Accident Analysis and Prevention 209 (2025) 107815

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Exploring patterns in older pedestrian involved crashes during nighttime

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ARTICLE INFO

Keywords:
Nighttime
Lighting Condition
Older Pedestrian
Crashes
Safety
Association Rules Mining

ABSTRACT

Nighttime crashes involving older pedestrians pose a significant safety concern due to their age-related vulnerabilities such as reduced vision and slower reaction times. This study analyzes crash data from Texas for six years (2017–2022) using Association Rules Mining (ARM) to identify patterns and associations affecting crash severity for older pedestrians aged 65–74 years and those over 74 years under varying lighting conditions. The findings reveal that high-speed limits and complex road environments significantly increase the risk of fatal or severe injuries for both age groups, particularly under inadequate lighting. Additionally, demographic factors, adverse weather conditions, and specific road features further influence crash outcomes. These insights highlight the need for interventions, including lower speed limits, enhanced street lighting, and the implementation of advanced technologies such as modern pedestrian detection systems, sensor technology, pedestrian bags, accessible pedestrian signals, to improve the safety of older pedestrians. Policymakers should leverage these insights to formulate strategies that improve road safety for older pedestrians, addressing their unique vulnerabilities in various nighttime conditions.

1. Introduction

Older (65 years and older) pedestrian crashes are a key safety concern. According to National Highway Traffic Safety Administration (2021) data, 1,375 older pedestrians were killed (a 19 % increase from 2016) and 7,580 were injured in the U.S. In 2021, 18 % of pedestrian fatalities with known ages were 65 and older (National Highway Traffic Safety Administration, 2024). The risk of fatality in pedestrian crashes significantly increases with age. Older pedestrians, specifically those aged 65 and above, face a mortality risk two to eight times higher than younger individuals when struck by motor vehicles. This elevated risk is partly due to the reduced physical resilience associated with aging. The mortality rate for older pedestrians was substantially higher than for other age groups.

Nighttime conditions intensify these risks for older pedestrians due to a combination of factors. Reduced visibility, coupled with age-related declines in night vision, makes it harder for older individuals to detect oncoming vehicles. Additionally, slower reaction times and mobility limitations impede their ability to avoid hazards. In a prior study, standard pedestrian crossing times at pelican crossings were found to be insufficient for older pedestrians, posing a safety hazard (Romero-Ortuno et al., 2009). Dark with no light condition on roadways can intensify these problems, as they can obscure obstacles and make it difficult for older pedestrians to navigate safely. Moreover, older pedestrians are more susceptible to severe injuries if struck by a vehicle due to their frailer physical condition (Niebuhr et al., 2016).

In Texas, these risks are further underscored by recent data. The Texas Department of Transportation's (TxDOT) Crash Records Information System (CRIS) indicates a 43 % rise in the state's population aged 65 and older between 2010 and 2019, accompanied by a more than

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https://doi.org/10.1016/j.aap.2024.107815
Received 9 August 2024; Received in revised form 15 October 2024; Accepted 17 October 2024
0001-4575/

doubling of fatalities and serious injuries among older pedestrians. Table 1 represents six years (2017–2022) of CRIS data that indicates the percentage of fatal and severe, moderate and minor, and no injury crashes within each age group. The orange-colored cells represent the highest percentage of the type of severity among each age group's crashes. Among the older pedestrians' crashes, it is observed that they are significantly more vulnerable to severe injuries in nighttime crashes, with 53.12 % of crashes involving pedestrians over 74 years. Similarly, for the 65–74 age group, fatal and severe crashes account for the highest proportion of all crash severities. Table 2 further provides more detailed information about older pedestrians' crashes that occurred during nighttime. The data underscores the higher number of crashes under nighttime conditions compared to dawn and dusk.

The population of older adults aged 65 and older in the United States was 39.6 million in 2009, and by 2030, this number is expected to rise to approximately 72.1 million (Brewer et al., 2014). With this growing demographic of older pedestrians, age-related challenges such as reduced visual acuity, contrast sensitivity, diminished peripheral vision, and common eye conditions like cataracts and macular degeneration significantly impact their ability to detect road hazards, interpret signs, and respond to other road users. While it is true that all age groups face heightened crash risks at night, older adults are a unique case due to their physical vulnerabilities, reduced vision, and mobility issues (Hossain et al., 2023). Additionally, the aging population in the U.S. means that a growing proportion of the pedestrian population will soon fall into this high-risk category. Existing research often lacks detailed analysis of how lighting conditions impact nighttime crash severity among older pedestrians. Investigating older pedestrian safety at night is crucial for developing policies and countermeasures to protect this vulnerable group. Thus, there is a pressing need to focus on the unique causes of nighttime crashes involving older pedestrians. This study used six years (2017–2022) of older pedestrian crash data from CRIS and utilized Association Rules Mining (ARM) to identify patterns of association between factors for two age groups (65–74 years and 75 years and older) for two different lighting conditions at nighttime (dark with lighting and dark without lighting).

The structure of this study is organized as follows: after the introduction, a detailed literature review is presented. This is followed by the methodology section, which includes ARM, data preparation, and descriptive statistics. The study then proceeds with the results, discussion, major findings, and conclusion.

2. Literature review

Older pedestrians face significant risk and mobility challenges due to age-related declines in sensory, cognitive, and physical abilities which lead to slower walking speeds, impaired balance, and inefficient wayfinding strategies (Dommes et al., 2013; Gorrie et al., 2008; Hendrie et al., 2006; Rod et al., 2021). This reduced physical ability makes it difficult for them to cross the streets (Asher et al., 2012; Langlois et al., 1997) and they often make unsafe road-crossing decisions leading to riskier behaviors on undivided roads (Oxley et al., 2005). According to Zito et al. (2015) and Butler et al. (2016), older pedestrians tended to overestimate the amount of time they had to cross the road. Holland and Hill (2010) found that individuals aged 60–74 were more prone to underestimate their walking time, while those aged 74 and above were more likely to overestimate how long it would take them to walk. In addition, older pedestrians struggle with processing noise and visual distractions, increasing their vulnerability (Wilmut and Purcell, 2022). Their lack of attention also negatively impacts their safety and mobility (Tournier et al., 2016).

Table 1
Percentage of Nighttime Crash Injury Severities by Pedestrian Age.

Crash Severity Type	15–24 years	25–54 years	55–64 years	65–74 years	Over 74 years
Major Injury (Fatal and Severe Injury)	37.53	45.15	45.83	50.72	53.12
Moderate and Minor Injury	57.58	50.42	50.13	45.34	44.72
No Injury	4.89	4.43	4.04	3.94	2.17

Table 2
Crash Statistics by Older Pedestrian's Age.

	Lighting condition				
Age	Dark, lighted	Dark, not lighted	Dawn	Dusk	Total
65–74 years	660	387	28	41	1116
Over 74 years	204	138	10	17	369
	864	525	38	58	1485

Several environmental and behavioral factors also play crucial roles in older pedestrians' safety. Koepsell et al. (2002) noted that marked crosswalks at unsignalized intersections pose a higher risk of collisions for older pedestrians, necessitating improved crosswalk designs and traffic controls. In addition, the number of traffic lanes, traffic volume, vehicle size, and speed influence the safety of older pedestrians (Wilmut and Purcell, 2022). These factors make it difficult for them to make safe gap decisions in traffic, particularly when vehicles approach from the far lane or at high speeds (Dommes et al., 2014; Lobjois and Cavallo, 2007; Stafford and Rodger, 2021; Zito et al., 2015) as they are more likely than younger pedestrians to misjudge and underestimate the time-to-arrival (TTA) of oncoming vehicles (Butler et al., 2016; Petzoldt, 2014; Schleinitz et al., 2016). Accurate road-crossing judgement requires pedestrians to possess strong perceptual abilities, effective executive function, and reliable memory (Lobjois and Cavallo, 2007). The crossing behavior of the older pedestrian also impacts their safety (Zhang et al., 2018). This group was found to be less willing to adopt a rolling gap strategy (crossing one lane at a time) while crossing a multilane roadway. They tend to cross all the lanes together at once.

Furthermore, time of the day and weather also play a significant role in older pedestrian crashes (Wilmut and Purcell, 2022). The risks faced by this group are exacerbated at night due to poor visibility and slower reaction times (Hossain et al., 2023, 2022; Zegeer et al., 1993). Noh et al. (2018) emphasized that older pedestrians, particularly those over 75, face higher injury severity at night, with common risk factors including roadside incidents and being struck by trucks. Ferenchak and Abadi (2021) identified that most of the increase in pedestrian fatalities between 2009 and 2017 occurred at night, primarily at non-intersection unmarked locations and on high-speed urban roads. Hossain et al. (2023) found that older pedestrians aged 65 years or over involved in nighttime crashes on roads with speed limits greater than 55 mph and in residential areas. Zegeer et al. (1993) found that low lighting conditions posed a greater risk to senior pedestrians due to their tendency to wear dark clothing at night.

Several studies emphasized the need for improved road designs, signal timings, and educational programs, to safeguard older pedestrians and enhance their mobility. Kunnah and Hassan (2024) demonstrated that street lighting at stop-controlled intersections significantly enhances safety by increasing time-to-collision and post-encroachment time and reducing driving speed. Tournier et al. (2016) emphasized the need for road design and safety measure interventions. Zegeer et al. (1993) recommended No Turn on Red signs, curb ramps, proper placement of street furniture, signalized intersections with adequate crossing time, audible signals for visually impaired pedestrians, pedestrian refuge islands, overpasses/underpasses with gradual ramps, and pedestrian malls to improve safety and reduce crashes for older pedestrians. Tarawneh (2001) recommended a pedestrian design speed of 0.97 m/s in areas frequented by older pedestrians. Langlois et al. (1997) suggested extending crossing times at signalized intersections could enhance their safety. Wilmut and Purcell (2022) suggested improvements in accessibility and visibility at crossings. Dommes et al. (2012)

assessed a training program that significantly improved road-crossing behaviors among older pedestrians, although it did not completely mitigate risks from high-speed vehicles. To enhance safety, Dommes et al. (2013) recommended addressing multiple dimensions of age-related declines, including physical, perceptual, and cognitive abilities.

In summary, while several studies have investigated traffic safety for pedestrians, only a few have specifically addressed the safety of older pedestrians during nighttime. This study filled this gap through the detailed analysis of nighttime crashes under various lighting conditions involving older pedestrians, examining how demographic variables, environmental conditions, and road features contribute to the crash outcomes.

3. Methodology

This section outlines the method used in this study and includes the data preparation, study design, and exploratory data analysis.

