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Data-driven Identification and Behavioral Assessment of Anxious Drivers Based on Fuzzy Analytic Hierarchy Processes

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Abstract: A significant aspect of enhancing road safety is the understanding and recognition of anxious driving behavior. In this paper, we present a comprehensive approach to identifying and assessing anxious drivers by leveraging factor analytical techniques and fuzzy Analytic Hierarchy Processes (FAHP) based on the effective responses from the Driving Behavior Survey (DBS). The factor analysis results indicate that anxious driving behavior is a multi-dimensional construct, comprising multiple key factors such as aggressiveness, distraction, exaggerated caution and driving performance deficits. These dimensions are intricately interconnected and collectively contribute to the overall assessment of a driver's anxious behavior. By utilizing the weights determined through the implementation of the FAHP method on the factor structure, the anxiety ratings for individual drivers generated from our data-driven approach provide invaluable information for various stakeholders, including traffic safety authorities, insurance companies, and drivers themselves.

Keywords: Driving anxiety, behavioral assessment, factor analysis, fuzzy logic, analytic hierarchy processes.

1. Introduction

While the automobile has revolutionized transportation, providing unprecedented convenience and accessibility, it has also introduced a range of challenges and risks. Among these challenges, anxious driving behavior has emerged as a critical concern due to its potential to significantly impact road safety and accident rates. Anxious drivers, characterized by heightened stress, fear, or other emotional distress behind the wheel, often exhibit behaviors that can lead to hazardous situations, including erratic maneuvers, impaired decision-making, and decreased focus. These manifestations of anxious driving have been identified as contributory factors to a substantial proportion of road accidents, injuries, and fatalities.

Given the potential ramifications of anxious driving, the identification and behavioral assessment of anxious drivers are of paramount importance. By discerning and quantifying the anxious behavior of drivers, we can initiate targeted interventions and support mechanisms to mitigate its impact and enhance road safety. Traffic safety authorities, insurance companies, and drivers themselves all have a vested interest in the effective identification and assessment of anxious drivers, as it can lead to safer roads, reduced accident rates, and lower insurance premiums.

Recent years have witnessed a growing trend of research dedicated to understanding and addressing anxious driving behavior [1-3]. Studies in the field of transportation psychology have delved into the causes, consequences, and potential interventions related to anxious driving [4-5]. Researchers have explored the psychological, cognitive, and emotional factors that contribute to anxious behavior on the road [6-7]. However, evaluating anxious driving behavior in a systematic and robust way remains a complex and multifaceted challenge. Traditional methods often rely on self-reported surveys and subjective evaluations, which can introduce biases and inaccuracies in the assessment process.

In this paper, we seek to contribute to the ongoing efforts to comprehensively address anxious driving behavior by introducing a data-driven approach to its identification and behavioral assessment. Leveraging a combination of factor analysis and the fuzzy Analytic Hierarchy Processes (FAHP), we aim to develop a systematic and precise framework for evaluating anxious driving. By extracting latent constructs and interrelationships from the original Driving Behavior Survey [8] results, we establish a factor structure that underpins the assessment of anxious driving, and the identified factors provide the foundation for the subsequent FAHP analysis.

We then apply a variant of the FAHP methodology [9], known for its ability to handle uncertainty and subjectivity in decision-making processes, to derive the weights for both the factors and alternatives within the assessment framework. This approach acknowledges the inherent imprecision and vagueness associated with human behavior and perceptions, ensuring a more realistic and nuanced evaluation. The culmination of our research is the provision of assessment ratings for individual drivers, which facilitate the identification of anxious drivers in a more objective and robust manner. By pinpointing anxious drivers, interventions and support mechanisms can be tailored to address their specific needs, ultimately contributing to enhanced road safety. Moreover, the identification of anxious drivers can lead to the development of targeted educational programs and awareness campaigns aimed at reducing anxiety-induced driving behaviors.

The rest of the paper is organized as follows. Section 2 elucidates the data sources utilized for identifying and assessing anxious driving while contextualizing the issue within a multicriteria decision-making framework. In Section 3, we expound upon the details of our data-driven assessment approach, offering a comprehensive explanation of the techniques employed, including factor analysis and the FAHP method. Section 4 unveils the outcomes of our analysis, presenting driver ratings that assist in identifying those exhibiting anxious driving behavior. Finally, Section 5 delves into a discussion of our study's findings and their broader implications.

2. Preliminaries and Data Sources

As the society becomes increasingly reliant on automobiles, the safety and well-being of drivers have emerged as paramount concerns. The assessment of anxious driving behavior is a multifaceted problem that necessitates a structured approach. We formulate the problem within a multicriteria decision making framework that involves multiple criteria, objectives, and decision makers. This framework enables us to consider the diverse factors and dimensions that contribute to a driver's behavior so that we can systematically weigh these factors and their associated uncertainties, leading to a more robust and nuanced evaluation of anxious driving. This framework forms the foundation upon which our data-driven approach is built.

