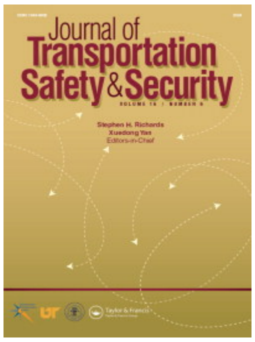

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Analyzing the time-varying patterns of contributing factors in work zone-related crashes

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ABSTRACT

Work zones are crucial for maintaining and enhancing road infrastructure, but they also pose a significant risk to traffic safety. Between 2016 and 2020, work zone-related crashes in the United States increased by 13%, highlighting the pressing need for effective safety measures. This study examines the factors that influence work zone crashes, including traffic control devices, geometric configurations, traffic operations, and human factors. The study also investigates how these factors vary by work zone type, day of the week, and time of day. To explore these temporal and spatial impacts, the study utilized five years of fatal crash data from the Fatality Analysis Reporting System (FARS) and applied association rules mining. The findings demonstrate that rear-end crashes and collisions with other vehicles are the primary contributing factors. Although some common patterns emerged in the association rules, the study revealed temporal instability, highlighting the importance of developing work zone-specific safety countermeasures. These findings will inform the development of targeted safety interventions and ultimately reduce the risk of work zone crashes.

KEYWORDS
work zone crashes; safety; temporal instability; association rules

1. Introduction

Work zones are essential for maintaining and upgrading roadway systems. However, work zones often change the traffic pattern and create a complex driving environment for drivers. Crashes at work zones have been a long-lasting problem that bothers drivers and transportation agencies. Crashes occurring at work zones not only endanger the lives of drivers and workers but also often lead to excessive delays compared with crashes at other locations. This is because work zones normally already reduce the roadway capacity, so any other disruptions could lead to severe delays. In the US,

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FHWA Work Zone Facts and Statistics reported that at least one fatality occurs at work zones for every 4 billion vehicle miles driven. In 2020, the FARS 2020 annual report showed that the fatal crashes in the US at work zones increased by 1.4%. FHWA also reported that a fatality associated with a work zone occurs every 15 h in the US, and a work zone-related crash injury happens every 16 min (Federal Highway Administration (FHWA), 2022).

Work zone-related studies have been of interest to transportation researchers for many years. Researchers try to understand the reasons for the causes and patterns of work zone crashes. Based on a review of the work zone-related articles published in recent years, research on work zone safety mainly consists of two parts (Yang et al., 2015). These two parts are descriptive analysis and modeling. Descriptive analysis has explored crash severity, crash rate, location of crash frequency, time of the crash, crash types, and others. The modeling part is mainly focused on modeling frequency and severity. However, only a few work zone related studies have mentioned temporal instability. Nevertheless, there is no evidence to show that the patterns in groups of factors affecting crashes at work zones differ across different time periods. Further, the work zone safety studies mainly applied regression models for analyses which presented the individual effect of risk factors on injury severity outcomes. Pattern recognition methods have been identified to unearth group of factors likely to collectively lead to crashes. These are useful as they allow policymakers create more targeted countermeasures for dealing with fatalities on the roads.

The current study aims to fill a significant gap in the existing literature by investigating the temporal instability of factors that influence fatal crashes at work zones using an association rules mining approach. To provide a thorough understanding of the factors associated with fatal work zone-related crashes, this study conducts a comparative analysis of key contributory factor patterns across different time periods. The analysis involves the grouping and examination of work zone-related crashes into two sets of temporal clusters: clusters based on the day of the week and clusters based on the time of day. The first set of clusters focuses on the day of the week, resulting in three distinct clusters: work zone crashes occurring from Monday to Thursday, work zone crashes on Fridays, and work zone crashes over the weekend. By applying association rules mining techniques, these clusters are carefully analyzed to uncover patterns and identify the factors that contribute to fatal work zone-related crashes within each specific temporal cluster. Following the examination of temporal clusters by day of the week, the analysis proceeds to temporal clustering based on the time of day. This results in two distinct clusters: daytime work zone crashes and nighttime work zone crashes. Similar comprehensive analyses are conducted within these clusters to gain in-depth insights into the factors influencing work zone-related crashes during different time periods.

The association rules mining method employed in this study is more advantageous as it is robust at identifying key combinations of factors affecting crashes and does not rely on prespecified assumptions that may affect the results' reliability (Hong et al., 2020). These combinations of factors can be collectively managed to mitigate fatal crashes efficiently (Hong et al., 2020). By exploring the temporal instability for different time periods, pertinent insights can be obtained from this research, which can help transportation agencies understand the key factors influencing work zone-related crashes at different time periods. This study used fatal work zone crashes from the Fatality Analysis Reporting System (FARS) for five years (2016–2020) to determine the association and significance of the variables. The current study aims to assess the temporal patterns of the influencing factors associated with zone crash occurrences to develop appropriate countermeasures to improve safety.

The remainder of the paper is divided into four sections. The following section provides a review of the literature on work zone studies. The third section is all about data integration, exploratory data analysis, and a quick overview of association rules mining. The fourth section contains the proposed approach's results and related discussions. The final section contains the research findings.

2. Literature review

Many studies have been conducted to explore influential factors related to work zone crashes. From the factor level perspective, most existing studies focused on analyzing the influence of key contributing factors on the severity of crashes in work zones. As rear-end crashes are more common in work zones, a number of studies also focused on work zone-related rear-end crashes. This section reviews previous studies discussing work zone-related crash injury severity outcomes, rear-ended collisions at work zones, and other safety issues, such as the effectiveness of variable speed limits and precrash behaviors associated with work zones to help clearly situate the literature gap this study seeks to bridge.

2.1. Injury severity of work zone-related crashes

Li and Bai (2008) established a series of crash severity index (CSI) models by modeling work zone crash severity outcomes and suggested using the CSI for work zone safety evaluation. The CSI models were created using a logistic regression technique and subsequently validated using current crash data. It has been demonstrated that CSI models are useful for simple assessments of work zone risk levels. Clark and Fontaine (2015) evaluated the extent to which work zone activities appeared to influence the frequency or severity of crashes within the work zone by using two years' worth of Virginia work zone crashes to identify crashes specifically related to work zones. Only 23% of coded crashes could be directly attributed to work zones, and coded crashes tended to overrepresent the proportional increase in rear-end crashes and underrepresent the proportional increase in fixed object-off-road crashes. This discrepancy between coded crashes and directly related crashes was discovered. To investigate factors influencing the severity of injury in passenger-car crashes in various work zone configurations, a database with ten years' worth of crashes involving at least one passenger car and taking place in a work zone was compiled by Osman et al. (2018). This database served as the basis for the Mixed Generalized Ordered Response Probit (MGORP) modeling framework. Elasticity analysis indicated that rural roads, limited access controls, crashes on weekends, crashes in the evenings, and curving roads are important factors raising the chances of severe outcomes.

Mokhtarimousavi et al. (2019) studied the prediction of work zone crash severity and contributing factors using a parametric method utilizing the mixed logit modeling framework and a non-parametric machine learning approach utilizing support vector machines (SVM). The whale optimization algorithm, particle swarm optimization, and harmony search were used as three metaheuristics to improve the SVM (WOA) performance. The mixed logit model was demonstrated to have worse prediction accuracy than the SVM, which was improved by the three metaheuristics. Mokhtarimousavi et al. (2021) employed a mixed logit model to identify key factors that affect crash severity at work zones, such as environmental features, crash-specific characteristics, and work-zone-specific characteristics. The Cuckoo Search (CS) algorithm was used to train a Support Vector Machine (SVM) model, which was then utilized to investigate the association between crash severity levels and time of day. It was established that the termination region of the work zone was crucial for both daytime and nighttime crashes, and it was established that the CS-SVM model performed better at making predictions than the SVM and logit models. Zhang and Hassan (2019) analyzed the differences in injury severity between daytime and evening crashes using data from long-term highway work zone projects in Egypt between 2010 and 2016. The number of lane closures, older and male drivers, rainy weather, and sideways crashes all had opposite effects on injury severity during the day and night crashes. Four variables were significant only at night, although four were significant only during the day.