3.1. Association rules mining (ARM)

In this study, ARM was utilized to investigate the underlying factors contributing to older pedestrian involved crashes. Unlike traditional statistical modeling methods typically used in crash data analysis, ARM offers several unique benefits. Statistical methods can provide insights into the individual impacts of various risk factors on crash risks but are often limited by their predefined assumptions. When these assumptions are violated, it can result in biased or inaccurate outcomes (Mondal et al., 2020). In contrast, ARM addresses these limitations by offering enhanced performance, flexibility in managing different data distributions, and the ability to efficiently handle large datasets while revealing hidden relationships among multiple variables. One of the most significant advantages of ARM is the ability to explore the underlying relationships within extensive databases. Unlike traditional statistical modeling that relies on predetermined assumptions, ARM facilitates the discovery and characterization of relationships between variables through rule formulation (Das et al., 2019; Montella et al., 2011). This method is highly effective in analyzing traffic crash data and providing valuable insights. It explores complex and non-linear relationships among various factors, leading to a detailed analysis of the risk patterns associated with traffic crashes. Additionally, ARM's ability to efficiently process large datasets makes it particularly well-suited for analyzing extensive and complex crash data typical in traffic safety research.

Regression models are widely used in many studies to explore the relationship between specific outcomes and their risk factors. However, they generally focus on average effects, overlooking subgroups that may have distinct risk profiles. As a result, interventions are often designed for the average population member, without accounting for the unique characteristics of different subgroups. This paper highlights the advantage of using rule-based analysis methods, which can uncover subgroups with varying risk profiles without requiring predefined assumptions. These rules capture the risk patterns of subsets of individuals by considering both the interactions between risk factors and their ranges—marking a crucial difference.

ARM is a powerful descriptive data mining technique and a commonly used rule-based machine learning method to uncover meaningful relationships between variables in extensive databases. This technique aims to reveal hidden patterns within an itemset, encompassing various factors like environmental conditions, traffic characteristics, roadway geometry, and pedestrian demographics in the context of this study. These factors concern a specific event, i.e., the severity of pedestrian-related crashes. Multiple algorithms exist for mining association rules, with the Apriori algorithm being extensively employed, initially introduced in a previous study (Agrawal et al., 1993). The Apriori algorithm utilizes a level-wise search strategy to extract frequent item sets, if subsets of frequently occurring item sets are themselves frequent. By employing this algorithm, subsequences or item groups recurrently appearing within a large dataset are extracted. In this study, the set of items $I = \{i_1, i_2, \ldots, i_m\}$ comprises crash classifications specific to pedestrian-involved incidents, and the collection of crash data $C = \{c_1, c_2, \ldots, c_n\}$ represents transactions in the database, where each crash record, c_i, consists of a subset of items selected from I. A $k-$itemset refers to an itemset containing k items, and an association rule is expressed as $Antecedent(A) \rightarrow Consequent(B)$, signifying that the occurrence of A implies a likelihood of B occurring. The selection of interesting rules and determination of association strength in this study is guided by four measures: support, confidence, lift, and coverage. Subsequent sections provide a comprehensive description of these measures.

3.1.1. Support

Support measures how frequently an item set appears in a dataset, representing the ratio of transactions that contain the item set to the total number of transactions (Hahsler et al., 2005). The mathematical representation of support is shown in Equation (1).

$$\text{Support}, S(A \rightarrow B) = \frac{A \cap B}{N} \tag{1}$$

Where,

$S(A \rightarrow B)$ = support of the association rule $(A \rightarrow B)$,

$A \cap B$ = frequency of occurrences with both antecedent and consequent, and

N = total frequency of occurrences.

3.1.2. Confidence

Confidence evaluates the reliability of a rule by measuring how often the consequent item set occurs in transactions that contain the antecedent item set. A high confidence value in an $A \rightarrow B$ rule indicates that B frequently appears in transactions where A is present (Hahsler et al., 2005). The mathematical representation of confidence is shown in Equation (2).

$$Confidence, C(A \rightarrow B) = \frac{S(A \rightarrow B)}{S(A)} \tag{2}$$

Where,

$C(A \rightarrow B)$ = confidence of the association rule $(A \rightarrow B)$,

$S(A \rightarrow B)$ = support of the association rule $(A \rightarrow B)$, and

$S(A)$ support of antecedent A.

3.1.3. Lift

Lift assesses the relationship between the occurrence of the antecedent and the consequent by comparing their joint frequency to their expected frequency if they were independent. A lift value greater than 1 suggests a positive association, meaning the antecedent and consequent appear together more often than expected, while a value less than 1 indicates a negative association (Montella et al., 2011).

The mathematical representation of lift is shown in Equation (3).

$$Lift, L(A \rightarrow B) = \frac{C(A \rightarrow B)}{S(B)} = \frac{S(A \rightarrow B)}{S(A).S(B)} \tag{3}$$

Where,

$S(A \rightarrow B)$ = support of the association rule $(A \rightarrow B)$,

$S(A)$ = support of antecedent, and

$S(B)$ = support of consequent.

3.1.4. Coverage

Coverage represents the support of the antecedent in the rule $(A \rightarrow B)$, i.e., $S(A)$ as shown in Equation (4). and reflects how often the rule can be applied within the dataset. Coverage can be quickly calculated from the rule's quality measures (support) stored in the quality slot. If this value is not present, then the support of the LHS is counted using the data supplied in transactions.

$$Coverage, CO = S(A) \quad (4)$$

3.2. Data preparation and study design

This section provides a brief overview of the dataset analyzed in this study, focusing on older pedestrian involved crashes at nighttime. Table 3 summarizes the crash data from Texas, spanning 2017 to 2022, categorized by severity levels: fatal injuries(K), severe injuries(A), moderate injuries(B), minor injuries(C), and no injuries(O). Over these six years, there was variation in the total number of crashes per year. The highest yearly total occurred in 2019 with 290 crashes, while the lowest was in 2017 with 223 crashes. The fluctuations in crash numbers may be influenced by various factors, including changes in traffic patterns and safety measures. When examining the severity of crashes, fatal injury crashes (K) and severe injury crashes (A) are particularly concerning due to their significant consequences. Over the six-year period, there were 406 fatal crashes and 356 severely injured crashes, indicating a substantial impact on public health and safety. The highest number of fatal crashes was recorded in 2022, with 87 fatalities, while the lowest was in 2017, with 38 fatalities. The data shows that while the number of crashes resulting in no injuries (O) was relatively low, moderate (B) and minor injury (C) crashes were more frequent, with 386 and 285 incidents respectively over the six years. To address data imbalance in the analysis, crashes were grouped by severity. Fatal and severe injury crashes (K and A) were combined as fatal or severe injury crashes, and moderate and minor injury crashes (B and C) were combined as moderate or minor injury crashes. This categorization helps in providing a clearer understanding of crash severity patterns among older pedestrians and facilitates more effective data mining techniques.

3.3. Exploratory data analysis

Table 4 presents the descriptive statistics of older pedestrians involved crashes, categorized by two age groups: 65–74 years and over 74 years. Notably, the crash data indicates that clear weather conditions were predominant for both age groups, with clear weather crashes accounting for 75.20 % and 76.70 % respectively. The p-value in Table 4 represents the statistical significance of the differences between the two age groups for each variable. A p-value less than 0.05 indicates that the difference is statistically significant. A significant difference was observed in the use of traffic control devices, where marked lanes were more frequently associated with older pedestrians aged 65–74 years involved in crashes (41.80 %) compared to those over 74 years (32.00 %). There was a notable disparity in gender distribution; males were involved in 70.90 % of crashes among older pedestrians aged 65–74 years, whereas the percentage was lower at 62.30 % for those over 74 years. Population density also played a role, with older pedestrians aged 65–74 years more frequently experiencing crashes in highly populated areas (55.30 %) compared to those over 74 years (46.30 %). Speed limits were also a crucial factor, with crashes occurring at 30–40 mph accounting for 60.7 % for older pedestrians aged 65–74 years, while this percentage dropped to 55.60 % for those over 74 years. Hispanic pedestrians aged 65–74 years accounted for 31.10 % of crashes involving

Table 3
Older Pedestrian Involved Crashes at Nighttime.

Year	K	A	B	C	O	Yearly Total
2017	38	51	70	56	8	223
2018	68	62	62	51	10	253
2019	66	55	83	73	13	290
2020	63	65	44	38	14	224
2021	84	49	58	34	4	229
2022	87	74	69	33	3	266
Total by Severity	406	356	386	285	52	1,485

Note: K = Fatal injury, A = Severe injury, B = Moderate injury, C = Minor injury, O = No injury.

Table 4
Descriptive Statistics of Older Pedestrian Involved Crashes by Age Groups.

Variable and attribute	Pedestrian aged 65–74 years (N = 1116)	Pedestrian aged 74 years or over (N = 369)	p-value
Weather Condition (Wthr_Cond_ID, identifier for the weather condition reported by the officer)			0.898
Clear	839 (75.20 %)	283 (76.70 %)	
Cloudy	164 (14.70 %)	52 (14.10 %)	
Fog	11 (0.99 %)	4 (1.08 %)	
Rain	89 (7.97 %)	28 (7.59 %)	
Other	13 (1.16 %)	2 (0.54 %)	
Road Classification (Road_Cls_ID, identifier for the road type at the scene of the crash)			0.545
City street	630 (56.50 %)	206 (55.80 %)	
Us & state highways	205 (18.40 %)	65 (17.60 %)	
Interstate	56 (5.02 %)	13 (3.52 %)	
Farm to market	73 (6.54 %)	24 (6.50 %)	
Other	152 (13.6 %)	61 (16.5 %)	
Traffic Control Device (Traffic_Cntl_ID, identifier for traffic control at the scene of a crash)			0.013
Marked lanes	467 (41.80 %)	118 (32.00 %)	
Signal light	149 (13.40 %)	51 (13.80 %)	
Stop sign	75 (6.72 %)	28 (7.59 %)	
None	249 (22.30 %)	106 (28.70 %)	
Other	176 (15.80 %)	66 (17.90 %)	
Population Density (Pop_Group_ID, identifier for the population density)			0.032
100,000——249,999 pop.	139 (12.50 %)	51 (13.80 %)	
250,000 pop. and over	617 (55.30 %)	171 (46.30 %)	
50,000——99,999 pop	74 (6.63 %)	25 (6.78 %)	
Rural	125 (11.20 %)	57 (15.40 %)	
Crash Speed Limit Category (Crash_Speed_LimitCat, identifier for the speed limit of the road where the crash occurred at the time of crash)			0.008
30–40 mph	677 (60.70 %)	205 (55.60 %)	
45–60 mph	241 (21.60 %)	68 (18.40 %)	
65–70 mph	42 (3.76 %)	18 (4.88 %)	
Season (Season, identifier for the season during which the crash occurred)			0.968
Fall	379 (34.00 %)	122 (33.10 %)	
Spring	173 (15.50 %)	58 (15.70 %)	
Summer	239 (21.40 %)	77 (20.90 %)	
Winter	325 (29.10 %)	112 (30.40 %)	
Ethnicity (Prsn_Ethnicity_ID, identifier of ethnicity of the person involved in crash)			0.001
White	473 (42.40 %)	162 (43.90 %)	
Hispanic	347 (31.10 %)	129 (35.00 %)	
Black	237 (21.20 %)	46 (12.50 %)	
Asian	39 (3.49 %)	23 (6.23 %)	
Other	20 (1.79 %)	9 (2.44 %)	
Gender (Prsn_Gndr_ID, identifier of the gender of the person involved in crash)			0.004
Female	324 (29.00 %)	139 (37.70 %)	
Male	791 (70.90 %)	230 (62.30 %)	
Driving License Type (Drvr_Lic_Type_ID, identifier for driver's license type)			0.233
Driver license	459 (41.10 %)	170 (46.10 %)	
ID card	173 (15.50 %)	51 (13.80 %)	
Commercial driver license	6 (0.54 %)	2 (0.54 %)	
Other	74 (6.63 %)	31 (8.40 %)	
Crash Severity (Crash_Sev_ID1, identifier for the crash severity)			0.243
KA (Fatal/Severe)	566 (50.70 %)	196 (53.10 %)	
BC (Moderate/Minor)	506 (45.30 %)	165 (44.70 %)	

