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Mental health conditions and unsafe driving behaviors: A naturalistic driving study on ADHD and depression

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ABSTRACT

Introduction: Road injuries remain a persistent public health concern across the world. The task of driving is complicated by mental health conditions, which may affect drivers' executive functioning and cognitive resource allocation. This study examines whether attention-deficit/hyperactivity disorder (ADHD) and depression are associated with unsafe driving behaviors. *Method:* Generalized linear mixed models were employed to estimate the association of self-reported ADHD and depression with 18 unsafe driving behavior types found prior to at-fault crashes and near-crashes using a large-scale naturalistic driving dataset. Driver demographics, cognitive traits, environmental factors, and driver random effects were included to reduce confounding and biases. *Results:* Controlling for other covariates, people with self-reported ADHD were more likely to have performed improper braking or stopping (OR = 4.89, 95% CI 1.82–13.17) prior to an at-fault crash or near-crash, while those with self-reported depression did not have a significant association with any unsafe driving behavior. *Conclusions:* After accounting for demographic, cognitive, and environmental covariates, individuals with ADHD and depression were not prone to purposefully aggressive or reckless driving. Instead, drivers with self-reported ADHD may unintentionally execute unsafe driving behaviors in particular driving scenarios that require a high level of cognitive judgment. *Practical Applications:* These findings can inform the curriculum design of driver's education programs that help learners with mental health conditions gain practice in certain road scenarios, for example, more practice on preemptively reducing speed instead of making sudden brakes and smooth turning on curved roads for students with ADHD. Furthermore, specific advanced driver assistance systems may prove particularly helpful for drivers with ADHD, such as detection of leading objects and curve speed warning.

1. Introduction

Road injuries remain a global health burden with geographical heterogeneity – many regions continue to experience increasing incidence rates, while other parts of the world see a decrease in age-standardized mortality rate (James, 2020). According to the latest report published by the World Health Organization (WHO), annual road traffic mortalities reached 1.35 million across the world, and between 20 and 50 million more people suffer nonfatal injuries and many incur lifelong disabilities (World Health Organization, 2018). In the United States, 36,096 lives were lost and 2.74 million injured due to motor-vehicle traffic crashes during 2019 (National Highway Traffic Safety Administration, 2020).

Improving the assessment of psychophysical abilities to drive was highlighted as one of the 17 emerging issues in road safety at the Safety 2016 World Conference (Seguí-Gomez, 2016). From work commute to grocery shopping, from ride-sharing to last-mile trucking services, driving provides not only a mode of transportation but also a means of living for a lot of people. Depressive disorders and attention-deficit/hyperactivity disorder (ADHD) are common mental health conditions (MHCs) (Clarke, Schiller, & Boersma, 2019; Degenhardt, 2019; Faraone, 2021), which means that those with the symptoms have to carry on with all facets of everyday life, including driving, while receiving treatment or remaining undiagnosed. This study aims to examine how ADHD and depression may impact driving behaviors.

1.1. ADHD and road safety

A meta-analysis suggested that ADHD was likely associated with higher than normal rates of negative driving outcomes (re-

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lated risk = 1.88, 95% CI [1,42, 2.50]) because of possible deficiencies in executive functioning (Jerome, Segal, & Habinski, 2006). Among adolescents and young adults, the adjusted risk of the first crash was 1.36 times higher among those with ADHD than without and did not vary by sex, licensing age, or over time (Curry, 2017). A meta-analysis of six studies suggested the positive effects of stimulant medications on driving performance (Barkley & Cox, 2007). Another study based on naturalistic driving data found that ADHD symptoms increased the crash risk by 5% for every increase in the ADHD severity score, and medication may not attenuate the risk (Aduen, 2018).

Previous studies on ADHD and driving behaviors primarily relied on self-report scales, such as the Driving Behavior Rating Scale and the Driving Behavior Questionnaire, which found more risky driving behaviors exist among ADHD groups compared to non-ADHD groups. Richards et al., using a series of psychological surveys found that both college students and adults with high ADHD symptoms reported a higher likelihood of risky and aggressive driving to express driving anger (Richards et al., 2002, 2006). Malta et al. reported that young adult drivers with self-reported high driving aggression have a significantly higher prevalence of ADHD (Malta, Blanchard, & Freidenberg, 2005). A few studies employed driving simulators to assess driving performance and found poorer steering control that may reflect poor motor control and coordination, however, the finding could not be reproduced using a large-scale study (Jerome et al., 2006).

