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Exploring association of contributing factors to pedestrian fatal and severe injury crashes under dark-no-streetlight condition

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A B S T R A C T

The pedestrian crash pattern in the dark-no-streetlight condition is a noteworthy ongoing traffic safety concern. The persistently high percentage of pedestrian fatalities at night in the U.S., as well as in the state of Louisiana, necessitates new research to supplement existing studies. This study utilized 10 years (2010–2019) of pedestrian fatal and severe injury crashes in Louisiana that occurred in the dark without streetlights to identify the associated crash patterns. The methodology is based on Multiple Correspondence Analysis (MCA), an exploratory approach used to discover the association of multiple categorical variables from a crash dataset. The findings suggest that driver characteristics (age, gender, and physical condition), pedestrian action, pedestrian alcohol impairment, and physical settings (posted speed limit, location, and roadway type) have a substantial impact on pedestrian collisions at night without streetlights. Moreover, the obtained combination clouds of MCA reveal associations such as elderly pedestrian (>64 years) alcohol impairment resulting in fatalities, crashes in an open country location with a high posted speed limit, crashes involving pedestrians in dark clothing on high-speed (50–55 mph) roadways, alcohol-impaired driver involvement in crashes on two-way roads without physical separation, severe injury crashes at intersections, male pedestrian crashes on midblock locations during weekends, and young (15–24 years) female driver's involvement in crashes while pedestrians were walking against the traffic. Based on the findings, this research also suggests safety recommendations that can assist highway safety practitioners in determining appropriate countermeasures to reduce pedestrian crashes in the dark-no-streetlight condition.

1. Introduction

Pedestrians are considered to be vulnerable road users due to their heightened risk of fatal and severe injury in the event of a motor vehicle crash [1,2]. Between 2010 and 2019, pedestrian fatalities in the United States climbed by 44%, whereas all other traffic fatalities increased by only 9% [3]. Darkness is cited as one of the primary causal factors in pedestrian fatal and injury crashes [4]. According to the Fatality Analysis Reporting System (FARS) database, 2019 is the tenth consecutive year in which pedestrian fatalities at nighttime accounted for >70% of all pedestrian fatalities in the United States. The situation is even worse in Louisiana, where approximately 80% of pedestrian fatalities occurred at night in 2019. However, the causes for the overrepresentation of pedestrian crash involvement at nighttime have not been explored in detail and therefore an investigation of pedestrian crash patterns in this unique setting is required. Pedestrian safety, particularly in dark lighting conditions, must be improved to reach the 'Destination Zero Deaths' target of Louisiana's Strategic Highway Safety Plan [5].

The issue of nighttime pedestrian crashes has been explored in previous research [6,7]. The majority of these investigations identified various crash risk factors, including pedestrian behavior, driver and vehicle characteristics, and physical settings [8,9]. Even if the crash is not fatal, pedestrian injuries are substantially more severe at night than during the daytime [10]. In a pedestrian crash report, the involvement of a pedestrian with a motor vehicle at night does not imply that the crash was caused solely by poor visibility. While visibility is undoubtedly the most critical factor affecting nighttime pedestrian safety, other underlying factors appear to interplay and exacerbate the problem [11]. Since any single crash is the consequence of a series of events [12], pedestrian

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crashes, particularly those that occur at night, could result from a complex mix of factors [13]. For illustration, crossing a high-speed road at night while wearing dark clothing without paying attention to oncoming vehicles creates a high probability of pedestrian death [14]. A combination of these crash risk factors needs to be studied in detail to develop an efficient strategy for improving pedestrian safety in dark lighting conditions. This research will help to establish the concept of a 'combination of risk factors' for pedestrian collisions in dark settings.

1.1. Contributing factors to pedestrian crashes in dark-no-streetlight condition

Understanding the mechanism of pedestrian collisions is challenging due to the complex interaction of numerous causative factors in the dark-no-streetlight condition. Several researchers have examined a variety of crash characteristics to uncover important contributory variables in such pedestrian crashes. A study conducted by Kemnitzer et al. detected lighting condition as the only statistically significant factor linked to the risk of pedestrian injury [15]. The authors also discovered that pedestrians struck on dark-not-lighted roadways have a higher chance of being injured. Increased pedestrian crash risk in darkness is more likely to be associated with female pedestrians compared to male pedestrians, elderly pedestrians compared to younger pedestrians, and adverse weather conditions (involving rain/snow/fog/mist) compared to fine weather conditions at the pedestrian crossing [16].

Around 80% of pedestrian crashes occur in dark hours while walking under the influence of alcohol [17]. A study by Sullivan and Flannagan focused on the extent of the influence of darkness on pedestrian risk and identified pedestrian alcohol consumption as one of the risk factors [18]. On limited access roads, poor illumination conditions combined with other crash contributing factors, such as alcohol influence on pedestrians, were found to significantly increase the likelihood of pedestrian injuries and fatalities [19]. A previous study focused on the impact of lighting conditions on the severity of pedestrian injuries in pedestrian crossing locations. They discovered that the likelihood of a pedestrian death when hit by a vehicle is higher at segments than at intersections, regardless of the lighting condition [20]. A substantially different outcome was discovered by another study, which reported that the dark unlighted midblock and roadway segments were strongly associated with higher odds of pedestrian fatality [21].

Using six years of law enforcement officer-reported pedestrian crash data in San Antonio, Texas, a study investigated the consequences of vehicle-pedestrian crash-associated variables on pedestrian injury severity [22]. The authors concluded that when pedestrians were at fault (i.e., pedestrian violations), the unexpected nature of the incident combined with reduced vision would most likely increase the severity of pedestrian injuries in the dark. An investigation of nighttime fatal midblock crashes found that pedestrians walking along the road in the opposite direction of the traffic were the most vulnerable to being struck by vehicles [23]. The frequency of pedestrians, and hence the exposure rates, might vary based on the day of the week, although fatal pedestrian crashes were more common on weekends night [24].

