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Distracted Driving Crashes: A Review on Data Collection, Analysis, and Crash Prevention Methods

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Abstract

Distracted driving is one of the top three reasons for traffic fatalities. Every year, thousands of people are injured or killed in motor vehicle crashes resulting from distracted driving and recent technological advancements have increased the sources and frequency of distractions. This study provides a comprehensive literature review and a summary of findings for identifying best practices to collect and analyze data on distracted driving and countermeasures to mitigate distracted driving. It identifies literature published since 2006 that focuses exclusively on distracted driving. The results found that the severity of crashes involving distracted driving depends primarily on driver behavior and the geometric design of roadway and temporal variables. It was also found that several techniques exist to collect driver behavior data using dashcam cameras integrated into the dashboard of vehicles. For the detection of distracted driving, deep learning techniques are most often used by researchers. It is also found that the integration of the three Es approach in countermeasures is needed to mitigate distracted driving. These findings will help decision-makers comprehend the significant contributing factors associated with crashes involving distracted driving and implement the necessary data collection, data analysis, and practical treatments to reduce the crash severity. Based on the literature review findings, future research recommendations to address distracted driving are proposed.

Keywords

safety, behavioral safety analysis and program development

According to the National Highway Traffic Safety Administration (NHTSA) definition, "anything that takes the drivers attention away from the task of safe driving is distracted driving." Each year, thousands of people lose their lives because of the crashes resulting from distracted driving. The NHTSA reported 3,142 fatal crashes and 424,000 injuries from motor vehicle crashes involving distracted drivers in the U.S.A. in 2019. Distracted driving contributed to 9% of total fatal crashes in the U.S.A. in 2012–2018 and, almost 23,000 people died as a result of these crashes (*1*).

Distracted driving has been the interest of traffic safety scholars, practitioners, and policymakers since the early 2000s. Researchers from various disciplines have put their efforts into investigating it from the perspective of addressing distracted driving. Depending on the focus of the studies, research on distracted driving can be divided into several categories. For instance, researchers conducted nationwide representative surveys to analyze drivers' perceptions of distracted driving (*2*, *3*). Several transportation agencies like NHTSA have published reports utilizing data from crash reports (*3*). Some researchers have conducted observational studies to interpret the underlying factors of distraction events (*4*, *5*). Other focused on finding the contributing factors of distraction events and associated crashes (*6*, *7*). Lastly,

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recent studies on distracted driving have been focusing more on the detection of distracted driving by capturing real-time images of drivers (*8*, *9*).

A comprehensive literature review needs to be conducted to interpret distracted driving events and associated crashes better. Because of the importance of the case, a literature review of distracted driving involves research from computer science, health care, psychology, human factors, law, and so forth. This study will synthesize the comprehensive literature review on distracted driving and recommend the gaps and future research directions to address this issue. Another important objective of this study is to prepare a summary of the findings from the extensive literature review.

This study highlights the state of knowledge and standard practices in the data collection, analysis, and crash prevention measures of distracted driving over the past two decades. Although endeavors to review distracted driving are made by many researchers, to the best of our knowledge, no previous studies have provided a comprehensive review of all elements (data collection, data analysis, and crash prevention measures) associated with the research on distracted driving. It is expected that the summary of these findings would be helpful to suggest appropriate countermeasures to reduce distracted driving to engineers, practitioners, and policymakers.

The remainder of this paper is structured as follows. The Research Methodology section describes the systematic process of identifying studies focusing on distracted driving. In the Data Collection section, an overall review of the different studies focusing on the collection of data on distracted driving is performed. The Data Analysis section gives a brief review of various techniques of data analysis with regard to distracted driving. In the following section, a description of the contributing factors for distracted driving is provided. Finally, a detailed review is provided of various safety countermeasures that have been proposed for distracted driving. In the conclusion, the previous studies' findings are explained and the gaps in the literature on distracted driving are emphasized.

Research Methodology

To provide a comprehensive view of the current state of practice and of the art in relation to distracted driving, it was necessary to conduct a comprehensive search into what parts of the scientific literature focus on this topic. Database searches were therefore conducted on two well-known databases: the Transport Research International Documentation (TRID) service and Google Scholar. Keywords such as "distracted driving," "distraction," and "texting while driving" were searched for in the title, abstract, and keyword fields, and the scope was restricted to academic papers in English (including journal papers and conference proceedings). To capture any relevant "gray" literature (e.g., professional and agency reports), a Google search was also employed. Although a handful of studies on the topic were published before 2006, the primary focus was given to studies appearing during the last 15 years.