1.2. Depression and road safety

In terms of driving outcomes, a meta-analysis of studies published between 1995 and 2015 estimated that depression increased crash risk by 2-fold (Hill, 2017). Using large-scale naturalistic driving data, researchers found that depression was not associated with increased risk of motor-vehicle crashes or collision fault, but increased risk of self-reported injuries following a collision (Aduen, Kofler, Cox, Sarver, & Lunsford, 2015). In terms of driving behaviors, multiple epidemiological studies reported mixed results on the association between depression and the risk of motor-vehicle collisions and injuries, but a more consistent association between depression and self-reported aggressive or risky driving behaviors, suggesting drivers with depressive symptoms exhibited difficulties in allocating cognitive resources to competing driving tasks (Wickens, Smart, & Mann, 2014). Using the Young Adult Driving Questionnaire, McDonald et al., reported that depressive symptoms were linked to reckless driving among adolescents and adults (McDonald, Sommers, & Fargo, 2014). One longitudinal study following a large cohort of Australian teen drivers found no significant association between depression and self-reported engagement in risky driving (Vassallo, 2008). Anxiety is frequently observed as a comorbidity with depression, and vice versa (Almeida, 2012). A study on a French cohort of drivers entering old age found that having depression, anxiety, or stress was associated with an increased crash risk despite increased driving avoidance (Turrado, 2021).

1.3. Limitations in current literature

Motor-vehicle crashes are not isolated events, rather, they happen in highly random and complex environments with a multitude of contributing factors. Contradicting findings on the effects of MHCs on driving can be attributable to methodological limitations including lack of control for driving exposure, lack of control for confounders (such as age, driving experience, and comorbidities), limited response rate or sample size, nonstandard definitions of collisions (e.g., less severe collisions were unreported), and self-report bias (Jerome et al., 2006; Kaye, Lewis, & Freeman, 2018; Wickens et al., 2014). Unsafe driving behaviors and risk factors do not generalize across different driving populations, therefore a multi-factor framework for specific risky driving behaviors is recommended (Fernandes, Job, & Hatfield, 2007).

In summary, past literature indicates that MHCs play an important role in driving performances, but there is a need to further verify these findings with naturalistic driving scenarios, in which confounding factors can be controlled. Few studies examined the association between MHCs and unsafe driving behaviors using naturalistic driving data to avoid self-report biases.

2. Materials and methods

2.1. Data source

Data from the Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) were used for this study (Dingus et al., 2014; Hankey, Perez, & McClafferty, 2016). The SHRP 2 is one of the largest NDS in the world, which recorded more than six million real-world driving trips by approximately 3,500 volunteer drivers across six U.S. states: Florida, Indiana, North Carolina, New York, Pennsylvania, and Washington. Participant vehicles were outfitted with a front-view camera, a rear-view camera, an in-cabin camera, a front-facing radar, and a data collection unit (DAS) that records data from the aforementioned devices as well as the vehicle's Controller Area Network (CAN bus). As a result, the SHRP 2 dataset provides a large collection of crashes, near-crashes, as well as non-eventful baselines, of which crucial data points characterizing the trips were recorded and analyzed. Human-expert annotated variables based on video recordings of the trips, as well as demographic, cognitive, behavioral, and medical information of the volunteer drivers, are known for each trip.

2.2. Human subjects protection

The SHRP 2 NDS was approved by the Institutional Review Boards of the Virginia Tech and National Academy of Sciences (NAS). Issuance of a Certificate of Confidentiality was initiated through the National Institutes of Health (NIH). Participants consented to have data collected from their main vehicle when it was driven during the study period, as well as to provide a broad set of functional assessments. Participants who were minors at the time of study provided assent to participate, and consent for participation was provided by a parent. Participants were compensated for study participation (Dingus et al., 2014).

This study is a secondary data analysis of the SHRP 2 NDS dataset. The data use of this study (Protocol Number 1902007017) was exempt by our Drexel University Institutional Review Board (IRB) because no identifiable private information of participants was obtained or analyzed.

2.3. Study population

This study included a total of 1,561 study participants whose 4,228 trips involved an at-fault crash or a near-crash. The driver selection process is presented in Fig. 1. We will elaborate on each step below.

The main criterion for identifying a crash is that the study participant vehicle came into physical contact with another object. Three crash severity levels ("severe crash," "police-reportable crash," and "minor crash") were included, but crashes labeled "low-risk tire strike" were excluded because they presented low risk to drivers. Near-crashes were circumstances that required an emergency evasive maneuver by an involved party but did not result in a crash. Further, only crashes and near-crashes that were

