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16. Abstract

The National Survey of Drowsy Driving Knowledge, Attitudes, and Behaviors used a nationally representative sample of U.S. adults to investigate knowledge, attitudes, and behaviors about drowsy driving. Using an address-based sampling method, the research team collected 10,700 completed surveys in 2022 from U.S. residents, while oversampling residents from States with laws against drowsy driving (Arkansas and New Jersey) or public education campaigns about drowsy driving (Massachusetts and Iowa). Using the theory of planned behavior as an underlying framework, the present study made comparisons between the national sample and the State oversamples to better understand the effects of laws and public education campaigns related to drowsy driving. The study also investigated effects of factors that may influence drowsy driving behavior. The results show that predictors of drowsy driving can be partially understood through the lens of the theory of planned behavior, and we found that the extent to which drivers believe they have control over whether they drive drowsy or not had the strongest relationship with reported drowsy driving. Our results also suggest State laws and the availability of ride share services may help deter drowsy driving, while those who drive or work at night, have less or poorer quality sleep, or who have sleep disorders may have increased risk of driving drowsy. The results of this survey may be useful to traffic safety stakeholders aiming to develop or target behavioral countermeasures intended to reduce the incidence of drowsy driving

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Executive Summary

The study used a nationally representative sample of adults in the United States to investigate knowledge, attitudes, and behaviors involving drowsy driving. Using an address-based sampling method, we collected 10,700 completed surveys from U.S. residents, while oversampling residents from Arkansas and New Jersey, which have laws against drowsy driving, and Massachusetts and Iowa, which have programs to mitigate drowsy driving.

The study found that some theory of planned behavior constructs (Subjective Norms, Perceived Behavioral Control, and Behavioral Intention) were predictive of drowsy driving, with Perceived Behavioral Control being the strongest predictor. The study also investigated the effects of factors that may influence drowsy driving behavior. Availability of shared ride services was associated with a reduced likelihood of ever falling asleep while driving, while those who drive for work have a significantly higher likelihood of having ever fallen asleep while driving. The results also showed that untreated sleep disorders such as sleep apnea and restless leg syndrome were significantly associated with higher likelihoods of drowsy driving, while those with treated sleep disorders reported an increased number of recent drowsy driving incidents.

Further, our study made comparisons between the national sample and the State oversamples to better understand the effects of State laws and public education drowsy driving campaigns. The results showed that respondents in States with laws against drowsy driving were significantly less likely to report falling asleep while driving than the national sample. However, we did not find evidence that respondents living in States that previously implemented drowsy driving public information campaigns had reduced the likelihood of falling asleep while driving. The results of the present study may be used to inform policymakers and other stakeholders when developing or targeting behavioral countermeasures to reduce drowsy driving.

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Introduction

NHTSA has found that in 2023 at least 633 people were killed in traffic crashes that involved drowsy drivers (NCSA, 2025). Like alcohol- and other drug-impaired driving, drowsy driving is a form of impaired driving, where "impaired" means anything that diminishes a person's ability to perform driving tasks and increases the likelihood of a crash (49 CFR Part 571, 2024). However, drowsy driving is not just falling asleep at the wheel. In cases of driving while excessively tired, driver alertness, attention, reaction time, judgment, and decision-making are all compromised, which may lead to a greater chance of crashing (Adanu et al., 2021; Rosekind, 2005).

The National Transportation Safety Board[1] has determined that while all drivers are at risk of drowsy driving at some point, certain subgroups are at higher risk. Commercial motor vehicle (CMV) drivers are of particular concern because they are overrepresented in fatal motor vehicle crashes in the United States: 13.5 percent of all fatal crashes involve at least one large truck or bus (FMCSA, 2024). In the Large Truck Causation Study, the Federal Motor Carrier Safety Administration (FMCSA) reported that 13 percent of CMV drivers were fatigued at the time of their crash (2007). In addition to CMV drivers, people engaged in shift work or who work long or irregular hours, including police officers, firefighters, emergency medical services (EMS) technicians, doctors, and nurses, are also at higher risk of drowsy driving (Green et al., 2020; James & Vila, 2015; Scott et al., 2007).

Currently, only two States—Arkansas and New Jersey—have laws that specifically address drowsy driving (GHSA, 2024). Other States, like Massachusetts and Iowa, are implementing other countermeasures (e.g., public awareness and education, infrastructure/engineering changes, vehicle technology) to combat drowsy driving. However, the impact of these strategies on the public's awareness, knowledge, attitudes, and behavior related to drowsy driving is unknown. This survey, conducted in 2022, provides national benchmarks on these measures, as well as for selected high-risk populations. The survey also includes State-specific information for Arkansas, New Jersey, Massachusetts, and Iowa. Findings from this study will help expand knowledge and understanding of drowsy driving; the survey results provide stakeholders with information for the development of workplace policies, public policy and other strategies to combat drowsy driving, and for the allocation of resources to combat key factors that contribute to drowsy driving.

[1] Official correspondence, Christopher A. Hart, Chairman, National Transportation Safety Board, to Anne S. Ferro. Administrator. Federal Motor Carrier Safety Administration, October 21, 2010, titled "Safety Recommendation." The letter reports the NTSB's finding about a chain-reaction crash that killed 10 people when a tractor-trailed rammed the rear of a vehicle setting off the chain reaction involving six vehicles, not counting the tractor trailer. The NTSB was reporting to the FMCSA that the cause of the crash was drowsy driving on the part of the tractor-trailer driver. www.ntsb.gov/safety/safety-recs/recletters/H-10-008-011.pdf

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Literature Review

Theory of Planned Behavior

One framework for understanding drowsy driving and how it may be prevented is the theory of planned behavior (TPB; Ajzen, 1991). TPB has been commonly used to understand and facilitate change in a variety of risky driving behaviors, including drinking and driving, speeding, close following, and dangerous overtaking (Bazargan-Hejazi et al., 2017; Elliott et al., 2003; Parker et al., 1992; Warner & Åberg, 2006).

TPB contends that the best predictor of a person's behavior is the person's intention to engage in that behavior (Ajzen, 1991), see Figure 1 below. This construct, known as behavioral intention, is preceded by three cognitive factors: attitudes toward the behavior, subjective norms, and perceived behavioral control. First, attitudes toward the behavior refer to whether the person views the behavior favorably or unfavorably; about drowsy driving, this includes the extent to which someone views drowsy driving as dangerous or not dangerous. Second, subjective norms refer to perceptions of judgements others have about a behavior, like the extent to which someone's friends, family, or other important people view drowsy driving as bad/negative or good/positive. Finally, perceived behavioral control is the extent to which the person believes they can perform or avoid performing the behavior (here, drowsy driving). A previous study on drowsy driving using TPB constructs reported that attitudes toward the behavior, subjective norms, and perceived behavioral control predicted behavioral intention, which, in turn, may predict drowsy driving (Lee et al., 2016).

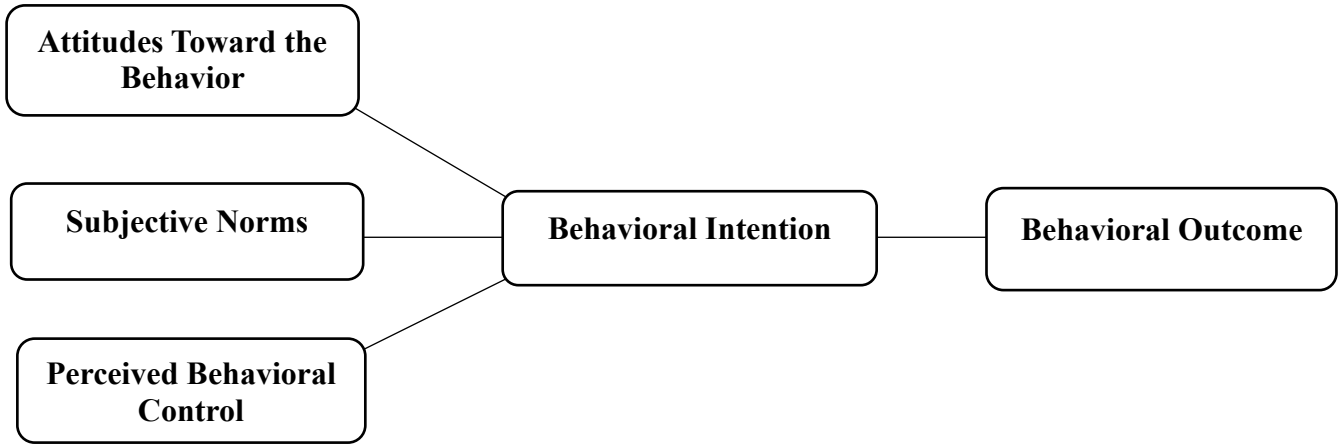


Figure 1. TPB conceptual diagram, adapted from Ajzen (1991)

Many studies have investigated predictors of drowsy driving (e.g., McCartt et al., 1996; Powell & Chau, 2011; Stutts et al., 1999). Some factors have been found to be related to drowsy driving, including lack of sleep; sex and age; environmental factors; medications; medical conditions that can affect sleep quality; work schedule; and alcohol and drug use (McCartt et al., 1996; Powell & Chau, 2011; Stutts et al., 1999).

Sleep Deprivation

One of the most often examined drowsy driving factors in the literature is sleep deprivation (Czeisler et al., 2016). When drivers do not get enough sleep, they may experience fatigue and daytime sleepiness, which affects their ability to drive safely (Johns, 2000). Lack of sleep can affect cognitive function, reaction time, alertness, decision-making skills, and the ability to judge distances accurately, all of which are critical for safe driving, and the impairment of which increases the risk of a crash (Killgore, 2010; Miyama et al., 2020).

Age and Sex

Men are more likely than women to engage in drowsy driving (Soares et al., 2020), and young men 18 to 32 years old are at the highest risk of drowsy driving and related crashes (Magaña et al., 2021). However, it is important to note that drowsy driving is a serious issue for both men and women (Soares et al., 2020).

Environmental Conditions

Environmental conditions can also be a factor in drowsy driving behavior (Miyama et al., 2020; Rahman et al., 2023). For example, driving in the dark can increase the risk of drowsy driving (Chipman & Jin, 2009). Another study showed driving on a long, straight road with little scenery or variety can be monotonous, increasing the risk of driver fatigue (Farahmand & Boroujerdian, 2018; Larue et al., 2010). According to Wang et al. (2017), warmer temperatures can make drivers feel drowsy, especially if they are already tired or sleep-deprived.

Medications, Alcohol, and Recreational Drugs

Some researchers have focused on how certain medications can increase the risk of drowsy driving (Brown et al., 2015; Farahmand & Boroujerdian, 2018; Verster et al., 2018). For example, certain allergy medications (antihistamines) can cause drowsiness (Zanier et al., 2010), as can medications used to treat conditions such as insomnia, muscle spasms, and anxiety (Watson et al., 2015). Opioid medications as analgesics can cause drowsiness (Hetland & Carr, 2014). In addition, some antidepressants and muscle relaxants can also cause drowsiness and affect driving ability (Cohen & Warfield, 2014; Zanier et al., 2010).

Another often examined factor related to drowsy driving is the use of alcohol and recreational drugs (Jones, 2022; Soares et al., 2020; Valen et al., 2019). Alcohol is a central nervous system depressant that can cause drowsiness, impaired judgment, and slowed reaction times, making it difficult for a driver to stay alert while driving (Valen et al., 2019). Similarly, certain drugs used recreationally such as cannabis can also cause drowsiness and impair driving performance (Micallef et al., 2018). The effects of alcohol and drugs on driving can be amplified when combined with sleep deprivation or fatigue (Horne et al., 2003).

Medical Conditions

Medical conditions such as sleep apnea, narcolepsy, and insomnia can affect driver performance and increase drowsy driving and the risk of crashes (Smolensky et al., 2011). For example, drivers with untreated sleep apnea are more likely to be involved in single-car crashes than those without sleep apnea (Haraldsson et al., 1990). Another study found that people with narcolepsy were even drowsier than those with sleep apnea and had reduced performance on driving tests

(George & Boudreau, 1996). Insomnia may also lead to daytime fatigue and increased crashes (Williamson et al., 2011).

Work Schedule

Several studies have focused on drowsy driving among occupational groups who tend to be at greater risk of these conditions due to the nature of their work such as shift and night workers, police and emergency responders, and health care workers (Imes et al., 2022; Smith et al., 2019, 2021). Research shows that work schedule also contributes to drowsy driving (Smith et al., 2021). Shift workers, people who work long hours, and those who work irregular schedules are most likely to be at increased risk of drowsy driving (Hagan-Haynes et al., 2022). These work schedules can disrupt the body's natural sleep-wake cycle and lead to sleep deprivation.

Countermeasures

Countermeasures to combat drowsy driving generally fall into two broad categories: those aimed at preventing/reducing the likelihood of drowsy driving and those aimed at preventing/reducing the consequences of drowsy driving (Fletcher et al., 2005). Several recommendations for drivers to prevent drowsy driving were found in the literature. One of the best ways to avoid drowsy driving is to ensure that drivers get enough sleep (Fischer, 2016). Adults typically need 7 to 9 hours of sleep per night, while teenagers and young adults may need more (Hirshkowitz et al., 2015). When driving long distances, taking regular breaks to rest and stretch helps prevent drowsy driving. Ideally, a driver should take a break from driving every 2 hours or 100 miles (Fischer, 2016). Drivers should avoid driving at night when they are more likely to feel drowsy. If drivers need to drive during these hours, they should take extra precautions. Among drowsy driving countermeasures are efforts to make drivers more aware of the warning signs that show drowsy driving such as frequent yawning or blinking, drifting out of one’s lane, missing an exit, or hitting a rumble strip (Higgins et al., 2017; Watling et al., 2015). Some medications can cause drowsiness, so drivers may wish to avoid taking them before driving. It is also important to avoid alcohol, as it can increase drowsiness (Sunwoo et al., 2017). Other countermeasures listed in the literature include treating medical problems that can contribute to drowsy driving (Fischer, 2016). Some studies showed that a wake-promoting drug (modafinil), typically used to treat sleep disorders, might reduce drowsy driving in healthy adults (Strohl et al., 2013). Another study produced a similar result showing the use of modafinil reduced lane deviation but had less effect on speed deviation, off-road incidents, and reaction time (Gurtman et al., 2008). Recommendations involving comprehensive fatigue management policies to reduce drowsy driving among occupational groups characterized by long working hours, working nights and overtime, and on-call duty have been suggested (Gander et al., 2005; Yassierli et al., 2015).

Messaging campaigns for the general driving public aim to raise awareness about the dangers of drowsy driving and provide tips on how to prevent it. Messaging themes have included drawing parallels between drowsy and drunk driving (Pacheco & Rehman, 2023) and challenging beliefs about personal ability to cope with fatigue (Stop Drowsy Driving, 2017). Messaging campaigns to specifically combat drowsy driving among non-commercial drivers are increasing (e.g., the *Drive Alert, Arrive Alive* national campaign in the United States; *Think!* campaign in the United Kingdom; and *Fatigue: The Hidden Killer* in New Zealand), but to our knowledge, none have been formally evaluated.

For CMV drivers, FMCSA has implemented “hours of service” laws and improved existing regulations that mandate rest breaks, limit the hours CMV drivers can be on the road, and prohibit driving under the influence of drugs or alcohol (Nidamanuri et al., 2021). For the general driving public, on the other hand, State laws that specifically target drowsy drivers are not widely used, and the effectiveness of this countermeasure has not been systematically examined (Kirley et al., 2023). Indeed, some researchers have suggested governments and other traffic safety stakeholders should invest in research and data collection to better understand the scope of the problem and develop effective solutions (Fischer, 2016). A 2016 Governors Highway Safety Association report analyzed several drowsy driving laws and related legislative initiatives based on surveys of State Highway Safety Offices in 33 States and the District of Columbia, feedback from an expert panel, and follow-up telephone calls with a subset of States (Fischer, 2016). According to the report, of the 50 States only New Jersey and Arkansas enacted laws addressing drowsy driving. New Jersey's law took effect in 2003 and considers driving while knowingly fatigued as recklessness and defines fatigue as being without sleep for over 24 consecutive hours. Arkansas' law defines fatigue similarly but adds the phrase “or in the state of being asleep.” The report stated that the court system has had limited success in convicting drowsy drivers under these statutes in both States. On the other hand, two other State policies have effectively reduced drowsy driving among teens: nighttime driving restrictions and later school start times (Fischer, 2016). However, only 11 States currently require drowsy driving information for driver education.

Efforts to reduce the consequences of drowsy driving often focus on monitoring and detecting drowsy driving using technology, e.g., OEM or third-party technologies for detecting fatigue during driving (Sikander & Anwar, 2019). These systems monitor or detect drowsiness and alert drivers (Biswal et al., 2021; Yang et al., 2020), for example, by displaying a coffee cup icon on the instrument panel or infotainment system and presenting an auditory alert (Gaspar et al., 2017).

Present Study

Using the TPB as a theoretical framework, our study investigated drowsy driving as it relates to each of the underlying TPB constructs: attitudes, subjective norms, perceived behavioral control, and behavioral intention. Further, Arkansas and New Jersey have drowsy driving laws. and Massachusetts and Iowa have implemented other countermeasures (public awareness and education, infrastructure/engineering, vehicle technology) to combat drowsy driving. However, the impact of these laws and countermeasures on the public's awareness, knowledge, attitudes, and behavior is uncertain. This study provides national benchmarks on these measures and for selected high-risk populations. It has State-specific information for Arkansas, New Jersey, Massachusetts, and Iowa. Our findings help expand knowledge and understanding of drowsy driving, as well as the development of policy, legislative action, strategies, tactics and actions to combat drowsy driving, and allocation of resources for combating the key factors that contribute to drowsy driving.

Directional Hypotheses About Theory of Planned Behavior

- H1: Attitudes toward the behavior will predict behavioral intention such that those with negative attitudes toward the behavior will have lower behavioral intention to engage in drowsy driving.
- H2: Subjective norms will predict behavioral intention, such that those who perceive that people around them have negative perceptions about drowsy driving will have lower behavioral intention to engage in drowsy driving.
- H3: Perceived behavioral control will predict behavioral intention, such that those who have higher perceptions of perceived behavioral control will have lower behavioral intention to engage in drowsy driving.
- H4: Perceived behavioral control will be the strongest predictor of self-reported drowsy driving behavior, as there may be lifestyle/work schedule barriers that make drowsy driving more likely.
- H5: Behavioral intention will predict drowsy driving behavior, such that those with low behavioral intention to drive drowsy will be less likely to report driving drowsy in the past 30 days.
- H6: The relationship between each of the three TPB factors and one's likelihood to report driving drowsy in the past 30 days will at least partially be explained by behavioral intention, such that those with more positive attitudes, stronger subjective norms, and higher perceived behavioral control will have lower levels of behavioral intention, resulting in a lower likelihood to report driving drowsy in the past 30 days.
- Exploratory question: The TPB factors will be associated with a higher likelihood of almost falling asleep compared to respondents who actually fell asleep. This model will include respondents who answer affirmatively to one of these two questions: "In the past 30 days, how many times have you felt tired or sleepy enough while driving that you thought you might fall asleep or nod off, even though you didn't?" and "Have you ever felt tired or sleepy enough while driving that you thought you might fall asleep or nod off, even though you didn't?". The two groups will be compared by TPB factor composite scores.

Directional Hypotheses About Impacts on Drowsy Driving Based on Laws, Health Issues, Alternative Transportation, Public Messaging, Work-Related Driving, Driving Frequency, and Sleep Patterns

- H7: Respondents in States with laws against drowsy driving or public information and education about drowsy driving will be significantly less likely to report driving drowsy, compared to the national sample.
- H8: Respondents living in States with laws against drowsy driving will be significantly less likely to report driving drowsy than residents of States with only public information and education campaigns.
- H9: Thinking there is a law against drowsy driving will result in less drowsy driving.
- H10: Those with diagnosed sleep disorders will be more likely to report drowsy driving than those not diagnosed.
- H11: The availability of taxis, Uber, Lyft or other ride share services will be predictive of one's likelihood to drive drowsy, such that those who do not have access to ride share services will be more likely to report driving drowsy.
- H12: There will be a difference between those who report seeing or hearing any messages about the dangers of drowsy driving and one's likelihood to drive drowsy, such that those who have heard messages will be less likely to report driving drowsy.
- H13: Driving as a part of one's job duties will be predictive of one's likelihood to report driving drowsy, such that the more often someone reports driving as part of their job duties, the more likely they are to report driving drowsy.
- H14: Higher frequency of driving will be associated with an increased likelihood and incidents of drowsy driving.
- H15: Fewer hours sleeping and difficulty sleeping will be associated with an increased likelihood and incidents of drowsy driving.
- H16: Shift and night work, longer hours (number of days worked), and longer work commutes will be associated with increased likelihood and incidents of drowsy driving.

Methodology

To examine the hypotheses outlined above, a survey was administered in 2022 to a nationally representative sample of U.S. adults. Further, the survey was administered to a representative sample of people in Arkansas, New Jersey, Massachusetts, and Iowa. The study goal was to examine knowledge, attitudes, and behaviors surrounding drowsy driving. We obtained OMB clearance to conduct this study (OMB Control Number: 2127-0752). We also obtained approval through the Institutional Review Board at Econometrica, Inc.

Survey Development

As part of the questionnaire development process, we convened an expert panel consisting of stakeholders with an interest in drowsy driving. Based on the initial findings of the literature review, our own experts, and feedback from NHTSA, we developed a list of suggested panelists for approval. Following approval, we invited panel members to attend a one-day meeting to gather feedback on the topics related to drowsy driving that would be most beneficial, as well as gathering feedback on other issues related to the questionnaire.

