FACTORS UNDERPINNING AND INFLUENCING DRIVERS' ABERRANT BEHAVIOURS ACROSS THE LIFE COURSE

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FACTORS UNDERPINNING AND INFLUENCING DRIVERS' ABERRANT BEHAVIOURS ACROSS THE LIFE COURSE

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Editorial: Factors Underpinning and Influencing Drivers' Aberrant Behaviors Across the Life Course

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Editorial on the Research Topic

Factors Underpinning and Influencing Drivers' Aberrant Behaviors Across the Life Course

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INTRODUCTION

Human factors play a fundamental role in driving performance and in the errors and violations that can be committed behind the wheel. While new technologies will soon allow "*automatic*" driving, it continues to be crucial to analyse and understand the factors determining human error during driving. Errors, carelessness, and driving violations can be linked to age and experience, as well as to the driver's internal characteristics (e.g., personality, cognitive, affective, and psychophysiological processes). Such characteristics can be either stable, or variable, i.e., dependent on the state of the individual, and in turn, they interact with contextual aspects–that is, the social environment, such as the presence of passengers, or the physical environment, including the type of road, and the condition of the vehicle. Such characteristics and specific processes, as highlighted in this Research Topic, are peculiar to specific age groups, while others are more general and studied over the course of the lifespan. Given the complexity of the topic, it is not surprising that it is addressed in the scientific literature using diverse methodological approaches and measurement tools to account for these different dimensions.

This Research Topic is intended to provide an overview of empirical studies referring to both internal and external factors related to driving performance and driving errors, and it is articulated in different age groups. The studies collected here address different issues and use different methodologies, providing an overview of the complexity and richness of this field.

STUDIES INVOLVING YOUNG DRIVERS

A first set of studies in the present special topic concerns young drivers, two studies look at young moped drivers, and five studies investigate young car drivers.

For young moped drivers, the focus in the literature has been on analyzing specific risk factors (e.g., personality) that can negatively impact driving performance by increasing the risk of errors, lapses, and violations. Lucidi et al. identified three personality sub-types (i.e., risky, worried, and careful moped riders) on a large sample of adolescent moped drivers, who also differ significantly in risky driving behaviors, attitudes toward traffic safety, risk perception, and self-reported accident involvement. The results empirically support the notion that certain combinations of personality characteristics are associated with risky driving in moped riders. The study by Gianfranchi et al., on the other hand, identified three different profiles (Imprudent, Prudent, and Insecure) on the basis of driving performance of inexperienced young people in a virtual driving environment. The results of the study showed that these three groups also present different combinations of personality traits and beliefs, empirically confirming the close and bidirectional relationship between the behavioral and personality profiles of young moped drivers.

Lazuras et al. studied young car drivers, and examined the impact on risky driving of two "clusters" of individual characteristics, on the one hand those defined as "hot," such as the impulsivity and sensation seeking, and on the other those defined as "cold" such as self-regulation and emotional regulation. An important finding was the mediation of self-regulation ("cold") in the relationship between sensation seeking ("hot") and self-reported errors, indicating that "hot" and "cold" individual characteristics are somewhat integrated in predicting self-reported driving behaviors. The study by Simon-Morton et al. focuses on an important issue in the literature, namely the effects of passenger presence on driving performance in young drivers. More specifically, the two studies carried out in a simulation context revealed that both male and female teenagers are influenced in their risk driving behavior by the attitude of passengers regarding risk-acceptance and associated potential distress experienced as an effect of social exclusion.

Three studies investigated basic cognitive processes and neurophysiological correlates of young drivers' performance. The study by Cassarino et al. looked at attentional demands depending on the road, urban or rural; they found that in a short simulated drive, the urban road was not more demanding than the rural road for these younger drivers. The study by Yan et al. utilized machine learning to distinguish between aggressive and conservative drivers based on power spectral density of the Elecroencephalography (EEG), showing distinct brain activity in these two types of drivers at different frequency bands. Finally, the study by Ding et al. sought to identify and analyse the neuro-physiological correlates of driving in a driving simulator and to relate them with the personality of drivers, thus integrating measures obtained with different methodologies (i.e., EEG and questionnaires).

STUDIES INVOLVING ADULT AND OLDER DRIVERS

A second set of studies focused on adult drivers with the purpose of evaluating the basic cognitive processes related to driving and the corresponding neurophysiological correlates. The review by Palmiero et al. summarizes empirical data related to the effects that a secondary task typically has on driving performance, as well as the corresponding neurophysiological correlates. The review indicated that there is substantial consensus across studies on occipital lobe deactivation and fronto-temporal lobe activation associated to the attentional shifting from driving to a secondary task, even in absence of evident modification of driving performance. However, neuroimaging studies present a series of methodological flaws; the authors also indicated personality as useful dimension to explore in relation to the attentional profile of individuals. The study by Yan et al. looked at a sample of adult drivers to analyse the complex relationships between drivers' behavior, studied with the driving simulator, drivers' personality characteristics, evaluated through self-reported questionnaires, and the neurophysiological activation, evaluated through EEG. The authors suggested that information on driving style gathered through those different methods should be integrated into advanced driving assistance system (i.e., ADAS) in order to anticipate risky driving behavior.

Finally, a third set of studies focused on the analysis of psychological processes and individual factors typically associated with driving performance in older drivers. The study by Spano et al. provided a contribution to the factorial validation of three high-reputation questionnaires on driving behavior, namely, the Driver Behavior Questionnaire, the Attitudes Toward Traffic Safety, and the Driving Mobility Questionnaire. A complex statistical analysis based on hurdle model showed that all sub-factors of Driver Behavior Questionnaire predicted the likelihood of self-reported road collisions (both as unique or multiple events) in a sample of older participants. Gormley and O'Neill, on the other hand, analyzed the role that driving, in terms "mobility," has for the older adults, highlighting its effects on their quality of life. Over 8,000 individuals were surveyed in the Irish Longitudinal Study on Ageing (TILDA) and the results indicated that men keep driving for longer than women; driving was more frequent in married participants and had a positive impact on quality of life and loneliness. The study by Saryazdi et al. directly compared older drivers with young drivers on their attention to the visual scene while driving, specifically "Inattentional Blindness," i.e., lack of awareness of people or objects at the side of the road. Both younger and older participants experienced inattentional blindness. However, while younger adults improved their performance across the experiment, the same did not occur for older, potentially indicating slower learning from experience.

CONCLUSIONS

This Research Topic highlights the importance to consider contextual and subjective human factors in driving, which impact on performance and co-determine safe driving, together with well-known factors such as experience. These factors, studied with different methods, should not be overlooked in understanding driving behavior.

AUTHOR CONTRIBUTIONS

All the authors have substantially contributed to the development and preparation of the editorial. Furthermore, all authors have approved the final version of the manuscript. The authors have agreed to be accountable for all aspects of the manuscript in ensuring that questions related to the accuracy or integrity of any part of it are appropriately investigated and resolved.

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Personality Traits and Beliefs About Peers' On-Road Behaviors as Predictors of Adolescents' Moped-Riding Profiles

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Several efforts aimed at discriminating between different degrees of on-road risky attitudes have been devoted to the identification of personality profiles among young drivers. However, the results are often inconsistent because of the limits of self-report measures. To overcome these limits, we tried to identify different profiles based on our study participants' driving performances in a virtual environment and to look for psychological predictors of inclusion in one of three profiles. One-hundred and fourteen inexperienced adolescents were involved in this study, which included two experimental sessions. During the first, before riding along five virtual courses on a moped simulator, participants' sensation seeking, locus of control, aggressiveness and beliefs about their peers' on-road behaviors were measured by means of self-report tools. During the second session, the participants drove the simulator along six courses that were different from those faced in the first session. A cluster analysis was run on a wide number of indexes extracted from the participants' performances to detect different riding profiles. Three profiles emerged (Imprudent, Prudent and Insecure), with specific riding patterns. The profiles also differed in terms of riding safety, assessed by means of the scores automatically given by the simulator to the participants' performances. Reporting an external locus of control, underestimating peers' on-road risky behaviors and showing less concern for fate among the possible causes of crashes are predictors that increase the risk of being included in the Imprudent profile. Low levels of dangerous thrill seeking predict inclusion in the Prudent profile, whereas high rates of self-reported anger play a role in discriminating the Insecure riders from the other profiles. The study indicates that it is possible to identify riding profiles with different degrees of on-road safety among inexperienced adolescents by means of simulated road environments. Moreover, inclusion in these profiles is predicted by different patterns of personality variables and beliefs. Further research is needed to verify the validity of these conclusions in real road conditions.

Keywords: adolescents, personality, beliefs, driving simulator, driving profiles

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INTRODUCTION

Road crashes were the major cause of death in adolescents worldwide in 2015, especially in males, whose mortality rates are consistently higher than those of females (World Health Organization [WHO], 2017). In 2014, road crashes were one of the main causes of death in Europe for people aged 15–19, representing 25% of the deaths at this age (Eurostat, 2017). Several efforts have been devoted to identifying the causes of this overrepresentation, resulting in a variety of explanatory models that include, among others, driving experience (Mayhew et al., 2003), hazard perception (Crundall, 2016), peers' influence and adolescents' beliefs about peers' behavior (Allen and Brown, 2008) and personality traits (Arnett et al., 1997).

Mayhew et al. (2003) examined the month-to-month change in crash rate of adolescents, finding that the highest drop in the number of accidents occurred after 6 months of on-road experience. Some studies (Kinnear et al., 2013; Crundall, 2016) proved that driving experience is also linked to hazard perception, defined as the ability to predict dangerous on-road situations so as to act to prevent their negative outcomes (Tagliabue et al., 2017). Crundall (2016) verified that hazard prediction (*i.e.*, the prediction of an imminent hazard) can discriminate between novice and experienced drivers. During three different experiments, participants watched video clips showing risky or safe on-road scenes, spotting for hazards (Crundall, 2016). The hazards could vary in terms of source, type and timing of the clues. Experienced drivers performed better than novice drivers across all three experiments, showing higher accuracy in spotting hazards and proving that hazard perception is modulated by different degrees of driving experience.

However, many other factors become important in shaping adolescents' driving behavior, among which peer influence, beliefs about peers' conduct, and personality traits have central roles.

The Role of Beliefs and of Personality Traits in Adolescents' Driving Behavior

Research has proven that the crash rate among adolescents rises consistently when they are with a peer (Preusser et al., 1998) and that teenagers tend to drive faster and to show more aberrant behaviors when carrying a peer than when carrying adults (Baxter et al., 1990). Baxter et al. (1990) claimed that these effects depend on both the tendency of teenage passengers to urge a driver to take risks (*e.g.*, speeding or cutting a corner) and the need of teenage drivers to show off for their peer passengers. These behaviors are part of what Allen and Brown (2008) call direct (proximal) peer influence, which occurs when adolescents are driving and carrying their peers as passengers and which seems to affect drivers and passengers equally (Baxter et al., 1990; Ulleberg, 2004). Ulleberg (2004) examined the features affecting the likelihood of adolescents to ask their peers to drive safely when they feel unsafe as passengers. Overall, the results showed that young males are less prone to discouraging unsafe driving behaviors. Moreover, the majority of the sample, although reporting high rates of risky behaviors among their peers, found it acceptable to be their passengers. Peer influence can also be expressed indirectly (distal influence; Allen and Brown, 2008). Indeed, so-called "caravan peers" (*i.e.*, peers driving other vehicles on the road), whose conduct is observed by adolescents, also have a role in influencing teenagers' driving behavior (Allen and Brown, 2008). This indirect influence may shape adolescents' norm setting and their beliefs about peers' behavior and, in turn, it may lead to different degrees of risk in adolescents' behaviors (either drivers or passengers).

For instance, about 11,000 adolescents in the United States participated in a survey on their beliefs about factors that affect driving safety (Ginsburg et al., 2008). More than a half of the respondents stated that they often or always see their peers involved in risky behaviors while driving, such as speeding or talking on the phone. However, only 15% of the respondents perceived the teenage drivers as inexperienced, although the 60% of the sample stated that inexperience heavily affects road safety. These results suggest that, although adolescents can detect risky driving behaviors among their peers, they do not perceive teenagers as inexperienced and as potentially dangerous drivers. Thus, beliefs about peers' driving skills and behaviors may affect the development of adolescents' defensive driving strategies (*e.g.*, self-regulation on the basis of beliefs about others' driving behaviors), contributing to the increased crash rate.

Among personality traits, sensation seeking (SS) is consistently linked to driving behavior. SS is usually defined as the tendency to seek novel, varied, exciting and intense sensations (Zuckerman, 1994). In a systematic review, Jonah (1997) found associations between high SS levels and risky driving in most of the examined articles. These associations were steady across cultures, stronger for males and tended to decline with age (Jonah, 1997). Overall, SS seems to account for up to 15% of variance in risky driving and, when the sub-dimensions of SS are considered, thrill seeking (TS) is the most related to on-road risky behaviors (Jonah, 1997). Among adolescents, high levels of SS are associated with driving while intoxicated, driving over the speed limit and racing other vehicles (Arnett et al., 1997). Moreover, SS predicts teenagers' self-reported aggressive driving and driving anger (Dahlen et al., 2005).

Sensation seeking is frequently associated with aggressiveness in predicting reckless driving in adolescents (Arnett, 1996; Arnett et al., 1997; Ulleberg and Rundmo, 2003). Higher levels of aggressiveness (*i.e.*, the tendency to act in a verbally and physically aggressive way and to experience anger and frustration) correspond to higher frequency of speeding behaviors among teenagers (Arnett, 1996; Arnett et al., 1997). Nevertheless, this relation might not be very clear. In a study that considered a variety of personality traits as possible predictors of self-reported risky driving behaviors, Ulleberg and Rundmo (2003) found only an indirect relationship between high aggressiveness and risky on-road behaviors, with a small-to-moderate effect size. The authors explained this result by claiming that personality traits in general may influence attitudes toward driving safety rather than the behavior itself. Another possible explanation may rely on the difficulty of assessing risky on-road behaviors with self-report measures. Moreover, the authors did not include in their model a trait that has been frequently reported as related to driving behaviors, *i.e.*, locus of control (LC; Özkan and Lajunen, 2005), which may have a key role in moderating the relations between other personality variables and driving behaviors.

Özkan and Lajunen (2005) defined LC as a personality trait that reflects the degree to which people perceive events to be under their control or under the control of external forces that cannot be managed. The latter case is usually labeled "external LC" and it is associated with higher crash rates (Montag and Comrey, 1987). On the other hand, the results of Özkan and Lajunen (2005) showed a link between a more internal LC and higher number of self-reported crashes, violations and errors in a sample of young drivers. More recently, Warner et al. (2010) found a positive relation between internal LC and speeding behavior. A possible explanation of these results may be the involvement of overconfidence and of optimism bias (previously considered by Özkan and Lajunen, 2005). Indeed, drivers who think that their likelihood of incurring accidents depends only on their behaviors and skills may become overconfident and may develop fewer defensive driving strategies.

Given the inconsistency of some results, many studies have tried to identify profiles that combine specific personality traits and that can systematically account for risky driving behaviors.

The Identification of Personality Profiles

The first approach adopted was to assess the relations between self-reported driving behaviors and drivers' profiles that were identified through self-assessment personality measures. A survey of 6,000 Norwegian drivers, between 18 and 23 years old, was carried out by Ulleberg (2001). The author measured five personality traits (SS, anxiety, altruism, aggressiveness, and normlessness) and participants' self-reported angry driving. In addition, several items were included to assess participants' risky on-road attitudes and behaviors. A cluster analysis of the personality variables identified six groups. Two of them were considered at risk for road crashes: The first one was mostly composed of males and characterized by high levels of SS and normlessness but by low anxiety and altruism. The second at-risk cluster included participants with high scores in SS, anxiety, aggressiveness and angry driving. These two groups reported the riskiest driving habits and the highest frequency of road crashes and of harmful attitudes toward traffic (*e.g.*, violating rules or speeding). The author concluded that, given the heterogeneity of the profiles' characteristics and of their relations with self-reported risky driving behaviors and attitudes, young drivers cannot be treated as a homogenous group.

In Italy, Lucidi et al. (2010) detected different young drivers' personality profiles and verified their relationship with self-reported aberrant on-road behaviors (Reason et al., 1990). The authors measured a wide number of personality traits (*e.g.*, SS, anger, anxiety, and LC) and self-reported driving violations, errors, lapses and amount of accident involvement. Three clusters emerged: risky drivers (characterized by high levels of SS, angry driving and normlessness and by an external LC), worried drivers (high levels of anxiety and hostility) and careful drivers (high levels of altruism and low levels of anger, hostility, SS, and normlessness). The participants in the first group reported the highest crash rate and the riskiest driving attitudes while perceiving themselves as less prone to accidents. Careful drivers showed a reverse profile, reporting the lowest rates of errors, violations, lapses and crashes. Finally, worried drivers were classified as a medium-risk profile, because they reported better attitudes than risky drivers but also a comparable number of lapses.

These two studies proved that young drivers of different cultures can be grouped in clusters with specific personality patterns and that the personality profiles show different degrees of risky driving behaviors and attitudes as measured by self-report questionnaires. Moreover, the results by Lucidi et al. (2010) indirectly address the importance of drivers' beliefs, showing that risky drivers may have less insight into their driving skills than both careful and worried drivers, overestimating themselves. However, the approach of these studies was based only on self-report measures, without a direct reference to behavioral variables.

Deery and Fildes (1999) tried to partially overcome the limits of self-report measures. First, they identified five clusters in a sample of adolescents (16–19 years old) on the basis of their personality traits and driving attitudes (*e.g.*, hostility, assertiveness, SS, competitive speed and driving aggression). The most at risk cluster was characterized by, among others, high levels of hostility and of SS and by risky driving attitudes, such as high levels of competitive speed. Furthermore, participants in this cluster also reported high rates of risky driving behaviors but, at the same time, low crash rates. Then, the authors randomly selected a subsample of participants to test, through a driving simulator, whether the personality profiles differed in their behaviors during five courses with different features (*e.g.*, driving while performing a calculation task, facing potentially hazardous scenes and facing an emergency situation). The results showed that the more at-risk cluster was also more prone to the negative effects of workload, had difficulties in facing the hazardous scenes, and was less cautious in terms of driving speed in the emergency situation. Overall, these results show that it is possible to identify different profiles among adolescent drivers and that the profiles differ in terms of personality patterns and attitudes toward risky driving. These differences were confirmed when the driving behavior was assessed by means of a simulator: the risky drivers had the least safe performance and showed a lack of hazard anticipation.

Marengo et al. (2012) considered fewer personality traits to identify different profiles among Italian adolescents (14–15 years old) with various degrees of moped-riding experience. Three clusters emerged: The so-called profile B showed high levels of SS and impulsivity and low levels of altruism and anxiety, being considered the most at-risk. Profile A was characterized by high levels of anxiety and low levels of SS and altruism. Profile C reported high levels of altruism and a more internal LC. Starting from the evidence that most of the previous studies used only self-report measures to assess the relation between the profiles and their driving behaviors (Ulleberg, 2001; Lucidi et al., 2010), Marengo et al. (2012) compared the clusters on the basis of self-report and simulated driving measures. Participants' performances were assessed through 12 courses on a moped-riding simulator (Honda Riding Trainer, HRT), divided into three sessions. For each course, a letter score was provided: A (*safe performance*), B (*almost safe*), C (*near miss*), and D (*accident*). The first measure analyzed was the number of accidents (D score). In addition, the authors developed a safe driving index based on scores A, B, and C. The at-risk cluster showed the highest rate of self-reported risky driving behaviors (*e.g.*, driving under the influence of substances and violations) and had the worst performance on the simulator, with the highest number of accidents and the lowest safe driving index score.

The main contribution of the study by Marengo et al. (2012) was its focus on adolescents, going beyond the limits of self-report measures, as Deery and Fildes (1999) suggested. The identified profiles were largely comparable to those that emerged in previous studies. For example, profile B was similar to the "risky drivers" in Lucidi et al. (2010), whereas profile A was comparable to one of the low-risk groups of Ulleberg's (2001) study. The similarity between the teenagers' clusters identified by Marengo et al. (2012) and previous results from samples with different ages suggests the presence of consistent differences also exists in adolescents in the early stage of driving experience.

Simulator as a Tool to Assess Driving Profiles

The approach examined in the previous paragraph (the identification of different driving profiles on the basis of self-report measures of personality traits, driving attitudes and behaviors), albeit extremely useful, has three main limits: (1) self-report measures of driving attitudes and behaviors can be influenced by a number of biases (*e.g.*, social desirability and overconfidence), preventing one from drawing predictions of real behaviors; (2) the use of these measures limits the inclusion of inexperienced drivers in the sample, resulting in the inability to discriminate between the role of driving experience and of personality traits in determining driving behaviors; and (3) the identification of profiles on the basis of personality traits led to inconsistent results, probably due to cultural peculiarities and to the instability of some personality traits during the lifespan (*e.g.*, SS).

Driving simulators have been used to provide a behavioral correlate for the identification of driving profiles (Deery and Fildes, 1999; Marengo et al., 2012). An innovative approach was recently proposed by Gianfranchi et al. (2017a,b), aimed at identifying riding profiles on the basis of participants' behavior on a moped-riding simulator. Reversing the approach of previous works, Gianfranchi et al. (2017a,b) monitored the performance of two samples of young drivers on five courses on the HRT simulator, measuring a wide number of variables (*e.g.*, mean speed, mean pressure on the brakes, number of crashes and the overall performance evaluation) used to identify specific profiles. In the first study (Gianfranchi et al., 2017a), two clusters were identified (Imprudent and Prudent riders), with an opposite riding profile. Results showed that the two clusters also differed in terms of self-reported driving behaviors as measured by the Driver Behaviour Questionnaire (Reason et al., 1990) and the Dula Dangerous Driving Index (3DI; Dula and Ballard, 2003). For instance, Imprudent riders who answered the questionnaires after using the simulator (*i.e.*, after having the chance to prove themselves in a series of potentially risky scenarios) reported lower rates of on-road errors and lapses, but they also reported a higher rate of on-road risky behaviors. In the second study (Gianfranchi et al., 2017b), a wider sample of young drivers was assessed by applying the same clustering procedure and measuring participants' SS and non-contextual decision making through the Sensation Seeking Scale V (Zuckerman, 1994) and the Iowa Gambling Task (Bechara et al., 1994), respectively. Three clusters emerged: two of them resembled those already identified in the previous study, whereas the third showed mixed characteristics and was labeled "Insecure." The results showed that the worst performance in terms of number of crashes and of overall performance evaluations was reached by participants with high levels of TS and poor decision-making ability.

These two studies were the first to adopt this procedure with the HRT simulator, which has already proved to be an effective tool for the enhancement of hazard perception among adolescents (Vidotto et al., 2011) and novice drivers (Tagliabue and Sarlo, 2015; Tagliabue et al., 2017), and this improvement is still present after 12 months (Vidotto et al., 2015). Among others, the roles of attention (Tagliabue et al., 2013), workload (Di Stasi et al., 2009), feedback (Megías et al., 2017), and of visual exploration (Di Stasi et al., 2011) in driving behaviors have been assessed through the HRT, adding important evidence to psychophysiological and cognitive models of driving behaviors. In respect to these previous findings, the results of the studies by Gianfranchi et al. (2017a,b) indicate that this simulator can be also used as an assessment tool, allowing the identification of different profiles based on a deep monitoring of a variety of driving variables. Moreover, the profiles have shown to be linked to self-reported driving behaviors, sensation seeking and decision making. However, none of these studies aimed at identifying predictors of the inclusion in the driving profiles, nor have they focused on totally inexperienced participants so as to isolate the role of personality or of cognitive predictors.

Aims of the Study

Starting from the previous evidence, we speculated that because personality variables and beliefs have a central role in adolescents' on-road behaviors (Arnett et al., 1997; Allen and Brown, 2008), they may be predictors of the inclusion in different riding profiles that can be identified by the HRT simulator. Thus, we reversed the methodology used by Marengo et al. (2012), using the simulator to test inexperienced participants and to identify potentially risky riding profiles that can be predicted by specific combinations of personality traits and beliefs. This approach would lead to the possibility of overcoming the limits of self-report driving behavior measures and of the problematic identification of personality profiles, allowing a direct link to be drawn between personality, beliefs and driving behaviors, with important preventive implications. Thus, the aims of the present study are (1) the identification of different profiles of simulated moped-riding in adolescents with no on-road experience and (2) the assessment of the relations between the driving profiles and personality traits and beliefs about their peers' on-road risky behaviors.

For the first aim, we based our work on the methodology developed by Gianfranchi et al. (2017a,b) so as to test participants' driving behaviors directly, even if inexperienced. Indeed, after a proper familiarization, we speculated that adolescents, although inexperienced, would show different degrees of risk while driving and that the differences in the identified profiles would depend not on experience but on other variables, such as personality traits and beliefs. The familiarization would allow to overcome the limits of the participants' inexperience with the virtual environment and with the driving task in general. To do so, we decided to divide the procedure into two sessions: the first one was intended as a familiarization session, whereas the second was employed to test the participants' driving behaviors.

For the second aim, we measured adolescents' self-reported SS, LC, aggressiveness and beliefs, considering them as predictors of inclusion in the profiles. Beliefs were assessed through the 3DI questionnaire (Dula and Ballard, 2003). The original 3DI questionnaire does not assess the behavior of the peers. However, considering that participants could not answer to the items on the basis of their own driving experience (since they had no on-road experience), they were asked to rate the frequency of the behaviors described in the items among their peers. Indeed, although developed to assess experienced drivers' dangerous actions, the 3DI items refer to behaviors that most people can judge as dangerous or inappropriate (*e.g.*, "I will weave in and out of slower traffic" or "I verbally insult drivers who annoy me"), even without proper driving or riding experience.

THE STUDY

Participants

One hundred and fourteen adolescents (mean age: 14.85; range: 13–19 years; 59 males) enrolled in high schools of Padua, Italy, took part in the study. All of them had no on-road driving or riding experience, but they all used bicycles (60% of participants declared they rode a bike several times a week or each day). All of the participants had correct or correct-to-normal vision. They were not paid for their participation. Written informed consent was obtained by all the participants and, for the participants under the age of 18, also by their parents. The project has been approved by the Ethical Committee for the Psychological Research of the University of Padova.

Tools

The HRT Simulator

The HRT is a riding simulator that includes a Pentium 4 PC with a Windows XP operating system and an LCD monitor (1024 × 768 resolution) placed on a base connected to a chassis equipped with moped-like controls that allow a person to ride along virtual courses. A speaker is placed on each side of the monitor through which instructions are given on the path to follow, in addition to reproducing the acoustic effect of the moped engine and the traffic.

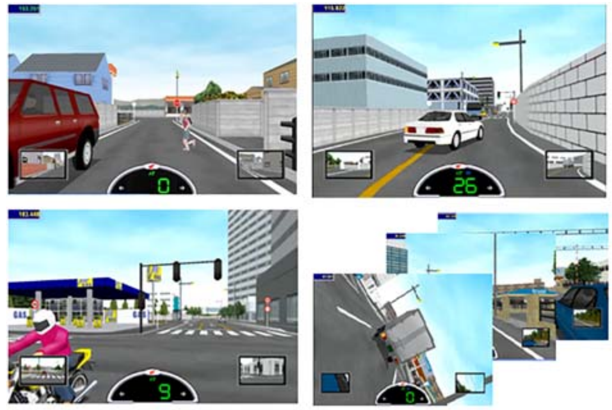

FIGURE 1 | Examples of hazardous scenes classified on the basis of their risk degree: **(A)** (left top panel) and **(B)** scores (right top panel) vs. **(C)** (left bottom panel) and **(D)** (right bottom panel) scores.

The simulator provides a wide range of virtual courses, five on secondary roads and six on main roads. Each course includes seven or eight hazardous scenes [*i.e.*, reconstructions of the most frequent hazardous on-road situations, based on the Maids Motorcycle Accidents In Depth Study (2004) classification]. The simulator gives a letter score for each scene, depending on how well a participant has prevented a crash (**Figure 1**). The scores can be A (*safe performance*), B (*almost safe*), C (*near miss*), and D (*crash*).

Questionnaires

All of the participants filled in a battery of questionnaires aimed at assessing their personality traits and their beliefs about peers' on-road behaviors.

Sensation seeking

Sensation seeking was assessed through the Sensation Seeking Facets measure from the International Personality Item Pool (Hoyle et al., 2002), which includes 30 items divided into three subscales (10 items each) aimed at measuring different aspects of TS. Each subscale includes 10 items that, respectively, assess the seeking of dangerous activities (Dangerous TS; "I might enjoy a free fall from an airplane"), the tendency to be impulsive and unpredictable (Impulsive TS; "I am unpredictable, people never know what I am going to say") and the willingness to take calculated risks or to face the most common fears (Calculated TS; "I would love to explore strange places"). The items are scored on a 5-point Likert scale ranging from 1 (*strongly agree*) to 5 (*strongly disagree*).

Locus of control

We assessed participants' LC through two self-report measures. The first one is the driving locus of control scale of the Italian Cognitive Behavioral Assessment (CBA BG; Vidotto et al., 1995), which includes 27 items (*e.g.*, "Even an experienced and prudent driver can cause a serious accident" and "Prudence does not matter to avoiding traffic accidents") on a 5-point Likert scale (from *strongly agree* to *strongly disagree*).

The second measure is the multidimensional Traffic Locus of Control scale (T-LOC; Özkan and Lajunen, 2005), aimed at discriminating between different dimensions of on-road LC. It is composed of four subscales (Others, Self, Vehicles and Environment, and Fate) in which participants have to rate whether a crash can result from different types of circumstances (*e.g.*, "Other drivers' risk-taking," "Bad weather or lighting conditions," and "My own risk-taking"). The items are on a 5-point Likert scale (from *not at all possible* to *highly possible*).

Aggressiveness

The New–Buss questionnaire (N–B; Gidron et al., 2001), an eight-item self-report tool, was employed to assess participants' aggressiveness. The questionnaire is the brief version of the Buss–Perry Aggression Questionnaire (Buss and Perry, 1992), and each of the four subscales that compose the tool includes two items of the original scale. The subscales are Verbal Aggression ("I can't help getting into arguments when people disagree with me"), Anger ("Sometimes, I fly off the handle for no good reason"), Physical Aggression ("Given enough provocation, I may hit another person"), and Hostility ("I sometimes feel that people are laughing at me behind my back"). All the items are on a 5-point Likert scale (from *extremely uncharacteristic of me* to *extremely characteristic of me*).

Beliefs about peers' on-road behaviors

Participants' beliefs about peers' on-road behaviors were assessed through the Dula Dangerous Driving Index (3DI – Dula and Ballard, 2003). The questionnaire includes 28 items divided into three subscales: Aggressive Driving (AD; 7 items; "I flash my headlights when I am annoyed by another driver"), Risky Driving (RD; 12 items; "I will drive if I am only mildly intoxicated or buzzed"), and Negative Emotions while driving (NE; 9 items; "When I get stuck in a traffic jam, I get very irritated"). Participants were asked to answer each item on a 5-point Likert scale from *never* to *always*, rating the occurrence of the on-road behaviors described by the sentences among their experienced peers.

Procedure

The procedure included two experimental sessions that were scheduled a few days apart from each other. At the beginning of the first session, all of the participants filled in the questionnaires. Then, they were invited to sit on the HRT simulator, where an experimenter illustrated the riding controls and gave all the necessary information regarding the task. Participants were told to ride along the virtual paths as safely as they could, trying to avoid accidents. The HRT was set with moped controls, daylight conditions and automatic transmission so as to prevent any bias derived from riding inexperience.

During the first session, participants faced five courses on secondary roads, preceded by a practice course of 3 min during which they could explore the virtual environment and learn to use the controls. These five courses were introduced to allow participants (who were all inexperienced drivers) to familiarize with the virtual environment and the task. Six courses on main roads were faced during the second session: these courses were employed to test the presence of differences in terms of driving profiles among participants, after the familiarization phase (first session). Before starting the practice, all of the participants were asked about their knowledge on the main road rules and signals (*e.g.*, traffic lights and stop signs), and all of them proved to be aware enough of the main rules and signals.

Coding

Participants' performances were constantly monitored through the HRT simulator, which collects a wide number of riding indexes with a sample rating of 30 Hz. As in previous works (Gianfranchi et al., 2017a,b), we extracted 18 indexes from participants' performance in the second session. The indexes were mean and standard deviation of the throttle opening (%), the pressure on front and rear brakes (kg), on-road instability (horizontal deviations from the right side of the road), speed (km/h), number of braking, points on the path in which participants exceeded the speed limit, number of prevented accidents, time spent over the speed limit (in terms of number of frames), and mean and maximum over the limit speed value reached (km/h). Finally, a summary index (called Evaluation score) was extracted, based on the mean of the scores that the simulator automatically gave to the performance in each scene. The indexes were computed only on the courses of the second session. Indeed, we speculated that because our participants were all inexperienced, a proper riding profile could emerge only after familiarization with the virtual environment and the riding task. For the questionnaires, the original scoring instructions were followed.

Design

The statistical analyses were divided into two main steps. After the inspection of the self-report measures (descriptive statistics, Cronbach's alpha and correlations), the first main step was aimed at identifying the riding profiles among the participants in the second session through a cluster analysis. Then, we assessed differences between clusters in terms of risky behaviors through a multivariate analysis of variance (MANOVA) on the percentages of A, B, C, and D scores obtained during the second session, with *Cluster* as the between-participants factor. *Post hoc* analyses using Bonferroni's correction were conducted, with α set at 0.05. Moreover, in order to rule out that the effects observed are due to differences in learning or driving skills already present before the test procedure in the second session, an identical MANOVA was carried out on the A, B, C, D scores of the first session (familiarization).

The second main step was aimed at identifying the psychological predictors of the inclusion in the riding profiles. Thus, we ran a multinomial logistic regression with the cluster solution as the dependent variable and the scores from the questionnaires as the predictors. All the analyses were performed with the IBM SPSS 23 statistical software package.

ANALYSIS AND RESULTS

As a preliminary step, descriptive and reliability statistics (Cronbach's alpha) were calculated for the employed scales, along with Pearson's correlations among them (**Table 1**).

The correlation coefficients show the presence of significant links among personality traits and between personality traits and beliefs. Cronbach's alpha levels ranged from moderate (>0.50, for some of the scales with a low number of items) to high (>0.70) except for the subscales Verbal Aggression and Hostility of the N–B questionnaire. However, this last result is not surprising because the N–B scales include only two items each. Thus, following Briggs and Cheek's (1986) suggestion, we calculated the inter-item correlations for each N–B scale. The coefficients are 0.26 for Verbal Aggression, 0.58 for Physical Aggression, 0.25 for Hostility, and 0.53 for Anger. Inter-item correlation coefficients higher than 0.20 are considered optimal (Briggs and Cheek, 1986).

The next step was the identification of the riding profiles through a cluster analysis with the 18 HRT indexes of the second session used as grouping variables. The indexes were standardized (*Z*-scores) and analyzed with Ward's method of hierarchical clustering with squared Euclidean distance measures. The inspection of the dendrogram and of the merging coefficients showed the presence of three clusters (profiles), with different riding patterns (**Figure 2**).

As depicted in **Figure 2**, the profiles report different trends on the riding indexes. The first profile, labeled "Imprudent" (21 participants; mean age: 14.90 years old; 15 males), showed a less safe behavioral pattern, with the highest values in almost all the riding indexes (*e.g.*, speed, throttle opening, and Evaluation score). The second profile shows an opposite trend with respect to the Imprudent profile, with low values in all the riding indexes and high rates of prevented accidents. Thus, we labeled this profile "Prudent" (47 participants; mean age: 14.89 years old; 17 males). Finally, the third cluster, which in a previous work (Gianfranchi et al., 2017b) was labeled "Insecure," shows a mixed pattern, with an overall safe performance, but with elements that can be potentially dangerous (*e.g.*, tendency to exceed speed limits and, at the same time, hardly pressing on the front brake). This last cluster includes 46 participants (27 males) with a mean age of 14.78 years old. Although the profiles are homogenous in terms of age, a chi-squared test showed significant differences in terms of sex [$\chi^2(2) = 8.71$, $p < 0.05$]: females are predominant in the Prudent cluster (30 F vs. 17 M), whereas males are predominant in the Imprudent cluster (6 F vs. 15 M).

In order to better understand the differences among the identified riding profiles in terms of risky behaviors, a MANOVA was run on the percentages of A, B, C, and D scores of the second session (calculated over the total of the scenes) with the profiles as the between independent variable. At the multivariate level, the results show that the three profiles are significantly different with Wilks' $\lambda = 0.69$, $F(6, 218) = 7.43$, $p < 0.001$, $\eta_p^2 = 0.17$. Univariate results indicate that significant differences are present in the percentages of each score, with $F(2,111) = 16.64$, $p < 0.001$, and $\eta_p^2 = 0.23$ for A score; $F(2, 111) = 9.99$, $p < 0.001$, and $\eta_p^2 = 0.15$ for B score; $F(2, 111) = 6.58$, $p < 0.01$, and $\eta_p^2 = 0.11$

TABLE 1 | Pearson's correlations, Cronbach's alpha and descriptive statistics for the scales of the questionnaires.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	α	Mean (SD)	Range
1	Dangerous TS	–															0.81	26.1(7.3)	11–50
2	Impulsive TS	0.73**	–														0.89	27.7(8)	11–48
3	Calculated TS	0.57**	0.52**	–													0.69	36.7(5.8)	22–50
4	CBA BG	0.39**	0.57**	0.24*	–												0.72	69.2(9.6)	51–91
5	T – LOC Others	−0.18	−0.16	0.02	−0.22*	–											0.53	20.2(2.1)	14–25
6	T – LOC Self	−0.11	−0.02	0.11	−0.17	0.59**	–										0.63	19.7(2.6)	10–25
7	T – LOC VE	0.15	0.27**	0.21*	0.13	0.25**	0.13	–									0.55	15.5(2)	10–20
8	T – LOC Fate	0.32**	0.45**	0.15	0.44**	−0.03	−0.07	0.30**	–								0.82	6.7(2.6)	3–15
9	N-B verbal aggression	0.16	0.31**	0.14	0.33**	−0.09	−0.13	0.11	0.20*	–							0.41	5.4(1.9)	2–10
10	N–B Anger	0.19*	0.40**	0.07	0.32**	−0.07	−0.01	0.10	0.16	0.59**	–						0.70	5.2(2)	2–10
11	N-B physical aggression	0.26**	0.37**	0.25**	0.29**	−0.08	0.02	0.15	0.17	0.44**	0.53**	–					0.73	5.6(2.3)	2–10
12	N-B Hostility	0.10	0.23*	0.01	0.16	0.04	−0.07	0.25**	0.07	0.41**	0.42**	0.30**	–				0.40	5.6(1.8)	2–10
13	3DI AD	0.21*	0.22*	0.09	0.31**	−0.19*	−0.16	0.07	0.12	0.31**	0.31**	0.29**	0.14	–			0.74	12.9(4.1)	7–32
14	3DI NE	0.09	0.27**	0.09	0.43**	0.01	0.08	0.11	0.10	0.43**	0.38**	0.31**	0.20*	0.64**	–		0.73	22.7(5.1)	12–38
15	3DI RD	0.37**	0.39**	0.38**	0.48**	−0.22*	−0.14	0.05	0.18	0.27**	0.19*	0.26**	0.07	0.62**	0.52**	–	0.81	21.2(6.6)	12–47

Double and single asterisks indicate $p < 0.01$ and $p < 0.05$, respectively.