In the first step, 115 relevant papers and reports on distracted driving were gathered. In the second step, their titles, keywords, and abstracts were manually checked and refined to yield only papers specifically dealing with distracted driving. This filtration process reduced the number to 97. A final refinement based on the texts themselves was made, and all the papers for which the full text was available were sorted through this third step. After performing all of these steps, 75 papers were ultimately selected for this literature review. Figure 1 illustrates the stepwise track of this process.

Data Collection

Traditionally, data collected from surveys, crash reports, and observational studies have been used to investigate the dangers of distracted driving. More real-time approaches (e.g., from naturalistic driving studies, dash-cam footage, or eye-glance recorders) have also been introduced. This section will cover these various methods of data collection employed in distracted driving studies.

Survey-Based

Previous researchers have conducted numerous surveys to investigate driver concern and its involvement in distracted driving. Most of these survey studies ranked the level of driver involvement with secondary tasks and correlated this with drivers' behaviors and their perception of distraction. For instance, Braitman et al. (*10*) conducted an ordinal/rank-based online survey of 266 young adult drivers. They demonstrated that those people

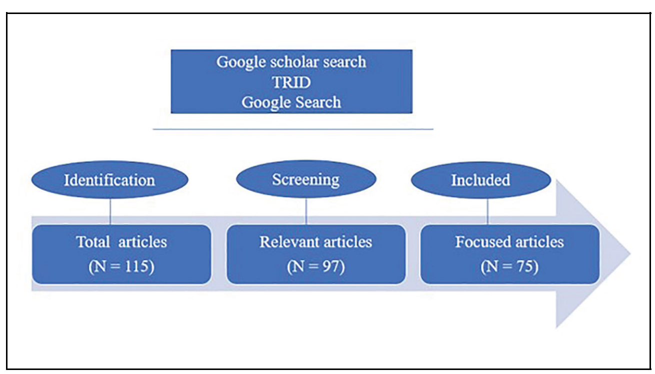

Figure 1. Stepwise track of selection process of the reviewed papers.

engaging in distracting tasks like cellphone usage tend to rate these tasks as moderately risky. In contrast, those people undertaking less distracting tasks admitted that such visually demanding tasks do increase crash risk.

To investigate the driving behaviors and attitudes of Americans, an auto insurance company, The Zebra, operated a closed-end survey of 2,000 people across the U.S.A. (*11*). The authors utilized the Google consumer survey platform and found that 24% of drivers text while driving. Although 36% of the respondents believe that texting is risky, half of them feel cognitive stress about texting back while driving. Through the Survey Sampling International (SSI) platform, the National Security Council (*12*) conducted a poll on 2,409 drivers across the U.S.A., with 75% of respondents admitting that the main pressure on them to receive calls while driving comes from their family. Among these drivers, only 25% admitted that distraction creates dangers to other non-distracted drivers on the road.

Gliklich et al. (*13*) developed a nationwide web-based questionnaire to quantify the frequency of distraction events experienced by adult drivers in the U.S.A. These authors demonstrated that there is a large correlation between cellphone-related distractions and younger driver age. Curry et al. (*14*) performed their research using the National Motor Vehicle Crash Causation Survey (NMVCC), finding that distracted driving is responsible for 20% of the critical errors made by teen drivers.

The NHTSA has conducted the most comprehensive series of surveys on distracted driving, titled the National Survey on Distracted Driving (NSDDAB). Tison et al. (*3*) summarized the findings of a nationwide telephone survey on distracted driving conducted in 2012 by the NHTSA, which utilized household landline phones and cellphones to interview 6,016 drivers across the nation. They found that talking with passengers, adjusting radios, eating, and drinking, and cellphone use are the leading sources of distraction. The younger drivers surveyed in this study were two to three times more prone to cellphone distractions than the other drivers. Overall, talking to passengers, tuning the radio, receiving calls, and eating were the leading sources of distraction while driving (*2*). In a later 2015 telephone survey study, it was found that 42% of respondents admitted that they received calls while driving. Interestingly, 8% of respondents used mobile apps while driving, with over half (56%) of those users believing that using apps while driving is not risky (*15*).

The findings from these nationwide surveys demonstrate that technology is a key factor behind the increased amount of distraction in recent years. Moreover, these studies also indicated that the involvement of younger drivers in distractions and subsequent crashes increases because of technology-oriented secondary tasks (i.e., texting, using apps, or receiving calls).