The survey included questions related to each of the TPB's constructs in relation to drowsy driving. Further, the survey contained questions about knowledge and attitudes toward drowsy driving laws, the occurrence of drowsy driving, events which occurred while drowsy driving, methods to combat drowsy driving, frequency of motor vehicle use, health conditions that might affect sleep, employment, and demographics. A final copy of the questionnaire is in Appendix A.

We developed the study questionnaire to be suitable for both online and paper formats. After the English version was finalized, a Spanish version was created by a professional translation firm and quality checked by people fluent in three different Spanish dialects. We tested the English and Spanish questionnaires to ascertain any irregularities in the data collection process. The questionnaire was also tested on a PC, Mac, tablet, iPad, and iPhone and Android cellphones to ensure optimization and compatibility.

Cognitive Testing

We conducted cognitive interviews on the English survey questionnaire to reduce questionnaire- and respondent-related measurement errors by determining appropriate wording and sequencing of the questionnaire items, by evaluating the quality of questions, and by evaluating the extent to which questions gather the intended information. We made cognitive interviews to eight participants in Philadelphia, PA. Each had to be at least 18 years old, a licensed driver, and have driven a motor vehicle in the past month. They were each given an incentive of $100 for their time. During cognitive interviews, participants were asked to read all survey questions and instructions out loud. While answering a question, they verbalized their thoughts and explained how they arrived at their answers. Interviewers asked follow-up questions to probe for more information about item clarity. Based on the results, revisions were made to the definition and wording of "drowsy driving" throughout the survey. No other substantive changes were made.

Usability Testing

We also conducted usability testing via remote interviews with nine participants over 18 years old who had each driven a vehicle in the past month. We assigned participants to complete the revised survey on an iPhone, Android phone, paper, or computer. They were recruited via

Craigslist and given an incentive of $100 each for their time. This usability testing's goal was to identify problems in the delivery of the survey among the four different modes, and to identify any confusion in question flow or aspects of the questions themselves. Participants completed the survey as they would in real life while thinking aloud. Unlike the cognitive testing, the session moderator intervened as little as possible during usability testing. At the end of each session, participants completed a 10-question system usability scale on a scale of Strongly Disagree (1) to Strongly Agree (7). The final survey showed an overall high satisfaction level across modes. We used feedback from this testing to improve upon the different survey modes prior to pilot testing.

Sample Construction

Selection of Oversample States

States were identified for oversampling to make comparisons about the effects of State driving laws and public education campaigns on drowsy driving behavior. Only Arkansas and New Jersey currently have laws making falling asleep while driving its own violation, in contrast with other States that may prohibit behaviors associated with drowsy driving, such as driving "in wanton or willful disregard for the safety of persons or property" (reckless driving definition in Maryland viz. Maryland Transportation Code § 21-901.1, 1977). Thus, we picked Arkansas and New Jersey to be oversampled.

NHTSA also requested that two additional States be identified for oversampling among those States with demonstrated commitment to reducing drowsy driving as a traffic safety issue. The intent was to identify what impact statewide public information and education (PI&E) efforts may have on the attitudes and driving behavior of survey respondents despite not having a dedicated drowsy driving law. Nine States were advanced for consideration due to some level of programmatic commitment to drowsy driving PI&E: Iowa, Massachusetts, Maryland, Minnesota, Montana, Nevada, New York, Oregon, and Utah. NHTSA ultimately selected Massachusetts and Iowa to be oversampled for this study. Massachusetts was selected due to its messaging campaign, conducted in partnership with the Harvard School of Public Health, AAA Northeast, and the Drowsy Driving Prevention Project. Massachusetts' campaign targeted young drivers and used social media platforms and combined partner resources to communicate the dangers of drowsy driving. Iowa was selected due to its public awareness campaign that compared drowsy driving with other risky driving behaviors such as drugged, drunk, and distracted driving. Iowa used messages strategically placed at rest areas and on social media to encourage drivers to rest when they are feeling tired. Note, however, that public information campaigns for these States were not active at the time of data collection and had not been for several years. However, these States nevertheless had demonstrated commitments to reducing drowsy driving.

Sample Frame

The survey used an address-based sample (ABS) approach to select a national probability sample of households. It was also used for each of the four oversampled States, Arkansas, New Jersey, Massachusetts, and Iowa. The source of the ABS frame was the computerized Delivery Sequence File (DSF), a database containing millions of residential addresses, covering nearly all households in the United States. The DSF further classifies residential addresses according to type of delivery point. Appendix C includes more information about the delivery point classifications and whether specific delivery points were included in the sample.

Stratification

A major concern with ABS studies is systematic non-response that leads to samples of respondents who are not representative of the general population, so the design and stratification used in this survey was selected to increase the representativeness of the sample. Specifically, the samples were stratified by census block groups based on the percentages of the block group population identified as African American or Hispanic based on the American Community Survey 5-year estimates, termed "geographic" level or strata in the sampling plan.

The sample was also stratified using appended data on the likely age of the residents of the sampled address. We derived this data from listed commercial data appended to the sample frame by the sample vendor. For the national sample, this resulted in a four-region (Northeast, Midwest, South, West) x three-geographic-level (High % Hispanic, High % African American, Residual) x four-age-group (Younger, age 18-29; Older, age 30+; no age info; not listed) listed design with 48 total strata. The same sampling strata were used for the State oversamples, leading to a three-geographic-level x four-age-group listed design for 12 strata per State. Once defined, strata that allow for a greater probability of reaching either a young or a Black or Hispanic respondent were oversampled. Tables showing the household distribution across strata, along with the distribution of sample pulled, are included in Appendix C.

Sample Verification

The first step in the analysis was to check that the sample had been selected according to the sampling plan devised. By visually examining variables from the sample frame, we confirmed the mailed sample matched the sampling plan in terms of the allocation by region, geographic strata, and age, and there were no addresses labeled as seasonal or vacation homes, nor were any listed as vacant.

Respondent Eligibility

Respondents were eligible if they reported that they were older than 18 and had driven a motor vehicle in the past year. Of those in the national sample, 189 were found to be ineligible, while 55 in the Arkansas sample, 79 in the New Jersey sample, 68 in the Massachusetts sample, and 68 in the Iowa sample were found to be ineligible.

Pilot Study

The pilot study identified challenges in data collection and management and provided recommendations for the larger study. The pilot study included a three-wave mailing to 1,004 sample members, with half of the sample members receiving a $2 non-contingent incentive, while the other half received no incentive. This data collection effort resulted in 29 responses. Of the 29 who completed the entire survey, 15 received the non-contingent incentive while 14 did not. Thus, in the pilot study, the non-contingent incentive did not improve response rates. However, this was likely due to the overall small sample. As a result of this pilot study, the main data collection was split into two phases so the first phase could be used to further investigate the impact of non-contingent incentives on response rates, and the results of that investigation informed potential changes to administration of the second phase.

Data Collection

As described above, data collection for the full survey was executed in two phases. During Stage 1, from January to March 2022, 10,002 sample members received invitations to participate. Half of these sample members received a $2 non-contingent incentive, while the other half did not. During Stage 2, from September to December 2022, the remaining 71,440 sample members received invitations to participate and a non-contingent $1 incentive. Further, all sample members in Stage 2 were each offered a contingent $20 e-gift card upon completion of the survey. The incentive structure was changed in Stage 2 to attract greater participation from potential respondents.

Mailing Protocol

The mailing protocol had five waves of communication.

1. An initial invitation letter in English and Spanish
2. A reminder postcard in English
3. A second invitation letter and a questionnaire in English with business reply envelope (potential respondents in areas identified as being in a high percentage Hispanic stratum were provided with both English and Spanish materials)
4. A second reminder postcard in English
5. A third invitation letter and a second questionnaire in English with business reply envelope (potential respondents in areas identified as being in a high percentage Hispanic stratum were provided with both English and Spanish materials)

Households that completed the questionnaire or mailings that were returned as "undeliverable" did not receive further mailings. Appendix C lists in-depth mailing protocols for Stage 1 and Stage 2 of data collection.

Assignment of Unique PIN

Each sample member was assigned a unique PIN to access the online survey. A list of 6-digit PINs was created starting with PIN number 100000 and ending with PIN number 899992. Researchers assigned 81,442 PINs to a randomly sorted list of sample members. The PINs used in Stage 1 were not used as PINs in Stage 2.

Spanish Speaking Respondents

All materials were translated into Spanish. We flagged records to receive materials in both languages if they were identified in the sample as being in a high percentage Hispanic stratum. All respondents in the sample could request materials in Spanish.

Addressing Respondents

The way the mailings were addressed depended on the availability of name data from the sample file. For those with a name associated with the address, the envelopes were addressed with their name and "or current resident" appended. For those without a name associated with the address, "Current Resident" was used.

Incentives

Stage 1 Incentives. To determine the effectiveness of a non-contingent incentive on increasing response rates, the researchers randomly selected half of the sample to each receive a $2 bill included in their first mailing. The other half of the sample did not receive incentives. Stage 1 resulted in 601 completed surveys. Of these, 214 did not receive incentives while 387 received the $2 non-contingent incentive. Those who received incentives had a higher response rate than those that did not receive the incentives (7.7% vs. 4.3% AAPOR Response Rate 1).

Stage 2 Incentives. Each sample member received a $1 non-contingent incentive. Upon completion of the survey, those who took the survey on the web were redirected to a page where they could enter their email to receive their $20 e-gift cards. The e-gift card was then sent to that email. Those who took the paper survey were instructed to call an interactive voice response system where they could leave a message with their email. Those who did not have email were sent hard-copy gift cards.

Within Household Selection

For both data collection phases we randomly assigned households to one of two in-household selection methods. Households were either instructed to have the person with the "most recent" birthday take the survey, while other households were instructed to have the person with the "next coming" birthday take the survey. There were an equal number of households that received "most recent" and "next coming" within-household selection instructions.

Response Rates

We used AAPOR's (2023) definitions for determining completed surveys ("completes"), partially completed surveys ("partials"), and breakoffs. Specifically, a response was considered complete when the respondent answered more than 80 percent of the relevant survey items. A response was considered a partial when the respondent answered greater than or equal to 50 percent and less than or equal to 80 percent of the relevant survey items. A response was considered a breakoff when the respondent answered less than 50 percent of the relevant survey items.

Table 1. Numbers of survey completes, partials, and breakoffs by sample

Sample	Completes	Partials	Breakoffs
National	3,765	66	270
Arkansas	1,516	29	100
Iowa	2,251	28	105
Massachusetts	1,631	23	111
New Jersey	1,537	21	116

We examined the response rate both overall and by sampling strata. The strata examined were the "Census Regions," "Geographic Strata," "Age Listed Strata," and incentive experiment groups. We calculated four response rates: (1) a response rate of completed surveys divided by mailed sample (AAPOR RR1); (2) the response rate of completed, partial, and breakoff surveys divided by mailed sample (AAPOR RR2); (3) a similar response rate to AAPOR RR1 that

accounts for undeliverable mail and respondent eligibility (AAPOR RR3); and (4) a similar response rate to AAPOR RR2 that accounts for undeliverable mail and respondent eligibility (AAPOR RR4). Note that refusals refer to those people who answered the first two screener questions and were deemed to be eligible but did not answer any other items. Undeliverables refer to those addresses whose mail was returned as "undeliverable" by the U.S. Postal Service. Finally, ineligibles are those who showed they were either under age 18 or had not driven a motor vehicle in the past year.

Table 2. National response rates by strata

	Mailed Sample	Undeliverable	Ineligible	Completes	Partials/Break offs	Refusals	AAPOR RR1	AAPOR RR2	AAPOR RR3	AAPOR RR4
Overall	**33,442**	**700**	**189**	**3,765**	**336**	**25**	**11.3%**	**12.3%**	**12.0%**	**13.1%**
Census Region										
Northeast	5,309	115	49	590	69	5	11.1%	12.4%	12.2%	13.6%
Midwest	6,655	131	32	863	64	8	13.0%	13.0%	13.7%	14.7%
South	14,337	304	69	1,499	121	8	10.5%	10.5%	11.1%	12.0%
West	7,141	150	39	813	82	4	11.4%	11.4%	12.1%	13.4%
Geographic Strata										
High % African American	8,517	206	57	884	73	4	10.4%	11.2%	11.3%	12.2%
High % Hispanic	4,493	84	30	411	54	3	9.1%	10.3%	9.9%	11.2%
Residual	20,432	410	102	2,470	209	18	12.1%	13.1%	12.8%	13.9%
Age Listed Strata										
Listed, 18-29	14,572	166	67	1,816	169	15	12.5%	13.6%	13.0%	14.2%
Listed, 30+	9,877	139	62	1,379	102	6	14.0%	15.0%	14.8%	15.8%
Listed, no age info	7,849	326	52	503	62	4	6.4%	7.2%	7.3%	8.2%
Not listed	1,144	69	8	67	3	0	5.9%	6.1%	6.9%	7.3%

Table 3. Response rates for oversampled States

	Mailed Sample	Undeliverable	Ineligible	Completes	Partials/Break offs	Refusals	AAPOR RR1	AAPOR RR2	AAPOR RR3	AAPOR RR4
ARKANSAS										
Overall	**12,000**	**314**	**55**	**1,516**	**129**	**13**	**12.6%**	**13.7%**	**13.4%**	**14.5%**
Geographic Strata										
High % African American	4,548	156	26	512	48	6	11.3%	12.3%	12.2%	13.3%
High % Hispanic	368	9	2	36	3	1	9.8%	10.6%	10.5%	11.4%
Residual	7,084	149	27	968	78	6	13.7%	14.8%	14.8%	15.5%
Age Listed Strata										
Listed, 18-29	6,608	129	23	864	76	9	13.1%	14.2%	13.7%	14.9%
Listed, 30+	3,771	83	20	514	44	4	13.6%	14.8%	14.4%	15.7%
Listed, no age info	1,018	47	9	97	8	0	9.5%	10.3%	10.8%	11.7%
Not listed	603	55	3	41	1	0	6.8%	7.0%	8.0%	8.2%
IOWA										
Overall	**12,000**	**183**	**68**	**2,251**	**133**	**10**	**18.8%**	**19.9%**	**19.6%**	**20.7%**
Geographic Strata										
High % African American	816	29	5	133	13	1	16.3%	17.9%	17.5%	19.2%
High % Hispanic	125	0	1	12	2	0	9.6%	11.2%	10.3%	12.0%
Residual	11,059	154	62	2106	118	9	19.0%	20.1%	19.8%	21.0%

	Mailed Sample	Undeliverable	Ineligible	Completes	Partials/Break offs	Refusals	AAPOR RR1	AAPOR RR2	AAPOR RR3	AAPOR RR4
Age Listed Strata										
Listed, 18-29	6,781	85	27	1293	76	5	19.1%	20.2%	19.7%	20.8%
Listed, 30+	4,249	51	25	842	51	2	19.8%	21.0%	20.6%	21.9%
Listed, no age info	697	31	14	88	5	3	12.6%	13.3%	15.1%	16.0%
Not listed	273	16	2	28	1	0	10.3%	10.6%	11.6%	12.1%
MASSACHUSETTS										
Overall	**12,000**	**127**	**68**	**1,631**	**134**	**9**	**13.6%**	**14.7%**	**14.3%**	**15.4%**
Geographic Strata										
High % African American	1,679	23	19	153	24	3	9.1%	10.5%	10.2%	11.8%
High % Hispanic	849	22	9	69	9	1	8.1%	9.2%	9.3%	10.5%
Residual	9,472	82	40	1409	101	5	14.9%	15.9%	15.4%	16.5%
Age Listed Strata										
Listed, 18-29	6,554	52	29	923	77	5	14.1%	15.3%	14.6%	15.8%
Listed, 30+	4,065	34	25	592	42	4	14.6%	15.6%	15.3%	16.3%
Listed, no age info	826	25	9	78	11	0	9.4%	10.8%	10.7%	12.2%
Not listed	555	16	5	38	4	0	6.8%	7.6%	7.9%	8.7%

	Mailed Sample	Undeliverable	Ineligible	Completes	Partials/Break offs	Refusals	AAPOR RR1	AAPOR RR2	AAPOR RR3	AAPOR RR4
NEW JERSEY										
Overall	**12,000**	**167**	**79**	**1,537**	**137**	**14**	**12.8%**	**14.0%**	**13.6%**	**14.8%**
Geographic Strata										
High % African American	3,409	81	33	357	47	8	10.5%	11.9%	11.6%	13.1%
High % Hispanic	1,661	30	18	152	16	1	9.2%	10.1%	10.3%	11.4%
Residual	6,930	56	28	1028	74	5	14.8%	15.9%	15.3%	16.4%
Age Listed Strata										
Listed, 18-29	6,274	68	34	879	78	10	14.0%	15.3%	14.7%	16.0%
Listed, 30+	3,818	44	28	508	43	2	13.3%	14.4%	14.1%	15.3%
Listed, no age info	1,246	25	10	105	9	2	8.4%	9.1%	9.3%	10.1%
Not listed	662	30	7	45	7	0	6.8%	7.9%	8.1%	9.3%

Sample Stratification Outcomes

We analyzed the stratification effectiveness for people responding to the survey, regardless of whether they were eligible or provided a complete response. The tables below show how successful the stratification was at targeting specific respondents. The "Respondents" column shows how much of the targeted strata were included in the sample. The next columns show how many people from that stratum reported being a part of the targeted population.

The strata that target areas with high densities of African American and Hispanic populations led to higher incidences of the intended respondents. The geographic stratification achieved 36.8 percent and 50.1 percent incidences of African American and Hispanic, respectively, in the high-density strata, which is much higher than the overall incidence of African American (11.0%) and Hispanic (9.5%) respondents. Similarly, the age listed stratification was effective at targeting younger respondents. The stratum that targeted the 18 to 29 age cohort produced a higher incidence of 18 to 29-year-old respondents (29.8%) than the overall age 18 to 29 incidence of 18.8 percent. The remaining listed age strata produced significantly lower incidences of younger respondents.

There were higher incidences of African American respondents in the South stratum (21.5%) and Hispanic respondents in the West (22.6%). Incidences of 18-to-29-year-old respondents were similar across the Midwest, South, and West regions, ranging from 18.0 percent to 19.9 percent. The incidence of 18-to-29-year-old respondents in the Northeast was slightly lower (13.4%).

Table 4. Geographic stratification

Geographic Strata	Respondents		African American Respondents		Hispanic Respondents	
	Counts	%	Counts	Incidence	Counts	Incidence
Overall	11,569	100.0%	1,268	11.0%	1,094	9.5%
High % African American	2,244	19.4%	825	36.8%	201	9.0%
High % Hispanic	764	6.6%	103	13.5%	383	50.1%
Residual	8,561	74.0%	340	4.0%	510	6.0%

Note. The "Respondents" column shows how much of the targeted strata were included in the sample. The African American Respondents and Hispanic Respondents columns show how many people from that stratum reported being a part of the targeted population.

Table 5. Age listed stratification

Age Listed Strata	Respondents		Age 18-29 Respondents	
	Counts	%	Counts	Incidence
Overall	11,569	100.0%	2,170	18.8%
Listed, 18-29	6,251	54.0%	1,860	29.8%
Listed, 30+	4,117	35.6%	98	2.4%
Listed no age	966	8.3%	158	16.4%
Not listed	235	2.0%	54	23.0%

Note. The "Respondents" column shows how much of the targeted strata were included in the sample. The Age 18-29 Respondents columns show how many people from that stratum reported being a part of the targeted population.

Table 6. Census region stratification

Census Region	Respondents		African American	Hispanic	Age 18-29
	Counts	%	Incidence	Incidence	Incidence
Overall	4,101	100.0%	15.0%	14.0%	18.2%
Northeast	659	16.1%	13.9%	9.5%	13.4%
Midwest	927	22.6%	12.9%	6.2%	19.0%
South	1,620	39.5%	21.5%	15.6%	19.9%
West	895	21.8%	5.8%	22.6%	18.0%

Note. The "Respondents" column shows how much of the targeted strata were included in the sample. The African American, Hispanic, and Age 18-29 columns show how many people from that stratum reported being a part of the targeted population. This table only includes the national sample, as Census region was not a relevant stratum for the oversampled States.

Non-response Bias Analysis

Researchers conducted a non-response (NR) bias analysis on the resultant data. NR bias occurs when non-responders differ systematically from respondents. The purpose of the non- response bias analysis was to identify potential areas of bias in the responses to the survey to inform the generalizability of the findings. The NR bias analysis focused on 14 key variables, including Q1, Q11, a combined scale of Q13 and Q16, composite scores formed from questions about drowsy driving attitudes, subjective norms, and perceived behavioral control, the Intention Composite score, Q25, Q26, Q50, Q70, Q71, Q83, and Q84. (See the questionnaire in Appendix A for specific questions.)

The researchers carried out four major analytical stages for this NR bias investigation; the rationale underlying these stages followed from what is known to cause NR biases. First, characteristics of respondents and nonrespondents that correlate with the key variables in a survey are important to identify from among the data gathered in the survey questionnaire. For example, which respondent characteristics (age, education, etc.) correlate with how often someone drives a car after 9 p.m.? Second, two approaches investigated possible NR biases in the survey: (1) the level-of-effort approach and (2) the auxiliary-data-matched-to-sampled-units

approach. These two approaches generated independent/separate sets of findings about possible NR biases. The two sets of findings supplemented each other by identifying (1) whether easy-to-recruit respondents differed from hard-to-recruit respondents in the data that were gathered for each key variable and (2) which unit (household) characteristics correlated with whether a given sampled unit completed or did not complete the survey questionnaire. After these analyses were completed, the findings from the two approaches were compared to determine which of the key variables, if any, were likely biased due to NR in the survey.