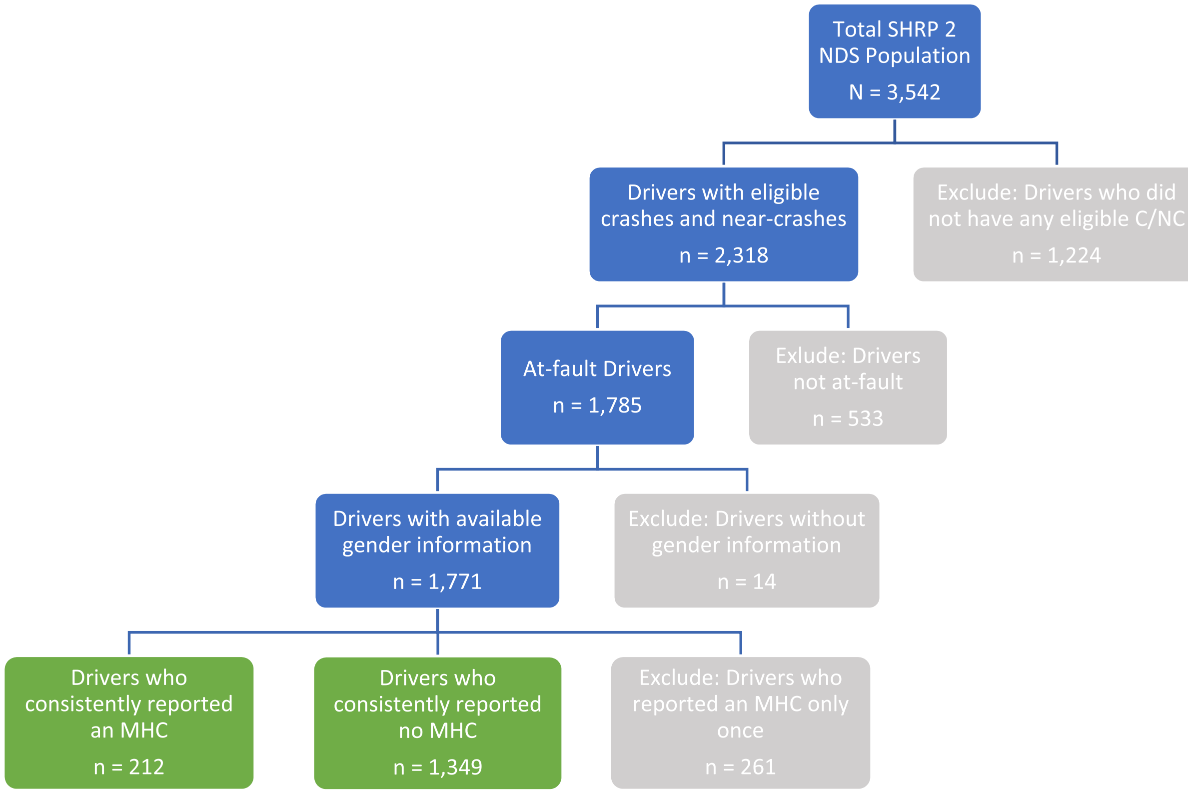


Fig. 1. Driver selection flowchart.

deemed at-fault by human experts were included because we aim to examine the unsafe driving behaviors that contributed to safety critical events. The distribution of trips by outcomes is in Table 1. Because each study participant drove multiple trips during the study and each trip had distinct environmental elements, the unit of analysis must be on the trip level, instead of the driver level.

To determine whether the study participant reported an MHC, two questionnaires were used. They are the same "medical conditions and medications" questionnaire that was dispensed at the beginning and end of the study, with questions focused on identification of conditions that could affect driving performance and safety. Study participants were asked to check all that apply among six possible MHCs, including: "ADD/ADHD/Tourette's Syndrome," "anxiety or panic attacks," "depression," "personality disorders," "psychotic disorders," and "bipolar disorder." We processed them as binary variables to allow for possible comorbidities. Because the SHRP 2 NDS lasted for an extended period, only those that consistently checked a condition at both the intake and exit surveys were included in this study as having such a condition; and only those that did not check any mental condition throughout the study were included as the control group.

We consider study participants who selected "ADD/ADHD/Tourette's Syndrome" to represent the self-reported ADHD group because Tourette's Syndrome is rare in adulthood (0.002–0.04%) (Aduen et al., 2015) and there is a significant difference ($p < 0.001$) in the mean Barkley's ADHD score between study participants who selected the answer choice "ADD/ADHD/Tourette's Syndrome" and those who did not. The self-reported ADHD and depression were treated as the main independent variables, while the other MHCs as covariates due to their limited number of responses (personality disorder, psychotic disorders, bipolar disorder) or lack of information (anxiety). Anxiety disorders alone usually are not studied with driving safety, because anxiety disorders encompass a heterogenous set of underlying concerns that may affect driving in different ways ranging from driving with exaggerated caution to hostile driving (Zinzow & Jeffirs, 2018). In this study, we do not have enough information to determine the type of anxiety or whether it is driving-related. This treatment is also seen in previous literature using the SHRP 2 dataset (Aduen et al., 2015; Aduen, 2018). The study population distribution by self-reported MHC is in Table 2. Note the numbers of study participants in each MHC category will not add to the total number of participants because some participants reported multiple MHCs. The demographics of the study population are summarized in Table 3.

Table 1
Trip outcomes ($N = 4{,}228$).