Observational Studies

Many researchers have conducted observational studies on roadways to analyze distracted driving behavior. Most of these focused on investigating the prevalence of driver distractions involving handheld cellphones and receiving calls (*4, 5, 16–18*). The NHTSA performs nationwide observational studies on intersections during the daytime, titled the National Occupant Protection Use Survey (NOPUS). The 2019 study found that 3.2% of surveyed drivers used handheld phones while driving. Traffic at red light signals was recorded nationwide across 1,612 different intersections during daylight hours (7:00 a.m. to 7:00 p.m.) (*19*).

Bommer et al. (*20*) collected field data in relation to distraction by cellphone use and found that it is more prevalent on local roads and in drive-alone cars compared with highways and in the presence of occupants, respectively. Kidd and Chaudhary (*21*) conducted a roadside observational study across North Virginia and found 23% of the recorded drivers were distracted. Prat et al. (*4*) performed a cross-sectional observational study in Spain to investigate driver distraction events, and demonstrated that distracted driving behaviors vary with temporal variations (e.g., during weekdays or at different times of the day). Sullman et al. (*22*, *23*) conducted two cross-sectional observational surveys in six English cities and found that talking to passengers, smoking, and cellphone use were the leading types of distraction. Gras et al. (*5*) found similar trends in their cross-sectional study across urban areas in Spain.

The findings from these studies give us a perception of the rate of distractions occurring on the observed roadways. However, these studies showed a wide range of variation in the recorded distraction rate (between 5% and 15%). Four reasons contributed to these variable distraction rates: different definitions of distraction, differences in data collection methods, regional differences, and lack of temporal diversity in the data. Regional variations in the observed studies may arise from different traffic densities, roadway geometries, and the strictness of law enforcement (*24*, *25*). More diverse observational studies on distracted driving should be conducted to address the regional and temporal biases of the data.

Cellphone Tracking

Cellphone apps can help in the collection of onboard data related to distracted driving. For example, Bloomberg (*26*) utilized the TrueMotion app to encourage drivers to refrain from using their cellphones by offering incentives. The data it provided showed that handheld cellphone use increases during the holidays. Zendrive (*27*), a smartphone-based platform that collects driver behavior data, is another platform that can be used to analyze cellphone usage while driving. By collecting driver behavior data, State Farm has produced a database of images that can be further used by researchers for training and detecting distracted driving behaviors (*28*).

Crash Reports

Researchers in this field have also made use of crash reports as a way of comprehending the patterns of driving behaviors that contribute to distracted driving crashes. One of the latest reports on distracted driving by the NHTSA investigated distracted driving crash data from 2018 and demonstrated that cellphone use in drivers of less than 40 years of age represents 69% of total drivers that are distracted. The Insurance Information Institute (*29*) used the data provided by the NHTSA to publish an article on the facts in relation to distracted driving occurring in 2017 and 2018. The authors demonstrated that cellphone use accounts for 13% of fatal crashes involving distracted driving.

Stimpson et al. (*30*) investigated the Fatality Analysis Reporting System (FARS) records for 2005–2010 and found that pedestrians and bicyclists have a 1.6 times greater chance of being hit by a distracted driver than by a non-distracted driver. Thus, the authors suggested implementing clear and lighted crosswalks and separate bicycle lanes, as well as measures to prevent distractions while driving. Marchese (*31*) also used data from FARS for crashes from 1991–2015 and found that young males were represented as the group most involved in fatal crashes involving distracted driving. Once again, cellphone use was found to be the leading type of distraction in fatal crashes. These studies utilizing crash reports have been helpful in suggesting countermeasures to policymakers.

Eyeball Tracking/Gaze Detection

Eyeball tracking has also been widely used by researchers to detect distraction by recording pupil movement and recognizing the direction of glance. Liang and Lee (*32*) compared the performance of three detection algorithms—a dynamic Bayesian network (DBN), a layered Bayesian network, and a support vector machine (SVM)—by tracking the eye movements of participants with the faceLAB eye tracker.

Foss and Goodwin (*33*) installed g-force cameras to monitor the behavior of teen drivers and found that they engaged in more cellphone distractions when driving alone than when they drove with another occupant. Owens et al. (*34*) built an in-car system that integrated multiple dashcams, mobile systems, and eyeball tracking technologies to collect data on driver behavior. They found that texting had the effect of degrading driver steering performance, being accompanied by a more prolonged glance away from the road. Carbrall et al. (*35*) utilized an eye tracker to measure gaze direction and found a deterioration in driving performance during visual distractions.