A fundamental aspect of our data-driven approach to assess anxious driving behavior relies on the effective responses of the DBS survey (Table 1) adapted from [8], where respondents were asked to indicate how frequently they perform each of the items when a stressful driving situation occurs which make them nervous, tense, or uncomfortable, based on their personal experience. Scales for the frequency selection are: Never – 1, Infrequently – 2, Sometimes – 3, Frequently – 4, Always – 5. In Table 1, the numbers in each cell along the survey items indicate number of respondents n that indicate the corresponding frequency selection with fraction $\frac{n}{N}$ (%), where $N = 258$ is the effective number of respondents.

Table 1. The Driving Behavior Survey (DBS) and the response statistics ($N = 258$).

Index	Item	Never	Infrequently	Sometimes	Frequently	Always
1	I lose track of where I am going.	28 (10.85%)	169 (65.50%)	43 (16.67%)	11 (4.26%)	7 (2.71%)
2	I yell at the driver/drivers who make me nervous.	30 (11.63%)	35 (13.57%)	119 (46.12%)	44 (17.05%)	30 (11.63%)
3	I slow down when approaching intersections, even when the light is green.	1 (0.39%)	5 (1.94%)	13 (5.04%)	69 (26.74%)	170 (65.89%)
4	I have trouble staying in the correct lane.	201 (77.91%)	20 (7.75%)	27 (10.47%)	7 (2.71%)	3 (1.16%)
5	I drift into other lanes.	120 (46.51%)	47 (18.22%)	79 (30.62%)	18 (6.98%)	21 (8.14%）
6	I forget to make appropriate adjustments in speed.	80 (31.01%)	48 (18.60%)	28 (10.85%)	18 (6.98%)	36 (13.95%)
7	I let the driver who made me nervous know that I am upset.	28 (10.85%)	36 (13.95%)	117 (45.35%)	46 (10.08%)	31 (12.02%)
8	I maintain a large distance between myself and the driver in front of me.	0 (0%)	21 (8.14%)	86 (33.33%)	93 (36.05%)	58 （22.48%）
9	I forget where I am driving to.	29 （11.24%）	158 （61.24%）	51 (19.77%)	10 (3.88%)	3 （1.16%）
10	I make gestures at the driver/drivers who made me nervous.	42 (16.28%)	96 (37.21%)	72 (27.91%)	28 (10.85%)	20 (7.75%)
11	I try to put distance between myself and other cars.	0 (0%)	12 (4.65%)	75 (29.07%)	82 (31.78%)	89 (34.50%)
12	I maintain my speed in order to calm myself down.	7 (2.71%)	87 (33.72%)	96 (37.21%)	58 (22.48%)	43 (16.67%)
13	I try to stay away from other cars.	1 (0.39%)	12 (4.65%)	72 (27.91%)	84 (32.56%)	89 (34.50%)
14	I have trouble finding the correct lane.	15 (5.81%)	49 （18.99%）	130 (50.39%)	53 (20.54%)	38 (14.73%)
15	I pound on the steering wheel when I'm nervous.	10 (3.88%)	64 (24.81%)	103 (39.92%)	52 (20.16%)	30 (11.63%)
16	I decrease my speed until I feel comfortable.	5 (1.94%)	83 (32.17%)	93 (36.05%)	67 (25.97%)	10 (3.88%)
17	I honk my horn at the driver who made me nervous.	12 (4.65%)	79 (30.62%)	98 (37.98%)	48 (18.60%)	21 (8.14%)
18	I try to find ways to let other drivers know that they are making me nervous.	3 (1.16%)	77 (29.84%)	104 (40.31%)	50 (19.38%)	24 (9.30%)
19	During bad weather, I drive more cautiously than other vehicles on the road.	10 (3.88%)	69 (26.74%)	102 (39.53%)	65 (25.19%)	12 (4.65%)
20	I swear/use profanity while I am driving.	15 (5.81%)	55 (21.31%)	119 (46.12%)	60 (23.26%)	18 （6.98%）
21	I have difficulty merging into traffic.	2 (0.78%)	25 (9.69%)	69 (26.74%)	119 (46.12%)	43 (16.67%)

The survey comprises a comprehensive set of 21 items designed to evaluate how drivers typically respond in various stressful driving situations that provoke feelings of nervousness, anxiety, tension, or discomfort. It is important to note that the responses are based on the driver's personal experience, capturing their actual behavioral tendencies rather than idealized or aspirational responses. The DBS survey was administered to 265 local automobile drivers out of which $\mathrm{N} = 258$ effective responses were obtained (see Table 2 for relevant demographics information).

Table 2. Demographics of the effective DBS respondents ($\mathrm{N} = 258$)

Characteristics	Statistics Numerical: mean (variance); Categorical: categories, # (%)
Age	27.5 (1.6)
Gender	Male, 168 (65.12%) Female, 90 (34.88%)
Number of years since obtained license	3.9 (1.1)
Driving frequency	Daily, 38 (14.73%) Few times a week, 26 (10.08%) Few times a month, 131 (50.78%) Few times a year, 51 (19.77%) Few times for a couple years, 12 (4.65%)
Driving violations	No violations, 46 (17.83%) 1 to 2 violations, 139 (53.88%) 3 to 6 violations, 45 (17.44%) 7 to 12 violations, 22 (8.53%) > 12 violations, 6 (2.33%)

The DBS responses serve as the primary source of data to identify the underlying factors that contribute to anxious driving behavior. The dataset forms the basis for factor analysis, allowing us to discern latent constructs and relationships among the survey items.

