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Data Visualization of Traffic Violations in Maryland, U.S.

Mumen Rababah*[1]; Mohammad Maydanchi[2]; Shaheen Pouya[2]; Mina Basiri[3]; Alireza Norouzi Azad[4]; Fatemeh Haji[5]; Mohammad Amin Jarrahi[6]

1. Department of Industrial Engineering, Faculty of Engineering the Hashemite University, P.O. Box 330127, Zarqa 13133, Jordan
2. Department of Industrial and Systems Engineering, Auburn University, AL, United States
3. Department of Industrial and Systems Engineering, Faculty of Information Technology Engineering, Tarbiat Modares University, Tehran, Iran
4. Department of Engineering Science, College of Engineering, University of Tehran, Tehran, Iran
5. Department of Computer Engineering, Ferdowsi University of Mashhad, Mashhad, Iran
6. Department of Industrial Management, Shahid Beheshti University, Tehran, Iran

Corresponding author: *mumenh@hu.edu.jo*

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ABSTRACT

Nowadays, car use has become so common and inevitable that with a high approximation, it can be said that every family has at least one car. This study analyzes traffic violation data from Montgomery County, Maryland to identify patterns and factors influencing road safety. A dataset with over 1 million records on traffic stops was explored using R and Python. Analysis focused on the most frequent stop causes, seasonal and hourly distribution of stops, and the role of alcohol. Results indicate that failure to obey traffic devices was the top stop reason. Stops peaked in summer months and nighttime hours. The age group with the highest accident rate was young males in their 20s. While alcohol impaired driving is a major concern, the data did not show a significant link between alcohol use and fatalities or injuries. This research provides useful insights into road safety patterns and risk factors. The methodology of data mining and visualizing a large traffic violations dataset demonstrates an effective approach for uncovering actionable insights. Key findings on high-risk driver demographics and stop causes can inform policies to improve road safety.

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1. Introduction

Owning a car in the United States is popular as around 95% of American families own a car [1]. About 1.2 million people die each year from road injuries and between 20 and 50 million live with non-fatal injuries, one of the leading causes of disability for the rest of their lives. With the advancement of technology, medical care can help reduce road traffic deaths in industrialized countries [2,3].

Machines have changed the lives of individuals and communities, but their benefits have come at a price. In recent decades, the number of people killed in road accidents in high-income countries has been declining, but it cannot be ignored that the damage caused by road traffic has been increasing socially and economically for most of the world's population. In developing countries, more than 85% of all deaths and 90% of life years are associated with moderate disability due to road traffic injuries. The approach to enforcing existing laws and regulations to prevent road accidents is often inefficient and flawed [4].

Key risk factors for traffic accidents include distracted or reckless driving, speeding, drunk driving, poor infrastructure, etc. However, the underlying patterns and contributors to road incidents are often complex. Data-driven analysis of traffic violations and associated factors can provide useful insights to enhance road safety policies and strategies.

Studying trends in violations through large datasets reveals high-risk driving behaviors, accident-prone locations and times, demographic factors, and other actionable patterns. For instance, an analysis may find that a certain intersection has a high frequency of accidents due to failure to obey traffic signals. This could lead to interventions like modifying road infrastructure or increasing enforcement at that spot.

Prior research has applied data mining techniques to traffic records to identify risk factors for accidents. However, additional large-scale, in-depth analyses are needed to uncover nuanced trends and influences. This can in turn inform effective interventions tailored to local contexts.

This study provides an example of mining and visualizing patterns from a dataset of over 1 million traffic stops in Montgomery County, Maryland. By exploring factors like stop causes, timing, driver demographics and alcohol involvement, useful insights are derived to improve road safety. The methodology demonstrates the value of leveraging data-driven approaches to deeply understand and address this major public health challenge.

