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16. Abstract

This report examines the state of the art and availability of technology to prevent alcohol- and drug-impaired driving by reviewing the progress of automakers, suppliers, and technology developers since 2007, when the *Review of Technology to Prevent Alcohol-Impaired Crashes (TOPIC)* was published. The present examination increases the scope of the 2007 report and focuses on preventing alcohol- and drug-impaired specifically, while considering technologies intended to address other forms of impairment (i.e., drowsiness and distraction).

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Executive Summary

This report examines the state of the art and availability of technology to prevent alcohol-impaired driving by reviewing the progress of automakers, suppliers, and technology developers since 2007 when the *Review of Technology to Prevent Alcohol-Impaired Crashes (TOPIC)* was published (Pollard et al., 2007). The present examination increases the scope of the 2007 report and focuses on detecting and preventing substance-impaired driving specifically, while considering technologies intended to address other forms of impairment (i.e., drowsiness and distractedness) given that these technologies might be able to identify substance impairment in the future.

Alcohol-impaired driving remains a safety concern. In 2020 there were 11,654 fatalities in motor vehicle traffic crashes in which at least one driver was alcohol-impaired, 30 percent of all traffic fatalities in the United States for the year. This represented a 14.3 percent increase in fatalities from alcohol-impaired-driving crashes from the previous year. One alcohol-impaired-driving fatality, in which an alcohol-impaired driver was involved in the crash, occurred every 45 minutes, on average, in 2020 (NCSA, 2022a). Technologies to prevent impaired driving offer the potential to reduce these rates and may provide additional highway safety benefits if they address the crashes that other impairments (i.e., drugs, drowsiness, or distractions) can cause.

This study included three information gathering components: (1) a review of relevant literature, (2) interviews and a site visit to laboratories of a technology developer, and (3) a review of responses to the NHTSA Impaired Driving Technology Request for Information (NHTSA, 2020). First, the literature reviewed relevant studies of alcohol and drug effects on drivers and driving that a technology might detect, and studies of the performance of technologies that can detect the presence in drivers of the substances themselves, and limit or prevent vehicle operation. Second, the research team conducted interviews with a safety advocacy organization, original equipment manufacturers (OEMs), Tier 1 suppliers, researchers, and firms that develop relevant technologies. Third, this report benefited from descriptions of technologies in public responses to the NHTSA Impaired Driving Technology Request for Information published in the Federal Register on November 12, 2020 (NHTSA, 2020). The technologies described in these responses (and others) are summarized later in this report.

The first three sections of this report provide background. After describing the characteristics of impaired driving and impaired drivers, the report reviews literature related to the potential benefits of technology that detects impaired driving and drivers. A recent analysis using data from the Fatality Analysis Reporting System (FARS) suggested that technology that prevents crashes by drivers with blood alcohol concentrations (BACs) $\geq .08$ g/dL would prevent the loss of more than 9,000 lives annually (Farmer, 2020). According to the author's analysis, equipping all vehicles with devices that precisely detect alcohol in drivers, and that prevent vehicle movement if the alcohol exceeds a given limit would achieve this result. Preventing crashes due to drug-impaired, fatigued, or distracted driving would likely further decrease fatal crashes.

This report provides a synopsis of more than 200 identified technologies. The technologies are presented according to their detection function and the sensors used to identify impairment. They include driver monitoring systems (DMSs) that are intended to detect distracted driving and drowsy driving. They also include technologies that are intended to detect distracted driving, drowsy driving, and driving behaviors such as hard braking, rapid acceleration, and speeding. No systems, however, were found that both monitor for distracted or drowsy driving and monitor for substance impairment.

Additional technology types have been conceptualized but not developed into products. These include technologies revealed in patents: detectors of alcohol in the vehicle cabin near the driver's head, and physiological (heartrate and respiration) impairment monitors intended to detect sleep or medical incapacity.

Several technologies have been developed to detect alcohol impairment outside of the vehicle. These include a transdermal sensor in an ankle bracelet that a court can order a person to wear and that transmits results to a probation officer. Transdermal devices detect alcohol through the skin. A study also identified a portable device that tests saliva for various drugs, an ocular device that performs the horizontal gaze nystagmus test for alcohol impairment, and other technologies for use outside of the vehicle. While these are outside of the present scope of in-vehicle technologies to detect alcohol-impaired drivers, additional information was provided in response to the RFI and is included in the Appendix of the report.

Several technologies are currently under development to detect alcohol impairment of drivers. These include technologies that the Driver Alcohol Detection System for Safety (DADSS) program is developing. These technologies detect the presence of alcohol in drivers via breath alcohol concentration (BrAC) or BAC through directed breath analysis, distant breath analysis, and tissue spectrometry. Drivers currently must blow a breath sample toward a sensor (potentially located in the door of the vehicle) in a directed breath analysis. The sensor for distant breath analysis could be located near the speedometer or other location near the mouth of the driver. Tissue spectrometry entails contact between the vehicle (e.g., start button or steering wheel) and the driver's skin. If these technologies detect BrAC or BAC greater than a specified value, the vehicle can activate a countermeasure. Other technologies currently in use to detect driver state use inward facing cameras combined with other sensors. These are currently in use for distraction and drowsiness and are under further development by some OEMs, Tier 1 suppliers, and other companies for alcohol-impairment.

As the 2007 report (Pollard et al.) also found, tissue spectrometry was found to be capable of greater accuracy in alcohol detection than other technologies but, like other technologies, faced vehicle integration and cost challenges. Direct breath technologies require the driver to hold the sensor within an inch or two of their mouth, requiring active driver interaction. Distance breath technologies require no driver actions, but they rely on more diluted breath samples and have the potential to be less precise in alcohol measurement.

Driver monitoring systems require no additional driver-vehicle interactions, but their accuracy in detecting specific substance impairment is unknown. No production-ready vehicle technologies were found in the literature or identified in interviews with stakeholders that specifically detect alcohol.

Introduction

Drivers who have consumed alcohol and other drugs[1] are highly represented in fatal crash statistics (Culhane et al., 2019; Azagba et al., 2019; Elvik, 2013; Romano & Voas, 2011). Efforts to eliminate alcohol-impaired driving have not resulted in decreased alcohol-related crashes over the past decade (NCSA, 2019). For these reasons, it is important to examine the potential for recent developments in vehicle technology to reduce the incidence of alcohol- and driver-impairment-related crashes.

Goal: Updating the TOPIC Report

In 2007 NHTSA published a research report titled *Technology to Prevent Alcohol-Impaired Crashes (TOPIC)* (Pollard et al.). This work identified vehicle-based technologies capable of detecting and preventing alcohol-impaired driving. The report included descriptions and assessments of technologies in use at the time and those under development.

Technologies considered in the 2007 TOPIC report included those that could detect alcohol-impaired driving as part of a primary interlock system (i.e., devices installed on all vehicles regardless of whether or not the driver had any prior driving under the influence (DUI) offenses), as well as devices designed to be used as secondary interlocks only (i.e., devices installed on a vehicle as a result of a DUI offense).

The report also considered countermeasures to reduce alcohol-impaired driving by methods other than directly assessing the driver's BAC or BrAC. Systems assessing vehicle and driver behavior (e.g., standard deviation of lane position (SDLP)[2] and eyelid closure) were included. The report briefly discussed countermeasure alternatives in the form of warnings about their impaired driving (for drivers and law enforcement authorities) that might be used to deter alcohol-impaired driving in the general population.