In the dark, roads with higher speed limits are associated with a higher likelihood of pedestrian severe injuries [25]. At higher speeds, the visual acuity distance at night often exceeds the SSD (stopping sight distance), increasing the risk of pedestrians suffering incapacitating injuries or fatalities [26]. Several driver characteristics, such as male drivers, intoxication, fatigue, and distraction, are strongly associated with pedestrian crashes at night. Few studies have investigated the effect of driver age on nighttime pedestrian recognition, finding that older drivers can spot pedestrians at only 60% of the distance that a younger driver age group is able to [26]. Another study reported that older drivers traveling at 55 mph would hit almost all dark-clothed pedestrians at night [27].

Most of the pedestrian-vehicle crash investigation studies utilized parametric models, which can only conduct pairwise comparisons of exploratory and response factors. Furthermore, these models can only show how a single factor influences the severity or likelihood of a pedestrian crash. Since crashes frequently occur due to the complex interaction of numerous factors, it is necessary to explore the relationship between multiple crash factors simultaneously [28]. Although association rule mining (ARM) is frequently used to reveal hidden factorial associations, such an approach does not belong to fully unsupervised learning as the crash severity level is used as a 'consequent' while modeling [29,30]. On the contrary, MCA is an unsupervised learning process that is able to find crash patterns from a multitude of factors [31]. Therefore, MCA can be a powerful technique for analyzing categorical data, and a viable choice to uncover critical hidden patterns of key pedestrian crash contributing factors at night without streetlight condition [32,33].

1.2. Studies associated with Multiple Correspondence Analysis (MCA) for pedestrian crash analysis

Using Multiple Correspondence Analysis (MCA) to discover pedestrian crash patterns has become more common in recent years. A study first employed MCA to discover the pattern of fatal pedestrian accidents in France [34]. Another investigation used MCA to explore the correlations between the features and situations (at fault pedestrian, severe injury, location, and temporal factors) of crash-involved pedestrians in Hawaii [35]. Utilizing eight years of pedestrian crash data from Louisiana (2004–2011), a previous study analyzed underlying patterns in vehicle-pedestrian collisions using MCA [12]. Another study also employed MCA to explore the association between crash variables (demographics, temporal, and geographic) and established pedestrian crash characteristics in Malta [36]. Other research papers utilized MCA to discover pedestrian crash patterns at particular locations, including signalized intersections [37] and rural regions [38]. However, none of the aforementioned MCA-based studies discovered the pattern of pedestrian crashes that occurred in the dark-no-streetlight condition.

1.3. Study objectives

After a careful examination of closely related literature, the research team identified that the association of contributing factors leading to pedestrian crashes in the dark-no-streetlight condition is relatively less unexplored and there is scope for further research. Therefore, the objective of this study was to apply MCA to investigate the complex and comprehensive associations among driver and pedestrian characteristics, roadway, and environmental factors that result in pedestrian fatal and severe injury crashes occurring in the dark-no-streetlight condition. Another objective was to provide safety recommendations for improving pedestrian safety, especially at night. The findings of this research can assist traffic engineers and transportation professionals to develop efficient crash mitigation strategies, countermeasures, and policies that would alleviate this rising safety issue.

2. Methods

2.1. Data source

The research team utilized ten years (2010–2019) of crash data collected from the Louisiana Department of Transportation and Development (LADOTD). Fig. 1. shows the data extraction process in detail. The primary database of 16,669 unique pedestrian crashes was prepared by merging three tables (pedestrian table, crash table, and DOTD table) with the help of using the crash identification number as a matching criterion. The database consists of information on the crash lighting condition in ABCDEFYZ scale (A = Daylight, B = Dark-no-streetlight, C = Dark-continuous streetlight, D = Streetlight at intersections only, E = Dusk, F = Dawn, Y = Unknown, Z = Other) in addition to information on the severity level of crashes in KABCO scale

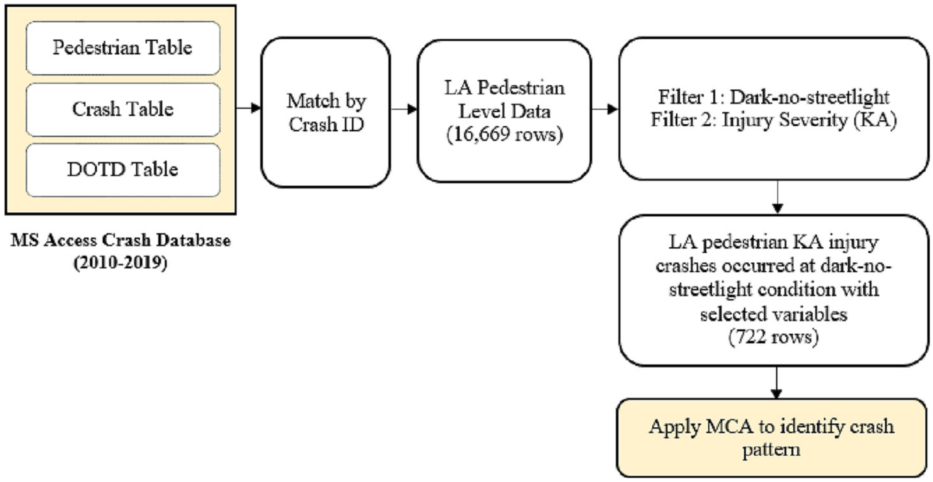

Fig. 1. Data integration and analysis flow chart.

(K = Fatal, A = Severe, B = Moderate, C = Complaint, O = No injury). To focus on the top two levels of pedestrian injury severity, the research team chose only the KA (fatal-severe) injury class and skipped the rest of the injury classes of 'B', 'C', and 'O'. Finally, the study came up with a total of 722 unique pedestrian crashes by using two-step filter criteria (lighting condition = dark-no-streetlight and injury severity = KA). Around 64% of these collisions were fatal, with the remaining 36% resulting in severe injuries.

Fig. 2**.** illustrates the spatial distribution of pedestrian fatal-severe injury crashes that occurred in the dark-no-streetlight condition in

Fig. 2. Spatial distribution of pedestrian KA injury crashes in dark-no-streetlight condition.

Louisiana during the 2010–2019 period. The top five parishes in the state of Louisiana that experienced a high number of fatal-severe injury crashes were East Baton Rouge (53 crashes), Calcasieu (48 crashes), Tangipahoa (40 crashes), Orleans (38 crashes), and Ouachita (34 crashes). It is worth noting that most of these crash locations were in urban areas with high walk commute trips.