(continued on next page)

Table 4 (*continued*)

Variable and attribute	Pedestrian aged 65–74 years (N = 1116)	Pedestrian aged 74 years or over (N = 369)	p-value
O (No Injury)	44 (3.94 %)	8 (2.17 %)	
First Harmful Event (FHE_Collsn_ID1, identifier for the manner of collision in relation to the first harmful event.)			< 0.001
Single vehicle going straight	809 (72.50 %)	262 (71.00 %)	
Left turn related	171 (15.30 %)	53 (14.40 %)	
Backing	57 (5.11 %)	24 (6.50 %)	
Right turn related	51 (4.57 %)	21 (5.69 %)	
Same direction one straight-one stopped	7 (0.63 %)	0 (0.00 %)	
Rear-end	5 (0.45 %)	1 (0.27 %)	
Sideswipe	1 (0.09 %)	1 (0.27 %)	
Other	15 (1.34 %)	6 (1.63 %)	

and 35.00 % of those involving pedestrians over 74 years. Additionally, there was a significant difference in crash severity; 50.70 % of crashes involving older pedestrians aged 65–74 years resulted in fatal or severe injuries, compared to 53.10 % for those over 74 years, indicating a slightly higher severity for the older age group. The exploratory analysis identified significant variables such as Traffic Control Device, Population Density, Crash Speed Limit Category, Ethnicity, Gender, and First Harmful Event (as p-value is less than 0.05). Non-significant variables included Weather Condition, Road Class, Season, Driving License Type, and Crash Severity as indicated by the p-value. However, even if a variable is not statistically significant ($p > 0.05$), it can still be explored in data mining because data mining methods, like ARM, focus on discovering hidden patterns and relationships that may not be captured by traditional statistical analysis. This table serves as an exploratory tool, and the strength of data mining lies in its ability to find associations and rules, even if individual variables are statistically insignificant. Such patterns can reveal valuable insights that may not be evident from conventional methods.

The flow chart in Fig. 1 outlines the research methodology used to extract association rules from crash data involving older pedestrians. This methodology divides older pedestrians into two distinct groups: Older Pedestrian Group (1) (aged 65–74 years) and Older Pedestrian Group (2) (aged over 74 years). Each group is analyzed under two specific lighting conditions: Dark with Lighting and Dark with No Lighting. For each combination of age group and lighting condition, the top 30 association rules are identified, with the top 10 rules representing each severity level. These rules are selected based on their higher lift values. Additionally, these rules are visualized to better understand the factors affecting crash severity among older pedestrians.

4. Results and discussions

This section presents an analysis and discussion of the study's findings. The ARM was applied separately to two age groups: Older Pedestrian Group (1) (65–74 years old) and Older Pedestrian Group (2) (over 74 years old). The resulting rules are discussed in the following subsections, categorized by lighting conditions.

4.1. Older pedestrians aged 65–74 years

For older pedestrians aged 65–74 years old, the analysis identifies key patterns and associations in crashes, emphasizing how different lighting conditions affect crash severity.

4.1.1. Dark with lighting

Rules A01-A30 in Table 5 represent the rules for different levels of crash severity involving older pedestrian aged 65–74 years during nighttime with street lighting that reveal several significant patterns. Rules A01-A10 provide attributes related to fatal or severe injury crashes. Rules A01 and A02 highlight that marked lanes combined with various population groups, such as other populations and those with 100,000 to 249,999 people, significantly increase the likelihood of fatal or severe injuries (LaScala et al., 2000). This may be due to the complexity of navigating marked lanes under nighttime lighting conditions. Both these rules have a lift value of 1.61 and 1.516 indicating that the chances of fatal or severe injury crashes at marked lanes with such condition are 1.61 and 1.516 times higher than other combinations in the dataset for similar types of crashes. Rule A03 shows that older pedestrians involved in single-vehicle crashes where the vehicle is going

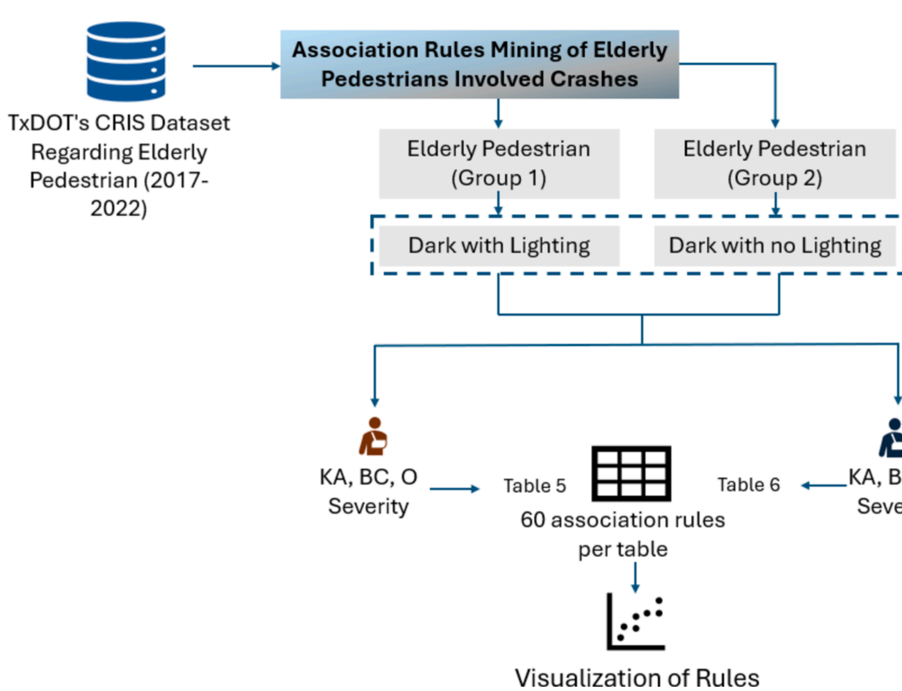


Fig. 1. Flow chart explaining research approach.

Table 5
Association Rules for 'Dark with Lighting' and 'Dark without Lighting' Condition Involving Older Pedestrian aged 65–74 Years.

Rule ID	Antecedent	S	C	L
Association Rules for 'Dark with Lighting' Condition Crashes				
Consequent 'Severity = KA'				
A01	{Traffic_Cntl_ID = Marked lanes, Pop_Group_ID = Other} => {Crash_Sev_ID1 = KA}	0.033	0.759	1.610
A02	{Traffic_Cntl_ID = Marked lanes, Pop_Group_ID = 100,000——249,999 pop.} => {Crash_Sev_ID1 = KA}	0.038	0.714	1.516
A03	{Drvr_Lic_Type_ID = Other, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.038	0.694	1.474
A04	{Traffic_Cntl_ID = Marked lanes, Crash_Speed_LimitCat = 45–60 mph} => {Crash_Sev_ID1 = KA}	0.068	0.692	1.469
A05	{Road_Cls_ID = Us & state highways, Traffic_Cntl_ID = Marked lanes} => {Crash_Sev_ID1 = KA}	0.058	0.691	1.466
A06	{Season = Winter,Drvr_Lic_Type_ID = Id card} => {Crash_Sev_ID1 = KA}	0.033	0.688	1.459
A07	{Wthr_Cond_ID = Cloudy,Traffic_Cntl_ID = Marked lanes} => {Crash_Sev_ID1 = KA}	0.036	0.686	1.455
A08	{Traffic_Cntl_ID = Marked lanes, Drvr_Lic_Type_ID = Id card} => {Crash_Sev_ID1 = KA}	0.042	0.683	1.449
A09	{Traffic_Cntl_ID = Marked lanes,Season = Spring} => {Crash_Sev_ID1 = KA}	0.042	0.683	1.449
A10	{Traffic_Cntl_ID = Marked lanes, Prsn_Ethnicity_ID = Hispanic} => {Crash_Sev_ID1 = KA}	0.080	0.679	1.442
Consequent 'Severity = BC'				
A11	{Crash_Speed_LimitCat = Other, Drvr_Lic_Type_ID = Unknown} => {Crash_Sev_ID1 = BC}	0.030	0.909	1.863
A12	{Road_Cls_ID = Other,Pop_Group_ID = 250,000 pop. And over} => {Crash_Sev_ID1 = BC}	0.053	0.897	1.839
A13	{Pop_Group_ID = 250,000 pop. And over, Crash_Speed_LimitCat = Other} => {Crash_Sev_ID1 = BC}	0.038	0.893	1.830
A14	{Pop_Group_ID = 250,000 pop. And over, FHE_Collsn_ID1 = Backing} => {Crash_Sev_ID1 = BC}	0.030	0.870	1.782
A15	{Road_Cls_ID = Other,Crash_Speed_LimitCat = Other} => {Crash_Sev_ID1 = BC}	0.044	0.853	1.748
A16	{Road_Cls_ID = Other,Traffic_Cntl_ID = None} => {Crash_Sev_ID1 = BC}	0.065	0.827	1.695
A17	{Road_Cls_ID = Other,Drvr_Lic_Type_ID = Unknown} => {Crash_Sev_ID1 = BC}	0.042	0.824	1.688
A18	{Crash_Speed_LimitCat = 30–40 mph, FHE_Collsn_ID1 = Right turn related} => {Crash_Sev_ID1 = BC}	0.035	0.821	1.684
A19	{Prsn_Gndr_ID = Male, FHE_Collsn_ID1 = Right turn related} => {Crash_Sev_ID1 = BC}	0.030	0.800	1.640
A20	{Traffic_Cntl_ID = Other, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.03	0.800	1.640
Consequent 'Severity = O'				
A21	{Wthr_Cond_ID = Other,Pop_Group_ID = Rural} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A22	{Wthr_Cond_ID = Other, Crash_Speed_LimitCat = Unknown} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A23	{Wthr_Cond_ID = Other,Road_Cls_ID = Other} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A24	{Traffic_Cntl_ID = Signal light, Crash_Speed_LimitCat = Unknown, Prsn_Ethnicity_ID = Hispanic} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444

Table 5 (*continued*)