The authors concluded that secondary interlocks are effective in practice. However, only 8 percent of DUI offenders use them. It also concluded that primary interlocks installed on all vehicles have the potential for wider impact. An analysis of technologies in use and under development concluded that there were no technologies ready for near-term implementation. Other approaches, such as technologies that issue warnings, and adaptive automation[3] had not been tested to determine whether they reduce impaired driving.

Purpose of the Update

Over a decade has passed since the publication of the original TOPIC report and technology has evolved. The goal of this report is to consider current and near-term technologies to eliminate impaired driving crashes, focusing on those technologies that have emerged since 2007. Specifically, drug-impaired driving is also a major concern of many, particularly with the legalization of cannabis in a growing number of States. As a result, the scope is expanded to

[1] As used in this report, "drugs" refers to drugs of abuse. For more information see www.drugabuse.gov/drug-topics.

[2] Standard deviation of lane position is a measure of how much a vehicle's lane position varies. It is frequently used as a measure of a driver's lateral control of the vehicle.

[3] For the purposes of this report, "adaptive automation" is defined as a system that modifies control authority dynamically and flexibly to driving automation systems or to the driver depending on situations (Inagaki, 2003).

address technologies that may have the ability to detect and prevent drug-impaired driving, as well as detecting distraction and fatigue. NHTSA estimates that distracted driving claimed 3,522 lives in 2021 (Stewart, 2023) and drowsy driving resulted in 633 fatalities in 2020 (Stewart, 2022).

Scope of the Update

The current report evaluates vehicle technologies that detect and prevent alcohol-impaired, drug-impaired, drowsy, and distracted driving. One goal of this update is to identify technologies with the potential to detect substance-impaired driving before or during vehicle movement. Furthermore, the study considered technology that may detect alcohol- and/or drug-impaired driving through indirect means such as monitoring the driver's eye closure status and gaze location or lane keeping. This also includes technology designed to detect and potentially prevent other types of problematic driving, such as distracted and/or drowsy driving, while potentially detecting alcohol- or drug-impaired driving at the same time.

This report briefly describes the technologies deemed relevant to detecting or inferring impaired driving, including distracted and drowsy driving. Given the broad scope, this report primarily focuses on some key parameters, including technologies and techniques that are:

- **Intended for all drivers**. The current report emphasizes primary detection methods, that could be used in all vehicles (as opposed to secondary detection methods targeted for DUI offenders).
- **Minimally invasive and passive**. The current report primarily focuses on technologies that OEMs could potentially incorporate into vehicles. For example, the report includes technologies that require only minimal direct driver interactions, such as blowing a breath toward a sensor above the steering column. Although this is the primary focus, technologies are also included in the appendix that are more intrusive or intended to measure alcohol and drugs outside of a vehicle.
- **Near-term**. This is defined as technologies projected to be available for widespread use within the next 5 years.
- **Discoverable**. Technologies and techniques included in the evaluation were limited to those described in articles or patents that can be found in the public domain, those submitted to the RFI (NHTSA, 2022b), or that technology developers described in interviews with the authors.
- **Sufficiently described to evaluate**. To be included, technologies must have sufficient information provided to evaluate. The researchers looked for descriptions of working prototypes with hardware small enough to fit into a private car. Several patents that appear relevant, but which are only high-level concepts without information about how the proposed technology would work are listed, but not described in detail.

Given that this is an update of a previous report, it constrains the literature search to identify relevant publications since 2007 and identifies technologies and techniques that have developed since the publication of the last report.

Range of Countermeasures Under Consideration

This report describes research findings but does not summarize research on the effectiveness of countermeasures taken when the technology detects impaired drivers or impaired driving. The countermeasures in this report include:

- **Primary alcohol interlocks:** Alcohol interlocks are technologies that prevent an alcohol-impaired driver from driving the vehicle.[4]
- **Telematics Service Providers:** Some automakers currently provide telematics connectivity between the vehicle and human operators who can obtain safety services for the driver. An interview with one automaker indicated interest in developing a new concept, where the vehicle would transmit warnings about impaired drivers to a service provider who then would direct the driver to pull over to a safe location or possibly take control of the vehicle.
- **Warnings and Driver Feedback:** Some driver monitoring systems detect drowsy driving and display visual alerts or warnings (e.g., coffee cup symbol). Warnings and alerts are currently issued to the driver, but could, in theory, also include passengers, drivers of surrounding vehicles, an insurance company, or a control center (see telematics service providers, above). In some current vehicle models, distracted and drowsy driving leads to the vehicle giving warnings coupled with continuous attention-level feedback to the driver.
- **Adaptive Automation:** For the purposes of this report, a system that dynamically modifies the allocation of lateral and/or longitudinal control of vehicle performance to the driver or to driving automation systems depending on the situation. Currently under development, adaptive automation could permit greater control of the vehicle by the system when the vehicle detects impaired driving.

Approach

Literature Review

The literature review was conducted in several stages. First, the research team searched for sources and technologies related to alcohol- or drug-impaired driving in three databases: Compendix, Medline, and PsychInfo. Second, the research team reviewed the articles for relevancy. Finally, a last round of literature search was completed by performing a retrospective search examining the references in the relevant articles that were published in 2019-2020 and then a forward search from the references cited in the 2007 TOPIC report. We used the same criteria for relevancy. In addition, Google searches were performed to identify technologies announced in press releases and trade publications.

Patents were searched using the U.S. Patent and Trademark Office website and Google Patents. We also reviewed a list of technologies and patents provided by Mothers Against Drunk Driving

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[4] While there are a number of secondary alcohol interlocks – breath alcohol ignition interlock devices (BAIIDs) -- installed in the vehicles of DUI offenders, the current report concerns primary interlocks that would apply to all drivers.

(MADD) and all comments sent in response to the NHTSA Impaired Driving Technology Request for Information (NHTSA, 2020).

Interviews and Site Visits

As part of the information-gathering process, the team conducted unstructured discussions with subject matter experts and other stakeholders in technology that can detect driver alcohol- and drug impairment or in technology that can detect distracted or drowsy driving but detecting alcohol- or drug-impaired driving would require further development. Additionally, the team conducted site visits to learn more about the DADSS, a system under development to prevent alcohol-impaired driving.

Characteristics of Alcohol- and Drug-Impaired Drivers and Drug-Related Crashes

This chapter examines the findings of recent research on the characteristics of alcohol-impaired crashes and drivers, and on the characteristics of drug-related crashes and of the drivers in those crashes. Understanding these characteristics contributes to the evaluation of preventive technologies and their benefits because the technology may use them to identify impaired driving.

Challenges

Alcohol-impaired driving is a significant problem in the United States and a top concern for the National Highway Traffic Safety Administration. In 2020 there were 11,654 fatalities in motor vehicle traffic crashes in which at least one driver was alcohol-impaired (i.e., 30 percent of all traffic fatalities in the United States for the year). This represented a 14.3 percent increase from the previous year. One alcohol-impaired-driving fatality, in which an alcohol-impaired driver was involved in the crash, occurred every 45 minutes, on average, in 2020 (NCSA 2022a; see Figure 1). These statistics indicate a need to consider alternative strategies, like vehicle technologies, that in conjunction with law enforcement and media campaigns, have the potential to reduce the rate of fatalities associated with alcohol-impaired crashes.

