Koçar, O., and E. Dizdar. 2021. "A Risk Assessment Model for Traffic Crashes Problem Using Fuzzy Logic: A Case Study of Zonguldak, Turkey." *Transportation Letters* 14, no. 5: 492–502.

Kou, Y., J. Wang, W. Xu, and Y. Xu. 2023. "Multi-Attribute Group Decision-Making Based on Linguistic Pythagorean Fuzzy Copula Extended Power Average Operator." *Expert Systems* 40, no. 7: e13272.

Kumar, A., A. Aswin, and H. Gupta. 2019. "Evaluating Green Performance of the Airports Using Hybrid BWM and VIKOR Methodology." *Tourism Management* 76: 103941.

Li, J., J. Wang, and J. Hu. 2019. "Multi-Criteria Decision-Making Method Based on Dominance Degree and BWM With Probabilistic Hesitant Fuzzy Information." *International Journal of Machine Learning and Cybernetics* 10: 1671–1685.

Lo, H. W., L. Y. Wang, A. K. W. Weng, and S. W. Lin. 2024. "Assessing Supplier Disruption Risks Using a Modified Pythagorean Fuzzy SWARA–TOPSIS Approach." *Journal of Soft Computing and Decision Analytics* 2, no. 1: 169–187. https://doi.org/10.31181/jscda21202440.

Lord, D., and F. Mannering. 2010. "The Statistical Analysis of Crash Frequency Data: A Review and Assessment of Methodological Alternatives." *Transportation Research Part A, Policy and Practice* 44, no. 5: 291–305. https://doi.org/10.1016/j.tra.2010.02.001.

Mahdiraji, A., H. Arzaghi, S. Stauskis, and G. E. Zavadskas. 2018. "A Hybrid Fuzzy BWM-COPRAS Method for Analyzing Key Factors of Sustainable Architecture." *Sustainability* 10: 1626.

Mannering, F. L., and C. R. Bhat. 2014. "Analytic Methods in Accident Research: Methodological Frontier and Future Directions." *Analytic Methods in Accident Research* 1: 1–22. https://doi.org/10.1016/j.amar.2013.09.001.

Mi, X., M. Tang, H. Liao, W. Shen, and B. Lev. 2019. "The State-of-the-Art Survey on Integrations and Applications of the Best Worst Method in Decision Making: Why, What, What for and What's Next?" *Omega* 87: 205–225.

Moslem, S. 2023. "A Novel Parsimonious Best Worst Method for Evaluating Travel Mode Choice." *IEEE Access* 11: 16768–16773.

Moslem, S. 2024. "A Novel Parsimonious Spherical Fuzzy Analytic Hierarchy Process for Sustainable Urban Transport Solutions." *Engineering Applications of Artificial Intelligence* 128: 107447.

Moslem, S., and Y. Çelikbilek. 2020. "An Integrated Grey AHP-MOORA Model for Ameliorating Public Transport Service Quality." *European Transport Research Review* 12: 68.

Moslem, S., M. Deveci, and F. Pilla. 2024. "A Novel Best-Worst Method and Kendall Model Integration for Optimal Selection of Digital Voting Tools to Enhance Citizen Engagement in Public Decision Making." *Decision Analytics Journal* 10: 100378.

Moslem, S., D. Farooq, O. Ghorbanzadeh, and T. Blaschke. 2020. "Application of the AHP-BWM Model for Evaluating Driver Behavior Factors Related to Road Safety: A Case Study for Budapest." *Symmetry* 12, no. 2: 243.

Moslem, S., F. K. Gündoğdu, S. Saylam, and F. Pilla. 2024. "A Hybrid Decomposed Fuzzy Multi-Criteria Decision-Making Model for Optimizing Parcel Lockers Location in the Last-Mile Delivery Landscape." *Applied Soft Computing* 154: 111321.

Moslem, S., and F. Pilla. 2024. "Planning Location of Parcel Lockers Using Group Analytic Hierarchy Process in Spherical Fuzzy Environment." *Transportation Research Interdisciplinary Perspectives* 24: 101024.

Moslem, S., M. K. Saraji, A. Mardani, A. Alkharabsheh, S. Duleba, and D. Esztergár-Kiss. 2023. "A Systematic Review of Analytic Hierarchy Process Applications to Solve Transportation Problems: From 2003 to 2022." *IEEE Access* 11: 11973–11990.

Nagendra, S. M. S., and M. Khare. 2003. "Principal Component Analysis of Urban Traffic Characteristics and Meteorological Data." *Transportation Research Part D: Transport and Environment* 8: 285–297.

OECD/ITF. 2016. *Road Safety Annual Report*. OECD/ITF.

Omidi, L., K. M. Dolatabad, and C. Pilbeam. 2023. "Differences in Perception of the Importance of Process Safety Indicators Between Experts in Iran and the West." *Journal of Safety Research* 84: 261–272.

Omrani, H., M. Amini, and A. Alizadeh. 2020. "An Integrated Group Best-Worst Method—Data Envelopment Analysis Approach for Evaluating Road Safety: A Case of Iran." *Measurement* 152: 107330.

Ortega, J., and S. Moslem. 2023. "Decision Support System for Evaluating Park & Ride System Using the Analytic Hierarchy Process (AHP) Method." *Urban, Planning and Transport Research* 11, no. 1: 2194362.

Ortega, J., S. Moslem, J. Tóth, and M. Ortega. 2023. "A Two-Phase Decision Making Based on the Grey Analytic Hierarchy Process for Evaluating the Issue of Park-and-Ride Facility Location." *Journal of Urban Mobility* 3: 100050.