Rule ID	Antecedent	S	C	L
Association Rules for 'Dark with Lighting' Condition Crashes				
A25	{Crash_Speed_LimitCat = 45–60 mph,Season = Summer,Drvr_Lic_Type_ID = Other} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A26	{Wthr_Cond_ID = Cloudy,Road_Cls_ID = Other,Traffic_Cntl_ID = Marked lanes} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A27	{Road_Cls_ID = Other,Traffic_Cntl_ID = Other,Season = Summer} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A28	{Pop_Group_ID = 250,000 pop. And over, Crash_Speed_LimitCat = 45–60 mph,Season = Summer,Prsn_Gndr_ID = Female} => {Crash_Sev_ID1 = O}	0.002	1.000	24.444
A29	{Wthr_Cond_ID = Other, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = O}	0.002	0.500	12.222
A30	{Pop_Group_ID = Rural, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = O}	0.003	0.500	12.222
Association Rules for 'Dark without Lighting' Condition Crashes				
Consequent 'Severity = KA'				
B01	{Traffic_Cntl_ID = Marked lanes, Pop_Group_ID = 50,000——99,999 pop} => {Crash_Sev_ID1 = KA}	0.034	1.000	1.720
B02	{Traffic_Cntl_ID = Marked lanes, Crash_Speed_LimitCat = 65–70 mph} => {Crash_Sev_ID1 = KA}	0.041	0.941	1.619
B03	{Crash_Speed_LimitCat = 65–70 mph, Prsn_Ethnicity_ID = White} => {Crash_Sev_ID1 = KA}	0.039	0.938	1.612
B04	{Traffic_Cntl_ID = Other,Prsn_Ethnicity_ID = Hispanic} => {Crash_Sev_ID1 = KA}	0.036	0.933	1.605
B05	{Road_Cls_ID = Us & state highways, Prsn_Ethnicity_ID = Hispanic} => {Crash_Sev_ID1 = KA}	0.036	0.933	1.605
B06	{Crash_Speed_LimitCat = 65–70 mph,Season = Fall} => {Crash_Sev_ID1 = KA}	0.034	0.929	1.597
B07	{Wthr_Cond_ID = Clear, Crash_Speed_LimitCat = 65–70 mph} => {Crash_Sev_ID1 = KA}	0.052	0.909	1.564
B08	{Crash_Speed_LimitCat = 65–70 mph, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.049	0.905	1.556
B09	{Crash_Speed_LimitCat = 65–70 mph, Drvr_Lic_Type_ID = Driver license} => {Crash_Sev_ID1 = KA}	0.047	0.900	1.548
B10	{Road_Cls_ID = Us & state highways, Prsn_Gndr_ID = Female} => {Crash_Sev_ID1 = KA}	0.047	0.900	1.548
Consequent 'Severity = BC'				
B11	{Season = Fall, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.041	0.800	2.092
B12	{Road_Cls_ID = City Street, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.072	0.800	2.092
B13	{Road_Cls_ID = City street,Traffic_Cntl_ID = Stop sign} => {Crash_Sev_ID1 = BC}	0.054	0.778	2.034
B14	{Pop_Group_ID = 250,000 pop. And over, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.041	0.762	1.992
B15	{Drvr_Lic_Type_ID = Unknown, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.031	0.750	1.961
B16	{Traffic_Cntl_ID = Stop sign, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.036	0.737	1.927
B17	{Traffic_Cntl_ID = Stop sign,Prsn_Gndr_ID = Male} => {Crash_Sev_ID1 = BC}	0.052	0.714	1.868
B18	{Wthr_Cond_ID = Clear, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.065	0.694	1.816
B19	{Crash_Speed_LimitCat = 30–40 mph, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.052	0.690	1.803

(*continued on next page*)

Table 5 (*continued*)

Rule ID	Antecedent	S	C	L
Association Rules for 'Dark with Lighting' Condition Crashes				
B20	{Drvr_Lic_Type_ID = Driver license, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.039	0.682	1.783
Consequent 'Severity = O'				
B21	{Prsn_Ethnicity_ID = Other,Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B22	{Traffic_Cntl_ID = Stop sign,Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B23	{Season = Spring,Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B24	{Prsn_Gndr_ID = Unknown,Drvr_Lic_Type_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B25	{Pop_Group_ID = 250,000 pop. And over, Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B26	{Road_Cls_ID = City street,Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B27	{Crash_Speed_LimitCat = 30–40 mph, Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B28	{Wthr_Cond_ID = Clear,Prsn_Gndr_ID = Unknown} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B29	{Prsn_Gndr_ID = Unknown, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643
B30	{Crash_Speed_LimitCat = Other, Prsn_Ethnicity_ID = Other} => {Crash_Sev_ID1 = O}	0.003	1.000	27.643

Notes: S = Support, C = Confidence, L = Lift.

straight are more likely to sustain fatal or severe injuries, possibly due to the vulnerability and slower reaction times of older pedestrians, especially in nighttime driving conditions. These findings are in line with Guo et al. (2021). Moderate speed limits (45–60 mph) on roads with marked lanes also contribute to fatal or severe crashes (Rule A04), indicating that higher speeds reduce drivers' reaction times and increase the severity of impact on older pedestrians (Dommes et al., 2012). Furthermore, crashes on US and state highways with marked lanes (Rule A05) are likely to result in severe injuries to older pedestrians, possibly due to higher traffic volumes and speeds (Pour-Rouholamin and Zhou, 2016). The influence of seasonal factors, such as winter (Rule A06), suggests that adverse weather conditions contribute to the severity of crashes involving older pedestrians (Pour-Rouholamin and Zhou, 2016). Cloudy weather with marked lanes (Rule A07), crashes in the spring (Rule A09), and specific pedestrian demographics such as Hispanic older pedestrians on marked lanes (Rule A10) further highlight the role of environmental and socio-cultural factors in severe crashes. These findings are in line with the previous study of Campos-Outcalt et al. (2002).

For moderate or minor injury crashes involving older pedestrians aged 65–74 years, rules A11 to A20 illustrate various factors that influence the crash severity. Rule A11 indicates that crashes at unknown speed limits involving pedestrians hit by drivers with unknown license types are highly likely to result in moderate or minor injuries, suggesting that uncertainties in driving conditions contribute to crash outcomes. Crashes on other road classes in areas with over 250,000 population (Rule A12) and those at unknown speed limits in highly populated areas (Rule A13) show that urban environments with high traffic volumes increase the likelihood of moderate injuries for older pedestrians (Pour-Rouholamin and Zhou, 2016). The involvement of left-turn-related crashes in populated areas (Rule A14) underscores the risk associated with complex maneuvers under nighttime conditions. These findings are in line with the study of LaScala et al. (2000). Other road classes with unknown speed limits (Rule A15) and roads without traffic control devices (Rule A16) highlight the importance of clear traffic regulations and road classifications in reducing injury severity for older pedestrians. Right-turn-related crashes at moderate speeds (Rule A18) suggest that specific driving actions and conditions contribute to moderate injuries for older pedestrians (Guo et al., 2021). Male pedestrians involved in right-turn-related crashes (Rule A19) and left-turn-related crashes with other traffic control types (Rule A20) further emphasize gender-specific risk factors in these injury outcomes (Kemnitzer et al., 2019).

Rules A21 to A30 showcase attributes involving crashes of older pedestrians aged 65–74 years that are likely to result in no injuries. Rules A21 to A23 indicate that crashes in various weather conditions and on different road classes, particularly in rural areas, often result in no injuries for older pedestrians. This is likely due to lower traffic densities and speeds in these regions (LaScala et al., 2000). The presence of signal lights combined with unknown speed limits and pedestrian's demographic being Hispanic (Rule A24), high-speed limits with drivers holding other types of licenses (Rule A25), and cloudy weather on other road classes with marked lanes (Rule A26) suggest that certain environmental and driver factors can mitigate crash severity for older pedestrians. These findings are in line with the study of Guo et al. (2021). Additionally, crashes on other road classes during summer with different traffic control types (Rule A27), highly populated areas with high-speed limits during summer involving female pedestrians (Rule A28) show that specific combinations of conditions can lead to no injury outcomes for older pedestrians. According to Guo et al. (2021), older female pedestrians had relatively lower odds of severe injuries, while crashes at non-intersection unmarked locations accounted for the majority of additional fatalities. Finally, rural areas with left-turn-related crashes (Rule A30) indicate that less complex driving environments contribute to non-injury crashes involving older pedestrians. According to Hu and Cicchino (2022), larger passenger vehicles are more common in rural areas, potentially leading to higher involvement in crashes typical of these areas, such as walking-along-roadway crashes.

4.1.2. Dark with no lighting

Rules B01-B30 in Table 5 represent the rules for different levels of crash severity involving older pedestrians aged 65–74 years during nighttime without street lighting that reveal several significant patterns. Rules B01-B10 provide attributes related to fatal or severe injury crashes. Marked lanes in areas with populations of 50,000 to 99,999 significantly increase crash severity (as indicated by rule B01), likely due to increased likelihood of pedestrian activity in these populated areas and insufficient lighting exacerbating visibility, making it harder for older pedestrians to be seen. This finding aligns with Haleem et al. (2015) who found that dark lighting conditions is associated with increased risk of fatal or severe injury pedestrian crashes. Another study by Noh et al. (2018) revealed that nighttime crashes, intoxicated drivers, and hilly roads significantly increase the likelihood of severe pedestrian injuries. Most of the rules emphasize the critical impact of high-speed limits (65–70 mph) in various contexts, such as clear weather, fall season, and straight single-vehicle collisions, underscoring the danger for older pedestrians in poorly lit conditions. Higher speeds reduce the reaction time available for drivers to notice and avoid pedestrians, and the impact at such speeds is more likely to result in fatal or severe injuries for older pedestrians, who are generally more physically vulnerable and go through physiological changes associated with aging, such as reduced walking anility, slower reaction times, diminished vision, and reduced cognitive functions. This finding is in line with Haleem et al. (2015) who found that high speed limit is associated with higher older pedestrians' crash severity risk. Another study by Liu and Tung (2014) also found that when deciding whether to cross the road, older pedestrians may underestimate their reduced walking ability, which puts them at a comparatively higher risk. In addition, the time interval is the most important risk factor for older pedestrians. The speed and distance of approaching cars influence the time interval, and older pedestrians are more likely to misjudge these factors. Rules B04 and B05 point to the heightened risk for Hispanic individuals on roads with other traffic control types and US and state highways. This could be due to a combination of factors including different crossing behaviors, socioeconomic conditions, and potential language barriers affecting the understanding of traffic signals that may impact understanding of traffic signals and signs (Pour-Rouholamin and Zhou, 2016). Rule B10 highlights the increased vulnerability of female pedestrians on US and state highways, likely due to a combination of high-speed driving.

Rules B11-B20 provide attributes related to moderate or minor injury crashes. Most of the rules consistently show that left-turn-related crashes, especially on city streets, during clear weather, in highly populated areas, or involving unknown driver licenses, are prone to moderate or minor injuries. This may be because left-turn maneuvers are risky for drivers in nighttime conditions without lighting. Additionally, due to blind spots, it may be possible that drivers cannot see older pedestrians, resulting in crashes. According to Ferenchak and Abadi (2021), pedestrian fatalities strongly correlated with nighttime crashes. Some rules indicate the significance of stop signs in contributing to moderate injuries, suggesting that traffic control measures and pedestrian demographics influence crash outcomes. Rules B21-B30 provide attributes related to no injury crashes. Every rule in this category (B21 to B29) indicates that the likelihood of no injuries is remarkably high across various conditions, such as different seasons, road classes, and weather conditions for older pedestrians.