The results of the NR bias analysis showed NR bias related to age, male/female, ethnicity (Hispanic/Latino), and education. Specifically, the NR bias analysis showed there were too many adults 25 or older in the responding sample compared to the nonresponding sample. Further, there were too many males and too few females in the responding sample compared to the nonresponding sample. There were also too few respondents who reported that they were Hispanic and too many who reported that they were non-Hispanic in the responding sample compared to the non-responding sample. Finally, the NR bias analysis showed that there were too few adults with only a high school or less education in the responding sample compared to the non-responding sample.

Sample Weighting

The samples were weighted to ensure the final data set was representative of the target population, thus improving the validity and generalizability of survey estimates. The weighting followed a standard procedure of first applying a base weight that accounts for initial sampling probabilities, then making unknown eligibility and NR adjustments. The final step in the weighting was to calibrate the data to match target population benchmarks.

Base Weight

The base weight, d_{0i}, also referred to as a "sampling weight" or a "design weight," adjusts for sampling rates within strata and was computed as $d_{0i} = N_i/n_i$ where N_i is the frame size in stratum i and n_i is the amount of sample drawn in stratum i. Sampling strata for the national sample were defined as the cross of the four U.S. census regions, three geographic strata, and four age-listed strata, leading to 48 sampling strata in total. Each State's sample was defined as the cross of three geographic strata, and four age-listed strata, giving a total of 12 sampling strata for each State.

Unknown Eligibility Adjustment

Samples often contain units (i.e., potential respondents) whose eligibility to be in a specific stratum cannot be determined. Weight adjustments for unknown eligibility and NR allow the respondents to be weighted up to the size of the eligible sample frame where weighting cannot be greater than the general population for that group. After the application of the base weight, an unknown eligibility adjustment was made using a class-based approach. The base weights for cases with unknown eligibility were distributed among cases whose eligibility status was determined. Weights for addresses with unknown eligibility status were set to zero after this calculation. The unknown eligibility adjustment for sample units in class b can be expressed as

$$a_{1b} = \begin{cases} \sum_{i \in s_b} d_{0i} \Big/ \sum_{i \in s_{b,KN}} d_{0i} & if\ i \in s_{b,KN} \\ 0 & if\ i \in s_{b,UKN} \end{cases}$$

where d_{0i} is the base weight. The adjusted weight for unit i in $s_{b,KN}$ is $d_{1i} = a_{1b} d_{0i}$. Classes were defined by sample stratum.

Non-response Adjustment

An NR adjustment was then made to account for cases who did not progress beyond the questions used to determine eligibility, despite being eligible to do so. The unknown eligibility adjusted base weights for non-responders were distributed among cases who did respond. Classes for the NR adjustment were defined geographically using block-group level characteristics from the Census Planning Database, namely, the percentage of the population from 18 to 24 and the percentage of the population without high school diplomas or equivalent. Block groups were twice split into quartiles based on these two percentages, and the final NR adjustment classes are the cross of two quartile variables for a total of 16 adjustment classes. Quartiles and classes were defined separately for the national sample and each of the four State samples. The NR adjustment for sample units in class *c* can be expressed as

$$a_{2c} = \begin{cases} \sum_{i \in s_{c,E}} d_{1i} \Big/ \sum_{i \in s_{c,ER}} d_{1i} & if\ i \in s_{c,ER} \\ 1 & if\ i \in s_{c,IR} \\ 0 & if\ i \in s_{c,ENR} \end{cases}$$

where d_{1i} is the unknown eligibility adjusted base weight, $s_{c,ER}$ is the sample of eligible respondents in class c, $s_{c,IR}$ is the sample of ineligible respondents in class c, and $s_{c,ENR}$ is the sample of eligible non-respondents in class c.

The weight for unit i in the initial sample, after adjustments for unknown eligibility and NR, can be expressed as $d_{3i} = d_{0i} a_{1bi} a_{2ci}$.

Calibration

With the base weight applied, the samples were calibrated to target population benchmark distributions based on the 2016 Motor Vehicle Occupant Safety Survey (MVOSS; Bailly et al., 2019). The parameters used were male/female and race/ethnicity. For the national sample, these parameters were crossed with the 10 NHTSA Regions.

Missing data in the calibration variables were imputed using hot decking.[2] Hot deck imputation replaces the missing values of a respondent randomly with another similar respondent without missing data. Additionally, to minimize the potential impact of large weights on survey estimates, the weights were trimmed at 2nd and 98th percentiles.

Tables comparing sample demographic distributions (national and State) to population benchmarks derived from the 2021 Current Population Survey (CPS; Flood et al., 2021) are in Appendix C. It should be noted that the benchmark distributions are based on the total 18+

[2] Hot decking was done using an SPSS macro detailed in "Goodbye, Listwise Deletion: Presenting Hot Deck Imputation as an Easy and Effective Tool for Handling Missing Data" (Myers, 2011).

residential population while the data distributions are based on adults who have driven in the past month. These two groups are likely to have slightly different demographic distributions.

Margins of Sampling Error

Post-data collection statistical adjustments require analysis procedures that reflect departures from simple random sampling. The effects of these design features were calculated so that an appropriate adjustment could be incorporated into tests of statistical significance when using these data. The so-called "design effect," or *deff,* represents the loss in statistical efficiency that results from a disproportionate sample design and systematic NR. The composite design effect for a sample of size *n* was calculated, with each case having a weight, *w*, as $n\sum w^2/(\sum w)^2$ (Kish, 1992).

The survey's margin of error is the largest 95 percent confidence interval for any estimated proportion based on the total sample—the one around 50 percent. For example, the margin of error for the national sample is ± 2.1 percentage points. This means that in 95 out of every 100 samples drawn using the same methodology, estimated proportions based on the entire sample will be no more than 2.1 percentage points away from their true values in the population. Margins of error for subgroups will be larger. Table 7 shows sample sizes, design effects and maximum margins of sampling error for the national and State samples. It is important to remember the sampling fluctuations captured in the margin of error are only one possible source of error in a survey estimate. Other sources, such as respondent selection bias, questionnaire wording, and reporting inaccuracy, may contribute additional error of greater or lesser magnitude.

Table 7. Sample sizes, design effects, and margins of sampling error

Sample	Sample Size*	Design Effect	Max. Margin of Sampling Error
National	4,101	1.81	+/-2.1 percentage points
AR oversample	1,645	1.91	+/-3.3 percentage points
IA oversample	2,384	1.85	+/-2.7 percentage points
MA oversample	1,765	1.78	+/-3.1 percentage points
NJ oversample	1,674	1.98	+/-3.4 percentage points
* Includes completes, partial completes, and breakoffs.			

Data Management

We used the services of an optical character recognition (OCR) company to process the data from incoming paper surveys. Weekly exports of the data collected from paper surveys were securely sent to us. Once the weekly data exports were received, these data were then imported into Voxco,[3] the survey management software. All data files were checked weekly as a standard to maintain quality. The researchers checked the files for logic/consistency, missing codes and to make sure that all questions were being answered in accordance with the skip patterns of the survey questionnaire. Additionally, the data files were checked to ensure there were no respondents who answered the survey in both formats (web and paper).

[3] Groupe Voxco, Inc., Montreal, Canada.

Due to delays in identifying completed questionnaires prior to sending out new mail packages, 160 households completed both the web and paper instruments. If a household completed both questionnaires, only data from the paper questionnaire were retained. If a household returned more than one mail questionnaire, the questionnaires were evaluated for completeness, and only the most complete survey was retained. If a household submitted two mail questionnaires with equal levels of completeness, only the first questionnaire received was retained.

Results

There were 10,700 complete responses to the survey. Of these, the unweighted sample size was 3,765 for the national sample. For the State oversamples, the sizes were 1,516 for Arkansas, 1,537 for New Jersey, 1,631 for Massachusetts, and 2,251 for Iowa. All results below are for the national sample unless otherwise stated. Weights were constructed for the dataset as described in the 'Sample Weights section, above. Unless otherwise noted, all descriptive statistics and models below used the sample weights.

The national sample was collected in two stages. After comparing the mean responses between the two sample stages, no substantive differences were found. There were also two modes of completion for the survey: web and paper. Comparing the mean responses, the only substantive difference found was that respondents completing the paper survey were, on average, 12 years older than people completing the web survey. Therefore, the responses for Stages 1 and 2 and the web and paper response modes were combined.

The key outcome variables were whether someone had ever fallen asleep while driving and how many times someone had fallen asleep while driving in the past 30 days. In the national sample, 55 percent of respondents reported falling asleep while driving, with respondents reporting falling asleep an average of 0.23 times in the past 30 days. In the States' oversamples, 44 percent to 62 percent of respondents reported falling asleep while driving, with an average of 0.19 to 0.27 times in the past 30 days. These results are summarized in the table below.

Table 8. Frequency of drowsy driving across all samples

Sample	% Ever Fallen Asleep While Driving	Average Number of Times Falling Asleep in Past 30 Days	*N* (Weighted)
National	55%	0.23	3,800
Arkansas	58%	0.27	1,519
New Jersey	44%	0.19	1,535
Massachusetts	52%	0.22	1,641
Iowa	62%	0.24	2,251

Demographic and Other Characteristics and Drowsy Driving

Table 9 presents demographic characteristics about the national sample of respondents, including the percentage of respondents who reported having fallen asleep while driving and the average number of times respondents had fallen asleep in the past 30 days. Table 10 presents this same information by characteristics of respondents' work and sleep.

Table 9. Reported drowsy driving by key demographic characteristics of national sample

Characteristic		% of Total Sample	% Ever Fallen Asleep	Avg. Times Asleep in Past 30 Days	*N* (Weighted)
Age	18-29	11%	50%	0.32	401
	30-49	35%	55%	0.32	1,304
	50-64	27%	57%	0.18	1,026
	65+	27%	56%	0.11	1,032
Male/Female	Male	47%	64%	0.27	1,799
	Female	50%	47%	0.15	1,904
Education Level	Less than HS Diploma	3%	36%	0.31	132
	HS Graduate/GED	27%	49%	0.19	1,040
	Associate degree	17%	56%	0.20	628
	Bachelor's degree	29%	57%	0.21	1,092
	Graduate degree	23%	62%	0.28	878
Race	American Indian or Alaska Native	4%	50%	0.09	150
	Asian	10%	54%	0.42	378
	Black or African American	15%	50%	0.25	561
	Native Hawaiian or Pacific Islander	1%	55%	0.58	36
	White	73%	57%	0.19	2,756
Ethnicity	Hispanic or Latino	14%	51%	0.30	546
	Not Hispanic or Latino	83%	56%	0.21	3,163
Annual Income	<$24,999	10%	45%	0.15	387
	$25,000-$49,999	17%	55%	0.26	661
	$50,000-$74,999	16%	56%	0.20	611
	$75,000-$99,999	12%	58%	0.21	452
	>$100,000	26%	65%	0.30	977
	"Prefer not to say"	18%	44%	0.15	683

Note. Not all variable row categories sum to 100 percent because of "don't know" and missing responses, or because respondents could select more than one option for the "Race" variable.

Table 10. Reported drowsy driving by key exposure, sleep, and work characteristics of national sample

Characteristic		% of Total Sample	% Ever Fallen Asleep	Avg. Times Asleep in Past 30 Days	*N* (Weighted)
All Drivers					
Driving frequency	A few days a year	2%	48%	0.28	87
	A few days a month	4%	53%	0.17	164
	A few days a week	19%	48%	0.4	716
	Almost every day	25%	59%	0.11	946
	Every day	49%	56%	0.24	1,863
Frequency of night driving (after 9 p.m.)	Never	10%	33%	0.14	366 861
	A few times a year	23%	49%	0.55	861
	A few times a month	37%	60%	0.52	1,414
	A few times a week	22%	61%	0.10	824
	Almost every day	5%	65%	0.32	189
	Every day	3%	54%	0.19	128
Avg. hours of sleep per night	Less than 4 hours	2%	61%	0.62	63
	4 to less than 5 hours	4%	71%	0.70	163
	5 to less than 6 hours	13%	62%	0.35	497
	6 to less than 7 hours	28%	58%	0.27	1,037
	7 to less than 8 hours	34%	55%	0.15	1,256
	8 hours or more	20%	44%	0.07	731
Frequency of difficulty sleeping (in past 3 months)	Never	22%	44%	0.20	814
	Once or twice	27%	52%	0.21	1,019
	Once or twice a month	16%	57%	0.14	605
	Once or twice a week	16%	62%	0.26	597
	Three or four times a week	10%	68%	0.29	368
	Five or six times a week	4%	68%	0.25	162
	Every day	5%	61%	0.43	194

Characteristic		% of Total Sample	% Ever Fallen Asleep	Avg. Times Asleep in Past 30 Days	*N* (Weighted)
Drivers With Paid Employment (Working)					
Days worked per week	1 day	2%	48%	0.09	45
	2 days	2%	62%	0.24	42
	3 days	5%	53%	0.15	124
	4 days	9%	55%	0.19	223
	5 days	65%	66%	0.28	1555
	6 days	13%	58%	0.30	303
	7 days	4%	50%	0.26	88
Shift worked	Day	81%	57%	0.26	1890
	Afternoon	5%	46%	0.16	121
	Night	5%	63%	0.44	124
	Rotating	9%	59%	0.23	210
Commute length	No commute	18%	57%	0.08	434
	Less than 30 minutes	57%	54%	0.24	1336
	30 minutes or more	25%	65%	0.46	585
Note. Not all variable row categories sum to 100 percent because of "don't know" and missing responses.					

Drowsy Driving: Circumstances, Results, and Reactions

The survey asked respondents who had fallen asleep while driving about the circumstances of the most recent time they fell asleep while driving. The greatest number of respondents (27%) reported falling asleep from midnight to 5:59 a.m., and the second most (25%) were in the 6 p.m. to midnight period. The 6 a.m. to 11:59 a.m. period had the lowest reports of drowsy driving (12%).

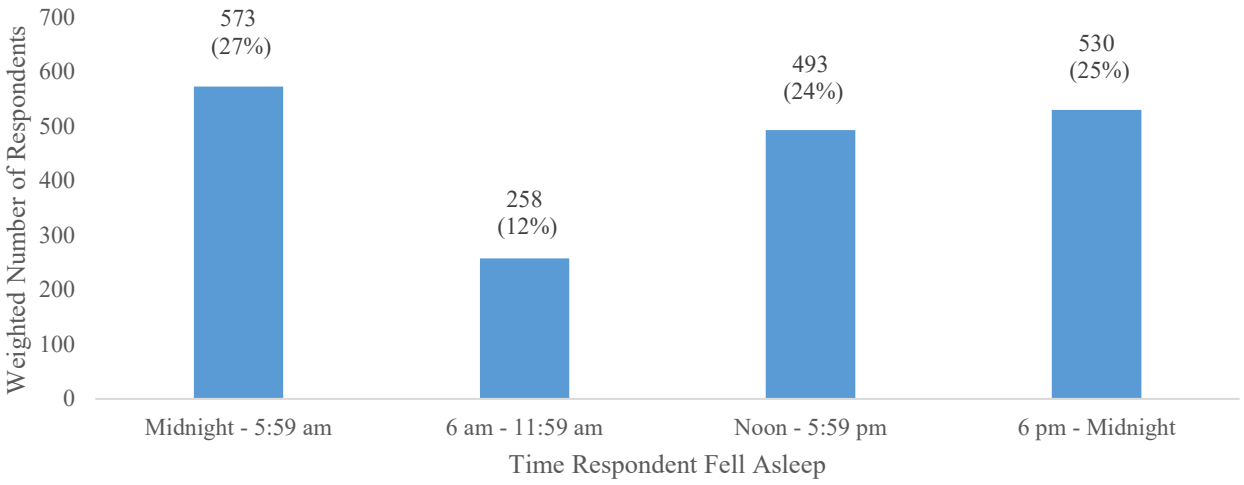
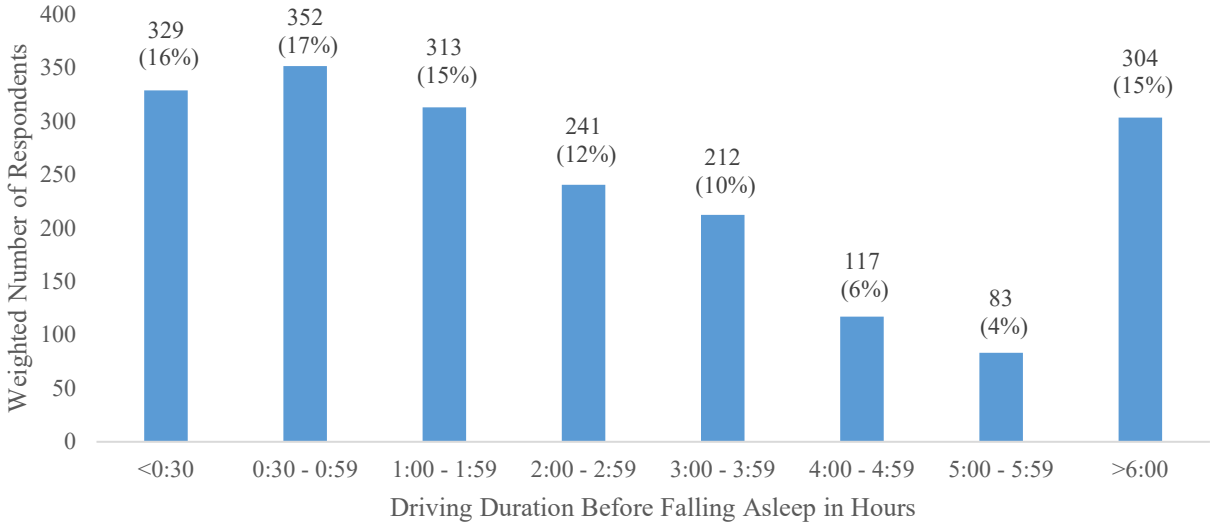


Figure 2. Circumstances of most recent time falling asleep by time of day respondent fell asleep/nodded off

Note. Percentages do not sum to 100 percent because of "don't know" and missing responses.

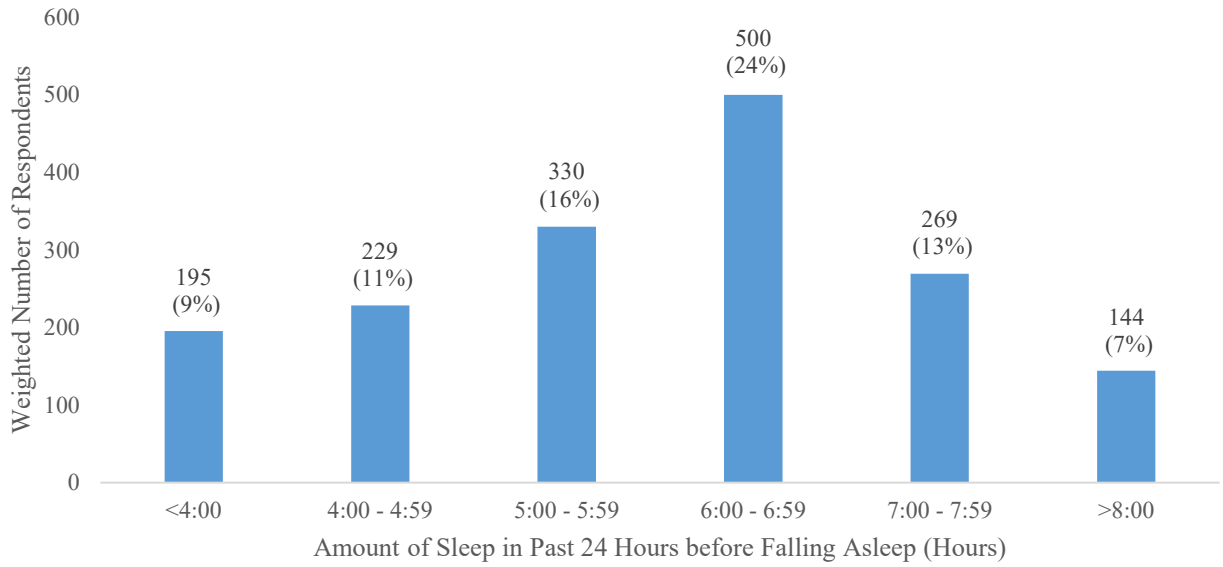
Among the respondents who had fallen asleep while driving, the most common driving duration before their most recent time falling asleep was 30 to 59 minutes (17%). This was followed closely by less than 30 minutes (16%) and greater than 6 hours (15%).



Note. Percentages do not sum to 100 percent because of "don't know" and missing responses.

Figure 3. Circumstances of most recent time falling asleep while driving by driving duration before falling asleep

The survey also asked respondents how much sleep they had before their most recent time falling asleep while driving. The most common response was 6 to 7 hours (24%), while the least common response was greater than 8 hours (7%).



Note. Percentages do not sum to 100 percent because of "don't know" and missing responses.

Figure 4. Circumstances of most recent time falling asleep while driving by amount of sleep in the prior 24 hours

Respondents who had fallen asleep while driving were asked what type of road they were driving on when they last fell asleep. The most common response was a multilane highway with a speed limit greater than 55 mph (62%).

Table 11. Circumstances of most recent time falling asleep while driving by type of road

Type of Road	Percent	*N* (Weighted)
Multilane Highway >55 mph	62%	1,298
Bidirectional Rural Road > 45 mph	13%	273
In-town Street < 45 mph	10%	205
Non-interstate Multilane > 45 mph	9%	194
Don't Know	6%	117

Last, the survey asked whether respondents had consumed alcohol, drugs, or medication within two hours prior to their most recent time drowsy driving, with 3 percent of respondents reporting having consumed alcohol and 3 percent reporting having taken medication or drugs.