2.2. Methodology

MCA, an extension of correspondence analysis (CA), is a technique used to reveal the patterns of relationships among categorical variables in a large complex dataset, and it represents datasets as 'clouds' in the multidimensional Euclidean space [39,40]. It is an unsupervised learning approach that does not require distinguishing between the explanatory and decision variable [41].

In this study, 17 categorical variables and 722 unique pedestrian crash records were considered. Therefore, the dimension of the final prepared dataset of this research was '722 × 17'. For a table with dimension 722 × 17, MCA can be described by looking at a unique crash record (in a row), r (beginning from $r = 1$ to 722), where 17 categorical variables (characterized by 17 columns) have several numbers of categories. Based on these 17 variables, MCA can produce a spatial distribution of the points in multiple dimensions, where the distance between points illustrates how similar individual points are [42]. The shorter the distance, the more similar the points are [43]. Three unique steps are implemented in the creation of the spatial distribution of the points: the creation of the indicator matrix, calculation of individual clouds, and computation of category clouds.

At first, two separate data matrices need to be generated. The number of variables (i.e., columns, V) and the number of unique crash records (i.e., rows, R) is multiplied to produce the first data matrix, called 'R × V'. Again, another data matrix, 'R × C,' is generated where C is the total number of categories for all variables and $C = \sum_{k=1}^{k} C_k$ (C_k is the number of categories for variable k). Each variable will have multiple columns in this matrix to display all possible category values. For example, the variable roadway alignment in the original dataset has four different categories: straight, curve, hillcrest, and on grade. The indicator matrix would contain four columns for each of these categories. If an individual crash record has a 'straight' type of roadway alignment in this particular crash, the 'straight' column in the indicator matrix will contain '1', and the rest of the columns will have '0'. The following Table 1 demonstrates the design of an indicator matrix from an original crash dataset from this study.

In the indicator matrix, a straight alignment would be coded as '1 0 0 0', a curve alignment as '0 1 0 0', a hillcrest alignment as '0 0 1 0', and an on-grade alignment as '0 0 0 1'. The same procedure was repeated on all variables of original crash data to generate the indicator matrix. The final indicator matrix has multiple binary columns, with just one column per categorical variable containing the value '1'.

Suppose the number of unique records associated with category y is represented by n_y ($n_y > 0$). Again, $n_y/n = f_y$, which denotes the relative frequency of individuals who are associated with category y. The variables that each have separate categories produce the distance between two individual records. Assume that, for a given variable k, unique record x contains category y, and another unique record x' contains category y'. The squared distance (between unique records x and x') is defined by the equation below:

$$s_c^2(x, x') = \frac{1}{f_y} + \frac{1}{f_{y'}}$$

The overall squared distance between the unique records x and x' is defined by

$$s_c^2(x, x') = \frac{1}{V} \sum_{v \epsilon V} s_c^2(x, x')$$

A weighted combination of R points is used to represent the cloud of categories. Category r is represented by a point (denoted by C^r) with the weight of n_r. The sum of weights of category points is n for each of the variables. In this way, the sum is nV for the whole dataset R. The relative weight m_r for the point C^r is $n_r/nV = f_r/V$. The sum of the relative weights of category points is 1/V, making the sum of the whole dataset 1. Suppose $p_{gg'}$ represents the number of unique records for both categories g and g'. Then, the squared distance between the two category points B^g and $B^{g'}$ can be expressed by the following equation:

$$\left(B^g B^{g'}\right)^2 = \frac{p_g + p_{g'} - 2p_{gg'}}{p_g p_{g'} / p}$$

This study performed MCA using the 'FactoMineR' package in R statistical software (version 4.0.1) [44]. Some of these studies contain more details on the basic theory of MCA and model development: Greenacre [47]; Greenacre and Blasius [45]; Husson and Josse [46]; and Di Franco [48].

3. Results

3.1. Data summary

Table 2 summarizes the descriptive statistics of all the critical variables for pedestrian fatal-severe injury crashes that occurred in the dark-no-streetlight condition. The variable selection method utilized prior relevant research [49–51] along with the engineering judgment and findings from studies on pedestrian crash analyses [10,52–55]. The final dataset contains a total of 17 variables relevant to this research, including pedestrian severity (fatal, severe). These variables cover a wide range of crash contributing factors related to:

- Pedestrian characteristics (age, gender, action, primary contributing factor, alcohol or drug involvement, presence of dark clothing).
- Driver characteristics (age, gender, driver condition)
- Roadway characteristics (roadway type, alignment, presence of intersection, posted speed limit),
- Environmental condition (location type, weather condition)
- Temporal factors (day of the week)
- Crash characteristics (pedestrian injury severity)

All this relevant crash information was extracted from the LADOTD crash database. Each variable category was broken down into two different pedestrian injury severity levels (fatal or severe). For instance, out of 526 crashes with alcohol or drug-involved pedestrians, 74% were on scale K (fatal), and the remaining 26.1% were on scale A (severe).

3.2. Data exploration by injury levels

Some variables were substantially skewed, according to the preliminary analysis presented in Table 2. For example, most pedestrian fatal-severe injury crashes occurred on straight roadways (89.3%), at

Table 1
Design of Indicator Matrix.

Original crash data		Indicator matrix				
Crash ID	Roadway alignment	Crash ID	Straight	Curve	Hillcrest	On grade
CID 1	Straight	CID 1	1	0	0	0
CID 2	Curve	CID 2	0	1	0	0
CID 2	Hillcrest	CID 3	0	0	1	0
CID 3	Straight	CID 4	1	0	0	0
CID 5	On grade	CID 5	0	0	0	1

Table 2
Distribution of key crash variables by injury levels.