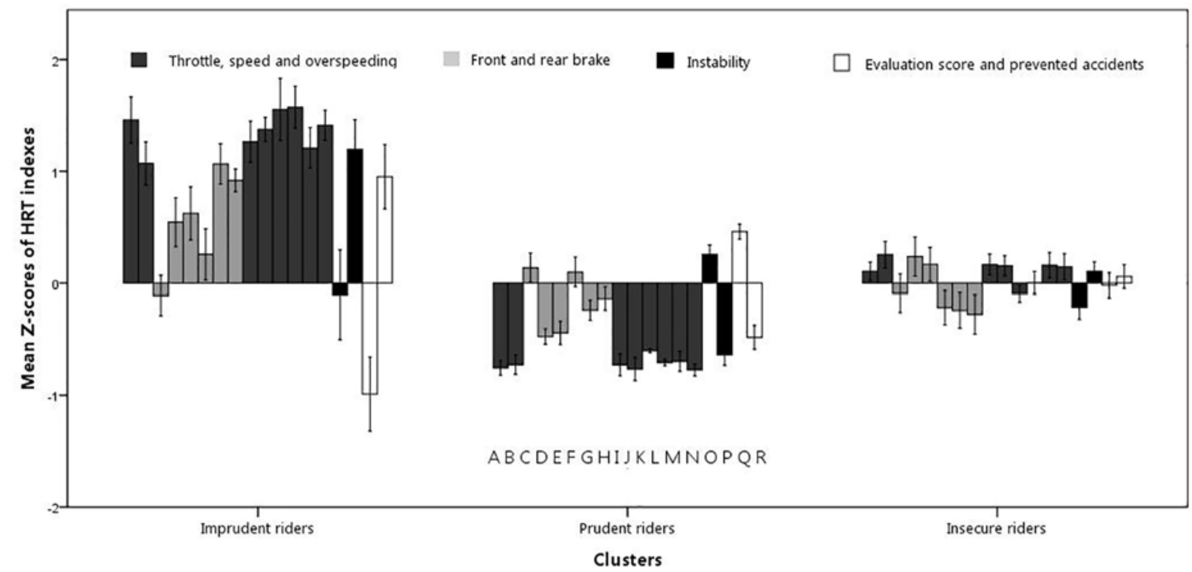

FIGURE 2 | Mean *Z*-scores of the 18 HRT indexes in the three clusters. The indexes are listed in the order displayed by the letters on the bottom of the panel for each cluster. The indexes are the mean of the throttle opening (A) and its SD (B); number of times using the front brake (C); mean (D) and SD (E) of front brake pressure; number of times using the rear brake (F); mean (G) and SD (H) of rear brake pressure; mean (I) and SD of speed (J); time spent over the speed limit (K); number (L), mean (M), and the highest value (N) of speeding; mean (O) and standard deviation (P) of on-road instability; number of prevented accidents (Q); and mean Evaluation score (R; a higher score corresponds to a less safe performance). Vertical bars represent SE.

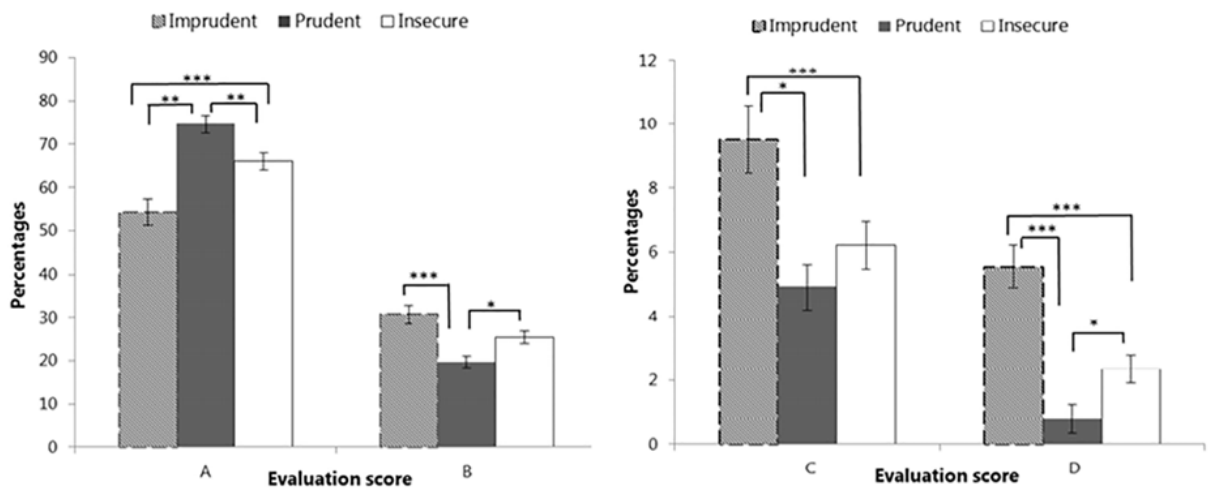

FIGURE 3 | Differences in evaluation scores among the clusters. Vertical bars represent SE. Asterisks indicate significant differences in the *post hoc* comparisons with Bonferroni correction (*$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$).

for C score; and $F(2, 111) = 17.74$, $p < 0.001$, and $\eta_p^2 = 0.24$ for D score.

As depicted in **Figure 3**, Imprudent riders showed a less safe performance, with the lowest percentages of A scores (54.3%) than both Prudent (74.6%, $p < 0.001$) and Insecure riders (66%, $p < 0.01$). Imprudent riders showed also the highest percentages of C and D scores: C scores were 9.5% in Imprudent participants vs. 4.9% in Prudent ($p < 0.001$) and 6.2% in Insecure ones ($p < 0.05$); D scores were 5.6% in Imprudent riders vs. 0.8% in Prudent ($p < 0.001$) and 2.4% in Insecure riders ($p < 0.001$).

On the other hand, Insecure riders obtained lower percentages in A scores than Prudent riders (66 vs. 74.6%, $p < 0.01$) but higher than Imprudent riders (66 vs. 54.3%, $p < 0.01$), and higher D percentages than Prudent riders (2.4 vs. 0.8%, $p < 0.05$) but lower than Imprudent participants (2.4 vs. 5.6%, $p < 0.001$). Finally, they did not differ from Prudent riders in terms of C scores and from Imprudent riders in terms of B scores.

Overall, we can conclude that participants in the Imprudent cluster showed a less safe riding performance, with high percentages of scenes with crashes (D), near misses (C), and almost safe behaviors (B), reporting at the same time the lowest frequency of totally safe scenes (A). Prudent riders showed the opposite pattern, but they did not differ from Insecure riders in terms of near misses (C). Finally, participants in the Insecure cluster reported similar B percentages to those of the Imprudent cluster, testifying that Insecure riders' performances, although overall better than those of Imprudent riders, included a significant amount of not totally safe scenes (*e.g.*, hard braking or disrespecting safe distance).

As said, an identical MANOVA on the A, B, C, D scores obtained during the first session was carried out. Here, the factor *Cluster* failed to reach significance at the multivariate level ($p = 0.111$, $\eta_p^2 = 0.06$), thus allowing to rule out that the effects just described are due to differences in learning or driving skills already present before the test procedure (second session).

The last step of the statistical analysis consisted in a multinomial logistic regression (stepwise backward method) on the cluster solution as the dependent variable and the scores on all the questionnaires' scales as predictors. The aim of the regression was to identify patterns of personality traits and beliefs that can predict inclusion in the riding profiles.

The final model was significant with $\chi^2(18) = 44.99$, $p < 0.001$, explaining 33% of the variance (Cox and Snell's Pseudo $R^2 = 0.33$) with a classification accuracy of 60.5%. Seven predictors reached significance in the final model (**Table 2**); that is, two dimensions of SS (Dangerous TS and Impulsive TS), two measures of locus of control (CBA BG and T-LOC Fate subscale), two dimensions of aggressiveness (N–B Anger and N–B Verbal Aggression), and beliefs about peers' risky driving behaviors (3DI RD).

The regression coefficients reported at the top of **Table 3** show that the likelihood of being included among Imprudent riders with respect to Prudent and Insecure profiles was increased by lower scores on the 3DI Risky Driving scale ($p < 0.05$) and on the T-LOC Fate scale ($p < 0.05$ compared with Prudent riders and $p < 0.01$ compared with Insecure riders) but by higher scores at the CBA BG ($p < 0.01$ with respect to Prudent participants and $p < 0.05$ with respect to Insecure participants). Moreover, higher scores on the Dangerous TS and N–B Verbal Aggression scales play a significant role ($p < 0.05$) in discriminating between Imprudent and Prudent profiles.

TABLE 2 | Likelihood ratio test of the final regression model.

	Likelihood ratio test		
	χ^2	*Df*	*p*-value
Intercept	16.73	2	0.000
Dangerous TS	10.69	2	0.005
Impulsive TS	7.67	2	0.022
Calculated TS	5.35	2	0.069
CBA BG	8.58	2	0.014
T-LOC fate	8.91	2	0.012
N-B anger	7.75	2	0.021
N-B verbal aggression	7.29	2	0.026
3DI RD	6.40	2	0.041
3DI AD	5.00	2	0.082

When the Insecure profile is used as the reference category (bottom of **Table 3**), the coefficients show that higher scores on the N–B Anger scale predict inclusion in the Insecure profile, with respect to the other two profiles ($p < 0.05$). Moreover, reporting high scores on the Dangerous thrill-seeking scale ($p < 0.05$) but, at the same time, low scores on the Impulsive thrill-seeking scale ($p < 0.05$) increased the risk of being included in the Insecure profile, with respect to the Prudent profile.

Overall, aspects such as an external locus of control, the underestimation of fate among the causes of crashes and of the frequency of peers' on-road risky behaviors played a critical role in discriminating Imprudent riders from the other profiles (**Figure 4**). Moreover, participants with high levels of verbal aggression had a higher likelihood of being included in the Imprudent profile than in the Prudent profile. A low tendency to seek dangerous situations raised the probability of being included in the Prudent profile. Finally, inclusion in the Insecure profile was predicted by high levels of anger, whereas low levels of impulsivity played a role in discriminating between Insecure and Prudent riders.

DISCUSSION

This study has two main aims: the identification of different moped-riding profiles among inexperienced adolescents by means of a moped simulator and the assessment of the relations between the identified profiles and psychological predictors, such as sensation seeking, locus of control, aggressiveness and beliefs about peers' on-road behaviors. The idea is to overcome the limits of previously employed methods, because the identification of a variety of drivers' profiles based on self-reported personality traits and driving attitudes are rarely compared with objective driving indexes (in a real and in a simulated environment).

Following the procedure developed by Gianfranchi et al. (2017a,b), a cluster analysis was performed on 18 riding indexes of the second experimental session on the HRT simulator, allowing the identification of three moped-riding profiles in the present sample: Imprudent, Prudent and Insecure riders.

The profiles showed different riding patterns. The Imprudent riders exhibited the most unsafe pattern, with high speed and acceleration levels, high frequency of speeding behavior, and high rates of accidents and instability. The Prudent profile showed the opposite tendency, whereas the Insecure riders had intermediate characteristics. Moreover, a significant difference in terms of sex has emerged between the profiles. The Prudent profile is mostly composed of females, whereas the Imprudent profile is mostly composed of males. A number of studies (for a brief review see Oltedal and Rundmo, 2006) have proved that males are more prone to the effects of sensation seeking and to showing risky driving behaviors. This characteristic was also found in samples composed of adolescents (Oltedal and Rundmo, 2006; Marengo et al., 2012), and it seems to be present when a direct assessment of riding behaviors is performed, too.

TABLE 3 | Parameter estimates of the regression with imprudent (top of the table) and insecure (bottom of the table) profiles as reference categories.

Prudent riders	**Beta**	χ^2	***Df***	***p*-value**	**Insecure riders**	**Beta**	χ^2	***Df***	***p*-value**
Intercept	*13.51*	*11.19*	*1*	*0.001*	*Intercept*	*12.94*	*10.55*	*1*	*0.001*
Dangerous TS	−0.18	6.48	1	0.011	Dangerous TS	−0.05	0.43	1	0.512
Impulsive TS	0.09	1.82	1	0.177	Impulsive TS	−0.06	0.69	1	0.406
Calculated TS	−0.11	2.01	1	0.157	Calculated TS	−0.17	4.81	1	0.028
CBA BG	−0.12	7.38	1	0.007	CBA BG	−0.10	4.83	1	0.028
T-LOC fate	0.30	3.87	1	0.049	T-LOC fate	0.42	7.58	1	0.006
N-B anger	0.14	0.51	1	0.475	N-B anger	0.50	5.71	1	0.017
N-B verbal aggression	−0.53	6.41	1	0.011	N-B verbal aggression	−0.37	3.28	1	0.070
3DI RD	0.17	4.61	1	0.032	3DI RD	0.18	4.79	1	0.029
3DI AD	−0.06	0.42	1	0.518	3DI AD	−0.20	3.79	1	0.052
Imprudent riders	**Beta**	χ^2	***Df***	***p*-value**	**Prudent riders**	**Beta**	χ^2	***Df***	***p*-value**
Intercept	*−12.94*	*10.55*	*1*	*0.001*	*Intercept*	*0.56*	*0.06*	*1*	*0.803*
Dangerous TS	0.05	0.43	1	0.512	Dangerous TS	−0.13	6.35	1	0.012
Impulsive TS	0.06	0.69	1	0.406	Impulsive TS	0.15	6.67	1	0.010
Calculated TS	0.17	4.81	1	0.028	Calculated TS	0.62	1.45	1	0.229
CBA BG	0.10	4.83	1	0.028	CBA BG	−0.02	0.46	1	0.499
T-LOC Fate	−0.42	7.58	1	0.006	T-LOC Fate	−0.12	1.29	1	0.257
N-B Anger	−0.50	5.71	1	0.017	N-B Anger	−0.36	4.33	1	0.038
N-B verbal aggression	0.37	3.28	1	0.070	N-B verbal aggression	−0.15	0.84	1	0.359
3DI RD	−0.18	4.79	1	0.029	3DI RD	−0.01	0.02	1	0.881
3DI AD	0.20	3.79	1	0.052	3DI AD	0.14	2.96	1	0.086

Further analyses of the present data confirmed significant differences among the profiles in terms of risky behaviors. Indeed, Imprudent riders reported the lowest percentage of safe scenes and the highest percentage of near misses and crashes, whereas Prudent riders showed the opposite results. Insecure riders had overall a mid-range performance, with a percentage of near misses comparable to that of the Prudent profile but, at the same time, lower percentages of safe scenes and higher percentages of almost safe scenes; these last were comparable to those of the Imprudent profile.

Previous works (Lucidi et al., 2010; Marengo et al., 2012) identified three different profiles on the basis of self-report personality measures. In particular, Lucidi et al. (2010) detected three clusters (risky, worried, and careful drivers) that showed specific patterns of self-reported aberrant driving behaviors and risky attitudes, largely comparable to those showed on the HRT by the profiles in the present study. On the other hand, the three clusters identified by Marengo et al. (2012) in a sample of adolescents with various degrees of on-road experience, after being judged differently at-risk of road crashes on the basis of their personality traits, differed from each other in terms of riding safety on the HRT simulator. The present study, although confirming the results of previous studies, tries to go beyond them in three ways. First, it aimed to categorize different profiles based on a quantitative evaluation of their performance on the simulator. Second, it considered personality traits and beliefs as predictors of the profiles in an attempt to find a direct relation between them. Finally, the use of the questionnaire subscales allowed us to assess deeply, when present, the relation between personality traits, beliefs and riding performance.

Moreover, because this method has the advantage of allowing the direct assessment of participants' driving behaviors and attitudes in a safe environment, it is also possible to test inexperienced road users to look for predictors of their performance. Indeed, contrary to previous studies (Gianfranchi et al., 2017a,b), here we decided to focus on totally inexperienced participants, so as to disentangle the role of on-road experience from that of other variables. Our results, besides identifying a cluster solution consistent with the one that emerged in a sample of novice drivers (Gianfranchi et al., 2017b), show that it is also possible to find inter-individual differences in driving behaviors among adolescents with no on-road experience, thus stressing the role of personality traits and beliefs.

As for the role of the predictors, our results are in line with the previous literature. Sensation seeking (especially dangerous TS) and locus of control seem to play key roles in the predictions of participants' riding profiles, with high levels of SS and an external locus of control being associated with an increase in the risk of an imprudent behavior (Lucidi et al., 2010; Marengo et al., 2012). It is worth noting that lower scores on the Fate scale of the T-LOC predicted inclusion among Imprudent riders in our sample. Although attributing the causes of crashes to coincidence or fate may be interpreted as an index of external locus of control, at the same time also considering the role of unmanageable factors may have a role in developing defensive driving strategies, which in turn may lead to more cautious behavior.

Low levels of impulsivity and high levels of anger increased the risk of showing an insecure riding style among adolescents in our sample. Being less impulsive, although frequently associated with cautious behavior (Marengo et al., 2012), might also lead

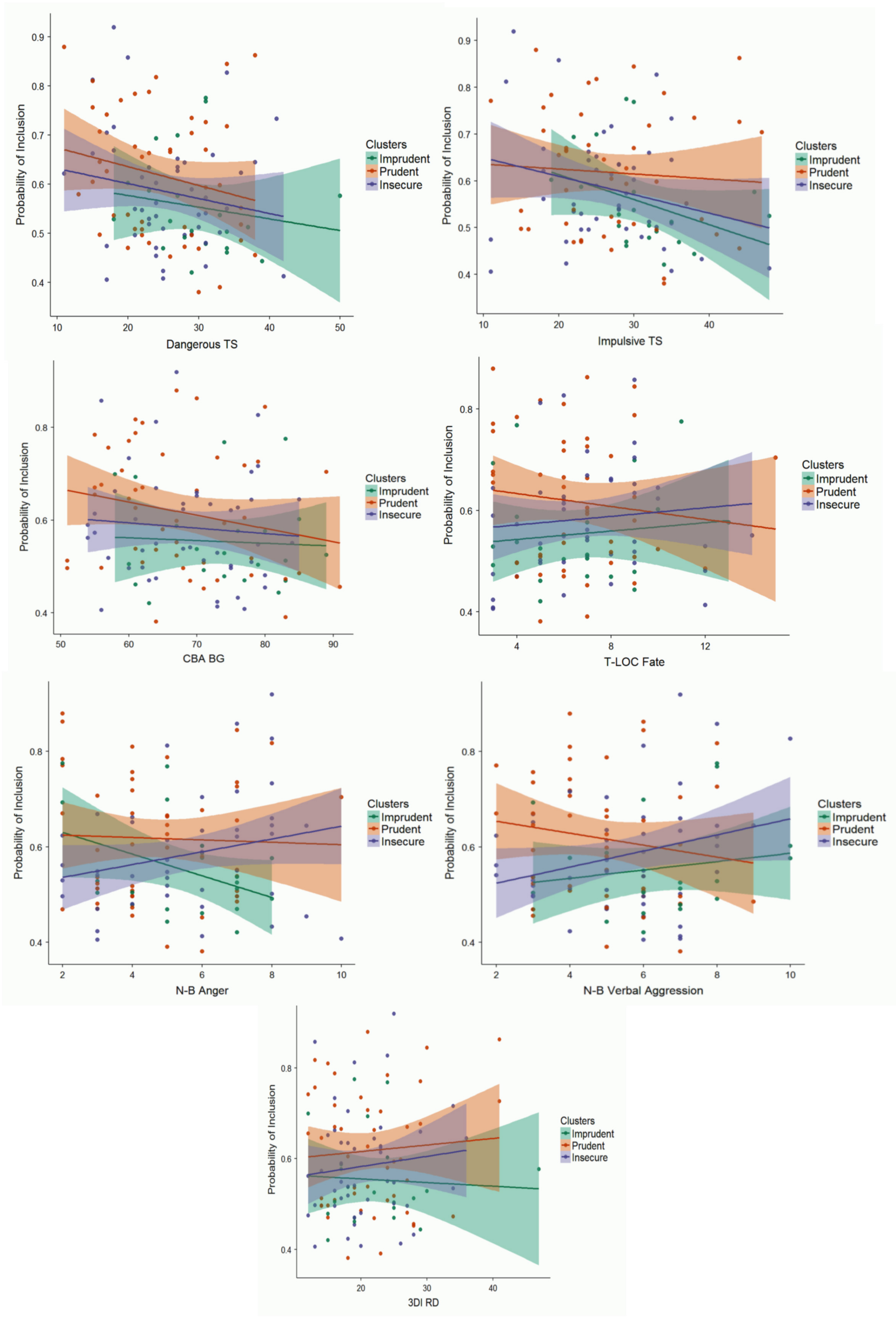

FIGURE 4 | Probability of inclusion in the three profiles for the scores of each significant predictor. Shaded areas represent SE.

to difficulties in self-regulation of driving behaviors when a quick decision is required to face impending hazardous scenarios. This might explain how, in the present research, low levels of impulsivity are associated with insecure but not imprudent behaviors. However, further research is needed to support this conclusion.

Concerning the role of anger, Dahlen et al. (2012) tested a theoretical model of associations between different personality traits, aggressive driving and driving outcomes in a sample composed of adult drivers. Their results showed the existence of a positive relationship between low emotional stability (*i.e.*, anger, depression, and anxiety) and aggressive driving, which in turn led to more on-road violations, near misses and crashes. In our sample, anger has proved to be predictive of the inclusion in the Insecure profile. At the same time, Insecure riders showed more reckless behaviors than Prudent riders, as attested by the lower frequency of safe scenes (A scores) and the higher frequency of both almost safe scenes (B scores) and crashes (D scores). These results are in line with the conclusions by Dahlen et al. (2012) as to road violations and crashes, indicating that higher levels of anger may represent a risk factor for less cautious driving behaviors. However, the result related to near misses has not been replicated. This discrepancy may be due to differences in age and experience of the involved samples or in the adopted questionnaires. Nevertheless, our study confirmed the key role of anger in predicting driving behaviors among adolescents.

Finally, underestimating peers' on-road risky behaviors increased the risk of showing imprudent behavior on the HRT, with significantly higher percentages of crashes and near misses. Indeed, a correct estimation of others' potentially hazardous behavior is crucial to preventing crashes and it represents the basis of the development of hazard perception and defensive driving strategies.

The principal limitation of the present study is related to the generalizability of the results to real on-road behaviors. Indeed, although it is true that the identification of profiles based on participants' performances in a simulated environment rather than on self-report measures represents progress in the assessment methods of driving behaviors, there is still controversial evidence on the ecological validity of the simulators (de Winter et al., 2012). Thus, a further and necessary step will be following up on self-reported data and real on-road performance, especially focused on participants' crash rates. Moreover, the application of the methodology reported in the present research to a sample of experienced adolescents (*i.e.*, with at least 1 year of on-road experience) would offer the possibility to study the role of experience relative to that of personality traits.

Finally, a further limitation deals with the restricted battery of questionnaires used to assess personality variables. Indeed, risky driving is influenced by a number of variables, among which impulsivity or risk proneness play a prominent role (Megías et al., 2018). In addition, cognitive aspects (*e.g.*, attention and decision making) are also thought to influence on-road behaviors (Tagliabue et al., 2013; Torres et al., 2017). Thus, further studies are needed to assess the role of other important personality traits and of cognitive predictors in determining the development of different driving and riding profiles.

CONCLUSION

The present data indicate, first of all, that detecting different moped-riding profiles on the basis of a deep monitoring of the performance on a simulator is possible also among adolescents with no on-road experience. Second, the present study provides evidence that the identified profiles are not only dissimilar in terms of driving behaviors, but that they are also predicted by different personality patterns. These results represent the first step toward the development of an assessment method able to allow the early detection of risk-prone on-road profiles and of their predictors, along with potential protective factors. The practical implications of this new approach could range from the use of more complex virtual environments to identify driving profiles in specific populations with peculiar characteristics (*e.g.*, older drivers or clinical populations) to the development of *ad hoc* training protocols that may provide a crucial contribution to preventing crashes.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of guidelines for psychological research of the AIP – Associazione Italiana Psicologia with written informed consent from all subjects. All subjects, and the parents of the subjects aged less than 18 years old, gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Ethical Committee for the Psychological Research of the University of Padua.

AUTHOR CONTRIBUTIONS

EG conducted data collection, statistical analysis, and manuscript writing. MT supervised data collection and contributed to statistical analysis and manuscript writing. All authors contributed to research planning, results discussion, and revision of the paper.

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Testing Attention Restoration in a Virtual Reality Driving Simulator

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Objectives: Attention Restoration Theory (ART) suggests that walking or being in natural settings, as opposed to urban environments, benefits cognitive skills because it is less demanding on attentional resources. However, it is unclear whether the same occurs when the person is performing a complex task such as driving, although it is proven that driving through different road environments is associated with different levels of fatigue and may engage attention differently. The present study investigated whether exposure to rural vs. urban road environments while driving would affect attentional capacity in young people after the drive, in line with the classic ART paradigms.

Methods: We asked 38 young participants to complete the Sustained Attention to Response Task (SART) before and after being exposed to a rural or urban road in a virtual reality environment while driving in a full vehicle immersive driving simulator. Changes in SART performance based on environmental exposure where explored in terms of target sensitivity, accuracy, reaction times, and inverse efficiency. We analyzed potential road type effects on driving speed and accuracy. Possible effects of driving on attention were tested by comparing the sample performance to that of a control group of 15 participants who did not drive and sat on the passenger seat instead.

Results: Exposure to rural or urban road environments in the driving sample was not associated with any significant changes in attentional performance. The two exposure groups did not differ significantly in terms of driving behavior. Comparisons between the driving sample and the control group controlling for age indicated that participants who drove were more accurate but slower at the SART than those who were passengers.

Conclusion: The present study does not support the hypothesis that a short drive in a natural setting may promote attention restoration as compared to an urban setting. Methodological considerations as well as recommendations for future research are discussed.

Keywords: attention restoration, driving simulator, virtual environment, driving behavior, mental fatigue, cognitive load

INTRODUCTION

Increasingly, research has demonstrated that road characteristics can impact both driving behavior and the activities the driver will undertake once arrived to destination (Antonson et al., 2009; Keay et al., 2009; Calvi, 2015; Murphy and Greene, 2016; Cassarino and Murphy, 2018). Urban roads present higher road complexity than rural roads and can impose more cognitive demands on the driver (Murphy and Greene, 2016). Higher cognitive demands translate not only into less safe driving, but also into poorer cognitive performance after the drive (Murphy and Greene, 2016). These findings support the idea that environmental situations that are perceptually complex (e.g., presenting visual clutter) engage more attentional resources and are thus more cognitively fatiguing (Lavie et al., 2004). Complementing this hypothesis, encouraging evidence suggests that the impact of road characteristics on drivers' attentional resources may depend on the presence of natural elements. A review on roadside features and driving safety (Wilde, 2010) suggested that green scenery on the road can have restorative effects on attention. Similarly, a recent review indicated that roadside vegetation can reduce drivers' stress and frustration (Van Treese et al., 2017). This research is informed by Attention Restoration Theory (ART, Kaplan and Kaplan, 1989; Kaplan, 1995); ART suggests that natural environments are more restorative for attention than urban settings because engaging bottom-up involuntary attention (defined as "soft fascination") while "freeing-up" top-down directed attentional resources (Kaplan and Berman, 2010; Bratman et al., 2012; Berto, 2014). Several behavioral studies support ART by showing that even a brief exposure to natural vs. urban settings, either through walking or seeing images, can relieve from the attentional fatigue caused by a cognitive task completed prior to the environmental exposure (Hartig et al., 2003; Berto, 2005; Berman et al., 2008). Supportive evidence has come from neuroimaging as well (Martínez-Soto et al., 2013; Bratman et al., 2015; Chen et al., 2016), although recent systematic reviews have shown that restorative effects are small (de Keijzer et al., 2016; Ohly et al., 2016).

While most studies on attention restoration have used walking as a form of real-life exposure to nature, very little is known about cognitive restoration in relation to driving, which requires monitoring of the road, and therefore a certain level of attentional engagement. If nature engages bottom-up attention only, one should expect that driving in roads with natural elements, such as rural roads, should be associated with less attentional fatigue than driving on urban roads. In line with this hypothesis, an experimental study used a pre- and post- design where participants were mentally stressed before being exposed to video-tapes of either highway vegetation or roads with man-made material of 5-min duration (Cackowski and Nasar, 2003); an assessment of mental stress after exposure found higher tolerance to frustration in participants who viewed natural rather than urban roads. However, no studies to our knowledge have tested ART while driving using the classic experimental paradigm described above (i.e., changes in attention).

In the present study, we used a simulated driving paradigm to test the hypothesis that driving in an urban or rural virtual environment would differentially impact on attentional fatigue after completing a demanding cognitive task (Sustained Attention to Response Task or SART, Robertson et al., 1997), as shown in previous studies on nature and sustained attention (Berto, 2005). The SART is a measure of attentional capacity as well as the ability to inhibit unwanted responses for a prolonged time; it has been used in previous investigations of ART as a way to mentally fatigue participants *before* exposure to natural or urban scenes and to measure attention restoration *after* exposure (Berto, 2005). In the present study, a pre-post design was employed, whereby participants performed the SART task before and after either a rural or urban drive. Assuming that rural roads are more restorative (i.e., less cognitively demanding) than urban roads due to the presence of green, we hypothesized that driving through a rural rather than urban environment after having been mentally fatigued would be associated with improvements in attentional performance at the end the drive. Given the very high usage of cars in our society, investigating the impact of road nature on drivers' cognitive abilities has important implications for enhancing our understanding of how road characteristics influence cognitive performance.

MATERIALS AND METHODS

Participants

In line with Berto (2005), a total of 38 participants (Mean age = 22.1, *SD* = 3.43; 44% female) were recruited through convenience sampling among undergraduate and graduate students at University College Cork, Ireland. Participants were randomly assigned to an urban or rural environmental exposure ($n = 19$ in each group). Half of the participants ($n = 19$) were fully licensed drivers with an average of 5.5 years of driving experience (*SD* = 3.24), whereas the other half ($n = 19$) included individuals with no full license and mean driving experience of 2.3 years (*SD* = 3.81). All participants read and signed a consent form prior to data collection in accordance with the Declaration of Helsinki. Ethical approval for the study was received by the School of Applied Psychology Ethics Committee, University College Cork. All participants read an information sheet briefing on the aims of the study and all were asked to read and sign a written consent form prior to participation in the study. No vulnerable populations were included in the study.

Design

A 2 × 2 mixed between-within design was employed, with the participants' performance at SART, (assessed pre- vs. post-exposure to virtual reality environments in a full vehicle driving simulator) as the within-subjects factor; and Environment type (urban vs. rural) as the between-subjects factor.

Material and Apparatus

Sustained Attention to Response Task (SART)

The SART is an experimental paradigm used to measure sustained attention (Robertson et al., 1997). In this task, participants viewed a random sequence of digits (1–9) appearing on the central projector screen of the simulator, while sitting in the vehicle (see **Figure 1A**). A computer keyboard was placed on the participant's lap and they were asked to press the spacebar as quickly as possibly at the appearance of each digit, except for the digit three. The numbers appeared on the center screen of the simulator. The task was programmed in E-Prime 2.0 software.

Before the experimental block there were 18 practice trials so that participants were accustomed to the task and apparatus. The experimental block consisted of 252 trials (28 of each digit between one and nine) presented in one of five semi-randomly assigned fonts in the range of 12–29 centimeters. In the test trial, the target stimulus (i.e., the number 3) appeared 28 times, while the remaining 224 digits were non-lures. Digits appeared on the screen every 1,125 ms, for the duration of 200 ms, followed by a 900 ms mask, which was a diagonal cross contained within a 29-centimeter ring. Both the digits and the mask were white against a black background. Instructions on how to complete the task were showed on the computer screen prior to the appearance of both the practice and the test trial.

Virtual Reality Environments

The driving simulator we utilized is considered to be a medium-level driving simulator (not high as it is not placed on a steward platform). It consists of a full-size Volkswagen Polo vehicle with manual transmission which has all vehicle controls available including functional speedometer and tachometer. The vehicle faces 3 large projection screens and has LCD screens in the wing mirrors and a rear projection screen which can be viewed through the rear-view mirror. The vehicle is equipped with 7.1 Dolby surround sound, enabling the creation of a more immersive environment with engine sounds as well as noises from other road users such as beeping or harsh braking. The simulator is housed in a dark, cool room with black-out blinds, black walls and a fan to provide airflow. In the adjacent control room, the experimenter can monitor the participants' progress. The simulator uses STISIM 400W software (STISIMdrive.com) which allows for flexible programming various driving environments.

A computerized graphic rural drive and an urban drive were designed for the study, as shown in **Figures 1B,C**. The rural drive (**Figure 1B**) presents a road surrounded by trees (isolated or in groupings) and fields; while the urban drive presents the same kind of road surrounded by some pedestrians and buildings either low rise commercial or tall commercial or residential buildings (**Figure 1C**). All drives were designed to minimize the occurrence of features which are known to cause simulator sickness, such as curves or sudden stops (Classen et al., 2011). Similar to previous studies on ART, the scenarios were pilot

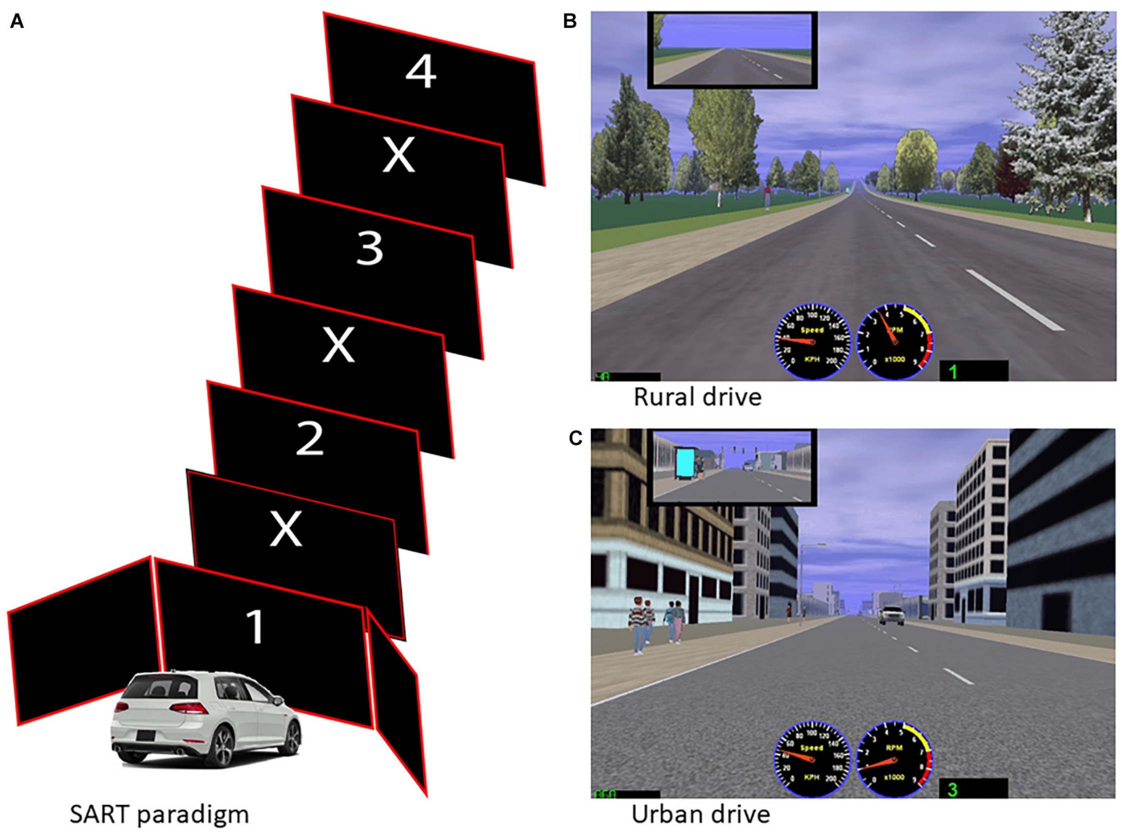

FIGURE 1 | (A) Sustained Attention to Response Task (SART) paradigm: A sequence of digits was viewed by the participants while sitting in the vehicle; digits appeared in the central project screen of the simulator. Participants completed the SART before and after driving in the simulated environment, consisting of a computerized graphic depicting a rural **(B)** or urban **(C)** scenario.

tested for perceived pleasantness and restorative potential with a separate group of participants utilizing the Attention Restoration Scale (Hartig et al., 1997). Participants were assessed for motion sickness through a questionnaire before and after the drive, closely monitored for any signs of sickness, offered regular breaks and reminded that they could withdraw from the study at any point.

Driving behavior was recorded in terms of average speed, standard deviation from the average speed, lane position, and mistakes (including, number of occurrences of red-light tickets, speed excess, collisions, and road lane excursions).

Procedure

Participants were first introduced to the vehicle and its controls. They were then given a 10-min practice drive to become accustomed to the responsiveness of the vehicle. This practice drive consisted of a mix between urban and rural environments. Once participants were comfortable the practice drive was stopped, and they were presented with the first SART task. Once they completed the SART task they were randomly assigned to drive in the rural or urban environment. During the drive, which lasted 10 min, participants were asked to maintain a speed of approximately 60 Km/h. The duration of the test drive was based on Berto (2005), who found that 10 min of viewing images of natural scenes was enough for participants to experience restoration. Also, previous studies have demonstrated differences in cognitive performance between drivers exposed to different scenarios after a 10–12 min test drive (Murphy and Greene, 2016). This duration was also chosen to avoid potential discomfort for the participants. The participants were then asked to complete the SART again (Session 2), after which they filled a short demographic questionnaire.