Trip Outcomes		Trips (n)
Crashes		
	Most Severe	57
	Police-reportable	78
	Minor Crash	507
Near-Crashes		3,586

Table 2
Study population ($N_{trips} = 4{,}228$, $N_{participants} = 1{,}561$).

Mental Health Condition	Trips (n)	Study Participants (n)
No MHCs	3,176	1,349
ADHD	278	66
Depression	400	113
Anxiety	342	97
Personality Disorder	0	0
Psychotic Disorders	1	1
Bipolar Disorder	31	8

Table 3
Study population demographics ($N_{participants}$ = 1,561).

		Participants *n* (%)
Gender		
	Females	761 (48.8)
Age Group		
	Adolescents and young adults (Age 16–24)	705 (45.2)
	Adults (Age 25–64)	521 (33.4)
	Seniors (Age 65+)	335 (21.4)
Education		
	High school	290 (18.6)
	College	869 (55.7)
	Advanced degree	402 (25.7)
Marital status		
	Not Married	1 038 (66.5)
Income level		
	Under $50,000	682 (43.7)
	$50,000 to $99,999	536 (34.3)
	Above $100,000	343 (22.0)
Annual miles		
	Under 10,000 miles	555 (35.6)
	10,000–20,000 miles	752 (48.2)
	20,000–30,000 miles	170 (10.9)
	Above 30,000 miles	84 (5.3)

2.4. Pre-crash unsafe driving behavior

We examined 60 unsafe driver behaviors qualitatively annotated from the NDS video reduction process (Virginia Tech Transportation Institute, 2015). Unsafe driver behaviors are what drivers did to cause or contribute to a crash or near-crash, for example, "exceeding speed limit" or "illegal passing." In other words, these behaviors preceded only trips that resulted in a crash or near-crash. Note this is to differentiate from risky driving behaviors as a generic term: only those of negative consequences were annotated in the SHRP 2 NDS. To emphasize on this difference, we will reference this variable as "*pre-crash* unsafe driving behaviors" in this study. These behaviors were semantically grouped into 18 types: *aggressive driving, distracted driving, driving slowly, drowsiness, following too closely, improper backing, improper braking or stopping, improper turning, inexperienced driving, lane changing error, neighbor lane conflict, no unsafe behavior, other unsafe behavior, right of way error, signal or sign violation, speeding, unfamiliar with environment or vehicle, and vehicle signaling error*. The mapping of the pre-crash unsafe driving behavior categories can be found in Appendix I.

2.5. Statistical analyses

We chose the generalized linear mixed-effect model (GLMM) to study the association between MHCs and pre-crash unsafe driving behaviors. The GLMM design allows one to control for multiple covariates, as well as the random effect of latent characteristics of individual drivers. The model is as follows:

$$g(E(y)) = X\beta + Zu + \epsilon$$

$$E(y) = P(Y = y|X, Z)$$

$$g(\cdot) = log\left(\frac{p}{1-p}\right)$$

where y is the outcome variable; $g(\cdot)$ is the logistic link function for a binomial outcome; p is the estimated probability of a positive outcome; X is a matrix of N trips and q variables; β is a $q \times 1$ vector of the fixed-effect regression coefficients; Z is a matrix of N trips and d drivers designating the driver-specific random effects; u is a $d \times 1$ vector of the random intercepts; and ϵ is the general error term not explained by the model.

To be specific, the null model has whether a driving behavior was present during the trip sample as a binary outcome, self-reported ADHD and depression as the independent variables, and the anonymous driver ID as the random effects variable. In addition to the two MHCs and driver random effect, the full model included the other MHCs, the cognitive traits, demographic characteristics, and environmental factors as control variables. These variables can be found in Table 4. Among the variables, the participant ID, gender, and MHCs must have values. For the other variables, missing values were imputed by the sample median for continuous variables to reduce the influence of outliers and sample mode for categorical variables. The numeric variables were then standardized because the variable "total trip duration" was recorded in milliseconds, thereby had a very different order of magnitude (median = 1,440,500 milliseconds, approximately 24 min) compared to the other numeric variables whose medians were between 2 and 17. The total trip duration was included to account for the time-variant risk exposure, since fatigued drivers may be more prone to some of the unsafe driving behaviors.

Take speeding, an unsafe driver behavior, as an example. The full model proved to be superior to the null model by analysis of variance (ANOVA) ($\mathcal{X}^2_{28} = 478.72$, $p < 0.001$). The Variance Inflation Factor (VIF) analysis suggested that there was high collinearity between age group and years of driving experience. Removing the age groups but preserving the years of experience further reduced the Akaike information criterion (AIC) while maintaining significantly reduced variance compared to the null model.

Finally, the p-value was adjusted following the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995) to ensure the overall false discovery rate was less than 0.05, because multiple driver behaviors were tested for each MHC. The statistical analysis was performed in R version 4.0 (Fay, 2010; R Core Team, 2020).