Simulation

Yannis et al. (*36*) conducted a 5 min driving simulation with 34 young drivers by exposing them to different weather conditions and roadway features (e.g., rural roads, rainy weather, or jumping animals). The authors found that texting during driving resulted in slower speeds, an increase in driver reaction time, and an increase in the likelihood of being involved in rear-end crashes.

Klauer et al. (*37*) utilized data from the 100-car naturalistic study to demonstrate that visual distractions decrease a driver's ability to stay in their lane during driving, resulting in safety-critical situations. Using the same data, Liang et al. (*38*) found a positive correlation between crash risk and the degree of distraction estimated from driver eye-glance patterns.

Later on, Liang et al. (*39*) also conducted a simulation of driver behavior on a straight highway and found that driving errors increase by 10% while texting. Gallahan et al. (*40*) utilized the Microsoft Kinect motion-sensing device to detect distraction and to develop a distracted driving warning system in a driving simulator located at the Virginia Driving Safety Laboratory. Using skeletal tracking, this model achieved a classification accuracy of 66%.

Use of Camera

To collect additional data on driver behavior, previous researchers have made use of cameras located on vehicle dashboards and on roadside poles. Victor et al. (*41*) used onboard data from test cars and found that visually demanding tasks (like texting while driving) are associated with high crash risks. Wang et al. (*42*) used images of drivers taken from various angles to assess their attention to driving under distracted and non-distracted conditions and calculated the entropy rate and a glance proportion matrix. They found that a higher scanning randomness level during visual-manual distractions shifts the attention of drivers from their primary task of driving.

Streiffer et al. (*43*) created a unified data analysis framework called DarNet to collect and analyze images of distracted test drivers, finding an increased classification accuracy compared with existing baseline models. De Castro et al. (*44*) used cameras inside the car to track the eye gaze of drivers using the OpenFace model, and achieved a detection accuracy of 84% for distracted driving. Tran et al. (*8*) used dual (front and side) cameras on a driving testbed to capture driver images, and they achieved a detection accuracy of 97%.

Johnson et al. (*45*) captured still images from the NJ Turnpike (https://en.wikipedia.org/wiki/New_Jersey_Turnpike) and found cellphone use was the major source of distraction. Elqattan et al. (*46*) used innovative techniques to collect data from outside the car, either by mounting a camera to a police car or at locations on the roadside. The authors used the Xception model to detect distraction levels, and OpenALPR (with the help of GPS tracking) to detect and report the license plate numbers of distracted drivers.

Data Analysis

Statistical Models/Discrete Choice Models

In their work, researchers have used logistic regression models, ordered logit models, and probit models to analyze the results of distracted driving studies. These statistical and discrete choice models have helped researchers to discover the factors contributing to distracted driving events and crashes. For example, Qin et al. (*47*) used Tukey's test, the chi-square test of independence, the Nemenyi posthoc test, and the Marascuilo procedure in their analysis, and found that vehicle devices (such as GPS, radio, music player) are the major source of distraction-related fatalities among young drivers.

Furthermore, D'Souza (*48*) used multinomial logistic regression and found that driver age and fatigue levels are the most influential factors behind distractions. Jenkins (*49*) likewise used the same method on the SHRP2 NDS data, showing that drivers' performance is affected by their involvement in secondary tasks. Neyens and Boyle (*7*) studied four types of distractions in teen drivers using a multinomial logit model, while Claveria et al. (*50*) analyzed crash severity data on 515 distracted truck drivers using a random parameter logit model.

Many researchers have also employed mixed logit models to address the heterogeneity of the contributing factors. For instance, Hasan et al. (*6*) investigated five years of New Jersey crash data involving cellphone use with a mixed logit model. They found that the urban setting and the age of the driver contribute significantly to the severity of crashes. Cao et al. (*51*) also investigated the SHRP2 naturalistic driving data using a mixed logit model and found that senior drivers are less distracted by cellphones while driving.

Machine Learning/Deep Learning

Machine learning algorithms are helpful in analyzing and detecting distractions, with Liang et al. (*52*) achieved an accuracy of 81% using an SVM. In comparison, Ahangari et al. (*53*) used a Bayesian network to detect distracted driving, with an overall accuracy of 67.8%.