Variable	Variable code	Attribute description	Total crashes	% of all crashes	% of fatal crashes	% of severe crashes
Pedestrian alcohol/drug presence	alcohol_drug	yes	526	72.9	74.0	26.1
		no	147	20.4	38.8	61.2
		others	49	6.8	38.8	61.2
Pedestrian action	ped_action	walk_w_traffic	140	19.4	63.6	36.4
		walk_a_traffic	63	8.7	60.3	39.7
		xing_int	54	7.5	59.3	40.7
		xing_seg	161	22.3	65.8	34.2
		others	304	42.1	65.8	34.2
Pedestrian age	ped_age	< 15y	24	3.3	45.8	54.2
		15-24y	123	17.0	49.6	50.4
		25-40y	264	36.6	65.9	34.1
		41-64y	256	35.5	69.9	30.1
		> 64y	43	6.0	76.7	23.3
		unk	12	1.7	58.3	41.7
Pedestrian gender	pen_gen	male	531	73.6	64.6	35.4
		female	191	26.5	63.9	36.1
Pedestrian dark cloth presence	dark_cloth	yes	361	50.0	67.0	33.0
		no	361	50.0	61.8	38.2
Driver age	dri_age	15-24y	129	17.9	66.7	33.3
		25-40y	248	34.3	62.9	37.1
		41-64y	203	28.1	65.0	35.0
		> 64y	40	5.5	65.0	35.0
		unk	102	14.1	63.7	36.3
Driver gender	dri_gen	male	418	57.9	65.1	34.9
		female	205	28.4	62.9	37.1
		unk	99	13.7	64.7	35.4
Driver condition	dri_cond	normal	462	64.0	64.3	35.7
		ill_fatigue_asleep	8	1.1	75.0	25.0
		inattent_distract	45	6.2	48.9	51.1
		alcohol_drug	64	8.9	62.5	37.5
		unk	143	19.8	69.9	30.1
Location type	loc_type	biz_ind	141	19.5	53.2	46.8
		biz_res	172	23.8	64.5	35.5
		res	233	32.3	57.9	42.1
		open_country	155	21.5	86.5	13.6
		others	21	2.9	47.6	52.4
Roadway type	rd_type	one_way	25	3.5	36.0	64.0
		two_no_sep	451	62.5	58.5	41.5
		two_sep	212	29.4	80.2	19.8
		two_bar	34	4.7	64.7	35.3
Roadway alignment	alignment	straight	645	89.3	63.1	36.9
		curve	43	6.0	65.1	34.9
		hillcrest	10	1.4	100.0	0.0
		on_grade	24	3.3	83.3	16.7
Intersection presence	int	yes	126	17.5	55.6	44.4
		no	596	82.6	66.3	33.7
Speed limit (mph)	SL	<30	53	7.3	20.8	79.3
		30–35	97	13.4	39.2	60.8
		40–45	180	24.9	56.1	43.9
		50–55	234	32.4	77.4	22.7
		>55	131	18.1	87.8	12.2
		unk	27	3.7	70.4	29.6
Primary contributing factor	contri_fact	ped_act	380	52.6	73.2	26.8
		ped_cond	36	5.0	69.4	30.6
		ped_vio	53	7.3	47.2	52.8
		prior_move	44	6.1	47.7	52.3
		others	209	29.0	55.5	44.5
Weather condition	weather_cond	clear	558	77.3	63.1	36.9
		cloudy	102	14.1	68.6	31.4
		rain	47	6.5	63.8	36.2
		fog_sleet_snow	15	2.1	86.7	13.3
Day of week	dow	FSS	362	50.1	66.0	34.0
		MTWT	360	49.9	62.8	37.2

Note: walk_w_traffic = walking with traffic; walk_a_traffic = walking against traffic; xing_int = crossing intersection; xing_seg = crossing segments; biz_ind = business/industrial; biz_res = business/residential; res = residential; two_no_sep = two way with no physical separation; two_sep = two way with physical separation; two_bar = two way with physical barrier; ped_act = pedestrian action, ped_cond = pedestrian condition; ped_vio = pedestrian violation; prior_move = prior movement; FSS = Friday, Saturday, Sunday; MTWT = Monday, Tuesday, Wednesday, Thursday.

non-intersection locations (82.6%), on two-way roads with no physical separation (62.5%), in clear weather conditions (77.3%), and involving male pedestrians (73.6%). Among the alcohol/drug-impaired pedestrian crashes in the dark without streetlights, approximately three-quarters of them resulted in pedestrian fatalities. Additionally, pedestrians were killed in around 66% of crashes while crossing segments at night without streetlights. Although elderly pedestrians (age 65 years or higher) represent a small portion (6%) of the total crashes, approximately 77% of them were fatal crashes (the highest among all other age groups). About 87% of the

Table 3
Eigen values and percentage of variance for top 10 dimensions.

Dimension	Eigen value	Percentage of variance	Cumulative percentage of variance
Dimension 1	0.183	6.486	6.486
Dimension 2	0.149	5.286	11.771
Dimension 3	0.114	4.022	15.793
Dimension 4	0.110	3.894	19.687
Dimension 5	0.090	3.183	22.871
Dimension 6	0.085	2.998	25.869
Dimension 7	0.081	2.862	28.730
Dimension 8	0.077	2.720	31.451
Dimension 9	0.075	2.647	34.098
Dimension 10	0.073	2.597	36.695

fatal pedestrian crashes occurred in open country locations (the highest among all other location types).

3.3. Eigenvalue and variance information

According to the primary analysis, the final database was comprised of 722 rows with 17 variables and 65 variable categories. Initially, the crash data points were presented in N dimensions. The value of N was calculated as the difference between the sum of variable categories and the number of variables (65 - 17 = 48). With that, the total variance was calculated as the ratio of the maximum number of MCA dimensions and the total number of variables (48/17 = 2.82). This step allowed exploring the variance of each dimension using the total variance score (2.82) as the denominator. For example, the eigenvalue for dimension 1 is 0.183; therefore, the percentage of variance explained by dimension 1 is 0.183 divided by 2.82, which is 6.485% (second row of Table 3). It is worth noting that an eigenvalue (range 0 to 1) is a measure of the strength of an axis, and it reflects how much category information each dimension accounts for [56]. The greater the eigenvalue, the higher the amount of the total variance among the variables on that dimension. The obtained low eigenvalues for the database reveal that the variables are heterogeneous due to the complex random nature of the occurrence of crashes. The following table shows eigenvalues, percentage of variance, and cumulative percentage of variance for the top 10 dimensions.