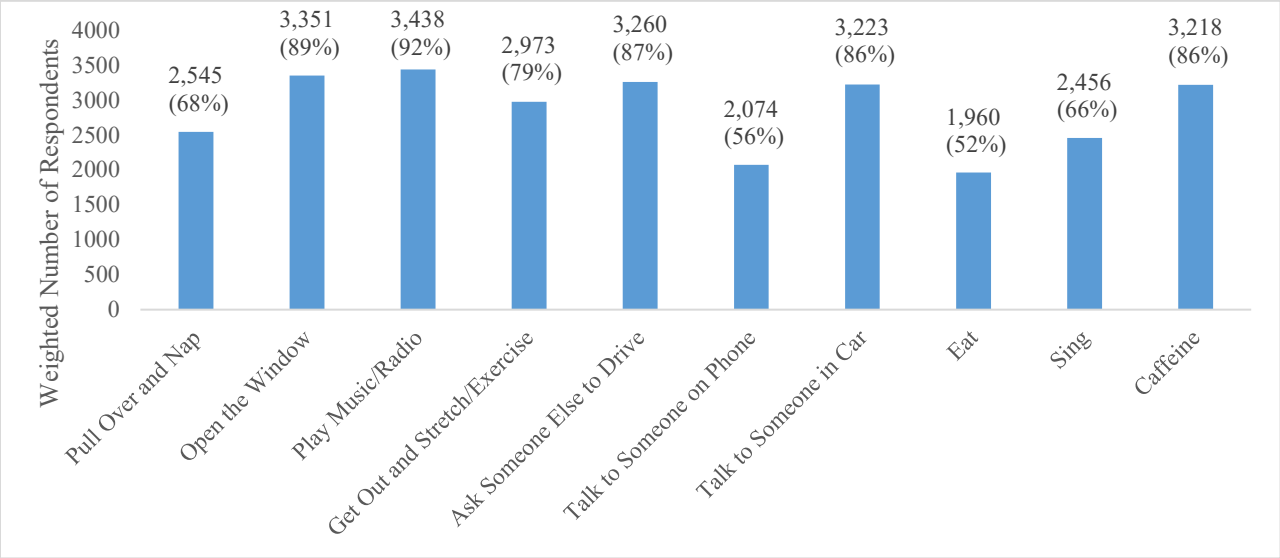
Consequences of Drowsy Driving

The survey asked respondents what happened during the most recent time they fell asleep while driving. The most frequent reaction was to be "startled awake" (55%), and the next most frequent was to drift into another lane or the shoulder of the road (42%). Thirty-two percent of respondents said they unintentionally decreased their speed, and 34 percent forgot driving the last few miles. Only 3 percent reported they crashed, and 2 percent mentioned being pulled over by the police.

Table 12. Type of reaction to most recent time falling asleep while driving

Type of Reaction	Percentage	*N* (Weighted)
Startled awake	55%	1,153
Drifted into other lane/shoulder	42%	884
Unintentionally decreased speed	32%	680
Forgot driving the last few miles	32%	680
Crossed centerline	13%	281
Intentionally increased speed	9%	185
Ran off road	8%	167
Missed exit	5%	104
Crashed	3%	57
Pulled over by police	2%	33
Note. Percentages will not add up to 100 percent because respondents could select more than one option.		

The survey asked *all* respondents what they do when they are driving and feel as though they might fall asleep. The most often reported action was to play music or the radio (92%), followed by opening the window (89%), and asking someone else to drive (87%).



Note. Percentages will not add up to 100 percent because respondents could select more than one option.

Figure 5. Ways of mitigating drowsy driving

Regression Analysis

The purpose of the regression analysis was to understand the relationship between certain composite variables, which we describe below, and the respondent's intention to drive while drowsy. The primary framework for this part of our analysis is the TPB (Ajzen, 1991). We also

used regression models to understand the relationship between State laws and information campaigns and drowsy driving.

Creation of Composite Scores

The first 24 questions of the survey gauged a respondent's orientation to drowsy driving. All items were rated on a 7-point Likert scale. See Appendix B for a list of each question included in the composite.

- Questions 1 to 6 and 12 measured a person's attitude toward drowsy driving and are collectively referred to as the **Attitude Composite**. A high Attitude Composite shows strong attitudes against drowsy driving. Questions asked about the respondent's opinions of having State laws, concerns about personal safety, if they thought drowsy driving was dangerous, if they would take action if falling asleep while driving, if others' drowsy driving was a threat, if driving drowsy while having family in the car was a threat to the family's personal safety, and if it was important to avoid driving while falling asleep/nodding off.
- Questions 8 to 11 measured the strength of norms around drowsy driving and the respondent's experiences in their personal, family, and work life. These questions are collectively referred to as the **Subjective Composite**. A high Subjective Composite shows that the person experiences strong subjective norms against drowsy driving. These questions focused on the respondents' views of the actions of friends and family related to drowsy driving and if their workplace would accept them falling asleep/nodding off as an excuse for being late.
- The third set of questions (7, 13 to 19) measured the level of perceived behavioral control a person has surrounding drowsy driving. These questions are collectively referred to as the **Perception Composite**. A high Perception Composite shows that a person perceives themselves to have a high level of behavioral control to not drive while drowsy. These questions asked if the respondent could lower their risk by not driving while drowsy, if it is difficult to avoid drowsy driving, if they could have avoided drowsy driving, if they could afford a ride service, if they often do not get enough sleep, if they have friends or family who could drive them, if they have a flexible work schedule, and if they generally avoid driving late at night or times they would normally be sleeping.
- The last set of questions (20 to 24) measured an individual's behavioral intention to engage in drowsy driving in the future. These questions are collectively referred to as the **Intention Composite**. A low score on the Intention Composite shows a person has a low intent to drive while drowsy in the future. The questions ask how the respondent will handle situations that could lead to drowsy driving. For example, would they find alternative transportation, would they still drive with little sleep or if falling asleep/nodding off before getting on the road, if they would not drive if tired, and if they planned to get more sleep during the next work week.

Prior to the creation of the composite scores, a principal component analysis was executed to confirm the loadings of each of the TPB constructs. The results of the principal component analysis found that Q1 (importance of a State having a drowsy driving law) did not fit well with the remaining items included in the Attitude Composite. Further, Q11 (whether work would accept falling asleep while driving as a reason for being late) did not fit well with the remaining

items included in the Subjective Composite. Finally, Q13 (whether it's difficult to avoid drowsy driving because of responsibilities) and Q16 (whether respondent often had sleep disruptions that result in driving without enough sleep) did not fit well with the remaining items included in the Perception Composite. Thus, these items were removed from the calculation of the composite scores. After removal of the ill-fitting items, the Cronbach's alpha was calculated to determine internal consistency. The Cronbach's alpha for the attitude scale showed good internal consistency ($\alpha = 0.86$). The Cronbach's alpha for the subjective norm scale ($\alpha = 0.78$) and perception scale ($\alpha = 0.74$) showed acceptable internal consistency. Finally, the Cronbach's alpha for the behavioral intention scale showed questionable yet acceptable internal consistency ($\alpha = 0.68$; Taber, 2017).

Composite scores for each of the TPB constructs were then created by first reverse coding any necessary items and summing the individual item scores. The maximum score for the Attitude Composite was 42, for the Subjective Composite was 21, for the Perception Composite was 42, and for the Intention Composite was 35.

Within the context of the TPB framework, it was hypothesized that an individual's Attitude, Subjective, and Perception Composites will all affect their Intention Composite and that all composite scores predict the likelihood of drowsy driving. Throughout this section, we refer to the Attitude, Subjective, and Perception Composites as the "TPB factors."

Regression Modeling

We estimated linear and logistic regression models to examine the extent to which drowsy driving was associated with the following.

- TPB composites: Attitude, Subjective, Perception, and Intention.
- State laws and public information campaigns to deter drowsy driving.
- Sleep disorders and treatment.
- Alternative ride availability (taxis, Uber, Lyft, other ride share options).
- Information and messaging about drowsy driving.
- Work-related driving frequency (primary, frequent, occasional).
- More frequent driving, in general.
- Sleeping less and difficulty sleeping.
- Shifts worked, days worked, and commute.

The analysis also explored differences between:

- Drowsy driving outcomes in States with laws and States with public information campaigns, as well as examining the effects of laws and public information campaigns/education on those States' respondents in comparison to the national sample; and
- Respondents who fell asleep and those who almost fell asleep.

The key dependent variables for the analysis were based on Q25 and Q26. Q25 asked whether the respondent has ever fallen asleep while driving (yes/no). For respondents who answered "yes" to Q25, Q26 asked for the number of times in the last month they fell asleep while driving. Q26 had six response categories which were recoded to numbers representing the average of

each category.[4] For models using Q25 as the dependent variable, we used logistic regression. For models using Q26 as the dependent variable, we used linear regression.

Note that the logistic regression models using Q25 as the dependent variable and the linear models using Q26 as the dependent variable have different underlying populations and explore different aspects of the hypotheses. In particular, the models using Q25 are constructed using the entire sample and explore whether the independent variables affect whether respondents had ever fallen asleep while driving. On the other hand, the models using Q26 are constructed using only those respondents who have fallen asleep while driving and explore whether the independent variables are significant predictors of the number of times a respondent has fallen asleep in the past 30 days. *P*-values for the omnibus tests are denoted with either $p >$ ChiSq for the logistic regression models or $p >$ F for the linear models, respectively.

For each model with drowsy driving (both versions of the outcome variable) as the dependent variable, we ran two models: one with only one independent (predictor) variable of interest, and a second model that added a set of control variables. The control variables added to each model were:

- Male/female;
- Race (Native American, Asian, Black/African American, Pacific Islander, and/or White);
- Ethnicity (Hispanic or Latino);
- Education (Some High School [HS], HS diploma/GED, Associate degree, Bachelor's degree, or Graduate degree);
- Age (continuous);
- Age-squared (continuous);[5]
- Income (ordinal treated as continuous); and[6]
- Income-squared.[7]

The sample sizes for most regression models were over 2,000 observations, which was more than sufficient to obtain statistically significant estimates. Throughout the discussion, the two distinct models were referred to as the basic model and the control model. The coefficients and other statistics for the demographic control variables were not reported in the results below because we did not have a priori hypotheses about them. However, descriptive statistics by demographic characteristics are reported in Tables 9 and 10.

[4] Original categories: none, once, 2-3, 4-6, 7-9, 10+. The variable used in the analysis has the following categories: 0, 1, 2.5, 5, 8, 11.

[5] People at younger (e.g., under 30) and older (e.g., 65 and older) ages may be more likely to drive while drowsy. By including age and age-squared, we can account for this potential effect. For example, if a positive effect of age and a negative effect of age squared is present in the data, it means that as people get older the effect of age is lessened. A positive effect of age and a positive effect of age squared means that as people get older the effect is stronger. The reason for including income-squared is similar. It accounts for a decreasing effect of income as income increases.

[6] Respondents who selected the "I prefer not to say" income category were recoded to the variable's mid-point ($50,000 - $74,999).

[7] The reason for including income-squared is similar to the reason for including age-squared (see footnote 3, above): it accounts for a decreasing effect of income as income increases.

Regression Models: Theory of Planned Behavior

Hypotheses 1, 2, 3: TPB Factors Predict Lower Behavioral Intention for Drowsy Driving

We hypothesized that each of the TPB composites individually would predict behavioral intention, such that those with negative attitudes toward the behavior of drowsy driving (i.e., higher scores on the Attitude, Subjective, and Perception Composite scores) would have lower behavioral intention to engage in drowsy driving (i.e., lower scores on the Intention Composite).

Specifically:

- H1 was that attitudes toward the behavior will predict behavioral intention, such that those with negative attitudes toward the behavior (i.e., higher scores on the Attitude Composite score) will have lower behavioral intention to engage in drowsy driving (i.e., lower scores on the Intention Composite).
- H2 was that the TPB factor of subjective norms will predict behavioral intention, such that those who perceive that people around them have negative perceptions about drowsy driving (i.e., higher scores on the Subjective Composite score) will have lower behavioral intention to engage in drowsy driving (i.e., lower scores on the Intention Composite).
- H3 was that the TPB factor of perceived behavioral control will predict behavioral intention, such that those who have higher perceptions of perceived behavioral control (i.e., higher scores on the Perception Composite) will have lower behavioral intention to engage in drowsy driving (i.e., lower scores on the Intention Composite).

To test these hypotheses, we estimated basic and control models predicting the Intention Composite from the Attitude, Subjective, and Perception Composites simultaneously. Table 13 shows the results for simultaneous models, basic and with controls.

Table 13. Linear regression models predicting behavioral intention to drive drowsy from attitudes, subjective norms, and behavioral control related to drowsy driving

	B	**SE (B)**	***t***	***p***	**95% CI**	
Basic Model (Adjusted R^2 = .36, N = 3,704, p < .0001)						
Intercept	30.433	0.565	53.84	<0.001	29.325	31.541
Attitude Composite	0.009	0.015	0.61	0.540	-0.020	0.038
Subjective Composite	-0.206	0.027	-7.71	<0.001	-0.259	-0.154
Perception Composite	-0.430	0.011	-38.25	<0.001	-0.452	-0.408
Control Model (Adjusted R^2 = .40, N = 3,657, p < .001)						
Intercept	32.645	0.916	35.66	<0.001	30.850	34.440
Attitude Composite	-0.001	0.015	-0.10	0.923	-0.030	0.027
Subjective Composite	-0.211	0.027	-7.96	<0.001	-0.263	-0.159
Perception Composite	-0.410	0.012	-35.40	<0.001	-0.434	-0.388
Note. Dependent measure for both models is the Intention Composite score. B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

In both the basic and control models, the Attitude Composite was not a significant predictor of the Intention Composite, while the Subjective and Perception Composites had negative associations with the Intention Composite, i.e., higher scores on these two composites were associated with lower Intention Composite scores. Specifically, in the control model, a one-point increase in the Subjective Composite score was associated with a 0.21-point decrease in the Intention Composite score, while a one-point increase in the Perception Composite yielded a 0.41-point decrease in the Intention Composite. In the control model, 40 percent (adjusted R^2) of the variation in the Intention Composite is explained by these three TPB factors and the control variables.

The results of these two models show support for H2 and H3, i.e., respondents with stronger subjective norms about the dangers of drowsy driving and stronger feelings of control over whether they drive drowsy or not had lower intentions to drive drowsy in the future. However, the results did not support H1—more negative attitudes towards drowsy driving did not predict lower intention to drive drowsy in the future.

Hypothesis 4: Perceived Behavioral Control Is the Strongest Predictor of Self-Reported Drowsy Driving Behavior

We hypothesized that the Perception Composite would be the strongest predictor of self-reported drowsy driving because there may be lifestyle/work schedule barriers that make drowsy driving more likely. We also included the other composite scores, Attitude and Subjective, in the same model, to compare their relative predictive power. The results of this logistic regression model are in Table 14 below.

Table 14. Logistic regressions predicting likelihood of self-reported drowsy driving from attitudes, subjective norms, and behavioral control related to drowsy driving

	B	**SE (B)**	***OR***	***p***	**95% CI**	
Basic Model [X^2 (3, N = 3,695) = 246.894, p < 0.0001]						
Intercept	2.161	0.292		<.0001		
Attitude Composite	0.047	0.008	1.048	<.0001	1.032	1.064
Subjective Composite	-0.076	0.014	0.927	<.0001	0.902	0.953
Perception Composite	-0.073	0.006	0.930	<.0001	0.919	0.941
Control Model [X^2 (17, N = 3,648) = 425.563, p < 0.0001]						
Intercept	1.274	0.484		<.0001		
Attitude Composite	0.049	0.008	1.050	<.0001	1.034	1.067
Subjective Composite	-0.058	0.014	0.944	<.0001	0.918	0.971
Perception Composite	-0.085	0.007	0.919	<.0001	0.907	0.931
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. OR = odds ratio. CI = confidence interval for OR.						

In both the basic and control logistic regression models, higher scores on the Subjective and Perception Composites were associated with lower likelihood of having ever fallen asleep while driving. By contrast, higher scores on the Attitude Composite were associated with increased

likelihood of drowsy driving. Considering H4, the odds ratio for the Perception Composite had a larger impact than the Subjective Composite on the likelihood of drowsy driving. However, to formally compare the results for the Subjective and Perception Composites, we conducted a Wald test of the difference between coefficients.[8] The test statistic ($Z = 1.637$) was not significant (one-tailed $p = .051$). Therefore, the results suggest but are not definitive that perceived behavioral control has a stronger effect on self-reported drowsy driving than subjective norms or attitudes towards drowsy driving.

For respondents who reported having ever fallen asleep while driving, we also estimated basic and control linear regression models predicting the number of times respondents had fallen asleep while driving in past 30 days.

Table 15. Linear regressions predicting self-reported number of drowsy driving episodes in past 30 days from attitudes, subjective norms, and behavioral control related to drowsy driving

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted $R^2 = .051$, N = 2,025, $p < .0001$)						
Intercept	1.548	0.200	7.73	<0.001	1.155	1.941
Attitude Composite	-0.004	0.005	-0.81	0.418	-0.014	0.006
Subjective Composite	0.007	0.008	0.81	0.418	-0.010	0.023
Perception Composite	-0.035	0.004	-9.88	<0.001	-0.042	-0.028
Control Model (Adjusted $R^2 = .093$, N = 2,025, $p < .0001$)						
Intercept	1.933	0.319	6.06	<0.001	1.308	2.558
Attitude Composite	-0.003	0.005	-0.55	0.585	-0.013	0.007
Subjective Composite	0.011	0.008	1.30	0.193	-0.005	0.027
Perception Composite	-0.033	0.004	-8.93	<0.001	-0.040	-0.026

Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.

In these linear regression models, only the Perception Composite score significantly predicted the number of times respondents had fallen asleep while driving in the past 30 days. Specifically, a 1-point increase in the Perception Composite was estimated to decrease the number of incidents of having fallen asleep by about .03 instances per month. The other two TPB factors, Attitude and Subjective Composites, were not significant. Considering the results from both the logistic and the linear regression models, we conclude there is evidence to support H4 (that perceived behavioral control is the strongest predictor of self-reported drowsy driving behavior).

Hypothesis 5: Lower Behavioral Intention Scores Will Predict Less Drowsy Driving

We hypothesized that the higher scores on the Intention Composite would have a positive association with whether the respondent had ever fallen asleep while driving and the number of times they fell asleep while driving in the last month. First, the results for the basic and control

[8] The test statistic was calculated as: $(B_{Subjective} - B_{Perception})/SE_{diff}$, where $SE_{diff} = sqrt(var(B_{Subjective}) + var(B_{Perception}) - 2 \times COV_{Subjective/Perception}$.

logistic regression models are presented in Table 16. These results show that higher scores on the Intention Composite were indeed associated with increased likelihood of having ever fallen asleep while driving.

Table 16. Logistic regressions predicting likelihood of drowsy driving from behavioral intention to drive drowsy

	B	**SE (B)**	***OR***	***p***	**95% CI**	
Basic Model [X^2 (1, N = 3,754) = 234.712, p < 0.0001]						
Intercept	-1.111	0.095		<0.001		
Intention Composite	0.102	0.007	1.108	<0.001	1.093	1.123
Control Model [X^2 (17, N = 3,704) = 395.737, p < 0.0001]						
Intercept	-1.956	0.395		<0.001		
Intention Composite	0.106	0.008	1.112	<0.001	1.095	1.128
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. OR = odds ratio. CI = confidence interval for OR.						

Table 17. Linear regressions predicting self-reported number of drowsy driving episodes in past 30 days from behavioral intention to drive drowsy

	B	**SE (B)**	***t***	***p***	**95% CI**	
Basic Model (Adjusted R^2 = .062, N = 2,048, p < .0001)						
Intercept	-0.295	0.064	-4.62	<0.001	-0.421	-0.170
Intention Composite	0.049	0.004	11.67	<0.001	0.041	0.058
Control Model (Adjusted R^2 = .097, N = 2,048, p < .0001)						
Intercept	0.356	0.258	1.38	0.168	-0.150	0.861
Intention Composite	0.043	0.004	9.95	<0.001	0.035	0.051
Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

In this model, Intention Composite scores were associated with increases in the number of times respondents reported having fallen asleep while driving in the past month, with each one-point increase in the Intention Composite yielding an increase in the number of incidents by 0.04 per month. The Intention Composite scores explained about 6 percent of the variation in monthly incidents per respondent (adjusted $R^2 = 0.062$), and, together with the controls, explained 9.6 percent of the variation. In the control mode, about 10 percent (adjusted R^2) of the variation in drowsy driving behavior is explained by behavioral intention and the control variables. Together, both the logistic and linear regression models support the hypothesis that lower behavioral intention to drive drowsy will predict less reported drowsy driving (H5).

Hypothesis 6: Intention Composite Functions as a Mediating Variable Between the TPB Factors and the Likelihood of Drowsy Driving

We hypothesized that the relationship between each of the three TPB factors (Attitude, Subjective, and Perception Composites) and the frequency of drowsy driving in the past 30 days would be partially explained by the Intention Composite. Thus, we examine whether behavioral intention is a mediating factor between the TPB factors and drowsy driving behavior. Using linear regression models, we predicted respondents with higher scores on each of the TPB Composite variables would have lower levels of behavioral intention, resulting in fewer drowsy driving incidents in the past 30 days. The figure below illustrates the question, "How much of the total effect of [Attitude/Subjective/Perception Composites] on Drowsy Driving (arrow 'A') is caused by the indirect effect through Intention Composite (arrow 'B' to 'C')?" To examine this hypothesis, we first estimated a linear regression model predicting drowsy driving from all four TPB Composite scores.