Several researchers have also been working on deep learning techniques to detect distracted driving. Liang and Lee (*32*) achieved 88% accuracy using a hybrid Bayesian model, while De Castro et al. (*44*) achieved 89% using OpenFace—a feature extraction software. Eraqi et al. (*54*) proposed a genetically weighted ensemble of convolutional neural networks (CNNs), producing a reliable deep learning-based system with a detection accuracy of 90%. Later, the authors proposed a thinned version of their ensemble with a classification accuracy of 84%. Abouelnaga et al. (*55*) also presented a robust vision-based system built with a genetically weighted ensemble of CNNs, achieving a 95.98% classification accuracy in driving posture estimation. Their simpler model AlexNet operates successfully in real time with a classification accuracy of 94.29%.

In further examples, Elqattan et al. (*46*) utilized pre-trained models of DarNet YOLO version 3 to detect the drivers inside the car and the Xception model to classify distraction, resulting in detection and classification accuracies of 89% and 95%, respectively. Leekha et al. (*56*) have proposed another CNN-based system to perform real-time distracted driving detection. They achieved 98.48% and 95.64% test accuracies by training their model with images provided by State Farm and the American University in Cairo (AUC).

Mase et al. (*57*) then presented a deep learning architecture that outclasses current CNN models (e.g., VGG-16, Resnet50, Inception V3-LSTM, and an ensemble of InceptionV3 with a GA-weighted algorithm) with an average accuracy of 92.7% when classifying distracted driving postures using static images. Later, Huang et al. (*58*) utilized a hybrid CNN framework (HCF) to detect distracted driving. The authors pre-trained three different detection architectures (i.e., ResNet50, Inception V3, and Xception) using transfer learning, and merged them together to extract driver facial features. Their proposed HCF achieved a classification accuracy of 96% and an average processing time of 0.042 s.

In another approach, Alotaibi and Alotaibi (*59*) proposed a model utilizing one block of ResNet, two layers of a hierarchical recurrent neural network (HRNN) built on top of the Inception architecture, and two dense layers with a softmax classifier. Their proposed method outperformed ResNet and HRNNs alone with an accuracy of over 92%. Baheti et al. (*60*) used the modified CNN architecture VGG-16, achieving a classification accuracy of 95.54%. Later, Baheti et al. (*9*) introduced the Mobile VGG network and achieved 95.24% and 99.75% accuracy after training on the AUC and State Farm datasets, respectively, and with less computational complexity and lower memory requirements. As a final example, Wang et al. (*61*) showed an enhancement of classification accuracy (to 96.97%) by detecting driving operation area during the image preprocessing stage, and they did so using gradient-weighted class activation mapping (grad-CAM).

Contributing Factors

The factors contributing to distracted driving events can be categorized as: driver characteristics, roadway features, environmental features, and crash attributes. This section will summarize the previous research findings in relation to these factors.

Driver Characteristics

Driver characteristics are the most important factors in distracted driving crashes. These include driver age, gender, and fatigue levels, each of which is described below.

Driver Age. This factor has been found to strongly affect the likelihood of being distracted, especially by cellphones. Claveria et al. (*50*), Neyens and Boyle (*7*), and D'Souza (*48*) all demonstrated that younger drivers are more prone to distraction than older drivers.

Gender. Distracted driving crashes are also significantly influenced by the gender of the driver. Behnood et al. (*62*) have found that young male drivers are more prone to distraction than female drivers. However, Qin et al. (*47*) found that young female drivers are more prone to being distracted by in-vehicle technology or devices.

Drivers Fatigue and Workload. Driver fatigue is responsible for many crashes, especially for truck drivers. Claveria et al. (*50*) and D'Souza (*48*) both analyzed crash severity data and found that increased driver workload or fatigue is one of the most important parameters contributing to the severity of distracted driving crashes for truck drivers.

Roadway Features

The geometric design of roadways and other road conditions can also play a vital role in the propensity of drivers to be distracted, and thus to becoming involved in crashes.

Surface Condition. Poor surface conditions are harmful to traffic in all cases. However, their impact is even greater when drivers are impaired by other tasks. Neyens and Boyle (*7*) found that poor surfaces are an important contributing factor to crashes caused by distracted driving.

Urban Setting. An urban driving setting contains more possible distractions than in rural environments because of factors such as congestion, speed limits, and intersections. D'Souza (*48*), Neyens and Boyle (*7*), and Chen and Lym (*63*) all investigated the influential factors behind the severity of distracted driving crashes and found that an urban setting was indeed one major influencing factor.