2.2. Rear-end crashes of work zone-related crashes

To analyze the relationship between rear-end crash risk at activity areas and its contributing components, as well as the effects of merging behavior on crash risk at merging zones, rear-end crash risk models were developed by Meng and Weng (2011) using work zone traffic data in Singapore. It has been demonstrated that the rear-end collision risk in work zone activity regions is statistically different from the risk in other lane locations and that the risk rises with the proportion of heavy vehicles and the pace of lane traffic in these areas. Trucks, the expressway work zone activity area, and the lane closest to the work zone were all highly linked to a higher probability of rear-end collisions. Four different vehicle-following patterns—truck-truck, truck-car, car-truck, and car-car—were evaluated by Weng et al. (2014) for their potential to cause rear-end collisions in work zones. The riskiest type of collision was a car-truck rear-end collision. Although lane position and work intensity had less of an impact on the truck-car pattern than on the car-truck pattern, there was a greater crash risk for each pattern when there was heavy work intensity, in the lane next to the work zone, with a higher proportion of heavy vehicles, and with greater traffic flow. Weng et al. (2015) used a mixed probit model and merging traffic data from a work zone site in Singapore to research drivers' merging behavior and the probability of rear-end crashes in merging sections of work zones. Merging vehicles were found to have a higher likelihood of successfully completing a merging maneuver if they proceeded swiftly, the merging lead vehicle was heavy, and there was significant space between them and the next through lane. The likelihood of a rear-end collision did not rise as merging vehicle speed increased, although it was influenced by vehicle type. Rear-end collisions are more likely when there is less space between vehicles and work zones and more time has passed because the merging maneuver was triggered.

2.3. Temporal stability-related issues in work zone crashes

Concerning temporal stability analyses, studies explored the yearly, time-of-day, and day-of-the-week variations and temporal instability of factors influencing injury severity outcomes in other safety domains. In the pedestrian safety field, a strong temporal instability of day-of-week and annual factors was found to exist in the crash data. Essentially, although curved roadways and ambulance rescue variables produced temporally stable effects over time, the effects of factors such as male pedestrian, hit and run, and pedestrian age between 45–64 decreased with time. Regarding day-of-the-week variations, it was established that some variables were significant only in the weekdays while others were significant only on weekends (Li et al., 2021). Concerning time-of-day variation analysis, a study conducted on truck crashes in Los Angeles showed that the effect of factors is temporally unstable. In particular, young truck drivers were found to have a higher affinity for no-injury crashes in the afternoon than in the mornings. Besides, hit-object crashes were twice likely to result in injury in the afternoons compared to mornings (Behnood & Mannering, 2019). Other studies also reported the presence of time-of-day variations in contributory factor influence on injury severity (Song et al., 2021).

Islam et al. (2020) published a work zone research paper on analyzing the unobserved heterogeneity and temporal instability. This study explored data from 2012 to 2017 and provided evidence for the existence of yearly temporal instability in work zone crashes using random parameters logit models. Essentially, this means that the individual factors affecting injury severity outcomes in work zones are likely to differ from year to year. Given the existence of temporal instability in work zone crashes, many important aspects of this research topic have not been investigated yet. In particular, it is unclear if temporal instability exists for other time periods, such as time of day and day of the week. Analyses of temporal stability for different time periods has been considered in other areas under traffic safety and have presented pertinent insights into understanding how the influence of variables influencing the severity of crashes (Li et al., 2021; Tamakloe et al., 2021). Weng et al. (2016) analyzed work-zone-related crashes and ensuing injury severities using work zone data from 2012 to 2017 and random parameter logit models. When combined with a fundamental change in unobserved heterogeneity, the significantly different parameters derived for each year show significant temporal instability. The distinctive characteristics of each work zone and how the sample of work zones varies from year to year may be more to blame for these findings than just variations in driver behavior.

2.4. Other safety concerns

Using the fusion of several years' worth of statewide work zone records, work zone-related crash reports, and traffic detection data, a safety estimation approach for work zone scheduling and configuration parameters was established by Cheng et al. (2016). The approach was developed by first integrating the data sets using a matching algorithm, then calculating the vehicle miles traveled in work zones as an exposure measure, and finally creating the collision cost prediction tool using a least median squares linear regression model. It was demonstrated that the model could correctly forecast the expenses of work zone crashes. Employing a statewide crash database from the Virginia Department of Transportation, hierarchical models were used by Liu et al. (2016) to explore connections between pre-crash behaviors and the seriousness of the injuries sustained by the drivers involved in crashes. If the driver deliberately engaged in an improper action or a violation (such as speeding, disobeying officers/flaggers/signals/-signs, following too closely), the risk of driver injury in work zone crashes was 9.9% to 10.3% higher, whereas the risk was only 1.7% to 5.7% higher in non-work zone crashes. Lyu et al. (2017) developed a thorough variable speed limit (VSL) control model for figuring out suitable speed restrictions to reduce travel time and possible crash risk at freeway work zones. According to a case study carried out at a field site in China, the proposed model can potentially reduce the average delay, the frequency of stops, and the average halted delay on the segment under examination. The user-defined benefit threshold ranged from 10% to 20%, and the proposed model performed better when the driver compliance rate exceeded a threshold of 60%. Ullman et al. (2018) presented significant insights into work zone parameters related to typical types of crashes and documented the results of numerous analyses to improve understanding of work zone crash characteristics and countermeasure effectiveness. The effectiveness of safety measures to prevent rear-end collisions at interstate lane closure queues was demonstrated, but the effects of specific highway characteristics on work zone crashes could not be separated. However, broad crash prediction models were computed to estimate the expected crash effects of work zones. Koilada et al. (2020) used crash data from North Carolina's Highway Safety Information System (HSIS) from 2010 to 2014 to analyze the likelihood of being involved in a collision in work zone regions (SAS). The study's findings suggested that cloudy weather, wet roads and interstates, no-passing zones, rigid post barriers, grass, and flexible post-barrier medians increase the likelihood of a work zone crash in an activity area. Interstates and we routes, stop-and-go roads, no-passing zones, and flexible post-barrier medians increase the likelihood of a work zone crash in a transition area. In the advance warning zone on roads with semi-flexible post barrier medians, in the transition zone on US routes, and in the activity zone on dark but illuminated highways, US routes, and State routes, curves increase the likelihood of being involved in severe or moderate injury crashes. Cheng et al. (2022) presented a work zone configuration detail and design parameter-only technique based on artificial neural networks to predict crash occurrence in work zones. The performance of the suggested model was determined to be satisfactory.

The literature review indicates less attention has been paid to exploring temporal stability-related issues in work zone crashes. It is noteworthy that although studies have explored time-of-day and day-of-the-week temporal stability of factors affecting injury severity of crashes in other fields, these analyses have not been considered in the area of crash safety. Besides, the studies conducted so far mostly applied parametric models which are unable to discover patterns of contributory factors likely to influence crashes. To the best of the author's knowledge, this is the first attempt to develop temporally clustered association mining rules using work zone fatal crash data. The framework developed in this study can be replicated in solving other safety issues. The findings of this study can assist safety researchers in designing better countermeasures to improve work zone safety.

3. Methodology

3.1. Data integration

The research team collected five recent years (2016–2020) work zone-related crash data from FARS. During 2016–2020, a total of 3,615 fatal work zone crashes occurred in the US. As displayed in Table 1, construction-related work zone crashes represent 60% of all work zone-related fatal crashes. It is also noteworthy that, from 2016 to 2020, there was an increase of 13% in fatal work zone crashes, which is staggeringly high.

The research team used a wide list of variables during the data preparation phase. The final dataset includes nine major variables. Variables and associated itemsets were determined based on correlation analysis and variable importance using random forest algorithm. These variables are temporal factors (time of the day and day of the week, roadway environment (rural vs. urban, work zone type, crash location or road relation, lighting condition), environmental condition (weather), and crash-related factors (collision type and most harmful event). For the day of the week temporal analysis, the crash data was segregated into three categories based on similar traffic patterns, like the data aggregation method used in previous research conducted in the US (Tribby et al., 2013). In this study, we considered crashes that occurred on Monday through Thursday (*MTWT*), crashes occurring on Fridays (F), and those occurring on Saturdays and Sundays (*SS*). This is because, from the literature, traffic on *MTWT* shows pronounced morning and afternoon peaks as many people commute to work on these days. On Fridays, there are morning peaks, however, it is

Table 1. Fatal crash data grouped based on work zone type.