In addition to the DBS responses, we engaged in interviews with three experts specializing in the domain of anxious driving. These experts provided valuable insights and perspectives on the factors that contribute to anxious driving behavior. Moreover, their expertise was instrumental in guiding our study and ensuring its alignment with the latest insights in the field.

The interviews also facilitated the collection of relative importance scales associated with anxiety driving factors. These scales were derived through the factor analysis of the DBS results. Factor analysis helps to uncover the latent dimensions that underlie the responses to the survey items. These dimensions represent the key constructs that contribute to anxious driving behavior. The experts' input, coupled with the results of the factor analysis, allows us to assign importance values to each of these factors, reflecting their relative impact on anxious driving. These relative importance scales are pivotal in our subsequent application of the FAHP method to weight the factors and alternatives within the assessment framework.

3. Proposed Approach

3.1. Exploratory factor analysis

To reveal the underlying structure of anxious driving behavior and extract latent factors inherently associated with this phenomenon, we employed an exploratory factor analysis on the survey items based on the responses collected from the DBS survey to identify patterns of shared variance among the survey items, which can then be attributed to common latent factors. This process serves to reveal the fundamental dimensions $\{C_1, C_2, \dots, C_m\}$ that contribute to anxious driving.

The determination of the optimal number m of latent factors is a crucial step in factor analysis. To ensure the appropriateness of our factor extraction, we employed multiple criteria, including the change in standardized root mean square residual (SRMR), the Tucker-Lewis index, and the percent of variances explained by the factors as a function of the number of factors considered. Furthermore, consultations with domain experts were instrumental in assessing the practical implications of the factors.

Once the number of factors was established, a varimax rotation technique was applied to optimize the interpretability of these latent factors. Varimax rotation minimizes the complexity of factor loadings by maximizing the variance of the squared loadings within each factor. These identified factors provided the foundation for the subsequent FAHP development.

3.2. The FAHP method

The FAHP method is a powerful and flexible approach employed to establish the relative weights of factors and alternatives within the assessment framework. This method is predicated on the principle that the eigenvector corresponding to the largest eigenvalue of a pairwise comparison matrix provides the relative priorities of the factors, effectively preserving the ordinal preferences among the alternatives, i.e., when one alternative is favored over another, its eigenvector component is larger, reflecting its higher priority. The vector of weights derived from the pairwise comparison matrix is instrumental in depicting the relative importance of the various factors.

In this study, we incorporate triangular fuzzy numbers to enhance the scaling scheme in the judgment matrices. This integration of fuzzy logic is essential for accommodating the inherent imprecision and subjectivity often associated with assessing anxious driving behavior. By utilizing triangular fuzzy numbers, we facilitate a more nuanced representation of the preferences and judgments of experts and respondents.

The six-step process of the FAHP approach we used is detailed as follows:

Step 1: Determine the relative importance of factors and alternatives.

Through experts' interview findings, the relative strength linguistic variable $r_{C_i \to C_j}$ for the pair of factors (C_i, C_j) is determined, $i, j \in [1\!:\!m]$, where $r_{C_i \to C_j}$ indicates the relative importance of factor C_i compared to factor C_j for identifying anxious drivers. The anxious driver types, or the alternatives, $\{A_1, A_2, \dots, A_n\}$, given the latent factors also hold relative importance scales $r^{(C_i)}_{A_j \to A_k}$, where $r^{(C_i)}_{A_j \to A_k}$ indicates the relative importance of alternative A_j compared to alternative A_k given the factor C_i.

Step 2: Construct the fuzzy comparison matrices.

Triangular fuzzy numbers are employed to signify the relative strength of each pair of elements within the same hierarchy $r_{C_i \to C_j} \mapsto \{(v_{low}, v_{medium}, v_{high})\}$, $i, j \in [1\!:\!m]$, $r^{(C_i)}_{A_j \to A_k} \mapsto \{(v_{low}, v_{medium}, v_{high})\}, i \in [1\!:\!m], j, k \in [1\!:\!n]$.

Table 3 shows the mappings used in this study.

Table 3. Triangular fuzzy numbers for linguistic variables

Linguistic variable	Triangular fuzzy number	Reciprocal triangular fuzzy number
Extremely strong	(9,9,9)	$(\frac{1}{9},\frac{1}{9},\frac{1}{9})$
Very strong	(6,7,8)	$(\frac{1}{8},\frac{1}{7},\frac{1}{6})$
Strong	(4,5,6)	$(\frac{1}{6},\frac{1}{5},\frac{1}{4})$
Moderately strong	(2,3,4)	$(\frac{1}{4},\frac{1}{3},\frac{1}{2})$
Equally strong	(1,1,1)	(1,1,1)

These triangular fuzzy numbers, determined through pairwise comparisons in Step 1, are utilized to construct the fuzzy judgment matrices $\mathcal{C} = \{\mathcal{C}_{i,j}\} = \{(\mathcal{C}_{i,j,low}, \mathcal{C}_{i,j,medium}, \mathcal{C}_{i,j,high})$ for comparison between factors, and $\mathcal{A}^{(C_i)} = \left\{\mathcal{A}_{j,k}^{(C_i)}\right\} = \{\mathcal{A}_{j,k,low}^{(C_i)}, \mathcal{A}_{j,k,medium}^{(C_i)}, \mathcal{A}_{j,k,high}^{(C_i)}\}$ for comparison between alternatives given factor C_i. These matrices encapsulate the comparative importance of the factors and alternatives, accounting for the inherent uncertainties and subjectivity in the assessment process.