3.4. Scree plot and first plane variable information

A Scree plot (see Fig. 3) is the graphical representation of MCA dimensions and the percentage of variances explained by each dimension obtained from the previous Table 3. The first dimension accounted for 6.5% of the total variance, whereas the second dimension accounted for 5.3% (11.8% in total). None of the remaining dimensions accounted for >4% of the variance. Therefore, only dimensions 1 and 2 were considered for further exploration. A similar percentage of total variances for the first two dimensions were reported in several other crash studies. For instance, a previous study explored fatal and severe pedestrian crash patterns in rural Illinois and found that the first two dimensions cover only 7.7% of the total variance [38].

Table 4 shows the coefficient of determination (R^2) and the *p*-value for each crash variable on the first plane. The value of R^2 ranges from 0 to 1, with 0 indicating no relationship and 1 indicating a strong association between the variable and MCA dimension [57]. The *p*-value denotes the level of confidence of the corresponding variable. Considering both measures (R^2 and p-value), the top five dominant variables in dimension 1 were related to driver characteristics (age, gender, physical condition), primary contributing factors, and pedestrian actions. In dimension 2, the influential variables were posted speed limit, location type, roadway type, injury severity, and pedestrian alcohol/drug involvement.

3.5. Factor map exploration

To define the number of dimensions to keep, some authors proposed two-dimensional data visualizations which make data interpretation easier [58]. Therefore, only the results of the first plane with the first and second dimensions were displayed and interpreted in this investigation. Fig. 4**.** is the complete representation of all variable categories in points on a factor map utilizing the first two dimensions. The more remote a variable category resides from the origin (0,0) of the factor map, the greater its contribution to the risk of a crash occurring [38]. Additionally, the contribution of variable categories was presented in paste-yellow-red gradient color. Therefore, crash attributes such as posted speed limit (>55 mph and <30 mph), open country location, and severe injury severity were found to be strongly associated with pedestrian crashes in the dark-no-streetlight condition.

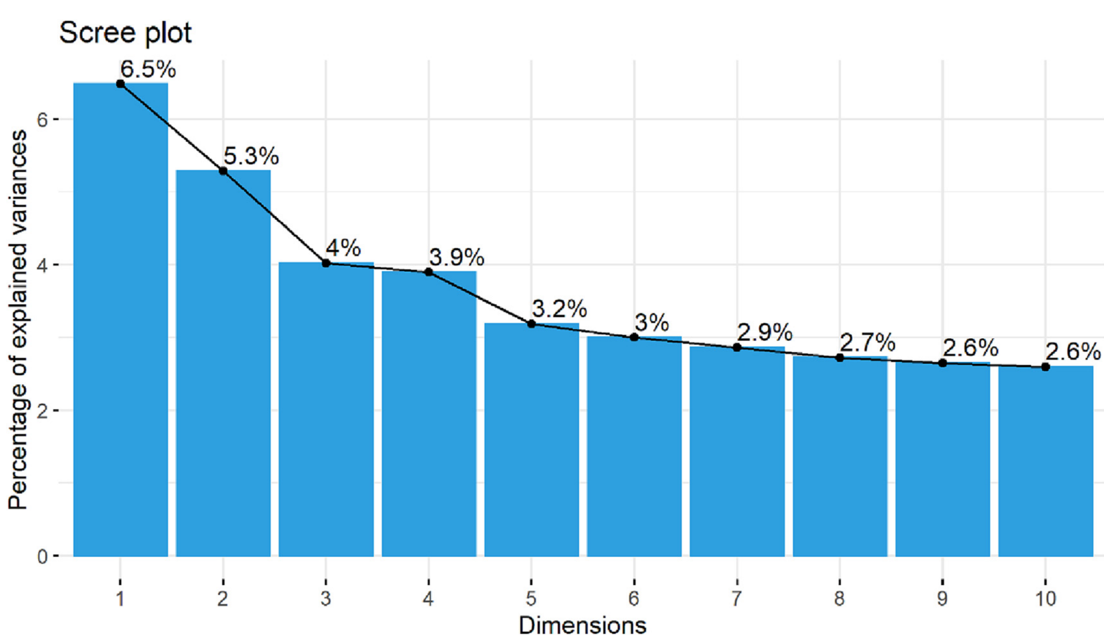

Fig. 3. Percentage of explained variances for the top ten dimensions.

Table 4
Significance of crash variables on the first plane.

Variables (Dimension 1)	R^2	p-value	Variables (Dimension 2)	R^2	p-value
Driver age	0.765	<0.001	Posted Speed limit	0.623	<0.001
Driver gender	0.745	<0.001	Location type	0.429	<0.001
Driver condition	0.723	<0.001	Roadway type	0.381	<0.001
Primary contributing factor	0.315	<0.001	Injury Severity	0.347	<0.001
Pedestrian action	0.177	<0.001	Pedestrian alcohol/drug involvement	0.181	<0.001
Posted speed limit	0.177	<0.001	Intersection presence	0.110	<0.001
Pedestrian alcohol/drug involvement	0.040	<0.001	Pedestrian action	0.081	<0.001
Pedestrian dark clothing	0.031	<0.001	Pedestrian age	0.078	<0.001
Roadway type	0.036	<0.001	Primary contributing factor	0.065	<0.001
Injury severity	0.014	0.0014	Driver condition	0.061	0.0004
Location type	0.023	0.0023	Driver gender	0.043	0.0101

According to previous research, pedestrians are at more risk on roads with high posted speed limits [59–61]. A driver can only avoid hitting a pedestrian if he/she can detect a pedestrian from a sufficient distance ahead. Driving at a high speed in the dark fundamentally implies that the driver's reaction time is reduced while the vehicle's stopping distance is increased. As a result, pedestrians were more likely to be involved in crashes on roadways with high posted speed limits in the dark. A different scenario is observed where pedestrians were involved in crashes on roadways having posted speed limits of <30 mph. In general, metropolitan locations have a higher volume of pedestrians [62],