Year	Construction	Maintenance	Utility	Unknown	Yearly total
2016	451	50	16	170	687
2017	448	48	11	213	720
2018	433	47	1	191	672
2019	430	41	14	277	762
2020	432	47	8	287	774
Total by work zone type	2,194	233	50	1,138	3,615

more relaxed compared to the other days. There is less traffic on *FF* compared to the weekdays. Table 2 shows the different variables with their attributes and their counts. For the day of the week (DOW), *MTWT* had the highest count (58.23%) compared to crashes on Fridays (15.85%) and on weekends (Saturday to Sunday; 25.92%). Day and night were about equally split, with the *day* variable making up 50.26% and *night* variable making up 49.24%. For 18 crash observations, the time of the crashes were unknown (0.5%). For rural/urban variable, crashes occurring in *urban* areas comprised 60.03% of the total, and rural comprised 39.75%. crashes at other locations accounted for 0.22% of the total. For road relations, crashes occurring on the roadway *(on-roadway)* accounted for 66.53% of the total crashes. *On-roadside,* denoting crashes that occurred on the road side made up 18.73% of the crashes, and all the other attributes comprised 14.75% of

Table 2. Descriptive statistics.

Attribute	Count	%	Attribute	Count	%
Day of the week (DOW)			*Work zone type (WZ_T)*		
F (Friday)	573	15.85	Construction	2194	60.69
MTWT (Monday–Thursday)	2105	58.23	Work zone, type unknown	1138	31.48
SS (Saturday–Sunday)	937	25.92	Maintenance	233	6.45
Sum	*3615*	*100*	Utility	50	1.38
Time			*Sum*	*3615*	*100*
Day	1817	50.26	*Collision type (Coll)*		
Night	1780	49.24	Not collision with motor vehicle (MV)	1124	31.09
Unk (Unknown)	18	0.50	Not a collision with a MV in transport	867	23.98
Sum	*3615*	*100*	Front-to-rear	796	22.02
Rural/urban (RU)			Angle	408	11.29
Urban	2170	60.03	Front-to-front	261	7.22
Rural	1437	39.75	Sideswipe – same direction	98	2.71
Other	8	0.22	Sideswipe – opposite direction	28	0.77
Sum	*3615*	*100*	Other	33	0.91
Road relation (RoadRel)			*Sum*	*3615*	*100*
On roadway	2405	66.53	*Most harmful event (HarmE)*		
On roadside	677	18.73	Motor vehicle in-transport	1622	44.87
On median	220	6.09	Pedestrian	529	14.63
On shoulder	107	2.96	Rollover/overturn	242	6.69
Outside traffic way	104	2.88	Other object (not fixed)	159	4.40
Gore	45	1.24	Concrete traffic barrier	136	3.76
Others	57	1.58	Working motor vehicle	103	2.85
Sum	*3615*	*100*	Parked motor vehicle	92	2.54
Light			Guardrail face	77	2.13
Daylight	1809	50.04	Tree (standing only)	68	1.88
Dark – not lighted	997	27.58	Curb	67	1.85
Dark – lighted	631	17.46	Pedalcyclist	51	1.41
Dawn	77	2.13	Impact attenuator/crash cushion	48	1.33
Dusk	58	1.60	Traffic sign support	45	1.24
Others	43	1.20	Ditch	37	1.02
Sum	*3615*	*100*	Embankment	37	1.02
Weather			Other fixed object	36	1.00
Clear	2639	73.00	Guardrail end	31	0.86
Cloudy	533	14.74	Other traffic barrier	29	0.80
Rain	205	5.67	Others	206	5.70
Not reported	163	4.51	*Sum*	*3615*	*100*
Fog, smog, smoke	36	1.00	*Int*		
Others	39	1.08	Junction	1315	36.40
Sum	*3615*	*100*	Non-junction	*2300*	*63.60*
			Sum	*3615*	*100*

the total. For light conditions, *daylight* made up 50.04%, *dark-not-lighted* made up 27.58%, and *dark-lighted* made up 17.46%. Crashes occurring at dawn, dusk, and others which are unknown made up 2.13%, 1.6%, and 1.2%, respectively. Regarding weather, the majority of the crashes occurred during *clear* weather (73%). *Cloudy* weather crashes made up less than 14.74%, *rain* made up 5.67%, and fog, smoke, and smog made up 1%. Other crashes, and those not reported accounted for 1.08% and 4.51% respectively. For collision type, *not collision with a motor vehicle (MV)* made up 31.09%, *not a collision with an MV in transport* made up 23.98%, and *front-to-rear* made up 22.02%. Angle collisions followed with a proportion of 11.29%. Front-to-front crashes were 7.22%, and the remaining crash types accounted for 4.39% of the total. For the most harmful event, *motor vehicles in-transport* made up 44.87%. Crashes involving *Pedestrians* comprised 14.63%, rollover/overturn made up 6.69%, and all other attributes comprised 28.09% of the total number of crashes.

3.2. Association rules mining

This study leveraged association rules mining to get a deeper understanding of the time-varying patterns of contributing factors in work zone-related crashes. There has been a notable surge in examining potential temporal fluctuations in the impact of explanatory variables in recent years. Mannering (2018) emphasized the significance of considering temporal elements, as neglecting them can result in flawed conclusions and the formulation of ineffective or potentially hazardous safety policies. Association rules mining by different temporal clusters offers several distinct advantages over commonly employed statistical modeling techniques when analyzing traffic crash data, particularly in the context of work zone crashes. This is primarily because work zone crashes exhibit variations depending on the day of the week, as weekends typically witness a reduced or no presence of workers. Consequently, it becomes necessary to examine the temporal changes in contributing factors using advanced modeling techniques. Researchers have traditionally employed various modeling techniques, such as Poisson regression, negative binomial regression, Poisson-lognormal regression, zero-inflated Poisson and negative binomial regression, to explore the contributing factors of traffic crashes (Lord & Mannering, 2010). Similarly, for investigating factors related to injury severity, approaches such as binary logit, nested logit, ordered logit, ordered probit, and random parameter mixed logit models have been widely utilized (Savolainen et al., 2011). Although these statistical approaches can provide insights into the marginal effects of different risk factors associated with crash risks, they are limited by their predefined assumptions. Consequently, these methods may yield biased or inaccurate findings if the underlying assumptions are violated (Mondal et al., 2020).

In contrast, association rules mining offers several advantages, including superior performance, flexibility in handling data distributions, efficient handling of large datasets, and the ability to uncover latent relationships among numerous variables. One key advantage of association rules mining is its capacity to reveal hidden relationships within large databases. Unlike statistical modeling techniques, association rules mining does not rely on predefined assumptions. Instead, it allows for the discovery and description of relationships between different variables through the formulation of rules (Das et al., 2019; Montella et al., 2012). By utilizing association rules mining, researchers can effectively analyze traffic crash data and gain valuable insights that may not be readily apparent through traditional statistical modeling techniques. This approach enables the identification of complex and non-linear relationships among various factors, providing a more comprehensive understanding of the contributing factors and risk patterns associated with traffic crashes. Moreover, the ability of association rules mining to handle big data efficiently makes it well-suited for analyzing large and complex crash datasets, which are common in traffic safety research

Agrawal and Srikant's apriori techniques were utilized to mine recurrent itemsets and count transactions in the actual world. This algorithm is gaining the attention of researchers in the transportation field due to its ability to identify patterns of contributory factors leading to a particular outcome. One of the key merits of this non-parametric machine learning method is that it does not rely on any prespecified hypothesis or assumptions, which may give rise to modeling issues, as in the case of parametric statistical and econometric methods. Besides, the technique is straight forward, easy to apply, and the results are easy to understand (Das et al., 2019; Pande & Abdel-Aty, 2009; Tamakloe et al., 2022; Tamakloe & Park, 2023). A priori assumes that recurrent sets' subsets frequently occur. The algorithm accomplishes its objectives by mining subsequences or groups of items that often recur in a very large dataset. By considering $I = \{i_1, i_2, \ldots, i_m\}$ as a set of items (for instance, a list of crash classifications for crashes involving motorcycles) and $C = \{c_1, c_2, \ldots, c_n\}$ as a collection of data on database crashes or transactions, where each crash record, c_i, has a subset of items chosen from I, a k-itemset is an itemset with k items. An association rule can be written as Antecedent (A) → Consequent (B). This means that B is likely to occur if A occurs or exists.