2. Literature review

Road traffic accidents around the world cause severe and irreparable public health problems. Road Traffic Mortality (RTM), Road Traffic Injury (RTIs), and Disability are at the top of the list of road accident results. Traffic injuries include those injured in a car accident but have not had a disability that varies in severity. The severity of road accidents is divided into five levels according to the KABCO scale: fatal injury, debilitating injury, obvious non-debilitating injury, non- repairable injury, and financial loss. More than 1.25 million people worldwide die in road traffic accidents every year. RTIs are the leading cause of death in people aged 15 to 29. According to the World Health Organization (WHO), in 2018, road accidents will cost 3% of GDP (GPD) for most countries. If no action is taken against it, it has the potential to be included in the top 10 causes of death in the world [5,6].

The observed and predicted trend of IRTI shows that men are two to three times more affected than women because men were more active outside the home and used more means of transportation, which led to the increasing number of men in car accidents. A comparison of road traffic accident data reveals that a very small percentage of road accidents in the United States result in death, which could be due to the speed with which injuries are transported and the quality of hospital care. By examining the age range of fatalities due to road traffic accidents, the death of young people (due to injury or death in road traffic accidents) has significant social consequences [7]. Legal restrictions on using a cell phone are crucial in decreasing the number of accidents. In a study of road traffic accidents, they found that 85% of participants in the study reported using a cell phone while driving [8].

The eighth leading cause of death in the world right now is road accidents. Reducing casualties from road traffic accidents is possible by strengthening national road safety laws and implementing proven road safety interventions at the city level. Cases that lead to injuries in road traffic accidents include vigilance control, blood alcohol content, road width, lack of development of mass media campaigns for awareness, hasty driving, lack of access to victims due to non-standard roads, and the darkness of the roads. No evidence that educating teenagers reduces traffic accidents and related injuries but educating teenager drivers only leads to early licensing and may lead to an increase in the average number of teenagers involved in traffic accidents [9,10].

The drivers are the key people in road traffic accidents and driver-centered interventions [11]. Research on road structure and traffic injuries at the international level, analysis of risk factors, and interventions for road traffic and injuries worldwide is growing in recent publications. The development of motor transport leads to a parallel increase in road traffic injuries. Road injuries are a major cause of death for road users between the ages of 15 and 19. Road traffic injuries on road user groups between 10-14, 20-24, and 5-9 years old are the second and third causes of death, respectively. The most vulnerable group is young men [12].

While many drivers obey traffic signs, there is the potential for misconduct due to issues such as driver distraction and aggressive or intentional driving behaviors. Eliminating traffic violations can reduce road accidents by up to 40% [13].The study concluded that red light cameras effectively reduced the total fatalities, but the evidence on the effect of RLCs on red light violations, total collisions, or certain types of fatalities and other violations was inconclusive. They concluded that larger studies with better control were needed, but it shows that RLCs can be reduced. Some types of traffic accidents, especially right-angle accidents, complete injured accidents, and reducing some driving violations such as speeding can be effective. Investigate the effectiveness of traffic lights and traffic regulations on traffic violations Indicates that deterrence may occur if accompanied by a violation [7,14].

There is undeniable growth in automobiles' existence, ownership, and applications these days [15]. The output of automobile ownership models has to be more detailed to address the current policy problems, including supplier selection-related problems [16]. It pertains to the segmentation of the expected automobile fleet, the segmentation of the population, as well as the need to have both short-term and long-term insight into the effect that policy initiatives would have [17,18]. Also, car ownership and vehicle type choice models are sometimes used as stand-alone models to forecast the kilometrage, fuel consumption, and emission of pollutants of the car fleet of some country or region. These models have been coupled with equations for car use (a uni-modal approach), energy use, and emissions. Existing textbook reviews of car ownership models are not very recent [19,20].