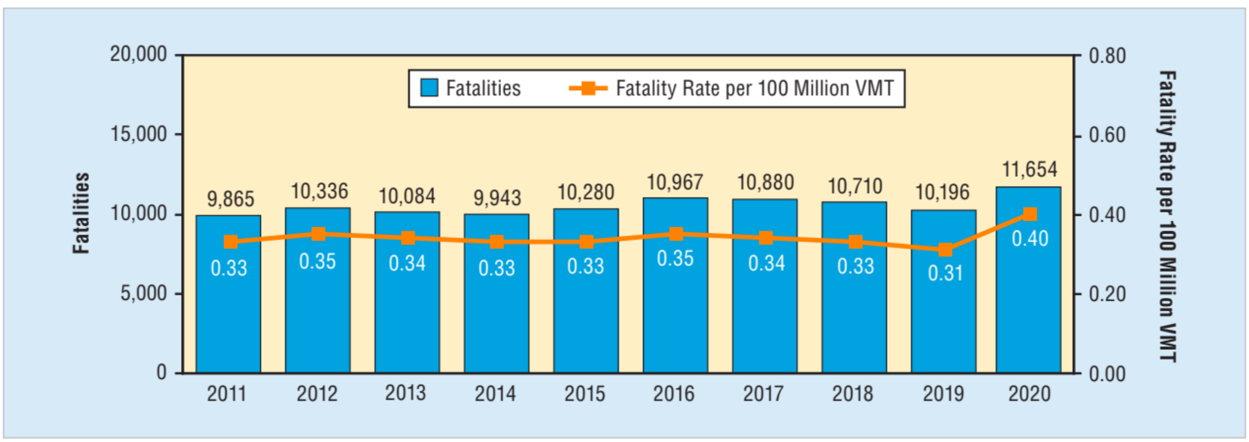

Figure 1. Fatalities and Fatality Rate per 100 Million VMT in Alcohol-Impaired-Driving Crashes. (Source: NCSA, 2022a).

Studies continue to link alcohol-impaired driving with a greater likelihood of a fatal crash (e.g., Culhane et al., 2019). Drugged driving is increasingly also a concern (Azagba et al., 2019; Elvik, 2013; Romano & Voas, 2011). As these studies show, drugs can negatively affect driving. Some drugs may be used with increasing frequency, as suggested by increased legalization of cannabis (Azagba et al., 2019), and more pervasive opioid addiction (Azagba et al., 2019). In this report, "drugs" and "drugged driving" refer to drugs other than alcohol that can cause intoxication while "substances" refers to both alcohol and other potentially impairing drugs.

It is difficult to quantify the extent of the drugged driving problem, given the large and varied number of substances and inconsistencies in testing and reporting (Berning & Smither, 2014). Police can more easily determine if a driver is alcohol-impaired than drug-impaired because testing methods and criteria for alcohol-impaired driving are legally defined. Research shows, however, that the drugged driving problem may be increasing. A study of fatally injured drivers from 2007 to 2017 found that the prevalence of drivers testing positive for drugs increased from 20.7 percent to 30.7 percent over that period (Azagba et al., 2019).

Another challenge in gathering accurate estimations of impaired driving is that the impairment can come from multiple concurrent sources. Drivers may use multiple drugs at a time and/or combine the use of alcohol with the use of other drugs. Further risk can occur when additional impairing factors are present, such as when drivers are drowsy or distracted in addition to being intoxicated. These effects are amplified among young, inexperienced drivers (Jongen et al., 2018).

Characteristics of Alcohol-Impaired Drivers and Crashes

The effects of alcohol on drivers and driving may provide cues that enable technologies to detect impairment. Maistros et al. (2016) examined reports of approximately 14,000 two-vehicle crashes involving an alcohol-impaired operator in Ohio from 2008 to 2012. The data showed that those driving under the influence of alcohol are more likely to engage in other high-risk behaviors, such as speeding and not wearing seat belts (which increase crash outcome severity). In 91 percent of the crashes, the non-impaired drivers were found to be wearing seat belts, whereas only 65 percent of the impaired drivers were wearing seat belts. The risk of serious or fatal injuries was most pronounced on horizontal and vertical curves. Crashes that occurred on curves along vertical grades increased the probability of an incapacitating or fatal injury by 57 percent for the non-impaired drivers. For impaired drivers, such crashes increased the probabilities of incapacitating and fatal injuries by 82 percent and 239 percent, respectively. The two collision configurations that resulted in the most-severe injuries were angle (including side impact) and head-on collisions. Zhou et al. (2015) analyzed wrong-way crashes on Illinois freeways from 2004 to 2009. They found that 50 percent of the drivers were alcohol-impaired and about 4 percent were impaired by other drugs.

Romano and Voas (2011) studied the characteristics of drug- and alcohol-impaired crashes. They used FARS data from 1998 to 2009 to compare the association of alcohol- and drugged driving in four types of fatal single-vehicle crashes: speeding, failure to obey/yield, inattention, and non-use of seat belt. They considered four BAC levels: BAC = .00; .00 < BAC < .05; .05 ≤ BAC < .08; and BAC ≥ .08 g/dL. Those who tested positive for BAC ≥ .08 were most frequently involved in speeding crashes (47%; odds ratio[5] (odds ratio) = 4.2), failure to yield (18%; odds ratio = 1.6), non-use of seat belt crashes (48%; odds ratio = 2.8) and crashes involving inattention (34%; odds ratio = 2.4).

Alcohol-impaired driving includes both impaired driving skill and increased risk-taking (Laude & Fillmore, 2015). Laude and Fillmore (2015) dosed drivers to BAC = .065 in a driving simulation experiment that included a measure of inhibitory control. While driving in the simulator, participants demonstrated reduced inhibitory control, more variation in lane position (reduced skill) and drove closer to the vehicle ahead (increased risk-taking) as compared to placebo-controlled drivers. Each of these effects can contribute to alcohol-impaired crashes.

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[5] An odds ratio expresses the relationship between an outcome such as a fatal crash and exposure, in this example, to BAC ≥ .08. It is the ratio of the outcome given exposure to the outcome with no exposure.

Yadav and Velaga (2019) found a dose-effect relationship between BAC aggressive braking and aggressive acceleration.

Alcohol-impaired driving also shows a dose-effect relationship in which the odds of a fatal crash increase dramatically with BAC ≥ .08 (NHTSA, 2012). In fatal, alcohol-involved, single-vehicle crashes, approximately 90 percent of alcohol-positive drivers tested positive for BAC ≥ .08 (Romano & Pollini, 2013). This study only concerned single-vehicle crashes where the driver was probably responsible for the crash. Shults et al. (2019) found that 82 percent of drivers aged 16 to 20 years who were evaluated at an Arizona trauma center following a crash, tested positive for alcohol BAC ≥ .08 and 60 percent of fatally injured drivers in this age group tested positive for alcohol BAC ≥ .15. Similar findings pertain to the population at large. NHTSA found that 67 percent of fatal alcohol-impaired crashes during 2021 involved a driver who tested positive for BAC > .15 (NHTSA, 2023). A higher driver BAC is typical of fatal crashes.

The Centers for Disease Control and Prevention (CDC) analyzed self-report data from the 2012 Behavioral Risk Factor Surveillance System survey to estimate the prevalence of alcohol-impaired driving (Jewett et al., 2015). The researchers found 80 percent of the alcohol-impaired driving episodes involved male drivers and 34 percent were 21 to 34 years old. NHTSA found similar driver involvement rates per 100,000 licensed drivers in fatal crashes for this age bracket (NCSA, 2022a). Drivers who reported binge drinking self-reported 85 percent of the impaired driving episodes (61% reported binge drinking at least four times monthly). CDC defines "binge drinking" as women drinking four or more alcoholic beverages or men drinking five or more alcoholic drinks on a single occasion (CDC, 2022). Like Maistros et al. (2016), Jewett et al. (2015) found that drivers who wore seat belts less than always were three times more likely to report alcohol-impaired driving than drivers who reported always wearing seat belts. These findings are like the findings of other studies that alcohol-impaired drivers are less likely than others to use seat belts (Romano & Voas, 2011; Shults et al., 2019). Most alcohol-impaired crashes occur during nighttime (e.g., Romano & Pollini, 2013).