In this study, the selection of interesting rules and the determination of association strength are guided by three measures: support (S), confidence (C), and lift (L). The subsequent section provides a comprehensive description of these measures.

3.2.1. Support (S)

Support quantifies the frequency of occurrence of an item set within the dataset. It represents the proportion of transactions covered by the rule in relation to the entire dataset (Hahsler et al., 2005). The support measure can be mathematically expressed using Equation 2.

$$\text{Support}, \ S(A \rightarrow B) = \frac{\sigma(A \cap B)}{N} \tag{2}$$

where $S(A \rightarrow B) =$ support of the association rule $(A \rightarrow B)$, $\sigma(A \cap B) =$ frequency of occurrences with both antecedent and consequent, and $N =$ total frequency of occurrences.

3.2.2. Confidence (C)

Confidence indicates the reliability of a rule by measuring how often it has been found to be true. It assesses the proportion of cases where the occurrence of item set A results in item set B. High confidence for a given $A \rightarrow B$ relationship signifies that B is consistently present in transactions where A is the antecedent (Hahsler et al., 2005). The confidence measure is computed using Equation 3.

$$\textit{Confidence}, \ C(A \rightarrow B) = \frac{S(A \rightarrow B)}{S(A)} \tag{3}$$

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.

3.2.3. Lift (L)

Lift quantifies the observed co-occurrence of the antecedent and consequence compared to the expected co-occurrence. It reflects the ratio between the observed frequency and the anticipated frequency. A lift value exceeding 1 suggests positive independence, indicating that the antecedent and consequent appear together more frequently than expected. Conversely, a lift value below 1 indicates negative independence, implying that the antecedent and consequent appear together less often than expected (Montella et al., 2012). The lift can be expressed using Equation 4.

$$\textit{Lift}, \ L(A \rightarrow B) = \frac{S(A \rightarrow B)}{S(A).S(B)} \tag{4}$$

Identifying the optimized support and confidence are crucial in identifying important and intuitive rules. After several trials and errors, this study used minimum support as 0.1 and minimum confidence of 0.5 for all temporal subsets of data.

4. Key findings

4.1. Temporal clusters by day of the week

Table 3 shows the variables considered antecedent-consequent rules contributing to road traffic crashes for Monday to Thursday work zone crashes. The rules are ordered according to decreasing lift value. Rules are categorized into n-itemsets based on the number of antecedents and consequents, i.e. a rule is a 2-itemset if there is a single antecedent for a single consequent. Rules range from 2-itemset to 4-itemset; nineteen of the rules are 4-itemset, ten of the rules are 3-itemset, and one rule is a 2-itemset. To better understand the rules in the following tables, there is an example of interpreting the rule -A01 *{HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Weather = Clear → Coll = Front-to-Rear}* with support = 0.17, confidence = 0.67 and lift value = 2.70 (frequency = 359). A01 is the rule with the highest lift value. It asserts that work zone crashes happening Monday to Thursday involved segment-related vehicles in transport front-to-rear-end collisions in clear weather. Three indices, support = 0.17, confidence = 0.67, and lift value = 2.75, mean that 17% of Monday to Thursday work zone-related crashes are associated with these three items. In this dataset, out of all work zone crash events, 67% of them have these three items. The percentage of all work zone crashes happening on Monday to Thursday containing this combination is 2.75 times higher than the percentage of work zone crashes happening on Monday to Thursday in the overall dataset. Note that all the variables used in this study, including relation to intersection (Int), were extracted from the FARS database. However, the categories of some of the variables were modified and reduced to achieve a more meaningful representation of the data.

To summarize the findings in Table 3, the most common attributes or common combinations are documented and discussed. The most common attribute is *HarmE = Motor Vehicle In-Transport*, occurring in all rules (six in antecedent and 24 in consequent). It means that the most common collision type for the work zone crashes that occurred from Monday to Thursday is *HarmE = Motor Vehicle In-Transport*. The next most frequent attribute is *Coll = Front-to-Rear* (appears in 29 rules; six in consequent and 23 in antecedents). The complex driving environment may lead to sudden slow-down maneuvers, often leading to front-to-rear (rear-end) crashes between motor vehicles in transport. The other frequent items are *Int = Non-Junction (segment)* in 12 rules, *RoadRel = On Roadway* in 9 rules,

Table 3. Monday to Thursday work zone crashes.

Rule No.	Antecedent	Consequent	S	C	L	#
A01	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Weather = Clear	Coll = Front-to-Rear	0.17	0.67	2.75	359
A02	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Light = Daylight	Coll = Front-to-Rear	0.14	0.65	2.69	300
A03	RU = Rural + HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.12	0.65	2.67	247
A04	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + RoadRel = On Roadway	Coll = Front-to-Rear	0.21	0.64	2.65	447
A05	HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.22	0.64	2.64	452
A06	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + WZ_T = Construction	Coll = Front-to-Rear	0.14	0.64	2.63	296
A07	Coll = Angle	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.15	232
A08	Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.24	1.00	2.15	510
A09	Coll = Angle + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.15	227
A10	RU = Rural + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.15	267
A11	Coll = Front-to-Rear + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.15	334
A12	RU = Urban + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.15	242
A13	Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.15	334
A14	Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.24	1.00	2.15	504
A15	Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.19	1.00	2.15	402
A16	Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.22	1.00	2.15	452
A17	RU = Rural + Coll = Front-to-Rear + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.10	1.00	2.15	217
A18	RU = Rural + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.15	264
A19	RU = Rural + Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.15	247
A20	Coll = Front-to-Rear + WZ_T = Construction + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.10	1.00	2.15	213
A21	Coll = Front-to-Rear + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.15	330
A22	Coll = Front-to-Rear + Light = Daylight + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.15	266
A23	Coll = Front-to-Rear + Int = Non-Junction + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.15	300
A24	RU = Urban + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.15	239
A25	Coll = Front-to-Rear + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.15	332
A26	Coll = Front-to-Rear + WZ_T = Construction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.15	271
A27	Coll = Front-to-Rear + Int = Non-Junction + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.15	296
A28	Coll = Front-to-Rear + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.19	1.00	2.15	397
A29	Coll = Front-to-Rear + Int = Non-Junction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.21	1.00	2.15	447
A30	Coll = Front-to-Rear + Int = Non-Junction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.17	1.00	2.15	359

Note: S: support; C: confidence; L: lift.

Light = Daylight in 7 rules, *Weather = Clear* and *WZ_T = Construction* in 6 rules, *RU = Rural* in 5 rules, *RU = Urban* and *Coll = Angle* in 2 rules. The frequent presence of rural segment and on-roadway crashes indicate that work zone crashes from Monday to Thursday may be highly associated with rural segment sections. The results also show that clear weather and daylight occurred more than six times, which infers that weather or light are not the factors that cause this type of crash. It is also found that the construction type work zone is the most frequent work zone type among the top 30 rules. Rules A08 *{Coll = Front-to-Rear → HarmE = Motor Vehicle In-Transport}* has the highest count of 510. All rules have a lift value over 2, with the highest lift value being 2.75.

Table 4 shows the variables considered as antecedent-consequent rules contributing to road traffic crashes for the Friday work zone crashes, ordered by decreasing lift values. Rules range from 2-itemset to 4-itemset; twenty-two of the rules are 4-itemset, five are 3-itemset, and three are 2-itemset. The rule with the highest lift value is B01 and B02. The rule B01 is *{HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Light = Daylight → Coll = Front-to-Rear},* which is similar to the top rule of work zone crashes from Monday to Thursday. It asserts that work zone crashes on Friday involved segment-related vehicles in transport front to rear-end crashes in clear weather. Three indices, support = 0.11, confidence = 0.67, and lift value = 3.12, mean that 11% of Friday work zone-related crashes are associated with these items. In this dataset, out of all work zone crash events, 67% of them have these items in the rule. The percentage of all work zone crashes happening on Fridays containing this combination is 3.12 times higher than the percentage of work zone crashes occurring on Fridays in the overall dataset.