Statistical Analyses

Participants' performance at the SART was analyzed in terms of d-prime (d': a measure of signal detection sensitivity, calculated as the standardized difference (z-scores) between the proportion of correct responses on non-lures minus the proportion of incorrect responses on lures), overall mean accuracy (proportion of correct responses on lures and non-lures), mean accuracy on non-lures (pressing the bar), accuracy on lures (not pressing the bar when number three appears), reaction times (in milliseconds) of correct responses (related to pressing the bar in the presence of a non-lure), and inverse efficiency, a measure of speed-accuracy trade-off calculated as the ratio of reaction times over accuracy on non-lures (Bruyer and Brysbaert, 2011). Comparisons between the two exposure groups in terms of gender were conducted using Chi-square test and potential differences in age and driving experience were investigated via an independent samples *t*-test. These comparisons were carried out to decide whether demographic status or driving experience should be included in the subsequent analyses as covariates. A 2 × 2 mixed-design ANOVA was conducted with Environment (rural vs. urban) as the between-subjects factor, and SART (pre- vs. post-drive) as the within-subjects factor to investigate effects of environmental exposure on changes in attentional performance pre- and post-drive. *Post hoc* comparisons were conducted via *t*-test statistics. Comparisons between exposure groups in terms of driving behavior were assessed via independent *t*-test. In addition, potential effects of driving on attention were tested through a 2 (SART session) × 2 (environmental exposure) × 2 (driving vs. passenger condition) ANOVA with Driving (driver or passenger) and Environment (urban vs. rural) as the between-subject factors, and SART (pre- vs. post-drive) as the within-subjects factor. We conducted a test of normality on the ANOVA unstandardized residuals as well as the Levene's test of homogeneity (see **Supplementary File 1**); for measures that did not appear to meet the assumptions of normality, we conducted the analyses using non-parametric tests and found no differences in results (see **Supplementary File 1**).

RESULTS

Environmental Exposure Effects on Attention

The two exposure groups (n = 19 in each group) did not differ significantly in terms of gender (χ^2_1 = 0.11, p = 0.74), age (t_{36} = −0.42, p = 0.67) or driving experience (t_{36} = 0.16, p = 0.87).

The 2 × 2 mixed-design ANOVA indicated no significant interaction between environmental exposure and SART pre- and post-drive for any of the measures of interest, as shown in **Table 1**.

There was a main effect of environmental exposure for the measure of d' ($F_{1,36}$ = 4.18, p = 0.048, μ^2 = 0.11), with participants in the rural exposure group (M = 1.26, SD = 1.07) showing overall higher sensitivity (i.e., better performance) than the urban exposure group (M = 0.62, SD = 0.84). There was also a main effect of environmental exposure for the measure of accuracy on lures ($F_{1,36}$ = 4.61, p = 0.04, μ^2 = 0.11), with participants in the rural group (M = 0.64, SD = 0.25) being overall more accurate than those in the urban group (M = 0.48, SD = 0.21). In both cases, however, the size of the effect was small.

We found that the driving behavior of two exposure groups did not differ significantly for any of the measures of interest: average speed (t_{35} = 0.21, p = 0.84), standard deviation from average speed (t_{35} = 0.61, p = 0.55), average lane position (t_{36} = 0.03, p = 0.97), standard deviation from average lane position (t_{36} = −1.71, p = 0.09), speed excess (t_{36} = 0.45, p = 0.65), or lane excursions (t_{36} = 1.67, p = 0.11).

TABLE 1 | Interaction between environmental exposure and SART session – driving sample.

Measure	*F*(1,36)	*P*-value
d'	0.96	0.76
Total accuracy	0.05	0.82
Accuracy on lures	0.003	0.96
Accuracy on non-lures	0.06	0.81
Reaction times	0.004	0.95
Inverse efficiency	0.008	0.93

F refer to a 2 × 2 mixed design ANOVA.

Testing for the Effect of Driving

As an additional check on our study, we conducted a control study whereby we recreated the same situation, but participants were not required to drive. This was included so that the act of driving could be dissociated from viewing motion. We initially recruited 24 participants (12 in the rural condition and 11 in the urban group); however, eight participants (four in each condition) did not complete the driving scenario due to motion sickness or unwillingness, leaving a final sample of 15 participants (Mean age = 31.26, *SD* = 6.69; 53.3%% female); these completed the SART before and after a 10-min exposure to the virtual environment (n = 8 rural vs. n = 7 urban road) while seating in the driver's seat but not driving.

We ran a 2 (SART session) × 2 (environmental exposure) ANOVA for this group with exposure (urban vs. rural) as the between-subject factors, and SART (pre- vs. post-drive) as the within-subjects factor. As shown in **Table 2**, no interactions emerged for any of the measures of interest.

Similarly, no main effects of environmental exposure emerged. A main effect of session was noted for total accuracy ($F_{1,13} = 5.22$, $p = 0.04$, $\mu^2 = 0.27$) with an overall small improvement from baseline ($M = 0.63$, $SD = 0.16$) to post-exposure ($M = 0.68$, $SD = 0.16$).

We then pooled together the data ($N = 53$) from the two samples (driving, $n = 38$; non-driving, $n = 15$), and ran a 2 (SART session) × 2 (environmental exposure) × 2 (driving vs. passenger condition) ANOVA with Driving (driver or passenger) and Environment (urban vs. rural) as the between-subject factors, and SART (pre- vs. post-drive) as the within-subjects factor. As the driving group was older than the non-driving group ($t_{51} = 6.59$, $p = 0.000$, Cohen's $d = 1.72$), we included age as a covariate in the ANOVA.

Controlling for age, we found no significant interactions (not shown); a main effect of driving condition emerged for all measures except inverse efficiency (d': $F_{1,48} = 49.93$, $p = 0.000$, $\mu^2 = 0.48$; total accuracy: $F_{1,48} = 65.41$, $p = 0.000$, $\mu^2 = 0.52$; accuracy on lures: $F_{1,48} = 6.85$, $p = 0.01$, $\mu^2 = 0.12$; accuracy on non-lures: $F_{1,48} = 50.02$, $p = 0.000$, $\mu^2 = 0.45$; reaction times: $F_{1,48} = 31.18$, $p = 0.000$, $\mu^2 = 0.38$). Specifically, participants who drove were significantly more accurate and slower at the SART than those in the control group (i.e., not driving) both before and after exposure, and independent of exposure condition.

TABLE 2 | Interaction between environmental exposure and SART session – control sample.

Measure	*F*(1,13)	*P*-value
d'	1.62	0.23
Total accuracy	1.32	0.27
Accuracy on lures	0.04	0.85
Accuracy on non-lures	0.91	0.36
Reaction times	1.36	0.26
Inverse efficiency	0.48	0.49

F refer to a 2 × 2 mixed design ANOVA.

Only in the case of accuracy on non-lures, a main effect of exposure also emerged ($F_{1,48} = 5.34$, $p = 0.03$, $\mu^2 = 0.05$), with participants exposed to the rural environment being overall more accurate ($M = 0.92$, $SD = 0.11$) than those exposed to the urban environment ($M = 0.88$, $SD = 0.21$); however, the effect size of environmental exposure was smaller than that of driving.

DISCUSSION

The present study tested attention restoration theory (ART) by investigating the potential effects on attention of exposure to urban or rural roads while driving. Overall our findings do not support the hypothesis that driving in a rural natural environment is more restorative of attentional fatigue. Our study is novel, as to our knowledge no other studies have employed the specific experimental paradigm of our study, particularly utilizing a driving simulator. The utilization of the driving simulator paradigm may be the reason why our results are in contrast with existing evidence of changes in sustained attention after exposure to images of urban vs. natural scenes (Berto, 2005) or after a walk in an urban or green environment (Hartig et al., 2003; Berman et al., 2008).

We investigated whether potential differences in driving behavior could have influenced these results, however the two exposure groups drove with similar speed (as requested, with few infractions) and accuracy. We also tested whether the driving task could influence the effect of being exposed to urban or rural environments by re-running the experiment in a sample of participants who seated in the car but did not drive, as a further control condition. No restorative effects were noted in this group either, while a small practice effect was found. When comparing the two driving groups (driving vs. passenger), we found that participants who drove were more accurate but slower at the SART than those who were passengers, showing more conservative performance in both sessions. These differences did not appear to depend on sample characteristics such as age. Notably, the passenger group showed an overall improvement in accuracy independent of exposure, which might indicate a practice effect and possibly that the virtual immersion served as a resting interval for both exposure groups (i.e., not driving might have led the participants to not engage enough with the virtual environment to generate restorative effects). However, this interpretation of the results needs to be considered with caution, as the differences between driving conditions at baseline did not depend on the type of environmental exposure and might be related either to a selection bias which we were unable to capture or to the potential effects of the different types of instructions provided to participants at the beginning of the experiment (i.e., one group was asked to drive while the other sat in the car, and this might have created different expectations as well as different levels of engagement with the experiment).

One could argue that completing the SART was an easy task for our sample, and therefore did not cause attentional fatigue. However, the performance of our sample was worse than that of Berto (2005), who used the same cognitive task in a sample of similar age. While this comparison supports the idea that our participants were mentally fatigued by the SART, future studies might assess other measures of mental fatigue other than the SART.

A limitation of our study is the realism of the urban and rural drives, which are clearly a simulation and therefore less rich than real natural scenes in terms of soft fascination features. Nonetheless, these scenarios were pilot tested for perceived pleasantness and restorative potential with a separate group of participants. When considering the study by Berto (2005), which also utilized the SART, it is important to note two critical differences: Firstly, the restorative scenes used in the driving simulator were not photographs of real environments. It is possible that a removal from a realistic scene does not provide scenery-related restoration. Secondly, in all situations the scenery was moving (to give the sense that the car was in motion). This is unlike previous studies where participants viewed static images for 10 min. Linked to this, it is possible that the short duration of the test drive (10 min) might have been insufficient to generate restorative effects; however, restorative effects of nature have been demonstrated after short exposures (Berto, 2005), and previous studies using simulated drives have shown effects on cognitive performance for durations similar to that of our study (Murphy and Greene, 2016).

While the small sample size of each subgroup, as well as the imbalanced number of participants in the two driving conditions, limited the power of our analyses, it is worth noting that the effect sizes were very small; in addition, previous studies on attention restoration have shown effects with samples comparable to the present study.

In light of our results, the present study shows that driving or being a passenger in a simulated drive with no particularly challenging situations does not overall determine a different load on attention after the drive. Of course, a different scenario could be envisaged whereby the drives are very demanding, for e.g., an urban drive with pedestrians suddenly crossing the road, however, such a scenario would differ substantially from the traditional ART paradigms (e.g., observation of scenes). Therefore, our study contributes to the current knowledge about cognitive restoration and natural settings by indicating that attention restoration may not occur when the individual is on a moving vehicle, therefore, potentially less engaged in soft fascination.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this manuscript will be made available by the authors, without undue reservation, to any qualified researcher.

AUTHOR CONTRIBUTIONS

MC, JC, and AS were major contributors in writing the manuscript. MC, MM, YE, DG, JC, and AS designed the study. MM, YE, and DG conducted the data collection and participated in the data analysis. MC, JC, and AS were major contributors in the data analysis. All authors read and approved the final manuscript.

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00250/full#supplementary-material

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Riding the Adolescence: Personality Subtypes in Young Moped Riders and Their Association With Risky Driving Attitudes and Behaviors

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The aim of the present study was to identify sub-types of moped riders based on a cluster analysis of specific personality characteristics (i.e., driving anger, anxiety, angry hostility, excitement-seeking, altruism, normlessness, and driving locus of control) within a large sample of Italian adolescents. The study had also the aim to compare the emerged sub-types of moped riders on measures of attitudes toward safe driving, risky driving behaviors (e.g., rule's violations and speeding, not using helmet, drinking and driving, etc.), and self-reported tickets and accident involvement. One thousand two hundred seventy-three Italian high school students aged from 13 to 19 years ($mean_{age}$ = 15.43, SD = 0.98) with a valid driving license for moped participated to the study. Results revealed three sub-types of moped riders (namely risky, worried and careful moped riders), which differ significantly for risky driving behaviors, attitudes toward traffic safety, risk perception, and self-reported accident involvement. Importantly, the results of the present study showed that the personality and behavioral characteristics of the three sub-groups of moped riders substantially resembled those identified by previous studies with vehicle drivers of different ages; thus, empirically supporting the notion that certain combinations of personality characteristics are associated with risk driving tendencies and behaviors in both young moped riders and car drivers. Safe driving interventions can tackle risky driving beliefs and behavioral tendencies in young moped riders and car drivers by tailoring their messages according to the personality sub-types of the target groups.

Keywords: moped riders, personality, attitudes toward safety, risky driving behavior, cluster analysis

INTRODUCTION

According to the World Health Organization, about 1.25 million people die in traffic crashes every year, and road traffic injuries represent the main cause of death among young adults between 15 and 19 years old (World Health Organization [WHO], 2018). The use of mopeds (50 cc and restricted top speed) or motorcycles, has increased over the last 15 years, especially among younger people and adolescents living in dense population areas and especially in Southern European countries, such as Italy and Greece (Theofilatos and Yannis, 2015). In Italy, for example, the 57.1% of the young people aged 15–24 drives habitually a moped, with about 6,5 million of moped circulating across the country (Censis, 2003). Despite providing an economic means of transportation, the use of mopeds and motorcycles accounts for a substantial proportion of road fatalities, and moped users have increased frequency and severity of traffic crashes (Vlahogianni et al., 2012). In particular, as of 2015, moped riders and motorcyclists represented 9% of all road fatalities in the EU and nearly a quarter (i.e., 23%) of world's fatal traffic injuries (World Health Organization [WHO], 2015). In Italy, moped drivers and motorcyclists represent about the 3% and the 20%, respectively, of the overall victims due to road accidents (ISTAT, 2018). Blackman and Haworth (2013) further argued that mopeds and motorcycles riders have 20–40 times higher risk for road fatalities as compared to car occupants. Accordingly, Brandau et al. (2011) stated that adolescent moped riders are at higher risk for traffic road injuries, and that the percentage of 15-year-old moped riders injured in traffic crashes in Austria increased from 6 to 32% between 2000 and 2008. The Decade of Action for Road Safety (DARS) 2011–2020 represents an international initiative led by the United Nations aimed to improve road safety and to reduce by 50% the number of deaths attributed to traffic injuries and crashes, especially among groups at higher risk for road traffic fatalities, such as young people. One of the key action areas of the global plan to achieve the DARS 2011–2020 goals concerns road users' behavior (UN Road Safety Collaboration, 2011). This indicates that a better understanding of the behavioral risk factors for traffic crashes can help in further promoting road safety, particularly in the most vulnerable groups of road users, such as young moped riders.

The extant research on the behavioral and psychological risk factors for traffic crashes among young car drivers has highlighted the role of personality traits using both bivariate analysis and more sophisticated data analytic approaches, such as structural equation modeling. In particular, in the "personality-attitudes-behavior" model, Ulleberg and Rundmo (2003) hypothesized that some general personality traits of drivers such as anxiety, excitement-seeking, hostility, altruism, and normlessness are relevant for driving behavior and they could also influence risk driving trends both directly and indirectly through their effects on attitudes toward traffic safety. This model considers the personality as a distal and stable predictor of behavior, as compared to more immediate and malleable antecedents of behavioral intention and the beginning of an action such as attitudes. Attitudes, in turn, are considered to mediate the personality-behavior relationship (Fishbein and Cappella, 2006). In their study on young Norwegian drivers, Ulleberg and Rundmo (2003) showed that most of the personality traits included in their model (i.e., anxiety, hostility, normlessness, excitement-seeking and aggression) were indirectly associated with risky driving through their effects on attitudes toward driving safety, while altruism was directly associated with risky driving. More specifically, the results of this study showed that normlessness, excitement-seeking and lack of emotional regulation – expressed through aggression – negatively affected attitudes toward safety, so these traits indirectly increased risky driving. Conversely, anxiety positively influenced attitudes and indirectly decreased the frequency of risky driving. Finally, altruism seemed to affect negatively and directly risky driving. Overall, these empirical evidences frame a clear pattern of relationships linking young drivers' specific personality traits with their attitudes and risky driving behaviors. These patterns suggest that for young drivers having higher levels of normlessness, excitement seeking and low emotional stability and regulation (i.e., high levels of aggression) may represent a risk factor since it seems to increment risky driving behaviors, inhibiting pro-safety attitudes. On the other hand, having higher levels of anxiety and altruism, may be considered a protective factor, as it seems to decrease risky driving behaviors, enhancing pro-safety attitudes.

Interestingly, a related but different line of research has focused on clustering different personality traits that increase the likelihood for risky driving and crash risk among young car drivers (e.g., Donovan et al., 1988; Deery and Fildes, 1999; Ulleberg, 2001; Lucidi et al., 2010). This line of research adopted a clustering approach whereby young car drivers are classified as high or low risk for crashes based on patterns of personality traits and individual differences. In an early study, Ulleberg (2001) used a cluster analysis of personality traits and found that six sub-types of risky car drivers emerged. Of them, two high-risk groups were identified, with the first group including drivers with higher scores in sensation seeking, irresponsibility, and driving-related aggression, and low rates of altruism and anxiety; the second group included drivers with high levels of sensation-seeking, driving-related aggression, anxiety and driving anger. Two low risk groups also emerged. The first one included drivers with higher levels of anxiety and altruism, and lower scores in sensation-seeking, driving anger, and normlessness, and the second low risk group included drivers with low levels of sensation-seeking, anxiety, aggression, and driving anger; thus, representing an emotionally well-adjusted group. In a subsequent study among Italian young novice car drivers, Lucidi et al. (2010) performed a cluster analysis of personality traits and identified three distinct groups: risky, worried, and careful drivers. Risky drivers had higher scores in normlessness, excitement-seeking, driving anger, and external locus of control (i.e., attributing traffic crashes to external factors, such as bad luck), and lower scores in altruism and anxiety. Risky drivers had also more negative attitudes toward safe driving, had engaged in more risky driving, were more likely to be involved in crashes, and perceived themselves as less susceptible to traffic crashes as compared to drivers in the other groups. On the other hand, worried drivers had higher scores in anxiety, angry hostility, external locus of control and driving anger and lower scores in excitement-seeking, normlessness and altruism – thus, although this group may follow traffic rules and abstain from risky driving behavior, they seem to pay less attention to others, to be more emotionally unstable, and more likely attribute crashes to external factors. In addition, worried drivers displayed more positive attitudes to safe driving than risky drivers but as many lapses as them. Finally, careful drivers displayed lower scores in normlessness, driving anger, anxiety, angry hostility, and excitement-seeking, and higher scores in altruism. Those drivers also displayed higher internal locus of control in driving; indicating their beliefs that to a greater extent, traffic crashes ascribed to drivers' behavior rather than to external causes. Careful drivers had also more positive attitudes toward safe driving, as compared to risky drivers; additionally they were less likely to be involved in a crash, and displayed less risky driving patterns, such as violations, errors, and lapses compared to risky and worried drivers.

In addition, other studies have shown that the association between personality, traffic safety attitudes, and risky driving can also be observed among young moped and motorcycle riders (Chen, 2009; Gianfranchi et al., 2017). Brandau et al. (2011), for instance, applied the cluster analysis approach to identify personality sub-types among young Austrian moped riders, aged between 14 and 17 years, and four distinct groups (Types) emerged. The first group (Type 1) had high levels of neuroticism, and low scores in extraversion and openness to experiences, Type 2 moped riders had high scores in risk taking and extraversion. Type 3 moped riders had low levels in several personality traits and psychological characteristics, including novelty seeking, risk-taking, reward dependence, inattention and impulsivity, and high rates in conscientiousness, agreeableness, and openness. Finally, the moped riders in Type 4 had higher scores in novelty seeking, risk-taking, reward dependence, inattention and impulsivity, and low rates in conscientiousness, agreeableness and openness. Brandau et al. (2011) also found that Type 3 moped riders had significantly less traffic injuries as compared to other Types, and that Type 4 moped riders had the highest rate of severe injuries. Marengo et al. (2012) assessed moped driver sub-types based on other personality measures in a sample of Italian adolescents aged 14–15 years, and they identified three clusters. Cluster A included mostly female adolescents with higher scores in anxiety, external locus of control and lower levels of sensation-seeking and altruism. Cluster B consisted of adolescents with high scores in impulsivity and sensation-seeking, and lower scores in altruism and anxiety; this group also displayed the greatest crash involvement in a riding simulator and displayed higher crash risk in relevant self-reported measures. Finally, adolescents in Cluster C displayed higher scores in altruism and internal locus of control, and were considered as the group with the least risk for traffic crashes/injuries. The study by Marengo et al. (2012) provided useful findings and also included a moped riding simulator to predict real-life crash risk. However, more than half (54%) of the adolescents in the study had no prior moped riding experience and this limited the external validity of the study.

The Present Study

The present study is in line with the remit of the United Nations Global Plan for the DARS 2011–2020 and responds to the need to better understand road users' behavior, especially among adolescent moped riders who represent a high-risk group for road traffic injuries and fatalities (Vlahogianni et al., 2012). Following from previous research on adolescent moped riders in Austria (Brandau et al., 2011) and Italy (Marengo et al., 2012) the present study set out to assess, in a large and representative sample of Italian adolescent moped riders, sub-types based on personality traits, and compare the different sub-types on measures of attitudes toward safe driving, and risky driving behaviors. Our study advances previous research on moped riders personality and risky driving in the following respects. Firstly, a large and representative sample of adolescents with a valid moped-riding license was used. Secondly, a wider range of measures of personality and risky driving-related outcomes (e.g., attitudes toward safe driving, risky driving behaviors) was included. Using an extensive set of measures of personality, safe driving attitudes and risky driving enabled previous research (i.e., Lucidi et al., 2010) to make indirect comparisons of risky driving psychological characteristics and behaviors among users of different types of vehicles, and allowed us to assess if previous findings could be usefully applied in adolescent moped riders. Based on the previous literature (i.e., Lucidi et al., 2010; Marengo et al., 2012) we expect three different personality subtypes of young moped drivers from the present study results, characterized also by both their attitudes toward safety and their risky driving behaviors. In particular, we expect a first cluster of moped riders, characterized mainly by high levels of excitement-seeking and normlessness, high levels of emotional instability (i.e., high driving anger and anger hostility), along with low levels of anxiety, altruism and driving internality. According to the "personality-attitudes-behavior" model introduced by Ulleberg and Rundmo (2003) we expect that these riders would be characterized as an high-risk group, showing low levels of attitudes toward safety and accidents risk perception, frequent self-reported risky driving behaviors as well as an high involvement in car accidents. Furthermore, we expect a second group of moped riders characterized by an opposite personality profile, showing low levels of excitement-seeking and normlessness, low levels of emotional instability (i.e., low anger and angry hostility), low levels of anxiety, as well as high levels of altruism and driving internality. Overall, we expect that this second cluster of moped riders would be characterized by a low risk, showing a low accident risk perception, high levels of attitudes toward safety, as well as a low frequency of risky driving behaviors and accidents involvement. Finally, we expect a third group that despite would be characterized by some personality traits related to risky driving, such as emotional instability (i.e., angry hostility and high driving anger) and low levels of altruism and internality, they would present several traits that typically predict safe driving, such as low levels of excitement-seeking and normlessness, as well as high levels of anxiety. Overall, we expect that the potential risk represented by the emotional instability and low altruism in this last cluster, may be greatly buffered by the latter traits, characterizing these moped riders as a low risk group, with high level of accident risk perception alongside with positive attitudes toward safety and low risky driving behaviors.

MATERIALS AND METHODS

Participants and Procedures

The study relies on a sample of 1,273 Italian high school students aged from 13 to 19 years (mean age = 15.43, SD = 0.98), who attended the first 3 years of the high school (28% first year, 42.4%

second year, 29.6% third year), distributed in different Italian regions (34.2% Northern, 23.4% Centre, 42.4% Southern) and with a valid driving license for moped. Participants were mainly males (70.4%), and they have held a valid driving license for moped for an average of 18.13 months (*SD* = 12.00). About one third of respondents (36.1%) reported daily moped riding, while the 12.8% drove 100 km or more on a weekly basis. The study was approved by the Ethics Review Board of the Department of Social and Developmental Psychology, "La Sapienza" University of Rome, and participants and their legal representatives were informed of the aims and purpose of the study, as well as their participation rights (e.g., confidentiality of responses, allowance to leave the study at any point without any consequences), in advance of data collection. Thus, written informed consent was obtained by all the participants and, for the participants under the age of 18, also by their parents.

Procedure

The study took place in 54 high schools all over Italy. The study was firstly presented to schools (teachers and managers) and parents through informed letters sent by the PI, and then by an assistant researcher (psychologist) who collected the informed consent by the parents of minors. Therefore, a psychologist introduced by the teacher presented the study to the participants face to face during a dedicated hour of lesson, one class at a time. At this time, informed consent was collected from participants aged over 18 years old, before the data collection. In order to guarantee for the anonymity, data collection instruments did not contain information that could identify participants. Participants were asked to complete a questionnaire, to envelope it in a folder and then to place it in a collection box. Folders and boxes were provided by the researcher.

Measures

For the purpose of this study, we used the measures listed below, which were previously translated in Italian and used in previous studies with Italian samples of drivers from different ages (i.e., Lucidi et al., 2010, 2014; Mallia et al., 2015).

General Personality Measures

Four facets of the Italian version (Caprara et al., 2001) of the "NEO-Personality Inventory" (Costa and McCrae, 1992) were used to evaluate general personality traits such as excitement-seeking (E5) (e.g., *I often crave excitement*), angry hostility (N2) (e.g., *I often get angry at the way people treat me*), anxiety (N1) (e.g., *I often feel tense and jittery*), and altruism (A3) (e.g., *I generally try to be thoughtful and considerate*). Each facet consisted of eight items, with responses given on five-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5).

Normlessness (which refers to "the belief that socially unapproved behaviors are required to achieve certain goals," Lucidi et al., 2014, p. 320) was assessed using the "Normlessness Scale" (Kohn and Schooler, 1983), which comprised four items (e.g., *If something works, it is less important whether it is right or wrong*), with responses made on a five-point Likert scale ranging from "strongly disagree" (1) to "strongly agree" (5).

Driving Related Personality Measures

The questionnaire also measured some personality characteristics specifically associated to driving. In particular, driving anger was assessed with the short version of the "Driving Anger Scale" (Deffenbacher et al., 1994), which consisted of 14 items and measured the tendency to become irritable, frustrated and angry in different traffic situations. Respondents were invited to imagine that they were experiencing a hypothetical situation (e.g., *Someone backs right out in front of you without looking, or Someone is weaving in and out of traffic*) and then they were asked to rate the extent to which they would experience anger using a five-point Likert scale, ranging from "I wouldn't get angry at all" (1) to "I would get very angry" (5). Higher scores in this measure represent higher scores in anger at driving.

Furthermore, the locus of control orientation in driving was measured with the "Driving Internality" (DI, e.g., *Accidents are only the result of mistakes made by the driver*) and "Driving Externality" (DE, e.g., *Driving with no accidents is mainly a matter of luck*) Scales (Montag and Comrey, 1987). Each scale consisted of 15 items with responses given on six-point Likert-type scales ranging from "strongly disagree" (1) to "strongly agree" (6).

Attitudes Toward Traffic Rules

The attitudes toward traffic rules were measured with the scale developed by Iversen and Rundmo (2004). The scale measured attitudes of participants toward the infraction of traffic rules and speeding (11 items, e.g., *Many traffic rules must be ignored to ensure traffic flow*), the negligent driving of others (3 items, e.g., *I will ride with someone who speeds if that's the only way to get home at night*) and driving after drinking (2 items, e.g., *I would never drive after drinking alcohol*). Participants were asked to rate each item on five-point Likert-type scale ranging from "strongly disagree" (1) to "strongly agree" (5), with higher scores representing a more negative attitude toward traffic safety.

Accident Risk Perception

Crash risk perception was assessed by two items (e.g., Lucidi et al., 2010). The first item evaluated the drivers' subjective probability of being involved in a traffic accident relatively to their peers, the second item their level of concern about this possibility. Responses were given on rating scales from "very low" (1) to "very high" (10) for both items. The responses on each item were aggregated in a single score, with higher scores reflecting higher crash risk perception.

Driving Behavior and Driving Experience

Different risky behaviors were assessed through measures derived from Iversen and Rundmo's (2004) study on the following dimensions:

(a) frequency of traffic rules' violations and speeding (five items, e.g., *Break traffic rules to secure more continuous driving*); (b) frequency of reckless driving and fun riding (five items, e.g., *Drive too close to the car in front to be able to stop if it should brake*); (c) frequency of not using helmet, (two items, e.g., *Drive short distances without wearing the helmet*); (d) frequency of cautious and watchful driving (four items, e.g., *Reduce speed when you see a sign indicating danger*); (e) frequency of drinking and driving (three items, e.g., *Drive after you have been drinking more than one glass of beer or wine*). For each of the described activities, participants were requested to indicate how often they carried out or experienced it, by using a five-point Likert-type scale ranging from "never" (1) to "very often" (5).

Additionally, participants were requested to indicate how often they drive and the number of kilometers they traveled weekly over the past 3 months. Finally, they were requested to report whether they have received tickets for traffic violations (Yes vs. No) and whether they were involved in crashes with vehicle damage (Yes vs. No) and physical injury (Yes vs. No) in the past year. **Table 1** reported the descriptive statistics and reliability coefficients for all the measures described above.

Data Analysis

Firs of all, in order to group together individuals whose characteristics are similar, a cluster analysis was performed through the "Classify" Package of SPSS 22.0 and using the squared Euclidean distance measure. The variables used to identify subtypes of young moped riders were the scores obtained at the personality measures (general and specific) used in previous studies (i.e., Lucidi et al., 2010): anxiety, angry hostility, excitement-seeking, altruism, normlessness, driving anger, driving internality, and driving externality. Participant who reported missing data on at least one of these variables, were excluded from the cluster analysis.

Standardized scores (Z-scores) of the key personality variables were computed and used for cluster analysis in order to overcome the issue of comparing Euclidean distances based on different measurement scales (Everitt, 1993). In particular, we initially employed a hierarchical cluster analysis, using a Ward's method of linkage and a squared Euclidean distance, to identify the number of cluster groups according to the parameter of the increment of the merger coefficients (Fabbris, 1997). At the point of marked flattening of the graph, the subsequent mergers of cluster portrayed no new information. Although the hierarchical clustering method is advantageous for determining the number of clusters, it does not allow the determination of the most optimal cluster solution pertaining to between-cluster heterogeneity. This is because the method cannot separate clusters created in previous steps. Thus, following the recommendations (Milligan and Sokol, 1980) concerning a K-means non-hierarchical method using centroids from the hierarchical cluster analysis (i.e., the cluster center means), we employed a K-means method to identify the most optimal three clusters solution that emerged from the data. Finally, a multivariate analysis of variance (MANOVA) was carried out using the raw scores of the key personality variables used in the cluster analysis (i.e., anxiety, angry hostility, excitement-seeking, altruism, normlessness, driving anger, driving internality and driving externality) as dependent variables and the cluster membership (Cluster A vs. Cluster B vs. Cluster C) as the independent variable, with the aim to confirm the differences on key personality variables between the groups generated by the cluster analysis.

The external validation of the cluster solution, was rather obtained by using significance tests on relevant criteria variables that were not used to generate the cluster solution (Alivernini et al., 2016). In particular a second multivariate analysis of variance (MANOVA) was utilized to examine whether the clusters identified differed on the raw scores of the three subscales measuring drivers' attitudes, of the accident risk perception scale, and of the five subscales measuring riders' driving behaviors. LSD *post hoc* tests were also used to determine which clusters differed from each other in their mean scores on these variables. In order to measure the strength of the association between the clusters and the various key dependent variables, the η_p^2 was calculated. Cramer V test was used to examine whether the clusters identified differed in dichotomous variables related to driving habits and experience, such as driving every-day (Yes vs. No), driving more than 100 km per week (Yes vs. No), having received at least one ticket (Yes vs. No), and being involved in at least one accident with vehicle damage (Yes vs. No) and/or physical injury (Yes vs. No) in the last year. Overall, missing data were treated listwise for all the multivariate analyses, while for the bivariate correlations a pairwise approach has been used.

RESULTS

The Cluster Solution and Cluster Profiles

Seven participants reported missing data on at least one of the personality variables, so the cluster analysis was carries out on 1,266 participants. An examination of the merger coefficients' graph and of the dendrogram (see **Supplementary Appendix S1**) indicates a three-cluster solution. In the subsequent non-hierarchical clustering procedure, we identified the most optimal three-cluster solution that emerged from the data. The final centers for each cluster and the distances between the final cluster centers are reported in **Supplementary Appendix S2**. The standardized (Z-scores) cluster means of the variables generated by the K-means analysis on the three-cluster solution are showed in **Figure 1**.

The moped riders grouped in Cluster A showed low rates in driving anger, anxiety, angry-hostility and excitement seeking. This pattern of personality scores indicates that the moped riders of this group are quiet and stable from an emotional point of view. Moreover, high levels of altruism and low levels of normlessness suggest that they seriously take into consideration the rules and traffic regulations and give attention to others on the road. Finally, these moped riders reported higher levels of internal driving control than on external driving control, this representing their beliefs that crashes are primarily the result of drivers' mistakes, and therefore there are preventable through own riding behavior. Based on the description above, these types of riders have been called "careful moped riders."

Moped riders in Cluster B are characterized by high levels of anxiety, angry hostility and driving anger, and low levels of excitement seeking, normlessness and altruism. This pattern suggests that although this group of riders may respect traffic rules (i.e., low normlessness) and avoid intentional risky behavior (i.e., low excitement seeking), their high level of emotional instability (i.e., high angry hostility and driving anger) and their lack of concern for others (i.e., low altruism) may make them

TABLE 1 | Correlations, mean scores, SD and Cronbach's alpha for the personality, attitudes, risk perception and driving behavior measures.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Anxiety	–																
2. Angry hostility	0.25	–															
3. Excitement seeking	−0.21	0.15	–														
4. Altruism	0.04	−0.29	0.01	–													
5. Normlessness	−0.20	0.17	0.35	−0.21	–												
6. Driving anger	0.04	0.22	0.25	−0.02	0.24	–											
7. Driving internality	0.06	−0.09	−0.11	0.14	−0.13	−0.09	–										
8. Driving externality	−0.03	0.13	0.22	−0.01	0.31	0.18	−0.05	–									
9. Attitude toward rule violation and speeding	−0.19	0.17	0.33	−0.24	0.58	0.28	−0.25	0.31	–								
10. Attitude toward careless driving of others	−14	0.09	0.26	−0.22	0.37	0.13	−0.18	0.14	0.48	–							
11. Attitude toward drinking and driving	−0.09	0.12	0.19	−0.22	0.28	0.10	−0.16	−0.01	0.33	0.41	–						
12. Risk perception	0.24	0.09	−0.05	0.03	−0.06	0.06	0.08	0.00	−0.10	−0.07	−0.02	–					
13. Violations of traffic rules/speeding	−0.21	0.14	0.39	−0.17	0.42	0.27	−0.14	0.19	0.53	0.30	0.24	−0.07	–				
14. Reckless driving/fun riding	−0.10	0.19	0.22	−0.28	0.36	0.20	−0.11	0.11	0.43	0.35	0.33	−0.01	0.57	–			
15. Not using helmet	−0.11	0.13	0.26	−0.14	0.32	0.13	−0.02	0.14	0.33	0.31	0.29	−0.01	0.37	0.49	–		
16. Cautious and watchful driving	0.14	−0.04	−0.11	0.23	−0.26	−0.07	0.14	−0.01	−0.29	−0.23	−0.22	0.13	−0.20	−0.25	−0.12	–	
17. Drinking and driving	−0.17	0.16	0.27	−0.23	0.37	0.18	−0.16	0.05	0.42	0.39	0.48	−0.06	0.45	0.57	0.43	−0.23	–
Mean	2.98	2.91	3.58	3.71	2.62	3.62	2.55	2.72	2.76	1.89	1.67	5.27	3.08	2.23	2.03	3.43	1.99
(SD)	(0.63)	(0.59)	(0.69)	(0.58)	(0.82)	(0.59)	(0.69)	(0.61)	(0.73)	(0.89)	(0.95)	(2.06)	(1.05)	(0.90)	(1.23)	(0.85)	(1.10)
Skewness	0.05	0.19	−0.37	−0.35	0.31	−0.19	−0.17	0.02	0.31	0.97	1.75	−0.02	0.01	0.93	1.03	−0.51	0.98
Kurtosis	0.09	0.00	−0.14	0.24	−0.21	0.05	0.14	−0.01	−0.20	0.48	2.54	−0.49	−0.82	0.57	−0.10	0.02	0.02
Alphas	0.60	0.52	0.63	0.62	0.60	0.74	0.78	0.69	0.78	0.63	0.84	0.42	0.87	0.81	0.76	0.66	0.80

All the correlation coefficients are statistically significant at least at a p-level of 0.05, apart from underlined coefficients.

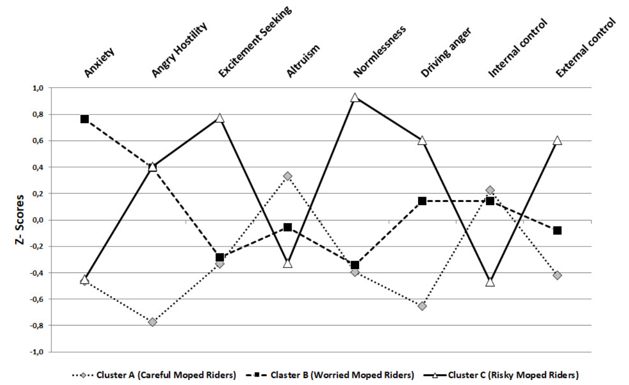

FIGURE 1 | Profile plot of the three clusters of moped riders identified.

potentially at risk on the road. However, similar to the moped riders of Cluster A, this group showed relatively higher levels of internal driving control than on external driving control, reflecting internal/driver-centered attributions for what happens on the road. At the same time, the high level of anxiety may stimulated worries about the possible consequences of their actions while driving, increasing the risk perception and the attention to not commit risky behaviors. Thus, the moped riders in Cluster B were labeled "worried moped riders."