In summary, studies have shown alcohol-impaired crashes tend to involve drivers with less ability to exercise lateral control and who are more willing to take risks. Additionally, alcohol has been shown to increase aggressive braking and acceleration. Studies have shown that drivers in fatal crashes often have BACs greater than the limit of .08 and they tend to not wear seat belts as regularly as other drivers.

Technology to prevent impaired driving crashes could use what is known about the characteristics of alcohol-impaired drivers and crashes to help in detecting instances of impairment and respond effectively prior to a crash. Among vehicle measures, a recent meta-analysis found that SDLP was more sensitive to alcohol impairment than other vehicle measures (Irwin et al., 2017). Machine-learning algorithms have correctly classified 81 percent of alcohol-impaired drivers using only vehicle measures (El Masri, 2017; Li et al., 2020). Other studies have found lower estimates of detecting alcohol-impaired driving using vehicle-based sensors, particularly in identifying alcohol-impaired driving when the driver was not also drowsy (Tagawa et al., 2017).

Technology to detect alcohol impairment can also use the physiological effects of alcohol as cues for an alcohol-impairment detection system (e.g., Wu et al., 2016). Chen and Chen (2017) found that a machine-learning algorithm classified alcohol-impaired and sober driving using 20 physiological measurements (heartrate, electromyography, skin conductance, etc.) and vehicle measurements (speed, lane position, steering, etc.) to achieve 70 percent accuracy. In Chen et al. (2018), a machine-learning algorithm correctly classified alcohol-impaired and sober participants with 85 percent accuracy using a photoplethysmogram to non-invasively measure blood pressure. Heartrate measures obtained from an electrocardiogram (ECG) enabled Wu et al. (2016) to achieve accuracy, sensitivity, and specificity of 88 percent, 88 percent, and 87 percent, respectively. Subramaniyam et al., (2018) found in a driving simulator study that alcohol impairment was accompanied by changes in both ECG and electroencephalogram (EEG) measurements. Other studies have demonstrated the effects of alcohol on eye fixation time as well as smooth pursuit and saccadic eye movements (Silva et al., 2017; Fransson et al., 2010), and gaze entropy (Shiferaw et al., 2019).[6] These studies exemplify research on the classification and detection of alcohol impairment technology that could apply to drivers.

Characteristics of Drugged Drivers and Crashes

Like the effects of alcohol on drivers and driving, the effects of other drugs may provide cues that enable technologies to detect impairment. These characteristics include the lateral control of the vehicle and characteristics of the crash (including seat belt use and time of day).

In a sample of 1,194 college students, Arria et al. (2011) found that one in six 19-year-olds with access to cars drove drugged in the past year and that this prevalence remained stable through age 22. The students reported driving during cannabis use in 97 percent of the drugged driving experiences, using cocaine in 13 percent, and misusing prescription analgesics in 4 percent. Of those driving after using cannabis, 16 percent combined cannabis with other drugs. Maistros et al. (2016) found 4 percent of drivers in Ohio to be potentially drug-impaired. O'Malley and Johnston (2013) analyzed a nationally representative sample of about 17,000 high school seniors. They found that 12.4 percent reported driving after using cannabis and 9.2 percent drove after drinking alcohol. The estimates of cannabis use vary, but many young people drive after consuming alcohol and other drugs. Studies that analyze drug data from the FARS database are subject to its limitations (Berning & Smither, 2014) and converging evidence may be required to draw valid conclusions. The detected presence of a drug in a driver, which FARS provides, is not sufficient to indicate impairment and valid comparisons cannot be made over time or across States for reasons that include inconsistent testing procedures.

Romano and Voas (2011) used FARS data from 1998 to 2009 to compare the presence of narcotics, depressants, stimulants, cannabinoids, other drugs, as well as BAC in fatally injured drivers. Their BAC findings are described above in the preceding section of this report. Alcohol and different types of drugs were found in the drivers of vehicles involved in the four types of fatal crashes (see above). Stimulants more than doubled the odds of speeding crashes (odds ratio = 2.5) and failure to obey/yield crashes (odds ratio = 2.1). Drivers who tested positive for stimulants were more frequently involved in crashes with speeding (25.5%) and non-use of seat belt (22.2%) compared with those who did not. Similarly, drivers who tested positive for cannabinoids were more frequently involved in speeding (26.8%) and non-use of seat belt (23.6%).

[6] A smooth-pursuit eye movement is one that follows a moving object. Saccadic eye movements direct the eye toward a stationary object. Gaze entropy measures quantify the spatial distribution of eye movements.

Romano and Pollini (2013) used FARS data from 1998 to 2010 to compare drug and alcohol-involved fatal single-vehicle crashes, and 26 percent tested positive for drugs. The authors indicate that they could not determine concurrent use of alcohol and other drugs. Time of day, gender, and age of driver differed by drug. Apart from stimulant-involved crashes, which tended to occur during the nighttime, other drug-related crashes occurred throughout the day and night. Leufkens and Vermeeren (2014) conducted a study of the effects of the non-benzodiazepine hypnotic drug zopiclone[7] in a highway driving test. Increases in SDLP after use of zopiclone compared with placebo "were significant …, varying from 1.94 cm in … elderly subjects to 4.88 cm in … young subjects" (p. 145), suggesting that the lateral control of younger and less experienced drivers was more sensitive to the lateral control effects of the drug.

Many crashes where drugs may have contributed to driver impairment involve the effects of both alcohol and drugs or two or more drugs, particularly cannabis and stimulants (Romano & Pollini, 2013) in combination with one another and with other types of drugs. In this study, cannabinols were the only type of drugs associated with alcohol in crashes.

In summary, drugs other than alcohol affect driving performance and offer cues that monitoring can potentially detect. Like alcohol, studies have shown that cannabis decreases lateral control (e.g., Hartman et al., 2015) leading to increased SDLP measurements, but also appears to produce compensatory longitudinal driving behaviors: increased headway and reduced speed (Hartman et al., 2016). Although cannabis reduces speed, it is associated with increased crashes involving speeding (Romano & Voas, 2011), suggesting that other factors such as concurrent alcohol impairment, may overcome the compensatory behaviors that are found with cannabis alone (Sewell et al., 2009). Using SDLP to detect cannabis impairment is also complicated by effects that may persist after a driver is no longer acutely intoxicated including steering and braking behaviors (Brown et al., 2019).

Like alcohol impairment, technology to detect impairment from other drugs can also use their physiological effects as cues. Cannabis affects pulse (Crancer et al., 1969) and produces ocular effects including pupil dilation (Bramness et al., 2010). Benzodiazepines[8] also affect both lateral control measurements (SDLP and lane departures, Rapoport et al., 2009) as well as physiological (EEG and heartrate) measurements producing a "signature" of benzodiazepine-impaired driving (Stone et al., 2015).

[7] Zopiclone is a sleeping pill and sedative sold under the brand names Imovane, Zimovane, and Dopareel, among others.

[8] Benzodiazepines are drugs used to treat seizures, insomnia, and anxiety. They include alprazolam (Xanax), clonazepam (Klonopin), and diazepam (Valium).