Step 3: Compute the priority and composite weight intervals for factors and alternatives.

The priority weight intervals for each factor and alternative, derived from the fuzzy comparison matrix are calculated. These weights provide a quantitative representation of the relative importance of the factors within the assessment framework. They serve as a key component for assigning priorities to the factors.

The priority weight interval for factor C_i, $\{(C_{low}^{(i)}, C_{medium}^{(i)}, C_{high}^{(i)})\}, i \in [1:m]$, can be computed as follows:

$$C_{low}^{(i)} = \frac{1}{m}\sum_{j=1}^{m} \mathcal{C}_{i,j,low} / \mathcal{C}_{j,low}^{row\_sum}, \quad (1)$$

$$C_{medium}^{(i)} = \frac{1}{m}\sum_{j=1}^{m} \mathcal{C}_{i,j,medium} / \mathcal{C}_{j,medium}^{row\_sum}, \quad (2)$$

$$C_{high}^{(i)} = \frac{1}{m}\sum_{j=1}^{m} \mathcal{C}_{i,j,high} / \mathcal{C}_{j,high}^{row\_sum}, \quad (3)$$

where

$$\mathcal{C}_{k}^{row\_sum} \coloneqq \left(\mathcal{C}_{k,low}^{row\_sum}, \mathcal{C}_{k,medium}^{row\_sum}, \mathcal{C}_{k,high}^{row\_sum}\right) \quad (4)$$

$$= \sum_{i=1}^{m}\left(\mathcal{C}_{i,k,low}, \mathcal{C}_{i,k,medium}, \mathcal{C}_{i,k,high}\right),\ k \in [1:m]$$

Similarly, the priority weight interval for alternative A_j given factor C_i, $\{\left(\mathcal{A}_{low}^{(ij)}, \mathcal{A}_{medium}^{(ij)}, \mathcal{A}_{high}^{(ij)}\right)\}, i \in [1:m]$, $j \in [1:n]$, can be computed as follows:

$$\mathcal{A}_{low}^{(ij)} = \frac{1}{n}\sum_{k=1}^{m} \mathcal{A}_{j,k,low}^{(C_i)} / \mathcal{A}_{k,low}^{(C_i)row\_sum}, \quad (5)$$

$$\mathcal{A}_{medium}^{(ij)} = \frac{1}{n}\sum_{k=1}^{m} \mathcal{A}_{j,k,medium}^{(C_i)} / \mathcal{A}_{k,medium}^{(C_i)row\_sum}, \quad (6)$$

$$\mathcal{A}_{high}^{(ij)} = \frac{1}{n}\sum_{k=1}^{m} \mathcal{A}_{j,k,high}^{(C_i)} / \mathcal{A}_{k,high}^{(C_i)row\_sum}, \quad (7)$$

Where

$$\mathcal{A}_{k}^{(C_i)row\_sum} \coloneqq \left(\mathcal{A}_{k,low}^{(C_i)row\_sum}, \mathcal{A}_{k,medium}^{(C_i)row\_sum}, \mathcal{A}_{k,high}^{(C_i)row\_sum}\right) \quad (8)$$

$$= \sum_{j=1}^{n}\left(\mathcal{A}_{j,k,low}^{(C_i)}, \mathcal{A}_{j,k,medium}^{(C_i)}, \mathcal{A}_{j,k,high}^{(C_i)}\right), k \in [1:n].$$

Then, the composite weight interval for alternative A_j given factor C_i, $\{\left(\hat{\mathcal{A}}_{low}^{(ij)}, \hat{\mathcal{A}}_{medium}^{(ij)}, \hat{\mathcal{A}}_{high}^{(ij)}\right)\}$, $i \in [1:m]$, $j \in [1:n]$, can be computed as follows:

$$\hat{\mathcal{A}}_{low}^{(ij)} = C_{low}^{(i)} \cdot \mathcal{A}_{low}^{(ij)}, \quad (9)$$

$$\hat{\mathcal{A}}_{medium}^{(ij)} = C_{medium}^{(i)} \cdot \mathcal{A}_{medium}^{(ij)}, \quad (10)$$

$$\hat{\mathcal{A}}_{high}^{(ij)} = C_{high}^{(i)} \cdot \mathcal{A}_{high}^{(ij)}. \quad (11)$$

Step 4: Compute the overall score interval of each alternative with respect to the factor scores

The FAHP method extends its utility to compute the overall score of each alternative concerning the factor scores S_i, $i \in [1:m]$ aggregated from the DBS survey results. This calculation integrates the weights assigned to the factors and alternatives, generating a structured and comprehensive assessment.

