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Remediation Ranking of High Crash Fatality Locations Involving Older Drivers in Florida's Rural Counties

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Abstract

In 2019, Florida's aging road users (65 years or older) accounted for 20% of the population and 37% of all crashes. The Florida Department of Transportation has identified aging road users as one of the emphasis areas toward achieving Vision Zero. Research has documented that fatality rates in motor vehicle crashes are higher in rural areas than in urban areas. Drivers in rural areas may be more vulnerable because they rely more on driving and consequently are reluctant to stop driving. This study identifies factors contributing to fatalities among aging drivers in 14 rural Florida counties that are experiencing high crash rates. The methodology used a multi-criteria decision-making model, namely the fuzzy analytic hierarchy process (FAHP), to identify and categorize the cause of fatal crashes among 65+ drivers and to rank their 14 rural counties for remediation measures. The FAHP methodology calculates crash factor weights and ranks the counties using pairwise comparisons of those factors to compare and quantify them. Results reveal that the top contributing factors to fatal crashes among the 65+ drivers are when the weather is cloudy, foggy, or rainy and when roadways are sandy and wet. Driving in the dark and at dawn also increases the risk of fatal crashes within the age group. These findings can help policymakers in each location focus on remediation measures such as older driver education and infrastructure improvements to address the most critical factors in fatal accidents.

Keywords: Older Drivers, Fuzzy Analytical Hierarchy Process, Pairwise Comparison, Road Safety, Fatality Crashes, rural counties.

1. Introduction

The world's aging population is expanding rapidly. By 2060, about 95 million Americans will be of age 65+ or nearly double the current population in that group [1]. Studies indicate older adults today will live longer and drive longer than any previous generation [2]. The proportion of licensed drivers aged 65+ steadily increased from 16% in 2010 to 20% in 2019 [3]. Age 65+ drivers have higher fatal crash rates, despite driving fewer miles than other age groups [4]. The National Highway Safety Administration (NHTSA) observed a 36.5% increase in fatalities for age 65+ drivers from 2010 to 2019, which was 22.3% above the national average growth for all age groups [5].

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Traffic risks increase with driver age. For example, an 80-year-old woman is seven times more likely to be killed than a 45-year-old woman when making trips of equal distance. A variety of variables increases an older driver's crash risk. The likelihood of more aged drivers being involved in a crash increases because their cognitive visual, and physical functions deteriorate with age [6]. Frailty (i.e., the likelihood of death because of a given injury) of crash-involved passengers increases with age and so does fragility (i.e., the likelihood of suffering severe injuries because of a given crash) [3].

A higher percentage of elderly drivers (55–64) suffer injury death due to motor vehicle crashes, despite driving fewer miles [4]. Age plays a large part in crashes involving older drivers because there is typically a decline in motor skills, sensory functions, and cognitive functions with increased age [7]. These declines are associated with unsafe behaviors by older drivers. On the other hand, older drivers exhibit safe driving by wearing seatbelts, refraining from driving under unfavorable circumstances, and abstaining from driving intoxicated [8].

According to Florida Department of Health (FDOH), Bureau of Vital Statistics, in 2019, 17 counties had a high rate of fatalities for older drivers, ranging from 24.92 to 150.43 per 100,000 population [38]. Figure 1 displays the number of fatalities for older drivers across Florida's counties in 2019. Figure 2 shows Sumter County that had the highest percentage of older population among Florida's counties 2019, with 45 to 58 percent of population falling into that category. Moreover, 21 to 45 percent of the older population lived in the southwest and southeast counties of Florida. By comparing Figure 1 and Figure 2, it is evident that most crashes occurred in counties with the lowest levels of the older population.

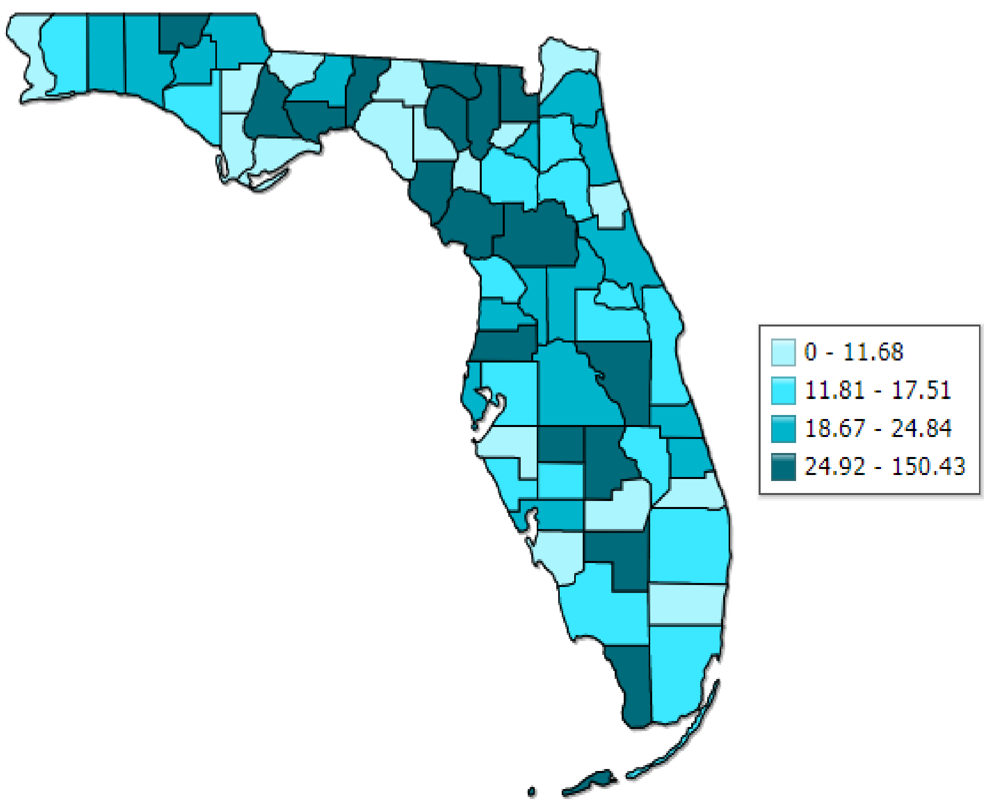

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Figure 1. Fatalities crash for older drivers per 100,000 population in 2019 [38]. (Data sources: Florida Department of Health (FDOH), Bureau of Vital Statistics).