The attention to traffic concerns has been steadily improving, reflected in the rapidly expanding investment in traffic-related infrastructure. The rise in the average quality of living of the population has not only resulted in an increase in the total road distance but has also led to an increase in the number of motor vehicles. It is still an essential direction for the government and academic institutions to investigate the elements that influence the number of people who are killed or injured in road traffic accidents and to provide remedies to improve road traffic safety [12,21]. At the moment, many researchers are concentrating their efforts on investigating the elements that impact the number of individuals killed or injured in automobile accidents. These factors include people, cars, and roads. Sun et al. [22], through the regression fitting of traffic accident data, using a zero-inflated negative binomial (ZINB) regression model, found that the seniority of drivers significantly impacts the number of road traffic accidents casualties. It was discovered that gender, accident pattern, driver type, responsibility reasons, and other variables are the primary contributors to the number of people killed or injured in highway traffic accidents [23]. The amount of new road miles is shown to have a considerable influence on the number of people killed or injured in car accidents, according to the findings of several academics whose research focused on road issues. With the increase of new road mileage, the number of road traffic accident casualties will decrease significantly [10].

Researchers have examined various aspects of road traffic accident casualties and road traffic safety. On the other hand, from the point of view of the effect of traffic accident casualties, it is primarily important to investigate the influence of people, cars, and roads on traffic accident casualties in an isolated fashion. At the same time, there is a paucity of research on the incremental influence of many variables. There are few methods to think about the economic-road-population aspects [24]. When it comes to the topic of road traffic safety, the focus is primarily on the macro level; policy recommendations are only based on theoretical analysis; there is a lack of effective data support, and there is very little research on road traffic safety that is conducted through data analysis related to the number of people killed or injured in traffic accidents [9,25].

The actions of drivers have a significant impact on the safety of the traffic. In recent years, the percentage of road traffic accidents that were the consequence of human causes has been as high as 80 percent to 90 percent, as shown by the data about traffic accidents that have been collected from different nations [26,27]. Gilandeh et al. recruited forty drivers to utilize a driving simulator and drive in a variety of settings so that they could determine the human elements that contribute to unsafe driving behaviors [28]. According to different findings, males are sometimes blamed to be responsible for a greater share of the road accidents caused by speeding than women, although in many researches there is no significant difference in the number of accidents caused by male or female drivers [29,30]. There was a link between hazardous behaviors and accidents, which suggests that initiatives to promote corporate safety culture may decrease risky driver behaviors. There was also an indication of a positive association between unsafe behaviors and accidents [31]. When Chuang and Wu tested the stressors of Taiwanese bus drivers using the effort-reward imbalance model (E.R.I.) and the universal ERI scale, they discovered that the primary stressors for professional drivers were physical demands, overtime, and stress-induced sleep problems [32].

It has long been established that drinking alcohol reduces one's ability to drive safely and raises the likelihood of being involved in an accident. Research has shown that when a person is operating a vehicle under the influence of alcohol, the probability of being involved in an accident that results in serious injury or death is high [33]. It is estimated that drunk driving claims the lives of 10,000 people annually in Europe[34]. Accidents caused by drivers under the influence of alcohol account for around 31 percent of all road deaths in the United States[35]. Driving under the influence of alcohol almost always results in a devastating accident. Even if just a trace quantity of alcohol is assumed, drivers have a more significant than twofold increased risk of being involved in a traffic collision compared to sober drivers [36]. Because of this, several nations have spent a significant amount of time and effort working on solutions to the problem of drunk driving over a significant length of time. These solutions include advertising, education, and strict legislation against drunk driving. Laws have been passed that make it illegal to get behind the wheel after consuming alcoholic beverages, and those who do so face harsh penalties [6]. Between 0.01 percent and 0.08 percent is the legal limit for blood alcohol content (BAC). For instance, the limit in Sweden is 0.02 percent, whereas the restriction in Israel, Korea, and Australia is 0.05 percent, and the limit in Canada, England, Mexico, and the United States is 0.08 percent. Drinking and driving are illegal in China if the driver has a blood alcohol concentration (BAC) of 0.02 percent or more, and the motorist will be punished for this offense. In addition, driving with a blood alcohol concentration (BAC) of 0.08 percent or greater is regarded as driving under alcohol, which is a criminal offense [37].