High rates of normlessness and low levels of altruism characterized riders in Cluster C, suggesting that moped riders in this cluster are less likely to respect the rules and to be concerned about others. Furthermore, they reported high levels of excitement seeking and low levels of anxiety, suggesting that they enjoy doing extreme actions without being scared or worried about possible consequences. Cluster C moped riders also showed low levels of tolerance to frustration in various traffic situations, as suggested by high rates of driving anger and angry hostility. Finally, they also reported higher rates of external driving control than of internal driving control, meaning that for them, accidents are primarily due to external causes, for instance related to bad roads or mechanical problems or simply to bad luck and therefore, they are not preventable through their own self-regulated behavior. Based on this description, and the fact that the riders in this group are expected to be at high risk for traffic violations and accidents, they were defined, "risky moped riders."

Overall, as expected, the three clusters described above resulted significantly different on the key personality variables included in the cluster analysis (Wilkin's Lambda $_{(16,2512)} = 0.214$; $p < 0.001$; $\eta^2_p = 0.55$). The mean raw scores of these personality measures for moped riders in each of the three clusters identified and the univariate tests are shown in **Table 2**.

Attitudes, Risk Perception, and Driving Behaviors of Moped Riders in Each of the Cluster Profiles

Results of the comparisons made between the three groups of moped riders on descriptive characteristics are shown in **Table 3**, results on the comparisons made on driving-related outcome measures are shown in **Table 4**.

The three clusters differed on age, being the moped riders of the risky cluster slightly older than riders of the other two clusters. The three clusters did not differ in the number of months they have held a driver's license; on the other hand the "risky moped riders" drove daily more frequently and were more likely to drive more than 100 km a week than the "worried moped riders" were. Furthermore, the higher risk for the risky moped riders, compared with the other two groups of riders (i.e., "careful moped riders" and "worried moped riders"), was confirmed by overall differences in several driving-related outcomes such as their past driving experience, their risk perception, their attitudes toward traffic safety and their self-reported risky driving behaviors (Wilkin's Lambda $_{(18,2446)} = 0.664$, $p < 0.001$; $\eta^2_p = 0.18$).

A significantly larger percentage of moped riders in Cluster C (i.e., "risky moped riders"), had received at least one ticket with respect to moped riders defined as "worried," and were involved in at least one accident with vehicle damage and with physical injury if compared with the other two clusters. Furthermore, the risky moped riders showed the most negative attitudes toward traffic safety, and, despite they were highly involved in accidents,

TABLE 2 | Cluster differences on the raw scores of personality (general and specific) measures included in cluster analysis.

	Cluster groups			F	η^2_p
	Cluster A "Careful moped riders"	Cluster B "Worried moped riders"	Cluster C "Risky moped riders"		
Anxiety	2.68 (0.49)^{B}	3.47 (0.48)^{AC}	2.69 (0.57)^{B}	340.84**	0.35
Angry hostility	2.46 (0.44)^{BC}	3.15 (0.47)^{A}	3.16 (0.58)^{A}	286.98**	0.31
Excitement seeking	3.36 (0.66)^{C}	3.39 (0.63)^{C}	4.11 (0.48)^{AB}	196.43**	0.24
Altruism	3.90 (0.53)^{BC}	3.68 (0.52)^{AC}	3.52 (0.65)^{AB}	47.35**	0.07
Normlessness	2.29 (0.70) ^{C}	2.34 (0.61) ^{C}	3.38 (0.69)^{AB}	325.50**	0.34
Driving anger	3.23 (0.51)^{BC}	3.70 (0.51)^{AC}	3.97 (0.51)^{AB}	218.47**	0.26
Driving internality	2.70 (0.60)^{C}	2.65 (0.66)^{C}	2.22 (0.74)^{AB}	59.56**	0.09
Driving externality	2.47 (0.57)^{BC}	2.67 (0.54)^{AC}	3.09 (0.56)^{AB}	125.91**	0.17

$^{**}p < 0.001$. ^{A,B,C}Cluster groups that result significantly different at LSD post hoc test ($p < 0.001$).

TABLE 3 | Cluster differences on descriptive measures.

	CLUSTER				
	Cluster A Careful moped riders	**Cluster B Worried moped riders**	**Cluster C Risky moped riders**	**Cramer V or F**	***p*-level**
% of the total	34.4%	37.3%	28.3%		
% Males	74.0%	61.4%^{C}	77.7%^{B}	0.15	< 0.001
Mean age	15.42 (1.02)^{C}	15.32 (0.91)^{C}	15.58 (1.00)^{AB}	6.81	0.001
Months that they have license to drive moped	18.07 (11.25)	17.22 (11.49)	19.44 (13.51)	2.82	0.06
Driving every-day	33.7%	32.6%^{C}	42.5%^{B}	0.90	0.007
Driving more than 100 km a week	11.2%^{C}	9.3%^{C}	18.2%^{B}	0.11	< 0.001

^{A,B,C} Cluster groups that result significantly different at LSD post hoc test ($p < 0.001$).

TABLE 4 | Cluster differences on the raw scores of driving outcome measures.

	Cluster groups					
	Cluster A Careful moped riders	**Cluster B Worried moped riders**	**Cluster C Risky moped riders**	**Cramer V or F**	***p*-level**	η_p^2
Received at least one ticket	13.3%	11.4%^{C}	19.8%^{B}	0.10	0.002	–
Had at least one accident with only vehicle damage	11.7%^{C}	11.9%^{C}	17.3% ^{AB}	0.07	0.03	–
Had at least one accident as driver with physical injury	7.1%^{C}	7.2%^{C}	14.5%^{AB}	0.12	< 0.001	–
Drivers' attitude toward						
Rule violation and speeding[2]	2.48 (0.64) ^{BC}	2.57 (0.62) ^{AC}	3.34 (0.66) ^{AB}	205.43	< 0.001	0.25
Careless driving of others[2]	1.69 (0.74)^{C}	1.72 (0.79) ^{C}	2.39 (0.98) ^{AB}	82.25	< 0.001	0.12
Drinking and driving[2]	1.48 (0.82) ^{C}	1.58 (0.87) ^{C}	2.04 (1.09)^{AB}	37.10	< 0.001	0.06
Risk perception[1]	4.99 (1.95)^{B}	5.63 (2.11)^{AC}	5.14 (1.80)^{B}	11.68	< 0.001	0.02
Driving behaviors						
Violations of traffic rules/speeding[3]	2.79 (0.97)^{C}	2.80 (0.93)^{C}	3.81 (0.94)^{AB}	142.80	< 0.001	0.19
Reckless driving/fun riding[3]	1.95 (0.71)^{BC}	2.14 (0.81)^{AC}	2.72 (1.04)^{AB}	81.65	< 0.001	0.12
Not using helmet[3]	1.78 (1.04)^{C}	1.83 (1.09)^{C}	2.62 (1.41)^{AB}	59.84	< 0.001	0.09
Cautious and watchful driving[4]	3.51 (0.79)^{C}	3.55 (0.79)^{C}	3.17 (0.94) ^{AB}	24.29	< 0.001	0.04
Drinking and driving[3]	1.70 (0.89)^{C}	1.80 (0.96) ^{C}	2.61 (1.25) ^{AB}	91.45	< 0.001	0.13

^{A,B,C} Cluster groups that result significantly different at LSD test ($p < 0.001$). [1] Range 1–10: a high score on the scale indicate high perception of risk to have a traffic accident. [2] Range 1–5: a high score on the scale reflects a negative attitude toward traffic safety. [3] Range 1–5: a high score indicates risky driving behavior. [4] Range 1–5: a high score indicates a safe driving behavior.

they showed lower accident risk perception than worried moped riders. With respect the self-reported risky driving behavior, the moped riders in Cluster C (i.e., "risky moped riders") reported significantly more frequent involvement in violations of traffic rules and speeding, more reckless driving and fun riding, driving without the helmet, and more drunk driving as compared to the moped riders in the other two clusters. Accordingly, the moped riders in Cluster C reported a lower frequency of safe driving behaviors such as cautious and watchful driving than worried and careful riders.

Moped riders in Cluster A, (i.e., "careful moped riders") demonstrated an opposite profile with respect to moped riders of Cluster C. In particular, a significant tinier percentage of them were involved in accidents with vehicle damage and with physical injury, they reported more positive attitudes toward traffic safety than moped riders of Cluster C, and a lower level of risk perception than moped riders of Cluster B. Furthermore, moped riders in Cluster A reported a lower frequency of risky driving behaviors (e.g., traffic rule violations, drink and driving, etc.) and a higher frequency of safe behaviors (e.g., cautious and watchful driving) at the wheel than the moped riders in Cluster C (i.e., risky moped riders).

Moped riders of Cluster B (i.e., "worried moped riders") showed a low risk profile, very similar to the careful drivers' profile in terms of driving experience, attitudes toward safety and driving behaviors. In fact, within the worried riders, a smaller percentage reported to be involved in accidents as compared to risky moped riders. Furthermore worried riders showed also higher positive attitudes toward traffic safety and a lower frequency of risky driving behaviors as compared to moped riders in Cluster C (i.e., "risky moped riders"). However, it is noteworthy that the moped riders in Cluster B reported the highest level of risk perception to be involved in an accident. Finally, the gender distribution was more balanced (i.e., 61.4% of males) within the worried moped riders than within the other two subgroups (i.e., 74% and 77.7% of males, respectively, for careful and risky moped riders).

DISCUSSION

The present study responds to the need to better understand adolescent moped riders behavior since they represent a high-risk group for road traffic injuries and fatalities in Europe (e.g., Brandau et al., 2011; Vlahogianni et al., 2012; Theofilatos and Yannis, 2015). Following previous studies on adolescent moped riders in different European countries (e.g., Brandau et al., 2011; Marengo et al., 2012), the present study investigated, within a large sample of Italian adolescent moped riders, sub-types of riders based on diverse personality traits, and compared them across a range of psychological and behavioral measures including attitudes toward safe driving, self-reported risky driving behaviors (e.g., rule's violations and speeding, not using helmet, drinking and driving, etc.), and self-reported issued traffic tickets and crash involvement.

Our findings showed that the adolescent riders of our sample can be grouped in three distinct clusters, which are related to different personality traits as well as to different attitudes and behaviors (as in the case of risky moped drivers). The analysis of the different personality characteristics led to the grouping of moped riders as careful, worried and risky. Importantly, in accordance with previous research (i.e., Ulleberg and Rundmo, 2003; Lucidi et al., 2010; Marengo et al., 2012), the present findings lend support to the notion that while some personality characteristics are associated to risky driving tendencies among moped riders, other personality characteristics may act as protective factors. The clusters identified in the present study resembled substantially those identified by Brandau et al. (2011) and Marengo et al. (2012); thus, showing that some of the measured psychological characteristics are associated with risky driving beliefs and behaviors across studies and independently of sample sizes nationality, and research methods used.

In particular, negative attitudes toward traffic safety were higher in those moped riders who reported higher levels of emotional instability (i.e., high rates of driving anger and angry-hostility) and excitement seeking, lower levels of altruism, and higher driving externality (i.e., the belief that accidents depends for the most part on bad luck or on external causes uncontrolled by the driver). The combination of such attitudes, risk perceptions and personality characteristics in these mopeds riders was associated with several indicators of risky driving behaviors, such as higher self-reported frequency of traffic rules' violations and speeding, reckless driving and fun riding, not wearing helmet while driving, as well as drinking and driving. Not surprisingly, adolescents in the "risky moped drivers" cluster were more likely to receive at least one traffic ticket and to be involved in a car crash with vehicle damage and/or physical injury in the last year, as compared to adolescent moped riders in the other two clusters. The profile of the moped riders identified here as at higher risk resembles the pattern of personality traits identified as at risk by Marengo et al. (2012) in adolescents moped riders and by Lucidi et al. (2010) in novice car drivers.

Although some moped riders in our study displayed similar personality characteristics with risky moped riders (i.e., high emotional instability, low altruism), they reported more positive attitudes toward traffic safety, and lower frequency of risky driving behaviors. These "worried moped riders" were characterized by the highest levels on anxiety, and by the highest levels of risk perception to be involved in an accident. In other words, high levels of anxiety in this group may buffer the relationship between emotional instability and risky attitudes and driving. In terms of a process, being anxious and worried to be involved in a crash could attenuate the effects of emotional instability on risky driving decision-making (e.g., deciding to violate traffic rules or ride the moped without a helmet). The present study had mainly a descriptive purpose and did not directly tested this process, therefore future studies addressing this issue are strongly recommended. Overall, the profile of "worried moped drivers" is very similar to the profiles identified by Lucidi et al. (2010) and Marengo et al. (2012). The only difference between the profile identified by Marengo et al. (2012) and the worried drivers of this study, is that in our study worried riders are characterized by higher internal driving control, whereas Marengo et al.'s (2012) riders showed higher external driving control. This difference was probably due to the fact that more than half of the adolescents in the Marengo et al.'s (2012) study did not have a direct experience in moped riding, so this may have fostered the perception of external driving control.

In any case, our findings related to worried moped riders have an applied value for safe driving interventions because they seem to suggest that fear appeals or message framing (emphasizing the "losses" of risky driving) may be effective in risk communication by eliciting greater fear of accidents and emphasizing the personal relevance and susceptibility for crash involvement and/or traffic injury. However, more research on this issue is needed, especially in the light of the findings by Carey et al. (2013) who meta-analyzed the impact of fear appeals on driver behavior: although fear appeals increased fear arousal, they did not have the desired impact on actual driving behavior. According to some authors (e.g., Stephens and Groeger, 2009) anxious drivers could be more likely to drive cautiously and comply with traffic rules, probably also because of a lack of confidence about their driving ability. From this perspective, it is plausible that, especially in very young drivers, the seemingly protective effect of anxiety can fade over time as young drivers become more experienced, and this change may be followed by changes in the respective attitudinal and behavioral profile of worried moped riders.

Furthermore, according to our hypothesis, moped riders with higher levels of emotional stability (i.e., low driving anger, low anger hostility), low anxiety, low scores on excitement seeking and high scores on altruism and driving internality appeared as a low risk group (labeled "careful drivers"). In particular these traits were associated with more positive attitudes toward traffic rules and with a lower frequency in all the indicators of risky driving behavior and also in self-reported crash involvement. This was in line with the "personality-attitudes" model introduced by

Ulleberg and Rundmo (2003). The "careful" profile identified in this study was also similar to the pattern of personality measures identified by previous study on moped riders (Marengo et al., 2012) and on novice car drivers (Lucidi et al., 2010).

The set of measures of personality, safe driving attitudes and risky driving used in the present study had never been used in previous research on moped riders. On the contrary, these measures were virtually identical to those used in previous research on car drivers (Lucidi et al., 2010), aged between 18 and 23 years, allowing us to draw an indirect comparisons between novice car drivers and adolescent moped riders. To ride a moped and to drive a car at a younger age are actions that need to be considered very differently, since drivers are exposed to different accident risks (e.g., Zambon and Hasselberg, 2006), require different skills and abilities such as hazard perception (e.g., Horswill and Helman, 2003; Rosenbloom et al., 2011), and bring drivers to experience different levels of aggression in traffic (e.g., Rowden et al., 2016) or of risky behaviors such as errors, lapses and violations (Topolšek and Dragan, 2015). Specifically, riding a moped is a complicated task that requires specific attentional and individual skills, and riders' perceptions and attitudes are important as they reflect their actual behavior on the road (Theofilatos and Yannis, 2015). Taken altogether, the results of present study clearly showed that the identified sub-types of moped riders substantially resembled the sub-types of moped riders identified by Marengo et al. (2012) and of novice car drivers identified by Lucidi et al. (2010). In other words, despite the specificities of the vehicle used (i.e., car vs. moped) the ways that personality characteristics are grouped and, consequently, are associated with risky driving attitudes and behavior appeared highly similar.

Practical Applications

Our study provided empirical support to the fact that the personality characteristics are consistently associated with attitudes toward traffic safety and risky driving behaviors in moped riders as in car drivers. This may suggest that an intervention designed to tackle risky driving messages on the basis of personality sub-types in young drivers can impact risky behaviors on diverse young populations, from adolescent moped riders to novice young adult drivers. By no means, this is not an assertion of an "one size fits all" approach, but rather a call for more concerted evidence-based interventions to reduce the risk for road fatalities by tackling specific psychological and behavioral factors. The characteristics of the highest risk group identified in the present study as well as in previous research involving both moped riders (e.g., Marengo et al., 2012) and car drivers (i.e., Ulleberg and Rundmo, 2003; Lucidi et al., 2010) suggested that such educational interventions could focus on the emotional characteristics (e.g., anger hostility levels) of the drivers. As Lucidi et al. (2010, p. 1695) claim "angry reactions in driving situations, for example, may trigger responses such as traffic rule violations and speeding, especially in young novice drivers who demonstrate high levels of excitement-seeking and normlessness." Furthermore, our results are in line with the evidences that educational interventions may benefit from a focus on emotional regulation on the road (Deffenbacher, 2016). Different studies in the behavioral sciences and neuroscience have shown that poor emotion and self-regulation were associated with a wide range of risk-taking and health compromising behaviors especially among young people (Magar et al., 2008; Steinberg, 2008; Spano et al., 2018). A large number of studies have shown that interventions that include physical and cognitive relaxation were effective in reducing driving anger and aggression in angry drivers (for a review, see Deffenbacher, 2016). For example, Deffenbacher et al. (2000) showed that a short-term intervention with the inclusion of relaxation coping skills or both cognitive and relaxation skills decreased traffic-related anger among drivers with higher levels of anger. Finally, based on our findings and those of previous studies (i.e., Lucidi et al., 2010) the association between emotional factors (e.g., anxiety), traffic safety attitudes and risky driving behavior seemed to emerge as early as adolescence. Therefore, interventions that will tackle the emotional and self-regulation aspects of driving could have an impact early on, as soon as or even before young people engaged in actual driving (e.g., moped riding) – thus, allowing for primary interventions on safe driving.

Limitations

The results of this study need to be interpreted in light of some limitations. Firstly, we used a cross-sectional design which may have limited the validity of the clusters identified. However, given that personality characteristics are stable over time, we can still claim that the attitudes and self-reported driving behaviors were improbably to have anticipated and affected personality traits. Nevertheless, prospective studies should be conducted in order to support the predictive validity of the driver sub-types identified in the present study, as well as to overcome the issue of reverse causality. Further, future studies aiming to replicate our study in different samples are also needed in order to provide additional evidences for the generalizability of our conclusions (Alivernini et al., 2016; Alivernini and Manganelli, 2015). Furthermore, within the limitations, it is worth to mention that the present study mainly aimed to describe how personality traits tended to group within a sample of moped drivers, using attitudes and behavioral outcomes merely as explicative variables, in order to validate these groups in view of past evidences. Future studies directly aimed to study the link between personality traits, attitudes and behaviors in moped drivers, thus, are strongly recommended. Another limitation of the present study is the use of self-reported driving behavior, which may have been affected by social desirability or recall biases, undermining the reliability of the study. However, the fact that the questionnaires were answered anonymously, decreased this risk (Lajunen and Summala, 2003). However, future studies that use more objective measures of driving behavior, such as for example driving simulator and/or external evaluation of road driving, are needed. Furthermore, it should be noted that the power of moped riders' sub-types to predict various driving-related outcome measures is limited. A final limitation of the study it is represented by the differences in terms of sample size between male (70.4%) and female (29.6%). However, this disproportion correctly represent the distribution of moped riders in Italy with a larger number of male than women riding during those ages (i.e., 4.8 per 100 male inhabitants versus 2.4 per 100 female inhabitants)[1].

Despite those limitations, these results confirmed the conclusions of the Organisation for Economic Co-operation and Development [OECD], 2006 report, that the associations between personality characteristics and accident involvement in young drivers may be limited, but still consistent across studies. After all, research on the psychological and behavioral aspects of risky driving is not panacea for all crash-related risk factors, but rather a useful approach to better understand one of the most important component of crash involvement, that is, the driver's behavioral outlook.

CONCLUSION

The study identified three subgroups of moped riders (risky, worried, and careful) characterized by different patterns of personality traits, and of self-reported risky driving behaviors, attitudes toward traffic safety, risk perception, and self-reported accident involvement. The personality and behavioral characteristics of these three sub-types of moped riders substantially resembled those identified by studies with vehicle drivers, showing that specific combinations of personality characteristics are associated with risk driving tendencies and behaviors both in young moped riders and novice car drivers. The results of the present study supported that safe driving interventions should tackle risky driving beliefs and behavioral tendencies in young moped riders and car drivers by tailoring their messages according to the personality sub-types of the target groups.

[1] http://dati.istat.it

AUTHOR CONTRIBUTIONS

All the authors substantially have equally contributed to the development and preparation of the manuscript. Furthermore, all authors have approved the final version of the manuscript. Finally, the authors have agreed to be accountable for all aspects of the manuscript in ensuring that questions related to the accuracy or integrity of any part of it are appropriately investigated and resolved.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00300/full#supplementary-material

APPENDIX S1 | Dendrogram of the hierarchical cluster analysis.

APPENDIX S2 | Centers for the three clusters and distances between the final cluster centers.

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Validating Driver Behavior and Attitude Measure for Older Italian Drivers and Investigating Their Link to Rare Collision Events

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The present study aimed to: (a) validate the factor structures of three scales assessing driving behavior, attitudes toward traffic safety (ATTS) and self-regulation in driving, in a sample of Italian older adults, through confirmatory factor analyses and (b) to determine the effectiveness of these measures in predicting the likelihood and the frequency of collision involvements in the following year. A 28-item driver behavior questionnaire (DBQ), a 16-item ATTS, a 21-item extended driving mobility questionnaire (DMQ-A) were administered to 369 active Italian drivers, aged between 60 and 91 years. Results showed a four-factor structure for the DBQ, a five-factor structure for the ATTS and a two-factor structure for the Extended DMQ-A, as the best fitting models. Hurdle model analysis of count data with extra-zeros showed that all factors of DBQ predicted the likelihood of road collisions. Risky behavior, except for aggressive violations, self-regulation and attitudes toward traffic rules were associated with the frequency of collision involvement. The aforementioned three scales seemed to be a useful and concise suite of instruments assessing risky as well as protective factors of driving behavior in elderly.

Keywords: driver behavior questionnaire, self-regulation, attitudes toward traffic, older drivers, confirmatory factor analysis, count data

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INTRODUCTION

There were 1.25 million road traffic deaths globally in 2013 (World Health Organization [WHO], 2015). Because the global population is gradually aging, older drivers, especially because of their age-related frailty, are likely to make up an increasing proportion of fatality statistics. Sometimes, it is necessary to require the cessation of driving in older people because of sensorial, physical and cognitive age-related deterioration that affects driving ability and leads to an increase in collision probability (Anstey et al., 2005). However, having a driving license and using a car leads to the maintenance of a high level of social and physical functioning among the elderly (Edwards et al., 2009). For instance, in a recent review, Chihuri et al. (2016) showed that the cessation of driving activity in a sample of drivers aged 55 and older, caused various health problems, particularly related to depressive symptoms. Given the importance of these two issues it is important to understand how psychological variables are linked to collision involvement. In a study by Ulleberg and Rundmo (2003), the authors generated a model which proposed personality traits (i.e., aggression, altruism, anxiety, sensation seeking, and normlessness), attitudes toward traffic safety (ATTS) and risk perception as predictors of risky driving behavior. Results showed that personality traits primarily have an effect on risk-taking behavior through the influence of attitude toward traffic safety as a mediator. More relevantly, Lucidi et al. (2014) confirmed the model in a sample of older Italian drivers. In general, novice drivers showed more difficulty in self-regulation, in terms of driving avoidance, than older drivers (Moták et al., 2014). Nonetheless, Gwyther and Holland (2012) suggested that younger and older drivers reported higher score for self-regulation than middle-years' drivers. According to the authors, these data could be affected by the perception about the driving expertise (i.e., low for younger drivers) and the cognitive functions (i.e., low for older drivers). Besides a wide interest in the theoretical study of risky driving behavior correlates, there is a great concern in developing assessment tests able to identify the relationship between psychological characteristics and probability of being involved in road traffic collision. The driver behavior questionnaire (DBQ – Reason et al., 1990) represents the prominent self-reported assessment tool of risky driving behavior, in terms of violations, errors and lapsus, and has shown to be highly reliable in the accident prediction (de Winter and Dodou, 2010). However, other self-reported behavioral components of the assessment, such as, the attitudes toward traffic rules (e.g., Ulleberg and Rundmo, 2003), and the driving self-regulation (e.g., Owsley et al., 1999), has shown to have an important role in the prediction of road accidents, and they could integrate and support the assessment through the DBQ scale. The three tests presented in this study represent an attempt to provide valid and reliable tools for the assessment of risky driving behavior, ATTS and self-regulation/inhibitory behaviors in the older Italian population, in order to verify which specific behavioral and attitude aspects can contribute to further improve the reliability of a global and general assessment in predicting the likelihood and the frequency of traffic accidents in the elderly population.

The Driver Behavior Questionnaire (DBQ)

The DBQ is the most used evaluation test on aberrant driving behavior. The original version by Reason et al. (1990), dates back to investigated three dimensions of aberrant driving behavior, namely, *violations*, *dangerous errors,* and *lapses*. A few years later, Parker et al. (1995) confirmed the three-factor structure. It is worth emphasizing that, despite a wide literature which considered the DBQ as the main tool for the evaluation of risky driving, it may be complex to connect the different studies because of the variety of versions used. A wide range of DBQ versions can be found, e.g., a 104-item version by Aberg and Rimmö (1998), a 28-item version (Mattsson, 2012, 2014), and a 9-item version, edited by Martinussen et al. (2013), consisting of the items with the highest factor loadings of the original version of DBQ. The most cited factorial structures seem to be those showing three factors, confirming the original formulation of Reason et al. (1990) and a four-factor solution, proposed by Aberg and Rimmö (1998). It is worth noting that, besides these simple factorial solutions, more complex ones have also been proposed, e.g., Rowe et al. (2015). They proposed a bifactor model of DBQ, including a general factor, which all items load onto, and four latent factors, i.e., *aggressive violations, ordinary violations, slips,* and *errors.* The DBQ has also been used in different cultural context, such as among samples of British, Finnish, and Dutch drivers (Lajunen et al., 2004) and among samples of Irish and Finnish drivers (Mattsson et al., 2015). Smorti and Guarnieri (2016) recently validated the DBQ in an Italian sample aged between 18 and 41 years. They used a 27-item version of the DBQ and found four first-order factors and two second-order factors. Alternatively, Lucidi et al. (2010) confirmed the three-factor model, as in Reason et al. (1990) using a 28-item DBQ, as originally developed by Lawton et al. (1997), on a large Italian sample of young drivers. The same three-factor structure was confirmed in two subsequent studies of older drivers (Lucidi et al., 2014) and professional bus drivers (Mallia et al., 2015). Despite the different ways in which the DBQ has been used, clarification has been provided in terms of its ability to predict involvement in a road traffic collision. In a highly cited meta-analysis, de Winter and Dodou (2010) considered 174 studies using the DBQ, excluding those in non-English language, and showed the predictive power of *errors* and *violations* on self-reported accidents. Subsequently, the authors published an update (de Winter et al., 2015), to provide further information on DBQ's validity with regard to predicting collisions. The authors confirmed previous findings regarding the preeminent role of errors and violations, especially of speed limits, in predicting self-reported accidents. Furthermore, the authors showed that the DBQ had a strong link also with the recorded violations, demonstrating the reliability of the scale. A recent re-meta-analysis (Af Wåhlberg et al., 2015) identified a number of methodological biases inherent in DBQ research, which led the authors to take a careful approach when interpreting its results. They confirmed the correlation between self-reported errors and violations and collision involvement, but that the correlations should be interpreted in the light of various methodological, statistical and dissemination biases (e.g., systematic measurement error and non-publication of negative results), and the need to take account of other features, such as driving exposure. Certainly, a self-reported evaluation of driving behavior cannot be addressed without the DBQ since it remains the most popular and used tool in traffic psychology. However, it would be interesting to expand self-reported evaluation with other behavioral components, such as attitude and self-regulation, which we will discuss in later sections.

Attitudes Toward Traffic Safety Scale (ATTS)

The association between attitudes and behavior has been explained by theory of planned behavior (TPB) (Ajzen, 1988, 1991). According to this theory, behavior is co-determined by intentions and by perceived behavioral control; the intentions are the summary of people's motives, while the perceived behavioral control reflects the perceived ease or difficulty in enacting certain behavior. Subsequently, a meta-analysis (Kraus, 1995) clarified the relationship between behavior and attitude, suggesting that the latter is a strong predictor of the former. In relation to driver behavior, Iversen and Rundmo (2004) analyzed the relationship between attitudes, behavior and involvement in collisions through a survey on a sample of 2614 Norwegian drivers. Their scale has 16 items, on a five-point scale ranging from 1 "strongly agree" to 5 "strongly disagree" to examine the ATTS issues and a 24-items scale to assess risky behaviors. The authors also recorded the number of collisions and near collisions that occurred. Confirmatory factor analysis confirmed a three-factor structure made up of Attitude toward rule violations and speeding, Attitude toward the careless driving of others and Attitude toward drinking and driving. Subsequently, the authors proposed a model involving the factors related to attitudes, those resulting from the analysis of the 24 items of risky behavior and the number of self-reported collisions and found that attitudes contributed to the prediction of self-reported risky behavior. In line with the approach adopted here, the authors encouraged the consideration of other factors beyond attitudes which contribute to collision involvement.

The Driving Mobility Questionnaire (DMQ-A)

Self-regulation of driving behavior depends on self-monitoring and, subsequently, on the need to change driving behavior should ability change, in order to maintain an acceptable level of safety (Baldock et al., 2006). As in the case of DBQ test, the history of measurement of self-regulation in driving is characterized by the use of a multiplicity of scales, with different numbers of items each corresponding to a potentially dangerous driving activity. Arguably the variability in the measures used has been contributes to by confusion around what constitutes self-regulation of driving behavior. In a recent study, Wong et al. (2015) investigated the factor structure of three variants of an item set that have been used to assess older adults' driving self-regulation, namely, the Driving Habits Questionnaire (DHQ) (Owsley et al., 1999), the driving mobility questionnaire (DMQ-A) (Baldock et al., 2006), and an extended version of DMQ composed of DMQ-A and twelve new items generated by Sullivan et al. (2011). Wong et al. (2015) intention was to develop a more comprehensive scale. The scale, called *Extended Mobility Driving Questionnaire* (Extended DMQ-A) was composed of 21 items, which required the respondents to indicate the frequency with which they avoided driving in certain conditions, such as, at night in the rain, or in foggy condition, rated on a scale ranging from 1 (never avoid) to 5 (always avoid). An exploratory factor analysis (EFA) revealed a two-factor structure, namely "Internal Driving Environment" and "External Driving Environment," on the basis of the meaning of the items, related to external factors (e.g., weather conditions) or internal to the car (e.g., driving with or without passengers). However, the authors identified the need to conduct further analysis of the instrument using confirmatory factor analysis.

Aims of the Study

The general aim of the present study was to combine the contribution of the risky behaviors (DBQ scale) with that of driving attitude (ATTS scale) and driving self-regulation (DMQ-A scale) in predicting the likelihood of collision in the year following the assessment in a sample of active older drivers. Specifically, the preliminary aim was to perform a series of confirmatory factor analysis (CFA) on the aforementioned three scales, involving a sample of active older Italian drivers. Tested models were: (a) a three-factor solution, as in the model confirmed by Lucidi et al. (2010) on a sample of young novice drivers aged between 18 and 23 years, and a four-factor solution, as in Stephens and Fitzharris (2016), for the DBQ scale; (b) a two-factor solution for DMQ-A, as reported by Wong et al. (2015); and (c) a three-factor solution, as reported by Iversen and Rundmo (2004) for the ATTS scale. A *data-driven* five-factor solution was also tested for the ATTS given that an Italian validation for the ATTS scale is lacking. The principal aim of the present study was to examine the role of behavior and attitudes in predicting separately the likelihood and the frequency of self-reported car collisions occurred over the year following the assessment through a Negative Binomial Hurdle (HNB) model (Hu et al., 2011; Hosseinpour et al., 2014). The aforementioned approach is particularly suitable whether the outcome is a count variable characterized by a relatively high number of non-occurrences.

MATERIALS AND METHODS

Participants

Data reported here were collected from 369 community-dwelling older drivers from an initial sample of 405 people (see par. Procedure and Materials for the applied exclusion criteria) recruited in the period between October 2015 and March 2016. They also agreed to be interviewed by phone every month for a total of 12 months to gather information about collisions in which they were involved. Of those who participated, 119 were female; they ranged in age from 60 to 91 years (M = 71.1, SD = 7.3) and their educational experience ranged from 5 to 23 years (M = 9.8, SD = 4.4). Each participant had the general aim of the research explained (specific hypotheses were omitted) and was required to provide informed consent to participate. The study was approved by the local ethical committee and was performed in accordance with the Helsinki Declaration and its later amendments or comparable ethical standards.

Procedure and Materials

Participants were interviewed in order to provide a range of demographic information including age, gender, education, as well as clinical history and current health status. Moreover, for the whole sample, the number of occasions of driving (less than once per month, once or twice per month, at least once a week and more than once a week) in the previous years was recorded. The inclusion criteria for the study were: (a) having a valid car driving license; (b) drive a car at least once per month; (c) absence of visual (uncorrected) and/or physical impairment;

(d) no history of cranial trauma, brain lesions, or stroke. The aforementioned data were evaluated through an anamnestic interview. Also, cognitive efficiency has been assessed through the Montreal Cognitive Assessment (MoCA, Nasreddine et al., 2005) where a score higher than 17 is considered as the best threshold to discriminate probable mild cognitive impairment in Italian population (Bosco et al., 2017). Autonomy in the management of daily activities has been assessed through the Activities of Daily Living (ADL, Katz, 1983) and the Instrumental Activities of Daily Living (IADL, Lawton and Brody, 1969). Finally, absence of geriatric depression was evaluated through the Geriatric Depression Scale (GDS_15, Brink et al., 1982). On the basis of these criteria, 36 drivers were excluded from the final sample (exclusion rate 9%). The following versions of the three scales mentioned above were used:

(A) The Italian 28-item version of *Driver Behavior Questionnaire* (DBQ), developed by Lawton et al. (1997), and adapted to the Italian context by Lucidi et al. (2010), rated on a six-point scale ranging from 0 (Never) to 5 (almost always). In this scale, high score indicated a high frequency of aberrant behaviors during driving activities.
(B) The 16-item scale of the *Attitudes Toward Traffic Safety Scale* (ATTSS), developed by Iversen and Rundmo (2004) and translated in Italian by Lucidi et al. (2010), on a five-point response scale ranging from "strongly disagree" (1) to "strongly agree" (5). A high score represented a negative attitude toward traffic safety rules.
(C) The 21-item version of *Driving Mobility Questionnaire* (Extended DMQ-A) by Wong et al. (2015), rated on a scale ranging from 1 (never avoid) to 5 (always avoid). The Italian translation of DMQ-A was created by the authors of the present study. The questionnaire was initially translated into Italian. This version was then given to a translator, fluent in English, who did not know of the existence of the original questionnaire, who was asked to translate the questionnaire back into English. This new English version was then compared to the original English version which proved to be grammatically and semantically equivalent, thus allowing the Italian version to be accepted as the final version of DMQ-A to be used in this study.

Each participant was interviewed by a well-trained research assistant who administered the questionnaire items to the interviewee and marked the answers on the response protocol. The entire procedure including the administration of the preliminary interview/tests to evaluate the inclusion criteria and the three driving questionnaires lasted approximately one and a half hours. A break was granted whenever requested.

Statistical Analysis

Confirmatory factor analysis (CFA) models were estimated using the R software (R Development Core Team, 2013) and the lavaan package (Rosseel, 2012), and graphically reported using the qgraph package (Epskamp et al., 2012). Internal consistency was determined using Cronbach's alpha. Confirmatory factor analysis (CFA) were carried out in order to test the most consistent factorial solutions existing in literature and to present the best factorial solution for each scale, namely, a four-factor DBQ solution, a five-factor solution for the ATTS and a two-factor solution for the Extended DMQ-A. The following fit indices and the respective cut-off for goodness of fit have been reported: the Chi-squared value (χ^2), to assess the overall goodness of fit of the model, even if very sensitive to sample size and no longer considered as a basis for acceptance or rejection of the model (Schermelleh-Engel et al., 2003), the Comparative Fit Index (CFI) (a value of CFI $\geq$ 0.95 is currently considered as indicative of good fit) (Hu and Bentler, 1999), the Tucker Lewis index (TLI) (a cut-off of 0.95 or greater stands for a good model fit), the Root Mean Square Error of Approximation (RMSEA) (a value lower than 0.05 is considered acceptable), and the Standardized Root Mean Square Residual (SRMR) (a value less than 0.08 is considered satisfactory) (MacCallum et al., 1996).

For the CFAs, a parametric method of data analysis has been adopted. In this respect, a variety of parametric, non-parametric and semi-parametric approaches have been explored in literature. Briefly, parametric statistics assumes that data produced by the sample comes from a population that follows a probability distribution based on a fixed set of parameters. An example of parametric method is the *Maximum Likelihood Estimation* who establishes values for the parameters of a model maximizing the probability that the model reflects the observed data (Jöreskog, 1978; Bollen, 2005). Non-parametric statistics do not need data fit with a normal distribution and therefore the model structure is determined from data instead of being specified *a priori*. An example is the *Partial Least Squares* analysis which estimates the latent variables as weighted aggregates (e.g., Lohmöller, 1989). Lastly, it is also worth mentioning the semi-parametric statistics which has both parametric and non-parametric components. Example of semi-parametric models are the *Cox Proportional Hazards* model (Balakrishnan et al., 2004) and the *Generalized Maximum Entropy* for estimating structural equation models (Ciavolino and Al-Nasser, 2009; Ciavolino and Dahlgaard, 2009; Carpita and Ciavolino, 2017).