The most common attribute was *HarmE = Motor Vehicle In-Transport*, occurring in all rules (5 in antecedent and 25 in consequent). *Coll = Front-to-Rear* and *RT = Interstate* occurred 21 times (5 in consequent and 16 in antecedent), which means that Friday work zone-related crashes are often caused by the motor vehicle in transport on the interstate with front-to-rear collision type. Front-to-rear end collisions are less frequent in Friday's top rules than Monday-Thursday. Among the rules in the Friday data, both urban and rural are the same in frequencies (3 times each), which is different from Monday-Thursday rules (rural in 5 rules and urban in 2 rules). The other frequent items are *RoadRel = On Roadway* in 15 rules, *Int = Non-Junction* in 11 rules, *Light = Daylight* in 9 rules, *WZ_T = Construction* in 7 rules, *Weather = Clear* in 5 rules, and *Coll = Angle* occurs in 2 rules. Similar to the Monday-Thursday rules, the construction type work zone is the most frequent work zone type among the top 30

Table 4. Friday work zone crashes.

Rule No.	Antecedent	Consequent	S	C	L	#
B01	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Light = Daylight	Coll = Front-to-Rear	0.11	0.67	3.12	65
B02	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Weather = Clear	Coll = Front-to-Rear	0.14	0.65	3.03	78
B03	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + RoadRel = On Roadway	Coll = Front-to-Rear	0.18	0.62	2.87	103
B04	HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.18	0.61	2.86	105
B05	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + WZ_T = Construction	Coll = Front-to-Rear	0.12	0.61	2.82	66
B06	Coll = Angle	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.34	64
B07	Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.22	1.00	2.34	123
B08	Coll = Angle + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.34	64
B09	Coll = Front-to-Rear + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.34	75
B10	Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.34	78
B11	RU = Urban + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.34	67
B12	Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.21	1.00	2.34	121
B13	Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.34	93
B14	Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.18	1.00	2.34	105
B15	Coll = Front-to-Rear + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.34	73
B16	Coll = Front-to-Rear + Int = Non-Junction + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.34	65
B17	Coll = Front-to-Rear + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.34	76
B18	Coll = Front-to-Rear + WZ_T = Construction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.34	60
B19	Coll = Front-to-Rear + Int = Non-Junction + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.34	66
B20	RU = Urban + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.34	67
B21	Coll = Front-to-Rear + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.34	93
B22	Coll = Front-to-Rear + Int = Non-Junction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.18	1.00	2.34	103
B23	Coll = Front-to-Rear + Int = Non-Junction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.34	78
B24	WZ_T = Construction + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.16	0.75	1.75	89
B25	RU = Rural + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.11	0.74	1.74	61
B26	RU = Rural + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.11	0.72	1.68	61
B27	RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.24	0.71	1.66	135
B28	Int = Non-Junction + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.16	0.71	1.65	94
B29	RU = Urban + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.13	0.71	1.65	74
B30	RU = Rural + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.17	0.69	1.61	95

Note: S: support; C: confidence; L: lift.

rules. Rule B27 had the highest counts of 135. Two rules have a lift over 3 (B01-B02), with the highest lift value being 3.12.

Table 5 shows the variables considered as antecedent-consequent rules contributing to road traffic crashes for 2018–2020, ordered by decreasing lift values. Rules range from 3-itemset to 4-itemset; twenty-one were 4-itemset, and nine were 3-itemset. The rule with the highest lift value is C01 {Coll = Angle → HarmE = Motor Vehicle In-Transport}. This rule has a support value of 0.12, a confidence value of 1.00, and a lift value of 2.35. The meaning of these indices is explained as follows – 12% of weekend work zone-related crashes are associated with these two items. Out of all work zone crash events, 100% of them have these two items. The percentage of all work zone crashes happening on weekends containing this combination is 2.35 times higher than the percentage of work zone crashes happening on weekends in the overall dataset.

The top three most frequent items in the top 30 rules are: HarmE = Motor Vehicle In-Transport occurred 27 times (2 in antecedent and 25 in consequent) RoadRel = On Roadway occurred 22 times (5 in consequent and 17 in antecedent), Coll = Front-to-Rear occurred in 15 rules. Angle collision-related rule having the highest lift value (with 112 occurrences) indicates a significant temporal switch in patterns compared with Monday-Thursday and Friday separately. The top three frequent items show that most crashes are vehicle-to-vehicle front-to-rear end crashes on the roadway segment (not run-off-road crashes). This general finding indicates that although there are some temporal instabilities, the patterns are mostly temporarily stable in a broader perspective. Other common frequent items are: WZ_T = Construction occurred in 8 rules, Int = Non-Junction and Weather = Clear occurred in 6 rules, Light = Daylight occurred in 5 rules, RU = Rural and Coll = Angle occurred in 4 rules, and RU = Urban occurred in 3 rules. Rural crashes are comparatively slightly higher during the weekends compared to weekdays. Rule C25 {WZ_T = Construction + RoadRel = On Roadway → HarmE = Motor Vehicle In-Transport} has the highest count of 258. A total of 14 of the rules have the highest lift value of 2.35 (C01-14), with all of the other rules having a lift value under 2.

The following are dominant patterns found in day-of-the-week-based clusters:

- Angle collision-related rule has the highest lift in weekend rules, which is unique compared to Monday-Thursday and Friday rules. However, the most frequent items for all three temporal clusters *are HarmE = Motor Vehicle In-Transport, RoadRel = On Roadway,* and *Coll = Front-to-Rear.* The results indicate that, while there are some temporal instabilities, the patterns are mostly temporarily stable. A

Table 5. Weekend work zone crashes.

Rule No.	Antecedent	Consequent	S	C	L	#
C01	Coll = Angle	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.35	112
C02	Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.17	1.00	2.35	163
C03	Coll = Angle + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.35	112
C04	Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.17	1.00	2.35	163
C05	Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.35	116
C06	RU = Urban + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.35	105
C07	Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.35	127
C08	Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.35	135
C09	Coll = Front-to-Rear + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.35	116
C10	RU = Urban + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.35	105
C11	Coll = Front-to-Rear + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.35	127
C12	Coll = Front-to-Rear + Int = Non-Junction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.14	1.00	2.35	135
C13	Coll = Front-to-Rear + Int = Non-Junction + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.10	1.00	2.35	97
C14	Coll = Front-to-Rear + Int = Non-Junction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.35	102
C15	WZ_T = Construction + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.15	0.84	1.98	136
C16	RU = Urban + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.13	0.84	1.97	117
C17	RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.22	0.83	1.95	205
C18	RoadRel = On Roadway + Light = Daylight + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.16	0.83	1.95	152
C19	RU = Rural + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.10	0.81	1.91	94
C20	Int = Non-Junction + RoadRel = On Roadway + Light = Daylight	HarmE = Motor Vehicle In-Transport	0.14	0.79	1.85	129
C21	RU = Rural + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.11	0.75	1.77	106
C22	RU = Rural + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.15	0.75	1.77	142
C23	RU = Rural + Int = Non-Junction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.12	0.74	1.74	115
C24	WZ_T = Construction + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.21	0.72	1.70	194
C25	WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.28	0.71	1.66	258
C26	Coll = Angle	RoadRel = On Roadway	0.12	1.00	1.63	112
C27	Coll = Front-to-Rear	RoadRel = On Roadway	0.17	1.00	1.63	163
C28	HarmE = Motor Vehicle In-Transport + Coll = Angle	RoadRel = On Roadway	0.12	1.00	1.63	112
C29	HarmE = Motor Vehicle In-Transport + Coll = Front-to-Rear	RoadRel = On Roadway	0.17	1.00	1.63	163
C30	Coll = Front-to-Rear + WZ_T = Construction	RoadRel = On Roadway	0.12	1.00	1.63	116

Note: S: support; C: confidence; L: lift.

previous study *(5)* examined the injury severity determinants at work zones and identified that rear-end crashes involving vehicles in transport mostly occur in work zones, particularly during inclement weather. Similar to other work zone crash-related studies, there was no temporal stability analysis because it was not considered *(6, 8)*.

- Work zone crashes are more frequent in urban areas on Friday compared to Monday-Thursday and weekends. Yang et al. (2018) showed that many work zones in the urban road network during the workday possess mobility and safety risks.
- Angle crashes are more frequent on weekends when compared with weekdays. Another study *(21)* also shows that angle crash is one of the predominant crashes associated with work zone.