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Potential for Crash Reduction With Technology to Prevent Alcohol- and Drug-Related Crashes

Potential Alcohol-Impaired Crash Reduction

Statistics from NHTSA's National Center for Statistics and Analysis (Blincoe et al, 2023) report there were 10,142 fatalities resulting from crashes involving alcohol-related driving in 2019. This analysis estimates alcohol-involved crashes account for $69 billion or 20 percent of all economic crash costs.

Using FARS data from 2015 to 2018, Farmer (2020) did an analysis considering the relative risk of involvement in a fatal crash for drivers with various BACs and adjusted for the age of the driver. This analysis found that if all drivers had BACs below .08, approximately 37,636 crash deaths could have been prevented during this 4-year period, an average of 9,409 per year. This assumed perfect performance from an alcohol detection and ignition interlock device and assumed universal use of the alcohol detection and interlock technology.

Carter et al. (2015) took a different approach. They estimated the benefits of primary alcohol interlocks over a 15-year implementation period at the end of which all vehicles would be equipped with devices that would prevent driving if driver BACs exceeded .02. They assert that this technology would prevent 83 percent of alcohol-related crash fatalities and between 84 percent and 88 percent of nonfatal alcohol-related crash injuries. Over the 15-year implementation, the gradual implementation of primary alcohol interlocks would result in 59,554 lives saved and 1.25 million nonfatal injuries prevented. The analysis assumed only vehicles less than 1 year old would have a primary interlock during the first year. The estimates of Carter et al. (2015) are based on 2006- to 2010 FARS and General Estimates System data and assume 100 percent effective technology. This analysis estimated that primary alcohol interlocks would decrease the economic cost of fatal injuries by $260 billion and of nonfatal injuries by $83 billion.

Potential Drug-Related Crash Reduction

If technology to prevent drug-related crashes was developed and implemented, it could further reduce crash-related injuries and fatalities. Interlock technologies exist for BAC, but this study identified no comparable technology that prevents driving when it detects other drugs in the bloodstream. Nevertheless, the benefits of a primary drug interlock, if one were to be developed, would correspond in part to the prevalence of driving after consuming drugs and its associated risk.

The 2013-2014 National Roadside Survey of Alcohol and Drug Use by Drivers tested oral fluid and blood samples of 11,100 nationally representative drivers for the presence of alcohol as well as potentially impairing drugs including cannabinoids, stimulants, sedatives, antidepressants, and narcotic analgesics (Berning et al., 2015). The survey found that 1.5 percent of drivers tested positive for BrAC > .08 (8.3% tested positive for BrAC >.005) during weekend nights when the most positive results were obtained. The researchers also found 15.2 percent of weekend nighttime samples and 12.1 percent of weekday daytime samples tested positive for illegal drugs, and 7.3 percent of weekend nighttime samples and 10.3 percent of weekday daytime samples tested positive for medications that could impair driving. Prescribed medications were found in 5.9 percent of weekend nighttime samples and 8.4 percent of weekday daytime samples. The authors emphasized the presence of a drug did not necessarily mean the driver was impaired by the drug.

Several states have determined legal per se definitions of cannabis impairment, but relatively little research supports their relationship to crash risk. Unlike the research consensus that establishes a clear correlation between BAC and crash risk, drug concentration in blood does not correlate to driving impairment. Together, the prevalence of alcohol- and drug-impairment and the associated risk of crashes result in substance-related admissions to trauma centers. Brubacher et al. (2019) examined 2,318 blood samples and police reports from drivers admitted to trauma centers in British Columbia, Canada. Toxicology analyses found at least one impairing substance in 38.2 percent of the drivers including alcohol (14.4%), tetrahydrocannabinol (THC) (8.3%), other recreational drugs (8.9%), and sedating antidepressant medications (19.8%). Polysubstance use appeared in 11.4 percent of the samples. A significant responsibility risk for alcohol (odds ratio = 6.0), other recreational drugs (odds ratio = 1.82), and sedating drugs (odds ratio = 1.45) was found meaning that police reports assigned responsibility for the crash to the drug-positive driver more than they assigned responsibility to drug-negative drivers. The responsibility analysis did not find a significant correspondence between cannabis and responsibility. Similarly, Thomas et al. (2022) conducted a study of alcohol and drug prevalence among seriously or fatally injured road users admitted to Level 1 trauma centers. The results revealed alcohol was highly prevalent, especially among fatally injured drivers. The most common substance was cannabis (active THC), followed closely by alcohol, with opioids, stimulants, and sedatives also present at notable levels.

Other studies provide evidence for the relatively high risk of alcohol-impaired driving compared to the risk of drugged driving. For example, a meta-analysis of five articles (10 datasets) on the dose-response relationship between alcohol consumption and fatal injury crashes found odds ratio = 13.0 for the risk of a fatal crash with BAC = .08 whereas with BAC = .05, the odds ratio was 1.74 (Taylor & Rehm, 2012). These findings are also generally consistent with those of Romano et al. (2014) who found odds ratio = 14.7 for fatal crashes among alcohol-positive drivers, about nine times higher than that for drug-positive drivers (odds ratio = 1.7).

A systematic review and meta-analysis of 66 epidemiological studies examined the effect of drug use on crashes (Elvik, 2013). This review concerned 11 drug categories excluding alcohol. It statistically combined 264 estimates of drug effects. Amphetamine effects stood out with odds ratios of 5.61 for fatal injury crashes, 6.19 for injury crashes, and 8.67 for property damage crashes. Cocaine (2.96) and benzodiazepines (2.30) also more than double the odds of a fatal crash. The drugs that significantly increased the odds of all three levels of crash severity (fatal, injury, and property damage) were amphetamines, benzodiazepines, and opiates.

Crashes Related to Cannabis

Chihuri et al. (2017) conducted a case control study of 1,944 drivers fatally injured in crashes from 2006 to 2008 and who had received drug tests. These cases were drawn from the FARS database. The 7,719 controls were drawn from the 2007 National Roadside Survey of Alcohol and Drug Use by Drivers (Lacey et al., 2009). Overall, fatal cases were significantly more likely than controls to test positive for cannabis (12.2% vs. 5.9%), alcohol (57.8% vs. 7.7%) and both cannabis and alcohol (8.9% vs. 0.8%). Compared to drivers testing negative for alcohol and cannabis, the adjusted odds ratios of fatal crash involvement were 16.33 for those testing positive for alcohol and negative for cannabis, 1.54 for those testing positive for cannabis and negative for alcohol, and 25.09 (95% CI: 17.97, 35.03) for those testing positive for both alcohol and cannabis. Alcohol use and cannabis use are each associated with significantly increased risks of fatal crash involvement. Dubois et al. (2014) found higher odds of committing a driving error leading to a fatal crash for the combined use of alcohol and cannabis than for either substance alone.

The risk associated with cannabis-impaired crashes is the subject of some disagreement. Rogeberg and Elvik (2016) reanalyzed data from two previous meta-analyses (Asbridge et al., 2012; Li et al., 2012) and conducted a new meta-analysis with an updated set of studies. The updated meta-analysis included 28 estimates from 21 studies. It found odds ratios between 1.07 and 1.81 for the effect of acute cannabis intoxication on the likelihood of crashes, considerably lower than the original studies reported.

Aydelotte et al. (2019) found that crashes increased following legalization relative to control states by 1.2 crashes/billion vehicle miles traveled (i.e., not a significant increase). However, the increase in annual fatal crash rates was larger and statistically significant following the availability of cannabis at commercial dispensaries (+1.8 crashes/billion vehicle miles traveled, CI: +0.4 to +3.7, $p = 0.020$). From this evidence, it appears that cannabis-impaired driving contributes to crash risk.