In addition, predictive validity of each factor was assessed, by determining which factors predict collision involvement in the following year. A hurdle negative binomial (HNB) model was performed using the "pscl" package (Zeileis et al., 2008), since classical regression models were not appropriate due to the shape of the distribution of the outcome data. Thus, although the use of Poisson models is strongly recommended in the case of count data, it is not with overdispersion – events that are much less likely to occur than the opposite (Gardner et al., 1995). The number of road collisions occurring in a one-year period fits into that category. As far as we know, there are many statistical models that could be considered to represent these data including: negative binomial (NB), zero-inflated Poisson (ZIP), zero-inflated negative binomial (ZINB), Poisson hurdle (HP), and HNB models but Hurdle Models are the most suitable to operate on this type of data (Hu et al., 2011; Hosseinpour et al., 2014). Unlike the zero-inflated model, hurdle models consider the distribution of zero and non-zero separately. They also attribute to zero the actual value of "structural zero," differently from zero-inflated, which consider the fact that zeroes can also arise from non-exposure to the phenomenon ("sampling zeros"). Given the sample was exclusively composed of active drivers, we can state that each participant is exposed to the risk of a collision. For this reason, Poisson Hurdle Model and HNB model seem to be the most appropriate. Although the two models may look similar, the use of the NBH model is recommended when the observed outcome has an average lower than its variance, as is the case for a crash involvement distribution.

RESULTS

Confirmatory Factor Analysis and Reliability of the Three Scales

Table 1 shows the fit indices for the models tested, namely, a three- and a four-factor solution for the DBQ scale, a three- and a five-factor solution for the ATTS, and two two-factor solutions for DMQ-A.

As reported by Stephens and Fitzharris (2016), a four-factor solution (see **Figure 1**), i.e., *Aggressive Violations* (AV – three items), *Violations* (V – nine items), *Lapses* (L – eight items), and *Errors* (E – eight items) has shown to be the best model for the DBQ. The model exhibited the following indices of goodness of fit: $\chi^2(343) = 470.256$, $p < 0.001$, CFI = 0.929, TLI = 0.921; RMSEA = 0.032; SRMR = 0.048. Internal consistency of each factor and the DBQ total score was also evaluated using Cronbach's alpha. As a scale, DBQ showed a consistency value of 0.86. In terms of single factors, Aggressive Violations, Violations, Lapses and Errors showed the following values: $\alpha = 0.69$, $\alpha = 0.68$, $\alpha = 0.73$, and $\alpha = 0.70$, respectively. All the reliability coefficients were close to or exceeded the threshold of $\alpha = 0.70$.

For the ATTS scale, the best factorial solution was a five-factor solution (see **Figure 2**) namely, *Rules* (RU – four items), *Risk* (RI – four items), *Speed* (SP – three items), *Careless of others* (CO – three items), and *Drinking and Driving* (D- two items). The model showed the following fit indices: $\chi^2(94) = 90.897$, $p > 0.5$, CFI = 1.000, TLI = 1.000; RMSEA = 0.000; SRMR = 0.030. Cronbach's alpha for the whole scale was $\alpha = 0.85$, revealing a satisfactory internal consistency. Rules, Risk and Speed sub-scales showed an acceptable internal consistency, i.e., $\alpha = 0.69$, $\alpha = 0.65$, $\alpha = 0.63$, respectively, whereas, Careless of Others and Drinking and Driving revealed excellent values of $\alpha = 0.89$ and $\alpha = 0.96$, respectively.

With respect to the DMQ-A, the model estimated revealed a two-factor structure (see **Figure 3**) with the latent factors labeled External Driving Environment (EDE) and Internal Driving Environment (IDE). Since some factor loadings were inadequate (<0.4), the corresponding items were removed from the model. Consequently, the final version of the scale was composed of 14 items. The seven deleted items were: item 2: "In the rain," item 4: "Peak hour," item 6: "High traffic roads," item 9: "At the start/end of school times," item 15: "Parallel parking," item 16: "Right turns," and finally, item 17: "Roundabouts." The final 14-item DMQ-A model's fit indices were as follows: $\chi^2(73) = 192.957$, $p < 0.001$, CFI = 0.951, TLI = 0.939, RMSEA = 0.067, SRMR = 0.075. As for the aforementioned scales, the two latent factors and the total scale showed acceptable internal consistency reliability; in particular EDE, IDE and the total scale's Cronbach's alpha values were $\alpha = 0.88$, $\alpha = 0.86$, and $\alpha = 0.68$, respectively.

Table 2 shows the correlations among all the factors' scales; mean and standard deviation for each factor.

The Link Between Driver Behavior, Attitude, and Rare Collision Events

Preliminary Chi squared analyses have been conducted to verify the relationship between age/education and collisions and to investigate the role of age and education variables as possible mediators. Given the large sample size and the well-known sensitivity of Chi-square distribution to sample size, we have chosen a conservative $p < 0.01$ as the reference level for statistical significance. Chi square analysis was performed by splitting the sample into two sub-samples according to age (60–74 and 75–91 years) and the median of education (i.e., 8 that corresponds to the achievement of high school graduation in Italy). No statistically significant differences emerged between age [X^2 (2, $N = 369$) = 6.41, $p = 0.04$] and education [$X^2(2, N = 369) = 3.60$, $p = 0.17$] with respect to the outcome, i.e., collision, thus age and education variables have not been considered in the subsequent analysis.

As described previously in the *Statistical Analysis* section, NBH model have the advantage of estimating both the likelihood of engaging in a specific event, that is, the hurdle portion, and the frequency with which that event occurs, that is, the count portion (Arens et al., 2014).

In the present sample, 33 drivers reported one crash over the year (about 8%) while 7 drivers reported 2 (about 2%). **Table 3** shows that all the DBQ variables (Violations, Aggressive

TABLE 1 | Fit indices of the model tested.

		Fit indices						
	Model	χ^2	*df*	**CFI**	**TLI**	**RMSEA**	**SRMR**	**AIC**
Reason et al., 1990	3 factors (28 items)	664.320	347	0.822	0.806	0.05	0.057	24523.528
Aberg and Rimmö, 1998	4 factors (28 items)	470.256	343	0.929	0.921	0.032	0.048	24337.464
Iversen and Rundmo, 2004	3 factors (16 items)	225.862	101	0.953	944	0.058	0.047	15601.311
Present study	5 factors (16 items)	90.897	94	1.000	1.000	0.000	0.030	15480.346
Wong et al., 2015	2 factors (21 items)	984.686	188	0.772	0.745	0.107	0.111	23689.237
Present study	2 factors (14 items)	192.957	73	0.951	0.939	0.067	0.075	15182.647

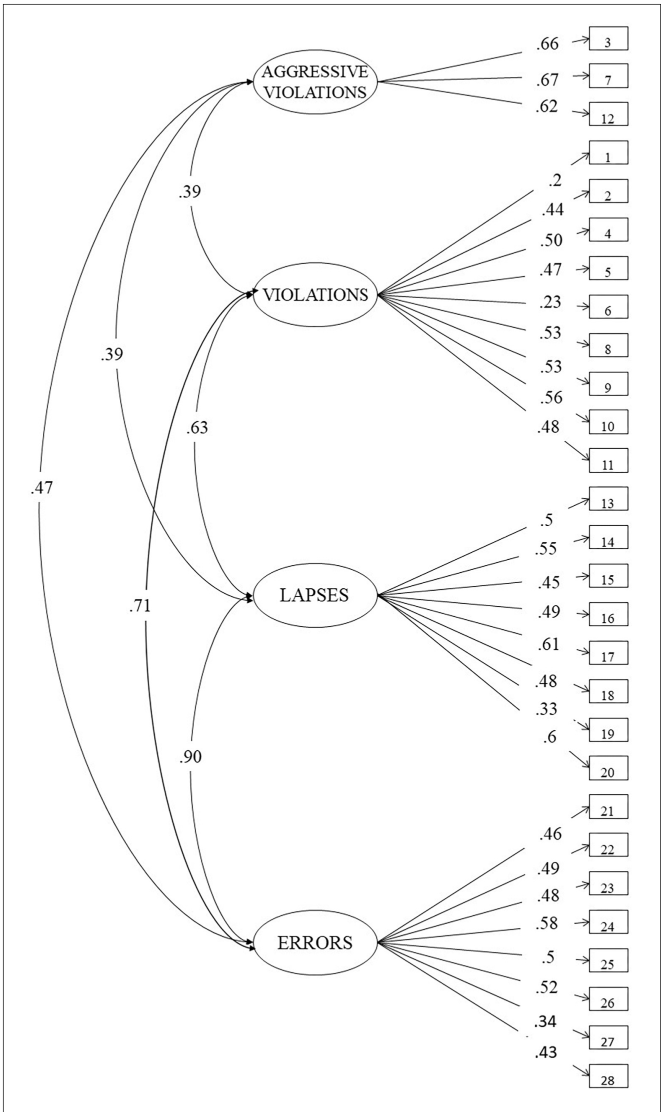

FIGURE 1 | Final model for the 28-item driver behavior questionnaire.

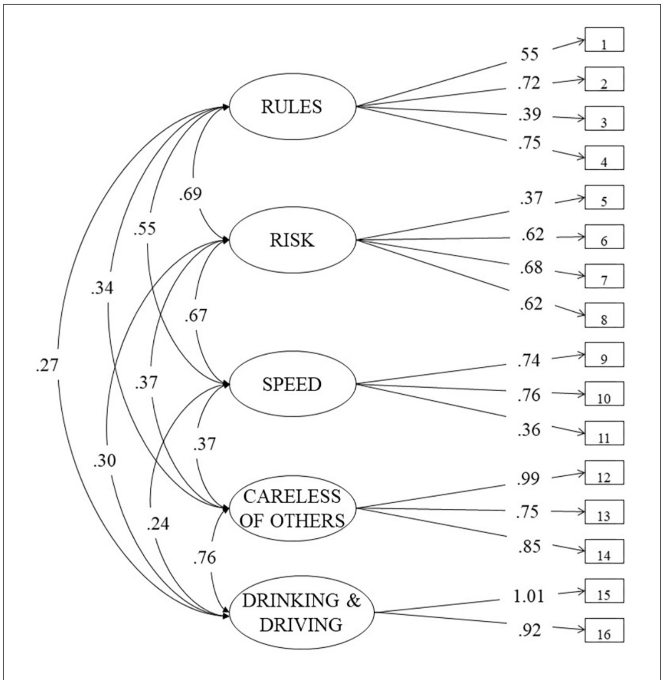

FIGURE 2 | Final model for the I6-item attitudes toward traffic safety.

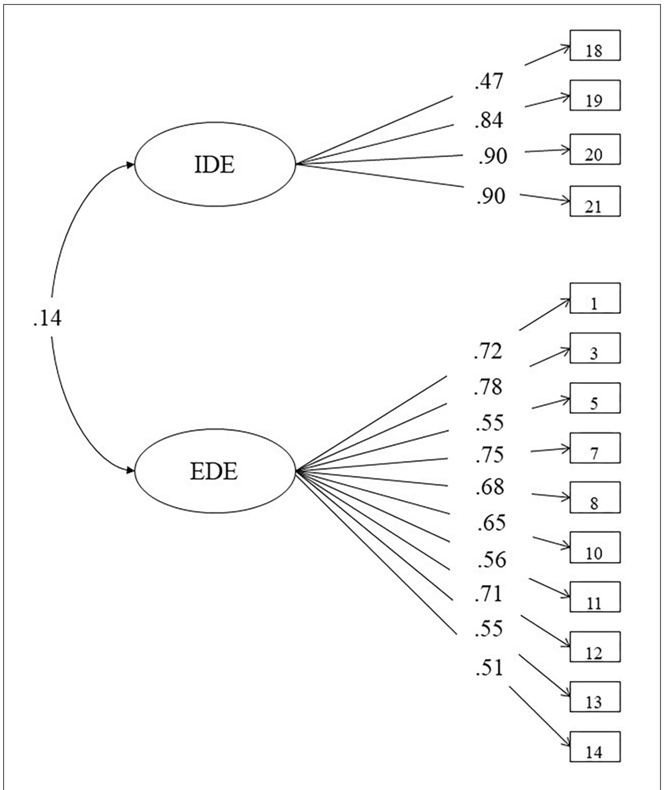

FIGURE 3 | Final model for the 14-item driving mobility questionnaire.

Violations, Lapses and Errors) are equally associated with the likelihood of engaging in a car collision. In other words, a higher frequency of self-reported aberrant driving behavior predicted the likelihood of having a collision. However, this is not the case for other variables, namely EDE, IDE, Rules, Speed, Risk, Careless of Others, and Drinking and Driving. In fact, it seemed that these variables do not significantly predict the likelihood of having a collision.

With respect to frequency (i.e., count model), Aggressive Violations became not significantly associated with the frequency of collisions. While, the other three variables maintained a significant relationship with the outcome. In other words, as the number of Violations and, with a larger extent, the number of Errors increased, the frequency of collision increased as well. An unexpected result relates to the variable Lapses. According to the NBH model, collisions were inversely associated with number of Lapses. Furthermore, both the DMQ-A variables showed to be associated with the frequency of accidents in a year. In particular, a higher self-regulation concerning environmental aspects (EDE) was positively associated with a lower frequency of collisions,

TABLE 2 | Correlation matrix of all the variables, mean, and SD.

Factor	AggViol	Viol	Lapses	Errors	EDE	IDE	Rules	Risk	Speed	CO	Mean	*SD*
AggViol											3.024	2.935
Viol	0.258**										5.152	4.705
Lapses	0.271**	0.446**									5.412	4.141
Errors	0.321**	0.469**	0.639**								2.921	3.023
EDE	−0.014	−0.208**	0.074	−0.005							25.924	10.574
IDE	0.069	0.047	0.015	0.060	0.207**						5.349	3.054
Rules	−0.127*	−0.410**	−0.223**	−0.227**	0.157**	0.010					17.076	3.413
Risk	−0.209**	−0.388**	−0.229**	−0.272**	0.121*	0.006	0.469**				15.328	3.799
Speed	−0.139**	−0.312**	−0.204**	−0.192**	0.092	0.102*	0.375**	0.452**			11.501	3.054
CO	−0.067	−0.170**	−0.065	−0.143**	0.070	0.045	0.290**	0.283**	0.299**		10.035	2.432
DD	−0.036	−0.151**	−0.017	−0.061	0.062	0.065	0.232**	0.237**	0.201**	0.724**	3.450	1.527

***Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).*

while, a higher self-regulation involving the personal, "internal" aspects of risk driving (IDE) was surprisingly associated with a higher frequency of collisions. Moreover, a positive attitude toward traffic rules (i.e., the variable labeled as Rules) was significantly associated with a lower frequency of collision in a year. In conclusion, Errors (DBQ) and Rules (ATTS) showed to be the most relevant predictors of frequency of collisions. Finally, Speed, Risk, Careless of Others and Drinking and Driving were not associated both with likelihood and frequency of car collision.

DISCUSSION

The first aim of the present study was to assess the factorial validity of three widely used scales on risky driving behavior, positive attitudes toward traffic rules and self-regulation in dangerous driving situations on a sample of Italian older active drivers, namely a 28-item DBQ, a 16-item ATTS and a 21-item Extended DMQ-A. Using confirmatory factor analysis, complied with the four-factor structure found in previous research, the final DBQ model was composed of four latent factors. The four-way distinction of the DBQ has been confirmed with respect to previous findings (e.g., Aberg and Rimmö, 1998; Rimmö, 2002; Bener et al., 2008; Martinussen et al., 2013; Mattsson et al., 2015; Cordazzo et al., 2016). Despite the presence of previous empirical evidence that supported the three-factor structure for the DBQ (e.g., Parker et al., 1995; Lucidi et al., 2014; Mallia et al., 2015), the four-factor solution appears to be the most appropriate in the present sample according to the fit indices. It is worth emphasizing that this is a further subdivision of "driving violations" dimension, which, therefore, does not seem to substantially change the original three-way distinction in violations, lapses and errors among risky driving behaviors.

TABLE 3 | Estimation of the Negative Binomial Hurdle (NBH) model with all factors as independent variables.

	Hurdle model		Count model	
	Estimate	***p***	**Estimate**	***P***
(Intercept)	−84.975	0.026*	4.693	0.490
Violations	2.753	0.026*	0.855	0.032*
Aggressive violations	2.908	0.026*	−0.737	0.249
Lapses	2.684	0.027*	−0.637	0.003**
Errors	2.054	0.024*	2.617	< 0.001***
EDE	−0.028	0.837	−0.649	0.004**
IDE	0.015	0.947	0.901	< 0.001***
Rules	−0.422	0.363	−1.134	< 0.001***
Risk	−0.437	0.202	−0.462	0.091
Speed	0.294	0.439	−0.044	0.852
Careless of others	0.069	0.842	−0.665	0.428
Drinking and driving	1.101	0.198	1.110	0.216

*Number of collisions is the dependent variable. Signif. codes: ***0.001, **0.01, *0.05.*

An interesting result is the high covariance between errors and lapses variables in the CFA model of the DBQ scale. This seems to be in line with the idea that errors and violations are underlined to different cognitive processes. Reason et al. (1990) suggested that errors as well as lapses are unintentional, and the latter are included in the former ones. On the contrary, violations are deliberate infringements of traffic rules, hence intentional. This was later confirmed by Özkan et al. (2006) who argued as a two-factor solution, i.e., errors (composed of lapses, slips, and mistakes) and violations, was the most stable model, over time. On the other hand, other scholars (Lajunen et al., 2004; Smorti and Guarnieri, 2016) suggested a second-order factor model based on errors (including mistakes and lapses) and violations (including general and aggressive violations).

As regards the ATTS scale, the three-factor structure showed very good fit indices and seemed to be consistent with that originally proposed by Iversen and Rundmo (2004) involving a sample of Norwegian middle-aged drivers. Nevertheless, the final choice fell on a five-factor structure, since it provided a better fit to the current data. The final model of DMQ-A scale was composed of two latent factors labeled EDE and IDE, as already suggested by Wong et al. (2015). The lack of an Italian validation requested to follow a *data-driven approach*. In our Italian DMQ-A version, the items 2, 4, 6, 9, 15, 16, and 17 have been removed because of irrelevant factor loading values.

The second aim was to find out which factors of each scale predicted collision involvement over the period of a year. As addressed by several scholars (e.g., Af Wåhlberg et al., 2015; de Winter et al., 2015) the data in literature revealing an association between aberrant behaviors at the wheel (i.e., violations, lapses and errors) and self-reported accidents data may be inflated by several methodological biases, including common method variance effect. In order to overcome this possible bias, the present study introduced a design in which the older drivers were contacted by telephone monthly for a year to register any collision may be occurred. This methodology has two main strong points: (a) introduces a prospective design allowing to explore the predictive capacity of each measure to predict collisions excluding a possible common method variance effect; (b) reduces the possibility of a recall effect, asking older drivers to analyze only a limited time frame (last month).

The results showed that driving violations, lapses and errors strongly affect the risk of collision, while the role of aggressive violations appears to be weaker than the others, as it seems to predict the likelihood of incurring in a collision but not its frequency. These results are in line with the literature in that risky driving in older drivers is positively related to self-reported crash involvement (e.g., Lucidi et al., 2014; Af Wåhlberg et al., 2015).

The results also revealed the significant impact of self-regulation on the frequency of collision between subjects who have already had an accident. Data on the present sample of older drivers showed that high self-regulation with respect to potentially hazardous external situations, such as, adverse weather conditions, are associated with a lower frequency of accidents in drivers who have already had an accident. On the contrary, self-regulating in a potentially risky internal environment, that is, for instance, the presence of children passenger in the car, was associated to a higher frequency of collisions. Indeed, these findings suggest that self-regulating behavior during these situations can even be a risk factor for the drivers and passengers. Self-regulation may be a mediator between other constructs, such as certain personality traits and/or cognitive variables (Devlin and McGillivray, 2016). Indeed, several studies argue that self-regulation is a multidimensional factor, affected by several components, such as decision making (Molnar et al., 2014), self-confidence (Molnar and Eby, 2008), and personality traits, such as attachment style (Gillath et al., 2017). It could also be hypothesized that other personality traits, such as anxiety, may affect self-regulation, especially if we take into account those situations in which the driver feels the responsibility for the safety of other passengers, even more if children. Thus, a cautious explanation of our result might be that a self-reported propensity to self-regulate associated to the presence in the car of other passengers could reveal an anxious personality inclined to implement potentially risky behaviors at the wheel. With respect to the ATTS factors, the analysis shows that only a positive attitude toward traffic rules was associated to the frequency of collision. Conversely, other factors regarding risk avoidance, high speed, caring for the others, and alcohol-driving did not significantly impact both on likelihood and frequency of collisions. Again, a possible explanation may be that ATTS could be dependent on specific personality dimensions, as is the case of the *personality-attitudes-risk driving behavior* model (Ulleberg and Rundmo, 2003). In addition, several studies showed that older drivers are less prone to participate in dangerous behaviors, such as reckless driving (Doroudgar et al., 2017), abuse of alcohol before and during driving (Bates et al., 2014), likely due to concerns over their own fragility, than young car drivers. In summary, it seems that the behavior, and therefore, the actual action, shows its close link with the consequence, that is, the accident. However, once the accident has occurred, other variables may be involved in affecting the likelihood of a relapse. The present results converged on the validity of the DBQ as the preferred tool for the prediction of self-reported accidents, and confirmed, also in the present sample of active older drivers, the strict relationship between attitudes toward safety (i.e., attitudes toward rules, risk and speed) and all the four dimensions of the DBQ. As in previous research (e.g., Lucidi et al., 2014; Mallia et al., 2015) attitudes are more related to ordinary violations than to other driving behaviors. This data is in line with the nature of the ordinary violations that are the results of a deliberate and conscious choice resulting more influenced by attitudes than other aberrant behaviors that are may be more linked to cognitive functioning (i.e., errors and lapses).

The components of the DBQ and self-regulation do not seem to have a direct link, as confirmed by previous findings (Rimmö and Hakamies-Blomqvist, 2002; Gabaude et al., 2010). On the contrary, in the older drivers, the role of attitudes toward respect for the law and the traffic rules seems to be very strong, unlike what happens for young people (Yagil, 1998). It is worthwhile to note that the involvement of other variables, such as self-regulation and attitude toward road safety, can be useful in assessing the likelihood of relapses (Iversen, 2004) and in their prevention, as well as in the prediction of types of accident with respect to different factors of attitudes and self-regulation examined (Slavinskiene et al., 2014). Overall, the relationship between attitudes, self-regulation and behaviors might be more complex than expected and, also be mediated by other factors not considered in the present study. Future studies will have to investigate the complex relationship between cognitive, personality variables and the three constructs under consideration here and how this relationship affects the number of short and long-term risks of being involved in collision.

The present study has some limitations. All the data are self-reported. Despite the monthly interviews with which the research assistants maintained regular contacts with participants, the role of memory deficits or social desirability on accident reporting cannot be ruled out. Despite the fact that Helman and Reed (2015) have argued for a clear association between self-reported and objective measures, when using a driving simulator, accesses to objective data relating to collision involvement would clearly have greater validity. A limitation is also the lack of other objective criteria, beyond the number of accidents, such as, traffic fines. This point is closely linked to the previous limitation, as the authors hypothesized that the participants were not inclined to declare the traffic fines. Future research may use more reliable methods to collect objective criteria, possibly in cooperation with local authorities. Despite the presence of the aforementioned limitations, the present study proposed a contribution to the creation of a suitable driving ability assessment procedure, as suggested by some scholars (e.g., Af Wåhlberg et al., 2015), in a specific and critical sample, namely active older drivers, in order to identify the specific risk and protection factors that act on the likelihood of being involved in risky behavior and collisions. A systematic approach to the assessment and prevention of incorrect driving behaviors could be a step to turn potential victims of traffic injuries into safer drivers. For this reason, it would be desirable to implement personalized educational programs, firstly, for the assistance of drivers at risk of loss of the driving license, and secondly, to amend such risky behaviors ensuring autonomy and functionality as essentials of cognitive reserve (Caffò et al., 2016) of older drivers in a safety way.

DATA AVAILABILITY

The raw data supporting the conclusions of this manuscript will be made available by the authors, without undue reservation, to any qualified researcher.

ETHICS STATEMENT

This study was carried out in accordance with the Declaration of Helsinki and its later amendments or comparable ethical standards. All subjects gave written informed consent. The protocol was approved by the Local Ethics Committee of the Department of Educational Sciences, Psychology, Communication, University of Bari (nr. 3660-CEL02/17).

AUTHOR CONTRIBUTIONS

GS, AC, AL, LM, FL, and AB conceived the original idea and were primarily responsible for the data collection, data analysis, and interpretation of results. GS, AC, and LM were primarily responsible for drafting the manuscript. MG, MI, FL, and AB critically revised the draft of the manuscript and supervised the general process.

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Inattentional Blindness During Driving in Younger and Older Adults

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Age-related changes to perceptual and cognitive abilities have been implicated in an increased risk of collision in older adults. This may be due, in part, to their reduced ability to attend to potentially relevant aspects of their driving environment. An associated general phenomenon of inattentional blindness involves a failure to notice visually presented objects or events when attention is directed elsewhere. Previous studies of inattentional blindness using computer paradigms report higher incidence of this effect in older compared to younger adults. However, little is known about whether these age-related effects are observed during more complex, realistic, everyday tasks, such as driving. Therefore, the goal of this study was to explore whether younger and older adults differ in their awareness of objects in their driving environment when their attention is directed toward another primary driving task. This study took place in a high-fidelity, full field of view, driving simulator. Thirty-two younger (M_{age} = 25.41) and 32 older (M_{age} = 73.41) adults drove through 19 short scenarios and were asked to first judge whether their vehicle could fit between two rows of vehicles parked on either side of the road and then to perform the associated driving maneuver (i.e., drive through or drive around). On four critical trials, objects were placed on the side of the road that differed in terms of animacy. Specifically, animate objects consisted of 3D humans standing by a bus shelter and inanimate objects consisted of photographs of the same individuals on a bus shelter advertisement. Inattentional blindness was measured via a post-drive, tablet-based recognition task immediately following the critical trials. Results revealed high rates of inattentional blindness across both age groups, with significantly lower levels of awareness for inanimate objects compared to animate objects. Further, whereas younger adults demonstrated reduced inattentional blindness following the first critical trial, older adults did not show this immediate improvement in recognition performance. Overall, this study provides unique insights into the factors associated with age-related changes to attention and how they may affect important driving-related outcomes.

Keywords: attention, aging, simulator, awareness, hazard, perceptual, cognitive, load

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INTRODUCTION

For many older adults, driving provides a sense of autonomy, contributes to community mobility, and helps to maintain overall quality of life. However, older adults are among the most vulnerable to traffic-related injuries and death caused by vehicle collisions (Transport Canada, 2014; Jackson and Cracknell, 2018). A recent systematic review by Vichitvanichphong et al. (2015) indicated that the most frequent driving errors made by older adults are those related to lane control, decision making, recognizing and responding to signs, visual scanning, and physical control of the vehicle. Older drivers are also particularly vulnerable to collisions during conditions of high sensory, perceptual, and cognitive load (e.g., when making left turns at intersections; Cantin et al., 2009; Road Safety Canada, 2011; Vichitvanichphong et al., 2015). These types of driving errors and increased collision rates are likely attributable to a variety of age-related changes, including but not limited to changes in sensory abilities (e.g., visual acuity, contrast sensitivity), perceptual abilities (e.g., time to contact estimation), and cognitive abilities (e.g., selective attention and working memory). Ultimately, the implications of these age-related effects on driving performance could include a reduced ability for older drivers to detect and/or interpret potential driving hazards, particularly when their perceptual and/or cognitive resources are taxed. Therefore, the goal of this study was to explore whether younger and older adults differ in terms of their awareness of objects in their driving environment when their attention is directed toward a primary driving task.

Inattentional Blindness, Perceptual, and Cognitive Load During Driving

The failure to notice an object or event when attention is directed toward a primary task or target is referred to as "inattentional blindness" (Mack and Rock, 1998). In a classic study demonstrating this effect, observers who were shown a video of a basketball game and asked to count the number of ball passes, often failed to notice a gorilla that walked purposely across the basketball court (Simons and Chabris, 1999). The extent to which inattentional blindness is observed can depend on several factors including the primary task demands, the nature of the unexpected object/feature, and the characteristics of the observer themselves (Kreitz et al., 2016). In terms of individual characteristics, a number of studies have shown the rate of inattentional blindness to vary as a function of age. For example, Graham and Burke (2011) replicated the Simons and Chabris (1999) study with younger and older adults and revealed that older adults were even more susceptible than younger adults to inattentional blindness in this task (i.e., much less likely to notice the gorilla). Other studies have replicated this increased susceptibility of older adults to exhibit inattentional blindness using a variety of computer-based paradigms (e.g., Stothart et al., 2015, 2016; Horwood and Beanland, 2016). Very little, however, has been explored with regards to whether age-related differences in inattentional blindness are also observed during complex and realistic everyday tasks such as driving.

During multisensory, multitasking activities such as driving, the ability to attend to objects in the environment that are not immediately relevant to the task itself can be particularly challenging. As such, broad object awareness may generally be limited during driving compared to less complex tasks, particularly during conditions of higher cognitive and perceptual load. For instance, cognitive load can be increased during driving by the introduction of multitasking requirements (e.g., listening/talking, holding information in memory, navigating; Strayer and Johnston, 2001; Strayer et al., 2003, 2013; Horrey and Wickens, 2006; Blalock et al., 2014; Cuenen et al., 2015; Donmez and Liu, 2015; Ebnali et al., 2016; Svetina, 2016; Murphy and Greene, 2017a; Caird et al., 2018; Wechsler et al., 2018) and perceptual load may be introduced by, for example, environmental clutter (e.g., traffic, buildings, signs, pedestrians; Marciano and Yeshurun, 2012, 2015; Stinchcombe and Gagnon, 2013; Ericson et al., 2017; Michaels et al., 2017), or by increasing perceptual task difficulty (e.g., judging maneuverability around closely arranged obstacles; Murphy and Greene, 2015, 2016). Previous studies with younger drivers have demonstrated more instances of inattentional blindness during conditions of higher compared to lower cognitive and perceptual load (e.g., Most and Astur, 2007; Blalock et al., 2014; Murphy and Greene, 2015, 2016, 2017a,b; Ericson et al., 2017; see Murphy et al., 2016 for a review). For instance, Murphy and Greene (2015, 2016) investigated the effects of perceptual load on inattentional blindness by asking drivers to make perceptual gap judgements about whether their car could fit between a row of parked cars while manipulating perceptual difficulty (i.e., clearly too wide/narrow vs. closely approximating the width of the driver's vehicle). Their results demonstrated greater rates of inattentional blindness to roadside objects during the higher load conditions compared to the lower load conditions.

Importantly, very little is understood about how perceptual load affects inattentional blindness in older adults. Because there are well-documented age-related changes to, for instance, attentional capacity (Craik and McDowd, 1987; McDowd and Craik, 1988) and inhibitory control of attention (Hasher and Zacks, 1988; Lustig et al., 2007), it may be expected that older adults would demonstrate differences in inattentional blindness under load compared to younger adults (Graham and Burke, 2011). For instance, the attentional capacity model of cognitive aging posits that older adults have a more limited attentional capacity than do younger adults (Craik and McDowd, 1987; McDowd and Craik, 1988). As such, older adults might be less likely to detect an object that is not relevant to the primary driving task and hence may be *more* susceptible to inattentional blindness (e.g., Graham and Burke, 2011; Horwood and Beanland, 2016). Other theories of age-related changes in attention posit that older adults are less able to inhibit their awareness of information that is irrelevant to their primary task (Hasher and Zacks, 1988), suggesting that they may have increased awareness of environmental objects/features and thus, may be *less* susceptible to inattentional blindness. Although past studies of inattentional blindness provide support for the predictions made by the attentional capacity model (e.g., Graham and Burke, 2011; Horwood and Beanland, 2016; Liu, 2018), less is understood about the role of perceptual/cognitive load on these effects, or the role of different object characteristics. It is possible, for instance, that under different primary task loads, when using different measures of awareness, and/or with different degrees of object relevance, these age-related differences in inattentional blindness may vary (Michaels et al., 2017). Driving experience is another important consideration as older adults typically have accumulated more years of driving than younger adults, which in turn could compensate for their age-related functional declines.

However, previous studies examining years of driving experience have revealed little to no effect on various driving measures (e.g., Shinar et al., 2005; Kass et al., 2007; Smahel et al., 2008) and very little is understood about the effects of lifetime driving experience on attention during driving.

Effects of Object Type: Role of Animacy

Objects that are more salient and/or more relevant to the primary task may receive greater levels of awareness. One object feature that has been shown previously to affect rates of inattentional blindness is animacy. Specifically, past studies using simple computer-based tasks with static stimuli have reported lower rates of inattentional blindness for animate (e.g., animals/humans) compared to inanimate stimuli (e.g., tools/transportation vehicles; Calvillo and Jackson, 2014; Calvillo and Hawkins, 2016). In the context of driving, the characteristic of animacy is particularly important because it determines whether the object could, at any moment, become relevant to the primary driving task (i.e., the need to initiate a reactive response to things that can move). A driver should be prepared to avoid an animate object that has the potential to enter the roadway, whereas a stable, inanimate roadside object would be less of a concern. A study by Pammer et al. (2015), in which participants were presented with photographs of driving scenes, revealed a reduction in the rate of inattentional blindness as the threat of a hazard increased (e.g., a child on the side of the road compared to an adult). What is not clear is whether these effects would be observed during dynamic driving tasks, and/or under conditions of higher load. Assuming there are limited attentional resources, the awareness of some objects (e.g., animate) may be prioritized over others. However, it is also possible that once the driving load (perceptual and/or cognitive load) becomes too great, the effects of animacy are diminished. What is also not yet known is whether older adults' awareness is differentially affected by animacy compared to younger adults'. For instance, age-related reductions of inhibitory control could be advantageous when an object is potentially relevant (animate) and leads to the detection of a hazard to be avoided, whereas it could be disadvantageous if the object is irrelevant (inanimate) and directs attention away from the primary task of driving. Therefore, the objectives of the current study were to evaluate inattentional blindness in younger and older adults, both in terms of animate and inanimate roadside objects during an active driving simulator task. Specifically, the animate objects consisted of 3D humans standing by a bus shelter and the inanimate objects were photographs of the same individuals on the bus shelter advertisement. To introduce load during driving, a gap judgment task (similar to Murphy and Greene, 2015, 2016) was implemented whereby the participants' primary task was to determine whether they could drive between two rows of parked vehicles or whether they had to drive around (and then execute the associated maneuver). The primary goal of the gap judgment task was to introduce a sufficiently attention-demanding secondary task and was not intended as a manipulation to evaluate the specific effects of high versus low perceptual and/or cognitive load. The rate of inattentional blindness was measured via a post-drive, tablet-based recognition task immediately following the critical trials.

MATERIALS AND METHODS

Participants

Seventy-one participants were recruited through advertisements posted in the local Toronto community. Due to simulator sickness, seven of the participants (5 older adults and 2 younger adults) were not able to complete the experimental task and were therefore excluded from the study. The final sample included 32 healthy younger adults (Age range = 20–35, M = 25.41, SD = 4.58, Male = 16) and 32 healthy older adults (Age range = 65–90, M = 73.41, SD = 6.19, Male = 18). All participants completed a pre-screening questionnaire to ensure that they met the eligibility criteria, namely age (younger adults 20–35; older adults 65+), and having a valid driver's license, 2 years of recent driving experience, normal or corrected-to-normal visual acuity (verified with in person screening – see below), and no history of serious physical, neurological, or psychological disorders. Individuals who were eligible were invited to participate in the experimental session and were compensated $10 per hour for their participation. The protocol for the present study was approved by the University Health Network's Research Ethics Board (REB 17-5596).

Demographics, Sensory, and Cognitive Measures

Participants were administered a series of assessments in person, including a health history and demographics questionnaire, driving habits questionnaire (Owsley et al., 1999), and motion sickness susceptibility questionnaire (Golding, 2006). Visual acuity was assessed using the Early Treatment Diabetic Retinopathy Study visual distance test (ETDRS; Ferris et al., 1982) and −0.2 to 0.5 logMar units was considered as the acceptable range for the normal to near-normal visual acuity cut-off (International Council of Ophthalmology, 2002). In order to characterize the cognitive abilities of younger and older adults, a series of standardized cognitive tests were administered. The WAIS-III forward and backward digit span (Wechsler, 1997) was administered as a measure of working memory, with lower scores indicating poorer performance. For all of the remaining cognitive measures described below, a lower score indicates better performance. The Stroop test (Stroop, 1935) was used as a measure of inhibition and was scored by subtracting the number of correct words uttered per second in the neutral condition (colored asterisks) from the incongruent condition (word-color match/mismatch). The Trail Making Tests A and B (Reitan, 1955) were used as a measure of executive function with the score calculated as the completion time difference between the two versions (B minus A). In addition, we administered the Useful Field of View Test (UFoV; Ball and Owsley, 1993), a computerized task in which participants must identify a central object and the location of a peripheral object in the presence/absence of distractors. This task computes sub-scores for selective attention, divided attention, processing speed,

FIGURE 1 | DriverLab at the Toronto Rehabilitation Institute – University Health Network (written informed consent was obtained from the depicted individuals for the publication of this image).

as well as a total composite score, and is considered to be a strong predictor of driving collision frequency in older adults (Ball and Owsley, 1993). Finally, all older adults were administered the Montreal Cognitive Assessment (MoCA; Nasreddine et al., 2005) to screen for mild cognitive impairment. Due to technical error, we were not able to compute scores for one older adult for the digit span, three younger adults for the Stroop, and one younger adult for Trails A and B.

Stimuli and Apparatus

Driving Simulator

The study took place at the Toronto Rehabilitation Institute's Challenging Environment Assessment Laboratory and used DriverLab, a state-of-the-art driving simulator (**Figure 1**). DriverLab is equipped with a full-sized passenger vehicle (Audi A3) containing all of its original internal components (e.g., steering wheel, gas/brake pedals, seats, and dashboards). The vehicle is completely surrounded by a 360-degree field of view visual projection system (12 Eyevis ESP-LWXT-2120, 1920 × 1200; 120 Hz projectors) and has vehicle-integrated surround sound (Pioneer VSX-45 Receiver, 5.1 sound; JL Audio powered sub and Focal speakers).