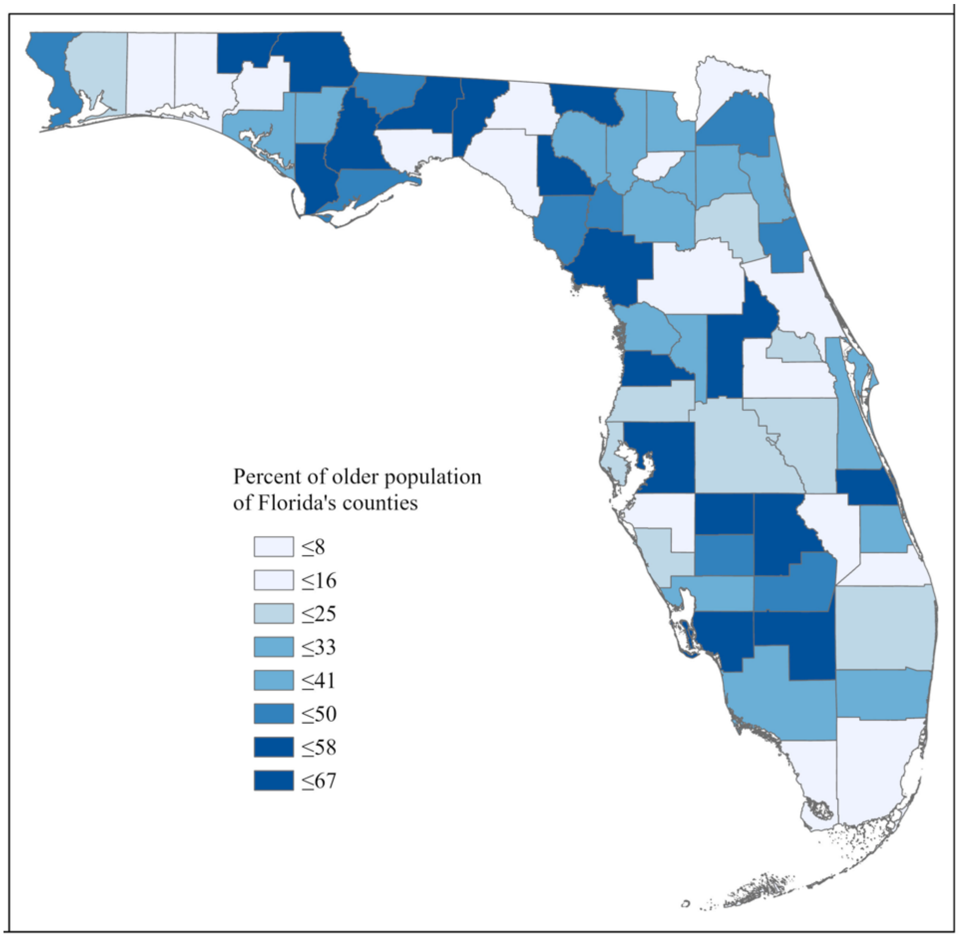

Figure 2. Percent of the older population of Florida's counties [39].

According to Figure 3, 14 of the 17 counties that had the highest level of fatalities for older drivers are rural. Figure 1 shows the main reason we choose those 14 counties from the 67 counties of Florida for the FAHP analysis. Those 14 counties have high rates of fatalities among older drivers. Those rates are between 24.92 and 150.43 per 100,000 populations. These 14 counties are Columbia, Hardee, Hamilton, Dixie, Liberty, Hendry, Wakulla, Jefferson, Levy, Baker, Hardee, Suwannee, Highlands, Monroe, and Holmes in highest order (Figure 4).

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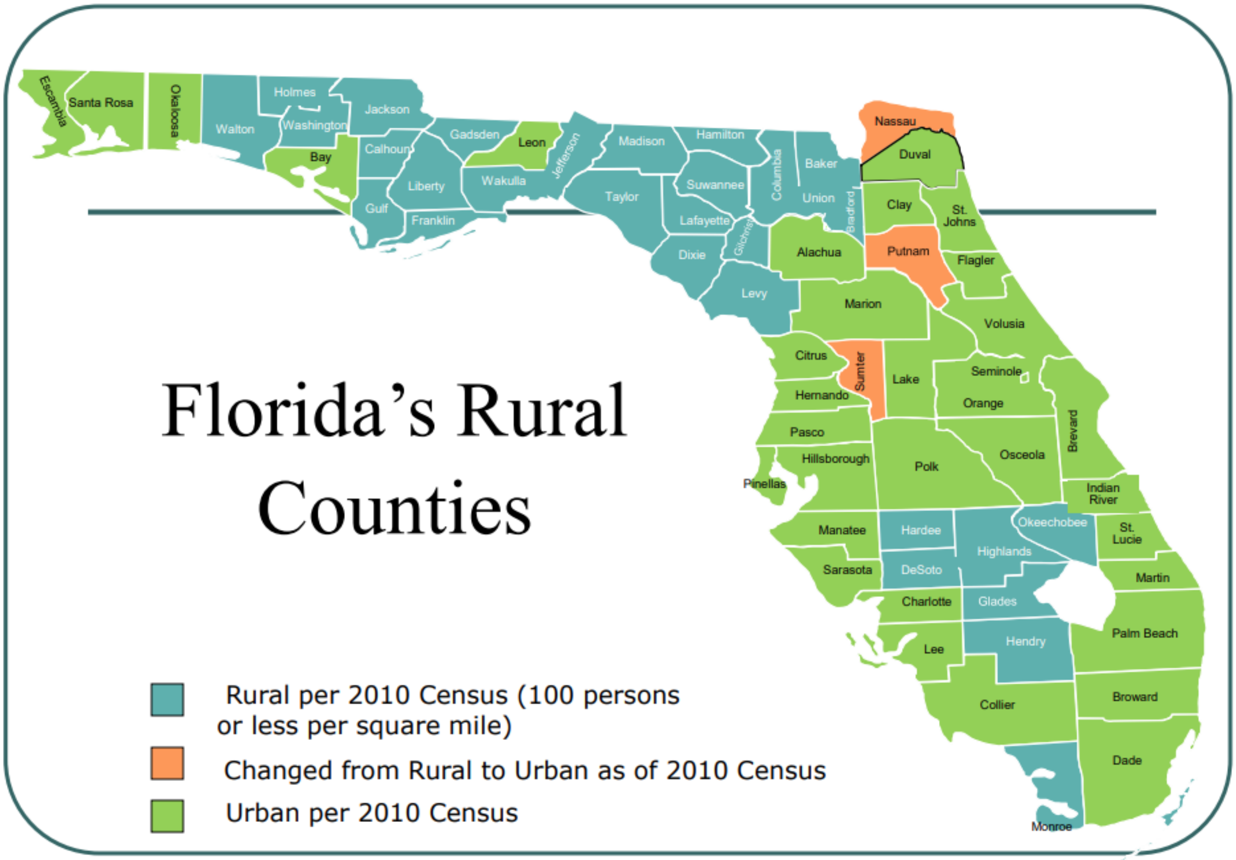

Figure 3. Rural counties map [40].