In addition to statistical analysis methods, machine learning and optimization techniques could also provide valuable insights into traffic violations data. Algorithms such as neural networks, random forests, and support vector machines enable detecting complex and subtle patterns in large datasets. These models can uncover nonlinear relationships and interactions between variables that may be difficult to discover through traditional analysis. Furthermore, optimization methods like linear programming and simulation can help determine optimal enforcement and infrastructure strategies based on the insights revealed through analysis. By applying these advanced computational approaches, there is potential to extract deeper knowledge and more nuanced understanding from traffic records. This could lead to improved predictive capabilities and data-driven decision making to enhance road safety. While this study focuses on statistical analysis, the integration of machine learning and optimization methods represents a promising direction for further work [38–43].

However, most existing literature has studied risk factors in isolation rather than through an integrated approach. There is a need for research that holistically analyzes the combined effects of demographic, behavioral, and environmental variables on traffic safety. Studies incorporating large datasets for more comprehensive analysis are also lacking.

This paper aims to address these gaps by performing an in-depth, integrated analysis of traffic violations data encompassing driver demographics, stop circumstances, alcohol impairment, and other factors. The use of data mining and visualization techniques to uncover patterns in a dataset of over 1 million records also represents a novel approach compared to prior work. The findings may provide new insights to guide targeted interventions based on high-risk driving behaviors and groups.

In summary, this study differentiates itself by adopting a multifaceted analytical approach grounded in a substantial dataset. The methodology and integrated perspective taken addresses limitations of previous compartmentalized analyses of traffic safety factors.

3. Methodology

The dataset analyzed was published by Montgomery County Government [44], covering traffic stops made by the county police department. It includes over 1 million records of traffic stops made between 2015-2020. The raw data has 35 attributes capturing information such as violation date and time, location coordinates, driver demographic data, vehicle details, and stop causes or charges. Key fields examined in this analysis include:

Date/time: Date and time of traffic stop, Driver age and gender: Age and gender of pulled over driver, Stop cause: Reason for the traffic stop, e.g. speeding, failure to obey traffic device, Alcohol involvement: Whether alcohol was a factor in the stop

The dataset was retrieved from the Montgomery County Open Data portal. Analysis focused solely on stops made in Maryland, which accounted for 87.3% of the total records. The R and Python programming languages were used to preprocess the data, generate visualizations, and identify patterns through data mining techniques.

The following aspects were analyzed to gain insights into traffic violations and factors influencing road safety: frequency of different stop causes, distribution of stops by time of day and season, demographic analysis of driver age and gender, and the role of alcohol in stops. Both aggregate trends and drill-down analyses were performed to uncover high-level patterns as well as specific relationships in the data.

Visualizations including bar charts, histograms, and heat maps were generated to identify patterns in the frequency of different stop causes, temporal distributions of stops across seasons, months, and times of day, and variations based on driver demographics.

Further investigation focused on examining potential correlations between specific factors like alcohol impairment and outcomes such as fatalities or injuries. Comparative analysis was done to assess the relationships between variables.

Through this mix of data mining, visual data analysis, and exploratory statistics, the patterns and risk factors outlined in the results section were discovered. This methodology enabled deriving actionable insights to improve road safety from the granular traffic violations data.

The use of a large dataset, programming for analysis automation, and focus on synthesizing multidimensional trends aligns well with the study's goal of identifying informative patterns and risk factors. The methodology reflects an effective approach to transform raw traffic violations data into applied intelligence.

4. Results and discussions

As could be seen in Figure 1. that when a driver failed to obey properly to instructions that are on a placed traffic control device was ranked as the most frequent cause for being pulled over among more than 9000 different stops causes, and a simple example for this one is that when a driver ignores no turn left sign.