Type of Roadway. Crash types caused by distraction can also depend on the type of roadway. Behnood et al. (*62*) found that more severe crashes from distracted driving occur on two-way roads. Different types of highway also have an impact on the severity of crashes caused by distracted driving, with Chen and Lym (*63*) finding that Interstate highways have a higher severity level than other roadway types.

Environmental Features

Weather. Because of vision impairment and susceptibility to glare, some drivers face problems in adverse weather conditions. However, clear weather can actually inspire drivers to be distracted, as Behnood et al. (*62*) demonstrated.

Crash Attributes

Type of Crash. Crash type is associated with the severity of a distracted driving event. Neyens and Boyle (*7*) demonstrated that teen drivers are more likely to be involved in fixed object and rear-end collisions, with cellphone distractions resulting in a greater likelihood of rear-end collisions.

Safety Countermeasures

Safety countermeasures are the most important way to reduce traffic crashes. The implementation of such countermeasures against distracted driving can be described with the three Es: engineering, education, and enforcement.

Engineering/Technology

Various transportation agencies and companies provide external and internal engineering countermeasures to minimize crashes involving distracted driving. Previous studies suggested that wider and brighter striping and lighting (*62*) or medians and shoulders (*63*) effectively

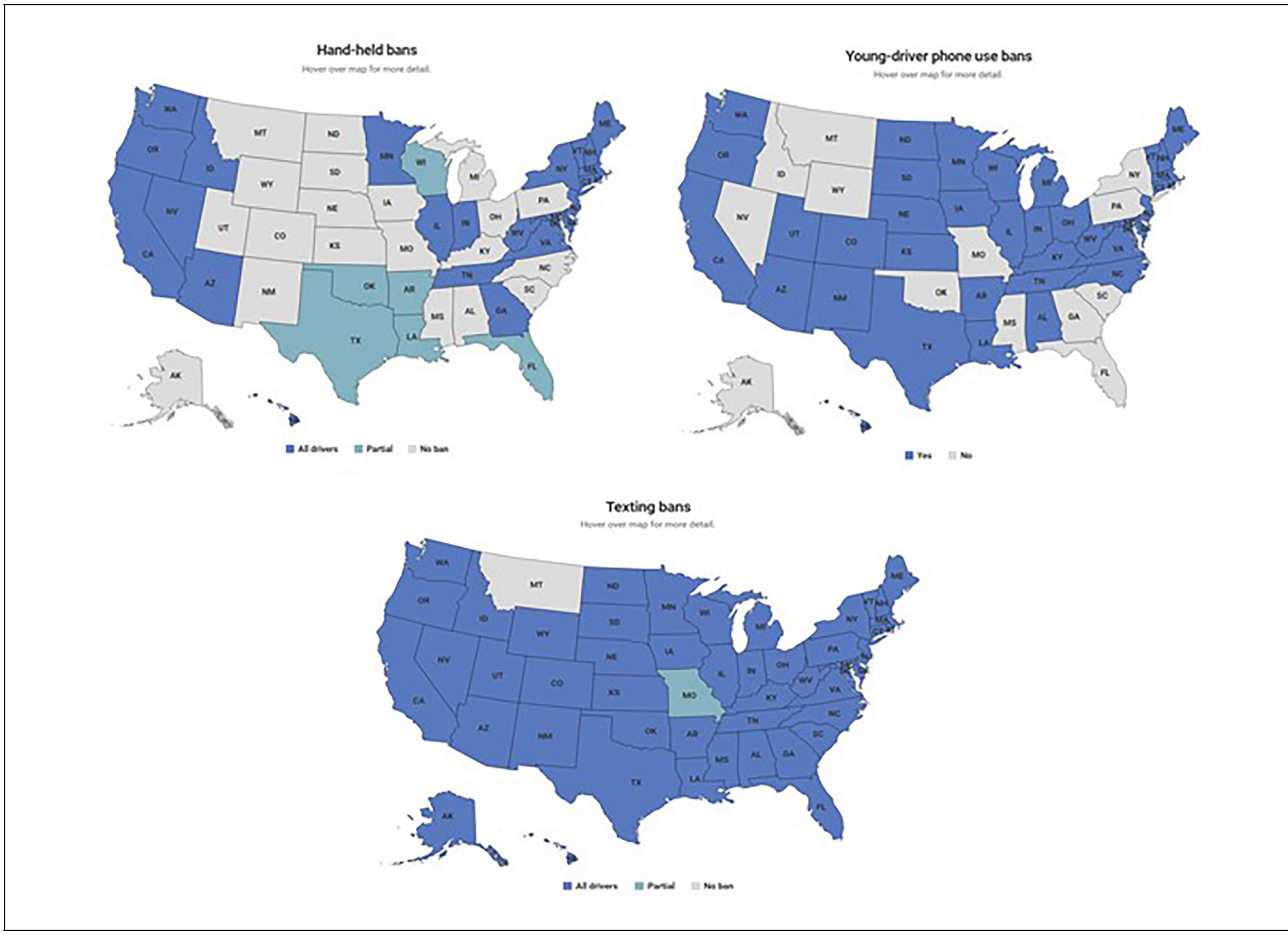

Figure 2. Maps showing bans on cellphone use by drivers across U.S. states: (*a*) handheld cellphone use, (*b*) cellphone use by young drivers, (*c*) texting (*29*).

reduce the severity of crashes caused by distracted driving. Donmez et al. (*64*) demonstrated that the real-time feedback provided to drivers can successfully bring their attention back to the road.

In another example, Ford SYNC helps reduce visual distractions by enabling navigation, mobile communications, and audio device controls through voice commands (*65*). By 2019, there were 29 cellphone applications that blocked features like texting, notifications, or receiving calls while driving. The app most widely used by Android users was Android Auto, while AT&T DriveMode was most widely used by iOS and Blackberry users (*19*).

Education/Awareness

The World Health Organization has suggested that awareness campaigns could help reduce distracted driving (*66*). To train new drivers in adjusting to the dangers of distracted driving, courses like "Impact Texas Teen Drivers" can prove useful (*67*). Other resources, like lesson plans from Toyota and safe driving training courses like Ford Driving Skills, can also be helpful in educating drivers about safe driving (*68*, *69*). Organizations like End Distracted Driving provide free educational materials, including safe driving agreements, quizzes, and surveys to help teen drivers deliver science-based presentations about the dangers of distracted driving to their parents (*70*).

Enforcement of Law