The scatter plots of the association rules of nighttime crashes involving 65–74 years old pedestrians, categorized by lighting conditions and crash severity levels, are shown in Fig. 2. These plots represent the relationship between support and confidence, with lift values represented by color. Fig. 2(a), Fig. 2(c), and Fig. 2(e) represent the scatter plots of KA, BC, and O crash severities during nighttime with lighting condition. In Fig. 2(a) for fatal or KA severity, higher confidence rules tend to have lower support, with high lift values (represented in red) scattered across the plot. This pattern indicates that rare conditions have a significant impact on severe crashes, emphasizing critical areas for safety interventions. The scatter plot in Fig. 2(c) for BC severity shows most rules exhibit moderate confidence and support. High lift values, indicated by red points, suggest that these conditions frequently lead to moderate injuries. In Fig. 2(e) for O crashes, numerous high-confidence rules have varying levels of support. Fig. 2(b), Fig. 2(d), and Fig. 2(f) represent the scatter plots of KA, BC, and O crash severities during nighttime with no lighting condition. For KA severity in Fig. 2(b) crashes, the scatter plot reveals that most rules have moderate to high confidence with low support. The scatter plot in Fig. 2(d) for BC severity

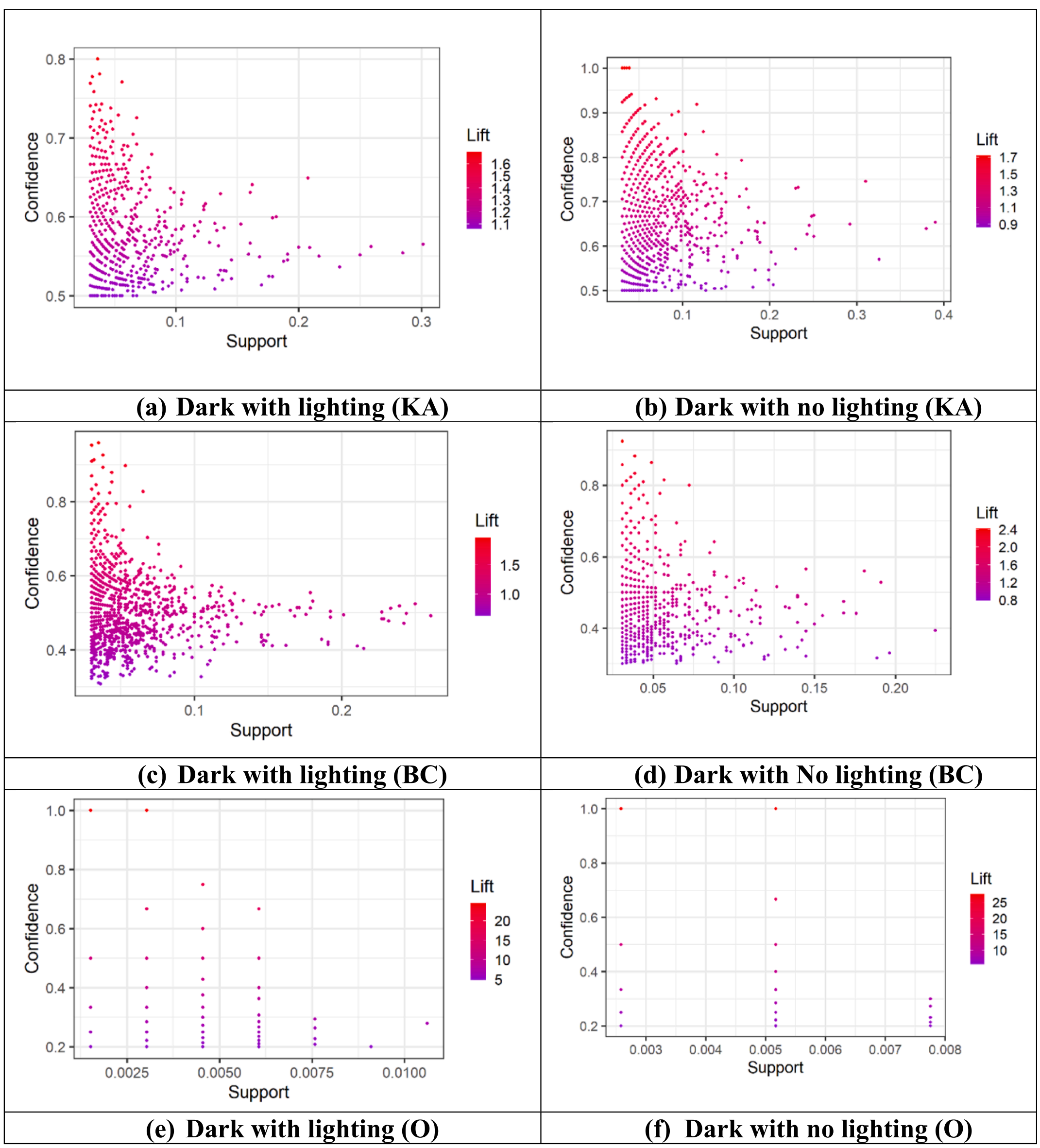


Fig. 2. Scatter plots of association rules of nighttime crashes involving 65–74 years old pedestrians by lighting condition and crash severity level.

reveals that most rules display moderate confidence along with varying levels of support. The scatter plot for no injury crashes in Fig. 2(f) shows a similar distribution with many high-confidence rules and varying support levels.

The scatter plots also illustrate that the presence of lighting affects the distribution of crashes. With lighting, there is a wider spread of rules across the confidence-support space. This suggests that lighting helps reduce the risk of crashes, including severe ones. On the other hand, Fig. 3(b), 3(d), and 3(f), which represent crashes in dark conditions without lighting, show a clustering of higher confidence rules at lower support. This means that without lighting, crashes are more likely to occur under specific, high-risk conditions.

Fig. 3(a), Fig. 3(c), and Fig. 3(e) depict the network graphs for KA, BC, and O crash severities respectively, during nighttime conditions with lighting. Fig. 3(a) shows strong associations between conditions like *'FHE Collsn_ID = Single vehicle going straight'* and *'Weather Cond_ID = Cloudy'*, which substantially increase the risk of fatal or severe crashes. Fig. 3(c) identifies key factors such as *'Pop_Group_ID = 250,000'* and *'Road_Cl_ID = Other'*, which are commonly linked to moderate or minor injuries. Fig. 3(e) emphasizes prevalent conditions such as *'Traffic Ctrl_ID = Marked lanes'* and *'Weather Cond_ID = Clear'* that typically result in no injury crashes. Fig. 3(b), Fig. 3(d), and Fig. 3(f) illustrate the network graphs for KA, BC, and O crash severities during nighttime conditions without lighting. Fig. 3(b) underscores strong association between *'Traffic_Cntl_ID = Marked lanes'* and *'FHE Collsn_ID = Single vehicle going straight'*, significantly raising the likelihood of fatal or severe crashes. Fig. 3(d) points out frequent conditions like 'Traffic Ctrl_ID = Stop sign' and 'Person Gender_ID = Male', which often lead to moderate or minor injuries. Lastly, Fig. 3(f) details conditions such as *'Weather Cond_ID = Clear'* and *'Driver Lic. Type ID = Other'*, which are

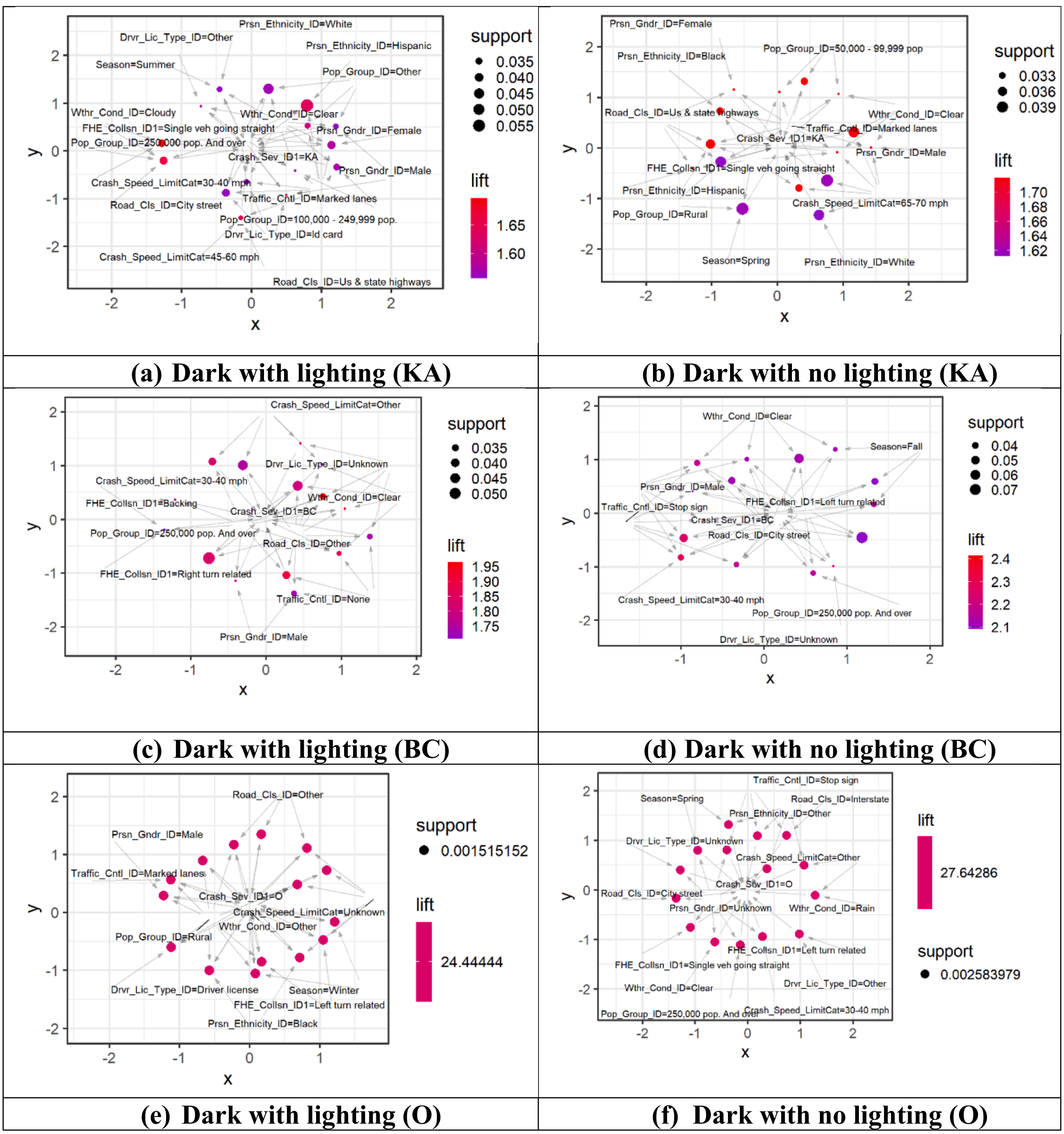


Fig. 3. Network graphs of association rules of nighttime crashes involving 65–74 years old pedestrians by lighting condition and crash severity level.

associated with no injury crashes.