3. Results

In the null model, self-reported ADHD saw a significant increase in the unadjusted odds ratio associated with aggressive driving (OR = 2.83, 95% CI 1.27–6.33), improper braking or stopping (OR = 5.44, 95% CI 1.92–15.40), improper turning (OR = 1.89, 95% CI 1.17–3.06), inexperienced driving (OR = 6.07, 95% CI 2.10–17.51), and speeding (OR = 2.22, 95% CI 1.42–3.48). Self-reported depression did not have a significant association with any pre-crash unsafe driving behavior.

Including cognitive traits eliminated the positive association of aggressive driving and speeding with ADHD. The association with

Table 4
Input variable groups.

	Groups	Variable Names
(a)	MHCs	ADHD, Depression, Anxiety, Psychotic Disorders, Personality Disorders, Bipolar Disorder
(b)	Cognitive Traits	Sensation Seeking Scale, Driving Knowledge Score, Risk Perception Score, Clock Drawing Assessment (for identifying signs of dementia or other neurological disorders)
(c)	Demographic Characteristics	Gender, Income Level, Education Level, Marital Status, Annual Miles, Years of Driving Experience, Age Group (removed due to high collinearity with Years of Driving Experience)
(d)	Environmental Factors (trip-specific)	Weather, Lighting, Road Surface, Road Grade, Road Alignment, Traffic Density, Total Trip Duration
(e)	Random Effect	Participant ID

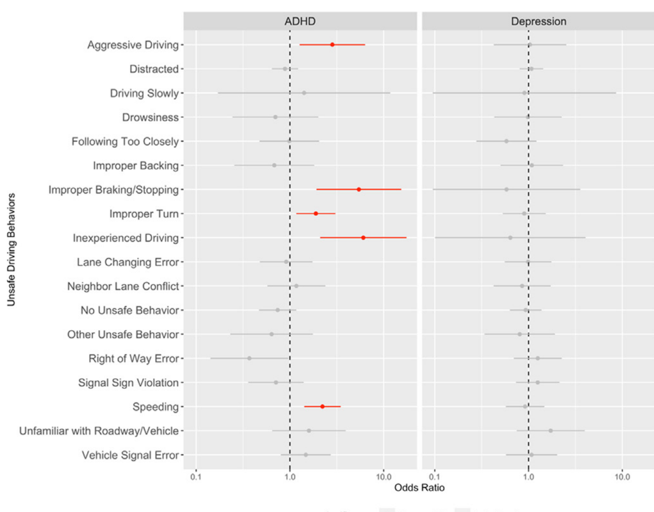
inexperienced driving also disappeared after adding demographic covariates to the model. Finally, controlling for environmental factors moved the risk associated with improper turning to the boundary of significance after adjusting the *p*-value using the Benjamini-Hochberg procedure (single test $p = 0.006$, BH adjusted $p = 0.057$).

Consequently, controlling for the impact of all covariates (cognitive, demographic, and environmental), drivers with self-reported ADHD were more likely to perform improper braking or stopping (OR = 4.89, 95% CI 1.82–13.17), while those who reported depression did not have an elevated association with any pre-crash unsafe driving behavior.

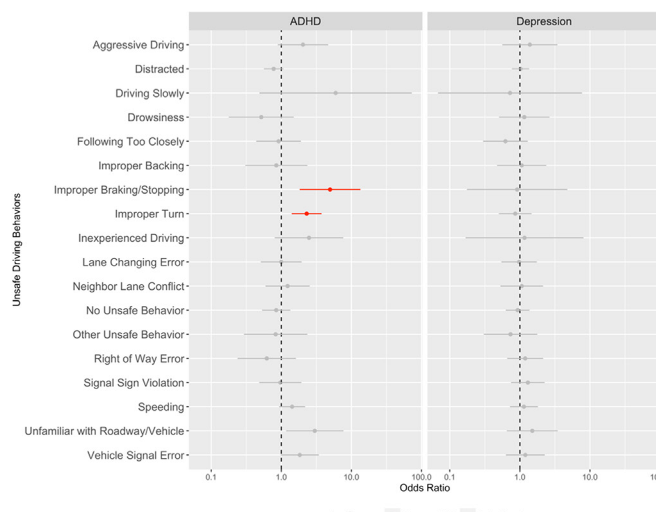
The estimated associations between the MHCs and unsafe driving behaviors can be found in Fig. 2 and Tables 5 and 6.