In general, there is a degree of temporal instability concerning the day-of-the-week clusters. Although angle collisions are prevalent on weekends, rear-end crashes are more common on Fridays and Mondays-Thursdays. Identifying this trend can better help policymakers set appropriate countermeasures considering the traffic conditions on different days of the week to mitigate the traffic safety problem.

4.2. Temporal clusters by time of the day

Table 6 shows the variables considered as antecedent-consequent rules contributing to road traffic crashes for daytime work zone crashes ordered by decreasing lift values. Rules ranged from 2-itemset to 4-itemset, with 19 of the rules being 4-itemset, 9 of the rules being 3-itemset, and 2 of the rules being 2-itemset. Rule D01 has the highest lift value among all rules for daytime work zone crashes. Rule *D01{RU = Rural + HarmE = Motor Vehicle In-Transport + Int = Non-Junction, Coll = Front-to-Rear}* means that daytime crashes often happen in rural areas, with the most harmful event as a motor vehicle in transport and front-to-end collision type at non-junction areas. It is reasonable to find that daytime work zone crashes occur more often in non-junction areas because drivers normally become more cautious driving at junctions. The three parameters associated with this rule are support = 0.15, confidence = 0.65, and lift = 2.52. Essentially, the parameters reveal that 15% of the work zone-related crashes occurring during the daytime are associated with these four items in rule D01. In the dataset, out of all work zone crash events, 65% of them have these four items. Also, the percentage of all work zone crashes in the daytime containing this combination is 2.52 times higher than the percentage of work zone crashes in the daytime in the overall dataset.

Table 6. Daytime work zone crashes.

Rule No.	Antecedent	Consequent	S	C	L	#
D01	RU = Rural + HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.15	0.65	2.52	263
D02	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Weather = Clear	Coll = Front-to-Rear	0.18	0.64	2.49	320
D03	DOW = MTWT + HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.16	0.64	2.47	281
D04	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + WZ_T = Construction	Coll = Front-to-Rear	0.15	0.62	2.40	268
D05	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + RoadRel = On Roadway	Coll = Front-to-Rear	0.23	0.62	2.40	408
D06	HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.23	0.61	2.38	413
D07	Coll = Angle	HarmE = Motor Vehicle In-Transport	0.14	1.00	1.90	256
D08	Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.26	1.00	1.90	468
D09	Coll = Angle + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.14	1.00	1.90	252
D10	RU = Urban + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.10	1.00	1.90	184
D11	RU = Rural + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.16	1.00	1.90	284
D12	Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.17	1.00	1.90	303
D13	DOW = MTWT + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.17	1.00	1.90	313
D14	Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.25	1.00	1.90	462
D15	Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.20	1.00	1.90	359
D16	Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.23	1.00	1.90	413
D17	RU = Urban + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.10	1.00	1.90	182
D18	RU = Rural + Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.10	1.00	1.90	189
D19	DOW = MTWT + RU = Rural + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.11	1.00	1.90	205
D20	RU = Rural + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.15	1.00	1.90	280
D21	RU = Rural + Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.12	1.00	1.90	217
D22	RU = Rural + Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.15	1.00	1.90	263
D23	DOW = MTWT + Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.11	1.00	1.90	196
D24	Coll = Front-to-Rear + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.17	1.00	1.90	301
D25	Coll = Front-to-Rear + WZ_T = Construction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.13	1.00	1.90	231
D26	Coll = Front-to-Rear + Int = Non-Junction + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.15	1.00	1.90	268
D27	DOW = MTWT + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.17	1.00	1.90	309
D28	DOW = MTWT + Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.13	1.00	1.90	243
D29	DOW = MTWT + Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.16	1.00	1.90	281
D30	Coll = Front-to-Rear + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.20	1.00	1.90	356

Note: S: support; C: confidence; L: lift.

The attribute *HarmE = Motor Vehicle In-Transport* occurred the most out of all of the attributes, appearing in all 30 rules, which means that, for daytime work zone crashes, motor vehicles in transport are always the harmful event that caused the accident. *Coll = Front-to-Rear* occurred in 28 of the rules. *Int = Non-Junction* occurred in 10 of the rules, and *RoadRel = On Roadway* occurred in 8 of the rules, meaning daytime work zone crashes are highly associated with front-to-rear collision type at non-junction rural roadways. Rural roadways often have less traffic, which may decrease the driver's attention on the road. A front-to-rear crash will likely occur if any work zone complexity leads to the leading vehicle's sudden slow down at non-junction roadways. Weather = Clear occurred in 6 of the rules. This indicates that daytime work zone crashes are less likely to be caused by severe weather conditions. The reason for this is that work zones often would set a lot of signs to remind drivers to be cautious. During severe weather conditions, drivers tend to be even more careful. Therefore, a crash is less likely to happen in that condition. The recurrent items are as follows: *RU = Rural* and *DOW = MTWT* occurred in 7 of the rules, *Weather = Clear* occurred in 6 of the rules, and *RU = Urban, WZ_T = Construction,* and *Coll = Angle* occurred in 2 of the rules. Rule D08 had the highest count of 468. Six rules had a lift count over 2 (D01-D06), with all the other rules having a lift count of 1.90.

Table 7 shows the variables considered as antecedent-consequent rules contributing to road traffic crashes for nighttime work zone crashes ordered by decreasing lift values. Rules ranged from 2-itemset to 4-itemset, with 4-itemset having 18 rules, 3-itemset having 11 rules, and 2-itemset having 1 rule. *E01 {RU = Urban + HarmE = Motor Vehicle In-Transport + Int = Non-Junction, Coll = Front-to-Rear}* means that nighttime work zone crashes often happen in urban areas, with the fault of motor vehicles at non-junction road segments and end up in-to-end collisions. It has a support value = 0.11, confidence value = 0.63, and lift value = 3.41. In particular, these three items are associated with 11% of daytime work zone-related crashes. In this dataset, out of all work zone crash events, 63% of them have these three items. Besides, the percentage of all work zone crashes happening at nighttime containing this combination is 3.41 times higher than the percentage of work zone crashes happening at nighttime in the overall dataset.

The attribute *HarmE = Motor Vehicle In-Transport* was the attribute that occurred the most, appearing in 28 of the rules, implying that nighttime work zone crashes are highly associated with a motor vehicle in transport as a harmful event. *Coll = Front-to-Rear* occurred in 15 rules, illustrating that the major collision type during the nighttime is the front-to-rear type. Similar to daytime work zone crashes, nighttime crashes are highly associated with clear weather, with *Weather = Clear* occurring in 9 rules.

Table 7. Nighttime work zone crashes.

Rule No.	Antecedent	Consequent	S	C	L	#
E01	RU = Urban + HarmE = Motor Vehicle In-Transport + Int = Non-Junction	Coll = Front-to-Rear	0.11	0.63	3.41	192
E02	HarmE = Motor Vehicle In-Transport + Int = Non-Junction + Weather = Clear	Coll = Front-to-Rear	0.12	0.60	3.27	219
E03	Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.18	1.00	2.69	328
E04	DOW = MTWT + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.69	197
E05	Coll = Front-to-Rear + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.69	225
E06	Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.18	1.00	2.69	326
E07	RU = Urban + Coll = Front-to-Rear	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.69	230
E08	Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.15	1.00	2.69	263
E09	Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.69	279
E10	DOW = MTWT + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.69	195
E11	Coll = Front-to-Rear + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.69	223
E12	Coll = Front-to-Rear + WZ_T = Construction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.69	189
E13	Coll = Front-to-Rear + Int = Non-Junction + WZ_T = Construction	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.69	191
E14	RU = Urban + Coll = Front-to-Rear + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.13	1.00	2.69	229
E15	Coll = Front-to-Rear + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.15	1.00	2.69	261
E16	Coll = Front-to-Rear + Int = Non-Junction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.16	1.00	2.69	277
E17	RU = Urban + Coll = Front-to-Rear + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.10	1.00	2.69	184
E18	RU = Urban + Coll = Front-to-Rear + Int = Non-Junction	HarmE = Motor Vehicle In-Transport	0.11	1.00	2.69	192
E19	Coll = Front-to-Rear + Int = Non-Junction + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.12	1.00	2.69	219
E20	RU = Rural + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.12	0.69	1.86	209
E21	WZ_T = Construction + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.20	0.63	1.70	347
E22	Int = Non-Junction + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.18	0.62	1.67	326
E23	DOW = MTWT + WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.14	0.61	1.65	242
E24	WZ_T = Construction + RoadRel = On Roadway	HarmE = Motor Vehicle In-Transport	0.24	0.61	1.63	428
E25	DOW = MTWT + RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.16	0.60	1.62	279
E26	RoadRel = On Roadway + Weather = Clear	HarmE = Motor Vehicle In-Transport	0.29	0.60	1.62	511
E27	DOW = SS + HarmE = Motor Vehicle In-Transport	RoadRel = On Roadway	0.11	1.00	1.59	193
E28	RU = Urban + Coll = Front-to-Rear	RoadRel = On Roadway	0.13	1.00	1.58	229
E29	RU = Urban + HarmE = Motor Vehicle In-Transport + Coll = Front-to-Rear	RoadRel = On Roadway	0.13	1.00	1.58	229
E30	RU = Urban + Coll = Front-to-Rear + Int = Non-Junction	RoadRel = On Roadway	0.11	1.00	1.58	191