The graphs show how lighting affects crash severity during nighttime. When there is lighting, factors like weather and speed limits (shown in Fig. 3a) become more important in severe crashes (KA). However, without lighting (Fig. 3b), road features like marked lanes play a bigger role. Clear weather is also a stronger predictor in crashes without lighting, especially in severe and moderate injury cases. This shows that the lack of lighting is a bigger issue than bad weather causing crashes at night. Population size influences crash outcomes as well. In severe and moderate crashes, large urban populations have higher risks, especially in both lighting conditions.

4.2. *Older pedestrians aged 74 years and above*

For older pedestrians aged 74 years and above, this section identifies key patterns and associations highlighting how various lighting conditions impact crash severity.

4.2.1. *Dark with lighting*

Rules C01 to C10 in Table 6 represent the rules for different levels of crash severity involving older pedestrians aged 74 years or above during nighttime with street lighting that reveal several significant patterns. The association rules C01 to C10 indicate fatal and severe crashes. Rule C01 indicates that marked lanes with speed limits of 65–70 mph significantly increase crash severity due to poor visibility and high-speed driving. Several other rules also highlight the critical impact of high-speed limits and clear weather on interstate roads. Rule C05 suggests that marked lanes and the presence of older pedestrians contribute to fatal or severe crashes, potentially due to their physical frailty, impaired vision, and cognitive limitations, which negatively impact their ability to cross the road safely (Dommes et al., 2012). Some rules emphasize the danger of single-vehicle collisions going straight on highways, indicating the severity of such crashes in lighted conditions.

For moderate or minor injury crashes involving older pedestrians aged 74 years or above, Rules C11 to C20 focus on the impact of various traffic and environmental conditions. Rule C11 highlights those crashes in areas with a population of 250,000 and over and other types of roads that lead to moderate or minor injuries. Some rules point out the role of unknown driver licenses and fall season on various road types, contributing to crash severity. Rules C14 and C19 indicate the significance of female pedestrians in crashes at locations with different speed limits and collision types. Rules C15, C16, C17, and C20 emphasize the impact of speed limits and seasons, along with the lack of traffic control measures, on the severity of crashes, demonstrating the contribution of these factors in nighttime conditions with lighting. These findings are in line with Guo et al. (2021).

Rules C21-C30 provide attributes related to no injury crashes. Each rule in this category (C21 to C29) indicates that rear-end collisions, across various conditions such as different driver licenses, traffic controls, seasons, demographic being Hispanic, and different road classes, result in no injuries, pointing to the lower impact severity of such crashes.

4.2.2. *Dark with no lighting*

Rules D01 to D30 in Table 6 represent the association rules for different levels of crash severity involving older pedestrians aged 74 years or above during nighttime without street lighting that reveal several significant patterns. The association rules from D01 to D10 for fatal or severe crashes highlight significant risk factors. Rules D01 and D02 indicate that single-vehicle collisions on interstates and US and state highways with speed limits of 65–70 mph notably increase crash severity due to poor visibility in dark conditions and high speeds. Crashes under these conditions are 1.643 times more likely to result in fatal or severe injuries. Some rules emphasize the increased risk associated with marked lanes, driver licenses, and white demographic pedestrians under high-speed conditions without street lighting. Rule D06

Table 6
Association Rules for 'Dark with Lighting' and 'Dark without Lighting' Condition Involving Older Pedestrian aged 74 Years and Above.

Rule ID	Antecedent	S	C	L
Association Rules for 'Dark with Lighting' Condition Crashes				
Consequent 'Severity = KA'				
C01	{Traffic_Cntl_ID = Marked lanes, Crash_Speed_LimitCat = 65–70 mph} => {Crash_Sev_ID1 = KA}	0.034	1.000	2.061
C02	{Crash_Speed_LimitCat = 65–70 mph, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.039	1.000	2.061
C03	{Road_Cls_ID = Interstate, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.034	1.000	2.061
C04	{Wthr_Cond_ID = Clear,Road_Cls_ID = Interstate} => {Crash_Sev_ID1 = KA}	0.039	1.000	2.061
C05	{Traffic_Cntl_ID = Marked lanes, Drvr_Lic_Type_ID = Id card} => {Crash_Sev_ID1 = KA}	0.044	1.000	2.061
C06	{Traffic_Cntl_ID = Marked lanes, Pop_Group_ID = Other} => {Crash_Sev_ID1 = KA}	0.039	0.889	1.832
C07	{Road_Cls_ID = Us & state highways, Pop_Group_ID = Other} => {Crash_Sev_ID1 = KA}	0.034	0.875	1.803
C08	{Pop_Group_ID = Other, Crash_Speed_LimitCat = 45–60 mph} => {Crash_Sev_ID1 = KA}	0.034	0.875	1.803
C09	{Pop_Group_ID = Other, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.078	0.842	1.735
C10	{Road_Cls_ID = Us & state highways, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.098	0.800	1.648
Consequent 'Severity = BC'				
C11	{Road_Cls_ID = Other,Pop_Group_ID = 250,000 pop. And over} => {Crash_Sev_ID1 = BC}	0.049	1.000	2.040
C12	{Drvr_Lic_Type_ID = Unknown, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.064	0.929	1.894
C13	{Road_Cls_ID = Other,Season = Fall} => {Crash_Sev_ID1 = BC}	0.064	0.929	1.894
C14	{Crash_Speed_LimitCat = Other, Prsn_Gndr_ID = Female} => {Crash_Sev_ID1 = BC}	0.049	0.909	1.855
C15	{Traffic_Cntl_ID = None, Crash_Speed_LimitCat = Other} => {Crash_Sev_ID1 = BC}	0.044	0.900	1.836
C16	{Crash_Speed_LimitCat = Other,Season = Fall} => {Crash_Sev_ID1 = BC}	0.044	0.900	1.836
C17	{Pop_Group_ID = 250,000 pop. And over, Crash_Speed_LimitCat = Other} => {Crash_Sev_ID1 = BC}	0.044	0.900	1.836
C18	{Crash_Speed_LimitCat = Other, Drvr_Lic_Type_ID = Unknown} => {Crash_Sev_ID1 = BC}	0.039	0.889	1.813
C19	{Prsn_Gndr_ID = Female, FHE_Collsn_ID1 = Backing} => {Crash_Sev_ID1 = BC}	0.034	0.875	1.785
C20	{Crash_Speed_LimitCat = Other,Season = Winter} => {Crash_Sev_ID1 = BC}	0.034	0.875	1.785
Consequent 'Severity = O'				
C21	{Drvr_Lic_Type_ID = Id card, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.800
C22	{Traffic_Cntl_ID = None, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.800
C23	{Season = Fall, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.800
C24	{Prsn_Ethnicity_ID = Hispanic, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.800

(*continued on next page*)

Table 6 (*continued*)

Rule ID	Antecedent	S	C	L
Association Rules for 'Dark with Lighting' Condition Crashes				
C25	{Pop_Group_ID = 250,000 pop. And over, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.8
C26	{Prsn_Gndr_ID = Male, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.8
C27	{Crash_Speed_LimitCat = 30–40 mph, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.8
C28	{Road_Cls_ID = City Street, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.8
C29	{Wthr_Cond_ID = Clear, FHE_Collsn_ID1 = Rear-end} => {Crash_Sev_ID1 = O}	0.005	1.000	40.8
C30	{Crash_Speed_LimitCat = Unknown, FHE_Collsn_ID1 = Right turn related} => {Crash_Sev_ID1 = O}	0.005	1.000	40.8
Association Rules for 'Dark without Lighting' Condition Crashes				
Consequent 'Severity = KA'				
D01	{Road_Cls_ID = Interstate, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
D02	{Road_Cls_ID = Us & state highways, Crash_Speed_LimitCat = 65–70 mph} => {Crash_Sev_ID1 = KA}	0.051	1.000	1.643
D03	{Traffic_Cntl_ID = Marked lanes, Crash_Speed_LimitCat = 65–70 mph} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
D04	{Crash_Speed_LimitCat = 65–70 mph, Drvr_Lic_Type_ID = Driver license} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
D05	{Crash_Speed_LimitCat = 65–70 mph, Prsn_Ethnicity_ID = White} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
D06	{Crash_Speed_LimitCat = 65–70 mph, Prsn_Gndr_ID = Male} => {Crash_Sev_ID1 = KA}	0.043	1.000	1.643
D07	{Wthr_Cond_ID = Clear, Crash_Speed_LimitCat = 65–70 mph} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
D08	{Crash_Speed_LimitCat = 65–70 mph, FHE_Collsn_ID1 = Single veh going straight} => {Crash_Sev_ID1 = KA}	0.065	1.000	1.643
D09	{Prsn_Ethnicity_ID = Black,Prsn_Gndr_ID = Female} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
D10	{Wthr_Cond_ID = Cloudy,Pop_Group_ID = Rural} => {Crash_Sev_ID1 = KA}	0.036	1.000	1.643
Consequent 'Severity = BC'				
D11	{Traffic_Cntl_ID = None, FHE_Collsn_ID1 = Backing} => {Crash_Sev_ID1 = BC}	0.036	1.000	2.706
D12	{Traffic_Cntl_ID = Other,Season = Winter} => {Crash_Sev_ID1 = BC}	0.036	0.833	2.255
D13	{Crash_Speed_LimitCat = 30–40 mph, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.051	0.778	2.105
D14	{Traffic_Cntl_ID = Signal light,Prsn_Gndr_ID = Male} => {Crash_Sev_ID1 = BC}	0.043	0.750	2.029
D15	{Road_Cls_ID = City street,Drvr_Lic_Type_ID = Id card} => {Crash_Sev_ID1 = BC}	0.065	0.750	2.029
D16	{Road_Cls_ID = City Street, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.08	0.733	1.984
D17	{Prsn_Gndr_ID = Male, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.058	0.727	1.968
D18	{Wthr_Cond_ID = Clear,Traffic_Cntl_ID = Signal light} => {Crash_Sev_ID1 = BC}	0.036	0.714	1.933
D19	{Pop_Group_ID = 250,000 pop. And over, Drvr_Lic_Type_ID = Other} => {Crash_Sev_ID1 = BC}	0.036	0.714	1.933
D20	{Season = Winter, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = BC}	0.036	0.714	1.933

Table 6 (*continued*)