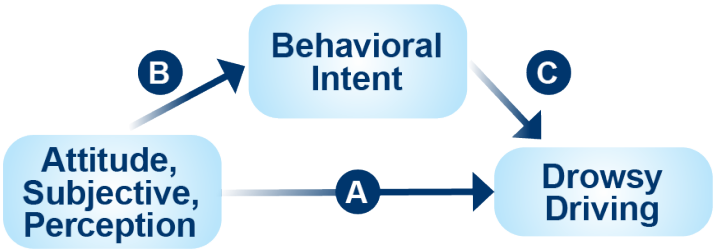


Figure 6. Behavioral intent as a mediating variable

Table 18. Linear regressions predicting drowsy driving behavior from attitudes, subjective norms, behavioral control, and behavioral intention related to drowsy driving

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .072, N = 2,025, p < .0001)						
Intercept	0.417	0.257	1.62	0.105	-0.087	0.921
Intention Composite	0.036	0.005	6.91	<0.001	0.026	0.047
Attitude Composite	-0.004	0.005	-0.77	0.440	-0.014	0.006
Subjective Composite	0.013	0.008	1.59	0.113	-0.003	0.029
Perception Composite	-0.020	0.004	-4.66	<0.001	-0.028	-0.011
Control Model (Adjusted R^2 = .107, N = 2,025, p < .0001)						
Intercept	0.922	0.360	2.56	0.010	0.216	1.628
Intention Composite	0.031	0.005	5.86	<0.001	0.021	0.042
Attitude Composite	-0.003	0.005	-0.51	0.609	-0.012	0.007
Subjective Composite	0.016	0.008	1.93	0.053	0.000	0.032
Perception Composite	-0.020	0.004	-4.59	<0.001	-0.028	-0.011

Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.

In Table 18, the model coefficients represent the "direct effect" of the TPB factors on drowsy driving behavior, while the coefficients in Table 15 represent the "total effect." We can subtract these to find the 'indirect effect' (represented by arrows B and C in Figure 6.) We used the methods of Sobel (1982) and computed the standard error for the indirect effect and the corresponding *p*-value. The full results are presented in Table 19 below. None of the indirect effects of the Attitude, Subjective, and Perception Composites on drowsy driving through the Intention Composite were significant.

Table 19. Behavioral intention as a mediating variable

TPB Factor	Total Effect	Direct Effect	Indirect Effect	SE (Indirect Effect)	*P* (Indirect Effect)
Attitude	-0.003	-0.003	-0.0002	0.034	0.498
Subjective	0.011	0.016	-0.005	0.041	0.450
Perception	-0.033	-0.020	-0.013	0.033	0.345

Exploratory Question: Comparison of Respondents Who Fell Asleep With Respondents Who Almost Fell Asleep

We compared respondents who reported actually falling asleep while driving to those who reported almost falling asleep. Here, we only included respondents who answered affirmatively to only one of these two questions: "In the past 30 days, how many times have you felt tired or sleepy enough while driving that you thought you might fall asleep or nod off, even though you didn't?" and "Have you ever felt tired or sleepy enough while driving that you thought you might fall asleep or nod off, even though you didn't?". We used logistic regression models to predict group membership (fell asleep vs. almost fell asleep) from TPB Composite scores. For these models, odds ratios greater than 1 show greater likelihood of belonging to the "fell asleep" group, while odds ratios less than 1 show greater likelihood of belonging to the "almost fell asleep" group.

Table 20. Logistic regressions predicting likelihood of belonging to "fell asleep" respondent group from attitudes, subjective norms, and behavioral control related to drowsy driving

	B	SE (B)	*OR*	*p*	95% CI	
Basic Model [X^2 (4, N =2,488) = 40.483, p < 0.0001]						
Intercept	3.066	0.656		<.0001		
Attitude Composite	-0.004	0.013	0.996	0.781	0.971	1.022
Subjective Composite	-0.024	0.021	0.976	0.246	0.937	1.017
Perception Composite	-0.037	0.011	0.963	<0.001	0.944	0.983
Intention Composite	0.016	0.013	1.016	0.213	0.991	1.042

	B	SE (B)	*OR*	*p*	95% CI	
Control Model [X^2 (18, N = 2,466) = 128.171, p < 0.0001]						
Intercept	3.325	0.901		<0.001		
Attitude Composite	0.008	0.013	1.008	0.525	0.983	1.034
Subjective Composite	-0.010	0.021	0.990	0.643	0.950	1.032
Perception Composite	-0.059	0.011	0.943	<.0001	0.923	0.964
Intention Composite	0.014	0.014	1.014	0.315	0.987	1.041

Note. Dependent variable for all models is 1 (for respondents who indicated they "ever fell asleep while driving) or 0 (for respondents who indicated they thought they might fall asleep but didn't"). B = unstandardized regression coefficients. SE(B) = standard error of B. OR = odds ratio. CI = confidence interval for OR.

Among the TPB factors, only the Perception Composite was significantly associated with group membership. Specifically, higher scores on the Perception Composite predicted decreased likelihood of belonging to the group of people who reported having fallen asleep while driving (i.e., increased likelihood of being a respondent who almost fell asleep but didn't).

Regression Models: Impacts on Drowsy Driving Based on Laws, Health Issues, Alternative Transportation, Public Messaging, and Work-Related Driving

Hypothesis 7: Respondents in States With Laws or Public Information/Education Campaigns About Drowsy Driving Will Report Less Drowsy Driving

We hypothesized that respondents in States that have public information and education campaigns about drowsy driving or States with laws against drowsy driving would be significantly less likely to report driving drowsy compared to the national sample. The survey asked respondents several questions to gauge attitudes about laws on drowsy driving. Among all respondents, 60 percent supported State laws against drowsy driving, and 62 percent of respondents believed that drivers who fall asleep should be ticketed. Only 20 percent of respondents said that drivers were currently receiving tickets for drowsy driving, while 26 percent said they were not receiving tickets; the majority (54%) did not know. The survey also asked respondents the likelihood of receiving a ticket while drowsy driving: 23 percent said it was very unlikely, 30 percent somewhat unlikely, 30 percent somewhat likely, and 14 percent said it was very likely.

We used logistic and linear regression models to examine whether State laws and/or information and education disseminated to prevent drowsy driving were associated with reduced incidents of self-reported drowsy driving. New Jersey and Arkansas have enacted laws against drowsy driving, while Massachusetts and Iowa have instituted information and education campaigns to inform and educate people on the dangers and risks of drowsy driving. This set of analyses tested the hypothesis that respondents in these four States would have fewer drowsy driving incidents than respondents in States without laws and information campaigns. The key independent variables in the models were an indicator for living in New Jersey or Arkansas (laws) and an indicator for living in Massachusetts or Iowa (public information). The sample for these models includes the national sample and all four oversamples.

Table 21. Logistic regressions predicting likelihood of self-reported drowsy driving from State laws and public information campaigns (along With TPB factors)

	B	SE (B)	*OR*	*p*	95% CI	
Basic Model [X^2 (6, N =10,524) = 955.85, p < 0.0001]						
Intercept	-0.138	0.226		0.543		
Attitude Composite	0.044	0.005	1.044	<.0001	1.035	1.054
Subjective Composite	-0.065	0.008	0.937	<.0001	0.922	0.953
Perception Composite	-0.036	0.004	0.965	<.0001	0.957	0.972
Intention Composite	0.080	0.005	1.083	<.0001	1.073	1.094
Laws (ref. = not living in NJ or AR)	-0.164	0.051	0.849	0.002	0.768	0.939
Public Info (ref. = not living in MA or IA)	0.017	0.049	1.017	0.733	0.924	1.118
Control Model [X^2 (20, N = 10,390) = 1307.30, p < 0.0001]						
Intercept	-0.998	0.332		0.003		
Attitude Composite	0.048	0.005	1.049	<.0001	1.039	1.059
Subjective Composite	-0.058	0.009	0.944	<.0001	0.928	0.960
Perception Composite	-0.047	0.004	0.954	<.0001	0.946	0.963
Intention Composite	0.077	0.005	1.080	<.0001	1.068	1.091
Laws (ref. = not living in NJ or AR)	-0.158	0.053	0.854	0.003	0.769	0.947
Public Info (ref. = not living in MA or IA)	-0.066	0.051	0.936	0.198	0.847	1.035
Note. Dependent variable for all models is "ever fell asleep while driving." B = unstandardized regression coefficients. SE(B) = standard error of B. OR = odds ratio. CI = confidence interval for OR.						

The logistic regression models supported the hypothesis that respondents in States with laws on drowsy driving would have lower likelihood of reporting drowsy driving than States without such laws. However, we did not find similarly reduced likelihood of drowsy driving among respondents living in two States with public information campaigns against drowsy driving relative to respondents living in other States.

Table 22. Linear regressions predicting drowsy driving behavior from State laws and public information campaigns (along with TPB factors)

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .074, N = 5,793, p < .0001)						
Intercept	1.251	0.152	8.200	<.0001	0.952	1.549
Attitude Composite	-0.003	0.003	-0.880	0.382	-0.009	0.003
Subjective Composite	-0.027	0.005	-5.130	<.0001	-0.037	-0.016
Perception Composite	-0.021	0.003	-8.010	<.0001	-0.026	-0.016
Intention Composite	0.027	0.003	8.040	<.0001	0.020	0.033
Laws (ref. = not living in NJ or AR)	0.030	0.035	0.860	0.392	-0.039	0.100
Public Info (ref. = not living in MA or IA)	-0.050	0.032	-1.550	0.122	-0.113	0.013
Control Model (Adjusted R^2 = .097, N = 5,742, p < .001)						
Intercept	1.514	0.219	6.930	<.0001	1.085	1.942
Attitude Composite	-0.001	0.003	-0.180	0.861	-0.006	0.005
Subjective Composite	-0.027	0.005	-5.290	<.0001	-0.037	-0.017
Perception Composite	-0.020	0.003	-7.290	<.0001	-0.025	-0.014
Intention Composite	0.026	0.003	7.800	<.0001	0.020	0.033
Laws (ref. = not living in NJ or AR)	0.035	0.035	1.010	0.314	-0.033	0.104
Public Info (ref. = not living in MA or IA)	0.012	0.033	0.360	0.720	-0.052	0.076

Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.

Neither the presence of State drowsy driving laws nor public information campaigns were significant predictors of the number of times respondents had driven drowsy in the past 30 days. One possibility is that while laws and public information campaigns discourage some drivers from driving drowsy, they may have less of an effect on drivers who (for whatever reason) are more frequent drowsy drivers. Also, note that the dependent variable in the logistic regression model was whether a respondent had *ever* fallen asleep while driving, and some remembered incidents may have occurred before States implemented drowsy driving laws or public information campaigns. The linear regression model, in which the dependent variable was the number of times falling asleep while driving in the past month, more accurately estimated current effects of laws and public information campaigns.

Hypothesis 8: There Will Be Significantly Less Drowsy Driving Reported in States With Laws Against the Practice Compared to States With Only Public Information Campaigns

While the previous models examined the effects of State drowsy driving laws (Arkansas and New Jersey) and State information and education campaigns (Massachusetts and Iowa) on drowsy driving in the national sample, the next set of analyses makes direct comparisons between drowsy driving behavior reported by only respondents in these States (i.e., the State oversamples), controlling for potential differences in demographic variables.

Table 23. Logistic regression predicting likelihood of drowsy driving from presence of State laws (AR and NJ) versus presence of public information campaigns only (MA and IA)

	B	SE (B)	*OR*	*p*	95% CI	
Basic Model [X^2 (1, N = 6,914) = 29.75, p < 0.0001]						
Intercept	0.320	0.033		<.0001		
Laws (ref. = living in MA or IA)	-0.266	0.049	0.767	<.0001	0.697	0.844
Control Model [X^2 (15, N = 6,825) = 289.38, p < 0.0001]						
Intercept	0.0542	0.2740		0.8431		
Laws (ref. = living in MA or IA)	-0.1357	0.0524	0.873	0.0096	0.788	0.967
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). Observations are from the four oversampled States only. B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

The results of the logistic regression model show that living in States with laws against drowsy driving (Arkansas and New Jersey) was associated with lower likelihood of ever having fallen asleep while driving, relative to respondents living in States with only public information campaigns (Massachusetts and Iowa).

Table 24. Linear regression predicting drowsy driving behavior from presence of State laws (AR and NJ) versus presence of public information campaigns only (MA and IA)

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .0001, N = 3,793, p < .267)						
Intercept	0.403	0.024	17.08	<.0001	0.356	0.448
Laws (ref. = living in MA or IA)	0.041	0.037	1.11	0.267	-0.031	0.113
Control Model (Adjusted R^2 = .031, N = 2,757, p < .0001)						
Intercept	1.013	0.207	4.88	<.0001	0.606	1.420
Laws (ref. = living in MA or IA)	-0.033	0.037	-0.88	0.377	-0.106	0.040
Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." Observations are from the four oversampled States only. B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

By contrast, among drivers who had ever engaged in drowsy driving, we did not observe a significant difference between the two groups of States in terms of frequency of reported drowsy driving in the past 30 days. Thus, our hypothesis was only partially supported.

Hypothesis 9: Thinking There Is a Law Against Drowsy Driving Results in Less Drowsy Driving

The survey asked all respondents if they thought there was a law in their State against drowsy driving. Arkansas and New Jersey were the only States with laws against drowsy driving at the time of the survey, and respondents did not seem well-informed about whether their State had a drowsy driving law—over 80 percent of respondents said they did not know if there was such a law in their State (Table 25). To test H9, we used logistic and linear regression models to examine whether thinking there is a State law against drowsy driving was associated with reduced likelihood or frequency of driving drowsy.

Table 25. Thinking there is a law against drowsy driving

	States With Drowsy Driving Laws		**States With Public Information/Education Campaigns but No Drowsy Driving Law**		
	Arkansas (*N* = 1,516)	**New Jersey (*N* = 1,537)**	**Iowa (*N* = 2,251)**	**Massachusetts (*N* = 1,631)**	**National (*N* = 3,765)**
Think there is a law	5%	10%	2%	5%	6%
Think there is not a law	14%	9%	14%	13%	11%
Don't know	81%	81%	84%	83%	83%
Note. Column percentages do not add to 100 percent due to missing responses.					

Table 26. Logistic regression predicting likelihood of drowsy driving from thinking there is a State law against drowsy driving

	B	**SE (B)**	***OR***	***P***	**95% CI**	
Basic Model [X^2 (1, N = 3,277) = 1.56, p < 0.211]						
Intercept	0.1714	0.0358		<.0001		
Think there is a law (ref. = no)	-0.1780	0.1425	0.837	0.212	0.633	1.11
Control Model [X^2 (15, N = 3,232) = 185.93, p < 0.0001]						
Intercept	-0.0155	0.3913		0.9684		
Think there is a law (ref. = no)	-0.2680	0.1494	0.765	0.0729	0.571	1.025
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

Table 27. Linear regressions predicting drowsy driving behavior from thinking there is a State law against drowsy driving

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .033, N = 1,763, p < .0001)						
Intercept	0.330	0.023	14.34	<.0001	0.285	0.375
Think there is a law (ref. = no)	0.746	0.096	7.78	<.0001	0.558	0.934
Control Model (Adjusted R^2 = .080, N = 1,750, p < .0001)						
Intercept	1.074	0.254	4.23	<.0001	0.577	1.571
Think there is a law (ref. = no)	0.637	0.095	6.70	<.0001	0.451	0.824

Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.

In the logistic regression models, thinking there was a State law against drowsy driving was not associated with significantly reduced likelihood of reporting ever having fallen asleep while driving. However, in the linear regression models, we found that among respondents who had reported ever falling asleep while driving, thinking their State had a drowsy driving law was unexpectedly associated with reporting *more* instances of drowsy driving in the past 30 days. This difference between models may reflect differences in the respondents included in each, with the linear regression model only including respondents inclined towards drowsy driving (i.e., those who reported having done it in the past). However, it's unclear why, among this potentially riskier set of respondents, thinking there was a State drowsy driving law was associated with more frequent drowsy driving. One possibility is that this small group of respondents who believed there was a State law (6%) held that belief because of their own awareness of engaging in drowsy driving more often. In other words, respondents may have been concerned there was such a law, or learned about the existence of a law, after having more frequent incidents of drowsy driving. However, this explanation is speculative and requires further investigation.

Hypothesis 10: Those With Diagnosed Sleep Disorders Are More Likely to Report Drowsy Driving Than Those Not Diagnosed

Respondents were asked whether a medical professional had told them that they have sleep apnea, narcolepsy, insomnia, and/or restless leg syndrome, and, if so, if they were receiving treatment. Our linear and logistic regression models compared likelihood and frequency of drowsy driving between those without any sleep disorder, those with a treated sleep disorder, and those with an untreated sleep disorder.

Table 28. Logistic regressions predicting likelihood of drowsy driving from presence of treated or untreated sleep disorders

	B	SE (B)	*OR*	*P*	95% CI	
Basic Model [X^2 (2, N = 3,755) = 39.65, p < 0.0001]						
Intercept	0.454	0.052		<.0001		
Sleep Disorder/Treatment						
No sleep disorder (ref.)	-	-	-	-	-	-
Treated sleep disorder	0.131	0.078	1.616	0.093	1.31	1.99
Untreated sleep disorder	0.218	0.084	1.764	0.010	1.39	2.23
Control Model [X^2 (16, N = 3,705) = 218.02, p < 0.0001]						
Intercept	0.219	0.366		0.549		
Sleep Disorder/Treatment						
No sleep disorder (ref.)	-	-	-	-	-	-
Treated sleep disorder	0.044	0.082	1.472	0.593	1.18	1.83
Untreated sleep disorder	0.299	0.088	1.900	0.001	1.49	2.43
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

Table 29. Linear regressions predicting drowsy driving behavior from presence of treated or untreated sleep disorders

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .005, N = 2,064, p < .002)						
Intercept	0.367	0.026	14.10	<.0001	0.316	0.418
Sleep Disorder/Treatment						
No sleep disorder (ref.)	-	-	-	-	-	-
Treated sleep disorder	0.243	0.067	3.61	0.0003	0.111	0.376
Untreated sleep disorder	0.036	0.074	0.48	0.629	-0.110	0.181
Control Model (Adjusted R^2 = .063, N = 2,048, p < .0001)]						
Intercept	1.150	0.250	4.610	<.0001	0.660	1.639
Sleep Disorder/Treatment						
No sleep disorder (ref.)	-	-	-	-	-	-
Treated sleep disorder	0.334	0.067	4.950	<.0001	0.201	0.466
Untreated sleep disorder	0.057	0.073	0.790	0.432	-0.086	0.201
Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

In the logistic regression models (Table 28), having an untreated sleep disorder was associated with increased likelihood of reporting ever having fallen asleep while driving; those reporting no sleep disorders or only sleep disorders for which they were receiving treatment did not have significantly increased likelihood of drowsy driving. In the linear regression models, however (Table 29), only having a treated sleep disorder was associated with more frequent drowsy driving incidents in the last 30 days. This result could show that among respondents who had ever driven drowsy, those with clinically diagnosed but untreated sleep disorders are more likely to refrain from driving when they feel drowsy.

Hypothesis 11: The Availability of Shared-Ride Services (Including Taxis and Uber) Reduces the Likelihood and Incidents of Drowsy Driving

We hypothesized that the availability of shared-ride services would reduce drowsy driving. We estimated logistic and linear models, basic and with controls, for four regressions in total. The results are presented in Table 30 and Table 31 below.

Table 30. Logistic regressions predicting likelihood of drowsy driving from availability of shared-ride services

	B	**SE (B)**	***OR***	***p***	**95% CI**	
Basic Model [X^2 (1, N = 3,721) = 5.718, p < 0.017]						
Intercept	0.388	0.080		<.0001		
Availability of shared-ride services (ref. = no)	-0.210	0.088	0.811	0.017	0.682	0.964
Control Model [X^2 (15, N = 3,678) = 186.88, p < 0.0001]						
Intercept	0.074	0.369		0.842		
Availability of shared-ride services (ref. = no)	-0.275	0.093	0.760	0.003	0.633	0.912
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

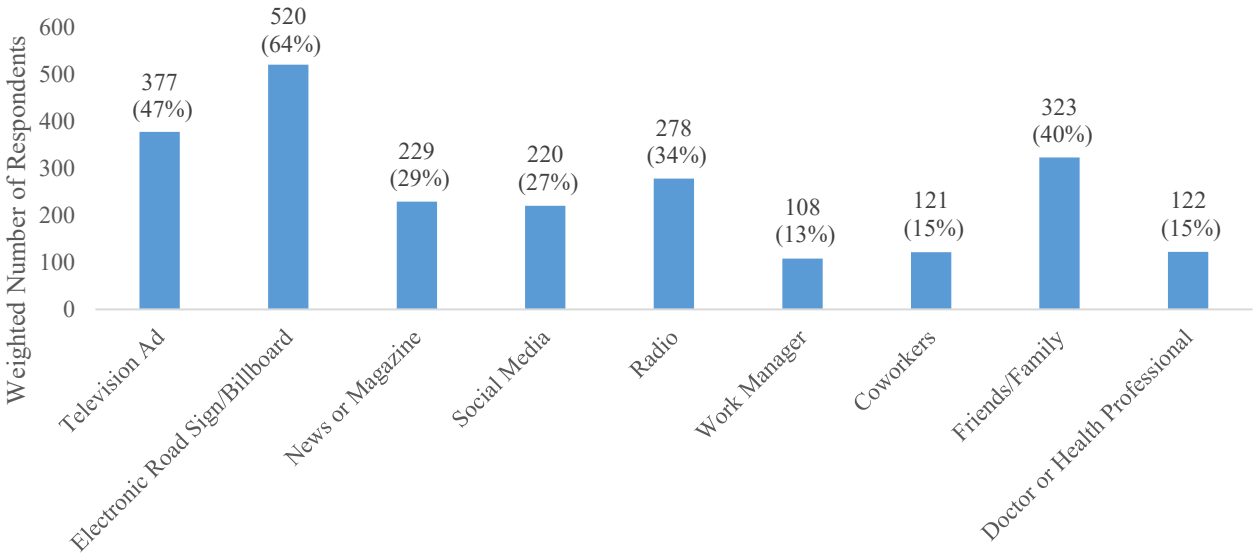
Table 31. Linear regressions predicting drowsy driving behavior from availability of shared-ride services

	B	**SE (B)**	***t***	***p***	**95% CI**	
Basic Model (Adjusted R^2 = <.001, N = 2,050, p < .412)						
Intercept	0.445	0.053	8.370	<.0001	0.341	0.549
Availability of shared-ride services (ref. = no)	-0.048	0.059	-0.820	0.412	-0.164	0.067
Control Model (Adjusted R^2 = ,953, N = 2,038, p < .0001)						
Intercept	1.235	0.256	4.830	<.0001	0.733	1.737
Availability of shared-ride services (ref. = no)	-0.111	0.060	-1.860	0.063	-0.229	0.006
Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

We found partial support for our hypothesis. In the logistic regression models, respondents who indicated that ride shares and/or taxis were available in their communities had reduced likelihood of ever having driven drowsy. However, the availability of rideshare did not predict the number of drowsy driving incidents in the past month among those who had ever driven drowsy.