4. Discussions

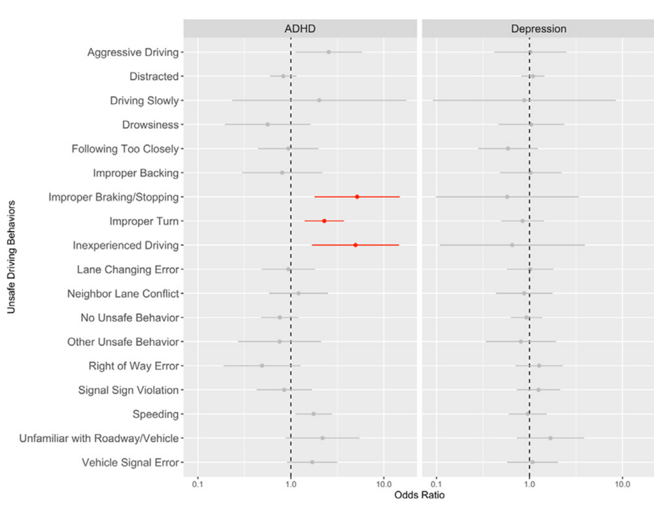
In this study, we examined the association of self-reported ADHD and depression with pre-crash unsafe driving behaviors. ADHD was significantly associated with improper braking or stopping; depression was not significantly associated with any unsafe driving behavior. Improper braking or stopping refers to sudden braking in an unsafe manner in the roadway, which may indicate that the driver was startled by a road scenario that elicited the sudden maneuver without regard to the potential impact on following vehicles. Improper turning, which approached significant association, refers to making wide turns to the extent of encroaching on neighbor lanes or road shoulders/curbs, which may suggest difficulty in maintaining stable vehicle dynamics in turning scenarios due to a lack of skills. These findings are consistent with previous research that ADHD may impact driver's executive functioning and negatively impacted their ability to master driving as a skill (Curry, 2017; Jerome et al., 2006). For drivers who report depression, this study found no significantly increased risk of any unsafe driving behaviors, which is consistent with one longitudinal study (Vassallo, 2008). Other research suggests difficulties in allocating cognitive resources to necessary or competing driving tasks both inside and outside of the vehicle among drivers with depression



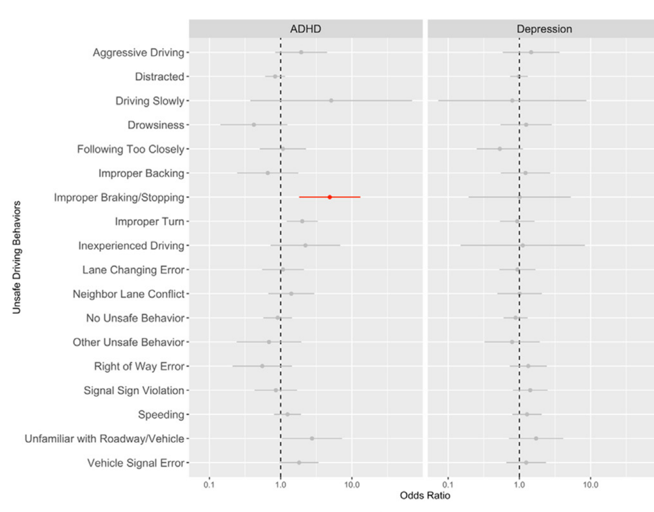
(a) Null Model



(c) Include Cognitive + Demographic Covariates



(b) Include Cognitive Covariates



(d) Include Cognitive + Demographic + Environmental Covariates

Fig. 2. Mental health conditions and pre-crash unsafe driving behaviors. (a) Null model: include only the MHCs and driver random effects; (b) Cognitive model: add cognitive traits to the null model; (c) Cognitive + Demographic model: add cognitive traits and demographic characteristics to the null model; (d) Full model: add cognitive traits, demographic characteristics, and environmental factors to the null model.

Table 5
Association of self-reported ADHD and pre-crash unsafe driving behaviors.

Behavior	ADHD					
	Null Model			Full Model		
	p-value	Adj. *p*-value	OR (95%CI)	*p*-value	Adj. *p*-value	OR (95%CI)
Aggressive Driving	0.011	0.040*	2.83 (1.27–6.33)	0.121	0.363	1.94 (0.84–4.49)
Distracted	0.463	0.641	0.89 (0.64–1.22)	0.278	0.500	0.84 (0.61–1.15)
Driving Slowly	0.747	0.827	1.42 (0.17–11.75)	0.220	0.450	5.13 (0.38–70.07)
Drowsiness	0.507	0.652	0.70 (0.24–2.01)	0.117	0.363	0.42 (0.14–1.24)
Following Too Closely	0.970	0.970	0.99 (0.47–2.05)	0.848	0.848	1.08 (0.51–2.27)
Improper Backing	0.444	0.641	0.68 (0.26–1.82)	0.408	0.566	0.66 (0.25–1.77)
Improper Braking/Stopping	0.001	0.009**	5.44 (1.92–15.40)	0.002	0.030*	4.89 (1.82–13.17)
Improper Turn	0.009	0.040*	1.89 (1.17–3.06)	0.006	0.057	2.01 (1.22–3.32)
Inexperienced Driving	0.001	0.008**	6.07 (2.10–17.51)	0.163	0.419	2.23 (0.72–6.87)
Lane Changing Error	0.781	0.827	0.91 (0.48–1.74)	0.826	0.848	1.08 (0.55–2.12)
Neighbor Lane Conflict	0.662	0.795	1.17 (0.57–2.39)	0.363	0.544	1.41 (0.67–2.96)
None	0.197	0.478	0.74 (0.47–1.17)	0.685	0.770	0.91 (0.57–1.44)
Other	0.385	0.630	0.64 (0.23–1.76)	0.479	0.616	0.69 (0.24–1.95)
Right of Way Error	0.041	0.124	0.37 (0.14–0.96)	0.225	0.450	0.55 (0.21–1.44)
Signal Sign Violation	0.324	0.583	0.71 (0.36–1.40)	0.658	0.770	0.86 (0.43–1.70)
Speeding	0.000	0.008**	2.22 (1.42–3.48)	0.318	0.520	1.25 (0.81–1.93)
Unfamiliar with Roadway/Vehicle	0.310	0.583	1.60 (0.65–3.93)	0.041	0.247	2.76 (1.04–7.29)
Vehicle Signal Error	0.212	0.478	1.48 (0.80–2.72)	0.063	0.283	1.82 (0.97–3.40)