Figure 4 illustrates the rate of motor vehicle crashes compared to a percentage of older people population in the Florida counties. According to Figure 4, Holmes, Monroe, and Suwannee have 10 to 20 percent, Highlands, Liberty, Hendry, and Suwannee have 20% to 30%, Hamilton, Dixie, Jefferson, Baker, and Hardee have 30 to 40 percent, Wakulla and Levy have more than 40 deaths in vehicle crashes per 100,000 population. Moreover, in some counties, the number of fatal crashes per 100,000 populations is more than those of other counties such as Highlands, Levy, and Colombia. Although the number of fatal crashes in Hamilton, Dixie, Liberty, Jefferson, Baker, Holmes, Hardee, and Suwannee are few, under ten fatal crashes per 100,000 populations, the deaths per 100,000 population are approximately 30 percent. Therefore, this data indicates that the total population age 65+ in these counties is low compared to deaths from vehicle crashes.

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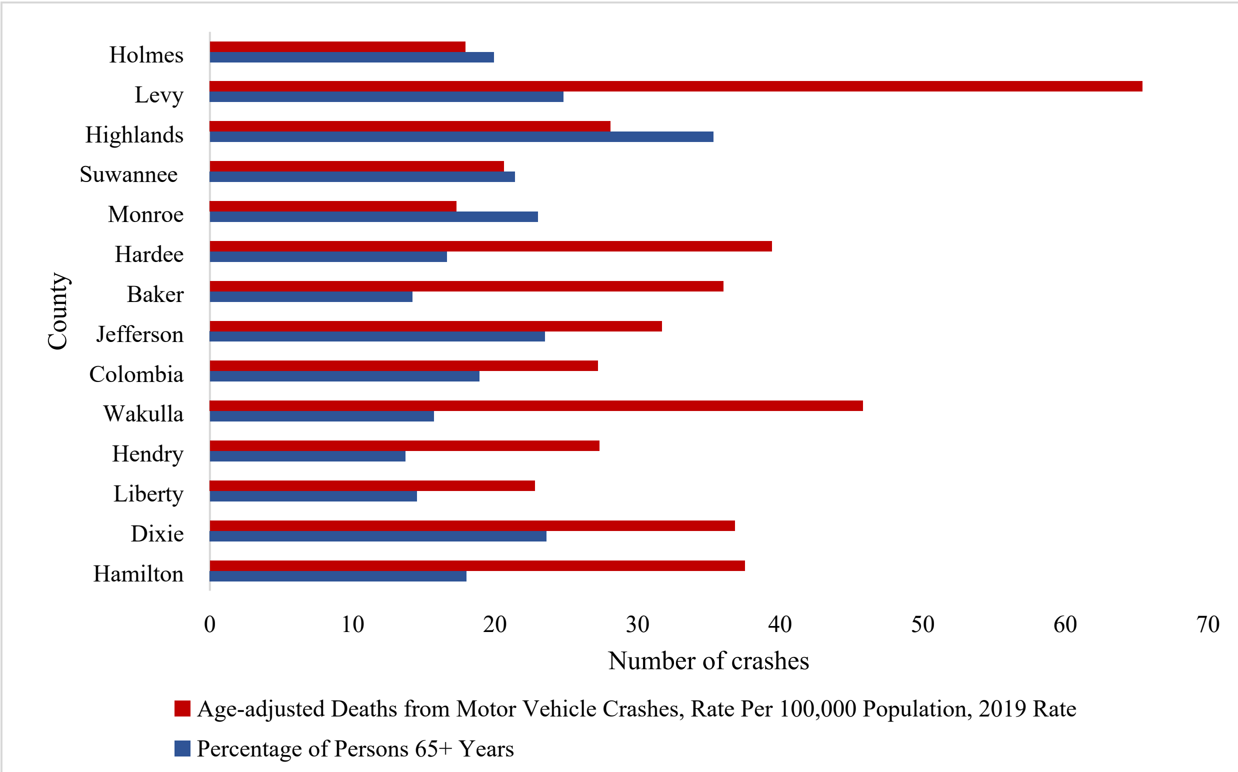

Figure 4. Age-adjusted death of motor vehicle crashes [38].

The main purpose of this study is to analyze fatal crashes resulting from accidents involving older drivers in Florida by investigating factors that may have contributed to those fatalities. Florida is one of the top three states in terms of the highest percentage of aging population. The 2019 census estimated that 20.9% of the approximately 21.5 million residents of Florida are age 65+, which analyst estimate will be 25% 2045. In 2018, Florida was among the top three states that experienced the highest rates of crashes among the age 65+ demographic with 634, 606, and 557 crashes, respectively [9].

This study evaluates factors associated with fatal crashes that involved older drivers in 2019. First, we ranked the main crash factors and their sub-factors involving older drivers in different counties of Florida. Second, we use the fuzzy analytic hierarchy process (FAHP) method to rank 14 counties from high to low priority for remediation strategies. The multi-criteria decision making (MCDM) technique, which uses pairwise comparisons between the stated crash factors, is the most common and useful instrument for studying traffic crashes among the age 65+ group [10].

The main contributions of this paper are as follows:

- Applying the FAHP method to rank factors in age 65+ driver crashes in Florida,
- Ranking remediation priorities for the 14 counties of Florida where crash rates are highest, and
- Suggesting policies for alleviating the crash rates among older drivers.

The structure of the remainder of this paper is as follows: section 2 reviews relevant work. Section 3 reports the material and method by reviewing background crash statistics across the Florida counties and discussing the AHP method. Section 4 presents the result of the proposed methodology. Section 5 presents the conclusions and recommendations for policymakers.

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2. Literature Review

With the number of older drivers increasing every year, it is critical to better understand their driving situations to reduce driving-related morbidity and death across their lifetimes. Even though older people drive less than younger people, they are more likely to be killed or wounded in vehicle crashes [11] [12]. This increased risk of traffic-related injury and mortality could be due to aging-related declines in visual, physical, and cognitive performance which are frequently linked to medical problems or drug usage [13]. Karali et al. [11] discovered that relative to younger drivers, elderly drivers have slower reaction times, have more difficulties driving in adverse weather, and find it more difficult to rotate their head and body when reversing. Lombard et al. [14] discovered that nearly 20% of older drivers are more likely to be involved in a fatal intersection crash than younger drivers, and the risk of a collision for age 85+ drivers doubles. Also, they indicated that older drivers were considerably more likely than younger drivers to experience fatal intersection crashes. Studies investigated that some driving errors, including inadequate surveillance, illegal maneuvers, medical events, misjudgment of vehicle distance or speed, and daydreaming are the most common errors incurred by older drivers [15] [16].