Hypothesis 12: Hearing Messages About the Dangers of Drowsy Driving Reduces Incidents of Drowsy Driving

The survey asked respondents whether they had heard information about the dangers of drowsy driving in the past year, and 21 percent of respondents indicated they had. Respondents who indicated they had heard these kinds of messages were then asked the source of the information. Respondents reported that most of the information they had encountered was on road signs or billboards, followed by television ads, friends and family, and radio.



Note. Percentages will not add up to 100 percent because respondents could select more than one option.

Figure 7. Sources of information about drowsy driving

We hypothesized respondents who remembered seeing messages about the dangers of drowsy driving would have decreased incidence and frequency of drowsy driving. We ran both logistic and linear models, basic and with controls. The results are presented in Tables 32 and 33 below.

Table 32. Logistic regressions predicting likelihood of drowsy driving from memory of messages about drowsy driving

	B	SE (B)	*OR*	*p*	95% CI	
Basic Model [X^2 (1, N = 3,794) = 24.400, p < 0.0001]						
Intercept	0.1229	0.0367		0.0008		
Heard messages about drowsy driving (ref. = no)	0.3989	0.0815	1.490	<.0001	1.270	1.748
Control Model [X^2 (15, N = 3,699) = 197.406, p < 0.0001]						
Intercept	-0.1241	0.3620		0.7319		
Heard messages about drowsy driving (ref. = no)	0.3075	0.0851	1.360	0.0003	1.151	1.607
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

Table 33. Linear regressions predicting drowsy driving behavior from memory of messages about drowsy driving

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .009, N = 2,063, p < .0001)						
Intercept	0.348	0.026	13.360	<.0001	0.297	0.399
Heard messages about drowsy driving (ref. = no)	0.228	0.053	4.320	<.0001	0.124	0.332
Control Model (Adjusted R^2 = .061, N = 2,047, p < .0001)						
Intercept	1.081	0.250	4.320	<.0001	0.590	1.572
Heard messages about drowsy driving (ref. = no)	0.198	0.052	3.800	0.0002	0.096	0.300
Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

In the logistic regression model, respondents who had heard messages about drowsy driving unexpectedly had *higher* likelihood of engaging in drowsy driving. Similarly, among respondents who had ever driven drowsy, hearing messages about drowsy driving was associated with a significant increase in the number of drowsy driving incidents in the past month. Thus, we did not find support for our hypothesis. We speculate that one reason for this result could be because drivers who have fallen asleep while driving find information about drowsy driving more salient and memorable.

Hypothesis 13: Higher Frequency of Work-Related Driving Increases the Likelihood and Incidents of Drowsy Driving

We hypothesized that respondents who engaged in work-related driving more often would have higher likelihood and frequency of drowsy driving. In the models, we compared respondents who said they drive as part of their job duties "occasionally," "frequently," or said "driving is my primary job" to respondents who never drove for work. The results are presented in Table 34 (logistic) and Table 35 (linear) below.

Table 34. Logistic regressions predicting likelihood of drowsy driving from engagement in work-related driving

	B	**SE (B)**	***OR***	***p***	**95% CI**	
Basic Model [X^2 (1, N = 3,755) = 15.937, p < 0.010]						
Intercept	0.126	0.038		0.001		
Engage in work-related driving (ref. = never)	0.292	0.074	1.339	<.0001	1.16	1.546
Control Model [X^2 (15, N = 3,705) = 187.899, p < 0.0001]						
Intercept	-0.068	0.361		0.850		
Engage in work-related driving (ref. = never)	0.194	0.079	1.214	0.014	1.040	1.418
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

Table 35. Linear regressions predicting drowsy driving behavior from engagement in work-related driving

	B	**SE (B)**	***t***	***p***	**95% CI**	
Basic Model (Adjusted R^2 = .008, N = 2,064, p < .0001)						
Intercept	0.339	0.027	12.470	<.0001	0.286	0.393
Engage in work-related driving (ref. = never)	0.207	0.049	4.220	<.0001	0.111	0.304
Control Model (Adjusted R^2 = .056, N = 2,048, p < .0001)						
Intercept	1.160	0.250	4.630	<.0001	0.668	1.651
Engage in work-related driving (ref. = never)	0.137	0.051	2.700	0.007	0.037	0.236
Note. Dependent measure for both models is "number of times fallen asleep while driving in past 30 days." B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.						

We found evidence driving for work as a primary duty, frequently, or occasionally was associated with an increase in the likelihood of engaging in drowsy driving. Similarly, among those who reported having ever driven drowsy, driving for work was associated with an increased number of drowsy driving incidents in the past month.

Regression Models: Impacts on Drowsy Driving Based on Driving Frequency, Work Circumstances, and Sleep Patterns

Hypothesis 14: Higher Frequency of Driving Increases Likelihood and Incidents of Drowsy Driving

Hypothesis 15: Fewer Hours Sleeping and Difficulty Sleeping Increases Likelihood and Incidents of Drowsy Driving

To examine H14 and H15, we used logistic and linear regression models to predict likelihood and frequency of drowsy driving from key exposure, work, and sleep characteristics among all respondents.

Table 36. Logistic regressions predicting likelihood of drowsy driving from key driving frequency and sleep characteristics

	B	**SE (B)**	***OR***	***p***	**95% CI**	
Basic Model [X^2 (1, N = 3,679) = 168.23, p < 0.0001]						
Intercept	-0.457	0.234		0.051		
Driving frequency (ordinal)	0.022	0.035	1.022	0.538	0.954	1.094
Frequency of night driving (ordinal)	0.227	0.032	1.254	<.0001	1.178	1.336
Avg. hours of sleep per night (ordinal)	-0.125	0.031	0.883	<.0001	0.831	0.937
Frequency of difficulty sleeping (ordinal)	0.158	0.021	1.171	<.0001	1.123	1.221
Control Model [X^2 (15, N = 3,636) = 344.905, p < 0.0001]						
Intercept	-0.787	0.438		0.073		
Driving frequency (ordinal)	0.004	0.037	1.004	0.909	0.935	1.079
Frequency of night driving (ordinal)	0.220	0.034	1.247	<.0001	1.166	1.332
Avg. hours of sleep per night (ordinal)	-0.157	0.033	0.855	<.0001	0.802	0.912
Frequency of difficulty sleeping (ordinal)	0.175	0.023	1.191	<.0001	1.139	1.246

Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.

Table 37. Linear regressions predicting drowsy driving behavior from key driving frequency and sleep characteristics

	B	SE (B)	*t*	*p*	95% CI	
Basic Model (Adjusted R^2 = .051, N = 2,035, p < .0001)						
Intercept	0.798	0.158	5.050	<.0001	0.488	1.109
Driving frequency (ordinal)	-0.002	0.024	-0.080	0.937	-0.049	0.045
Frequency of night driving (ordinal)	0.115	0.022	5.230	<.0001	0.072	0.159
Avg. hours of sleep per night (ordinal)	-0.162	0.020	-8.000	<.0001	-0.202	-0.122
Frequency of difficulty sleeping (ordinal)	-0.014	0.014	-1.020	0.309	-0.041	0.013
Control Model (Adjusted R^2 = .086, N = 2,022, p < .0001)						
Intercept	1.296	0.292	4.440	<.0001	0.724	1.868
Driving frequency (ordinal)	-0.003	0.024	-0.110	0.911	-0.050	0.045
Frequency of night driving (ordinal)	0.082	0.023	3.640	<0.001	0.038	0.126
Avg. hours of sleep per night (ordinal)	-0.142	0.021	-6.820	<.0001	-0.183	-0.101
Frequency of difficulty sleeping (ordinal)	-0.002	0.014	-0.170	0.865	-0.030	0.025

Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.

The results of the logistic regression models showed respondents who reported driving more frequently at night and more frequently experienced difficulty sleeping had increased likelihood of drowsy driving. On the other hand, respondents who reported typically getting more hours of sleep per night had reduced likelihood of drowsy driving. Overall driving frequency was not associated with drowsy driving likelihood. Similarly, among drivers who had ever driven drowsy (linear regression models), increased frequency of night driving was associated with a greater number of drowsy driving incidents in the last 30 days, while more sleep at night was associated with fewer drowsy driving incidents. Thus, we found partial support for our hypotheses.

Hypothesis 16: Number of Days Worked, Night and Shift Work, and Work Commute is Predictive of Increased Likelihood and Incidents of Drowsy Driving

To examine the effects of key work characteristics on drowsy driving, we conducted logistic and linear regression analyses only for drivers who reported having paid employment.

Table 38. Logistic regressions predicting likelihood of drowsy driving from key work characteristics among respondents with paid employment

	B	**SE (B)**	***OR***	***p***	**95% CI**	
Basic Model [X^2 (1, N = 2,541) = 26.229, p < 0.0002]						
Intercept	0.120	0.223		0.590		
Days worked per week (ordinal)	0.012	0.044	1.012	0.791	0.928	1.103
Shift worked						
Day (ref.)	-	-	-	-	-	-
Afternoon	-0.453	0.190	0.636	0.017	0.438	0.922
Night	0.223	0.194	1.249	0.250	0.855	1.826
Rotating	0.029	0.150	1.029	0.847	0.767	1.381
Commute length						
Less than 30 minutes (ref.)	-	-	-	-	-	-
No commute	0.113	0.112	1.12	0.313	0.899	1.395
More than 30 minutes	0.435	0.103	1.545	<.0001	1.263	1.891
Control Model [X^2 (20, N = 2,523) = 112.624, p < 0.0001]						
Intercept	-0.150	0.537		0.781		
Days worked per week (ordinal)	-0.002	0.047	0.998	0.965	0.910	1.095
Shift worked						
Day (ref.)						
Afternoon	-0.327	0.195	0.721	0.093	0.492	1.056
Night	0.483	0.204	1.621	0.018	1.086	2.420
Rotating	0.146	0.156	1.157	0.350	0.852	1.570
Commute length						
Less than 30 minutes (ref.)						
No commute	0.070	0.117	1.072	0.550	0.853	1.347
More than 30 minutes	0.378	0.106	1.459	0.0004	1.184	1.796
Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for OR.						

Table 39. Linear regressions predicting drowsy driving behavior from key work characteristics among respondents with paid employment

	B	**SE (B)**	***t***	***p***	**95% CI**	
Basic Model (Adjusted R^2 = .033, N = 1,459, p < .0001)						
Intercept	0.154	0.154	1.000	0.316	-0.147	0.455
Days worked per week (ordinal)	0.058	0.030	1.930	0.054	-0.001	0.117
Shift worked						
Day (ref.)	-	-	-	-	-	-
Afternoon	-0.112	0.141	-0.790	0.428	-0.390	0.165
Night	0.220	0.120	1.830	0.067	-0.016	0.456
Rotating	-0.113	0.098	-1.150	0.250	-0.306	0.080
Commute length						
Less than 30 minutes (ref.)	-	-	-	-	-	-
No commute	-0.289	0.076	-3.800	0.0001	-0.437	-0.140
More than 30 minutes	0.273	0.065	4.190	<.0001	0.145	0.401
Control Model (Adjusted R^2 = .052, N = 1,454, p < .0001)						
Intercept	0.970	0.366	2.650	0.008	0.252	1.689
Days worked per week (ordinal)	0.048	0.032	1.510	0.130	-0.014	0.111
Shift worked						
Day (ref.)	-	-	-	-	-	-
Afternoon	-0.137	0.145	-0.950	0.344	-0.421	0.147
Night	0.217	0.125	1.740	0.082	-0.028	0.462
Rotating	-0.071	0.099	-0.730	0.469	-0.265	0.122
Commute length						
Less than 30 minutes (ref.)	-	-	-	-	-	-
No commute	-0.274	0.077	-3.560	0.0004	-0.424	-0.123
More than 30 minutes	0.243	0.066	3.690	0.0002	0.114	0.372

Note. Dependent measure for both models is "ever fell asleep while driving" (yes/no). B = unstandardized regression coefficients. SE(B) = standard error of B. CI = confidence interval for B.

In the logistic regression models, respondents with typical commutes longer than 30 minutes had increased likelihood of ever having driven drowsy. There was also some evidence to suggest different work shifts affected drowsy driving differently. In the model without control variables, working an afternoon shift was associated with decreased likelihood of drowsy driving, and in the model with control variables, working a night shift was associated with increased likelihood of drowsy driving.

In the linear regression models, we also found that commute type affected drowsy driving: respondents with no commute reported decreased frequency of drowsy driving in the past 30 days, while respondents with commutes longer than 30 minutes reported increased frequency. No other work characteristics were significant predictors in the linear regression models.

Discussion

In this study, we investigated knowledge, attitudes, and behaviors about drowsy driving in a nationally representative sample of U.S. adults. We also investigated differences between the nationally representative sample and sub-samples from four States with legislation against drowsy driving or a public education campaign to reduce drowsy driving. The TPB was used to develop composite variables and test the connections between different behavioral patterns and outcomes related to drowsy driving.

Theory of Planned Behavior

Past research on drowsy driving using the TPB showed attitudes toward the behavior, subjective norms, and perceived behavioral control are all predictive of behavioral intention, which in turn may be predictive of drowsy driving behavior (Lee et al., 2016). The present study built on extant literature to determine if behavioral intention mediates the relationship between the TPB constructs and drowsy driving behaviors.

We found composite scores for subjective norms and perceived behavioral control predicted one's intention to engage in drowsy driving behaviors, while attitudes towards drowsy driving did not. In other words, those who perceive people around them have negative perceptions about drowsy driving and those who have higher perceptions of perceived behavioral control had reduced intentions to engage in drowsy driving in the future. We also explored whether attitudes, subjective norms, and perceived behavioral control predicted self-reported drowsy driving. We found while those with stronger subjective norms and increased perception of behavioral control had reduced likelihood of reporting ever having driven drowsy, those with stronger attitudes against drowsy driving actually had an increased likelihood of ever having driven drowsy. A possible explanation for this result is that drivers aware of having driven drowsy in the past are more aware of the risks associated with it and developed more negative attitudes, as a result; however, this explanation cannot be confirmed without further investigation. Additionally, we found strong intentions to drive drowsy in the future predicted increased likelihood and frequency of self-reported drowsy driving behavior. However, behavioral intention was not a statistically significant mediator of the relationship between the TPB factors (attitudes, subjective norms, and perceived behavioral control) and drowsy driving behavior.

This finding does not align with the TPB, which posits that subjective norms, attitudes, and perceived behavioral control predict one's behavioral intention, which in turn predicts behavioral outcomes (Ajzen, 1991). One explanation for this result may lie within more recent theoretical distinctions between behavioral intention and another construct called "willingness" (Gerrard et al., 2008; Gibbons et al., 1998). Willingness represents whether someone is open to engaging in a behavior in the right circumstances, even if they don't have any intentions to do so; here, respondents may be willing to drive drowsy if the opportunity to do so arises even if they don't report a conscious intention to drive drowsy in the future. The concept of willingness has been used to augment the TPB as applied to drowsy driving (Beck et al., 2018; Lee et al., 2016, 2019); however, the current survey did not include questions related to willingness to engage in drowsy driving. Given that the concept of willingness has mostly been used to explain impulsive risky health behaviors in young people and adolescents (e.g., Gibbons et al., 1998), additional research would be required to confirm whether willingness is a valuable concept for understanding intention and engagement in drowsy driving in an adult sample of drivers.

Other Hypotheses

State Laws/Public Information

We found respondents in the two States with laws specifically addressing drowsy driving (Arkansas and New Jersey) were less likely to report ever having fallen asleep while driving—specifically, they had about 0.85 times lower odds than respondents in other States, even controlling for respondents' scores on the attitude, subjective norms, perceived behavioral control, and behavioral intention composites. By contrast, we did not find evidence that respondents in Iowa and Massachusetts reported lower likelihood of drowsy driving, two States with public information campaigns against drowsy driving. When the two groups of States were directly compared, we similarly found that respondents in Arkansas and New Jersey had reduced likelihood of drowsy driving relative to respondents in Massachusetts and Iowa. One possible reason for the lack of an effect is that the public information campaigns in these States were not active at the time of data collection and had not been for several years.

Sleep Disorders and Treatment

We found respondents with untreated sleep disorders (sleep apnea, insomnia, narcolepsy, or restless leg syndrome) had increased likelihood of ever having driven drowsy, relative to those with treated sleep disorders or no sleep disorders. Unexpectedly, we also found that, among respondents who had ever driven drowsy, those treated sleep disorders actually reported an increased number of drowsy driving incidents in the past month, relative to respondents with untreated or no sleep disorders. One explanation for this result may be that those with clinically diagnosed and treated sleep disorders feel less need to refrain from driving in circumstances that could produce drowsy driving. Alternatively, respondents who seek treatment for their sleep disorders may have more severe forms of these disorders, which are associated with more driving drowsy incidents even while receiving treatment. Finally, it's possible drivers who notice they have frequent drowsy driving episodes are more likely to see treatment; this survey cannot establish whether treatment or the drowsy driving incidents occurred first.

Shared-Ride Services

Respondents living in areas where taxis or ride share services were available had reduced likelihood of ever driving drowsy and fewer drowsy driving incidents in the past 30 days. These transportation options may be particularly beneficial if people are impaired by alcohol or other drugs, for example, even small amounts of alcohol can worsen driving performance decrements associated with being sleepy (Horne et al., 2003). Thus, the results of this survey suggest increased availability of ride share services, or increased awareness of availability, may be a way that traffic safety stakeholders can reduce drowsy driving.

Information and Messaging

The survey asked respondents whether they remembered seeing or hearing information about the dangers of drowsy driving in the past year. Twenty-one percent of respondents had seen information or messages about the dangers of drowsy driving, and the sources of information they mentioned included road signs or billboards (64%), television ads (47%), friends and family (40%), and radio (34%). Surprisingly, we found that respondents who said they had heard these kinds of messages were more likely to report ever having driven drowsy. We speculate drivers

who have fallen asleep while driving may be more likely to remember receiving information about drowsy driving; in other words, people who drive drowsy find these messages more salient and memorable. However, further research would be required to confirm this hypothesis.

Work-Related Driving

People who work specific shifts, nights, long hours, and irregular schedules are at increased risk of drowsy driving (Hagan-Haynes et al., 2022; Imes et al., 2022; Smith et al., 2019, 2021). Our analyses showed respondents who engaged in work-related driving as a primary job responsibility, along with those who drove for work occasionally or frequently, were together more likely to report having ever driven drowsy and reported an increased number of drowsy driving incidents in the past 30 days. Thus, stakeholders interested in reducing drowsy driving behavior could consider targeting employers with employees who as part of their job duties, for instance, using messaging and public information campaign or promoting workplace policies. Indeed, one study found oil and gas companies with fatigue management and maximum work hour policies were less likely to have workers who reported driving while drowsy (Hagan-Haynes et al., 2022). Stakeholders may consider messaging or incentives which encourage companies to promote these policies.

Driving Frequency, Work Circumstances, and Sleep Patterns

Frequency of driving at night was a significant predictor of increased drowsy driving likelihood and frequency, but general driving frequency was not. Additionally, respondents reporting more frequent difficulty sleeping had increased likelihood of drowsy driving, while respondents reporting more hours of sleep at night had decreased likelihood and frequency of recent drowsy driving. Finally, respondents with no commute—which may allow for more hours of sleep at night—reported fewer incidents of drowsy driving in the past 30 days. Thus, our results are consistent with prior research demonstrating that less or poorer quality of sleep at night and working night shifts are associated with drowsy driving (McCartt et al., 1996; Scott et al., 2007).

Limitations

The present study has several limitations. The first limitation is the survey's low response rate, since those who responded may be different than those who did not and so their responses may not generalize to the United States adult population. Indeed, the results of the NR bias analysis showed there was NR bias related to age, male/female, ethnicity (Hispanic/Latino), and education. While responses by male/female and race/ethnicity were weighted to account for this NR bias, no weighting was applied to correct for the age- and education-related NR bias because the data were calibrated to be similar to the 2016 MVOSS study (Bailly et al., 2019). Thus, these aspects of the data may limit the generalizability of the results.