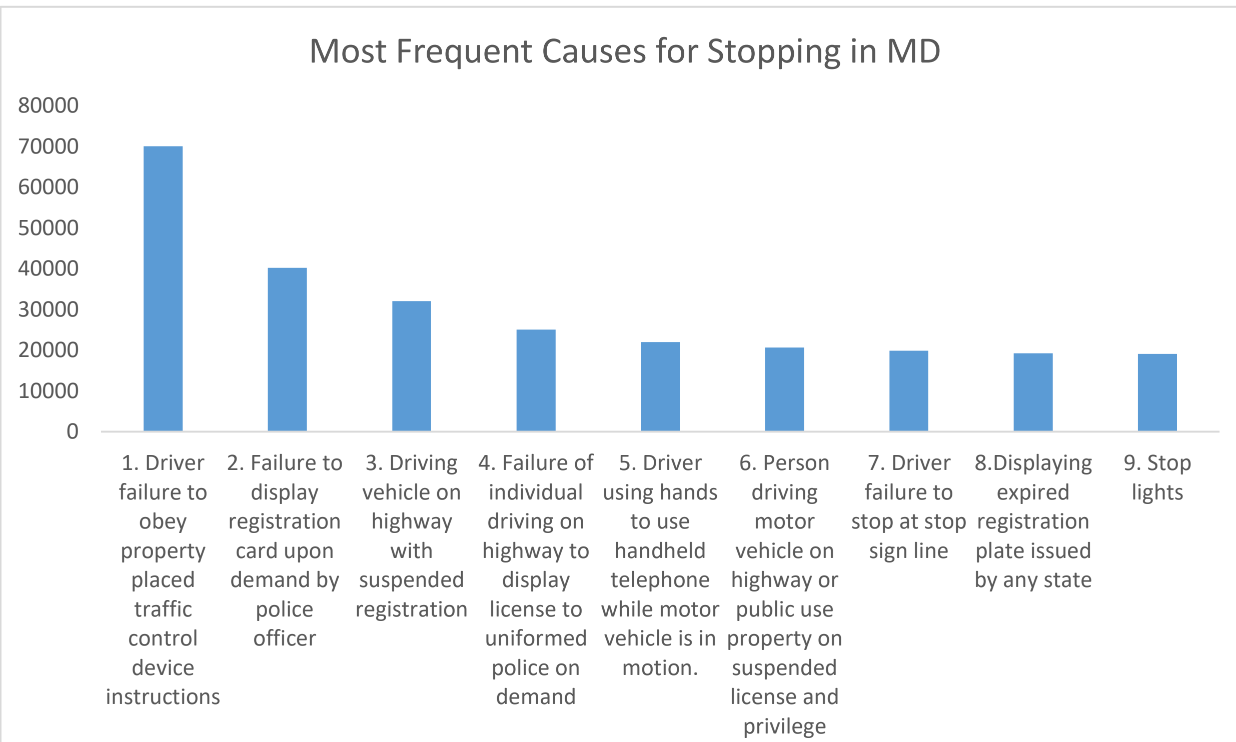

Fig. 1. Most frequent causes for stopping in MD.

More deep analysis regarding time and date was done by analyzing the frequency of stops during each season, as shown in Figure 2. As can be seen in the graph, that winter has 229,998 stops, spring has 215,492 stops, summer has 240,674 stops, and fall has 228,868 stops. So, based on this, a conclusion could be built that getting stops during summer is more probable. Also, the frequency of stops for each month was calculated, and Figure 3. describes the distribution of stops based on months. The significant finding was that the number of stops was the minimum in June.