Crashes Related to Other Drugs

Stoduto et al. (2012) examined a sample of 8,107 drivers in Ontario, Canada, who responded to ongoing cross-sectional telephone surveys in 2002, 2003, 2004, 2006, and 2008. They found that the prevalence of self-reported collision involvement within the previous requested year was 18.9 percent among those who used cocaine in that past year compared to 7.4 percent of non-users. The odds of collision involvement in the preceding year among cocaine users was more than twice that of non-users (odds ratio = 2.11).

A meta-analysis of 11 epidemiological and 16 experimental studies of the effect of benzodiazepines on crash risk found odds ratio = 1.6 for six case-controls and odds ratio = 1.6 also for three cohort studies (Rapoport et al., 2009). The combined six case-control studies using long-acting benzodiazepines produced the odds ratio = 1.61.

Brown et al. (2018) found adverse effects of a commonly prescribed combination of medications in a driving simulator: alprazolam (Xanax), a benzodiazepine combined with a hydrocodone preparation, a combination opiate (Norco), and acetaminophen. Alprazolam significantly decreased lateral control including more lane departures and increased speeds that exceeded the speed limit during the simulated drive. The study found very small to medium-size effects of the hydrocodone preparation, much smaller effects than alprazolam. However, the study used a small sample size of eight participants. As a result, no significant results were found, and no reliable conclusions can be drawn.

Effects of drugs on driving were not always found. Gjerde et al. (2015) examined epidemiological studies of the association between non-alcohol drug use and crash involvement published from January 1998 to February 2015. Statistically significant associations between drug use and crash involvement were found for benzodiazepines and z-hypnotics in 25 out of 28 studies, for cannabis in 23 out of 36 studies, for opioids in 17 out of 25 studies, for amphetamines in 8 out of 10 studies, for cocaine in 5 out of 9 studies, and for antidepressants in 9 out of 13 studies. Using a case control design, Lacey et al. (2016) found after adjusting for gender, age, race/ethnicity, and alcohol, there was no indication that any drug significantly contributed to crash risk. The adjusted odds ratios for THC were 1.00, 95 percent CI [.83, 1.22], indicating no increased or decreased crash risk. Odds ratios for antidepressants were .86, 95 percent CI [.56, 1.33]; narcotic analgesics were 1.17, 95 percent drugs as an overall category were .99, 95 percent CI [.84, 1.18], and prescription and over-the-counter medications were 1.02, 95 percent CI [.83, 1.26].

The results summarized above show consistently lower odds ratios for the effects of other drug categories compared to alcohol, but the odds ratio for drivers who test positive for cocaine, benzodiazepines, and opioids represent up to twice the crash risk compared to drivers who test negative. Although difficult to estimate the benefits, the prevention of drug-related crashes would benefit traffic safety.

The effects of a primary ignition interlock for alcohol or drug impairment (i.e., the vehicle does not shift into gear) may be easier to estimate than that of technology that only warns the driver, which is less certain. No studies supporting the effectiveness of technology that warns drivers when it detects alcohol or drug impairment were found in the literature review. A possible reason may be the fact that the technology may be emerging, and the potential effectiveness has not been evaluated.

On the other hand, the response to feedback from substance-impaired drivers may differ from how distracted drivers respond. Some authors believe that alcohol-impaired drivers would not respond effectively even to a “lane change assistant” that employs both warnings and active lane keeping assistance. A study on this technology sponsored by the European Commission suggests that “a lane change assistant system would not mitigate the effects of alcohol or drugs” (Visvikis et al., 2008). Similarly, Cicchino and Zuby (2017) in an analysis of NHTSA’s National Motor Vehicle Crash Causation Survey, found that 34 percent of drivers who departed their lanes and crashed were “sleeping or otherwise incapacitated … [and] would be unlikely to regain full control of their vehicles if an active safety system prevented their initial [lane] drift. An additional 13 percent of these drivers had non-incapacitating medical issues, BAC $\geq$ .08 g/dL, or other physical factors that may not allow them to regain full vehicle control.”

Adaptive automation provides a concept for countermeasures to alcohol- and drugged driving. It can be defined as a system that modifies control authority dynamically and flexibly to driving automation systems or to the driver depending on situations (Inagaki, 2003). Adaptive automation allows for sharing and trading of vehicle control when the vehicle detects impaired driving. Thus, the vehicle could adapt to impaired drivers with or without warning and drivers could request additional authority for the vehicles when appropriate. The literature search for this report did not yield studies or examples of how adaptive automation might address substance impairment in drivers of passenger vehicles. For this reason, its potential benefits remain unclear.

Costs and Acceptability

Some evidence suggests that not all drivers would pay for primary alcohol ignition interlocks as options when purchasing vehicles (McCartt et al., 2010). This nationally representative survey found that 54 percent of respondents said that they would not want interlocks and of those, 43 percent said that the reason was that they do not drink. Of the 42 percent who said that they would like to purchase this technology, the most common reason was to “prevent drunk driving” (56%).

As a comparison, Sanchez et al. (2012) examined subjective judgments about the acceptability of warning systems for drowsy and inattentive driving from a field test with 197 drivers. An impairment warning, bundled with a lane departure warning displayed a coffee cup with the text "take a break" when the system detected drowsy driving. It did not entirely prevent inattentive driving: 17 percent of the drivers drove while the alert displayed at least occasionally. The drivers said they found the bundled impairment warning and lane departure warning to be both satisfying and useful, particularly in terms of increased perceived safety. Also, they trusted its assessment of their attention/drowsiness. However, even though 60 percent of the drivers said that they were comfortable with the system, few said they would use it or that it was "attractive to buy."

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Metrics Used in Approaches to Prevention of Driving in Impaired States

Detection of additional driver states associated with increased risk are included because it is possible that technology that detects one form of impairment may also detect another or might undergo further development in the future so that it can detect alcohol and drug impairment as well as its original target. They could include technologies that can identify these conditions.

- Alcohol intoxication
- Substance abuse
- Fatigue or drowsiness
- Distraction
- Dementia and other cognitive deficits
- Emotional stress and road rage
- Incapacitating medical emergencies

By “metrics” we mean to include “variable behavioral correlates that may indicate impairment to a sensor.”

More than 200 devices and concepts were found that detect or measure various impairments in drivers. Given this variability, they are grouped in this report in two categories.

1. Assessment of driver state
2. Alcohol detection methods

The measures below are used as indicators of a driver’s state – the consciousness, alertness, and readiness of a driver to perform the dynamic driving task. For each one, sensor types and example systems are discussed, as well as limitations of the technology. Example systems, it should be noted, may employ more than one metric or sensor type.

Assessment of Driver State

Head Position

Head position may indicate a driver’s drowsiness and attentiveness to the forward roadway. That is, a downward head position may indicate drowsiness, or a driver looking at a mobile device. Sensors commonly used to assess or estimate head position include RGB (visible light, red-green-blue) cameras, IR (infrared) cameras, RGB-D (red-green-blue + depth) cameras, lidar (light detection and ranging), radar, and ToF (time-of-flight) cameras. Head position may be a reliable and valid indicator of driver drowsiness and alertness level (Gilbile et al., 2019; Rasna & Smithamol, 2021).

Eye Opening

Eye opening may indicate a driver's attentiveness to the forward roadway. The percentage of time the eyelid closes or "droops" over the pupil over a given period of time, termed "PERCLOS," may be a reliable and valid indicator of driver drowsiness and alertness level (Federal Highway Administration, 1998). Sensors commonly used to assess or estimate eye opening and PERCLOS) include RGB cameras (with algorithms processing recognition of open and closed eyelids), and IR cameras. Researchers have evaluated such systems in driving operational environments (e.g., Boyraz et al., 2008; Vitabile et al. 2010; Wang & Xu, 2016).