The overall score interval for alternative A_j, $\{\left(\mathcal{A}_{low}^{(j)}, \mathcal{A}_{medium}^{(j)}, \mathcal{A}_{high}^{(j)}\right)\}$, $j \in [1:n]$, can thus be computed as follows:

$$\mathcal{A}_{low}^{(j)} = \sum_{i=1}^{m} \hat{\mathcal{A}}_{low}^{(ij)} \cdot S_i, \quad (12)$$

$$\mathcal{A}_{medium}^{(j)} = \sum_{i=1}^{m} \hat{\mathcal{A}}_{medium}^{(ij)} \cdot S_i, \quad (13)$$

$$\mathcal{A}_{high}^{(j)} = \sum_{i=1}^{m} \hat{\mathcal{A}}_{high}^{(ij)} \cdot S_i. \quad (14)$$

Step 5: Compute the overall score of each alternative.

This step involves the computation of the overall score, or global priority, which pertains to the overall weights within the entire hierarchy, which consolidates the contributions of all factors as sub-criteria, allowing for a holistic evaluation of each driver's anxious driving behavior.

To represent a level of confidence, α-cuts are used to incorporate the experts' confidence in their preferences or judgments. Therefore, the overall confidence level representation of alternative A_j, $\{\left(\mathcal{A}_{conf-low}^{(j)}, \mathcal{A}_{conf-high}^{(j)}\right)\}, j \in [1:n]$, can be computed as follows:

$$\mathcal{A}_{conf-low}^{(j)} = \mathcal{A}_{low}^{(j)} + \alpha_{cut} \cdot (\mathcal{A}_{medium}^{(j)} - \mathcal{A}_{low}^{(j)}), \quad (15)$$

$$\mathcal{A}_{conf-high}^{(j)} = A_{high}^{(j)} - \alpha_{cut} \cdot (\mathcal{A}_{high}^{(j)} - \mathcal{A}_{medium}^{(j)}). \quad (16)$$

Finally, the overall score $\mathcal{A}^{(j)}$ of alternative A_j, $j \in [1:n]$, can thus be computed as $\mathcal{A}^{(j)} = (\mathcal{A}_{conf-low}^{(j)} + \mathcal{A}_{conf-high}^{(j)})/2$.

Step 6: Rank the alternatives and identify anxious drivers.

Upon completion of the FAHP method, the alternatives, in this case, the anxious driver types, are systematically ranked based on their overall score and the highest-scored alternative is selected for further consideration, $j^* \coloneqq argmax\, \mathcal{A}^{(j)}$. This selection, coupled with a predefined threshold score S^*, serves as the basis for identifying anxious drivers and enables stakeholders to tailor interventions and support mechanisms as needed. More specifically, when $\mathcal{A}^{(j^*)} \geq S^*$, the corresponding respondent would be identified as an anxious driver with type j^*; otherwise, it would be considered a normal case.

4. Results

Our data-driven approach to assessing anxious driving behavior involves exploratory factor analysis of the DBS survey responses collected from $N = 258$ respondents, for which the overarching goal is to uncover latent factors that underlie the observed responses, providing clarity and structure to the complex landscape of anxious driving. We performed factor analysis on the responses $\{x_1, x_2, \dots, x_N\}$, $x_i \in [1:5]^{21}$, where each response x_i comprises indications with scores 1 through 5 for overall 21 survey items (Table 1).

Table 4 shows the outcomes of the factor analysis, presenting the four latent factors that emerged as key contributors to anxious driving behavior. All variables are standardized with mean 0 and variance 1. Overall Standardized Root Mean Square Residual (SRMR): 0.06; Tucker-Lewis index: 0.82, Bayesian information criterion (BIC): -103.38. All variables are standardized with mean 0 and variance 1. Overall Standardized Root Mean Square Residual (SRMR): 0.06; Tucker-Lewis index: 0.82, Bayesian information criterion (BIC): -103.38.

Table 4. Exploratory factor analysis results with four key factors $\{C_1, C_2, C_3, C_4\}$ and respective standardized factor loadings of variab.

Factor	Standardized factor loading
C_1: Driving distraction	
1. I lose track of where I am going.	0.73
9. I forget where I am driving to.	0.71
C_2: Aggressive driving	
2. I yell at the driver/drivers who make me nervous.	0.89
7. I let the driver who made me nervous know that I am upset.	0.83
10. I make gestures at the driver/drivers who made me nervous.	0.92
15. I pound on the steering wheel when I'm nervous.	0.79
17. I honk my horn at the driver who made me nervous.	0.83
18. I try to find ways to let other drivers know that they are making me nervous.	0.88
20. I swear/use profanity while I am driving.	0.90
C_3: Exaggerated caution	
8. I maintain a large distance between myself and the driver in front of me.	0.67
11. I try to put distance between myself and other cars.	0.70
12. I maintain my speed in order to calm myself down.	0.82
13. I try to stay away from other cars.	0.71
16. I decrease my speed until I feel comfortable.	0.84
19. During bad weather, I drive more cautiously than other vehicles on the road.	0.58
C_4: Performance deficits	
3. I slow down when approaching intersections, even when the light is green.	0.76
4. I have trouble staying in the correct lane.	0.90
5. I drift into other lanes.	0.93
6. I forget to make appropriate adjustments in speed.	0.88
14. I have trouble finding the correct lane.	0.91
21. I have difficulty merging into traffic.	0.82

A Chi-squared test was conducted to ascertain that $m = 4$ latent factors $\{C_1, C_2, C_3, C_4\}$ were sufficient to encapsulate the essential dimensions underlying the respondents' reactions in stressful driving situations. The factors are characterized and named as follows:

Factor C_1: Driving distraction

This factor, which includes DBS survey item 1 (loading 0.73) and item 9 (loading 0.71), pertains to a crucial dimension linked to unawareness of situations or attention diverted away from the road, potentially leading to anxious and risky driving outcomes.