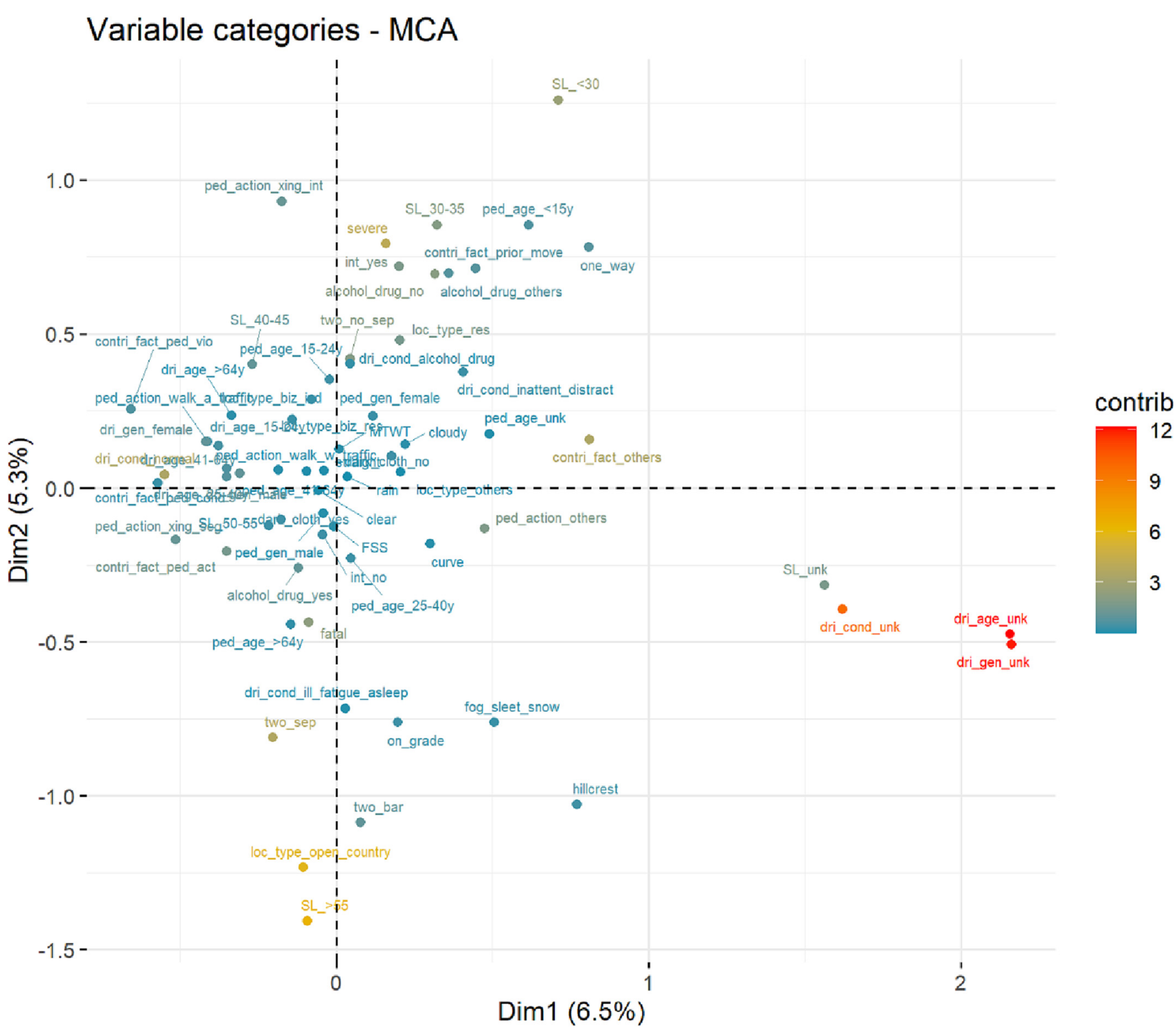

Fig. 4. MCA factor map for all variable categories.

especially on roads with low vehicle speeds. Such areas include residential or commercial areas or local roads in urban areas. The likelihood of pedestrian crashes is higher at those locations due to high levels of exposure, thus lower posted speed limits become a factor too. In areas of open countryside, drivers are less likely to expect pedestrians in dark lighting conditions. In addition, there is typically less traffic in rural areas, allowing for the flexibility of excessive speeding [63]. As mentioned earlier, pedestrians are at high risk on high-speed roadways.

3.6. Explanation of combination clouds

Clouds are formed based on the proximity of variable categories in a two-dimensional space. As MCA is only limited to providing the coordinates without providing clusters, it provides an opportunity for using engineering judgment in explaining the co-occurrence patterns. This approach has been used in most MCA-related studies [33,36,42,64,65]. The current study explained the clouds or 'co-occurrence patterns' that could provide a high-risk scenario of pedestrian crashes in the dark-no-streetlight condition. In many cases, clusters with redundant variable categories can be formed. Despite the proximity of such variable categories, combination clouds containing redundant information were not chosen. For example, 'no alcohol/drug involvement' and 'speed limit 30-35 mph' (closely located on the top right quadrant) do not provide any intuitive information leading to pedestrian crashes in the dark, which is why it was not chosen. Using Fig. 5, we identified seven meaningful combination clouds to explain the associations among variable categories most likely to have contributed to the pedestrian crashes occurring in the dark-no-streetlight condition.

3.6.1. Cloud 1 (speed limit >55 mph, location type = open country)

Cloud 1 suggests the involvement of pedestrians in crashes on high-speed roadways in open country locations during the dark-no-streetlight condition. As seen in previous studies, a high-speed rural roadway environment is critical for pedestrian safety [66–68]. Higher vehicle speeds, along with unusual geometrics, high pedestrian crossings, and unfamiliar drivers in such settings, make pedestrians more vulnerable at night without streetlights.