Although older drivers make errors during their driving, we need effective and accessible interventions to help older drivers remain safe. In this case, researchers found that it is necessary to provide targeted education interventions based on the needs and abilities of older drivers [17] [18]. Bédard et al. [18] found that educational programs could not increase road safety for older drivers. According to studies, older drivers that received training using a driving simulator improved their performance [19] [20]. Moreover, Oxley et al. [21] found that although older drivers were familiar with several critical in-vehicle technologies, such as automated emergency braking (AEB) and front collision warning systems, older drivers had low overall knowledge of such systems.

Different explanatory factors have been considered when analyzing and modeling crashes. Roadway factors including speed limit, road condition, the number of lanes, road class, driver factors such as age, gender, seatbelt use, and environmental factors such as lighting condition, weather condition, time of day, and days of the week are among the factors considered in previous studies [10] [22] [23] [24]. Haleem et al. [25] investigated pedestrian-intersection crash-related wounds by applying a mixed logit regression model. Crash modeling considered two severity levels, including fatal and non-fatal. According to Kim et al. [24], while the risk of fatal injury increased for male drivers, the severity of crash injuries increased for older drivers who drive older vehicles.

Some studies like Agarwal et al. [10] applied the AHP technique to rank hazardous road locations by computing the weights of different safety factors identified. They proposed a hierarchical structure to determine the safety factors, which they decomposed into hazardous conditions at straight and curved road sections and intersections. In a similar study, Moslem et al. [26] proposed the AHP technique based on the best-worst method to evaluate the aspects of driver behavior related to road safety in Budapest. Responses to the driver behavior questionnaire revealed the most significant driver behavior characteristics influencing road safety at each level by using the AHP approach. Similarly, other researchers used the AHP approach to collect linguistic judgment data to find variations between responses on perceived road safety hazards for 20 crash factors in a three-level hierarchical framework [27].

Some studies considered the FAHP variant of the technique. For instance, Nanda et al. [28] employed the FAHP technique to identify the most crucial road accidents in India. Yu et al. [29] applied FAHP to rank and implement highway safety projects with regard to technical, economic, and social impacts. Bao et al. [30]

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utilized the Eurostat dataset of crash and injury to evaluate road safety performance employing the improved hierarchical fuzzy TOPSIS method.

Also, some studies discussed the application of regression modeling in their studies [31] [32] [33]. Chin et al. [31] applied the logistic regression method to investigate the fault of light-vehicles drivers of age 65+ in Singapore. They found that older drivers are prone to dangers when they drink or drive during peak hours and festive periods. Furthermore, they found that older drivers are more likely to be at fault when they are at a junction, in the curb lane of a multi-lane or single-lane road, driving on wet surfaces, or exceeding the speed limit. Yan et al. [32] utilized the multiple logistic regression model to engage the characteristics of rear-end accidents at signalized intersections. Johnson et al. [33] utilized generalized linear mixed modeling to discover that driving under the influence of cannabis (THC-positive) was linked to a higher collision risk for older drivers than for younger drivers.

This literature review highlighted that few researchers used the FAHP technique to evaluate factors that contribute to fatal crashes involving age 65+ drivers. Researchers mainly employed the AHP methodology to rank the crucial factors in traffic fatalities involving older drivers. Applying the FAHP technique can avoid the vagueness and uncertainty of judgment when deliberating among the factors in crash risks.

3. Proposed Methodology

3.1 Older Drivers Hierarchical Structure

The hierarchical structure of investigated crash factors associated with older driver crashes in the 14 Florida counties is shown in Figure 5. The first level of the FAHP hierarchical structure is the analysis goal. The second layer displays the main crash factors to be ranked. Finally, the last layer enumerates the counties to be ranked for remediation measures, based on the most important crash factors.

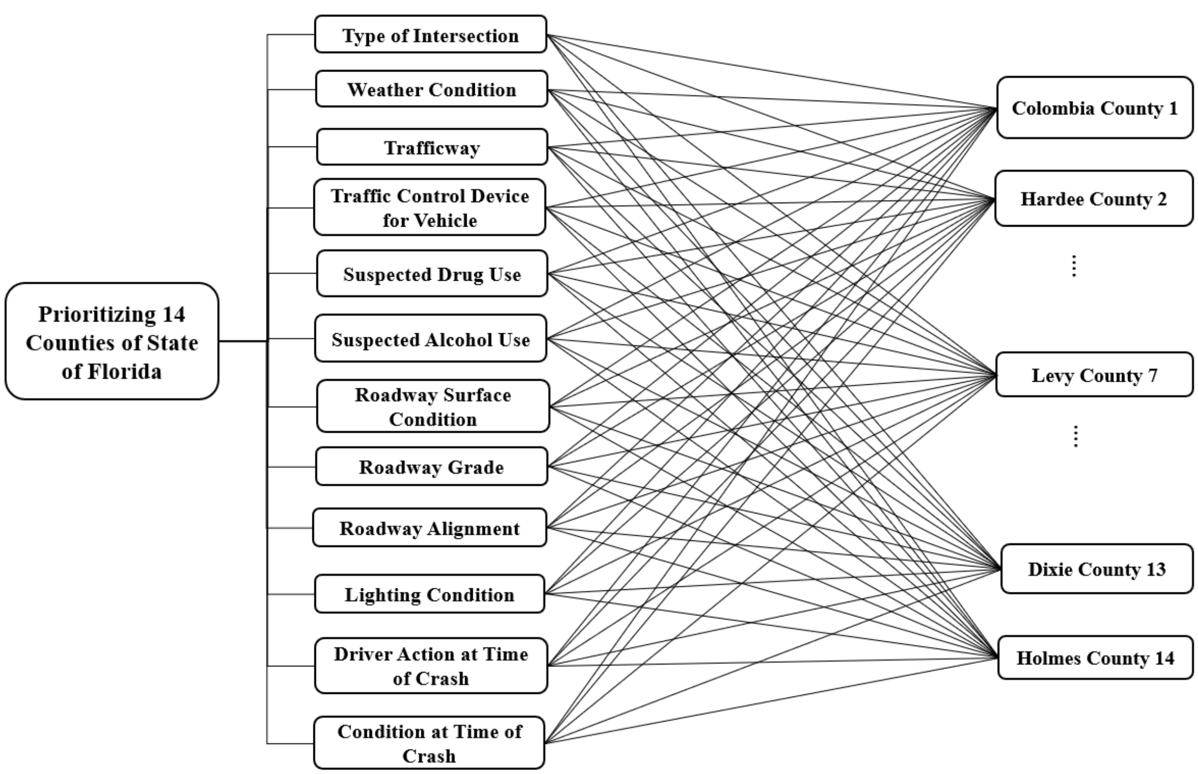

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Figure 5. The hierarchy of the FAHP framework

The following crash factors were selected for weight assignments by 12 experts working at the Florida Department of Transportation (FDOT): type of intersection, weather condition, trafficway, traffic control device for vehicles, suspected drug use, suspected alcohol use, roadway surface condition, roadway grade, roadway alignment, light condition, driver action at the time of the crash, and driver condition at the time of the crash.