Factor C_2: Aggressive driving

This factor, which includes DBS survey item 2 (loading 0.89), item 7 (loading 0.83), item 10 (loading 0.92), item 15 (loading 0.79), item 17 (loading 0.83), item 18 (loading 0.88) and item 20 (loading 0.90), reflects behaviors associated with impatience, assertiveness, and hostility on the road. Variables within this factor emphasize the driver's anxiety and inclination toward aggressive driving tendencies.

Factor C_3: Exaggerated caution

This factor, which includes DBS survey item 8 (loading 0.67), item 11 (loading 0.70), item 12 (loading 0.82), item 13 (loading 0.71), item 16 (loading 0.84) and item 19 (loading 0.58), represents a driver's propensity to exhibit excessive caution, often leading to overly timid and hesitant behaviors on the road.

Factor C_4: Performance deficits

This factor, which includes DBS survey item 3 (loading 0.76), item 4 (loading 0.90), item 5 (loading 0.93), item 6 (loading 0.88), item 14 (loading 0.91) and item 21 (0.82), encompasses challenges in speed and lane management. Variables within this factor are related to the driver's ability to maintain a steady and controlled position and speed within the designated lane.

The identification of the above factors form the basis for the subsequent application of the FAHP method, enabling us to assign relative weights to each of these factors and develop a structured framework for the assessment of anxious drivers.

For the implementation of the FAHP method, after consultation with domain experts, the anxious driver types, i.e., the alternatives, are set to be $\{A_1, A_2, A_3\}$, where A_1 refers to "Anxious driver with situational unawareness", A_2 refers to "Anxious driver with performance shortcomings", and A_3 refers to "Anxious driver with hostility". Table 5 and 6 show the fuzzy comparison matrices constructed that respectively quantify the relative importance between factors, and between alternatives given the factors.

Table 5. Fuzzy comparison matrix for the factors $\{C_1, C_2, C_3, C_4\}$.

	C_1	C_2	C_3	C_4
C_1	$(1,1,1)$	$(2,3,4)$	$(1/6,1/5,1/4)$	$(4,5,6)$
C_2	$(1/4,1/3,1/2)$	$(1,1,1)$	$(1/4,1/3,1/2)$	$(1/6,1/5,1/4)$
C_3	$(4,5,6)$	$(2,3,4)$	$(1,1,1)$	$(4,5,6)$
C_4	$(1/6,1/5,1/4)$	$(4,5,6)$	$(1/6,1/5,1/4)$	$(1,1,1)$
C^{row_sum}	$(65/12,98/15,31/4)$	$(9,12,15)$	$(19/12,26/15,2)$	$(55/6,56/5,53/4)$

Table 6. Fuzzy comparison matrices $\mathcal{A}^{(C_i)}, i \in [1:4]$, for the alternatives $\{A_1, A_2, A_3\}$.

C_1	A_1	A_2	A_3
A_1	$(1,1,1)$	$(1/6,1/5,1/4)$	$(6,7,8)$
A_2	$(4,5,6)$	$(1,1,1)$	$(6,7,8)$
A_3	$(1/8,1/7,1/6)$	$(1/8,1/7,1/6)$	$(1,1,1)$
$\mathcal{A}^{(C_1)row\_sum}$	$(41/8,43/7,43/6)$	$(31/24,47/35,17/12)$	$(13,15,17)$
C_2	A_1	A_2	A_3
A_1	$(1,1,1)$	$(6,7,8)$	$(4,5,6)$
A_2	$(1/8,1/7,1/6)$	$(1,1,1)$	$(4,5,6)$
A_3	$(1/6,1/5,1/4)$	$(1/6,1/5,1/4)$	$(1,1,1)$
$\mathcal{A}^{(C_2)row\_sum}$	$(31/24,47/35,17/12)$	$(43/6,41/5,37/4)$	$(9,11,13)$
C_3	A_1	A_2	A_3
A_1	$(1,1,1)$	$(1/6,1/5,1/4)$	$(1/4,1/3,1/2)$
A_2	$(4,5,6)$	$(1,1,1)$	$(4,5,6)$
A_3	$(2,3,4)$	$(1/6,1/5,1/4)$	$(1,1,1)$
$\mathcal{A}^{(C_3)row\_sum}$	$(7,9,11)$	$(4/3,7/5,3/2)$	$(21/4,19/3,15/2)$
C_4	A_1	A_2	A_3
A_1	$(1,1,1)$	$(2,3,4)$	$(1/6,1/5,1/4)$
A_2	$(1/4,1/3,1/2)$	$(1,1,1)$	$(4,5,6)$
A_3	$(4,5,6)$	$(1/6,1/5,1/4)$	$(1,1,1)$
$\mathcal{A}^{(C_4)row\_sum}$	$(21/4,19/3,15/2)$	$(19/6,21/5,21/4)$	$(31/6,31/5,29/4)$

Then, based on these comparison matrices, the computation results of composite weight intervals computed for alternative A_j given factor C_i, $\{(\hat{\mathcal{A}}^{(ij)}_{low}, \hat{\mathcal{A}}^{(ij)}_{medium}, \hat{\mathcal{A}}^{(ij)}_{high})\}$, $i \in [1:4]$, $j \in [1:3]$ are presented in Table 7.