Gaze Direction

Gaze direction, sometimes referred to as point-of-regard (POR), or simply "eyetracking" can be used as an indicator of driver drowsiness, distraction, and attention to the forward roadway. Gaze direction can be assessed with head-mounted (e.g., glasses) or vehicle-mounted cameras. Typically, specialized gaze direction systems employ IR cameras, and calculate a distance between the pupil and a corneal reflection to infer the direction of a person's field of view. Vehicle-mounted cameras may employ IR or RGB cameras. There is some evidence of applications of gaze tracking as an indicator of driver drowsiness and distraction (Choi & Kim, 2014; Sonet al., 2017; and Ledezma et al., 2021), however, these articles suggest that the sensitivity and accuracy of systems estimating gaze direction may vary substantially, depending on the methods used.

Pupillometry

Pupillometry, or the measurement of the pupillary response to stimuli, can indicate neurological dysfunction, as an indicator of (neurological) impairment, and as an assessment of cognitive load and attentional performance. Pupillometry had been conducted primarily with infrared cameras, but recent technologies employing algorithms make pupillary assessments with standard RGB cameras. Due to the need to account for external stimuli and lighting conditions, such an assessment may be difficult to conduct safely while driving and can be complicated by variance in lighting conditions when starting the vehicle, though some researchers have explored systems to overcome this challenge (Vitabile et al., 2010; Saifuddinet al., 2020).

Vehicle Control Inputs and Telematics

Recorded data reflecting the inputs a driver makes (e.g., steering, braking) may be recorded to the vehicle controller area network bus, may be indicative of driver drowsiness, attentiveness, or other impairment. By establishing a baseline of driver inputs (e.g., brake pressure, torque, and rate of torque on the steering wheel, acceleration, regularity of speed), prolonged deviation or variability from that baseline may be indicative of impairment. Factors such as time of day and location (via telematics), may be correlated with driver control inputs to account for roadway type and route typically driven. Due to the nature of these indicators, the timeliness of alerts generated may be slower than desired; some driving performance data must accumulate before the determination that a driver was exhibiting control inputs that deviated from those that are typical. Researchers typically explore the use of vehicle control inputs in combination with other metrics from this list (e.g., Gaspar et al., 2017), however, Baccour et al. (2022) found that the addition of driver control inputs in a model added little ability to detect drowsiness (as one example of a driver state) beyond the other metrics used.

Voice

A person's speech patterns are noticeably affected by alcohol consumption, which may give an indication of driver intoxication level. Advanced AI technology, leveraging vocal biomarker technology and machine-learning algorithms, can detect the presence of alcohol intoxication in drivers, based on voice alone (Bonela et al., 2023). By comparing a driver's speech patterns with thousands of previously recorded voice samples that are matched with BAC and functional impairment data, this technology can create highly sensitive sensors. Audio signal processing and machine learning are used to recognize changes in the human voice that may suggest alcohol impairment.

Heart Rate

Heart rate, pulse rate, and associated electrocardiogram (ECG) information may be used as an indicator of driver drowsiness. Heart rate can be assessed via sensors embedded in the steering wheel, seat belt, seat, or other areas of contact with the driver. Sensors may also be applied via dedicated wearable devices. While heart rate may indicate driver drowsiness, the reliability of the measure and conditions in which heart rate may also lower (e.g., calm, clear sections of highway) may make heart rate a less than adequate measure for driver monitoring system purposes. Researchers have described the feasibility of heart rate as an indicator or metric of drowsiness (e.g., Tateno et al., 2018; Wadhwa & Roy, 2021), however, researchers have not reached consensus as to the sensitivity and specificity of such technologies.

Respiration Rate

Respiration rate may serve as an indicator of driver drowsiness. Respiration rate may be measured by measuring the expansion and contraction of the chest or torso as a driver inhales and exhales. Typically, and in medical applications, this measurement is observed with a wearable "chest strap" type device. Technologies are being explored that aim to measure respiration via sensors in the seatbelt, while others use RGB or ToF cameras and computation of expansion and contraction of the torso, without requiring a wearable device. Teteno et al. (2018) suggested that respiration rate may be a feasible metric of drowsiness, and Guo et al. (2022) stated that noninvasive heart rate measures "could *one day* be a key enabler to sudden sickness or drowsiness detection in DMS" (p. 1) [emphasis added].

Electroencephalogram

Electroencephalogram (EEG), or brain wave data may be an indicator of driver alertness. By measuring components of the EEG, a measure of wakefulness may be determined. Typically, EEG recording requires a cap with an array of sensors, either across the entire scalp, or regions of interest. Some technologies are in development which may obtain an EEG signal via a smaller (e.g., in-ear) wearable device. The intrusiveness of such a wearable device, and the need for direct, physical contact with the driver, may present a substantial obstacle to adoption and user acceptance of such technologies in a driver monitoring application. Stancinet al. (2021) concluded that greater incorporation of EEG signatures is needed to improve drowsiness detection to desired levels. Houshmand et al. (2022) found that with specific calculations, a 91 percent sensitive detection system could be achieved from only one EEG sensor. It should be noted, however, that sensors placed directly on a driver's head would likely be too intrusive for broad implementation and user acceptance. Some systems purport to measure EEG via steering wheel mounted or wearable (e.g., earpiece) sensors, but presently it is too early in such systems' development lifecycle to evaluate their efficacy as a driver drowsiness detection system.

Cognitive Assessment Batteries

Many behavioral and physiological indicators are described above. These systems do not detect alcohol, but rather what they sense may be indicative of drowsiness, distraction, or incapacitation. It should be noted that this is not an exhaustive list of driver monitoring technologies, and that the description of driver monitoring technologies was gathered from company websites and may not reflect current iterations of these systems.

Example Systems

Table 1 below presents examples of proposed driver monitoring systems, including ones that detect alcohol or infer alcohol impairment from nystagmus.

Table 1. Example Systems and Metrics for Driver Monitoring

Vendor / Device	Metric														
	Head Position	**Presence of Distracting Options**	**Eye Opening**	**Gaze Direction**	**Pupillometry**	**Vehicle Control Inputs**	**Voice**	**Heart Rate**	**Respiration Rate**	**EEG**	**Cognitive Assessment**	**BrAC**	**BAC – Perspiration**	**BAC - Tissue Spectroscopy**	**Nystagmus**
Adient AI18 concept								X	X						
Affectiva Automotive AI	X	X	X												
AMS Driver Monitoring Systems	X		X	X				X	X	X					
Aptiv Driver State Sensing	X	X	X	X											
Automotive Coalition for Traffic Safety – patent US20170274768A1												X			
Automotive Coalition for Traffic Safety – patent US2019027886A1														X	
Automotive Coalition for Traffic Safety – patent US20200101982A1												X			
Baidu Apollo Driver Fatigue Detection	X	X	X												
Belesh Fatigue Monitoring System	X	X	X												
BMW Driver Attention Camera	X		X												
Bosch Interior Monitoring System	X	X	X			X									
Car and Driver Copilot Driving Fatigue Monitoring System	X	X	X	X											
CardioID Cardiowheel								X							