The FAHP methodology compares and ranks 12 factors in fatal crashes involving older drivers. Figure 6 displays sub-factors (F1, F2, F3, …., F27) that constitute the primary crash factors investigated. Some crash factors, such as suspected drug use and suspected alcohol use, are combined as one sub-factor. The other factors are weather conditions of cloudy (F1), sleet (F2), foggy (F4), and rainy (F5). Road surface factors are surface conditions of wet (F3), icy (F10), oily (F11), and sandy (F8). Light condition factors are dark (F6), dusk (F14), and dawn (F9). Factors involving the type of intersections are 4-way (F13), T-type (F15), Y-type (F19), traffic circle (F20), and roundabout (F17).

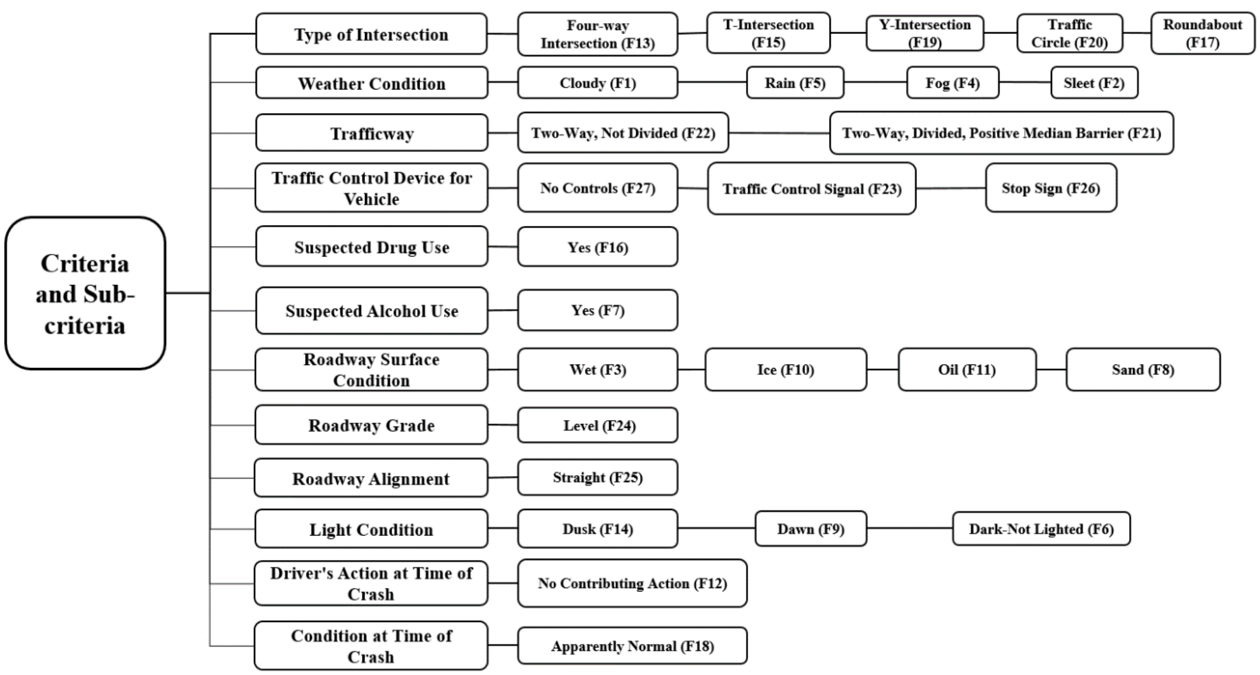

Figure 6. The main crash factors and their sub-factors.

3.2 Fuzzy Analytical Hierarchy Process Methodology

The procedure first ranks the main crash factors that affect the performance of older drivers. Next, the procedure ranks the 14 counties by performing a pairwise comparison between the incident reason for association with the main crash factors and their relative significance [37]. Figure 7 shows the FAHP framework to rank the 14 counties of Florida.

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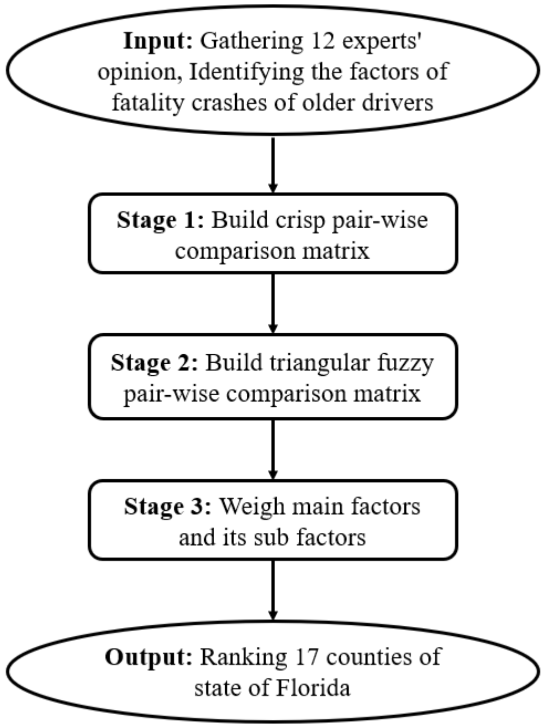

Figure 7. A framework of the proposed FAHP methodology

In 1996, Da-Yong Chang [38] proposed the fuzzy version of the AHP method called the FAHP by incorporating the fuzzy number. The FAHP approach decomposed the decision-making into a hierarchical form. The following are the main steps of the FAHP method:

Define $X = \{x_1, x_2, \ldots, x_n\}$ as an object set and $G = \{g_1, g_2, \ldots, g_n\}$ as a goal set. Each goal has *m* extents

$$M_{gi}^1, M_{gi}^2, \ldots, M_{gi}^m, \qquad i = 1, 2, \ldots, n \tag{1}$$

where $M_{gi}^j, j = 1, 2, \ldots, n$ are fuzzy triangular numbers. The fuzzy synthetic extent concerning the i^{th} object is:

$$S_i = \sum_{j=1}^{m} \tilde{M}_{gi}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1} \tag{2}$$