Table 7. The composite weight intervals computed for alternative A_j given factor C_i, $\{(\hat{\mathcal{A}}^{(ij)}_{low}, \hat{\mathcal{A}}^{(ij)}_{medium}, \hat{\mathcal{A}}^{(ij)}_{high})\}$, $i \in [1:4]$, $j \in [1:3]$.

$i\backslash j$	1	2	3
1	$(0.033,0.063,0.121)$	$(0.087,0.163,0.308)$	$(0.009,0.016,0.029)$
2	$(0.033,0.059,0.117)$	$(0.010,0.020,0.043)$	$(0.004,0.008,0.016)$
3	$(0.029,0.052,0.101)$	$(0.189,0.350,0.650)$	$(0.052,0.108,0.225)$
4	$(0.020,0.049,0.123)$	$(0.029,0.060,0.128)$	$(0.026,0.054,0.116)$

Combined with the factor scores S_i, $i \in [1:4]$, defined to be the average of the scores of the DBS survey items within each factor, the overall score intervals for all the alternatives can be determined.

Here we give three specific assessment examples for individual driver respondents:

Respondent ID = 28: The average of the frequency selection scores within each factor for the DBS survey is Factor C_1: 1.00; Factor C_2: 3.29; Factor C_3: 2.50; Factor C_4: 1.33, then combined with the composite weight intervals (Table 7), the overall score intervals for the alternatives are Alternative A_1: $(0.24, 0.45, 0.92)$; Alternative A_2: $(0.19, 0.38, 0.80)$; Alternative A_3: $(0.63, 1.18, 2.24)$. Setting the level of confidence α-cut to be 0.95, the confidence level representations of the alternatives are Alternative A_1: $(0.44, 0.47)$; Alternative A_2: $(0.37, 0.40)$; Alternative A_3: $(1.15, 1.23)$. Therefore, the overall scores for the alternatives are Alternative A_1: 0.457; Alternative A_2: 0.386; Alternative A_3: 1.193. The highest-scored alternative is Alternative A_3: 1.193.

Respondent ID = 112: The average of the frequency selection scores within each factor for the DBS survey is

Factor C_1: 1.50; Factor C_2: 1.43; Factor C_3: 1.50; Factor C_4: 1.83, then combined with the composite weight intervals (Table 7), the overall score intervals for the alternatives are Alternative A_1 : $(0.15, 0.30, 0.62)$; Alternative A_2 : $(0.48, 0.91, 1.73)$; Alternative A_3 : $(0.14, 0.30, 0.62)$. Setting the level of confidence α-cut to be 0.95, the confidence level representations of the alternatives are Alternative A_1: $(0.29, 0.32)$; Alternative A_2: $(0.89, 0.95)$; Alternative A_3: $(0.29, 0.32)$. Therefore, the overall scores for the alternatives are Alternative A_1: 0.304; Alternative A_2: 0.920; Alternative A_3: 0.304. The highest-scored alternative is Alternative A_2: 0.920.

Respondent ID = 200: The average of the frequency selection scores within each factor for the DBS survey is Factor C_1: 2.00; Factor C_2: 1.43; Factor C_3: 2.33; Factor C_4: 2.83, then combined with the composite weight intervals (Table 7), the overall score intervals for the alternatives are Alternative A_1 : $(0.24, 0.47, 0.99)$; Alternative A_2 : $(0.71, 1.34, 2.55)$; Alternative A_3 : $(0.22, 0.45, 0.93)$. Setting the level of confidence α-cut to be 0.95, the confidence level representations of the alternatives are Alternative A_1: $(0.44, 0.50)$; Alternative A_2: $(1.31, 1.40)$; Alternative A_3: $(0.44, 0.47)$. Therefore, the overall scores for the alternatives are Alternative A_1: 0.477; Alternative A_2: 1.355; Alternative A_3: 0.456. The highest-scored alternative is Alternative A_2: 1.355.

The distribution of the highest scores $\max_{j\in[1:3]} \mathcal{A}^{(j)}$ among alternatives for all the $N = 258$ respondents is shown in Figure 1.