Note: S: support; C: confidence; L: lift.

Interestingly nighttime crashes are highly associated with the urban environment, which is presented in 8 rules. Moreover, the non-junction and on-roadways are two characteristics of the locations highly associated with nighttime work zone crashes. Some of the recurrent attributes are *RU = Urban* occurred in 8 rules, *WZ_T = Construction* occurred in 6 rules, *Int = Non-Junction* occurred in 5 rules, *RoadRel = On Roadway* and *DOW = MTWT* occurred in 4 rules, and *RU = Rural* and *DOW = SS* occurred in 1 rule. Rule E26 had the highest count of 511. Two rules had lift values higher than 3, with the highest lift value being 3.41.

The following are dominant patterns found in the day-of-the-week-based clusters:

- Both daytime and nighttime work zone-related crashes are highly associated with non-junction roadways. Both have motor vehicles in transport as harmful events. The results are in line with Zhang and Hassan (2019).
- Both are highly associated with front-to-end collision types. Both are highly associated with clear weather. The findings are consistent with other studies (Meng & Weng, 2011; Weng et al., 2014).
- Daytime work zone crashes are highly associated with rural areas, and nighttime work zone crashes are highly associated with urban areas.

This finding essentially means that work zone crashes are likely to occur on non-junction roadways irrespective of the time of day. Besides, rear-end crashes are common both during the daytime and nighttime. Nevertheless, while daytime crashes are most likely to occur in rural areas, nighttime crashes are likely to occur in urban areas and may suggest insufficient lighting issues at work zones in urban areas and a high incidence of driver distraction or inattentive driving in rural areas. This finding highlights the need to create separate policies for both urban and rural areas to appropriately address the traffic safety problem.

5. Conclusions

Although there is a substantial body of literature on work zone safety, research on temporal patterns of contributing factors is lacking. Within each work zone type (construction, utility, maintenance, and others), traffic control devices, geometric configurations, traffic operations, and human factors. As a result, the likelihood of being involved in a crash and the factors associated with injury severity differ by work zone type, day of the week, and time of the day. In addition, the growing presence of work zones and the difference in driving conditions between day and night and day of the week provide compelling reasons for further research into work zone crashes.

This study contributes novel findings to the existing body of research on work zone crashes, shedding light on the temporal variations and associated factors. The analysis reveals the presence of temporal instability, consistent with previous studies conducted by Mokhtarimousavi et al. (2021) and Zhang and Hassan (2019). However, despite this temporal instability, certain variables consistently exhibit strong associations with work zone crashes, regardless of the temporal dimension considered. The results highlight the significance of front-to-end collision type, non-junction roadways, and clear weather as key contributing factors to work zone crashes. Specifically, drivers on non-junction roads tend to be less cautious while driving, particularly under clear weather conditions. This behavior increases the likelihood of rear-ended collisions, as drivers may become distracted and fail to notice road signs or safely maneuver within work zones. The presence of unexpected debris or obstacles on the roadway further exacerbates the risk of veering off or colliding with other vehicles. Additionally, the analysis reveals a distinct pattern in angle collision-related rules, with the highest lift observed on Fridays, setting it apart from the patterns observed on other weekdays. This finding underscores the importance of tailoring safety interventions and enforcement efforts specifically targeting Fridays, as they exhibit unique characteristics that contribute to work zone crashes. Moreover, the study uncovers a disparity between daytime and nighttime work zone crashes in relation to the surrounding areas. Daytime crashes are highly associated with rural areas, while nighttime crashes are more prevalent in urban areas. These findings emphasize the need for context-specific interventions to address the varying risk factors based on the time of day and the surrounding environment.

The findings of this study on work zone crashes have several practical applications for transportation agencies and road safety practitioners. Understanding the factors that contribute to work zone crashes and their temporal variations is essential for developing targeted safety interventions and reducing the risk of accidents. One practical application of this research is the development and implementation of work zone-specific safety countermeasures. By analyzing the association rules and identifying the primary contributing factors, transportation agencies can design and deploy effective measures to mitigate rear-end crashes and collisions with other vehicles. For example, enhanced signage, improved traffic control devices, and increased enforcement in work zones can help raise driver awareness and reduce the likelihood of crashes. Another practical application is the implementation of safety strategies based on work zone type, day of the week, and time of day. The study revealed that the likelihood of being involved in a crash and the factors associated with injury severity vary depending on these temporal dimensions. Transportation agencies can utilize this information to develop targeted safety campaigns and educational programs. For instance, specific training programs can be designed for drivers who frequently encounter work zones during certain times of the day or on particular days of the week, focusing on the identified high-risk factors associated with those temporal clusters. Furthermore, this research emphasizes the importance of maintaining consistent safety measures regardless of temporal variations. Although some temporal instabilities were observed, certain factors, such as front-to-end collision type, non-junction roadways, and clear weather, consistently showed a strong association with work zone crashes. Transportation agencies can prioritize these factors when implementing safety measures, ensuring their effectiveness across different temporal clusters.

Like any study, this study has several limitations. First, the analysis is only limited to fatal work zone crashes. Future studies can also explore temporal instability issues in all severity crashes. Second, the impact of COVID-19 in 2020 has not been examined separately. A future study can explore this specific issue. Third, the data analysis was conducted by selecting some of the dominating factors. Additional variables, notably exposure variables such as traffic volume information, were unavailable in the dataset. These variables are essential as they provide further insights into the cause of the crashes. These variables should be considered in future studies.

Authors' contributions

The authors confirm their contribution to the paper as follows: study conception and design: S. Das; data collection: S. Das; analysis and interpretation of results: S. Das; draft manuscript preparation: S. Das, A. Dutta, R. Tamakloe, and Md Nasim Khan; All authors reviewed the results and approved the final version of the manuscript.

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References

Behnood, A., & Mannering, F. (2019). Time-of-day variations and temporal instability of factors affecting injury severities in large-truck crashes. *Analytic Methods in Accident Research*, *23*, 100102. doi:10.1016/j.amar.2019.100102

Clark, J. B., & Fontaine, M. D. (2015). Exploration of work zone crash causes and implications for safety performance measurement programs. *Transportation Research Record: Journal of the Transportation Research Board*, *2485*(1), 61–69. doi:10.3141/2485-08

Cheng, Y., Parker, S., Ran, B., & Noyce, D. A. (2016). Work zone crash cost prediction with a least median squares linear regression model. *Transportation Research Record: Journal of the Transportation Research Board*, *2555*(1), 38–45. doi:10.3141/2555-05

Cheng, Y., Wu, K., Li, H., Parker, S., Ran, B., & Noyce, D. (2022). Work zone crash occurrence prediction based on planning stage work zone configurations using an artificial neural network. *Transportation Research Record: Journal of the Transportation Research Board*, *2676*(11), 377–384. doi:10.1177/03611981221092716

Das, A., Ahmed, M. M., & Ghasemzadeh, A. (2019). Using trajectory-level SHRP2 naturalistic driving data for investigating driver lane-keeping ability in fog: An association rules mining approach. *Accident; Analysis and Prevention*, *129*, 250–262. doi:10.1016/j.aap.2019.05.024