Then $\sum_{j=1}^{m} \tilde{M}_{gi}^j$ and $\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^j$ are calculated as:

$$\sum_{j=1}^{m} \tilde{M}_{gi}^j = (\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j) \tag{3}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^j = (\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i) \tag{4}$$

where $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1}$ is

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$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m}M_{gi}^{j}\right]^{-1}=\left(\frac{1}{\sum_{i=1}^{n}u_i},\frac{1}{\sum_{i=1}^{n}m_i},\frac{1}{\sum_{i=1}^{n}l_i}\right) \tag{5}$$

The second step is calculating the degree of possibility for each S_i. In this step, another pairwise comparison among the calculated S_i is completed. Given that $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$, the degree of possibility of $S_2 \geq S_1$ is:

$$V(M_2 \geq M_1) = \sup_{y \geq x}\left[\min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right] \tag{6}$$

and can be represented as:

$$V\left(M_2 \geq M_1\right) = hgt(M_2 \cap M_1) = \mu_{M_2}(d) = \begin{cases} 1 & \text{if } M_2 \geq M_1 \\ 0 & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases} \tag{7}$$

The d in equation (7) is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2}. Both values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ should be obtained to compare M_1 and M_2. Figure 8 shows the value of d, as discussed for the second step.

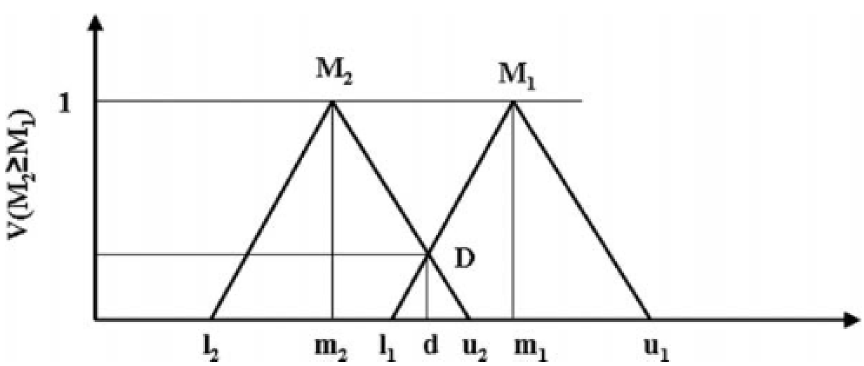

Figure 8. The hierarchy of the FAHP framework

For the third step, if a fuzzy number is more significant than k convex fuzzy number M_i $(i = 1,2,...,k)$, equation (6) can be expressed as follows:

$$V(M \geq M_1, M_2, ..., M_k) = \min V(M \geq M_i), i = 1,2,...,k \tag{8}$$

The fourth step is to calculate a weight vector. Assume that $d(M_i) = \min V(S_i \geq S_k)$ for $k = 1,2,...,k; k \neq i$, then the weight vector $M_i (i = 1,2,...,n)$ contains n elements:

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$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T \tag{9}$$

The last step is to calculate the vector of normalized non-fuzzy weight. W in the following formulation presents the normalized non-fuzzy weight vector:

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{10}$$

Eventually, the higher the associated normalized non-fuzzy weight of the factor, the more important that factor is.

4. Result and Discussion

The FAHP methodology used is coded on MATLAB software version 2021. This study used the opinions from 12 experts at the FDOT to create a crisp pairwise comparison matrix as input data for the method. Table 1 shows the pairwise comparison scale for the crisp and fuzzy numbers from 1 to 9. Table 1 indicates the degree of importance of one factor over another, with one being unimportant and nine being the most important. For example, one expert rated the importance of cloudy weather (weather condition factor) relative to rainy weather (weather condition factor) as 1. Hence, the opinion was that there was no difference between rainy weather and cloudy weather in influencing the driving performance of an older person.

In the first step, the pairwise comparison matrix is created by crisp numbers (see Table 1). The second step converted the decision makers' pairwise comparison matrix (crisp numbers) to a triangular fuzzy pairwise comparison matrix using the defined scale, Table 1.

Table 1. Pairwise comparison scale [24]

Comparison index	**Crisp number**	**Fuzzy number**
Extremely preferred	9	(9,9,9)
Very strongly preferred	7	(6,7,8)
Strongly preferred	5	(4,5,6)
Moderately preferred	3	(2,3,4)
Equal	1	(1,1,1)
Intermediate values	2	(1,2,3)
	4	(3,4,5)
	6	(5,6,7)
	8	(7,8,9)

Table 2 reports the weights of crash factors and sub-factor computed by running the method on the input data. The first set of weights is the local weights before normalizing, while the second set of weights is the globally normalized weights. Table 2 shows that the procedure assigns the highest weight to the weather condition factor (F1). In contrast, the traffic control device for the vehicle crash factors (F27) is assigned the lowest weight in terms of global weight.

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Table 2. Priority weights for crash factors and sub-factors.

Crash Factors	Sub-factors	Local weights	Global weights
Weather Condition	F1 (Cloudy)	0.1193	**0.1076**
Weather Condition	F5 (Rain))	0.0722	0.0651
Weather Condition	F4 (Fog)	0.0857	0.0773
Weather Condition	F2 (Sleet)	0.1113	0.1003
Roadway Surface Condition	F3 (Wet)	0.0885	0.0798
Roadway Surface Condition	F10 (Ice)	0.0431	0.0388
Roadway Surface Condition	F11 (Oil)	0.0389	0.0351
Roadway Surface Condition	F8 (Sand)	0.0513	0.0462
Light Condition	F14 (Dusk)	0.0363	0.0327
Light Condition	F9 (Dawn)	0.0501	0.0452
Light Condition	F6 (Light-not lighted)	0.0569	0.0513
Suspected Alcohol Use	F7 (Yes)	0.0514	0.0464
Suspected Drug Use	F16 (Yes)	0.0307	0.0277
Driver's Action at Time of Crash	F12 (No contributing	0.0385	0.0347
Type of Intersection	F13 (Four-way	0.0384	0.0346
Type of Intersection	F15 (T-intersection)	0.0318	0.0286
Type of Intersection	F19 (Y-intersection)	0.0204	0.0184
Type of Intersection	F20 (Traffic circle)	0.0184	0.0166
Type of Intersection	F17 (Roundabout)	0.0237	0.0214
Condition at Time of Crash	F18 (Apparently Normal)	0.0214	0.0193
Trafficway	F22(Two-Way, Not	0.0136	0.0123
Trafficway	F21 (Two-Way, Divided,	0.0159	0.0143
Roadway Grade	F24 (Level)	0.0112	0.0101
Roadway Alignment	F25 (Straight)	0.0101	0.0091
Traffic Control Device for the Vehicle	F27 (No controls)	0.0074	**0.0067**
Traffic Control Device for the Vehicle	F23 (Traffic control signal)	0.0133	0.0120
Traffic Control Device for the Vehicle	F26 (Stop sign)	0.0097	0.0087

Table 3 ranks all factors by global weight. Cloudy (F1) and sleet (F2) weather conditions are ranked first and second in crash factors followed by wet road condition (F3), foggy weather (F4), rainy weather (F5), dark condition (F6), drive with alcohol use (F7), sand surface condition (F8), and dawn condition (F9). Although F1 to F9 have significant crash factors, F21 to F27 identified as two-way divided and undivided trafficway, traffic control signal, level of roadway grade, straight roadway alignment, stop sign and have no control traffic devices are lower-ranked factors.