Driving Scene/Scenario

The driving scenes/scenarios were developed and presented using Oktal SCANeR Studio version 1.7 and MATLAB R2015b (The MathWorks Inc., 2015). The driving scenarios consisted of a straight rural road with no active traffic (see **Figure 2**). The number of objects in the scenarios (e.g., buildings and trees) was kept minimal and was balanced on both sides of the road. The entire road was approximately 1,000 m long. At approximately 820 m from the start of the drive, two rows of three vehicles were parked on either side of the road. The range of distances between the two rows of parked vehicles was 2.05–2.75 m apart. A bus shelter was positioned 14 m before the rows of parked vehicles on the right hand side of the road.

Target and Distractor Stimuli

The target objects within the driving scene and the target and distracter objects that were presented via the tablet during the post-drive recognition task were created using Google SketchUp, version 17.2.2 and the Google 3D warehouse. Target objects presented during critical driving trials were either animate or inanimate. Animacy was manipulated by presenting either a 3D person standing in the bus shelter (animate), or the same person depicted on a full height advertisement in the bus shelter (inanimate). Specifically, we included four people for the critical trials (2 males, 2 females depicted as either animate or inanimate) and four different people in filler trials (2 males, 2 females depicted as either animate or inanimate). In order to control for other non-animacy related differences between the two different animacy trial types, the advertisement content present in the inanimate trials was also replicated within the bus shelter during animate trials (i.e., in the animate trials, the same advertisement without the person was positioned directly behind the 3D person). This resulted in manipulating animacy while controlling for the general visual content in both the animate and inanimate trials (see **Figure 3**). Note that although the size of the person in the inanimate is smaller than the animate person, it is still quite large and clearly visible (e.g., the height of the inanimate man in the suit on **Figure 3** is 1.5 m).

Tablet-Based Response Measures

Additional sets of 3D images were obtained and converted to 2D graphics for the four trials involving the tablet test of inattentional blindness. Importantly, each of these trials included

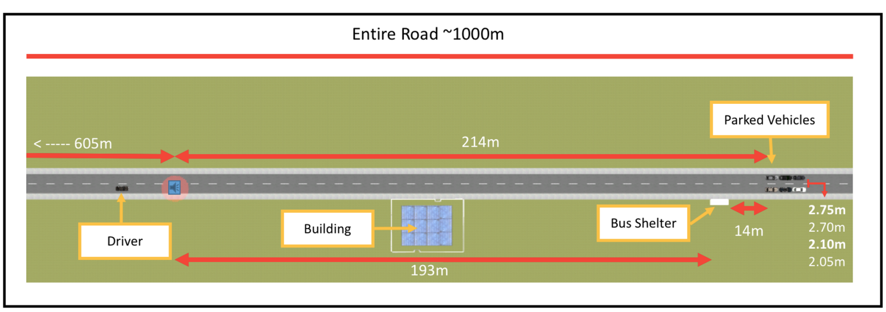

FIGURE 2 | A top-down view of the driving scenario.

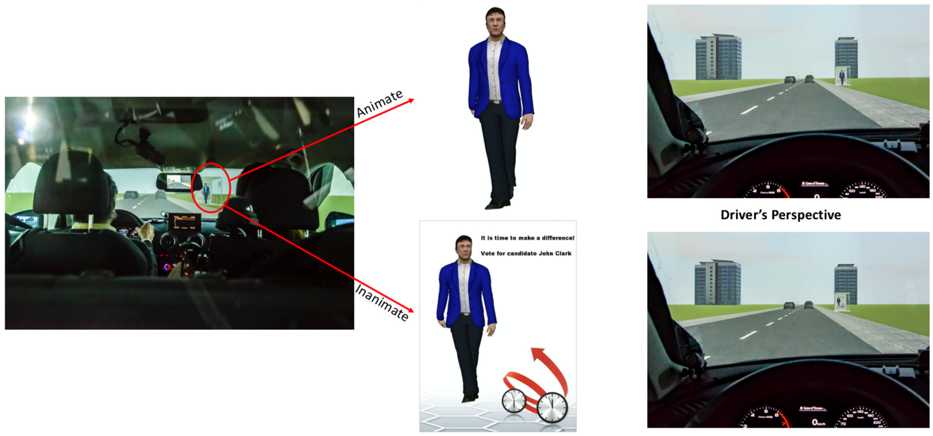

FIGURE 3 | Example stimuli including animate **(top)** and inanimate **(bottom)** objects (written informed consent was obtained from the depicted individuals for the publication of this image).

two human characters; one who was present in the driving scene (critical target) and one who was not (competitor), as well as two plausible, non-human roadside objects (e.g., bicycle, mailbox, and newspaper stand), none of which ever appeared in the driving scene. These four images were presented on a 10′′ Samsung Galaxy tablet. Each image was depicted on a white background at a 220 × 260 pixel resolution and the image location of each object type (within the four quadrants) was randomized across trials. Although the critical target and the human competitor for each trial matched in terms of their sex, they differed in terms of other characteristics (e.g., posture, clothing, and hairstyle), which provided additional unique identifiers apart from just different facial features across targets/competitors. This is an important detail, given that previous literature has suggested that face stimuli are unique in that they are processed to a greater degree than non-face stimuli under higher load conditions (Lavie et al., 2003).

PROCEDURE

After providing informed written consent, participants were asked to complete the set of questionnaires mentioned earlier. They were then guided to DriverLab and were assisted in adjusting their seat and getting familiarized with the vehicle. During the entire driving session, which lasted approximately 30 min, one researcher always sat in the passenger seat of the car with the participant, and another researcher monitored the experiment from outside the simulator.

Familiarization Phase

Participants were first required to complete a 5 min familiarization phase, which involved driving along a straight rural road that was similar in nature, but not identical to the main experimental scenarios. During this phase, participants were asked to maintain a speed of 80 km/h (∼50 miles/h), make several lane changes, and drive on the shoulder. Participants were instructed to obey all traffic rules as they completed the driving task (e.g., obey speed limits, use their indicator before changing lanes, and avoid obstacles). Upon completion of the familiarization phase, participants were asked to report any symptoms of motion sickness and confirm that they were comfortable with proceeding to the experimental phase.

Experimental Phase

Participants were instructed to drive along a straight, one-way rural road in a series of short driving trials. They started from a parked position on the road and drove straight forward within the right-hand lane. It was explained to them that they would come across a section of the road with vehicles parked on either side of the road and, upon approaching these vehicles, they would have to make a gap judgment to determine whether they could fit between the vehicles or whether they would need to navigate around the vehicles by driving on the shoulder. They were assured that the driving simulator car's physics had been turned off so they would not feel any physical impact if they made an error in the gap judgment. Gap values were either "plausible" to drive through (Wide: 2.75 m, 2.70 m) or "implausible" to drive through (Narrow: 2.10 m, 2.05 m) with respect to "fit-ability". The width of the driver's vehicle was 1.8 m and although physically they could drive through the narrow gap, it would have been difficult and perceived as potentially "dangerous" to do so.

At a defined decision point before reaching the parked vehicles (marked by an auditory tone, see red circle and sound icon on **Figure 2**), participants were instructed to signal left if they believed that they could drive through the parked vehicles and signal right if they believed that they had to drive around the parked vehicles. Importantly, they were asked to follow their signal by performing the associated driving maneuver. Participants were also told to maintain the same speed as during the practice phase (80 km/h) and to bring the car to a stop at their own comfortable pace after driving through/around the parked vehicles. After confirming that participants understood the instructions, they were informed that they could not converse with the experimenter while driving.

The experimental phase involved 19 short driving scenarios (2 practice + 16 experimental + 1 probe trial). The four different gap sizes were equally represented across the 16 experimental trials and the two practice trials included one narrow (2.05 m) and one wide gap (2.75 m). Across the 16 experimental trials there were also four instances of each of the following object conditions: bus shelter with an animate object (3D person), bus shelter with an inanimate object (advertisement), an empty bus shelter, and no bus shelter. The two practice trials had empty bus shelters. Across the experimental trials, these object conditions were equally divided among the gap conditions. The pairing of conditions was accomplished using a list design, varying whether a wide or narrow gap size accompanied an animate or an inanimate roadside object. Although all participants were presented with all four combinations across the four critical trials, they were only presented with a particular object once. For example, each participant would be presented with the man in the suit depicted in **Figure 3** only in one of the four critical trial combinations: (1) animate and narrower gap; (2) inanimate and narrower gap; (3) animate and wider gap; (4) inanimate and wider gap. The same character was associated with the same critical trial across participants (e.g., the man in the suit in **Figure 3** was always the first critical trial). Moreover, to ensure that the participants could, in fact, perceive the roadside object when their attention was not divided by the gap judgment task, we also included a probe trial at the end of all experimental trials, in which participants were presented with a bus shelter that contained an object (an animate or inanimate man) but they did not have to make a gap judgment (i.e., there were no parked vehicles on the road). All participants did in fact see the roadside object (performance was at 100% for both animate and inanimate probe trials) and thus no further exclusions were required.

On four of the 16 experimental trials, inattentional blindness was assessed using a forced-choice recognition task presented on a tablet immediately after the driving trial. Specifically, participants were asked to select an image of the object that they recognized from the preceding trial. Each trial was coded for accuracy (correct/incorrect) and incorrect trials were further coded for same category error (choosing the human competitor) versus different category error (choosing a non-human object). Upon the completion of the experimental task, participants were asked to rate their level of simulator sickness on a scale of 0 (no sickness) to 20 (extreme sickness, Keshavarz and Hecht, 2011). Both younger and older adults reported low and similar rates of sickness (M = 2.31, M = 2.02, respectively). Finally, participants were asked to complete the remaining set of cognitive performance measures. Overall, the study took approximately 1.5–2 h to complete. Considering the possibility that time of the day could differentially affect younger and older adults' performance (Anderson et al., 2014), we balanced the time of testing for each age group by having approximately the same number of younger and older adults tested in the morning and afternoon sessions.

Data Analyses

All statistical analyses were conducted using R Version 3.3.3 (R Core Team, 2017). The comparisons of younger and older adults' performance on baseline measures were analyzed with independent samples t-tests (see **Table 1**). All primary experimental dependent measures were analyzed using logistic mixed-effects analyses. These analyses were carried out using the lme4 package Version 1.1-15 (Bates et al., 2015) and lmerTest package Version 3.0-1 (Kuznetsova et al., 2017). Age (younger vs. older) was treated as a between-participants factor, and gap size (wide vs. narrow) and animacy (animate vs. inanimate) were treated as within-participant factors. The dependent measures were "accuracy" in gap judgment (accuracy here reflects driving *through* the parked vehicles when the gap was clearly wide enough and driving *around* the parked vehicles when the gap was too narrow to be considered safe to drive through) and accuracy in the rate of detection of the animate/inanimate object, which were both treated as binary outcomes (correct/incorrect). The random effects structure included a random intercept term for participant, a by-participant slope term for gap size in the analysis of gap judgment accuracy, and a by-participant slope term for animacy in the analysis of inattentional blindness. The results of these analyses are presented in **Table 2**.

TABLE 1 | Participant demographics and baseline measures.

	Younger adults (N = 32)	Older adults (N = 32)	
	M (SD)	*M (SD)*	p-value
Demographics			
Age (years)	25.41 (4.58)	73.41 (6.19)	<0.001*
Education (years)	17.19 (2.28)	18.25 (3.44)	0.151
Vision			
ETDRS left eye[1]	0.06 (0.18)	0.19 (0.16)	0.003*
ETDRS right eye[1]	0.03 (0.17)	0.18 (0.14)	<0.001*
Cognition			
MoCA[2]	–	26.09 (2.99)	–
Digit span[3]	18.13 (3.23)	16.61 (3.21)	0.067
Stroop[4]	0.56 (0.19)	0.47 (0.18)	0.077
Trails[5]	27.74 (9.97)	62.19 (52.07)	<0.001*
UFoV[6]			
Processing speed	17.41 (4.72)	21.91 (20.24)	0.229
Divided attention	18.41 (7.46)	70.03 (87.10)	0.002*
Selective attention	42.41 (23.78)	171.72 (96.49)	<0.001*
Total score	78.22 (29.22)	263.66 (164.22)	<0.001*

**Significance level of p < 0.05 when comparing younger and older participant group scores; [1]Early Treatment Diabetic Retinopathy study scores in logMAR units; [2]Montreal Cognitive Assessment, adjusted for years of education; [3]score out of 30; [4]number of correct words per second from neutral condition to incongruent condition; [5]Trails B-A; [6]Useful Field of View.*

RESULTS

Demographic, Sensory and Cognitive Measures

Both younger and older participants were similar in terms of demographic background, with most having completed, or were in the process of completing a university-level degree. To compare the driving habits of younger and older adult

TABLE 2 | Summary of the results for mixed effect analyses.

Effect	Estimate	*SE*	*Z*	*p*
Gap judgment accuracy				
(Intercept)	2.43	0.23	10.78	<0.001
Gap size	−0.23	0.29	−0.79	0.432
Age	0.38	0.19	2.06	0.039
Gap size × age	−0.47	0.26	−1.82	0.069
Inattentional blindness				
(Intercept)	0.59	0.25	2.36	0.018
Age	0.35	0.23	1.56	0.119
Animacy	0.83	0.21	3.99	<0.001
Age × animacy	0.29	0.18	1.55	0.121
Inattentional blindness growth curve analysis				
(Intercept)	0.75	0.25	3.00	0.003
Linear	−0.15	0.38	−0.38	0.702
Quadratic	0.52	0.42	1.24	0.216
Age	0.43	0.25	1.72	0.086
Animacy	0.95	0.21	4.58	<0.001
Linear × age	0.78	0.38	2.04	0.042
Quadratic × age	0.68	0.42	1.62	0.105
Linear × animacy	0.28	0.38	0.74	0.460
Quadratic × animacy	−0.30	0.50	−0.61	0.545
Age × animacy	0.30	0.21	1.47	0.142
Linear × age × animacy	0.12	0.38	0.31	0.759
Quadratic × age × animacy	0.21	0.50	0.43	0.669

Contrast coding: age (younger adults = 1, older adults = −1); perceptual gap judgment (narrow gap = 1, wide gap = −1); animacy (animate = 1, inanimate = −1).

participants, we compiled an average score from the information collected on the driving habits questionnaire, accounting for both the average number of trips driven and average distances traveled on a weekly basis. The two age groups were very similar in terms of the average kilometers driven per week (Younger Adults: M = 142.31 km, SD = 186.79; Older Adults: M = 131.48 km, SD = 142.72). Younger and older adults also did not differ in terms of their susceptibility to motion sickness.

Younger and older adults were also compared for each of the measures of sensory and cognitive functioning. Whereas younger adults had better visual acuity than older adults overall, both groups' average score of left and right eye acuity fell within the normal to near-normal range (−0.2 to 0.5 logMar units; International Council of Ophthalmology, 2002). In terms of the battery of cognitive measures, there were no significant group differences on the digit span test (p = 0.067) or the Stroop test (p = 0.077). However, younger adults performed significantly better than older adults on the Trail Making ($p < 0.001$) and the UFoV ($p < 0.001$) tests. Notably, the age-related differences in UFoV were evident for measures of divided attention (p = 0.002) and selective attention ($p < 0.001$), but not processing speed (p = 0.229).

Nine older adults scored below the MoCA cut-off for mild cognitive impairment (<26), however, these participants were still included in the analyses because their performance in the experimental task did not differ from their peers. To confirm and justify the inclusion of these individuals, a series of sensitivity analyses were conducted for all the primary measures of interest, which further revealed no significant effect of including versus excluding this group of participants. Therefore, all reported analyses are based on the full sample size of 32 younger and 32 older adults.

Gap Judgment Accuracy

The purpose of the gap judgment task was to introduce a need for divided attention during driving in order to strategically evaluate age-related differences in inattentional blindness within a driving context. Thus, in order to ensure that participants were actually performing the task as instructed, and to determine whether there were age-related differences in performing the gap judgment task itself, accuracy scores were calculated and compared between groups. Overall, participants were quite accurate in the gap judgment task (82% overall). In order to determine whether gap judgment accuracy varied as a function of gap size and age, we used a logistic mixed effect model with accuracy as a binary dependent measure (correct vs. incorrect) and gap size (wide vs. narrow), age (younger vs. older), and their corresponding interaction as fixed effects. Whereas there was no effect of gap size on overall accuracy of gap perception judgments, there was an effect of age group with younger adults being more accurate than older adults, $\beta = 0.38$, $SE = 0.19$, $Z = 2.06$, $p = 0.039$. This was further qualified by a marginal gap size × age interaction, $\beta = -0.47$, $SE = 0.26$, $Z = -1.82$, $p = 0.069$ whereby younger adults were more accurate than older adults in the trials with the wider gap size but not the narrower gap size (**Figure 4**). Nonetheless, both younger and older adults were overall quite accurate in making the gap judgments (87 and 77%, respectively), suggesting that they were able and compliant in performing the gap judgment task.

Inattentional Blindness

To measure the rate of inattentional blindness, the analysis file was subsetted to include only the four critical trials in which the forced-choice recognition test was administered. Furthermore, to ensure that participants were engaged in the gap judgment task on each critical trial, all trials in which participants made an incorrect gap judgment were excluded (the average rate of inattentional blindness was no different when incorrect gap judgments were included). The rate of inattentional blindness was measured in terms of accuracy (correct selection of target object during the recognition task), with lower accuracy indicating a higher level of inattentional blindness. The model for the analysis included age, animacy, and their interaction as fixed effects.

Results indicated that the only significant effect observed was that of animacy, $\beta = 0.83$ $SE = 0.21$, $Z = 3.99$, $p < 0.001$, with better recognition accuracy for animate than inanimate objects for both groups. As illustrated by **Figure 5**, the differences in detection of animate versus inanimate objects are more pronounced in the younger adults, although this was not statistically significant. We then conducted a follow-up growth curve analysis (Mirman, 2014) to analyze whether inattentional blindness varied across the four critical trials as a function of the order in which they were presented (trial numbers 3, 9, 12, and 17). It is, for

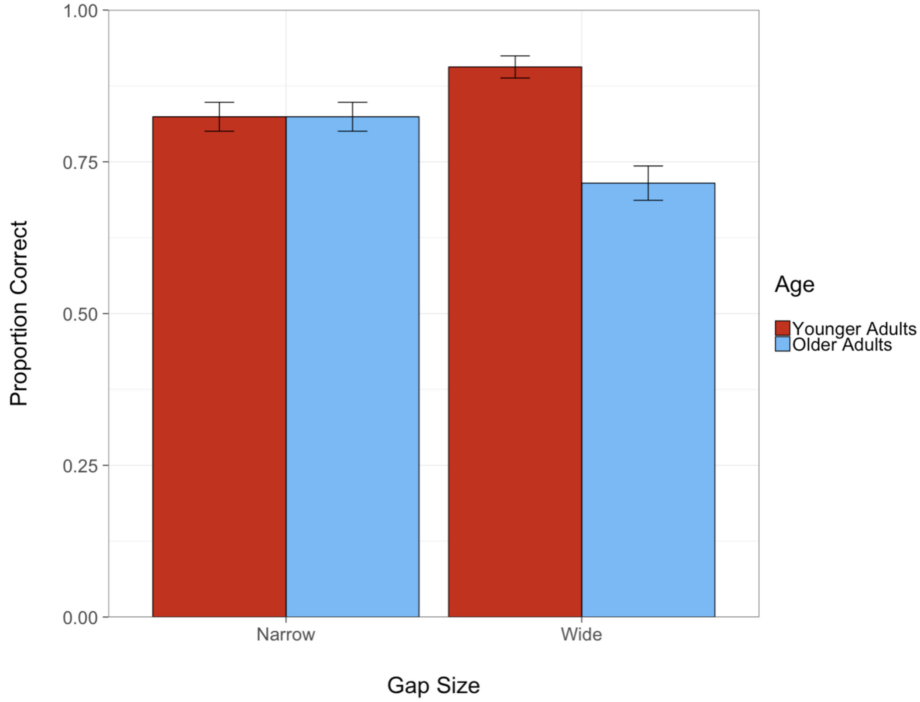

FIGURE 4 | Proportion of correct gap judgments as a function of gap size and age (error bars denote standard error).

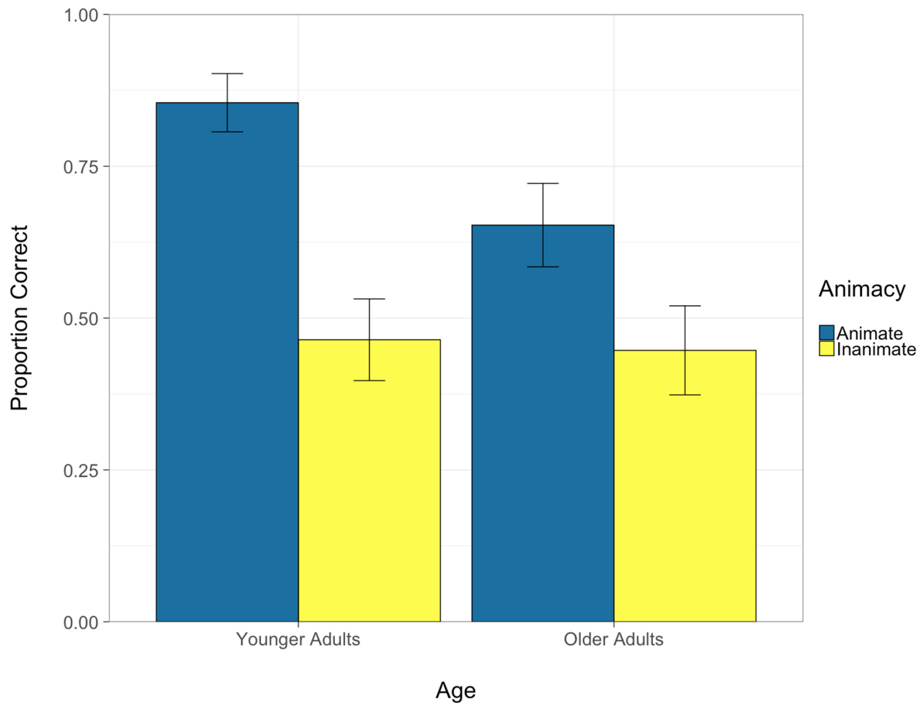

FIGURE 5 | Proportion of correctly identified objects as a function of age and object animacy (error bars denote standard error).

instance, possible that after the first critical trial, participants were primed to attend more to environmental objects than they had been previously, which could then have affected their distribution of attentional resources in later trials. The overall time course of accuracy was modeled with a second-order (quadratic) polynomial and included fixed effects of both age

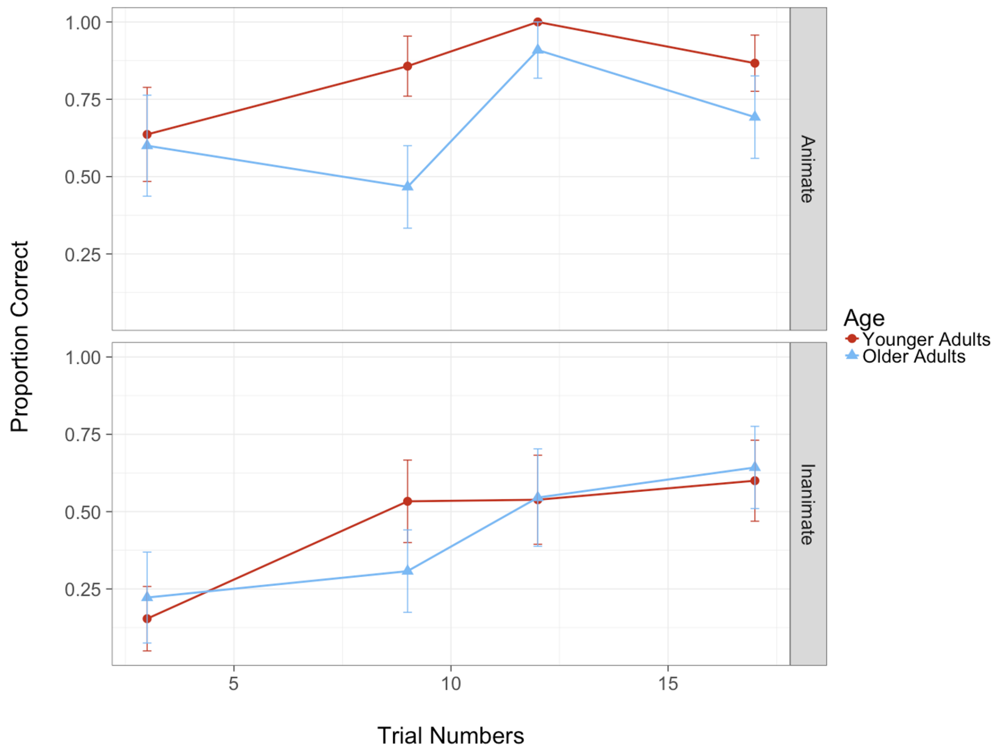

FIGURE 6 | Proportion correct across the four critical trials (3, 9, 12, and 17) as a function of age and animacy (error bars denote standard error).

and animacy conditions on all time terms. However, due to limited count of observations, the full model would not converge, thus the random effect structure was simplified to include only participant random effects on all time terms. In addition to the effect of animacy, β = 0.95, *SE* = 0.21, *Z* = 4.58, $p < 0.001$, we also observed a significant effect of age group on the linear time term, β = 0.78, *SE* = 0.38, *Z* = 2.04, $p = 0.042$. As illustrated in **Figure 6**, this is mainly driven by the performance on the second critical trial (Trial 9), whereby younger adults demonstrate reduced inattentional blindness in the second critical trial compared to older adults who did not show this effect. This pattern of results is evident in both animate and inanimate conditions with differences being more pronounced in the former. We describe the implications of this pattern in greater detail in the section "Discussion."

Incorrect Recognition Trials

Each response was coded not only in terms of correct and incorrect detection of the critical target, but for the type of incorrect responses, namely whether participants selected the human competitor or a non-human object that never appeared in the scene (e.g., newspaper stand and bicycle). Interestingly, the pattern of results revealed that participants were more likely to pick the non-human object than the human competitor. Furthermore, not only was this pattern of results consistent across both age groups, it was also consistent across trials. In fact, as can be seen in **Table 3**, it is only the last critical trial in which participants were more likely to incorrectly select the human competitor compared to the non-human object (similar patterns of results are observed after excluding trials with the incorrect gap judgment). We speculate that the reversal of the pattern in the last trial whereby the human competitor was selected more often than the non-human competitor may be due to the overall greater exposure to human characters in the preceding trials.

DISCUSSION

In the present study, patterns of inattentional blindness were compared between younger and older adults while they performed a simulated driving task. In particular, we examined whether the awareness of roadside objects differed between the two age groups and whether the animacy of the objects affected awareness. Load was introduced by asking participants to make a

TABLE 3 | The number (percentage) of incorrect decisions for human vs. non-human competitor.

	Younger adults		Older adults	
Trial numbers	**Human**	**Non-human**	**Human**	**Non-human**
All trials	17 (35%)	31 (65%)	23 (41%)	33 (59%)
3	6 (27%)	16 (73%)	7 (37%)	12 (63%)
9	3 (30%)	7 (70%)	6 (33%)	12 (67%)
12	1 (14%)	6 (86%)	3 (30%)	7 (70%)
17	7 (78%)	2 (22%)	7 (78%)	2 (22%)

perceptual gap judgment about whether they could drive through two rows of parked vehicles. In four critical trials participants were asked to identify roadside objects that differed in terms of their animacy. The results demonstrated that both younger and older adults were significantly more aware of animate compared to inanimate roadside objects, with a trend of this effect being more pronounced in younger compared to older adults. Further, younger adults demonstrated reduced inattentional blindness after the first critical trial, whereas older adults did not show this immediate improvement and continued to exhibit a high rate of inattentional blindness in the second trial. This implies that they did not distribute their attention differentially across the primary driving task and the roadside objects as a function of the prior task demands. Notably, when inattentional blindness *was* observed (i.e., failure to select the correct human), the erroneous choice was significantly more likely to be the non-human object rather than the other human competitor, for both animate and inanimate critical trials and across both age groups, suggesting that they were truly unaware.

Effects of Age on Inattentional Blindness During Driving

The previously described phenomenon of inattentional blindness during driving in younger adults (Most and Astur, 2007; Blalock et al., 2014; Murphy and Greene, 2015, 2016, 2017a,b; Ericson et al., 2017) was replicated in the current study and was expanded upon by demonstrating the same phenomenon in older adults. Specifically, participants were unaware of inanimate objects on 56% of all trials and animate objects on 25% of all trials (see **Table 4**). When only considering the very first trial, which is (a) the trial most comparable to other studies of inattentional blindness, which typically test awareness only once, and (b) the only trial preserved against priming or carryover effects, it was observed that participants were unaware of inanimate objects on 82% of the trials and were unaware of animate objects on 38% of the trials. Further, when considering the very last trial, when participants had already been asked three previous times to recognize an object present during driving, performance was still not at ceiling levels with 38% of inattentional blindness observed for inanimate objects and 22% observed for animate objects. This indicates that when performing a moderately difficult driving task, drivers very often lacked conscious awareness of potentially relevant aspects of their surroundings; particularly when they were probed unexpectedly (first trial), but even when they could anticipate being asked (last trial). This observation was bolstered by the fact that recognition errors were almost twice as likely to be due to selecting a non-human object (e.g., bicycle and newspaper stand) rather than the human competitor, suggesting that it was not just a matter of having difficulty distinguishing subtle human features, but rather a general unawareness.

Interestingly, however, older adults did not demonstrate overall higher or lower rates of inattentional blindness compared to younger adults, counter to initial predictions. This suggests that, within the constraints of this task, there was no evidence to support older adults' *reduced* awareness of roadside objects due to a generally *lower* attentional capacity, or an *increased* awareness of roadside objects due to *poorer* inhibitory control. There was, however, some indication that older adults did not as rapidly adjust their distribution of attentional resources after learning from previous trial demands. Specifically, whereas younger adults demonstrated significantly reduced inattentional blindness after having already been previously prompted to attend to roadside objects by the recognition task (perhaps priming them to anticipate that they may have to divide their attention in order to recognize future roadside objects), older adults did not. The need for flexible adjustment of task demands could be particularly important in the context of real world driving.

The largely comparable levels of inattentional blindness in younger and older adults observed in this study are different from some prior studies demonstrating higher rates of inattentional blindness in older compared to younger adults in non-driving tasks (e.g., Graham and Burke, 2011). The current results are also different from some driving-context specific studies of hazard detection that have shown lower detection rates in older compared to younger drivers (e.g., Bromberg et al., 2012; Feng et al., 2018; although see Borowsky et al., 2010). However, the results of the current study *are* consistent with other previous studies reporting measures of awareness as evidenced through explicit detection tasks and actual driving performance metrics under conditions of load (e.g., Strayer and Drews, 2004; Stinchcombe and Gagnon, 2013). For instance, Stinchcombe and Gagnon (2013) reported no age-related differences between middle aged and older drivers for driving performance measures or peripheral detection task accuracy during complex driving tasks known to be associated with real world collisions. Further, Strayer and Drews (2004) reported that while both older and younger adults were negatively affected by talking on a cell phone during simulated driving (e.g., slower reaction times and increased rear-end collisions), there were no age-related differences. Taken together, in the below discussion we consider the parameters that differ across these studies to highlight the potential role that particular factors may play in the observed results including, the nature of the task (e.g., recall vs. recognition vs. driving performance), the magnitude of load (e.g., lower vs. moderate vs. higher perceptual/cognitive load), the nature of the "unexpected" object/feature (e.g., relevance to the primary task), and how these factors may interact with age.

One of the primary differences across studies of inattentional blindness, situational awareness, and hazard detection across driving and non-driving tasks relates to the way that "awareness" is operationalized and measured. For instance, in the current

TABLE 4 | The rate of inattentional blindness as a function of age and animacy for each trial.

	Younger adults		Older adults	
Trial numbers	**Animate**	**Inanimate**	**Animate**	**Inanimate**
All trials	16%	54%	33%	57%
3	36%	85%	40%	78%
9	14%	47%	53%	69%
12	0%	46%	9%	45%
17	13%	40%	31%	36%

study, a post-drive recognition task was used, whereas other studies of inattentional blindness have asked participants to freely recall an object/event (e.g., "did you notice anything different/unusual on the last trial," Graham and Burke, 2011; Murphy and Greene, 2016), and yet others have considered driving performance measures like brake reaction times (e.g., Strayer and Drews, 2004; Ericson et al., 2017). These different task types may be uniquely targeting implicit versus explicit levels of awareness. Therefore, it is possible that older adults may have a reduced conscious awareness of scene/object differences across trials compared to younger adults (e.g., poorer recall accuracy; Graham and Burke, 2011), but they may still have an implicit awareness of having seen that object with comparable accuracy to younger adults (i.e., similar recognition accuracy as was observed in the current study). Indeed, there is significant evidence in the general aging and cognition literature that recall is more significantly affected by older age than is recognition (Craik and McDowd, 1987; Danckert and Craik, 2013) and explicit memory is more significantly affected (or oppositely affected) by older age than implicit memory (La Voie and Light, 1994; Gopie et al., 2011). There are also interesting implications regarding these distinctions when considering how implicit and explicit awareness are associated with actual driving performance measures. It is likely that even without explicit or conscious awareness, implicit detection may result in associated changes in driving performance. This interpretation is consistent with the agreement between comparable performance by older and younger drivers on the recognition-based responses in the current study and the comparable performance of older and younger drivers reported for other driving performance related measures across other studies (e.g., Strayer and Drews, 2004).

Differences across studies could also relate to the various types and levels of perceptual and/or cognitive load that are introduced (Lavie, 2005; Murphy et al., 2016) and the different effects of load on older compared to younger adults. It may be that under low load conditions younger and older drivers perform similarly well and under high load conditions younger and older drivers perform similarly poorly. Therefore, it may be during moderately loaded conditions that age-related effects are best revealed. Given that it is difficult to normalize load across studies, it is possible that the load introduced in the current study was higher or lower than in other previous studies of age-related effects on inattentional blindness, and/or age-related effects of object awareness during driving. It is also possible that the different methods of stimulus presentation could be contributing to differences in age-related effects. For instance, smaller field-of-view displays and/or video or photo-based stimuli may result in different age-related effects compared to larger field-of-view displays, or immersive simulation systems, as well as where the stimuli appear within these displays (e.g., within or outside of the useful field of view).

Effects of Animacy on Inattentional Blindness During Driving

In addition to the effects of the context, task, and load on inattentional blindness, the relevance of the unexpected object to the primary task itself may also be a contributing factor. In inattentional blindness studies, the target object of interest is often referred to as "irrelevant" to the main task or "unexpected." The same may not be true in contextualized tasks such as driving where the environmental features and objects can differ and vary dynamically in terms of their relevance (e.g., proximity to roadway, or ability to interfere with the primary driving task) (Pammer and Blink, 2013; Pammer et al., 2015; Topolšek et al., 2016; Murphy and Greene, 2017a). Animacy is a characteristic that is particularly relevant in the context of driving given that it introduces the increased probability that the object could interfere/interact with the driving task. The results of the current study revealed a highly significant effect of animacy, with much higher recognition rates of animate compared to inanimate objects. Importantly, the physical features of the animate and inanimate objects in this study were essentially identical, with the difference being how the object was contextualized (i.e., embedded in an advertisement or not). This effect of animacy was also observed across age groups and across trials and the effect is consistent with past studies involving both non-driving tasks as well as driving relevant scenes (Pammer and Blink, 2013; Calvillo and Jackson, 2014; Pammer et al., 2015; Calvillo and Hawkins, 2016; Topolšek et al., 2016).

Even though there was no significant interaction effect between age group and animacy, it is interesting to note that younger adults demonstrated quite a high rate of awareness for animate objects across trials (84%) compared to older adults who were relatively poorer (67%); which was in contrast to the inanimate trials, for which younger and older adults were much more comparable to each other (46 and 43%, respectively). This suggests that the influence of animacy on response selection was more pronounced for younger adults than older adults. The implications for this during a real driving context could mean that older adults may not be as strategically attending to potentially relevant environmental information in the same way as younger adults (Bromberg et al., 2012; Horwood and Beanland, 2016; Feng et al., 2018).

Potential Limitations and Future Directions

Although the current study was targeted at evaluating age-related effects on inattentional blindness during driving, it did not control for between-group differences in terms of lifetime history of driving experience. Whereas it was ensured that all participants had valid driver's licenses and that there were no statistically significant between-group differences in current driving habits (i.e., average km driven per week), older adults likely had driven for more years total than younger adults. Therefore, greater experience with driving overall may have allowed older adults to use acquired driving skills to compensate for any potential age-related declines in sensory, motor, or cognitive abilities, resulting in no overall age-related differences on task performance. Yet another possibility is that even though all participants received the same instructions to drive constantly at 80 km/h, with compliance verified during the practice trials, perhaps during experimental trials older adults modulated their speed differently

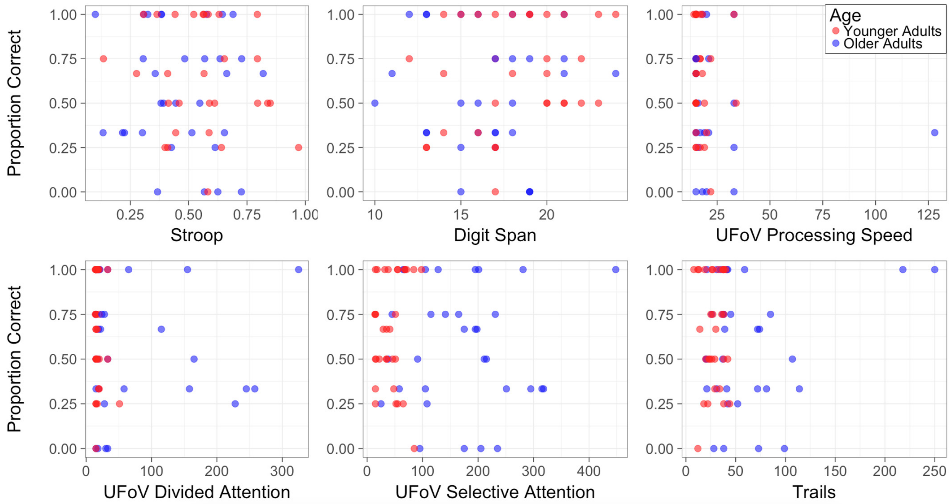

FIGURE 7 | Relation between cognitive assessments and the experimental recognition task performance (Stroop: number of correct words per second from neutral to incongruent condition; Digit Span: correct scores out of 30; UFoV measures are calculated in milliseconds; Trails: the difference in seconds between Trail B-A).

than younger adults. To explore this possibility, we verified the average speed of participants across the four critical trials (from the onset of the sound to the first parked vehicle). We found that younger and older adults were able to maintain the target speed with good accuracy (M_{Older} = 79 km/h and M_{Younger} = 84 km/h). Nonetheless, it is quite possible that when a speed limit is not strictly enforced, older adults may slow down in order to better manage the multiple tasks of driving (gap judgment and driving maneuvers), while also remaining aware of their surroundings (recognition task performance) (Bromberg et al., 2012). Similarly, even though all participants were asked to drive through the gap when it was wide enough to clear, older adults may have taken a more conservative approach and opted to drive around the vehicles during larger gap sizes than younger adults, even if they perceived it to be wide enough to fit through.