Das, S., Dutta, A., Avelar, R., Dixon, K., Sun, X., & Jalayer, M. (2019). Supervised association rules mining on pedestrian crashes in urban areas: Identifying patterns for appropriate countermeasures. *International Journal of Urban Sciences*, *23*(1), 30–48. doi:10.1080/12265934.2018.1431146

Federal Highway Administration (FHWA). (2022). Work zone facts and statistics. https://ops.fhwa.dot.gov/wz/resources/facts_stats.htm

Hahsler, M., Grun, B., & Hornik, K. (2005). Arules – A computational environment for mining association rules and frequent item sets. *Journal of Statistical Software*, *14*(15), 1–25. doi:10.18637/jss.v014.i15

Hong, J., Tamakloe, R., & Park, D. (2020). Application of association rules mining algorithm for hazardous materials transportation crashes on expressway. *Accident; Analysis and Prevention*, *142*, 105497. doi:10.1016/j.aap.2020.105497

Mannering, F. (2018). Temporal instability and the analysis of highway accident data. *Analytic Methods in Accident Research*, *17*, 1–13. doi:10.1016/j.amar.2017.10.002

Islam, M., Alnawmasi, N., & Mannering, F. (2020). Unobserved heterogeneity and temporal instability in the analysis of work-zone crash-injury severities. *Analytic Methods of Accident Research*, *28*, 100130. doi:10.1016/j.amar.2020.100130

Koilada, K., Mane, A. S., & Pulugurtha, S. S. (2020). Odds of work zone crash occurrence and getting involved in advance warning, transition, and activity areas by injury severity. *IATSS Research*, *44*(1), 75–83. doi:10.1016/j.iatssr.2019.07.003

Li, Y., Song, L., & Fan, W. (2021). Day-of-the-week variations and temporal instability of factors influencing pedestrian injury severity in pedestrian-vehicle crashes: A random parameters logit approach with heterogeneity in means and variances. *Analytic Methods in Accident Research*, *29*, 100152. doi:10.1016/j.amar.2020.100152

Li, Y., & Bai, Y. (2008). Development of crash-severity-index models for the measurement of work zone risk levels. *Accident; Analysis and Prevention*, *40*(5), 1724–1731. doi:10.1016/j.aap.2008.06.012

Lyu, P., Lin, Y., Wang, L., & Yang, X. (2017). Variable speed limit control for delay and crash reductions at freeway work zone area. *Journal of Transportation Engineering, Part A: Systems*, *143*(12), 1–10. doi:10.1061/JTEPBS.0000099

Liu, J., Khattak, A., & Zhang, M. (2016). What role do precrash driver actions play in work zone crashes? Application of hierarchical models to crash data. *Transportation Research Record: Journal of the Transportation Research Board*, *2555*(1), 1–11. doi:10.3141/2555-01

Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives. *Transportation Research Part A: Policy and Practice*, *44*(5), 291–305. doi:10.1016/j.tra.2010.02.001

Meng, Q., & Weng, J. (2011). Evaluation of rear-end crash risk at work zone using work zone traffic data. *Accident Analysis & Prevention*, *43*(4), 1291–1300. doi:10.1016/j.aap.2011.01.011

Mokhtarimousavi, S., Anderson, J. C., Hadi, M., & Azizinamini, A. (2021). A temporal investigation of crash severity factors in worker-involved work zone crashes: Random parameters and machine learning approaches. *Transportation Research Interdisciplinary Perspectives*, *10*, 100378. doi:10.1016/j.trip.2021.100378

Mokhtarimousavi, S., Anderson, J. C., Azizinamini, A., & Hadi, M. (2019). Improved support vector machine models for work zone crash injury severity prediction and analysis. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(11), 680–692. doi:10.1177/0361198119845899

Mondal, A. R., Bhuiyan, M. A. E., & Yang, F. (2020). Advancement of weather-related crash prediction model using nonparametric machine learning algorithms. *SN Applied Sciences*, *2*(8), 1–11. doi:10.1007/s42452-020-03196-x

Montella, A., Aria, M., Ambrosio, A. D., & Mauriello, F. (2012). Analysis of powered two-wheeler crashes in Italy by classification trees and rules discovery. *Accident; Analysis and Prevention*, *49*, 58–72. doi:10.1016/j.aap.2011.04.025

Osman, M., Paleti, R., & Mishra, S. (2018). Analysis of passenger-car crash injury severity in different work zone configurations. *Accident; Analysis and Prevention*, *111*, 161–172. doi:10.1016/j.aap.2017.11.026

Pande, A., & Abdel-Aty, M. (2009). Market basket analysis of crash data from large jurisdictions and its potential as a decision support tool. *Safety Science*. *47*(1), 145–154. doi:10.1016/j.ssci.2007.12.001

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. *Accident; Analysis and Prevention*, *43*(5), 1666–1676. doi:10.1016/J.AAP.2011.03.025

Song, L., Fan, W. (., & Li, Y. (2021). Time-of-day variations and the temporal instability of multi-vehicle crash injury severities under the influence of alcohol or drugs after the Great Recession. *Analytic Methods in Accident Research*, *32*, 100183. doi:10.1016/j.amar.2021.100183

Tamakloe, R., Das, S., Nimako Aidoo, E., & Park, D. (2022). Factors affecting motorcycle crash casualty severity at signalized and non-signalized intersections in Ghana: Insights from a data mining and binary logit regression approach. *Accident; Analysis and Prevention*, *165*, 106517. doi:10.1016/j.aap.2021.106517

Tamakloe, R., Lim, S., Sam, E. F., Park, S. H., & Park, D. (2021). Investigating factors affecting bus/minibus accident severity in a developing country for different subgroup datasets characterised by time, pavement, and light conditions. *Accident; Analysis and Prevention*, *159*, 106268. doi:10.1016/j.aap.2021.106268

Tamakloe, R., & Park, D. (2023). Factors influencing fatal vehicle-involved crash consequence metrics at spatio-temporal hotspots in South Korea: Application of GIS and machine learning techniques. *International Journal of Urban Sciences*, *27*(3), 483–517. doi:10.1080/12265934.2022.2134182

Tribby, C. P., Miller, H. J., Song, Y., & Smith, K. R. (2013). Do air quality alerts reduce traffic? An analysis of traffic data from the Salt Lake City metropolitan area, Utah, USA. *Transport Policy*, *30*, 173–185. doi:10.1016/j.tranpol.2013.09.012

Ullman, G. L., Pratt, M., Geedipally, S., Dadashova, B., Porter, R. J., Medina, J., & Fontaine, M. D. (2018). *Analysis of work zone crash characteristics and countermeasures*. Washington DC: *Transportation Research Board.*

Weng, J., Meng, Q., & Yan, X. (2014). Analysis of work zone rear-end crash risk for different vehicle-following patterns. *Accident; Analysis and Prevention*, *72*, 449–457. doi:10.1016/j.aap.2014.08.003

Weng, J., Xue, S., Yang, Y., Yan, X., & Qu, X. (2015). In-depth analysis of drivers' merging behavior and rear-end crash risks in work zone merging areas. *Accident; Analysis and Prevention*, *77*, 51–61. doi:10.1016/j.aap.2015.02.002

Weng, J., Zhu, J.-Z., Yan, X., & Liu, Z. (2016). Investigation of work zone crash casualty patterns using association rules. *Accident; Analysis and Prevention*, *92*, 43–52. doi:10.1016/j.aap.2016.03.017

Yang, H., Kaan, O., Ozgur, O., & Kun, X. (2015). Work zone safety analysis and modeling: A state-of-the-art review. *Traffic Injury Prevention*, *16*(4), 387–396. doi:10.1080/15389588.2014.948615

Yang, D., Zhao, X., Chen, Y., Zhang, X., & Chen, C. (2018). Study on the day-based work zone scheduling problem in urban road networks based on the day-to-day traffic assignment model. *Transportation Research Record: Journal of the Transportation Research Board*, *2672*(16), 14–22. doi:10.1177/0361198118757982

Zhang, K., & Hassan, M. (2019). Crash severity analysis of nighttime and daytime highway work zone crashes. *PloS One*, *14*(8), e0221128. doi:10.1371/journal.pone.0221128