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Table 3. The rank of crash factors and sub-factors.

Crash Factors	Sub-Factors	Rank	Global weights
Weather Condition	F1 (Cloudy)	1	0.1076
Weather Condition	F2 (Sleet)	2	0.1003
Roadway Surface Condition	F3 (Wet)	3	0.0798
Weather Condition	F4 (Fog)	4	0.0773
Weather Condition	F5 (Rain)	5	0.0651
Light Condition	F6 (Light-Not Lighted)	6	0.0513
Suspected Alcohol Use	F7 (Yes)	7	0.0464
Roadway Surface Condition	F8 (Sand)	8	0.0462
Light Condition	F9 (Dawn)	9	0.0452
Roadway Surface Condition	F10 (Ice)	10	0.0388
Roadway Surface Condition	F11 (Oil)	11	0.0351
Driver's Action at Time of Crash	F12 (No contributing action)	12	0.0347
Type of Intersection	F13 (Four-way intersection)	13	0.0346
Light Condition	F14 (Dusk)	14	0.0327
Type of Intersection	F15 (T-intersection)	15	0.0286
Suspected Drug Use	F16 (Yes)	16	0.0277
Type of Intersection	F17 (Roundabout)	17	0.0214
Condition At	F18 (Apparently Normal)	18	0.0193
Type of Intersection	F19 (Y-intersection)	19	0.0184
Type of Intersection	F20 (Traffic Circle)	20	0.0166
Trafficway	F21 (Two-Way, Divided, Positive Median)	21	0.0143
Trafficway	F22 (Two-Way, Not divided)	22	0.0123
Traffic Control Device for This Vehicle	F23 (Traffic control signal)	23	0.0120
Roadway Grade	F24 (Level)	24	0.0101
Roadway Alignment	F25 (Straight)	25	0.0091
Traffic Control Device for This Vehicle	F26 (Stop sign)	26	0.0087
Traffic Control Device for This Vehicle	F27 (No controls)	27	0.0067

Table 4 lists the 14 counties in Florida with a high rate of accidents involving older drivers in the order of their global weight. The top three counties for focused remediation are Hamilton (A6), Dixie (A10), and Liberty (A3) with weights of 6.1286, 6.1168, and 6.0151, respectively. The counties of Highlands (A5), levy (A9), and Holmes (A14) are lowest ranked with weights of 4.9416, 4.8853, and 4.8410, respectively.

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Table 4. Final ranking of 14 counties

Rank	Name of counties	Global weights
1	Hamilton (A6)	6.1286
2	Dixie (A10)	6.1168
3	Liberty (A3)	6.0151
4	Hendry (A8)	5.8996
5	Wakulla (A11)	5.6317
6	Colombia (A1)	5.6231
7	Jefferson (A12)	5.5396
8	Bakers (A7)	5.4724
9	Hardee (A2)	5.1816
10	Monroe (A13)	5.1172
11	Suwannee (A4)	4.9746
12	Highlands (A5)	4.9416
13	Levy (A9)	4.8853
14	Holmes (A14)	4.8410

Figure 9 shows that icy (F10) and oily (F11) road conditions, 4-way intersection (F13), dusk lightening condition (F14), T-type intersection (F15), drive with medicine use (F16), roundabout (F17), apparently normal at crash time (F18), Y-type intersection (F19), and traffic circle intersection (F20) have semi-significant ranked factors.

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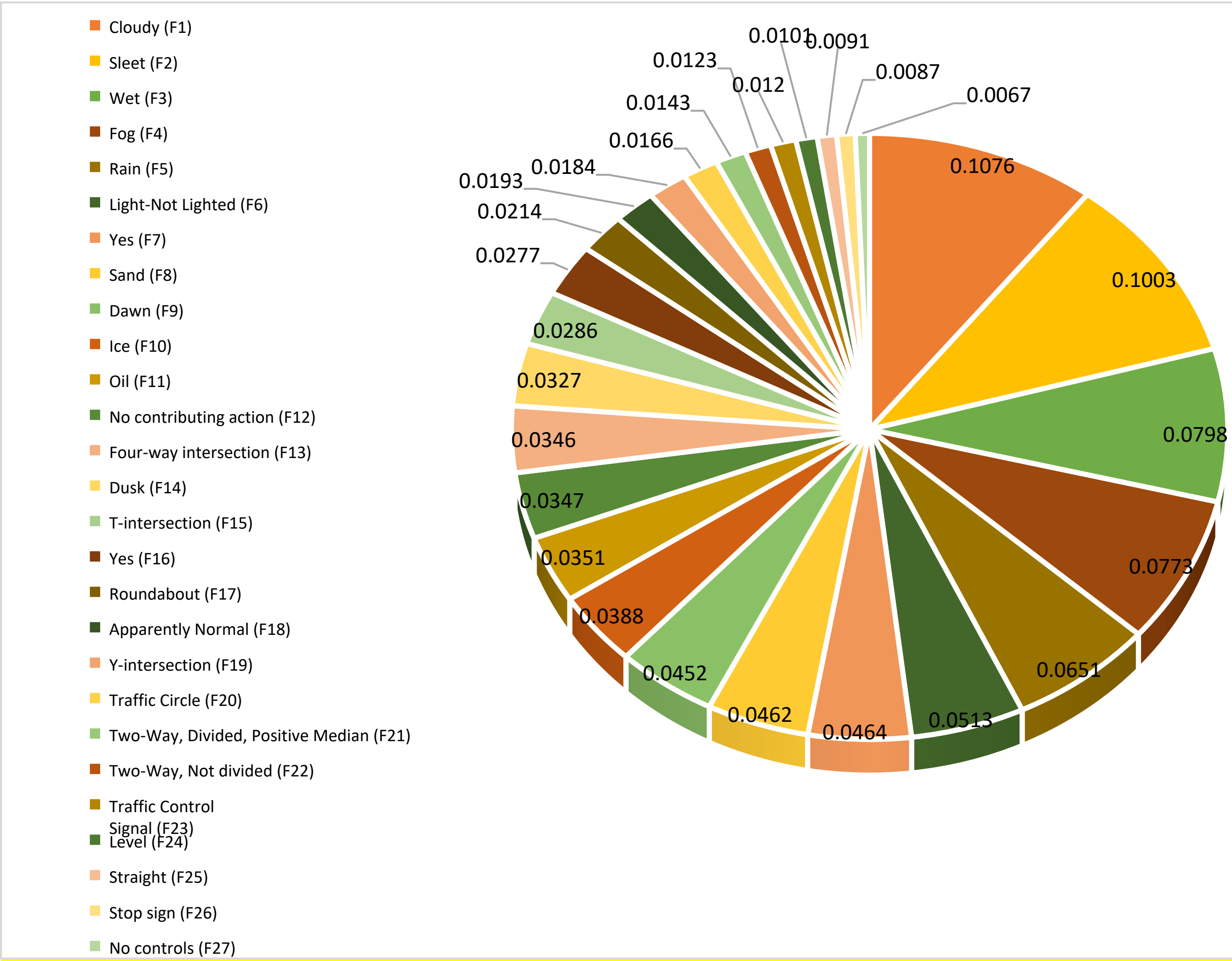