Rule ID	Antecedent	S	C	L
Association Rules for 'Dark with Lighting' Condition Crashes				
Consequent 'Severity = O'				
D21	{Traffic_Cntl_ID = Other, Crash_Speed_LimitCat = Unknown} => {Crash_Sev_ID1 = O}	0.007	1.000	46.000
D22	{Road_Cls_ID = Other, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = O}	0.007	1.000	46.000
D23	{Crash_Speed_LimitCat = Unknown,Season = Fall} => {Crash_Sev_ID1 = O}	0.007	0.500	23.000
D24	{Wthr_Cond_ID = Cloudy,Prsn_Ethnicity_ID = Hispanic} => {Crash_Sev_ID1 = O}	0.007	0.500	23.000
D25	{Pop_Group_ID = 250,000 pop. And over, Crash_Speed_LimitCat = Unknown, Drvr_Lic_Type_ID = Driver license} => {Crash_Sev_ID1 = O}	0.007	0.500	23.000
D26	{Pop_Group_ID = 250,000 pop. And over, Crash_Speed_LimitCat = Unknown, Prsn_Ethnicity_ID = White} => {Crash_Sev_ID1 = O}	0.007	0.500	23.000
D27	{Traffic_Cntl_ID = Other,Pop_Group_ID = 250,000 pop. And over,Season = Fall} => {Crash_Sev_ID1 = O}	0.007	0.500	23.000
D28	{Traffic_Cntl_ID = Other,Pop_Group_ID = 250,000 pop. And over,Drvr_Lic_Type_ID = Driver license} => {Crash_Sev_ID1 = O}	0.007	0.500	23.000
D29	{Traffic_Cntl_ID = None,Prsn_Ethnicity_ID = Black} => {Crash_Sev_ID1 = O}	0.007	0.333	15.333
D30	{Drvr_Lic_Type_ID = Driver license, FHE_Collsn_ID1 = Left turn related} => {Crash_Sev_ID1 = O}	0.007	0.333	15.333

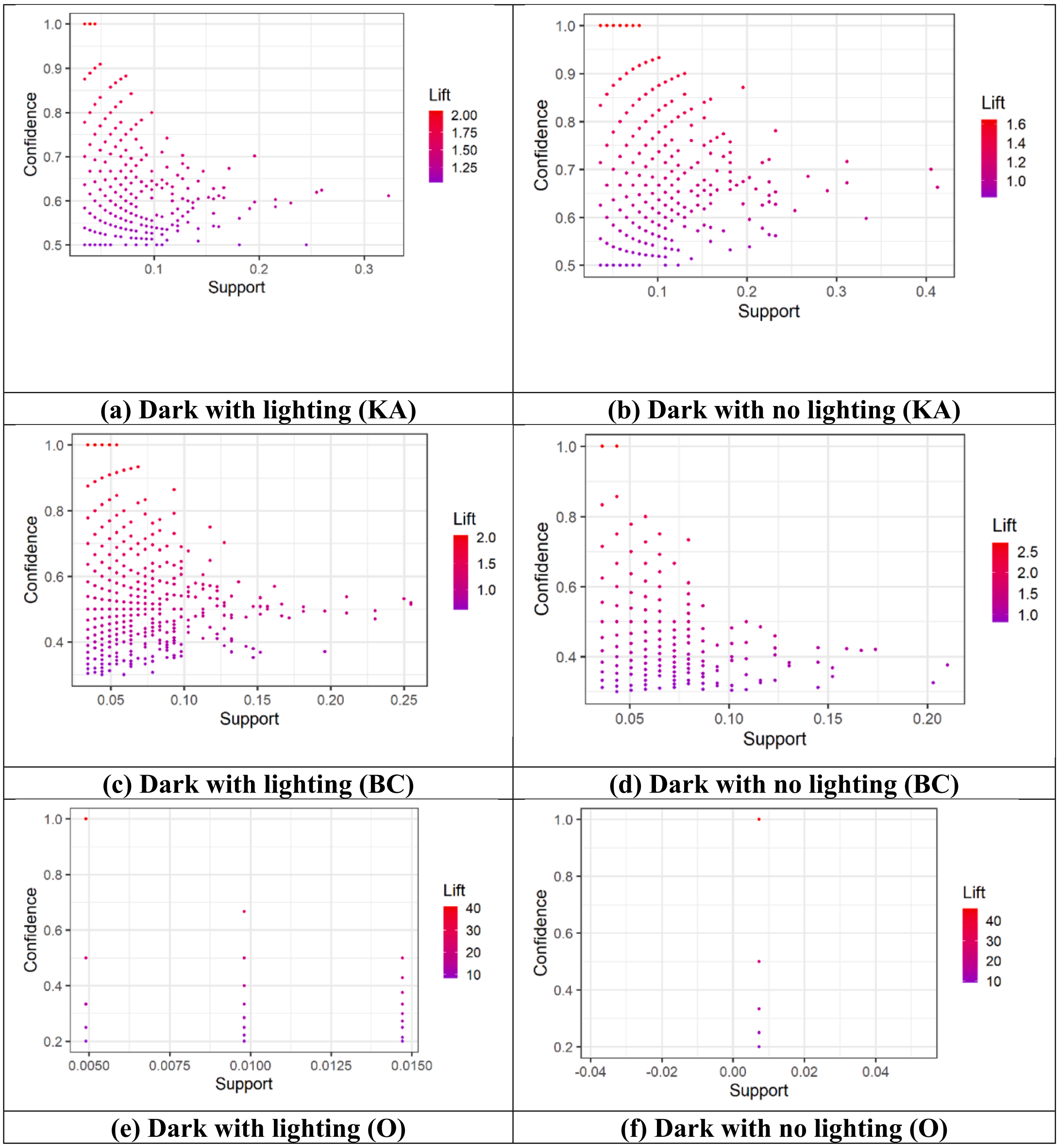
Notes: S = Support, C = Confidence, L = Lift.

highlights the increased danger for male pedestrians in high-speed crashes. Some rules underscore the risk of clear weather and single-vehicle collisions going straight. Rules D09 and D10 point to the increased vulnerability of African or African American females and rural populations under cloudy weather, suggesting that demographic and environmental factors significantly influence crash severity (Islam and Burton, 2020).

Rules D11 to D20 provide attributes related to moderate or minor injury crashes. Rule D11 indicates that crashes involving backing maneuvers without traffic control are prone to moderate injuries and 2.706 times more likely to occur. Rule D12 emphasizes the risk associated with other traffic control types during winter which is in line with the study revealed by Guo et al. (2021). Rules D13 and D16 highlight the significance of left-turn-related collisions on city streets and lower speed limits of 30–40 mph. Some rules focus on male pedestrians, clear weather, signal lights, and winter seasons in left-turn-related crashes which result in moderate or minor injury crashes. These findings are in line with the study of Mohamed et al. (2013) Rule D19 suggests that high-population areas with other driver licenses contribute to moderate or minor severity, underscoring the complexity of these factors in nighttime conditions without lighting. These findings are in line with the study of LaScala et al. (2000).

Rules D21 to D30 provide attributes related to no injury crashes. Rules D21 and D22 indicate that crashes involving unknown speed limits and left-turn-related collisions on other roads tend to result in no injuries. Some rules highlight the combination of fall season, cloudy weather, pedestrian's demographic being Hispanic, and high-population areas with unknown speed limits are associated with no injuries. Rule D30 highlights left-turn-related collisions involving drivers with licenses, suggesting these factors contribute to no injury older pedestrian crashes (Hu and Cicchino, 2022).

The scatter plots of the association rules of nighttime crashes involving older pedestrians aged 74 years or above, categorized by lighting conditions and crash severity levels, are shown in Fig. 4. These



(a) Dark with lighting (KA)

(b) Dark with no lighting (KA)

(c) Dark with lighting (BC)

(d) Dark with no lighting (BC)

(e) Dark with lighting (O)

(f) Dark with no lighting (O)

Fig. 4. Scatter plots of association rules of nighttime crashes involving older pedestrians aged 74 years or above by lighting condition and crash severity level.

plots represent the relationship between support and confidence, with lift values represented by color. Fig. 4(a), Fig. 4(c), and Fig. 4(e) represent the scatter plots of KA, BC, and O crash severities during nighttime with lighting condition. In Fig. 4(a) for KA severity, higher confidence rules often have lower support, with high lift values (represented in red) scattered across the plot. The scatter plot in Fig. 4(c) for moderate or minor (BC) severity crashes, most rules exhibit moderate confidence and support. The presence of high lift values, shown in red, indicates that certain conditions are frequently associated with moderate or minor injuries. Fig. 4(e) reveals numerous high-confidence rules with varied support levels for no injury crashes (O). Fig. 4(b), Fig. 4(d), and Fig. 4(f) represent the scatter plots of KA, BC, and O crash severities during nighttime with no lighting condition. For KA severity in Fig. 4(b), the plot reveals a pattern where most rules have moderate to high confidence but low support. This distribution demonstrates the increased risks and potential severity when lighting is absent, emphasizing the need for enhanced safety measures in unlit environments. The scatter plot in Fig. 4(d) for BC severity reveals most rules with moderate confidence and varying levels of support. The scatter plot for no injury crashes in Fig. 4(f) shows a distribution pattern with many high-confidence rules and varying support levels, like that observed with lighting.

The scatter plots also show that lighting plays a role in reducing the frequency of crashes. With lighting, moderate injury crashes are spread across a wider range of conditions, while without lighting, there is more clustering of high-confidence rules at lower support values. This indicates that moderate injury crashes are more frequent in unlit conditions, suggesting that the absence of lighting increases the risk of crashes even if they result in less severe injuries than KA crashes.

Fig. 5(a), Fig. 5(c), and Fig. 5(e) depict the network graphs for KA, BC, and O crash severities involving older pedestrians aged 74 years or over during nighttime conditions with lighting. Fig. 5(a) shows strong associations between conditions like '*Crash_Speed_LimitCat = 65–70 mph*' and '*FHE Collsn_ID = Single vehicle going straight*', which substantially increase the risk of fatal or severe crashes. Fig. 5(c) identifies key factors such as '*Person Gender_ID = Female*' and '*Pop_Group_ID = 250,000*', which are commonly linked to moderate or minor injuries. Fig. 5(e) emphasizes prevalent conditions such as '*Person_Ethnicity_ID = Hispanic*' and '*Drvr_Lic_Type_ID = Id card*' that typically result in no injury crashes. Fig. 5(b), Fig. 5(d), and Fig. 5(f) illustrate the network graphs for KA, BC,