Another limitation of the current survey relates to the selection of Massachusetts and Iowa as oversampled States to assess the relationship of State public information campaigns and drowsy driving. While both Massachusetts and Iowa previously had awareness programs targeting drowsy driving, these public information campaigns were no longer active in 2022, when these survey data were collected. Thus, because effects of the public information campaigns on drowsy driving behavior may have dissipated by that time, the results of our analyses examining differences between respondents in these States relative to others should be interpreted with caution.

Finally, some potential limitations apply to the responses provided by respondents. Social desirability biases may have resulted in respondents underreporting drowsy driving occurrences or consequences. For example, social desirability may have made respondents less likely to report crashes that occurred while drowsy driving. Further, respondents may have inaccurately recalled things like past instances of drowsy driving behavior or exposure to drowsy driving messaging. Finally, because the current study was not an experiment, we cannot infer that any of the factors we found to be associated with reported drowsy driving caused the drowsy driving.

Conclusion

Our results show predictors of drowsy driving can be partially understood through the lens of the TPB, and we found the extent to which a driver believes they have control over whether they drive drowsy or not had the strongest relationship with reported drowsy driving. However, it may be valuable for future investigations to incorporate the construct of "willingness," which may help to explain spontaneous and circumstantial decisions to drive drowsy. Our results also suggest State laws and the availability of ride share services may help deter drowsy driving, while those who drive or work at night, have less or poorer quality sleep, or have sleep disorders may have increased risk of driving drowsy. The results of this survey may be useful to traffic safety stakeholders aiming to develop or target behavioral countermeasures intended to reduce the incidence of drowsy driving.

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Appendix A: English Questionnaire

Appendix A: English Questionnaire

Under the Paperwork Reduction Act, a federal agency may not conduct or sponsor, and a person is not required to respond to collection of information subject to the requirements of the Paperwork Reduction Act unless that collection of information displays a current valid OMB Control number. The OMB Control Number for this information collection is 2127-0752 (expiration date: 05/31/2024). The average amount of time to complete the "Drowsy Driving Knowledge, Attitudes and Behaviors Survey" is 20 minutes. If you have comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden send them to Information Collection Clearance Officer, National Highway Traffic Safety Administration, 1200 New Jersey Ave, S.E., Washington, DC, 20590.

The "Drowsy Driving Knowledge, Attitudes and Behaviors Survey" is part of a research project to help us develop strategies to prevent drowsy driving. All responses to this collection of information are voluntary. There are no anticipated risks to participating in this study. No personal identifiable information is requested as part of the research or will be associated with your responses. You may discontinue participation at any time without penalty.

National Survey of Drowsy Driving
Knowledge, Attitudes and Behaviors

Thank you for taking part in the ***National Survey of Drowsy Driving Knowledge, Attitudes and Behaviors***.

SURVEY INSTRUCTIONS

For each question, please fill in the circle indicating the most appropriate answer.

For example:

CORRECT

●

INCORRECT

⊗ ⊘ ◒

Please answer all questions unless directed otherwise. For some questions, you will see instructions telling you to skip ahead to other questions in the survey. If you do not feel comfortable answering a question, please move to the next question with which you feel comfortable.

When you have completed the survey, please return it in the enclosed postage-paid envelope.

IF YOU HAVE ANY QUESTIONS:

Call: XXX-XXX-XXXX
Email: XXX

Please return in the enclosed postage-paid envelope to:
National Drowsy Driving Survey
XXXX
XXXXXX

Who Should Take This Survey?

A. Are you 18 years or older?
- ◯ Yes
- ◯ No

B. Have you driven a motor vehicle in the past month?
- ◯ Yes
- ◯ No

If you answered "No" to QA or QB—
Stop. Please do not proceed.
Return in the envelope provided.
We thank you for your participation!

If you answered "Yes" to each of the previous two questions, we invite you to participate in the *National Survey of Drowsy Driving Knowledge, Attitudes and Behaviors*!

Please read the following statements carefully and respond by filling in the circle that best describes your opinion.

Please use the scale shown to the right. ➔

1 = Strongly disagree
2 = Disagree
3 = Somewhat disagree
4 = No opinion
5 = Somewhat agree
6 = Agree
7 = Strongly agree
N/A = Not Applicable

Fill in one circle for each item.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**N/A**
1. It is important for my state to have a law to reduce falling asleep/nodding off while driving by making it a traffic violation (similar to a serious moving violation like reckless driving).	○	○	○	○	○	○	○	
2. It is a threat to *my personal safety* if I drive and fall asleep/nod off.	○	○	○	○	○	○	○	
3. Falling asleep/nodding off while driving is dangerous.	○	○	○	○	○	○	○	
4. When I am falling asleep/nodding off before beginning a trip, it is extremely important to find an alternate way to get to my destination (other than driving myself).	○	○	○	○	○	○	○	
5. When others on the road fall asleep/nod off while driving, it is a threat to me and/or my family's safety.	○	○	○	○	○	○	○	
6. When my family rides in the car with me, it is a threat to my family's personal safety if I fall asleep/nod off while driving.	○	○	○	○	○	○	○	○
7. I can lower my risk of being in a crash by not driving when I am falling asleep/nodding off.	○	○	○	○	○	○	○	
8. I think most of my friends don't drive when they are falling asleep/nodding off.	○	○	○	○	○	○	○	○
9. I think most of my family doesn't drive when they are falling asleep/nodding off.	○	○	○	○	○	○	○	○
10. Most people who are important to me think that I should never drive if I am falling asleep/nodding off.	○	○	○	○	○	○	○	○
11. My work would not accept falling asleep/nodding off while driving to work as a valid excuse for being late.	○	○	○	○	○	○	○	○
12. It is extremely important for me to avoid driving when I am falling asleep/nodding off.	○	○	○	○	○	○	○	

Please read the following statements carefully and respond by filling in the number that best describes your opinion.

Please use the scale shown to the right. ➔

1 = Strongly disagree
2 = Disagree
3 = Somewhat disagree
4 = No opinion
5 = Somewhat agree
6 = Agree
7 = Strongly agree
N/A = Not Applicable

Fill in one circle for each item.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**N/A**
13. It is difficult for me to avoid driving when I am falling asleep/nodding off because of my responsibilities.	○	○	○	○	○	○	○	
14. (Thinking of the most recent time you were driving falling asleep/nodding off) - I believe I could have avoided driving.	○	○	○	○	○	○	○	○
15. I usually have enough spare money that I could afford to take a ride service like Uber, Lyft, or a taxi if I was falling asleep/nodding off.	○	○	○	○	○	○	○	
16. I often have sleep disruptions that result in me driving without getting enough sleep.	○	○	○	○	○	○	○	
17. I have close friends and/or family who can drive so I don't have to drive if I'm falling asleep/nodding off.	○	○	○	○	○	○	○	
18. There is enough flexibility in my schedule that I can sleep longer before having to drive if I am falling asleep/nodding off.	○	○	○	○	○	○	○	
19. I can generally avoid driving late at night or at times when I would normally be sleeping.	○	○	○	○	○	○	○	
20. In the future if I find myself falling asleep/nodding off and need to go somewhere, I will find an alternate mode of transportation or not go.	○	○	○	○	○	○	○	
21. If I only had 4 hours of sleep the night before work or an important event, I would probably still drive.	○	○	○	○	○	○	○	○
22. If I find myself falling asleep/nodding off before getting on the road, I will still drive.	○	○	○	○	○	○	○	
23. I intend to not drive if I am falling asleep/nodding off.	○	○	○	○	○	○	○	
24. I plan to get about 8 hours of sleep per night during the next work week.	○	○	○	○	○	○	○	

The next set of questions ask about your experience falling asleep or nodding off, even for a moment, while driving.

25. Have you *ever* fallen asleep or nodded off, even for a moment, while driving?

◯ Yes – CONTINUE

◯ No – **SKIP** TO **QUESTION 45** ON **PAGE 6**

If you answered "Yes" to question 25, answer questions 26 to 44:

26. In the past 30 days, how many times have you fallen asleep or nodded off, even for a moment, while driving?

◯ None

◯ Once

◯ 2-3 times

◯ 4-6 times

◯ 7-9 times

◯ 10+ times

27. Thinking of the most recent time that you drove and fell asleep/nodded off, how long ago was it?

◯ Within the past 30 days

◯ 31 days – 6 months ago

◯ More than 6 months ago but less than 12 months ago

◯ 12 months ago or more

28. Thinking of the most recent time that you drove and fell asleep/nodded off, what time of day was it?

◯ 6 am – 11:59 am

◯ Noon – 5:59 pm

◯ 6 pm – 11:59 pm

◯ Midnight – 5:59 am

◯ I don't know

29. Thinking of the most recent time that you drove and fell asleep/nodded off, were you driving as part of your job (paid employment)?

◯ Yes

◯ No

30. Thinking of the most recent time that you drove and fell asleep/nodded off, how long had you been driving?

◯ 30 minutes or less

◯ More than 30 minutes, but less than 1 hour

◯ 1 hour to less than 2 hours

◯ 2 hours to less than 3 hours

◯ 3 hours to less than 4 hours

◯ 4 hours to less than 5 hours

◯ 5 hours to less than 6 hours

◯ 6 hours or more

◯ I don't know

31. Thinking of the most recent time that you drove and fell asleep/nodded off, what type of road were you on?

- ◯ Multi-lane highway with speed limits of 55 mph or above
- ◯ Non-interstate multi-lane roads with speed limits of 45 mph or above
- ◯ Two lane rural roads with one lane of traffic traveling in each direction, with speed limits of 45 mph or above
- ◯ City, town, or neighborhood street with speed limits of less than 45 mph
- ◯ I don't know

32. Before the most recent time that you drove and fell asleep/nodded off, how many hours did you sleep in the 24 hours before you drove?

- ◯ Less than 4 hours
- ◯ 4 hours to less than 5 hours
- ◯ 5 hours to less than 6 hours
- ◯ 6 hours to less than 7 hours
- ◯ 7 hours to less than 8 hours
- ◯ 8 hours or more
- ◯ I don't know

In the following yes/no questions, we are still referring to falling asleep or nodding off, even for a moment, while driving.

Thinking of the most recent time you fell asleep or nodded off, even for a moment, while driving…	**Yes**	**No**	**I don't know**
33. Did you run off the road?	◯	◯	◯
34. Did you cross the centerline?	◯	◯	◯
35. Did you drift into the other lane or onto the shoulder?	◯	◯	◯
36. Did you miss your exit?	◯	◯	◯
37. Did you get in a crash?	◯	◯	◯
38. Did you forget driving the last few miles?	◯	◯	◯
39. Did you unintentionally decrease your speed?	◯	◯	◯
40. Did you intentionally increase your speed (to get to your destination quicker)?	◯	◯	◯
41. Did you experience being startled awake?	◯	◯	◯
42. Did you get pulled over by the police?	◯	◯	◯
43. Did you consume alcoholic beverages (wine, beer, or liquor) within two hours prior to the most recent time you were driving drowsy?	◯	◯	◯
44. Did you take medication(s) or other drugs (legal or illegal) that made you drowsy within two hours prior to the most recent time you were driving drowsy?	◯	◯	◯

All respondents continue at Q45. Next are a few questions about drowsy driving in your state.

45. Does your State have a law banning drowsy driving?

- ◯ Yes
- ◯ No
- ◯ I don't know

46. Do you support State laws banning drowsy driving?

- ◯ Yes
- ◯ No
- ◯ I don't know

47. Do you believe that drivers who drive and fall asleep/nod off should be ticketed (similar to a serious moving violation like reckless driving)?

- ◯ Yes
- ◯ No
- ◯ I don't know

48. Do you believe people are receiving tickets (similar to a serious moving violation like reckless driving) for driving and falling asleep/nodding off?

- ◯ Yes
- ◯ No
- ◯ I don't know

49. If you are driving and falling asleep/nodding off, what is the likelihood that you will get a ticket?

- ◯ Very likely
- ◯ Somewhat likely
- ◯ Somewhat unlikely
- ◯ Very unlikely

50. In the past year, do you recall seeing or hearing any information or messages about the dangers of drowsy driving in your state?

- ◯ Yes **– CONTINUE**
- ◯ No **– SKIP TO QUESTION 60 ON PAGE 7**

If you answered "yes" to question 50, answer questions 51-59:

Did you see/hear the information/messages about the dangers of drowsy driving...?	**Yes**	**No**	**I don't know**
51. In a television ad	◯	◯	◯
52. On an electronic road sign or billboard	◯	◯	◯
53. In news or magazine articles	◯	◯	◯
54. On social media such as Facebook, Twitter, or Instagram	◯	◯	◯
55. On the radio	◯	◯	◯
56. From managers at your workplace	◯	◯	◯
57. From coworkers at your workplace	◯	◯	◯
58. From friends/family	◯	◯	◯
59. From a doctor or health care professional	◯	◯	◯

All respondents continue at question 60.

In general, if you feel like you might fall asleep/nod off while driving, do you do any of the following to wake up?	**Yes**	**No**
60. Pull over and take a nap	○	○
61. Open the window	○	○
62. Play music or radio	○	○
63. Get out of the car and stretch/exercise	○	○
64. Ask someone else in the car to drive	○	○
65. Speak to a friend on the phone	○	○
66. Speak to a passenger in the car	○	○
67. Eat	○	○
68. Sing out loud	○	○
69. Get coffee/caffeinated beverage	○	○

The next set of questions (questions 70–82) ask about when you have felt tired or sleepy enough while driving that you thought you might fall asleep or nod off, even though you didn't. *These questions are similar to the questions above; however, please keep in mind that we are now talking about feeling tired or sleepy enough while driving that you thought you might fall asleep or nod off, even though you didn't.*

70. In the past 30 days, how many times have you felt tired or sleepy enough while driving that you thought you might fall asleep or nod off **even though you didn't**?

- ○ None- **CONTINUE TO QUESTION 71**
- ○ Once
- ○ 2-3 times
- ○ 4-6 times
- ○ 7-9 times
- ○ 10+ times

For 1-10+ times **SKIP TO QUESTION 72 ON PAGE 8**

71. Have you ever felt tired or sleepy enough while driving that you thought you might fall asleep or nod off**, even though you didn't?**

- ○ **Yes – CONTINUE**
- ○ **No – SKIP TO QUESTION 83 ON PAGE 8**

Thinking of the most recent time you felt tired or sleepy enough while driving that you thought you *might* fall asleep or nod off, even though you didn't…	**Yes**	**No**	**I don't know**
72. Did you run off the road?	○	○	○
73. Did you cross the centerline?	○	○	○
74. Did you drift into the other lane or onto the shoulder?	○	○	○
75. Did you miss your exit?	○	○	○
76. Did you get in a crash?	○	○	○
77. Did you forget driving the last few miles?	○	○	○
78. Did you unintentionally decrease your speed?	○	○	○
79. Did you intentionally increase your speed (to get to your destination quicker)?	○	○	○
80. Did you get pulled over by the police?	○	○	○
81. Did you consume alcoholic beverages (wine, beer, or liquor) within two hours prior to the most recent time you were driving drowsy?	○	○	○
82. Did you take medication(s) or other drugs (legal or illegal) that made you drowsy within two hours prior to the most recent time you were driving drowsy?	○	○	○

83. How often do you drive a motor vehicle?

- ○ Every day
- ○ Almost every day
- ○ A few days a week
- ○ A few days a month
- ○ A few days a year

84. How often do you drive a motor vehicle at night, after 9:00 PM?

- ○ Every day
- ○ Almost every day
- ○ A few days a week
- ○ A few days a month
- ○ A few days a year
- ○ I never drive after 9:00 at night

The following are some questions related to health conditions that may affect your sleep.	**Yes**	**No**	**I don't know**
85. Are you currently taking any medications or supplements that have a drowsiness warning on the label?	○	○	○
86. Are you currently taking any medications or supplements that cause you to feel drowsy?	○	○	○
87. Has a medical professional ever personally advised you that a medication you have been prescribed may make you drowsy and affect your ability to drive?	○	○	○
88. Do you snore loudly (louder than talking or loud enough to be heard through closed doors)?	○	○	○
89. Do you often feel sleepy during the daytime?	○	○	○
90. Has anyone observed you stop breathing during your sleep?	○	○	○
91. Are you currently being treated for high blood pressure?	○	○	○

92. On average, how many hours of sleep do you get per day, not including naps?

- ○ Less than 4 hours
- ○ 4 hours to less than 5 hours
- ○ 5 hours to less than 6 hours
- ○ 6 hours to less than 7 hours
- ○ 7 hours to less than 8 hours
- ○ 8 hours or more
- ○ I don't know

93. How often do you take **prescription** medications to help you sleep?

- ○ Never
- ○ 1 – 2 times per year
- ○ 3 – 5 times per year
- ○ 6 – 11 times per year
- ○ Once or twice a month but less than weekly
- ○ 1 – 2 times per week
- ○ 3 – 4 times per week
- ○ 5 – 6 times per week
- ○ Every day

94. How often do you take **over-the-counter (OTC)** medications to help you sleep?

- ○ Never
- ○ 1 – 2 times per year
- ○ 3 – 5 times per year
- ○ 6 – 11 times per year
- ○ Once or twice a month but less than weekly
- ○ 1 – 2 times per week
- ○ 3 – 4 times per week
- ○ 5 – 6 times per week
- ○ Every day

Have you been told by a medical professional that you have:	Yes	No
95. Sleep apnea?	◯	◯
96. Narcolepsy?	◯	◯
97. Insomnia?	◯	◯
98. Restless leg syndrome?	◯	◯
	IF YES TO ANY, ANSWER Q99	**IF NO TO Q95-98, SKIP TO Q100**

99. If you answered "Yes" to 95, 96, 97, or 98, are your sleep disorder(s) currently being treated?

◯ Yes
◯ No
◯ I have more than one sleep disorder and some are being treated but others are not

All respondents continue at question 100.

100. Over the past three months, how often have you had difficulty falling asleep, difficulty staying asleep, or problems with waking up too early?

◯ Never
◯ Once or twice
◯ At least once or twice a month but not every week
◯ 1 – 2 times per week
◯ 3 – 4 times per week
◯ 5 – 6 times per week
◯ Every day

Now we have some questions about your work.
For this set of questions work is defined as paid employment that is *not* work from home.
Based on the definition above, If you do not work, please skip this section and go to question 109, page 11.

101. How many ***hours*** do you generally work in a week?

◯ 1 hour – less than 10 hours
◯ 10 hours – less than 20 hours
◯ 20 hours – less than 30 hours
◯ 30 hours – less than 40 hours
◯ 40 hours – less than 50 hours
◯ 50 hours or more

102. How many ***days*** do you generally work in a week?

◯ 1 day
◯ 2 days
◯ 3 days
◯ 4 days
◯ 5 days
◯ 6 days
◯ 7 days

103. How many days do you generally work ***at home*** in a week?

- ◯ 0 days
- ◯ 1 day
- ◯ 2 days
- ◯ 3 days
- ◯ 4 days
- ◯ 5 days
- ◯ 6 days
- ◯ 7 days

104. What shift do you generally work?

- ◯ Day
- ◯ Afternoon
- ◯ Night
- ◯ Rotating between day, afternoon, and/or night

105. What time do you usually begin work?

_____:_____ ◯ AM ◯ PM

106. What time does your work usually end?

_____:_____ ◯ AM ◯ PM

107. If you drive to work, how long is your commute one way?

- ◯ 30 minutes or less
- ◯ More than 30 minutes but less than 60 minutes
- ◯ At least 60 minutes but less than 90 minutes
- ◯ 90 minutes or more
- ◯ I don't drive to work

108. Not counting commuting from your home to your workplace and back, how often do you drive as part of performing your job duties?

- ◯ I never drive as part of performing my job duties
- ◯ I occasionally drive as part of performing my job duties
- ◯ I frequently drive as part of performing my job duties
- ◯ Driving is my primary job

All respondents continue at question 109.

109. Are taxis, Uber, Lyft, or other ride share services available where you live?

- ◯ Yes
- ◯ No

The following questions help us to understand what kind of people are participating in the Drowsy Driving Survey.