Figure 9. The global normalized weights for sub-factors.

Policymakers can use these crash factors and their rankings to prioritize remediation measures. Agencies can implement some improvements that would decrease the rate of fatal crashes. Hamilton, Dixie, and Liberty rank as the top counties that need improvements in traffic safety.

The FAHP method ranked weather conditions (cloudy, sleet, fog, and rain), roadway surface conditions (wet and sand), alcohol-impaired driving, and light conditions (Dark and dawn) as the top factors associated with older driver crashes. Traffic control devices (stop signs, speed controls, or no traffic controls), roadway alignment, roadway grade, and traffic flow-road type (two-way, divided, or not divided) also rank high in their crash influence among older drivers. Although some factors are human-related, agencies can examine others such as the type of intersections, trafficway, roadway grade, and roadway alignment for remediation measures.

5. Conclusions and Recommendation

According to FDOT, Bureau of Vital Statistics, in 2019, 17 counties had a high rate of fatalities for older drivers, ranging from 24.92 to 150.43 per 100,000 population [34]. Most of the identified counties (14 out of 17) are in rural areas. As such, the focus of this analysis was on the 14 of those counties that are rural.

This study used the FAHP methodology to investigate factors associated with crashes involving older drivers in the 14 rural Florida counties. Considered factors included weather conditions, roadway surface conditions,

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light conditions, suspected alcohol use, suspected drug use, driver's action at the time of the crash, types of intersection, condition at the time of the crash, trafficways, roadway surface conditions, roadway grade, roadway alignment, and traffic control device for the vehicle that impact older drivers' crashes. The FAHP methodology used pairwise comparisons of the incident reasons to rank crash factors and their relative significance based on the opinions of 12 experts.

The following were key findings:

- The most influential crash factors were weather, roadway surface, and light conditions.
- Sub-factors F1 (cloudy weather condition) through F6 (light, no-lighted) were the most influential.
- The three counties of Hamilton (A6), Dixie (A10), and Liberty (A3) ranked highest for prioritizing remedial measures.

Policymakers can use the findings to establish plans that would decrease the rate of fatal crashes in those top-ranking counties. For example, remediation measures could focus on improving lighting and reducing speed limits when the roadway surface is wet.

The 12 experts from FDOT that participated in the FAHP process proposed multiple values for the crash factors. However, the FAHP method decreased the vagueness and uncertainty due to their subjective and overlapping ratings.

Future research will focus on the three highest-ranking counties to investigate the number of fatal crashes in detail. Future work will also estimate how much each factor has impacted the fatal crashes among older drivers by using machine learning methods such as random forest and artificial neural networks. The dataset will include information from upcoming years.

Acknowledgment
We greatly appreciate the contributions from the 12 experts who provided their opinions to create the pairwise comparison matrix as input data for the method.

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Appendix

Table 5. Crisp pairwise comparison matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27
F1	1	1	1	1	1	0.33	0.33	0.33	0.25	0.25	0.25	0.25	0.2	0.2	0.2	0.2	0.13	0.2	3	3	8	8	7	7	3	3	3
F2		1	1	1	1	0.33	0.33	0.33	0.25	0.25	0.25	0.25	0.2	0.2	0.2	0.2	0.13	0.2	3	3	8	8	7	7	3	3	3
F3			1	1	1	0.33	0.33	0.33	0.25	0.25	0.25	0.25	0.2	0.2	0.2	0.2	0.13	0.2	3	3	8	8	7	7	3	3	3
F4				1	1	0.33	0.33	0.33	0.25	0.25	0.25	0.25	0.2	0.2	0.2	0.2	0.13	0.2	3	3	8	8	7	7	3	3	3
F5					1	0.33	0.33	0.33	0.25	0.25	0.25	0.25	0.2	0.2	0.2	0.2	0.13	0.2	3	3	8	8	7	7	3	3	3
F6						1	1	1	0.33	0.33	0.33	0.33	0.16	0.16	0.16	0.16	7	7	2	2	3	3	2	2	3	3	3
F7							1	1	0.33	0.33	0.33	0.33	0.16	0.16	0.16	0.16	7	7	2	2	3	3	2	2	3	3	3
F8								1	0.33	0.33	0.33	0.33	0.16	0.16	0.16	0.16	7	7	2	2	3	3	2	2	3	3	3
F9									1	1	1	1	8	8	8	8	7	7	1	1	5	5	8	7	7	7	7
F10										1	1	1	8	8	8	8	7	7	1	1	5	5	8	7	7	7	7
F11											1	1	8	8	8	8	7	7	1	1	5	5	8	7	7	7	7
F12												1	8	8	8	8	7	7	1	1	5	5	8	7	7	7	7
F13													1	1	1	1	8	8	1	1	2	2	7	8	8	8	8
F14														1	1	1	8	8	1	1	2	2	7	8	8	8	8
F15															1	1	8	8	1	1	2	2	7	8	8	8	8
F16																1	8	8	1	1	2	2	7	8	8	8	8
F17																	1	0.11	0.11	0.11	6	6	6	6	8	8	8
F18																		1	9	9	0.25	0.25	1	1	7	7	7
F19																			1	1	2	2	1	1	8	8	8
F20																				1	2	2	1	1	8	8	8
F21																					1	1	1	1	5	5	5
F22																						1	1	1	5	5	5
F23																							1	4	7	7	7
F24																								1	4	4	4
F25																									1	1	1
F26																										1	1
F27																											1

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