The enforcement of current laws related to distracted driving helps to reinforce the educational and engineering countermeasures. Several laws have so far been passed in many U.S. states, including prohibitions on texting while driving and incremental fiscal punishments for the use of cellphones in general. An overview of these laws across the states is illustrated in Figure 2. To date, 21 states have bans on handheld cellphone use, 48 states have banned texting while driving, and 38 states have banned cellphone use by young drivers (*1*, *2*).

Aceable (*71*) has developed a website that updates the fiscal punishments by state for texting while driving. The Governors Highway Safety Association (GHSA) has also listed the laws on distracted driving and cellphone use across the different states (*72*). The authors of one study by Stim et al. (*73*) demonstrated that the general trend with regard to distracted driving laws is that they have become stricter over time. For instance, the fiscal punishment in Colorado for texting while driving increased from \$50 to \$300 in 2017 (*74*). In Connecticut in 2019, the penalty for first-time violators was \$150, increasing to \$300 for the second violation and \$500 for any further offenses (*75*).

Some states also have rules whereby merit points are deducted for violations of traffic laws related to distracted driving. In Georgia, one point is deducted from the driver's license for the first conviction, two points for the second conviction, three points for the third violation, and so on (*76*). Figure 2 demonstrates that almost all states in the U.S.A. (except Montana) have laws restricting cellphone use while driving.

There have been various strategies employed across the U.S.A. to ensure that distracted driving laws are enforced. For instance, the Police Department of Austin, Texas, has taken the initiative of identifying texting while driving by monitoring drivers from the local mass transit lines running parallel to the roads. This action by officers is legal and is not a violation of drivers' rights (*77*).

Various government agencies have also participated in NHTSA's national high-visibility enforcement campaign "U Drive, U Text, U Pay." The goal of this campaign has been to increase law enforcement efforts against distracted driving by catching distracted drivers. As of February 2020, 21 states, as well as Washington D.C., Puerto Rico, Guam, and the U.S. Virgin Islands, have put into effect total bans on handheld phone use, according to the GHSA. This law prohibits all drivers from using handheld cellphones while driving and includes primary enforcement, thereby enabling an officer to cite a driver for using a handheld phone without there being any other traffic violation.

A study by the NHTSA emphasized that the predeployment training of officers and the reallocation of resources is important for the enforcement of distracted driving laws. Distracted driving enforcement is different from traditional patrol strategies as it requires specialized skills to detect violators who conceal distracting devices. Law enforcement officers should be familiar with distracted driving laws in their jurisdictions. Police departments should also provide training for officers to detect the observable cues of distracted driving and how to document violations appropriately (*78*).