Significance codes: <0.001 '***' [0.001–0.01) '**' [0.01–0.05) '*'.

Table 6
Association of self-reported depression and pre-crash unsafe driving behaviors.

Behavior	Depression					
	Null Model			Full Model		
	p-value	Adj. *p*-value	OR (95%CI)	*p*-value	Adj. *p*-value	OR (95%CI)
Aggressive Driving	0.939	0.972	1.04 (0.42–2.52)	0.417	0.991	1.46 (0.58–3.65)
Distracted	0.631	0.972	1.07 (0.80–1.43)	0.924	0.991	0.99 (0.74–1.31)
Driving Slowly	0.930	0.972	0.90 (0.10–8.58)	0.852	0.991	0.80 (0.07–8.71)
Drowsiness	0.972	0.972	0.99 (0.43–2.26)	0.604	0.991	1.24 (0.54–2.85)
Following Too Closely	0.149	0.972	0.58 (0.28–1.21)	0.097	0.991	0.53 (0.25–1.12)
Improper Backing	0.839	0.972	1.08 (0.50–2.34)	0.627	0.991	1.22 (0.55–2.71)
Improper Braking/Stopping	0.558	0.972	0.58 (0.10–3.56)	0.991	0.991	1.01 (0.19–5.26)
Improper Turn	0.695	0.972	0.90 (0.53–1.52)	0.810	0.991	0.93 (0.53–1.63)
Inexperienced Driving	0.635	0.972	0.64 (0.10–4.06)	0.915	0.991	1.11 (0.15–8.31)
Lane Changing Error	0.967	0.972	0.99 (0.56–1.75)	0.830	0.991	0.94 (0.52–1.68)
Neighbor Lane Conflict	0.659	0.972	0.85 (0.42–1.72)	0.985	0.991	1.01 (0.49–2.06)
None	0.722	0.972	0.93 (0.63–1.37)	0.537	0.991	0.88 (0.60–1.30)
Other	0.622	0.972	0.80 (0.34–1.91)	0.606	0.991	0.79 (0.32–1.93)
Right of Way Error	0.451	0.972	1.25 (0.70–2.26)	0.347	0.991	1.33 (0.73–2.42)
Signal Sign Violation	0.410	0.972	1.25 (0.73–2.14)	0.219	0.991	1.42 (0.81–2.49)
Speeding	0.723	0.972	0.92 (0.57–1.47)	0.306	0.991	1.28 (0.80–2.06)
Unfamiliar with Roadway/Vehicle	0.201	0.972	1.72 (0.75–3.97)	0.228	0.991	1.72 (0.71–4.13)
Vehicle Signal Error	0.818	0.972	1.08 (0.57–2.02)	0.499	0.991	1.25 (0.66–2.36)

Significance codes: <0.001 '***' [0.001–0.01) '**' [0.01–0.05) '*'.

(Wickens et al., 2014), but this study did not find such evidence (i.e., lack of association with signal or sign violation or with exhibiting unfamiliarity with road or vehicle).

Previous studies linked reckless or aggressive driving with ADHD and depression (Barkley & Cox, 2007; Jerome et al., 2006; Malta et al., 2005; Richards, Deffenbacher, Rosén, Barkley, & Rodricks, 2006). Our results did not show either condition had an increased association with the annotated behavior "aggressive driving" or "speeding" after adjusting for demographic covariates, even though the unadjusted odds ratios of aggressive driving and speeding were significantly higher among drivers with ADHD. We suspect several factors may be at play. First, the definition of aggressive driving is not standardized. Previous studies may have included several unsafe driving behaviors delineated in this study under the umbrella of aggressive driving such as improper braking and speeding. It is also possible that drivers with MHCs have more aggressive driving behaviors than those without do, when trip outcomes were not in consideration, but this study considered only behaviors that preceded an at-fault crash or near-crash. Second, previous studies measure aggressive driving by self-reported instrument results that are prone to recall bias, but the present study used video recordings of actual crash events to annotate aggressive driving behaviors. Third, as the study results demonstrated, there were significant unadjusted associations with aggressive driving and speeding among drivers with ADHD, which disappeared after accounting for demographic and environmental factors. This observation lends credence to the importance of controlling for driver and road confounders when studying driving behaviors (Barkley & Cox, 2007; Jerome et al., 2006).