110. How old are you? (write in your age) ☐

111. How do you currently identify yourself?

- ◯ Female
- ◯ Male
- ◯ I don't identify as male or female
- ◯ I prefer not to say

112. Which of the following describes your race? You can select as many as apply.

- ◯ American Indian or Alaska Native
- ◯ Asian
- ◯ Black or African American
- ◯ Native Hawaiian or Other Pacific Islander
- ◯ White

113. What is your ethnicity?

- ◯ Hispanic or Latino
- ◯ Not Hispanic or Latino

114. What is the highest degree or level of school you have completed?

- ◯ Some high school, no diploma
- ◯ High school graduate or GED Equivalent
- ◯ Associate Degree
- ◯ Bachelor's Degree
- ◯ Advanced Degree

115. What is your total annual household income before taxes?

- ◯ Less than $24,999
- ◯ $25,000 - $49,999
- ◯ $50,000 - $74,999
- ◯ $75,000 - $99,999
- ◯ $100,000 or greater
- ◯ I prefer not to say

**That completes the National Survey of Drowsy Driving Knowledge, Attitudes and Behaviors.
Thank you very much for your participation! Please call XXX-XXX-XXXX and let us know your 6 digit ID number (below) and your e-mail so we can send your $20 e-gift card! Gift cards take approximately 6-8 weeks to process.**

ID XXX-XXXA

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Appendix B: TPB Items and Constructs

Table B-1. TPB items and constructs

TPB construct	Question Number	Questions on the questionnaire	Reverse Coded	Removed from Scale
Attitude toward the behavior	Q1	It is important for my state to have a law to reduce falling asleep/nodding off while driving by making it a traffic violation (similar to a serious moving violation like reckless driving).		Removed
Attitude toward the behavior	Q2	It is a threat to my personal safety if I drive and fall asleep/nod off.		
Attitude toward the behavior	Q3	Falling asleep/nodding off while driving is dangerous.		
Attitude toward the behavior	Q4	When I am falling asleep/nodding off before beginning a trip, it is extremely important to find an alternate way to get to my destination (other than driving myself).		
Attitude toward the behavior	Q5	When others on the road fall asleep/nod off while driving, it is a threat to me and/or my family's safety.		
Attitude toward the behavior	Q6	When my family rides in the car with me, it is a threat to my family's personal safety if I fall asleep/nod off while driving.		
Perceived behavioral	Q7	I can lower my risk of being in a crash by not driving when I am falling asleep/nodding off.		
Subjective norm	Q8	I think most of my friends don't drive when they are falling asleep/nodding off.		
Subjective norm	Q9	I think most of my family doesn't drive when they are falling asleep/nodding off.		
Subjective norm	Q10	Most people who are important to me think that I should never drive if I am falling asleep/nodding off.		
Subjective norm	Q11	My work would not accept falling asleep/nodding off while driving to work as a valid excuse for being late.	Reverse Coded	Removed
Attitude toward the behavior	Q12	It is extremely important for me to avoid driving when I am falling asleep/nodding off.		
Perceived behavioral	Q13	It is difficult for me to avoid driving when I am falling asleep/nodding off because of my responsibilities.	Reverse Coded	Removed

TPB construct	Question Number	Questions on the questionnaire	Reverse Coded	Removed from Scale
Perceived behavioral	Q14	(Thinking of the most recent time you were driving falling asleep/nodding off) - I believe I could have avoided driving.		
Perceived behavioral	Q15	I usually have enough spare money that I could afford to take a ride service like Uber, Lyft, or a taxi if I was falling asleep/nodding off.		
Perceived behavioral	Q16	I often have sleep disruptions that result in me driving without getting enough sleep.	Reverse Coded	Removed
Perceived behavioral	Q17	I have close friends and/or family who can drive so I don't have to drive if I'm falling asleep/nodding off.		
Perceived behavioral	Q18	There is enough flexibility in my schedule that I can sleep longer before having to drive if I am falling asleep/nodding off.		
Perceived behavioral	Q19	I can generally avoid driving late at night or at times when I would normally be sleeping.		
Intention	Q20	In the future if I find myself falling asleep/nodding off and need to go somewhere, I will find an alternate mode of transportation or not go.		
Intention	Q21	If I only had 4 hours of sleep the night before work or an important event, I would probably still drive.	Reverse Coded	
Intention	Q22	If I find myself to be falling asleep/nodding off before getting on the road, I will still drive.	Reverse Coded	
Intention	Q23	I intend to not drive if I am falling asleep/nodding off.		
Intention	Q24	I plan to get about 8 hours of sleep per night during the next work week.		

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Appendix C: Survey Methodology Details

Delivery Point Details

Table C-1. Delivery points

Delivery Point	Description	Status
City style	Street addresses, including rural routes	Included
Educational	An educational facility (e.g., colleges, universities, dormitories, fraternities/sororities, apartment buildings) occupied by students	Included
Residential	Non-business addresses	Included
Address throwback indicator	City-style (street) addresses for which mail is redirected by the United States Postal Service (USPS) to a P.O. box	Included
P.O. box	Post office boxes	Included
Vacant	Was active in the past, but is currently vacant	Excluded
Business	Nonresidential addresses	Excluded
No-stats	The address is not receiving delivery and is not counted as a delivery point	Excluded
Drop point	Mail delivery points that serve multiple residences (e.g., shared door slot, boarding house) in which mail is distributed internally by the site	Included
Seasonal	Receives mail only during a specific season, and the months the seasonal address is occupied are identified	Excluded

Sampling Plan Details

Table C-2. National sampling plan in detail

Region	Geographic Strata	Age Listed Strata	U.S. Households	% of U.S. Households	RSF* (Stage 1/ Stage 2)	% of Sample	Sample
Northeast	High % Hispanic	Listed, 18-29	198,348	0.15%	10.0/7.0	0.65%	219
Northeast	High % Hispanic	Listed, 30+	665,563	0.50%	1.0/1.0	0.33%	111
Northeast	High % Hispanic	Listed, no age info	126,246	0.10%	3.0/1.0	0.33%	109
Northeast	High % Hispanic	Not listed	348,496	0.26%	0.75/0.50	0.10%	35
Northeast	High % African American	Listed, 18-29	489,532	0.37%	10.0/7.0	1.62%	541
Northeast	High % African American	Listed, 30+	1,686,356	1.28%	1.0/1.0	0.86%	286
Northeast	High % African American	Listed, no age info	210,101	0.16%	3.0/3.0	0.62%	206
Northeast	High % African American	Not listed	596,761	0.45%	0.75/0.50	0.18%	59
Northeast	Residual	Listed, 18-29	2,495,860	1.89%	10.0/3.5	4.52%	1,513
Northeast	Residual	Listed, 30+	12,222,715	9.26%	1.0/0.5	3.66%	1,223
Northeast	Residual	Listed, no age info	1,040,206	0.79%	3.0/1.50	2.63%	880
Northeast	Residual	Not listed	2,386,782	1.81%	0.50/0.25	0.38%	127
Midwest	High % Hispanic	Listed, 18-29	106,305	0.08%	10.0/7.0	0.35%	116
Midwest	High % Hispanic	Listed, 30+	259,886	0.20%	1.0/1.0	0.13%	45
Midwest	High % Hispanic	Listed, no age info	53,087	0.04%	3.0/3.0	0.13%	43
Midwest	High % Hispanic	Not listed	106,173	0.08%	0.75/0.5	0.03%	10
Midwest	High % African American	Listed, 18-29	617,494	0.47%	10.0/7.0	2.05%	684
Midwest	High % African American	Listed, 30+	2,277,175	1.72%	1.0/1.0	1.16%	387
Midwest	High % African American	Listed, no age info	295,806	0.22%	3.0/3.0	0.84%	280
Midwest	High % African American	Not listed	610,231	0.46%	0.75/0.5	0.18%	60
Midwest	Residual	Listed, 18-29	3,322,003	2.52%	10.0/3.5	6.02%	2,013
Midwest	Residual	Listed, 30+	16,798,987	12.72%	1.0/0.5	5.03%	1,681

Region	Geographic Strata	Age Listed Strata	U.S. Households	% of U.S. Households	RSF* (Stage 1/ Stage 2)	% of Sample	Sample
Midwest	Residual	Listed, no age info	1,562,488	1.18%	3.0/1.5	3.61%	1,206
Midwest	Residual	Not listed	2,371,991	1.80%	0.5/0.25	0.39%	130
South	High % Hispanic	Listed, 18-29	913,828	0.69%	10.0/7.0	2.95%	988
South	High % Hispanic	Listed, 30+	2,424,814	1.84%	1.0/1.0	1.21%	404
South	High % Hispanic	Listed, no age info	368,436	0.28%	3.0/3.0	1.06%	355
South	High % Hispanic	Not listed	588,046	0.45%	0.75/0.5	0.18%	61
South	High % African American	Listed, 18-29	2,476,712	1.88%	10.0/7.0	8.09%	2,706
South	High % African American	Listed, 30+	9,017,186	6.83%	1.0/1.0	4.53%	1,516
South	High % African American	Listed, no age info	1,278,567	0.97%	3.0/3.0	3.52%	1,176
South	High % African American	Not listed	2,163,739	1.64%	0.75/0.5	0.64%	215
South	Residual	Listed, 18-29	4,702,385	3.56%	10.0/3.5	8.36%	2,796
South	Residual	Listed, 30+	22,549,369	17.08%	1.0/0.5	6.55%	2,191
South	Residual	Listed, no age info	2,059,943	1.56%	3.0/1.5	5.15%	1,722
South	Residual	Not listed	3,849,567	2.92%	0.5/0.25	0.62%	207
West	High % Hispanic	Listed, 18-29	951,992	0.72%	10.0/7.0	3.10%	1037
West	High % Hispanic	Listed, 30+	2,540,231	1.92%	1.0/1.0	1.29%	430
West	High % Hispanic	Listed, no age info	566,785	0.43%	3.0/3.0	1.37%	459
West	High % Hispanic	Not listed	702,802	0.53%	0.75/0.5	0.21%	71
West	High % African American	Listed, 18-29	170,484	0.13%	10.0/7.0	0.56%	187
West	High % African American	Listed, 30+	655,791	0.50%	1.0/1.0	0.33%	110
West	High % African American	Listed, no age info	93,628	0.07%	3.0/3.0	0.26%	88
West	High % African American	Not listed	162,693	0.12%	0.75/0.5	0.05%	16
West	Residual	Listed, 18-29	2,984,335	2.26%	10.0/3.5	5.30%	1,772
West	Residual	Listed, 30+	15,322,996	11.60%	1.0/0.5	4.46%	1,493

Region	Geographic Strata	Age Listed Strata	U.S. Households	% of U.S. Households	RSF* (Stage 1/ Stage 2)	% of Sample	Sample
West	Residual	Listed, no age info	1,829,637	1.39%	3.0/1.5	3.96%	1,325
West	Residual	Not listed	2,833,527	2.15%	0.5/0.25	0.46%	153
Total			132,056,085	100%		100%	33,442
Note. RSF* stands for Relative Sampling Fraction. It refers to the rate a stratum is sampled relative to any other stratum.							

Table C-3. Arkansas sampling plan

Geographic Strata	Age Listed Strata	AR Households	% of AR Households	RSF*	% of Sample	Sample
High % Hispanic	Listed, 18-29	4,753	0.37%	7.00	2.1%	248
High % Hispanic	Listed, 30+	6,998	0.54%	1.00	0.4%	52
High % Hispanic	Listed, no age info	2,377	0.18%	3.00	0.4%	53
High % Hispanic	Not listed	2,641	0.20%	0.75	0.1%	15
High % African American	Listed, 18-29	46,609	3.61%	7.00	20.3%	2,434
High % African American	Listed, 30+	183,663	14.23%	1.00	11.4%	1,370
High % African American	Listed, no age info	18,221	1.41%	3.00	3.4%	408
High % African American	Not listed	60,077	4.66%	0.75	2.8%	336
Residual	Listed, 18-29	150,390	11.65%	3.50	32.7%	3,926
Residual	Listed, 30+	629,814	48.80%	0.50	19.6%	2,349
Residual	Listed, no age info	49,778	3.86%	1.50	4.6%	557
Residual	Not listed	135,205	10.48%	0.25	2.1%	252
Total		1,290,526	100.00%		100.0%	12,000
Note. RSF* stands for Relative Sampling Fraction. It refers to the rate a stratum is sampled relative to any other stratum.						

Table C-4. New Jersey sampling plan

Geographic Strata	Age Listed Strata	NJ Households	% of NJ Households	RSF*	% of Sample	Sample
High % Hispanic	Listed, 18-29	43,440	1.2%	7.00	7.1%	848
High % Hispanic	Listed, 30+	144,843	4.1%	1.00	3.4%	404
High % Hispanic	Listed, no age info	25,087	0.7%	3.00	1.7%	210
High % Hispanic	Not listed	95,066	2.7%	0.75	1.7%	199
High % African American	Listed, 18-29	96,254	2.7%	7.00	15.7%	1,880
High % African American	Listed, 30+	332,994	9.5%	1.00	7.7%	929
High % African American	Listed, no age info	42,647	1.2%	3.00	3.0%	357
High % African American	Not listed	116,059	3.3%	0.75	2.0%	243
Residual	Listed, 18-29	363,098	10.3%	3.50	29.6%	3,546
Residual	Listed, 30+	1,781,292	50.6%	0.50	20.7%	2,485
Residual	Listed, no age info	162,140	4.6%	1.50	5.7%	679
Residual	Not listed	314,773	8.9%	0.25	1.8%	220
Total		3,517,693	100.0%		100.0%	12,000
Note. RSF* stands for Relative Sampling Fraction. It refers to the rate a stratum is sampled relative to any other stratum.						

Table C-5. Massachusetts sampling plan

Geographic Strata	Age Listed Strata	MA Households	% of MA Households	RSF*	% of Sample	Sample
High % Hispanic	Listed, 18-29	16,112	0.6%	7.00	3.8%	457
High % Hispanic	Listed, 30+	53,618	1.9%	1.00	1.8%	217
High % Hispanic	Listed, no age info	7,396	0.3%	3.00	0.7%	90
High % Hispanic	Not listed	27,865	1.0%	0.75	0.7%	85
High % African American	Listed, 18-29	33,940	1.2%	7.00	8.0%	963
High % African American	Listed, 30+	115,820	4.2%	1.00	3.9%	469

Geographic Strata	Age Listed Strata	MA Households	% of MA Households	RSF*	% of Sample	Sample
High % African American	Listed, no age info	11,093	0.4%	3.00	1.1%	135
High % African American	Not listed	36,714	1.3%	0.75	0.9%	112
Residual	Listed, 18-29	361,854	13.0%	3.50	42.8%	5,133
Residual	Listed, 30+	1,667,302	59.9%	0.50	28.2%	3,379
Residual	Listed, no age info	98,916	3.6%	1.50	5.0%	601
Residual	Not listed	353,534	12.7%	0.25	3.0%	358
Total		2,784,164	100.0%		100.0%	12,000
Note. RSF* stands for Relative Sampling Fraction. It refers to the rate a stratum is sampled relative to any other stratum.						

Table C-6. Iowa sampling plan

Geographic Strata	Age Listed Strata	IA Households	% of IA Households	RSF*	% of Sample	Sample
High % Hispanic	Listed, 18-29	1,056	0.08%	7.00	0.5%	66
High % Hispanic	Listed, 30+	4,358	0.34%	1.00	0.3%	39
High % Hispanic	Listed, no age info	528	0.04%	3.00	0.1%	14
High % Hispanic	Not listed	924	0.07%	0.75	0.1%	6
High % African American	Listed, 18-29	8,056	0.62%	7.00	4.2%	503
High % African American	Listed, 30+	21,790	1.69%	1.00	1.6%	194
High % African American	Listed, no age info	2,905	0.23%	3.00	0.6%	78
High % African American	Not listed	6,075	0.47%	0.75	0.3%	41
Residual	Listed, 18-29	198,884	15.41%	3.50	51.8%	6,213
Residual	Listed, 30+	899,866	69.72%	0.50	33.5%	4,016
Residual	Listed, no age info	45,165	3.50%	1.50	5.0%	605

Geographic Strata	Age Listed Strata	IA Households	% of IA Households	RSF*	% of Sample	Sample
Residual	Not listed	101,159	7.84%	0.25	1.9%	226
Total		1,290,766			100.0%	12,000
Note. RSF* stands for Relative Sampling Fraction. It refers to the rate a stratum is sampled relative to any other stratum.						

Mailing Protocol Details

Table C-7. Stage 1 mailing protocol

Mailing	Mailing Description	Mailing Contents	Mail Drop Date	Population	Quantity
1	Mailed letter inviting web response	One-page letter (English and Spanish) inviting response by web $2 in cash for half of sample	1/26/2022	All sampled addresses	10,002
2	Mailed postcard reminder inviting web response	One 5x7 reminder postcard	2/5/2022	All sampled addresses	10,002
3	Questionnaire with Business Reply Envelope	One-page letter inviting response by web or mailed paper survey in English and in Spanish if identified as being in the high Hispanic stratum Questionnaire packet in English and in Spanish if identified as being in the high Hispanic stratum Business Reply Envelope	2/24/2022	All but completes, refusals, and undeliverables	9,579
4	Mailed postcard reminder inviting web response	One 5x7 reminder postcard	3/4/2022	All but completes, refusals, and undeliverables	9,413

Mailing	Mailing Description	Mailing Contents	Mail Drop Date	Population	Quantity
5	Questionnaire with Business Reply Envelope	One-page letter inviting response by web or mailed paper survey in English and in Spanish if identified as being in the high Hispanic stratum Questionnaire packet in English and in Spanish if identified as being in the high Hispanic stratum Business Reply Envelope	3/21/2022	All but completes, refusals, and undeliverables	9,292

Table C-8. Stage 2 mailing protocol

Mailing	Mailing Description	Mailing Contents	Mail Drop Date	Population	Quantity
1	Mailed letter inviting web response	One-page letter (English and Spanish) inviting response by web $1 in cash for entire sample	9/22/2022	All sampled addresses	71,440
2	Mailed postcard reminder inviting web response	One 5x7 reminder postcard	10/6/2022	All but completes, refusals, and undeliverables	69,537
3	Questionnaire with Business Reply Envelope	One-page letter inviting response by web or mailed paper survey in English and in Spanish if identified as being in the high Hispanic stratum Questionnaire packet in English and in Spanish if identified as being in the high Hispanic stratum Business Reply Envelope	10/25/2022	All but completes, refusals, and undeliverables	67,012
4	Mailed postcard reminder inviting web response	One 5x7 reminder postcard	11/4/2022	All but completes, refusals, and undeliverables	65,497

Mailing	Mailing Description	Mailing Contents	Mail Drop Date	Population	Quantity
5	Questionnaire with Business Reply Envelope	One-page letter inviting response by web or mailed paper survey in English and in Spanish if identified as being in the high Hispanic stratum Questionnaire packet in English and in Spanish if identified as being in the high Hispanic stratum Business Reply Envelope	11/17/2022	All but completes, refusals, and undeliverables	63,074

Comparison of Sample Demographics to Population Benchmarks

Table C-9. National and Arkansas demographic distributions

	National			Arkansas		
	CPS Benchmark	**Unweighted**	**Weighted**	**CPS Benchmark**	**Unweighted**	**Weighted**
Sex						
Male	48.8%	41.8%	44.4%	48.5%	35.7%	41.2%
Female	51.2%	48.8%	47.4%	51.5%	54.8%	50.3%
Other	NA	2.3%	2.1%	NA	2.4%	2.2%
Missing	NA	7.1%	6.1%	NA	7.1%	6.3%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*
Age						
18-29	19.9%	18.2%	9.8%	19.9%	19.8%	10.2%
30-49	33.5%	27.9%	31.9%	32.2%	28.1%	31.0%
50-64	24.6%	27.6%	25.3%	24.6%	27.6%	26.1%
65+	22.0%	18.5%	26.0%	23.3%	16.6%	25.2%
Missing	NA	7.8%	6.9%	NA	7.9%	7.5%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*

	National			Arkansas		
	CPS Benchmark	**Unweighted**	**Weighted**	**CPS Benchmark**	**Unweighted**	**Weighted**
Race/Ethnicity						
White, not Hispanic	62.0%	58.4%	56.0%	72.4%	66.3%	64.1%
African American, not Hispanic	12.0%	11.6%	11.8%	15.1%	15.0%	16.4%
Hispanic	17.2%	12.8%	13.4%	7.1%	6.0%	6.6%
Multiple races, not Hispanic	8.7%	9.4%	11.7%	5.4%	5.1%	6.1%
Missing	NA	7.9%	7.1%	NA	7.7%	6.7%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*

Table C-10. Demographic distributions for Iowa, Massachusetts, New Jersey

	Iowa			Massachusetts			New Jersey		
	CPS Benchmark	**Unweighted**	**Weighted**	**CPS Benchmark**	**Unweighted**	**Weighted**	**CPS Benchmark**	**Unweighted**	**Weighted**
Sex									
Male	50.1%	41.3%	50.0%	47.7%	45.7%	46.6%	49.0%	45.3%	47.3%
Female	49.9%	51.8%	43.9%	52.3%	44.9%	44.6%	51.0%	44.6%	42.5%
Other	NA	1.9%	1.5%	NA	2.4%	2.7%	NA	2.5%	2.6%
Missing	NA	5.0%	4.6%	NA	6.9%	6.1%	NA	7.6%	7.6%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Age									
18-29	19.1%	22.8%	8.5%	20.9%	17.7%	8.8%	19.1%	14.4%	8.1%
30-49	33.2%	28.1%	31.2%	32.2%	23.5%	31.2%	32.6%	23.5%	32.2%
50-64	23.4%	27.6%	26.0%	24.0%	31.6%	25.0%	25.9%	37.0%	29.8%
65+	24.2%	15.9%	29.0%	22.9%	19.7%	28.4%	22.3%	17.1%	21.9%

	Iowa			Massachusetts			New Jersey		
	CPS Benchmark	**Unweighted**	**Weighted**	**CPS Benchmark**	**Unweighted**	**Weighted**	**CPS Benchmark**	**Unweighted**	**Weighted**
Missing	NA	5.6%	5.3%	NA	7.5%	6.6%	NA	7.9%	7.9%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*
Race/Ethnicity									
White, not Hispanic	88.3%	85.0%	90.7%	72.2%	68.1%	65.0%	53.9%	54.7%	45.4%
African American, not Hispanic	3.5%	2.1%	0.9%	7.3%	5.7%	6.4%	12.9%	10.5%	10.7%
Hispanic	4.6%	4.0%	2.0%	10.9%	7.7%	8.6%	20.2%	14.4%	17.4%
Multiple races, not Hispanic	3.6%	3.4%	1.6%	9.6%	10.4%	12.6%	13.0%	12.1%	18.1%
Missing	NA	5.6%	4.8%	NA	8.1%	7.4%	NA	8.4%	8.3%
	100%	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*	*100%*

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