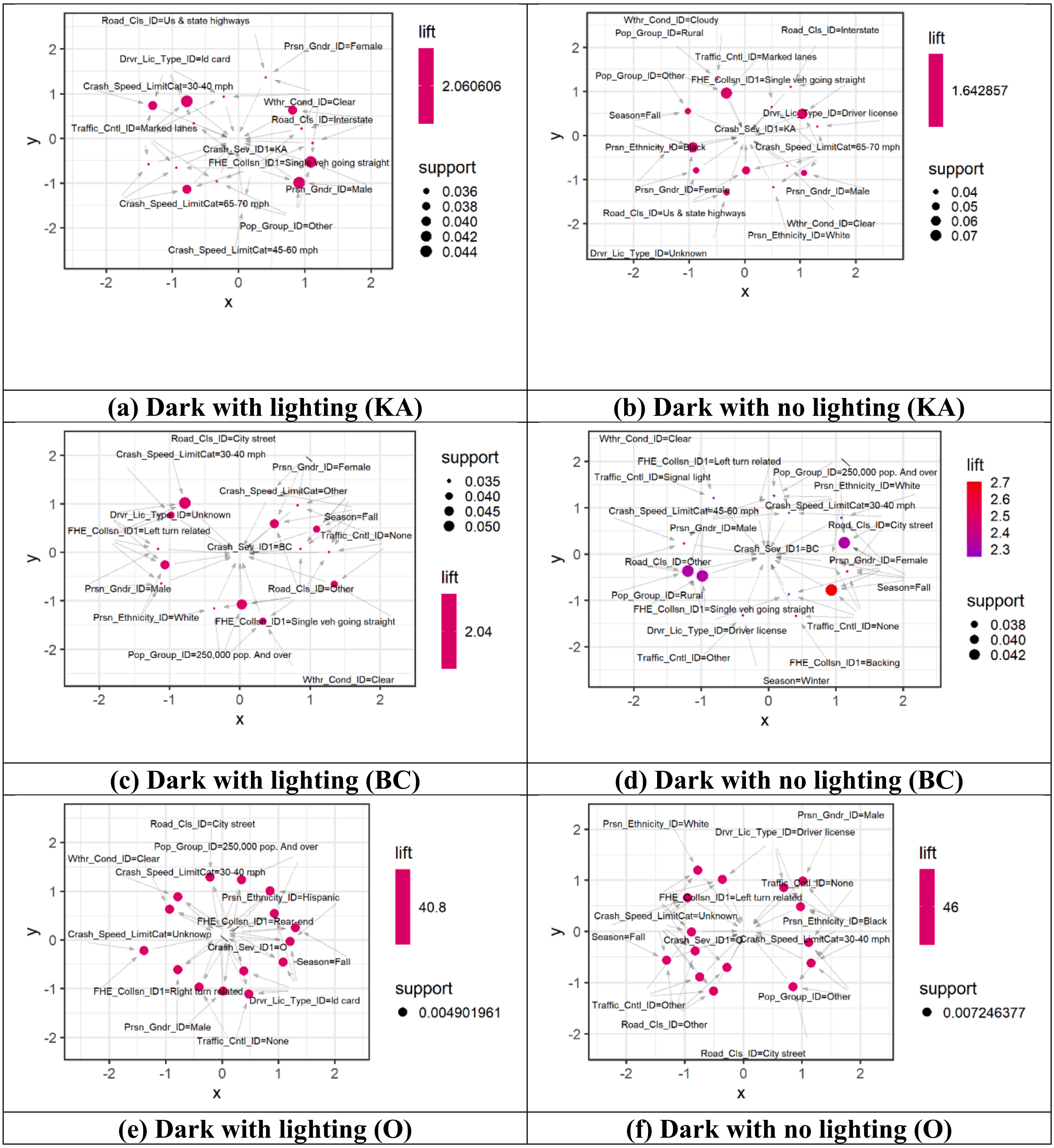


Fig. 5. Network graphs of association rules of nighttime crashes involving older pedestrians aged 74 years or above by lighting condition and crash severity level.

and O crash severities during nighttime conditions without lighting. Fig. 5(b) underscores strong association between '*Crash_Speed_LimitCat = 55–70 mph*' and '*Road_Cls_ID = Us & state highways*', significantly raising the likelihood of fatal or severe crashes. Fig. 5(d) points out frequent conditions like '*Traffic Ctrl_ID = None*' and '*Person Gender_ID = Female*', which often lead to moderate or minor injuries. Lastly, Fig. 5(f) details conditions such as '*Person_Ethnicity_ID = Black*' and '*Crash_Speed_LimitCat = 30–40 mph*', which are associated with no injury crashes.

The network graphs highlighted that higher speed limits (65–70 mph) consistently increase the likelihood of fatal crashes for older pedestrians, regardless of lighting condition. In urban areas with higher populations (250,000 and over), moderate injury crashes (BC) are more common, suggesting that dense environments present frequent but less severe risks. Under no-lighting conditions, females appear more vulnerable to moderate injuries compared to males. Additionally, ethnicity is found to play a role in no-injury crashes, with Hispanic and African American individuals more commonly involved, indicating potential demographic patterns in crash outcomes.

4.3. Policy implications and countermeasures

The study identified several significant patterns and associations in older pedestrian crashes aged 65 and above during nighttime, categorized by lighting conditions. The application of ARM revealed distinct factors influencing crash severity for two pedestrian age groups (65–74 years old and 74 years old and above). Specific risk factors for the two older pedestrian age groups (65–74 years and over 74 years) differ under varying conditions which are discussed in the following subsections.

For older pedestrians aged 65–74, moderate speed limits (45–60 mph) in urban areas with marked lanes were frequently associated with severe crashes, particularly in cloudy or winter weather. The complexity of urban environments, combined with these conditions, increased crash risk. Street lighting at night provided some mitigation, but crashes remained frequent due to the complex road features. Additionally, demographic factors, particularly for Hispanic pedestrians, heightened the risk. Left-turn crashes were more common for this group, often leading to moderate injuries. For the older group, those aged 74 and above, rural roads and highways with higher speed limits (65–70 mph) posed a greater threat. Single-vehicle crashes on straight roads, especially in poor lighting conditions, were often fatal due to the combination of high speeds and physical frailty. Unlike the younger group, even clear weather did not reduce crash severity, highlighting the vulnerability of this age group in rural environments. Demographic factors, including Hispanic and African American pedestrians, were also significant for this group, especially in high-speed, rural areas. Straight-path crashes at higher speeds were more likely to result in fatal injuries. Although both older age groups are associated with common traits, urban complexity and moderate speeds are more dangerous for the 65–74 age group, while rural roads and high speeds present greater risks for those 74 and above.

Based on the study's findings, it is important to develop and implement targeted policy measures to enhance the safety of older pedestrians. Policy measures should focus on implementing lower speed limits in areas frequently crossed by older pedestrians, particularly during nighttime conditions. Improving street lighting and visibility both at intersections and crosswalks is crucial, as is the installation of pedestrian-specific traffic signals, automated lighting systems, and clear road markings to aid navigation. Additionally, extended traffic signal times at crosswalks and increased lighting at intersections would allow older pedestrians more time to navigate crossings safely, considering their diminished vision and cognitive abilities. Incorporating refuge islands at intersections could also provide a safe space for pedestrians in the middle of the road, further reducing crash risks. Both age groups would benefit from these improvements. On the contrary, older pedestrians aged 74 and above, who often face crashes during left-turn maneuvers, require additional safeguards. Implementing protected left-turn phases at intersections, along with clearer and more prominent signage, could significantly reduce the risks associated with these complex traffic movements, specifically addressing the heightened vulnerability of this age group.

Advanced technologies, such as Intelligent Transportation Systems (ITS) and smart pedestrian detection systems, can play a pivotal role in mitigating risks. These systems can provide real-time alerts to both drivers and pedestrians about potential hazards, helping to prevent crashes. Some enhanced safety measures may also help mitigate older pedestrian's crash severity such as implementing pedestrian bags, Accessible Pedestrian Signals (APS) etc. APS can help older pedestrians who are blind or visually impaired to safely and independently cross intersections. These devices provide audible and vibrotactile information that corresponds with visual signals, indicating the start or end of the walk interval. This information assists pedestrians in assessing the intersection and deciding when to cross.

Furthermore, continuous education programs for older pedestrians on safe road-crossing practices, coupled with regular assessments of their vision and cognitive abilities, will further ensure their safety. Educational campaigns for specific age groups could raise awareness of pedestrian safety practices. Media campaigns using the Theory of Planned Behavior (TPB) model and community-based interventions can promote safe crossing behaviors. These campaigns should include simple, direct messages that resonate with older pedestrians, answering relevant questions and addressing concerns specific to this group. For example, brochures with larger fonts, low-gloss paper, and clear visuals of older pedestrians would be effective, as they are more likely to respond to printed materials and community outreach activities. Implementing these comprehensive measures will address the specific vulnerabilities identified in the study and contribute to safer urban and rural environments for older pedestrians.

5. Conclusion

This study investigated patterns and associations in nighttime crashes involving older pedestrians aged 65 and above, focusing on how different lighting conditions impact crash severity. By applying ARM to data from Texas (2017–2022), this study examined two distinct age groups: 65–74 years and over 74 years. The analysis revealed that high-speed limits, adverse weather conditions, and specific demographic factors significantly influence the severity of crashes for both age groups. Older pedestrians aged 65–74 years were more likely to experience fatal or severe injuries in high-speed zones and complex road environments, while those aged over 74 years faced greater risks in rural areas and during left-turn maneuvers.

Previous studies have not thoroughly explored how nighttime lighting conditions affect crash severity involving older pedestrians. The uniqueness of this research lies in its detailed exploration of crashes involving older pedestrians and the association of factors including demographic variables, environmental conditions, and road features in determining crash outcomes. The findings underscore the need for interventions addressing specific vulnerabilities of each age group. For instance, enhancing road safety measures in high-speed areas and improving visibility in diverse neighborhoods can significantly reduce severe crash incidents among pedestrians aged 65–74 years. Meanwhile, implementing safer intersection designs and better lighting in rural areas can mitigate the risks for those aged over 74 years. The study also highlights the potential of advanced technologies such as modern pedestrian detection systems, sensor technology, pedestrian bags, APS, and ITS in providing real-time alerts and preventing crashes, thus improving overall pedestrian safety.

This study has some limitations. It did not account for the influence of non-traffic-related factors such as older pedestrian's health conditions, disabilities, limiting mobility, and their behaviors. Future research should aim to include these additional variables to provide a more holistic understanding of the factors affecting older pedestrian's safety. Another limitation of this study is its reliance on historical crash data, which may not capture all relevant variables. In addition, there is a possibility of biases in the crash data, such as underreporting of minor crashes, which may lead to an overrepresentation of severe incidents. Additionally, inconsistencies in data recording practices across different police departments could introduce variability in how crash details are documented, potentially affecting the accuracy of variables like crash severity, road conditions, or pedestrian characteristics. These factors may influence the analysis results and should be considered when interpreting the findings and generalizing them in broader contexts. This study did not use built environment (BE) (for example, intersection density in a spatial area) and exposure variables from sources like the EPA Smart Location Database (SLD). However, incorporating such variables presents challenges. The SLD database is based on 2010 census data, which may not accurately reflect current BE characteristics, leading to potential misrepresentation. Additionally, assigning area-level BE information to person-level crash data would require complex geographical weighting techniques, which are beyond the scope of the current study. Future studies should aim to include non-traffic-related factors like pedestrian health, disabilities, and behaviors, along with updated built environment and exposure data, to provide a more comprehensive analysis of older pedestrian safety.

CRediT authorship contribution statement

Mahmuda Sultana Mimi: Data curation, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Rohit Chakraborty:** Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Jinli Liu:** Writing – original draft. **Swastika Barua:** Writing – original draft. **Subasish Das:** Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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