This study is limited by the lack of clinical information to validate study participants' self-reported MHCs. Differences in medication use and the severity of conditions among drivers should ideally be delineated. While the self-reported ADHD condition was corroborated by the Barkley score, it is hard to gauge the validity of self-reported depression. However, the advantage of analyzing self-reported MHCs is to capture individuals with undiagnosed conditions due to lack of access to mental health services. Another limitation is that the pre-crash unsafe driving behaviors in this study were restricted to those that resulted in a crash or near-crash. It is possible that the distribution of risky driving behaviors regardless of trip outcome is different, therefore the generalizability of the study findings should be applied within the scope of analyzing the contributing factors of crashes and near-crashes.

5. Conclusions

Drivers with MHCs may face extra challenges related to driving. This study estimates the association between ADHD and depression and pre-crash unsafe driving behaviors. We showed that, after accounting for demographic, cognitive and environmental covariates, individuals with ADHD and depression were not prone to aggressive driving, contradictory to previous studies. Instead, they may unintentionally execute unsafe driving behaviors in particular driving scenarios that require a high level of cognitive judgment. These findings can provide clinicians and educators with empirical evidence of how ADHD and depression may affect patient's ability to perform safe driving.

6. Practical Applications

The study findings can inform the curriculum design of driver's education programs that help learners with MHCs gain practice in certain road scenarios (e.g., more practice on preemptively reducing speed instead of making sudden brakes as well as smooth turning on curved roads for students with ADHD). Furthermore, specific advanced driver assistance systems (ADAS) may prove particularly helpful for drivers with ADHD, such as detection of leading objects and curve speed warning.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix I Mapping of unsafe driving behaviors.

Category	Unsafe Driver Behavior
Aggressive Driving	Aggressive driving, specific, directed menacing actions
	Aggressive driving, other
Distracted	Distracted
Driving Slowly	Driving slowly: below speed limit
	Driving slowly in relation to other traffic: not below speed limit
Drowsiness	Drowsy, sleepy, asleep, fatigued
Following too closely	Following too closely
Improper Backing	Improper backing, other
	Improper backing, did not see
Improper Braking/ Stopping	Sudden or improper braking
	Sudden or improper stopping on roadway
	Use of cruise control contributed to late braking
Improper Turn	Improper turn, wide left turn
	Improper turn, wide right turn
	Improper turn, other
	Improper turn, cut corner on left
	Improper turn, cut corner on right
	Making turn from wrong lane
Inexperienced Driving	Apparent general inexperience driving
	Apparent unfamiliarity with vehicle
Lane Changing Error	Cutting in, too close behind other vehicle
	Cutting in, too close in front of other vehicle
	Did not see other vehicle during lane change or merge
Neighbor Lane Conflict	Other improper or unsafe passing
	Passing on right
	Illegal passing
	Driving in other vehicle's blind zone
None	None
	No Additional Driver Behaviors
Other	Other
	Avoiding pedestrian
	Driving without lights or with insufficient lights
	Wrong side of road, not overtaking
	Avoiding other vehicle
	Avoiding animal
	Parking in improper or dangerous location
	Improper start from parked position
	Non-signed crossing violation
	Unknown
	Failure to dim headlights
Right of Way Error	Right-of-way error in relation to other vehicle or person, apparent recognition failure
	Right-of-way error in relation to other vehicle or person, apparent decision failure
	Right-of-way error in relation to other vehicle or person, other or unknown cause
Signal/Sign Violation	Signal violation, apparently did not see signal
	Stop sign violation, apparently did not see stop sign
	Stop sign violation, "rolling stop"
	Signal violation, tried to beat signal change
	Other sign (e.g., Yield) violation, apparently did not see sign
	Stop sign violation, intentionally ran stop sign at speed

(*continued on next page*)

Appendix I Mapping of unsafe driving behaviors. (*continued*)

Category	Unsafe Driver Behavior
	Signal violation, intentionally disregarded signal Other sign violation Other sign (e.g., Yield) violation, intentionally disregarded Disregarded officer or watchman
Speeding	Exceeded speed limit Exceeded safe speed but not speed limit Speeding or other unsafe actions in work zone
Unfamiliarity with Environment/ Vehicle	Apparent unfamiliarity with roadway
Vehicle Signal Error	Failed to signal Improper signal

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