3.6.2. Cloud 2 (pedestrian alcohol/drug presence = yes, pedestrian age = 65 years or higher, injury severity = fatal)

Cloud 2 is associated with the alcohol/drug-involved pedestrians of a specific age group (>64 years) resulting in fatalities in the dark-no-streetlight condition. Alcohol is probably the single most important contributing factor in fatal pedestrian crashes at night [17,69,70]. Impaired pedestrians have weak cognitive functions and physical skills, resulting in them making poor convictions and being much more likely to take unsafe activities while walking on roadways [71]. On the other hand, older pedestrians often have visual impairments, and adopt risky road crossing strategies, such as slow walking speed and delay in reaction [72]. With alcohol involvement, this specific age group of pedestrians is less capable of dealing with potentially dangerous situations, particularly at night without streetlights. To further investigate the matter, the research team compared pedestrian age and their alcohol involvement (yes, no, other) ratio. It was identified that out of the 43 cases of older pedestrians (>64 years), 31 of them were alcohol involved. This suggests that 72.1% of the older pedestrians involved in crashes were alcohol-impaired.

3.6.3. Cloud 3 (pedestrian dark clothing = yes, speed limit = 50–55 mph)

Cloud 3 addresses the crash situation of a pedestrian in dark clothing on roadways having a speed limit between 50 and 55 mph. Pedestrians were found to considerably overestimate their conspicuity and underestimate the impact of dark clothing configurations on their conspicuity [73]. A pedestrian in dark clothing visually blends in with the dark

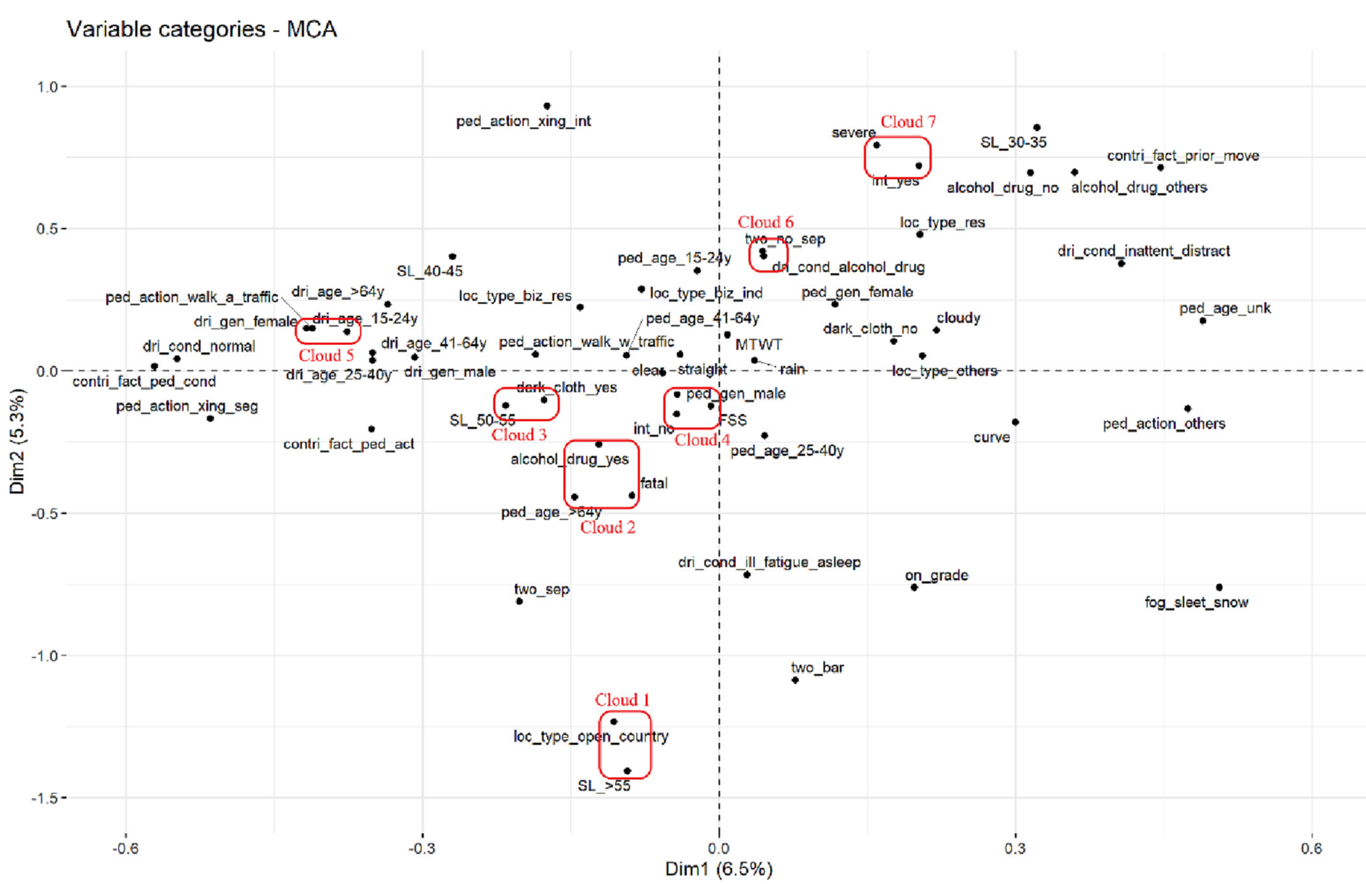

Fig. 5. Identified combination cloud in factor map (close view).

surroundings and dark road surface. Which limits a driver's ability to successfully perform a crash avoidance maneuver on high-speed roadways [27].

3.6.4. Cloud 4 (pedestrian gender = male, intersection = no, day of the week = FSS)

Cloud 4 associates several factors, such as male pedestrians, non-intersection crash location, and day of the week (Friday, Saturday, and Sunday). This cloud was expected because of the exposure pattern of male pedestrians during weekend nights. A prior study has supported the predominance of male pedestrians in crashes while crossing wide road sections at night [74].

3.6.5. Cloud 5 (pedestrian action = walking against the traffic, driver gender = female, driver age = 15–24 years)

Cloud 5 bunches the variable categories of walking against the traffic, female drivers, and young driver age group together. This suggests that young female drivers were involved in pedestrian crashes while they were walking against the traffic at night without streetlights. According to a prior study, young female drivers are associated with maneuvering through traffic with difficulty [75]. In addition, young drivers are strongly associated with excessive risk-taking behavior at night [76]. With reduced visibility at night without streetlights, young female drivers are more likely to be involved in pedestrian crashes.