Papantoniou, P., D. Pavlou, G. Yannis, and E. Vlahogiannid. 2019. "How an Unexpected Incident Affects Speed Related Driving Performance Measures." *Transportation Research Procedia* 41: 529–531.

Rezaei, J. 2015. "Best-Worst Multi-Criteria Decision-Making Method." *Omega* 53: 49–57.

Saaty, T. L. 1977. "A Scaling Method for Priorities in Hierarchical Structures." *Journal of Mathematical Psychology* 15: 234–281.

Sabaté-Tomas, M., L. Arnau-Sabatés, and J. Sala-Roca. 2014. "Factors Influencing a Risky Driving Profile Among a Cohort of Young University Students: Bases for Adopting Evidence-Based Prevention Interventions." *Anuario De Psicología* 44, no. 3: 295–310.

Savolainen, P. T., F. L. Mannering, D. Lord, and M. A. Quddus. 2011. "The Statistical Analysis of Highway Crash-Injury Severities: A Review and Assessment of Methodological Alternatives." *Accident Analysis & Prevention* 43, no. 5: 1666–1676. https://doi.org/10.1016/j.aap.2011.03.025.

Scheetz, L., J. Zhang, and J. Kolassa. 2009. "Classification Tree Modelling to Identify Severe and Moderate Vehicular Injuries in Young and Middle-Aged Adults." *Artificial Intelligence in Medicine* 45, no. 1: 1–10. https://doi.org/10.1016/j.artmed.2008.11.002.

Senapati, T., and R. R. Yager. 2020. "Fermatean Fuzzy Sets." *Journal of Ambient Intelligence and Humanized Computing* 11: 663–674.

Sharma, H., N. Sohani, and A. Yadav. 2022. "Comparative Analysis of Ranking the Lean Supply Chain Enablers: An AHP, BWM and Fuzzy SWARA Based Approach." *International Journal of Quality & Reliability Management* 39, no. 9: 2252–2271.

Shourideh Ziabari, S. P., and E. Kaboodvand. 2023. "Road Quality and Safety Ranking Using Fuzzy Logic and Multi-Criteria Decision Making." *Road* 31, no. 114: 119–137. https://doi.org/10.22034/road.2022.319467.2005.

Solomon, M. 2006. "Groupthink Versus the Wisdom of Crowds: The Social Epistemology of Deliberation and Dissent." *Southern Journal of Philosophy* 44, no. S1: 28–42.

Sun, C. C. 2010. "A Performance Evaluation Model by Integrating Fuzzy AHP and Fuzzy TOPSIS Methods." *Expert Systems with Applications* 37: 7745–7754.

Tian, Y. 2024. "Adaptive Control and Supply Chain Management of Intelligent Agricultural Greenhouse by Intelligent Fuzzy Auxiliary Cognitive System." *Expert Systems* 41, no. 5: e13117.

Varmazyar, S., S. B. Mortazavi, E. Hajizadeh, and S. Arghami. 2013. "The Relationship Between Driving Aberrant Behavior and Self-Reported

Accidents Involvement Amongst Professional Bus Drivers in the Public Transportation Company." *Health Scope* 2, no. 2: 110–115.

Wang, H., W. Zhao, and J. Zheng. 2024. "Improved Q-Rung Orthopair Fuzzy WASPAS Method Based on Softmax Function and Frank Operations for Investment Decision of Community Group-Buying Platform." *Journal of Soft Computing and Decision Analytics* 2, no. 1: 188–212. https://doi.org/10.31181/jscda21202442.

Wang, J., M. Li, Y. Liu, H. Zhang, W. Zou, and L. Cheng. 2014. "Safety Assessment of Shipping Routes in the South China Sea Based on the Fuzzy Analytic Hierarchy Process." *Safety Science* 62: 46–57.

Wang, Y., H. Yang, and X. Han. 2024. "Study on the Method of Selecting Sustainable Food Suppliers Considering Interactive Factors." *Journal of Operations Intelligence* 2, no. 1: 202–218. https://doi.org/10.31181/jopi21202420.

World Health Organization (WHO). 2023. "Global Status Report on Road Safety." [Online]. Accessed February 15, 2024. https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/global-status-report-on-road-safety-2023.

Wu, Q., L. Zhou, Y. Chen, and H. Chen. 2019. "An Integrated Approach to Green Supplier Selection Based on the Interval Type-2 Fuzzy Best-Worst and Extended VIKOR Methods." *Information Sciences* 502: 394–417.

Xu, X., Ž. Šarić, and A. Kouhpanejade. 2014. "Freeway Incident Frequency Analysis Based on CART Method." *Promet-Traffic-Transportation* 26, no. 3: 191–199. https://doi.org/10.7307/ptt.v26i3.1308.

Yılmaz, V., and H. E. Çelik. 2006. "Risky Driving Attitudes and Self-Reported Traffic Violations Among Turkish Drivers: The Case of Eskişehir." *Doğuş Üniversitesi Dergisi* 7, no. 1: 127–138.

Zeshui, X., and W. Cuiping. 1999. "A Consistency Improving Method in the Analytic Hierarchy Process." *European Journal of Operational Research* 116, no. 2: 443–449.

Zhao, Z., B. Fu, and N. Zhang. 2010. "A Fuzzy Assessment Model for Traffic Safety in City: A Case Study in China." In *Artificial Intelligence and Computational Intelligence. AICI 2010*, Lecture Notes in Computer Science, edited by F. L. Wang, H. Deng, Y. Gao, and J. Lei, vol. 6320. Springer.