A comprehensive way to mitigate distracted driving crashes or to change driver behavior can only be achieved by appropriate coordination of those entities that ensure the three Es: engineering, enforcement, and education. Technology is an additional tool that can increase the effectiveness of the aforementioned three approaches. For example, updated Bluetooth technologies, drowsiness alert systems, call blocking, and eyeball tracking technologies have added new dimensions to the fight against distraction. Mobile carriers and insurance companies have also enticed drivers by providing discounts or monetary benefits in return for avoiding distractions while driving. Furthermore, the federal government and the NHTSA (*2*) have prepared a blueprint for ending distracted driving through awareness and enforcement approaches, with the expectation of a reduced number of crashes caused by distraction. Finally, a continuous or periodic evaluation of the three Es could help to quantify the safety benefits of particular countermeasures.

Conclusion

Distracted driving is a concern in many fields, including academia, engineering, vehicle manufacturing, traffic safety and the healthcare industry. One of the most important objectives of the studies on distracted driving was to find the contributing factors of distraction-involved crashes. Researchers have found that heavy workloads and environmental factors along with other factors such as driver attributes (age, gender, etc.) and roadway characteristics (type of roadway, surface condition, etc.) contribute to the severity of distraction-related crashes. The most common finding in the literature is the increased involvement of distractions in young drivers, especially with electronic devices. Variations in research approaches are reflected in the different findings, with survey-based methods mainly emphasizing the likelihood of being distracted, while the more comprehensive methods like statistical modeling (logit model, regression model, etc.) and machine learning techniques (Bayesian network, SVM, etc.) investigate the impacts of various contributing factors on crash severity resulting from distracted driving. Recent research on distracted driving has mostly focused on collecting data on driver behavior during distractions by using newer types of equipment (dash camera, pole-mounted camera, eyeball tracker, etc.) and, later, detecting them using artificial intelligence (deep learning algorithms).

Engineering and technology countermeasures (traffic safety improvements like lighting, lane marking and shoulder widening, in-vehicle device synchronizations, tracking apps, etc.) are suggested by the researchers to mitigate distraction-involved crashes. As a measure of enforcement, most U.S. states have strict rules on distracted driving, including increasingly large fines for cellphone use. The lack of effectiveness of these legal measures and their enforcement brings into question their safety benefits. Therefore, education could prove to have a more effective role here. Every road user should be made aware of the dangers of distracted driving through the use of news media, television or radio channels, social media, posters, and awareness campaigns like "U Text, U Drive, U Pay." The U.S. Department of Transportation has arranged for several awareness months in an attempt to reduce distracted driving, and has funded effective awareness campaigns through the state police in various states.

Future survey studies on distracted driving should cover more sociodemographic variation to investigate driving exposure and the factors behind distraction more comprehensively. The inclusion of surrogate safety measures and near misses under various road or environmental conditions could help with research into distraction-related crashes. These studies would help to determine strategic approaches to developing campaigns or educational programs, specifically for those target groups prone to distracted driving. Also, these results can help us to evaluate the effectiveness of short- and long-term enforcement measures (like bans or fiscal punishments) enacted in various states.

When evaluating countermeasures, observational data can also play a significant role, combined with the appropriate use of technology. New techniques like dashcam recording, eyeball tracking, and glance recognition could be used to collect driver behavior data. At the same time, deep learning and other video processing algorithms could prove helpful in the identification of distracted driving. Future studies could also focus on the effectiveness of the countermeasure initiatives promoted by insurance companies and cellphone carriers, whereby cellphone usage is restricted while driving.

Although this study provides new insights into the current research and practice on distracted driving, it has inherent limitations. For instance, this study has only reviewed the literature on distracted driving for the last 15 years. Additionally, this study has covered the studies on distracted driving that focus specifically on data collection and analysis techniques and prevention methods to reduce crashes and incidents involving distracted driving. Any research focusing on the other aspects of distracted driving, such as medical and psychological perspectives, was not included in this study. Limitations of this study could be further improved in future research endeavors with a broader timeline and a cross-disciplinary approach.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: M. Jalayer, A. S. Hasan; data collection: A. S. Hasan, M. Jalayer; analysis and interpretation of results: A. Sajid Hasan, M. Jalayer; draft manuscript preparation: A. S. Hasan, M. Jalayer, E. Heitmann, J. Weiss. All authors reviewed the results and approved the final version of the manuscript.

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