3.6.6. Cloud 6 (roadway type = two-way with no physical separation, driver condition = alcohol/drug)

Cloud 6 depicts the complex interaction between the roadway type and driver condition in pedestrian crashes in the dark-no-streetlight condition. In general, pedestrians use medians to cross multi-lane traffic in phases [77]. Hence, crossing a two-way road with no physical separation in the dark is troublesome for pedestrians since they must scan for traffic in both directions and cannot pause in the middle of the road. Again, alcohol impairs driving skills by affecting judgment, nighttime vision, coordination, and reaction time [78]. In the absence of streetlights at night, a lethal combination of these two variable categories is most likely to result in pedestrian fatal-severe injury collisions.

3.6.7. Cloud 7 (injury severity = severe, intersection = yes)

Cloud 7 suggests the involvement of pedestrians in crashes at intersections resulting in severe injury. Previous research has also supported the relationship between pedestrian severe injury and intersection crash location [79]. Some specific intersection characteristics, such as the number of lanes, crossing roadway width, and traffic volume, are strongly linked with pedestrian crashes [60]. With the absence of streetlights at night, intersections are the most complex traffic situations for drivers and pedestrians.

Fig. 6. US Highway 190 @ LA 3174.

4. Conclusion

This research utilized ten years (2010–2019) of pedestrian fatal and severe crash data from LADOTD to identify the key contributory factors that interact together in crashes in the dark-no-streetlight condition. The findings demonstrated the suitability of MCA to establish meaningful relationships among various variable categories from a complicated multidimensional crash dataset.

The investigation discovered several noteworthy pedestrian crash scenarios (i.e., combination clouds) in the dark-no-streetlight condition. The high-speed roadway at an open country location was identified as a safety concern for pedestrian-related crashes. Pedestrians in dark clothing were more likely to be associated with crashes on similar high-speed highways having posted speed limits between 50 and 55 mph. Pedestrian alcohol/drug consumption was likely to be associated with elderly pedestrians (>64 years), resulting in fatalities in the dark-no-streetlight condition. This study also identified severe pedestrian crashes at intersection locations. Male pedestrians were found to be vulnerable at non-intersection locations during weekends (including Friday) night. Pedestrian crashes on two-way roads without physical separation were associated with alcohol/drug-involved drivers. Finally, female young drivers (15–24 years) were associated with pedestrian crashes who were walking against traffic.

According to the findings, several environmental, geographic, and demographic characteristics were associated with pedestrian crashes at night without streetlights. Therefore, each crash scenario necessitates distinct strategies to reduce pedestrian crashes. Since pedestrian crash patterns at night vary substantially depending on the age and gender of the pedestrian, a comprehensive long-term plan for a statewide educational campaign targeting the elderly pedestrian age group (>64 years) and the male gender is highly recommended. For instance, an educational brochure containing specific guidance, such as information on functional declines, the importance of vision and hearing checks, and advice on wearing reflective materials, may help to reduce elderly pedestrian crashes in the dark-no-streetlight condition [80]. To reduce alcohol-impaired pedestrian crashes at night, potential interventions should take place where alcohol is served and sold [81]. The mandatory use of a 'Breath Alcohol Tester' before leaving hotels, pubs, clubs, and other licensed shops at night would encourage drinkers to being sober for driving.

In this study, the percentage of pedestrian crashes that occurred at the non-intersection location cannot be ignored. In addition to streetlights, flashing LED warning sign systems, In-Roadway Warning Lights (IRWL), and midblock pedestrian crossing signals including High intensity Activated crossWalK (HAWKS), Rapid Rectangular Flashing Beacon (RRFB) may help to reduce midblock crossing-related crashes at night. The implementation of the smart adaptive lighting system with an automatic pedestrian detector at the midblock location has reportedly increased drivers' yielding behavior and pedestrians' observational behavior at night [82]. Enforcements against cellphone usage, intoxication, and driving infractions would improve pedestrian safety by focusing on all drivers, especially young driver age groups. Severe pedestrian crashes were more prevalent at intersections, and the research team further investigated this issue by visually inspecting each of the 126 crash locations using Google Street View. Most of these crash locations were T-intersection (71%), stop-controlled (62%), had a driveway link, or were in a rural setting. For an additional illustration, two street photographs of such locations (left: 30.539667, −91.772493, right: 32.5291, −93.778869) are provided below (See Fig. 6, and Fig. 7)

High-visibility crosswalks could be a viable solution in such areas. Additionally, crosswalks can be painted with retroreflective materials to ensure visibility at night [83]. Since there is no unique reason for pedestrian crashes in the dark-no-streetlight condition, no single countermeasure will likely significantly influence the number of pedestrian

Fig. 7. North Hearne Avenue @ Aero Drive.

crashes. Although the installation of streetlights is not always a practical solution due to the significant costs associated with lighting large areas, special consideration can be given to the identified intersection crash locations. Pedestrian safety in dark-no-streetlight conditions can be improved with a comprehensive program that combines environmental, educational, and enforcement approaches.

There are certain limitations to this research. The results were graphically represented in a two- dimensional plane which only explained 11.8% of the total variance in the whole dataset. Explanations on more dimensions would allow for more knowledge extraction. The future scope of this research might include a more in-depth analysis by utilizing site-specific variables (i.e., presence of crosswalk, median, sidewalk, number of lanes) which would aid in discovering more associations with a multitude of factors. Additionally, this study does not clarify how the correlation of contributing factors varies with different levels of injury severity. A future study is recommended in which the MCA model can be built for each severity level and then compare the results. This study only considered Louisiana pedestrian crash data; therefore, the findings may not be generalized to other states and jurisdictions until further investigations are performed. In addition, the existing crash data used in this study have several unknown in a few factors, such as pedestrian alcohol level, pedestrian action, and so on. These underreporting issues regarding pedestrian information may influence the outcomes of this research. Therefore, other data sources, Highway Safety Information System (HSIS), can be used in future studies to minimize the specified constraint.

However, the findings of this study are expected to aid traffic safety experts in identifying the hidden associations of a group of variable categories in pedestrian crashes occurring in the dark-no-streetlight condition and aid in discovering effective countermeasures.

Declaration of Competing Interest

The authors state that they have no known competing financial interests or personal relationships that could have influenced the findings of this study.

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