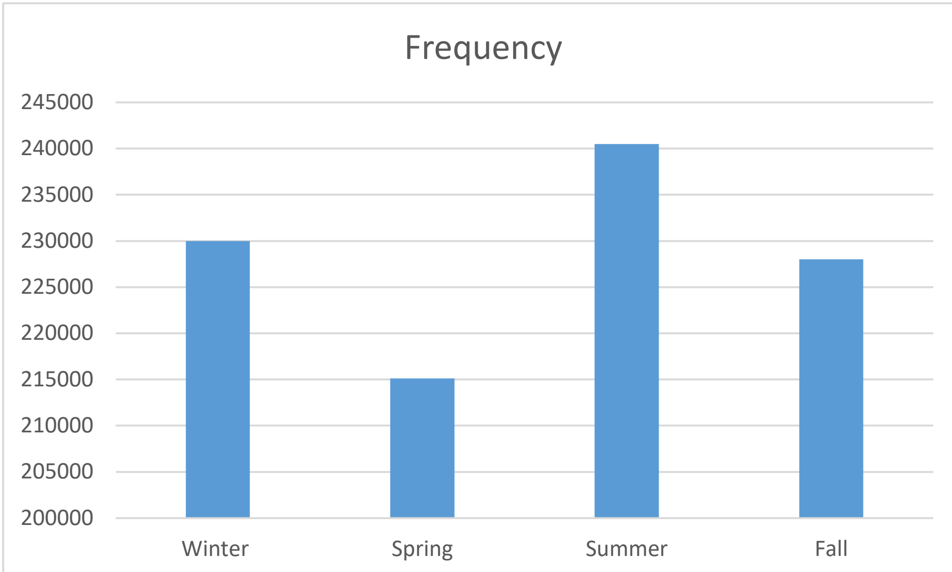

Fig. 2. Distribution of stops based on season in MD.

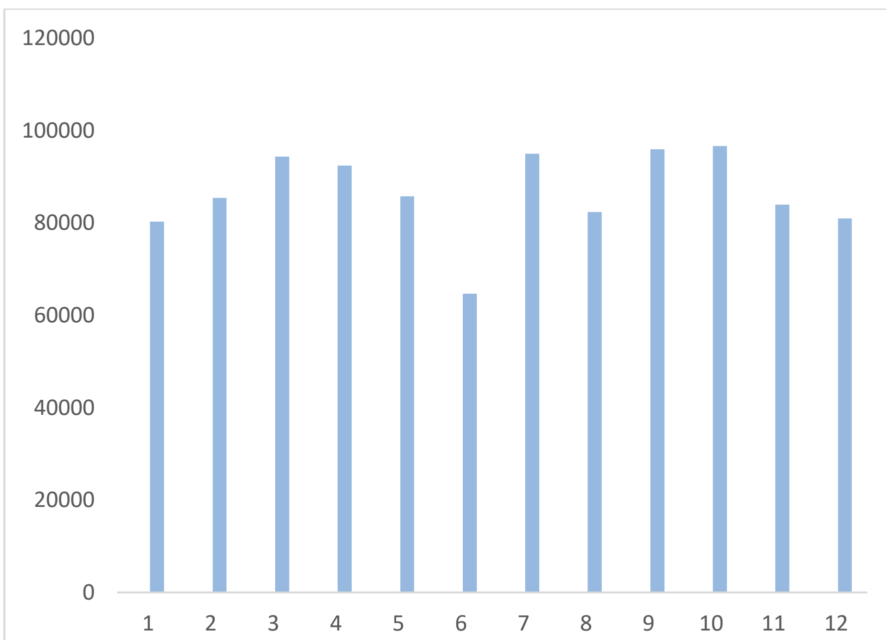

Fig. 3. Frequency of stops per month in MD.

Moreover, knowing which hours of the day have gotten the most stops were questionable. Figure 4. shows the traffic load per hour [45]. These percentages are the rate of stops (relatively to the cars on the streets) per time of day. Notice that we assumed 6 am -12 pm as the morning, 12-6 pm as afternoon, 6 pm -12 am as night, and 12-6 am as midnight. Based on the pie chart, the lowest number of stops was in the mornings with 11%. Also, 17% of stops occurred during afternoons. Nevertheless, most of the stops in Maryland occurred during the midnights. It is reasonable as, during the night, it is possible for drivers not to see signs or be more tired.