The older adult sample included here may also not be representative of the wider older adult driving population due to the strict eligibility criteria requiring no sensory, motor, or cognitive impairments and requiring an active driving status (licensed and frequent drivers). Indeed, the younger and older adult groups in this study were generally well matched on baseline tests of general functioning. For example, there were no significant between-group differences on tests of working memory (digit span), inhibition (Stroop), and processing speed (UFoV subset). Likewise, there were no observable differences in terms of participants who scored below the cutoff for mild cognitive impairment on the MoCA (see also Rapoport et al., 2013). However, older adults did perform significantly poorer on the Trail making test (visual attention and task switching) and the divided and selective attention subsets of the UFoV test. In order to explore the potential associations between individual participant's scores on the baseline measures and their recognition task performance during the main driving experiment, these data were plotted relative to each other (**Figure 7**). Visual inspection suggests that, for older adults, faster performance on the UFoV divided and selective attention tasks may be associated with better recognition task performance during driving. However, because of the nature of the binary recognition task measure, analyses to test for statistical associations were not possible. It is, therefore, evident that more studies are required to determine the role of individual differences on inattentional blindness in younger and older adults, particularly in the context of driving. Moreover, although the current sample size was similar to previous studies comparing younger and older drivers (e.g., Strayer and Drews, 2004; Stinchcombe and Gagnon, 2013), it may have lacked the sufficient power to detect more subtle age-related differences.

Because the same characters were presented in the same trial order either as animate or inanimate, there might be concern that the characteristic of the particular object in that trial could have differentially influenced the performance, despite the efforts made to ensure that characters were similar in composition, size, and saliency. In order to examine whether target features could have differentially affected recognition, we compared performance differences across different target types and observed no discernable patterns. For instance, we considered whether the sex of the target person affected recognition performance, but it did not appear to, given that the low performance observed in the second critical trial was for a female target and highest performance in the third critical trial was also a female target. Similarly, the first trial with low performance was a male in a suit, but the last probe trial with perfect performance was also a male in a suit.

Finally, as is the case for all simulator studies, the effects observed here may not generalize completely to real world driving. Particularly relevant here is that the consequence of making a gap judgment error (e.g., driving through a gap that is too small) in the simulator is much more benign than if the same error were made during real on-road driving. This consideration may also be influenced by age, as the consequences of a collision for older adults is likely to be much more serious than for younger adults given increases in fragility with age and poorer outcomes associated with injury and recovery (Vichitvanichphong et al., 2015).

CONCLUSION

Overall, the current results demonstrate that younger and older drivers had similar rates of inattentional blindness when evaluated using a recognition task within a driving paradigm. The most robust factor affecting inattentional blindness was the animacy of the roadside object, with animate objects being recognized significantly more often than inanimate objects. The effects of inattentional blindness were most pronounced on the very first trial, but persisted even after being primed three times prior. While younger adults appeared to distribute their attention more strategically after becoming aware of the potential task of recognizing roadside objects after the first trial, it took more trials for the older adults to redistribute their attention. Factors associated with whether age-related changes influence the rate of inattentional blindness could include the nature of the task/context, the magnitude of perceptual and cognitive load, and the features of the environment to be attended and/or ignored.

ETHICS STATEMENT

All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the University Health Network's Research Ethics Board (REB 17-5596).

AUTHOR CONTRIBUTIONS

RS and JC conceived the study. RS and KB collected the data. RS, JC, and KB contributed to the analyses and to the writing of the manuscript.

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The Effect of Teenage Passengers on Simulated Risky Driving Among Teenagers: A Randomized Trial

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Teenage passengers might influence risky driving, particularly in certain mental states. Notably, social exclusion could increase social conformity. Two studies examined simulated intersection management among young drivers after a social exclusion activity (Cyberball). In Study 1 [112 males (mean = 17.3 years)], risky driving was significantly greater among excluded males driving with a risk-accepting vs. passive passenger; no effect of social exclusion. In Study 2 [115 females (mean = 17.1 years)], risky driving was significantly greater among excluded females driving with a risk-accepting vs. a passive passenger, and greater among those included (fair play) vs. excluded when driving with a risk-accepting passenger. Risky driving behavior among male and female teenagers may be influenced uniquely by passenger norms and social exclusion.

Keywords: risk behavior, driving simulator, Cyberball, conformity, social exclusion, social norms

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INTRODUCTION

High crash rates among novice teenage drivers are thought to be due to deficiencies in driving skill and judgment due to young age (Twisk and Stacey, 2007), inexperience; (McKnight and McKnight, 2003; Simons-Morton et al., 2011), and risky driving behavior (Williams, 2003; Curry et al., 2011; Simons-Morton et al., 2011, 2015; Peake et al., 2013). Risky driving among teenagers is thought to vary according to driving conditions, including passenger presence (Ouimet et al., 2015; Simons-Morton and Ouimet, 2017). Moreover, the influence of teenage passenger presence may vary according to the mental state of the teenage driver (Falk et al., 2014).

Fatal crash risk is lower with adult passengers, but higher with teenage passengers, particularly among teenage drivers (Ouimet et al., 2010). A recent systematic review found relatively consistent evidence for an association between passenger presence and fatal crash outcomes, with odds ratios ranging from 1.24 to 1.89 across studies, increasing to 1.70–2.92 for two or more passengers, and with higher risk among male than female drivers and younger versus older young drivers (Ouimet et al., 2015). Fatal crashes tend also to involve high speeds, inclement weather, and late-night driving, so passenger presence is only one important factor. Curiously, teenage passenger presence was inconsistently associated with crash risk in studies that examined non-fatal or the combination of fatal and non-fatal crashes (Ouimet et al., 2015), which are vastly more prevalent, if less harmful, than fatal crashes. A tentative conclusion of the systematic review was that crash risk in the presence of teen passengers might be higher or lower depending on characteristics of the driver and the passenger.

Passenger influences on teenage driver behavior are thought to occur through social influence and/or distraction (Ouimet et al., 2015; Simons-Morton and Ouimet, 2017). Teenage passenger influences may be conditional, with some teenage passengers increasing risk among some teenage drivers under certain conditions and decreasing risk under other conditions (Ouimet et al., 2015; Simons-Morton et al., 2016). Notably, risky driving behaviors are greater when the driver perceives that peer norms favor these behaviors (Simons-Morton et al., 2011), when the driver is sensitive to social threats (Falk et al., 2014), and when the driver is emotionally aroused (Abdu et al., 2012; Taubman-Ben-Ari, 2012). Hence, it is of interest to examine passenger influences on risky driving behavior in variable driver mental states.

Simulation, even in an actual vehicle with high fidelity sounds and motion representing acceleration, braking, and turning; and realistic graphics of scenarios based on actual roads, cannot fully capture actual on-road driving experience. However, simulated driving performance has consistent been associated with on-road performance (Mullen et al., 2011) and has the decided advantage of being completely safe. Therefore, simulation can be a useful method for experimentation, allowing experimental manipulation that could not be done safely in traffic. Three recent randomized trials reported significant effects of passenger presence on the simulated risky-driving behavior of young drivers. In these studies, simulated risky driving was measured variably, but each assessed failure to react to a stop signal or stop at red lights positioned carefully within the scenarios and timed to require the driver to make immediate decisions to stop or risk running some of the lights. Ross et al. (2016) compared the simulated risky driving in the presence of each participant's own peer as the passenger in samples of 17–18 (n = 30) and 21–24 (n = 20) year-old males and females. Key measures of risky driving included average speed and reaction time to a stop signal at variable time intervals. Among drivers in both age groups, red light running was greater in the presence of passengers. Also, among participants with low inhibitory control, speeding was more prevalent in the presence of passengers. However, passenger presence seemed to improve hazard management and reduced time in the intersection when the light was red, providing additional support for the contention that peer passengers can increase some risks and decrease others, possibly conditional on characteristics of the driver, passenger, and/or driving conditions.

Bingham et al. (2016) examined the effect of norms and peer pressure on red light management and the decision to pass a slowing lead vehicle. Licensed male teenagers (n = 53) were randomized to drive with a young male passenger (a study confederate) who in the risk-promoting group presented himself as risk accepting and when riding as the passenger exercised mild peer pressure to complete the course quickly; those in the other group drove with the confederate passenger who presented himself as risk averse and when riding as the passenger exercised mild pressure to complete the drive safely by taking few risks. Risky driving (running a red light, time in the intersection, and passing the slowing vehicle) and distraction (failure to stop at an intersection with an occluded stop sign) were greater in the passenger compared to the solo drives, a main effect for passenger presence, consistent with theory and research indicating that adolescent reward sensitivity increases in the presence of peers (Chein et al., 2011). In addition, Bingham et al. (2016) found interactions by passenger type where, relative to the group that experienced mild passenger pressure-to-drive safely, those who experienced mild pressure-to-take-risks ran more red lights and were more likely to pass the slowing vehicle. These findings are consistent with the contention that risk in the presence of passengers is conditional on peer pressure.

Simons-Morton et al. (2014) examined the effect of social norms without overt pressure on simulated risky driving measures identical to Bingham et al. (2016). Young male drivers (n = 66) were randomized to drive solo and with a confederate passenger portraying either risk-accepting or risk-averse social norms. The results confirmed the independent effect of passenger presence and significant interactions by passenger social norms, with those in the group exposed to the confederate passenger with risk-accepting norms, relative to those exposed to the passenger with risk-averse social norms, more likely to run the red light and spend more time in the intersection while the light was red. These findings are consistent with other research indicating that teenage risk taking is greater in the presence of peers, perhaps by sensitizing the brain's reward system to risk taking (Chein et al., 2011), conditional on passenger social norms (Ouimet et al., 2015).

Social Exclusion and Risky Driving

In the study just described (Simons-Morton et al., 2014), a week before driving the simulator, in an fMRI setting in which participants' brain activity was assessed, participants played the Cyberball (social exclusion) game (Falk et al., 2014). Cyberball is a computerized game of "catch" in which the participant (using a mouse) and other (unseen) players pass a "ball" on the computer screen visible in the scanner (Williams and Jarvis, 2006). Although the participant is made to believe he is playing with two other actual people, a pre-set computer program, rather than the other players, controls the ball's movement from other players. Thus, initially all players receive the ball approximately equally (i.e., fair play). In a later "exclusion" round, however, the other participants (the computer actually) stop passing the ball to the participant. When excluded, participants experience variable levels of distress or social pain. Eisenberger argues that the neural basis of rejection is that the pain system has co-opted the social attachment system, making social rejection among the most "painful" human experiences. Accordingly, individual differences in increased activity in neural systems associated with distress during the exclusion task predicted increased simulated risky driving the following week in the presence of a confederate peer passenger (Falk et al., 2014).

Likewise, in the study by Bingham et al. (2016), participants also played Cyberball in an fMRI scanner one week before the driving simulator experiment. In that study, the extent to which participants' brains changed their patterns of connectivity between the inclusion (fair play) and exclusion conditions predicted the degree to which they later conformed to the passenger norms in the subsequent driving simulator session (Wasylyshyn et al., 2018). Both sets of findings are consistent with literature demonstrating that greater sensitivity to exclusion is associated with conformity to peer norms (Williams and Nida, 2011; Falk et al., 2012). Other studies have shown that this is particularly true among those low in resistance to peer influence (Steinberg and Monahan, 2007; Peake et al., 2013). Thus, sensitivity to social pain, and more broadly social cues, such as cues experienced when excluded during Cyberball and measured by social pain and mentalizing regions in the brain during the task (Falk et al., 2014; Wasylyshyn et al., 2018), is thought to increase subsequent conformity to normative behavior as a means of social compensation (Williams and Nida, 2011). According to the need-threat model of ostracism, we expected that experiencing social rejection prior to driving in the presence of a peer would threaten psychological needs such as self-esteem, control, and belonging (Bastian and Haslam, 2010; Pharo et al., 2011; Williams and Nida, 2011). In this case, social exclusion could lead to subsequent conformity to peers' risk-taking preferences to attain or regain acceptance and avoid rejection (DeWall, 2010; Spear, 2011; Williams and Nida, 2011; Falk et al., 2012). On the other hand, prior work notes that social exclusion prompts attempts at re-connection (e.g., through conformity) only when people expect to be able to easily connect with subsequent interaction partners (Maner et al., 2007). It is also possible that the boost in reward sensitivity and risk behavior, observed in the presence of peers in prior studies (Chein et al., 2011), would be augmented in the presence of a study confederate who is liked and/or when the participant believes there is a high likelihood of connection. In this case, if a recent experience of being socially included or at least treated fairly signals a greater possibility of later social inclusion, conformity to a risk promoting peer could be higher following inclusion (fair play) than exclusion.

Study Purpose

To examine the conditional effects of teenage passengers on risky driving, we conducted two randomized trials in which we measured simulated driving behavior among teenagers in the presence of confederate peer passengers immediately after drivers were either socially excluded or included during a computer activity. The current research builds on the findings of previous driving studies of passenger effects on risky driving and on the finding just described that individual variability in the brain's sensitivity to exclusion was associated with greater susceptibility to peer influence on teenage male risky driving one week later (Falk et al., 2014; Wasylyshyn et al., 2018). The purpose of the current research is to evaluate the effect of experimental manipulation of social exclusion vs. inclusion (fair play) on male and female teenage simulated risky driving in the presence of confederate peer passengers who exhibited either risk accepting or passive social norms with respect to risky driving. Two research questions were examined: (a) What is the effect on simulated risky driving of exposure to a risk accepting or passive passenger after social exclusion? (b) What is the effect on simulated risky driving of social exclusion or social inclusion (fair play) when exposed to a risk accepting passenger?

MATERIALS AND METHODS

Design

Two simulation studies were conducted using the same methods and procedures. Study 1 included 112 males 15 to 18 years old (mean = 17.3) and Study 2 included 115 females 16 to 18 years old (mean = 17.1); participants had a Level 2 Michigan driver license (allowing independent driving with restrictions). Participant assent and parent consent were obtained and participants were compensated according to the protocol approved by the University of Michigan IRB.

In the between subject designs (shown in **Figure 1**), participants were randomly assigned to drive solo and in one of three groups with a male confederate passenger: (a) exclusion with passive passenger presence (Exclusion + Passive passenger); (b) exclusion with risk accepting passenger presence and norms (Exclusion + Risk accepting passenger); and (c) inclusion (i.e., fair play condition) with risk accepting passenger presence and norms (Inclusion + Risk accepting passenger). (A full factorial design was not feasible within the available resources.) Exclusion was manipulated by computer activity as programmed in the Cyberball computer activity. Those assigned to drive with a risk-accepting passenger were exposed to a social-norms priming activity. Participants in the Exclusion + Passive passenger group were not exposed to the social norms priming activity, but drove with a passive (i.e., not risk-accepting) confederate passenger who interacted minimally with the participant.

Social-Norms Priming Manipulation

Consistent with prior research on peer driving norms (Simons-Morton et al., 2014; Bingham et al., 2016), predrive social norms-priming activities, conducted with those assigned to the risk accepting passenger groups, included two confederate passenger activities: (a) arriving late, explaining ("Sorry I was a little late getting here. Normally I drive way faster, but I hit like every red light."); and (b) watching and rating with the participant two driving videos, the first providing a view from the passenger seat of being in a car racing at high speed, weaving in and out of traffic on an expressway, the second of being in a car driven carefully at a slower speed than the other expressway vehicles. Immediately after each video the participant was asked to respond verbally to two questions on a scale of 1 to 10: (a) How similar is your driving to the driver in the video? and (b) How likely would you be to ride with the person in this video? The confederate responded after the participant so that he could always respond in a manner that was more-or-less risk accepting, depending on treatment condition, relative to the participant's response. The experimenter then indicated that the study participant had been randomly selected to be the driver for the experiment and the confederate was assigned to be the passenger. The research assistant then

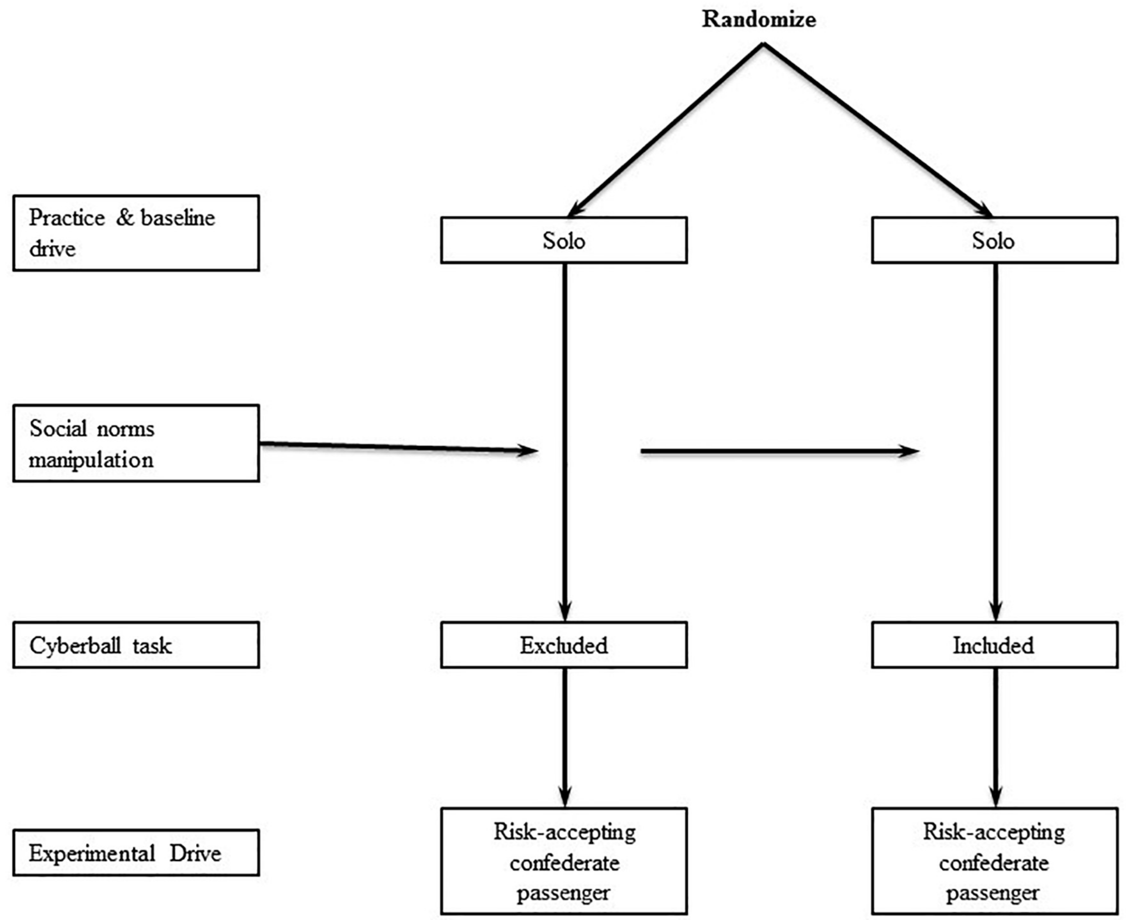

FIGURE 1 | Team passenger study design.

announced that the passenger (confederate) would drive the simulated vehicle while the participant played the Cyberball game in another room.

Manipulation of Social Exclusion or Inclusion (Fair Play) Using Cyberball Approach

Cyberball has been validated as a reliable way of simulating the experience of social exclusion (Williams, 2007; Eisenberger, 2012). The experimenter explained that Cyberball was ("a virtual ball tossing game and participants will be playing the game live with two other participants who are in other rooms"). The participant was then logged on to a virtual room in which he or she encountered two additional players (controlled by a preset computer algorithm). Participants thought they were playing teens other than the confederate, but the game was controlled by a computer program. A fair game of Cyberball was always played first, in which the participant and two virtual players received the ball equally often. For those in the exclusion condition, this fair game was followed by an unfair game, in which the participant and virtual players started out receiving the ball equally often, but after the first few throws, the other players stopped throwing to the participant all together, simulating social exclusion. Those randomized to inclusion (fair play) experienced fair play through out and received the ball equally as often as the other players. At the completion of the Cyberball game, which took 6 to 7 min to play, the participants completed a survey that assessed their reactions to the game.

Equipment

A fixed-base high-fidelity simulator located in a dedicated lab space was used for this study. The simulator comprised a full vehicle cab (Nissan Versa) surrounded by three forward screens and one rear screen. The forward screens were projected at a resolution of 1400 × 1050 pixels each and the rear screen at 1024 × 768 pixels, providing a 120-degree forward field of view and a 40-degree rear field of view. The simulator runs RTI's (Realtime Technologies, Inc., Royal Oak, MI, United States) SimCreator software. The simulator system included steering feedback, road vibration, a virtual LED instrument cluster, sideview mirrors, and simulated audio. The driving simulator recorded vehicle and driving performance data, up to six synchronized channels of video, and two channels of audio at 30 Hz (see **Appendix 1**).

Procedure

During the experimental drives, the confederate (as either risk accepting or passive) was passive with respect to risk and rode quietly to minimize variability in passenger behavior. Participants completed three drives: 5-min coaching/practice drive; 10-min baseline (solo) drive (after which participants played the Cyberball game); and 15-min experimental (passenger) drive. All three drives included typical roadway features (e.g., four-way intersections, straight and curved rural road, expressway) and a wide range of roadway geometries, speed limits, traffic conditions, and visual elements. The drives differed in the ordering of residential, rural, urban, and freeway road segments, with distinct layouts and alterations to surface features (e.g., trees, buildings), but included identical driving scenarios for eliciting participant behavior, including a car passing task and multiple four-way signalized intersections. Construction barrels at intersections and junctions guided participants to the destination and included a lead vehicle that served to minimize variability in the speeds at which intersections were encountered.

Intersection management, particularly when in the dilemma zone when the light turns amber as the driver approaches the intersection and must quickly decide to brake sharply or pass through the intersection as or after the light turns red, which is a traffic violation and dangerous behavior zone' (Huang et al., 2008). Accordingly, participants encountered signalized intersections at periodic intervals of 13 to 15 s (at 35 mph), exposing them to green and yellow lights of different durations (2.6, 3.0, 3.4 s), and red lights. The different durations of lights sometimes forced participants to choose to stop without entering the intersection, go through the intersection before the light turned red, or be caught in a 'dilemma.' The measurement of signalized intersection management is useful for several reasons: intersection are a common driving experience; intersection crashes are relatively common and often result in serious damage; there is considerable variability within and between drivers in intersection management; and it is possible to introduce in a single drive multiple intersections, including many that place drivers in the "dilemma zone," where the light turns yellow and the driver must make a quick decision to stop or go (Liu and Herman, 1996).

Measures

Outcomes

The average treatment group percent was calculated for three intersection management/risky driving measures: (a) stopping for the red light (% Failed to Stop) in the 10 (of 18) intersections with relatively shorter durations between yellow lights (i.e., dilemma zone intersections); this measured the percent of appropriate stopping at the 10 short duration lights; (b) time vehicles were in intersections while the light was red light (% Time in Red); the measure assessed the average amount of time the was in the intersection while the light was red as a reflection of the duration of potential risk for a crash; and (c) passing the slowing lead vehicle (% Passed Slow Vehicle); passing the slowing vehicle represented greater acceptance of risk.

Baseline Tests of Randomization

To assess individual variability, the week prior to the exclusion task and simulation drives participants completed the following baseline measures: susceptibility to peer pressure (Steinberg and Monahan, 2007), included 10 items that asked "what would you do if. . .," with response options of no (1), probably not (2), probably (3), and yes (4); self-esteem (Robins et al., 2001) is a single item, "I have high self-esteem," with response options from strongly disagree (1) to strongly agree (5); risky driving behavior (Simons-Morton et al., 2015) includes 28 items with response options from never (1) to always (5); and perceived social status (Adler and Stewart, 2007) is a single item that asks respondents to rate themselves from the bottom (1) to the top (1) of the ladder of people in the United States who are best off; and demographics; and impulsive behavior was assessed with 16 items from the UPPS (Cyders et al., 2007) with response options from strongly disagree (1) to strongly agree.

Effect of Social Exclusion

Cyberball has been validated in behavioral and neuroimaging studies to simulate the experience of social exclusion (Williams, 2007; Eisenberger, 2012). Immediately after playing the Cyberball game participants were asked, "How much did they throw you the ball?" with options from 1 = not at all to 5 = a lot. Then participants completed the 20 item Need-Threat Scale (van Beest and Williams, 2006; Williams, 2007) that asked their agreement (1 = strongly disagree to 7 = strongly agree) to five questions in each of the following four subscales: belonging (e.g., "I felt as one with the other players"); self-esteem [e.g., "Playing the game made me insecure (reverse coded)"]; meaningful existence (e.g., "I felt in control over the game"); and control (e.g., I think my participation in the game was useful"). Higher scores reflect lower psychological need.

Effect of Social Norms Priming

The following items, administered in a post-drive survey, were adapted or created for this study and provide additional information about the participants' experience. *Identification with passenger* was measured by six items that asked participants to indicate (1 = no, 2 = maybe, 3 = yes) their identification with the passenger (i.e., Is the passenger someone you would like to know better or someone you liked?). *Passenger approval*, a measure of subjective norms, was measured by five items asking participants how likely it was (1 = very unlikely to 5 = very likely) that the passenger would approve of the participant's involvement in five risky driving behaviors such as driving 10 mph above the speed limit and closely following a slow vehicle.

Power and Sample Size

Power analysis was based on data from previous simulation studies (Simons-Morton et al., 2014; Bingham et al., 2016) for the variable, percentage of correct stops at 18 yellow light intersections that invoke a stopping dilemma. Accordingly, an effect size of 0.53 was expected. Thus, detecting a treatment group difference of this magnitude with a power of 0.80 and alpha of 0.05 a sample size of 40 per group is required. Given the experimental design and counterbalancing requirements, the three-group design requires a total sample size of 120 participants for each study.

Statistical Analysis

Treatment group differences on the pre-drive randomization and post-drive assessment variables (evaluating passenger norms manipulation) were assessed using one-way ANOVA (2X2 ANOVA might bias against possible effects) and *post hoc* comparisons with Tukey–Kramer adjustment. Between treatment groups psychological needs differences for excluded and included participants were assessed after the exclusion task using independent *t*-tests.

The primary driving performance comparisons were examined as the differences (passenger minus solo drive) of the treatment groups on each measure of risky driving. The solo drive served to control for individual differences in driving behavior. PROC GLIMMIX in SAS (version 9.4) was used to fit generalized linear mixed models (GLMMs) where the outcomes were % Not Stopping for Red light (average of binary outcomes generating odds ratios), % Time in Red (normal outcome of the average across multiple intersections generating β, and % Passing Slowing Vehicle (average of binary outcomes generating odds ratios). The GLIMMIX model follows:

$$\mu = \beta_0 + \beta_1 \text{ (BaseExp)(Condition1)} + \beta_2\text{(BaseExp)}$$
$$\text{(Condition2)} + \beta_3\text{(BaseExp)(Condition3)} + b_\text{i}$$

where $\mu = \log(\frac{\pi}{1-\pi})$ for the variables pf "Failure to Stop at a red light" (binary variable), "Pass Slow Vehicle" (binomial random variable) and "mean % Time in Red" (continuous variable); BaseExp (0 = solo baseline and 1 = experimental driving with confederate); b_i denotes a subject specific random effect, β_0 denotes baseline value, and β_1, β_2, and β_3 characterize the effect of each exclusion/inclusion and passenger risk comparison. There were two treatment group comparisons (in relation to baseline values): comparison 1 was the effect of a risk accepting vs. passive passenger given exclusion, where 1 = Excluded + Passive passenger; 2 = Excluded + Risk accepting passenger; Comparison 2 was the effect of inclusion (fair play) vs. exclusion, given a risky passenger; 1 = Exclusion + Risk accepting and 2 = Inclusion (fair play) + Risk accepting Passenger. The models were then rerun adjusting separately for baseline self-esteem and susceptibility to peer pressure. Odds ratios are considered the effect size for GLIMMIX models with binary outcomes and the beta is the effect size for mixed models. In addition, we calculated the standardized mean treatment group differences.

RESULTS

Study Participants

In Study 1, 112 of the 134 recruited participants and in Study 2, 115 of the 137 recruited participants completed the protocol and were included in the analyses. Exclusions were due to simulator sickness or technical issues with the simulator, a rate that is consistent with other driving simulator studies (Caird and Horrey, 2011). As a check on randomization we assessed at baseline, before any treatment group manipulation or simulated driving, measures of self-esteem, susceptibility to peer pressure, risky driving behavior, social status, and sensation seeking, none which differed by group. Shown in **Table 1**, non-significant treatment group differences for five item self-esteem scale had small to moderate effect sizes of 0.6 in Study 1 and 0.25 in Study 2; effect sizes for the four-item susceptibility to peer pressure scale were 0.6 in Study 1 and 0.09 in study 2. These findings are consistent with successful randomization.

Randomization and Confederate Passenger Manipulation

The top half of **Table 1** for Study 1 (males) and bottom half for Study 2 (females) show the post-treatment values for identification with the passenger and perceived passenger approval of risky driving, assessed the success of the confederate passenger manipulation. Participants in both studies were more likely to identify with the risk-accepting passenger than the passive passenger, with effect sizes for the scale with response options of 1–3 of 0.47 (moderate) and 0.19 (small) in Study 1 and 0.47 (moderate) and 0.46 (moderate) in Study 2, consistent with previous research (Simons-Morton et al., 2014). Also, in both studies participants perceived that the risk accepting passenger was more approving of risky driving than the passive passenger, with effect sizes on the scale with response options ranging 1–5 of 0.73 (moderate to large) and 0.17 (small) in Study 1 and 0.84 (large) and 0.51 (moderate) in Study 2, consistent with the planned manipulation of confederate passenger norms.

Manipulation of Exclusion

Shown in **Table 2** are the values for each study assessing the Cyberball manipulation and psychological needs variables immediately after Cyberball. Means in response to the question, "How much did they throw you the ball?" were higher (one-way ANOVA, three groups) for the inclusion (fair play) than the exclusion groups in both studies, with small effect sizes of 0.20 and 0.16 when the two excluded groups were compared and large effect sizes of 1.06 and 1.02 when the included group was compared to the included (fair play) group, consistent with successful manipulation of exclusion. Need threat values were somewhat higher in Study 1 (males) than in Study 2 (females), but in both studies the values did not differ between the two exclusion groups and were lower in the exclusion groups than the inclusion (fair play) group; moderate to large effect sizes of 0.44 to 1.55 across the two studies for inclusion (fair play) with risk accepting passenger vs. exclusion with risk accepting passenger, as expected and consistent with successful manipulation.

Treatment Group Differences

Shown in **Table 3** (top half for Study 1 and bottom half for Study 2) are the means (and SDs) for each measure of risk for each group for the solo and experimental passenger drives. The differences in the baseline values of the three outcome

TABLE 1 | Pre-drive check on randomization and post-drive check on passenger social norms.

		Excluded + passive passenger			Excluded + risk-accepting passenger				Included (fair play + risk-accepting passenger				
		N	Mean	*SD*	*N*	Mean	*SD*	Effect size §	*N*	Mean	*SD*	*p*	Effect size §§
	Measure (items; range)				**Pre-drive randomization check**†								
Study 1: males (*N* = 112)	Self-esteem^{ns} (1; 1–5)	40	4.03	0.83	36	4.28	0.61	0.34	36	3.94	0.53	0.10	0.60
	Susceptibility to peer pressure^{ns} (10; 1–4)	40	1.69	0.52	36	1.85	0.41	0.34	36	1.81	0.53	0.33	0.63
					Post-drive check on norms manipulation/perceptions of confederate passenger‡								
	Identification with passenger*** (6; 1–3)	39	1.99	0.40	36	2.39^{aaa}	0.47	0.92	36	2.30^{a}	0.50	<0.001	0.19
	Passenger approval of risky driving** (5; 1–5)	39	2.83	0.68	36	4.13^{aaa}	0.73	1.84	36	4.25^{aaa}	0.70	<0.001	0.17
					Pre-drive randomization check†								
Study 2: females (*N* = 115)	Self-esteem^{ns} (1; 1–5)	39	3.63	0.71	39	3.62	0.94	0.01	37	3.38	0.98	0.39	0.25
	Susceptibility to peer pressure^{ns} (10; 1–4)	39	1.59	0.45	39	1.73	0.46	0.31	37	1.77	0.47	0.23	0.09
					Post-drive check on norms manipulation/perceptions of confederate passenger‡								
	Identification with passenger*** (6; 1–3)	39	2.04	0.26	39	2.27	0.47	0.61	37	2.46	0.34	<0.001	0.46
	Passenger approval of risky driving** (5; 1–5)	39	2.47	0.50	39	4.12	0.84	2.39	37	4.47	0.50	<0.001	0.51

†Prior to eventual group assignment; ‡Administered after randomization and experimental drives. One-way ANOVA; post hoc comparisons with Tukey–Kramer adjustment; $^{ns}p > 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$ for overall model. $^{a}p < 0.05$, $^{aaa}p < 0.001$ when compared to excluded + passive passenger group. § Standardize mean differences for Excluded + passive passenger vs. Excluded plus risk-accepting passenger; §§ Standardized mean differences for Excluded plus risk-accepting vs. Included vs. risk-accepting passenger.

TABLE 2 | Cyberball manipulation check and need threat scores after exclusion or inclusion.

							Exclusion				Inclusion (fair play)				
			Excluded + passive passenger				Excluded + risk- accepting passenger				Included (fair play) + risk-accepting passenger				
	Measures (item; range)	Alpha	*N*	Mean	*SD*	*N*	Mean	*SD*	Effect size §	*N*	Mean	*SD*	*p*	Effect size §§
Study 1: males (*N* = 112)	Cyberball manipulation check (1; 1–5)	–	36	2.87	0.80	39	2.72	0.66	0.20	36	$3.50^{aa,bb}$	0.81	<0.001	1.06
	Belongingness (5; 1–7)	0.81	36	3.30	0.95	40	3.20	1.03	0.10	35	$4.79^{aaa,bbb}$	1.11	<0.001	1.48
	Self-esteem (5; 1–7)	0.76	36	4.58	0.95	40	5.13	0.99	0.57	35	5.61^{aaa}	1.17	<0.001	0.44
	Control (5; 1–7)	0.82	36	3.41	0.90	40	2.90	1.21	0.48	35	$4.61^{aaa,bbb}$	1.06	<0.001	1.50
	Meaningful existence (5; 1–7)	0.86	36	4.05	1.16	40	3.85	1.26	0.17	35	$4.83^{a,bb}$	1.30	<0.01	0.75
Study 2: females (*N* = 115)	Cyberball manipulation check (1; 1–5)	–	39	2.56	0.79	39	2.69	0.83	0.16	36	$3.54^{aaa,bbb}$	0.84	<0.001	1.02
	Belongingness (5; 1–7)	0.87	39	2.81	1.06	38	2.81	1.18	0.00	37	$4.38^{aaa,bbb}$	1.19	<0.001	1.32
	Self-esteem (5; 1–7)	0.80	39	4.44	1.14	38	4.47	1.36	0.02	37	$5.17^{aa,b}$	1.14	0.015	0.56
	Control (5; 1–7)	0.85	39	2.64	0.96	38	2.57	1.05	0.07	37	$4.38^{aaa,bbb}$	1.27	<0.001	1.55
	Meaningful existence (5; 1–7)	0.89	39	3.38	1.26	38	3.60	1.37	0.17	37	$4.45^{aaa,bb}$	1.22	0.001	0.66

$^{a}p < 0.05$, $^{aa}p < 0.01$, $^{aaa}p < 0.001$ when compared to excluded + passive passenger group; $^{b}p < 0.05$, $^{bb}p < 0.01$, $^{bbb}p < 0.001$ when compared to excluded + risk-accepting passenger group. § Standardized mean differences for Excluded + passive passenger vs Excluded plus risk-accepting passenger; §§ Standardized mean differences for Excluded plus risk-accepting vs Included vs risk-accepting passenger.

variables between the three groups were not significant in ANOVA (data not shown), providing evidence of successful random assignment and consistency in the baseline simulation drives. Note that baseline measures of risky driving were higher for Study 1 males than Study 2 females, as might be expected, particularly in passing the slowing vehicle, with (30 to 34% of males and only 3 to 11% of females passing). The last three rows for each study show the differences between the solo and the passenger drive for each measure and group, values that are useful for interpreting the treatment group differences. Note declines from baseline to passenger drive for excluded participants, at least for the two intersection tasks, and increases for most measures among included participants.

Effect of Passenger Type

In **Table 4** the columns on the left show the estimates for the effect of passenger type on the three risky driving measures among participants in the two exclusion groups, adjusted for self-esteem. In Study 1 (males) there were significant effects of passenger type for 2 of 3 measures, % Not Stopping for Red Lights (OR = 2.09), which declined from 59.3% at baseline to 50.0% in the passive passenger group and from 48.6 to 46.4% for the risk accepting passenger group (see **Table 3**), and % passing the slowing vehicle (OR = 3.41), which declined from 30.0 to 27.5% in the passive passenger group and increased from 34.3 to 52.8% in the risky passenger group, consistent with an effect of increased risk in the presence of the risk accepting passenger. The effect sizes were large for all three measures of risky driving.

In Study 2 female drivers were significantly more likely to pass the slowing vehicle in the presence of a risk accepting passenger, increasing from 10 to 21%, but not changing among those driving with the passive passenger (see **Table 3**). Overall, the treatment group comparisons for the risky driving variables favored increased risky driving among those exposed to the risk accepting passenger on 2 of 3 measures for males and 1 of 3 for females, with large effect sizes.