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Cipia Driver Sense (and partners)	X	X	X	X											
Continental Cabin Sensing	X	X	X												
Daimler patent DE10201800900A1					X										
DENSO Driver Status Monitor	X		X												
DENSO patent US10398368B2								X		X					
DENSO patent US7821382B2				X	X			X		X					
Dot Netix Nexus	X	X	X												
DS Automobiles Driver Attention Monitoring	X	X	X	X		X									
DTS Autosense	X	X	X												
Faurecia	X					X		X	X						
Ford Co-Pilot 360	X		X	X		X									
Ford Heart Monitoring System								X							
Fuso Active Attention Assist	X		X	X											
Harman In-Cabin Monitoring System	X			X	X										
Harman Ready Care			X	X	X			X							
Hyundai Mobis Departed Driver Rescue and Exit Maneuver (DDREM)	X		X	X		X									

Vendor / Device	Metric														
	Head Position	**Presence of Distracting Options**	**Eye Opening**	**Gaze Direction**	**Pupillometry**	**Vehicle Control Inputs**	**Voice**	**Heart Rate**	**Respiration Rate**	**EEG**	**Cognitive Assessment**	**BrAC**	**BAC – Perspiration**	**BAC - Tissue Spectroscopy**	**Nystagmus**
Impirica - ExceleRATE and DCAT											X				
Infineon In-Cabin Sensing	X	X	X												
Jaguar and Land Rover Mind Sense Project										X					
Jaguar E-PACE						X									
Lear Biobridge								X							
Magna Driver Monitoring System	X			X											
Magna Electronics patent US20200283001A1															
Melexis In-Cabin Monitoring	X	X	X	X											
Mercedes-Benz Attention Assistant						X									
Nauto, Inc. Driver Behavior Alerts	X	X	X												
NVIDIA Drive IX	X	X	X	X											
Ocular Data Systems - DAX Evidence Recorder															X
Optalert Automotive Drowsiness Detection	X		X												
Seat and Xplora - in development	X	X	X	X											
Seeing Machines Guardian, FOVIO	X		X	X											
Seeing Machine	X			X											

	Metric														
Vendor / Device	**Head Position**	**Presence of Distracting Options**	**Eye Opening**	**Gaze Direction**	**Pupillometry**	**Vehicle Control Inputs**	**Voice**	**Heart Rate**	**Respiration Rate**	**EEG**	**Cognitive Assessment**	**BrAC**	**BAC – Perspiration**	**BAC - Tissue Spectroscopy**	**Nystagmus**
Senseair												X			
Smart Eye	X		X	X											
Sonde							X								
Sony Depthsensing Solutions	X	X	X												
Sumitomo Riko DMS								X							
Tobii Driver Monitoring System	X		X	X											
Toyoda Goesei - in development	X		X												
Toyota - in development								X							
Toyota - in development					X								X		
Toyota Driver Monitoring Camera	X		X												
Toyota patent - US8954238B2	X		X					X		X					
Veoneer Interior / Driver Monitoring System				X											
Viseton AllGo Embedded Camera Based DMS	X		X	X											
Volvo		X	X	X											

Summary

These technologies aim to make inferences to driver state such as drowsiness, distraction, or incapacitation. As such, the systems are designed to alert the driver to their state and take appropriate actions such as attending to the forward roadway, pulling over to rest, having a cup of coffee, and similar actions. None of these systems are designed as ignition interlock devices. The impact to the driver of a false positive (i.e., a drowsiness alert when the driver was not actually drowsy) would be minimal, requiring no involvement of law enforcement nor inability to drive the vehicle. Thus, a driver's tolerance for false positives may be expected to be greater than for ignition lockout designs employed by alcohol detection systems.

While articles describing the use of these metrics are cited above, a sufficient body of research describing the efficacy of these systems to detect driver states like drowsiness or distraction, in a driving operational environment, does not exist for development of consensus or best practice for applying these metrics. None of these systems assert a capability of detecting alcohol itself, nor BAC or BrAC. No research was found in this literature review documenting the ability of these technologies to reliably detect substance impairment. While there is evidence that some of these metrics are correlated with alcohol impairment (Lobato-Rincon et al. 2013; Maurage et al., 2020) none demonstrate the necessary certainty, the sensitivity, and specificity required for an ignition interlock implementation (see further discussion below). It is plausible that in combination, devices assessing these metrics may contribute to a driver monitoring system that includes direct alcohol detection.

Alcohol (i.e., Ethanol) and Substance Detection Methods

Breath alcohol concentration

A driver's breath can be chemically analyzed to assess the concentration of alcohol present in an exhaled breath, the BrAC. As that breath passes through the lungs, exchanging carbon dioxide for oxygen from oxygenated blood, evaporated ethanol present in the bloodstream is also mixed with the air in that breath. A chemical sensor can then measure the concentration of alcohol in that exhaled breath. Technologies are being developed for implementation *within* drivers' vehicles, which could prevent or lock out an impaired driver from starting the vehicle, or potentially safely bring the vehicle to a stop if impairment is detected while the vehicle is in motion. These devices require either a directed or passive (e.g., ambient air movement within the vehicle) breath sample.

Blood alcohol concentration

Like above, a driver's blood may be analyzed chemically to assess the concentration of alcohol present in the bloodstream. This may be assessed, of course, via a blood sample, or a saliva sample. However, in a driving application less intrusive measures are required. BAC is presently a legally defined measurement for enforcement of driver alcohol impairment, using a device external to the vehicle operated by a law enforcement officer. BACs may be assessed via ethanol's diffusion through the skin, its concentration in sweat on the surface of the skin, a saliva sample, or tissue spectroscopy. A less intrusive measure may be recorded by the driver's skin contacting sensors embedded in the steering wheel.

Nystagmus

Horizontal and vertical gaze nystagmus are involuntary, rhythmic motions of the eyes, and can be indicators of impairment from substance use. Pendular nystagmus is exhibited by a back-and-forth "pendulum" movement; jerk nystagmus is exhibited by a slow drift in one direction followed by a "jerk" in the opposing direction. Nystagmus is typically assessed via the presentation of a moving visual stimulus or stimuli; the person being assessed is asked to track the stimulus or stimuli with the eyes as an observer (or software application) observes the movement of the eyes while tracking. Such an assessment would be difficult or impossible to conduct safely while driving. While nystagmus may indicate alcohol or substance-related impairment, several congenital and circumstantial conditions may result in temporary or permanent nystagmus. Researchers exploring this indicator have found that it lacks sensitivity (Verstraete, 2014; Høiseth et al., 2022).

Summary

Each of these systems have high detection rates for the standard indicator of driver alcohol impairment, BAC. Of great importance in the development of the in-vehicle systems is specificity, or false positive rate. For the technology to be accepted and adopted by the driving public, the false positive rate must be as low as possible, while maintaining a high sensitivity (or true positive) rate. Overcoming this challenge is the goal of ongoing research in these technologies.

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Conclusion

Systems may use several types of measurement as indicators of driver fatigue, distraction, or incapacitation. The European New Car Assessment Program (Euro NCAP) version 10.0.1, implemented in 2023, includes a rating factor for inclusion of driver monitoring systems capable of detecting "Distraction, drowsiness, and unresponsive driver." The systems described above demonstrate the feasibility of systems to monitor driver drowsiness, some forms of overt distraction, and incapacitation, especially when a system combines two or more inputs. However, presently, the sensitivity and specificity of the systems described above have not been described in a robust research literature. For systems intended to improve driver alertness, moderate sensitivity may be adequate, if the systems and mitigation strategies employed are minimally intrusive to the driver.

In contrast, very high levels of sensitivity and specificity are an important consideration for alcohol detection systems. The impact to the driver, for example an ignition interlock system preventing the use of the vehicle, is much greater. Research and development efforts continue to improve the sensitivity and specificity of in-vehicle alcohol detection systems. Doing so will improve traffic safety while minimizing erroneous vehicle lockouts from false positive results.

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