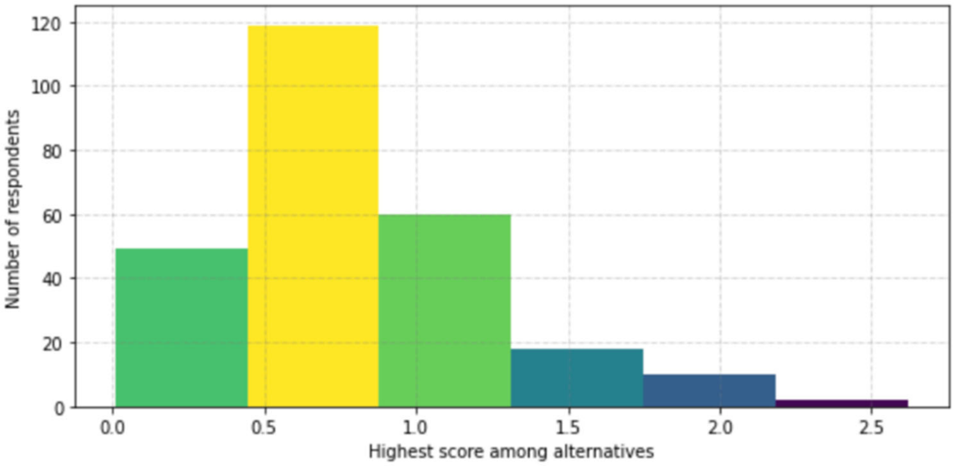

Figure 1. Histogram of highest scores $\max_{j\in[1:3]} \mathcal{A}^{(j)}$ among alternatives for the respondents ($N = 258$)

After consulting with domain experts and further analyzing the ratings results, the threshold score S^* is set to be 1.15 for all highest-scored alternatives in this study. Therefore, for the above individual driver examples, the Respondent ID = 28 is identified with Alternative A_3, i.e., "anxious driver with hostility", while the Respondent ID = 200 is identified with Alternative A_2, i.e., "anxious driver with performance shortcomings". Overall, out of the DBS survey respondents, 7 are identified as "anxious driver with situational unawareness", 17 are identified as "anxious driver with performance shortcomings", and 23 are identified as "anxious driver with hostility", thus comprising a total of 18.22% of the driver respondents.

The results of this study indicate that anxious driving behavior is a multi-dimensional construct, which involves various factors such as aggressiveness, fear, distraction, and inattention. These dimensions are intricately interconnected and collectively contribute to the overall assessment of a driver's anxious behavior. The FAHP process can assign appropriate weights to these factors based on domain experts' professional views, thereby capturing relative importance of each factor within a respective area. Consequently, our framework produces a holistic and refined assessment of drivers' driving anxiety, offering a comprehensive perspective on their behavior behind the wheel.

5. Discussion

This paper introduces a comprehensive, reliable, and adaptable data-driven solution to identifying and assessing anxious drivers, addressing a critical aspect of road safety and driver well-being. By integrating factor analysis and FAHP methods, the proposed approach provides a structured and flexible means of evaluating anxious driving behavior. The resulting assessment scores and ratings empower stakeholders to take informed actions, enhancing road safety and promoting a more relaxed and secure driving environment. This research contributes to the evolving field of transportation psychology and underscores the potential of data-driven methodologies in improving the assessment and management of driver behavior.

The FAHP method, in particular, was employed to derive weights for both the factors and alternatives within the anxious driving assessment framework, which introduces a level of flexibility and adaptability by considering the inherent uncertainties associated with human behavior. By utilizing fuzzy logic, the evaluation system accounts for the vagueness and subjectivity that often surround assessments of driver behavior. Through a meticulous pairwise comparison process, the importance of each factor and alternative was quantified, considering the professional judgment of domain experts. The FAHP method takes into account the inherent imprecision in assessing anxious driving behavior, resulting in a more realistic and nuanced evaluation of drivers.

Our approach allows for the precise classification of anxious drivers into distinct types, such as those with situational unawareness, performance shortcomings, or hostility. This detailed categorization enables traffic safety authorities to design tailored interventions and educational programs that address the specific needs and behaviors of each type of anxious driver. By targeting the root causes of anxiety-induced driving tendencies, authorities can effectively mitigate risk factors and enhance road safety. Meanwhile, Drivers themselves can benefit from the assessment results. Understanding their own anxious driving behavior and type can motivate them to adopt safer driving practices and seek relevant training or support. This self-awareness can lead to safer roads and reduced stress for the drivers themselves.

While our research provides valuable insights into the identification and assessment of anxious drivers, there are certain limitations to consider. First, our analysis primarily focuses on behavioral data derived from the DBS survey. Incorporating additional demographic information, such as age, gender, and driving experience, could yield a more comprehensive understanding of anxious driving tendencies. One future research direction would be to explore the interplay between demographic factors and anxious driving.

Also, the absence of historical data related to traffic violations or accidents limits our ability to correlate the identified anxious driver types with real-world driving outcomes. Integrating such data could enhance the predictive accuracy of our assessment and contribute to more targeted interventions. Additionally, our FAHP method relies on expert judgments to establish the relative importance of factors and alternatives. The subjectivity of expert input introduces an element of uncertainty in the assessment process. Future research could explore ways to reduce this subjectivity through more objective data sources or larger expert panels.

To enhance the predictive power of the assessment, integrating multidimensional real-world data on automobile states and movements, drivers' traffic violations, accidents, and near-miss incidents is crucial, which enables a more robust assessment of the correlation between anxious driving behavior and road safety outcomes. Future research can also focus on developing and evaluating behavioral interventions tailored to the identified types of anxious drivers. Such interventions could involve driver training, stress management, and cognitive-behavioral approaches aimed at reducing anxiety-induced driving behaviors.

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