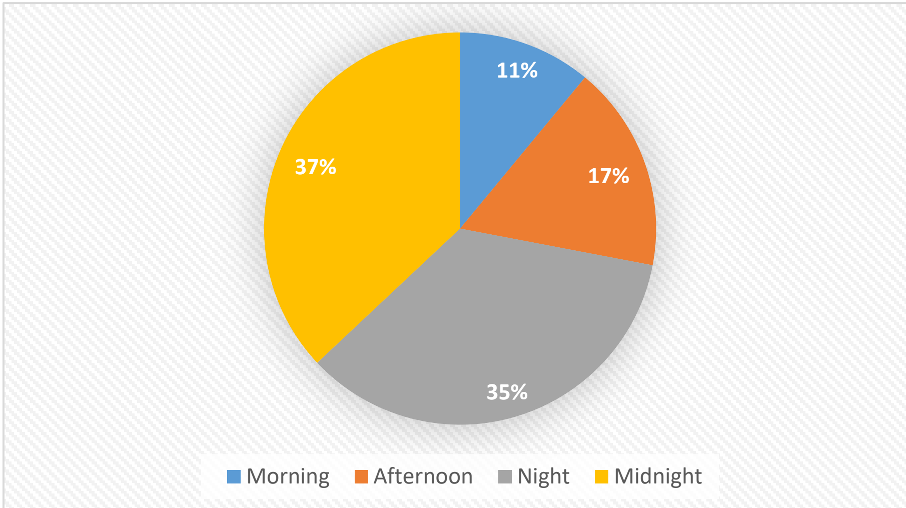

Fig. 4. Percentage of traffic violations based on the hours of the day.

One of the essential questions that a lot of people is asking is if there is a relationship between alcohol and different attributes such as fatal, personal injuries, and properties damaged, and the results were based on Table 1, 2, and 3 that alcohol does not have a significant effect on these attributes.

Table 1
Effect of alcohol on fatal.

Alcohol vs fatal	No	Yes
No	913271	212
Yes	1549	0

Table 2
Effect of alcohol on personal injuries.

Alcohol vs fatal	No	Yes
No	902246	11237
Yes	1508	41

Table 3
Effect of alcohol on properties damage.

Alcohol vs fatal	No	Yes
No	894856	18627
Yes	1391	158

5. Conclusions

This study performed an in-depth data mining analysis of over 1 million traffic violations records to uncover insights into road safety trends and risk factors. Key findings include the identification of failure to obey traffic devices as the top stop cause and young males in their 20s as the top high-risk demographic.

The research makes several notable contributions. It demonstrates the utility of applying data science techniques to extract patterns from traffic violations data. The visualizations and integrated analysis of variables such as stop reasons, time, demographics, and alcohol impairment provides a more holistic perspective compared to compartmentalized analyses.

Another key contribution is the methodology establishing the feasibility of automated analysis of large transportation datasets to inform road safety strategies and interventions. The study also produced specific actionable insights around focusing enforcement and education efforts on high-risk driving behaviors and groups.

However, as an exploratory data-driven study, the research has limitations in establishing causal relationships. Follow-up studies can validate and expand on the identified patterns through more controlled experiments and investigations. There are also opportunities to apply similar big data analytics approaches to traffic records from different contexts.

In summary, this work pioneered a data mining approach for traffic violations analysis to derive insights of value to road safety efforts. It demonstrated the usefulness of leveraging data science to uncover actionable patterns from transportation data. The findings and methodology can inform further research as well as targeted interventions to improve road safety.

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Conflicts of Interest

The authors declare no conflict of interest.

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