Effect of Exclusion vs. Inclusion (Fair Play)

The right half of **Table 4** show the treatment group differences for each risky driving measure for participants in the excluded and included (fair play) groups in the presence of a risk accepting passenger. In Study 1 (males) no significant treatment group differences were found, although % Not Stopping and % Time in Red ($p = 0.11$ and $p = 0.10$) had moderate effect sizes favoring increased risk in the inclusion (fair play) group, with slight declines in the exclusion group

TABLE 3 | Mean values for each drive and measure of risk (unadjusted).

	Measure	Excluded + passive passenger			Excluded + risk-accepting passenger			Included (fair play) + risk-accepting passenger		
		N	Mean	*SD*	*N*	Mean	*SD*	*N*	Mean	*SD*
Study 1: males (*N* = 112)	Failure to stop – baseline solo (%)	40	59.25	40.91	36	48.61	36.27	36	55.00	37.83
	Failure to stop – experiment/ passenger (%)	40	50.00	43.85	36	46.39	39.51	36	58.06	37.33
	Percent time in red – baseline solo (%)	40	36.30	25.67	36	28.92	22.22	36	32.73	24.18
	Percent time in red – experiment/passenger (%)	40	28.75	26.25	36	25.49	22.59	36	32.63	22.58
	Passed slow vehicle – baseline solo (%)	40	30.00	46.41	35	34.29	48.16	35	34.29	48.16
	Passed slow vehicle – experiment/passenger (%)	40	27.50	45.22	36	52.78	50.63	36	52.78	50.63
	Difference failed to stop	40	−9.25	19.13	36	−2.22	20.02	36	3.06	16.87
	Difference percent time in red	40	−7.56	12.63	36	−3.44	11.77	36	−0.10	11.21
	Difference pass slow vehicle	40	−0.03	0.36	35	0.17	0.45	35	0.17	0.51
Study 2: females (*N* = 115)	Failure to stop – baseline solo (%)	39	46.41	37.10	39	47.69	35.05	37	55.94	31.57
	Failure to stop – experiment/ passenger (%)	39	38.97	34.24	39	44.87	35.16	37	59.46	33.50
	Percent time in red – baseline solo (%)	39	27.48	22.73	39	29.25	22.16	37	33.61	20.83
	Percent time in red – experiment/passenger (%)	39	21.14	19.78	39	25.39	20.42	37	34.11	20.43
	Passed slow vehicle – baseline solo (%)	39	2.56	16.01	39	10.26	30.74	37	10.81	31.48
	Passed slow vehicle – experiment/passenger (%)	39	2.56	16.01	39	20.51	40.91	37	16.22	37.39
	Difference failed to stop	39	−7.44	24.03	39	−2.82	21.14	37	3.51	18.14
	Difference percent time in red	39	−6.34	15.19	39	−3.86	14.04	37	0.54	11.21
	Difference pass slow vehicle	39	0.0	0.0	39	10.26	30.74	37	5.41	32.88

TABLE 4 | Treatment group differences*.

		Excluded + risk-accepting passenger vs. Excluded + passive passenger (effect of risk-accepting passenger)				Excluded + risk-accepting passenger vs. Included (fair play) + risk-accepting passenger (effect of exclusion)			
		Est.	95% CI		*p*-value	Est.	95% CI		*p*-value
Study 1: males (N = 112)	Failed to stop (OR)	2.09	1.14	3.81	**0.02**	0.63	0.35	1.12	0.11
	Percent time in red (β)	3.60	−0.72	7.93	0.10	−3.73	−8.22	0.75	0.10
	Pass slow vehicle (OR)	3.41	1.03	11.35	**0.05**	1.04	0.32	3.42	0.94
Study 2: females (N = 115)	Failed to stop (OR)	1.40	0.84	2.32	0.19	0.60	0.36	0.98	**0.04**
	Percent time in red (β)	2.56	−2.24	7.36	0.30	−5.30	−10.16	−0.45	**0.03**
	Pass slow vehicle (OR)	9.94	1.16	85.31	**0.04**	1.46	0.44	4.81	0.53

**Controlling for self-esteem; Odds ratio is the effect size for GLIMMIX model with binary outcomes and the beta is the effect size for mixed models. The significant (<0.05) p values are in bold.*

and slight increases or little change in the inclusion (fair play) group. Analyses adjusted for susceptibility to peer pressure resulted in negligible differences in the estimates (available upon request).

For females in Study 2, shown in the right half of **Table 4**, % Not Stopping ($B = 0.60$, $p = 0.04$) was significant, with declines in the socially excluded group (from 47.7 to 44.9%) and increases in the socially included (fair play) group (from 55.9 to 59.4%), and % Time in Red was significant ($B = -5.30$, $p = 0.03$) with a decline from 29.3 to 25.4% in the excluded group and an increase from 33.6 to 34.1% in the socially included group.

DISCUSSION

This research examined influences of peer passengers and social exclusion on simulated risky driving among male and female teenagers. Identical trials were conducted separately with males and females, in which participants were randomized to one of three treatment conditions allowing evaluation of the following research questions about simulated risky driving: (a) What is the effect of exposure to a risk accepting or passive passenger after social exclusion? (b) What is the effect of social exclusion or social inclusion (fair play) when exposed to a risk accepting passenger? We discuss the findings for each trial (males and females) in relation to each research question.

Peer Influence on Risky Driving After Social Exclusion

To test the possible effect of peer influence on risky driving, it was necessary for participants to perceive differences in the risk acceptance of the confederate passengers. In post-treatment analyses, both males and females identified more strongly with the risk accepting passenger and perceived that the risk accepting passenger was more approving of risky driving than the passive passenger, consistent with successful manipulation of confederate passenger norms, thus allowing for logical interpretation of passenger effects. Accordingly, the findings generally support increased simulated risky driving in the presence of a risk accepting passenger after social exclusion. For males, 2 of the 3 risky driving variables, not stopping for the red light and passing the slowing vehicle, indicated significantly greater risk among those exposed to a risk accepting passenger relative to those exposed to a risk passive passenger. For females, 1 of 3 measures, passing the slowing vehicle, indicated significantly greater risk among those exposed to a risk accepting passenger, consistent with conformity to social norms. Hence, 2 of 3 variables for males and 1 of 3 for females indicated greater risky driving in the presence of a risk accepting passenger relative to a passive passenger after social exclusion, with moderate or large effect sizes.

These findings are generally consistent with social norms theory (Simons-Morton et al., 2009), with participants conforming in their driving behavior to passenger norms regarding risky driving. These findings are also consistent with previous simulation trials that found that simulated risky driving was greater among young males in the presence of risk accepting confederate peers who exerted mild pressure to drive in a more risky manner, which the authors attributed to peer pressure and social norms (Bingham et al., 2016); and in the presence of risk accepting confederate peers who exerted no explicit pressure during the drive, which the authors attributed to perceived social norms (Simons-Morton et al., 2014). Other research found that simulated risky driving was greater among young males and females in the presence of their own peers (Ross et al., 2016), attributable to greater reward sensitivity in the presence of peers, similar to the finding of Chein et al. (2011), who reported greater risky driving among teens (compared to adults) whose peers observed them driving a desktop simulator.

Social Exclusion or Social Inclusion (Fair Play) in the Presence of a Risk Accepting Passenger

Both male and female participants in the social inclusion (fair play) group reported being passed the Cyberball more than those in the exclusion group, consistent with successful manipulation of exclusion. In addition, both male and female participants in the inclusion (fair play) groups reported consistently higher scores than those in the exclusion groups on need threat variables (representing lower psychological needs) consistent with previous research indicating similar post-Cyberball need threat scores for both males and females (Pharo et al., 2011; Pharo, 2012). The findings for social exclusion on driving behavior generally favored increased risk for those included than for those excluded. For male participants, there were trends in two variables, with declines in risk from baseline among those in the exclusion group and no change in the inclusion group. For female participants, there were significant differences in two measures, with declines in the exclusion group and increases or no change in the inclusion (fair play) group. These findings are counter to our expectation that exclusion (vs. inclusion) would increase risk taking in the presence of risk accepting peers because conformity is a good way to gain, regain, or increase social acceptance after social exclusion (Williams, 2007). There are several possible explanations.

Some literature suggests that teenage males exert greater peer influence than females on both teenage males and females (Jacobs et al., 2017) and females may be more susceptible to peer influences, particularly from opposite sex friends (Dick et al., 2007). Viewed from this perspective, our findings suggest that social inclusion in the form of fair play, particularly among females, might reduce inhibition and increase susceptibility to peer influence in the presence of male peers with risk accepting attitudes. This is consistent with research suggesting specific boundary conditions on the effects of exclusion, such that participants who anticipate easily connecting with others are more likely to conform (Maner et al., 2007), and presumably inclusion (fair play) would increase the anticipation of easily connecting with others. Thus, teenagers who experienced fair play may have been more confident than teenagers who were excluded about connecting with the risk accepting male passenger and this effect might have been stronger among females than males. This possibility seems particularly likely given that the differences in risk taking between excluded and not-excluded participants are driven both by increases in risk taking in the inclusion (fair play) group and decreases in the excluded group.

Alternatively, other research has shown that being rejected does not always cause affiliative behaviors, but instead can cause antisocial responses, not only toward the excluder but also toward neutral others (Twenge et al., 2001). A large body of research demonstrates that feelings of arousal or threat can carry across situations, encouraging the exertion of control over non-social sources of threat. For example, chronic rejection is associated with decreases in school engagement among school age children (Buhs et al., 2006). Thus, it is possible that our exclusion priming threatened participants' sense of safety and well-being, causing them to retreat and conform less to the social norms of the risk accepting confederate passenger by driving more cautiously. Relatedly, Park and Baumeister (2015) reported an increase in cautious response bias with social exclusion among adults. Their recognition task was designed to identify a preference for finding correct answers (at the risk of including some incorrect responses) or a preference for avoiding mistakes. The excluded group sought to avoid mistakes (cautious response bias) and hesitated for longer before responding whereas the included group favored finding correct answers (risky response bias).

Study strengths include experimental design using a high-fidelity simulator and proven risky driving protocol applied in separate studies with males and females. Moreover, our experimental manipulations were successful in that participants who were excluded reported lower values on the need threat measures; participants perceived the risk accepting passenger to be more accepting of risk than the passive passenger; and participants identified post-treatment with the risk accepting confederate passenger relative to the passive passenger.

The primary study limitation is the lack of a full factorial design (due to budget and time limitations), which would have provided a more elegant and complete test of passenger (with male and female participants exposed to male and female peers) and exclusion vs. inclusion (fair play) effects. We did not actually manipulate inclusion by allowing the participants who experienced fair play that others were being excluded, so our inclusion condition was actually a fair play or not-exclused condition. Also, the protocol called for the passive passenger to be neutral with respect to risk, but it is possible the participants interpreted passiveness as rejection, which could have affected their behavior, although we found no evidence of this possibility.

CONCLUSION

After being socially excluded, male and female teenage study participants engaged in relatively greater risky simulated driving in the presence of a risk accepting compared to a passive passenger, consistent with social norms theory and previous research. Teenage female study participants in the presence of a risk-accepting passenger engaged in more risky driving after experiencing fair play, compared to those who had been socially excluded, contrary to prevailing theory; males exhibited similar but non-significant trends. These findings provide additional support for the contention that social norms influence teenage risky driving behavior, indicate that inclusion might increase and exclusion might reduce risk taking behavior in the presence of a risk-accepting male peer, suggesting that social relationships among teens matter with respect to their influence on risk behavior. The findings suggest important new avenues for research on gender differences with respect to the effects of social exclusion on adolescent risk behavior.

ETHICS STATEMENT

The study was reviewed and approved by the University of Michigan IRB. Written and informed consent was obtained from the parents of all participants and assent was obtained from all participants.

AUTHOR CONTRIBUTIONS

BS-M, CB, and JS conceptualized the study, obtain funding, and participated in the conduct, data analyses, and manuscript preparation. KL and CZ participated in methods development, analyses, and manuscript preparation. LB and EF participated in analyses and manuscript preparation.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.00923/full#supplementary-material

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Neural Correlates of Simulated Driving While Performing a Secondary Task: A Review

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Distracted driving consists in performing a secondary task while driving, such as cell-phone conversation. Given the limited resources of the attentional system, engaging in a secondary task while driving increases the risk to have car accidents. The secondary task engagement while driving can depend on or be affected by different factors, including driver's individual characteristics, necessities, environmental conditions, and so forth. In the present work, the neuroimaging studies that investigated the brain areas involved in simulated driving during the execution of a secondary task (visual and overall auditory tasks) were reviewed in light of driving settings. In general, although there are also differences in decrease and increase brain activations across studies, due to the varieties of paradigms used (simulators, secondary tasks and neuroimaging techniques), the dual-task condition (simulated driving plus secondary task), as compared to the simulated driving-alone condition, was generally found to yield a significant shift in activations from occipital to fronto-parietal brain regions. These findings show that when a secondary task is added during driving the neural system redirects attentional resources away from visual processing, increasing the possibility of incorrect, dangerous or risky behavioral responses. The shift of the attentional resources can occur even if driving behavior is not explicitly affected. Limits of the neuroimaging studies reviewed and future research directions, including the need to explore the role of personality factors in the modulation of the neural programs while engaging distracted driving, are briefly discussed.

Keywords: distracted driving, language, audio, visual, attention, prevention

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INTRODUCTION

Driving is a complex activity that involves several mental cognitive processes requiring the coordination of different abilities, such as visuo-spatial attention, visuo-motor, and auditory skills (Graydon et al., 2004). In particular, the driving task is based on continuous adjustments and reallocation of attention, that can be affected by different sources of distraction. In the real-world, distraction may be due to different factors that generally lead drivers' eyes or mind off the road, such as traffic density, speed, driver psychophysiological conditions (e.g., sleepiness, mood), type of road, weather and so forth (Oron-Gilad and Ronen, 2007; McGehee, 2014). In addition, despite the complexity of the driving task, drivers usually engage in secondary tasks for different reasons, including the attempt to make the time spent on the roadway more productive (Reschovsky, 2004). These secondary tasks include more traditional activities, such as talking to passengers, listening to the radio, eating, drinking, lighting a cigarette, applying makeup (e.g., Stutts et al., 2003), as well as cell-phone related activities, that is having conversations by mobile, surfing the internet, sending and receiving e-mails, or faxes and texting. Thus, the secondary task generally involves removing cognitive resources off the immediate driving task and sometimes also removing driver's eyes off the road or hands off the wheel (National Highway Traffic and Safety Administration (NHTSA), 2015). It generally increases the working memory load and is not appropriate for maintaining alertness (Oron-Gilad et al., 2008).

In this vein, activities performed using new technologies (e.g., Smartphone) are more distracting because they are more cognitively engaging and are performed over longer periods of time (Strayer et al., 2006). According to different experts and studies the use of cellular phones while driving enormously contributes to collisions between motor vehicles (e.g., Violanti and Marshall, 1996). For example, holding a complex conversation by cell-phone also affects driving performance (e.g., McKnight and McKnight, 1993). Even processing of a single, verbally presented word was found to negatively affect driver braking response (Rossi et al., 2012). For these reasons, different countries (e.g., Brazil, Israel, Australia, Italy) prohibited using smartphones/cellular phones (hand held) while driving. However, Dingus et al. (2011) revealed that eating or reaching for objects in the vehicle while driving were also associated with high increased odds of having a motor vehicle collision or near-crash.

Given these implications, the understanding of factors that lead drivers to get engaged in distracted driving (e.g., driver's individual characteristics, driving experience, necessities, environmental conditions) is extremely important to better implement strategies aimed at preventing fatal accidents. For example, as concerns personality traits, Parr et al. (2016) revealed that in teens high openness and conscientiousness predicted the secondary task engagement while driving, such as texting frequency and interacting with a phone, whereas low agreeableness predicted lesser texting frequency and interacting with a phone; in older adults, extraversion predicted talking on and interacting with a phone. However, the engagement in secondary tasks requiring drivers to look away from the road ahead is generally more risky for novice than expert drivers (Klauer et al., 2014). Interestingly, the individual attitude toward daydreaming/mind wandering can also be risky while driving, especially under monotonous driving circumstances. In such cases, the engagement in a secondary task can be the lesser of the two evils, reducing the chance of mind wandering to intrude the primary activity, when the driving setting is monotonous (Nijboer et al., 2016).

Although the study of the role of factors related to the drivers' individual characteristics or environmental conditions in distracted driving appears to be crucial, research in the field is scarce. In addition, the way in which such factors affect neural correlates of distracted driving is even more neglected by the experimental research. In the last two decades the application of neuroimaging techniques has been used in association with simulated driving and multitasking using different methodologies, but no study has considered the modulation of personality factors. Only some studies considered to some extent the environmental conditions associated to the secondary task engagement, mainly using simulation contexts. In this direction, more insights might be gained moving from the general driving settings. Therefore, in the present paper the brain systems that are mostly involved in distracted driving are explored in light of the driving setting, that is, on the basis of the type of the primary driving task (that also relies on the driving scene) combined with the secondary task. More specifically, here we aimed at understanding whether brain activations associated with driving decrease when a secondary task is added, in spite of driving and distracting tasks draw on different cortical areas. This would allow to understand if during distracted driving changes in brain activations occur also in absence of behavioral changes.

INCLUSION CRITERIA FOR PAPERS

The literature was reviewed using a systematic method. PubMed, Science Direct and Web of Science were used as databases with the following strings "driving and multitasking" or "distracted driving" plus one of the following words: "neuroimaging," "fMRI," "MEG". Sixteen papers were found. The a priori inclusion criteria were seven: (1) neuroimaging studies had to be based on fMRI and Magnetoencephalography (MEG) techniques. These studies were preferred because of their relative satisfactory spatial and temporal resolution; on the contrary, Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT) were not included due to their very low temporal resolution, whereas Electroencephalography (EEG) and Near-infrared Spectroscopy (NIRS) studies were not included due to their very low spatial resolution. (2) Studies had to include at least one condition in which participants were specifically instructed to drive and simultaneously to perform on a secondary task (e.g., visual, auditory in nature); thus, neuroimaging studies focused on driving only were excluded. (3) All participants in the studies had to be healthy adults. (4) All neuroimaging studies had to include a control condition (baseline), that is an appropriate matched control condition (e.g., driving + secondary task vs. driving only), to exclude all the activations that were not directly connected to distracted driving. (5) Only group studies were included, that is studies with at least five participants. (6) There could be no pharmacological manipulation. (7) Only peer-reviewed original articles published in established scientific journals were included; conference papers were excluded.

Using these criteria, we selected 11 papers, 9 fMRI, and 2 MEG papers (see **Table 1**).

DRIVING SETTINGS

In some studies the driving setting consisted in straight driving (Sasai et al., 2016), also on real world highways (Graydon et al., 2004; Bowyer et al., 2009; Hsieh et al., 2009). In other studies it

TABLE 1 | Neuroimaging studies included in the present review.

Study	*N*	Mean age	Age range	DE	SD	Secondary task	Behavioral results	Contrast condition and main neuroimaging results
fMRI (Graydon et al., 2004)	6–3F	–	22–28	.	Real world highway presented in a fronto-parallel viewing perspective	Visual event detection task (CEDR—central event detection response, to red colored stimuli	SD + CEDR Task = 611 ms	SD + CEDR vs. SD
							CEDR Task = 550 ms	Activation of Fronto-parietal regions
							$t = -2.68$, $p < 0.05$	
fMRI (Just et al., 2008)	29–14F	–	18–25	.	Steering a vehicle along a curving virtual road using a trackball or mouse in the right hand	Listening and answering to true/false pre-determined questions	SD + Audio Task = 92% (ACC)	SD + Audio Task vs. SD
							Mean road-maintenance errors:	Activation of the bilateral temporal language areas, left inferior frontal gyrus;
							SD = 8.7 (9.7)	Decrease of activation in spatial brain areas
							SD + Listening = 12.8 (11.6)	
							$t_{(28)} = 2.22$, $p < 0.05$	
							The mean root mean squared deviation from the ideal path:	
							SD + Listening = 2.64 (0.56)	
							SD = 2.48 (0.51)	
							$t_{(28)} = 2.79$, $p < 0.01$	
MEG Bowyer et al., 2009	28–17F 19 MEG	36.5 (13.8)	18–65	–	Similar to Bowyer et al. (2007)	Listening and answering to pre-determined questions – 1 question = short conversation; multiple questions = long conversation	Results 19 subjects in MEG	SD + Long Conversation Task vs. SD
							SD + Long Conversation Task:	Decrease of activation in the visual cortex and in the right superior parietal region
							RT = 1,043 ms-SE = 65 ms;	
							SD = RT = 944 ms-SE = 48 ms	
fMRI (Hsieh et al., 2009)	10–6F	36.9	19–61	–	Similar to Bowyer et al. (2007, 2009)	Listening and answering to pre-determined questions in order to carry on short and long conversations	Results in fMRI:	SD + Long Conversation vs. SD
							SD + Long Conversation:	Activations of language areas (e.g., Wernicke's and Broca's areas) and fronto-parietal areas
							RT = 770 ms;	
							SD (no conversation) = RT = 726 ms	

(Continued)

TABLE 1 | Continued

Study	N	Mean age	Age range	DE	SD	Secondary task	Behavioral results	Contrast condition and main neuroimaging results
MEG (Fort et al., 2010)	13 M	25.4 (2.1)	21–28	≥3 year	Driving on single or dual roadways, following traffic light rules, and direction signs, with little traffic and few pedestrians on the roads	Listening to broadcast and answering to 3 pre-determined questions (for half of participants)	SD (traffic lights) + Audio Task	SD + Audio Task vs. SD
							RT = 430 ms	In both conditions, with traffic light or arrows, sensory visual areas and right fronto-parietal network were activated
							SD (traffic lights): RT = 399 ms	With traffic lights: decreases of brain activity in primary visual areas, dorsolateral prefrontal cortex, and right temporo-parietal junction; increase of activation in the posterior parietal cortex. With arrows: decreases of brain activity in occipital visual areas, frontal areas, including the premotor area and left posterior parietal area; increase of activity in the frontopolar cortex
							$F = 8.167$; $p = 0.013$	
							SD (arrows) + Audio Task	
							RT = 875 ms	
							SD (arrows): RT = 890 ms	
							$F = 2.301$; $p = 0.153$	
fMRI (Uchiyama et al., 2012)	18–8F	27.7 (4.3)	–	–	Following a car at the distance of 5 m using a joystick with the right hand. No intersections, other vehicles, or obstacles were included	(1) Sentence comprehension: judge whether the subject of the verb corresponded to the person in the paired words; (2) tone discrimination: judge whether the beep tone in the response phase was high or low	Sentence comprehension accuracy:	SD + Audio Task vs. SD
							SD + Audio Task: 86.2%	Decrease of activations in the medial prefrontal cortex and left superior occipital gyrus
							Audio Task: 88.9% ($SD = 12.23$)	Car-following performance showed positive correlation with brain activity in the bilateral lateral occipital complex and the right inferior parietal lobule
							$t_{(17)} = 0.90$, $p = 0.381$	
							Sentence comprehension RT:	

(Continued)

TABLE 1 | Continued

Study	*N*	Mean age	Age range	DE	SD	Secondary task	Behavioral results	Contrast condition and main neuroimaging results
							SD + Audio Task: 1,668 ms (320)	
							Audio Task: 1,841 ms (300)	
							$t_{(17)} = 2.77$, $p < 0.05$	
							Car-following performance worse during SD + Audio Task than during SD alone	
fMRI (Schweizer et al., 2013)	16–7F	25.8 (1.5)	20–30	7.4 (2.5)	Straight driving, turning left or right at intersection with or without incoming traffic using steering wheel and pedals	Listening and answering to pre-determined questions	SD (Straight Driving) + Audio Task	SD + Audio Task vs. SD
							Speed: 58.69 (2.34)	Shift in activation from the posterior to the anterior brain during the dual-task condition
							SD (Straight Driving) – Speed: 58.57 (3.36)	
							SD (Left turn traffic) + Audio Task – Speed: 28.98 (3.76)	
							SD (Left turn) – Speed: 26.79 (5.17)	
							SD (Left turn traffic) – Speed: 29.35 (4.26)	
fMRI (Chung et al., 2014)	16 M	26.6 (2.1)	–	2.7 (1.5)	Using the wheel and pedals to drive at a constant speed (110 km/h) on a straight road with very few distracting elements, without changing lanes	Listening and answering to questions regarding double-digit carry-over calculation with sums <100	–	SD + Calculation Task vs. SD
								Activations of cingulate gyrus and sub-lobar region
								Decrease of activation of regions associated with spatial processing, movement planning and execution
fMRI (Al-Hashimi et al., 2015)	31–14F	38.4 (6.3)	30–40	–	Keeping the car within a target box. Right and left turns, and inclining and declining hills formed the tracks, varying from mild to severe	Discrimination sign task (green circles −33% frequency—with a right button press)	Mean accuracy no significant differences	SD + Discrimination Sign Task vs. SD
							SD + Discrimination Sign Task: 513.9 ms	Activation of the right superior parietal lobule
							SD: 530.7 ms	
							$t_{(30)} = 3.77$, $p = 0.00042$	

(Continued)

TABLE 1 | Continued

Study	*N*	Mean age	Age range	DE	SD	Secondary task	Behavioral results	Contrast condition and main neuroimaging results
fMRI (Sasai et al., 2016)	13 M	–	22–34	–	Minimizing the deviation from the simulated track centerline	GPS instructions (integrated task) or radio show (split task)	No significant difference in any measures between the integrated and split task conditions	Reduced multivariate functional connectivity during the split task between driving and listening network; higher integration of information content of driving and listening networks during the integrated task
fMRI (Choi et al., 2017)	15 M	26 (1.4)	–	2.5 (1.6)	Using the wheel and pedals to drive at a constant speed (80 km/h) on a straight road with very few distracting elements, without changing lanes	Similar to Chung et al. (2014)	Accuracy for SD + Calculation Task 78.5 ± 11.7%; For Calculation Task: 84.8 ± 10.9% *t*-test (PASW Statistics 18), $p = 0.196$	SD + Calculation Task vs. SD Inferior frontal gyrus and the superior temporal gyrus enhanced activation

DE, driving experience; SD, simulated driving.

consisted in driving on computerized roads at constant speed (Chung et al., 2014; Choi et al., 2017), following a car at the distance of 5 m (Uchiyama et al., 2012), or even following traffic light rules, and direction signs (Fort et al., 2010), including left and right turns, from simple (Just et al., 2008) to more complex driving scenes (Schweizer et al., 2013; Al-Hashimi et al., 2015). The settings of simulated driving were implemented using specific devices, such as, a trackball or mouse (Just et al., 2008), a joystick (Uchiyama et al., 2012), a game controller (Al-Hashimi et al., 2015), a steering wheel and foot pedals to control the accelerator and brake (Schweizer et al., 2013; Chung et al., 2014; Choi et al., 2017), or more sophisticated simulators (e.g., wheel, turning indicator, accelerator and brake pedal) (Fort et al., 2010). The type of simulator device was not specified in Sasai et al. (2016). In some studies only driving videos were presented, that is participants were instructed to watch and actively attend these videos without using a wheel or any other specific device (Graydon et al., 2004; Bowyer et al., 2009; Hsieh et al., 2009).

SECONDARY TASKS

With the exception of Sasai et al. (2016), who presented a radio show (with no questions to be answered), the most of studies used auditory distracting tasks based on listening and answering to questions. In general, questions were presented through headphones (e.g., Just et al., 2008; Bowyer et al., 2009; Hsieh et al., 2009; Uchiyama et al., 2012; Schweizer et al., 2013), but also by radio broadcast (Fort et al., 2010) and using an audio system attached to the MR-compatible driving simulator (Chung et al., 2014; Choi et al., 2017). Different types of pre-determined questions were used: true/false questions, such as "A triangle has four sides?" (e.g., Just et al., 2008; Schweizer et al., 2013); questions requiring to answer whether the subject of the verb corresponded to the person in the paired words (Uchiyama et al., 2012); questions about double-digit carry-over calculation with sums <100 (Chung et al., 2014; Choi et al., 2017). Answering the pre-determined questions required to press true/false buttons or verbalize the response carrying-over calculations. In addition, open questions were also used, such as "…Do you have time to talk now?" or "What is your address?" (e.g., Bowyer et al., 2009; Hsieh et al., 2009; Fort et al., 2010), which were aimed at simulating short (1 question) and long (multiple questions) conversations (e.g., Bowyer et al., 2009; Hsieh et al., 2009). Participants were asked to covertly verbalize their responses. Only two studies used visual distracting tasks based on discrimination of signs, such as detecting red stimuli (Graydon et al., 2004) or green circles among other colored geometrical stimuli (Al-Hashimi et al., 2015) presented on the driving screen.

NEURAL CORRELATES

In the study conducted by Fort et al. (2010) following traffic lights rules while listening and answering to ordinary open questions (dual task condition) yielded to decreased activations in the dorsolateral prefrontal cortex, the right temporo-parietal junction and in the primary visual areas, compared to the simulated driving-alone condition (single task). In addition, following direction signs during driving produced reductions in activations in the visual areas and in premotor area compared to the single task condition. On the contrary, increased activations were found in the left posterior parietal cortex both while following traffic lights rules and direction signs as compared to the single task condition.

In Uchiyama et al.'s (2012) study, following a car while answering questions about grammatical problems produced decreased activations in the medial prefrontal cortex and the left superior occipital gyrus as compared with the simulated driving-alone condition; instead, increased activations were found in the middle frontal gyrus. Interestingly, in this study the right inferior parietal lobe and the bilateral lateral occipital complex were found to correlate positively to the car-following performance during the dual-task, with decreased activation associated with worse performance.

Driving at constant speed while responding to questions about calculation problems yielded decreased activation in the left middle frontal gyrus (Chung et al., 2014; Choi et al., 2017), the middle occipital gyrus and the right superior parietal lobe (Choi et al., 2017), the right inferior parietal lobe, the supramarginal gyrus and the cuneus (Chung et al., 2014) as compared with the simulated driving-alone condition. In addition, increased activations were found in the orbitofrontal cortex, the bilateral lateral prefrontal cortex, the frontal eye field regions, the anterior and the posterior cingulate gyri, the lentiform and the caudate nuclei (Chung et al., 2014; Choi et al., 2017), inferior frontal gyrus and right superior temporal lobe (Choi et al., 2017).

Driving on computerized roads with left and right turns while responding to true-false questions damped activations in the bilateral superior parietal lobe, the bilateral intraparietal sulci, the bilateral superior extrastriate occipital cortex (Just et al., 2008) and the occipital visual regions (Schweizer et al., 2013) as compared with the simulated driving-alone condition. In addition, the bilateral temporal lobe, the left inferior frontal regions, the right supplementary motor area (Just et al., 2008), and the bilateral anterior brain areas, especially the dorsolateral prefrontal cortex and the frontal polar region (Schweizer et al., 2013) were found activated during dual-task as compared with driving-alone condition.

Watching and actively attending driving scenes while answering to open questions yielded decreased activations in the right superior parietal lobe and in the visual areas (Bowyer et al., 2009) as compared with the simulated drivingalone condition; on the contrary, brain activity in language-specific areas was found enhanced (Bowyer et al., 2009). Increased activations were confirmed in language specific areas (i.e., Broca and Wernicke's areas) extending also to the orbitofrontal cortex, the bilateral lateral prefrontal cortex, the frontal eye fields, the supplementary motor cortex, the anterior and posterior cingulate gyrus, the inferior frontal gyrus, the middle frontal gyrus, the right superior parietal lobule, the right intraparietal sulcus, the right precuneus, and the cuneus (Hsieh et al., 2009).

Watching and actively attending driving videos while detecting visual stimuli yielded increased activations in the superior parietal lobule, the bilateral precentral gyrus, the bilateral superior frontal gyrus, the middle frontal gyrus, the frontal eye fields, the cingulate cortex, the inferior parietal lobule, and the cerebellum as compared with the simulated driving-alone condition (Graydon et al., 2004). Driving on complex computerized roads while detecting visual stimuli confirmed the increased activation of the right superior parietal lobule, compared to the simulated driving-alone condition (Al-Hashimi et al., 2015).

DISCUSSION

In the present review the neural correlates of distracted driving were explored on the basis of the type of the primary driving task combined with the secondary distracting task, in order to gain insights on some of the environmental characteristics that can cause unsafe driving. The aim was to clarify if brain activations associated with driving decrease when a secondary task is added, even though the two tasks rely on different cortical areas, in order to gain insight on changes of neural activities even when driving behavior is not explicitly affected. Taken together the neuroimaging results showed, with some exceptions, that during the simulated distracted driving a significant shift in activations occurs from the posterior to the anterior cerebral regions. Actually, the occipital areas were less involved during simulated distracted driving compared to the simulated driving-alone condition; also, greater recruitment of frontal areas occurs during simulated distracted driving (e.g., Just et al., 2008; Bowyer et al., 2009; Uchiyama et al., 2012; Schweizer et al., 2013; Choi et al., 2017). This general shift seems to be consistent across studies, regardless the type of questions posed (i.e., closed or open) and the type of response given (i.e., button press or vocal), and sometimes occurs even in absence of clear change in driving behavior, such as while driving following direction signs (e.g., Fort et al., 2010) or during straight driving (e.g., Schweizer et al., 2013), with the implication that the risk of having car accidents increases anyway.

In detail, in some studies that involve language-based secondary tasks, the shift of activation is more consistent toward the fronto-temporal language areas (e.g., Bowyer et al., 2009; Hsieh et al., 2009; Choi et al., 2017), especially using open questions and vocal responses. According to Liu et al. (2012) the prefrontal cortex is involved in the preparation processing before the turning behavior regardless of the cognitive load. However, these authors also showed an increasing pattern of prefrontal activation from the pre- to the post-turning throughout the actual-turning period when participants had to follow verbal instructions regarding turns (extrinsically driven cognitive load), as compared with driving using a memorized map (intrinsically driven cognitive load). Thus, the greater involvement of frontal areas during distracted driving might reflect a possible competition for limited resources and attentional reallocation (Wickens, 2008). In particular, the prefrontal cortex plays a key role on goal-directed stimulus selection and response as a top–down attention control, coordination of temporal order for task interference and mapping concurrent sensory information in terms of motor behavior (e.g., Adcock et al., 2000; Stelzel et al., 2006).

This means that visual attention is sacrificed while people are engaged in distracted driving, even though there are no significant changes in some indices of driving behavior. This view is supported by the evidence that the frontal eye field (e.g., Graydon et al., 2004; Hsieh et al., 2009; Choi et al., 2017) mediates visual attention for visual fields, and visual attention influence for the sensitivity of extrastriate visual cortex (Ruff et al., 2006; Silvanto et al., 2006). In other words, a secondary task decreases foveal attention to visual information while driving, even though fixation is not affected (Strayer et al., 2003). In this direction, the "inattention blindness" phenomenon (Simons and Chabris, 1999), that is the individual's failure to see unexpected and often salient stimuli that are in plain sight, has to be considered. Indeed, the inattentional blindness occurs when one is simply attending to something else, such as happens during distracted driving, and can relate directly to specific road accidents, especially among novice drivers.

Different studies also found increased activation in the right superior parietal lobe during distracted driving, when the secondary task was visual (e.g., Graydon et al., 2004; Al-Hashimi et al., 2015) or auditory (Hsieh et al., 2009) in nature. This area is also involved in visual attention and awareness, as well as into the modulation of the neural activity in extrastriate visual cortex (Beck et al., 2006) and shifts in attention (Vandenberghe et al., 2001). Specifically, this parietal area may reflect attentional engagement or cognitive control that subserve the switch between the primary and secondary tasks (Shapiro et al., 1997; Dux and Marois, 2009). However, other studies based on auditory secondary tasks found that the activations of the right superior parietal region decreased in the dual-task condition as compared to the simulated driving-alone condition (e.g., Just et al., 2008; Bowyer et al., 2009; Choi et al., 2017). This might suggest that the activation of the right superior parietal lobe seems to be sensitive to the type of the secondary task. However, the extent to which this area is really crucial for attentional engagement should be clarified by future studies.

Interestingly, a shift of activation seems to occur more specifically in terms of motor areas. Indeed, on the one hand, different regions of the motor systems were found activated (e.g., Graydon et al., 2004; Choi et al., 2017); amongst others, the supplementary motor cortex, that contributes to different cognitive functions, such as the coordination of temporal sequences of actions (Lee and Quessy, 2003) and bimanual coordination (Serrien et al., 2002), was recruited using both simple computerized and more complex real-world driving scenes (e.g., Just et al., 2008; Hsieh et al., 2009). On the other hand, the activation of the middle frontal gyrus, which is involved in movement planning and execution, decreased during driving at constant speed on computerized roads while performing double-digit carry-over calculations (e.g., Chung et al., 2014). In other words, during the distracting driving there are decreased activations of the motor brain areas directly associated to driving, with detrimental effects on vigilance, coordination, preparatory components and timing of motor responses, and increased activation of those brain areas that mediate error monitoring and unnecessary movements control. This pattern of results seems to occur regardless of the type of the secondary task and questions posed.

These preliminary neuroimaging results show that distracted driving yields a reallocation of attentional resources at neural level, with the possibility that incorrect or dangerous behavioral responses are adopted while driving. Attentional resources are re-directed away from visual or motor processing when a secondary task is performed during driving, and some of the neural programs going on can cause car accidents, even if driving behavior is not explicitly affected. From this picture it seems that attention and arousal at neural level are affected earlier than observed behavioral measures. This new evidence poses the issue of the extent to which distracted driving is compatible with effective distributed attention resources. In this direction, Sasai et al. (2016) found that when participants were engaged in simulated driving while listening to radio show (split task) the functional connectivity between the two hemispheres decreased, giving rise to "functional split brain" as normally occurs in patients with a Corpus callosotomy. On the contrary, when participants listened to Global Position System (GPS) instructions while driving (integrated task), the connectivity between the two hemispheres increased. Well, although from this study the decrease of functional connectivity from high to low information integration is compatible with the split in consciousness, that is with two independent functional streams, the possibility that performing a secondary task absorbs attentional resources primarily at neural level, making driving unconscious, as on autopilot, with obvious consequences for safety, should be considered.

In conclusion, from this review appears that more work is necessary to clarify the extent to which the factors related to driving settings affect neural correlates of distracted driving. The number of studies available is scarce and the substantial differences due to the varieties of paradigms used (simulators, secondary tasks and neuroimaging techniques) make difficult to draw definitive conclusions, even though it is possible to get some indications for future research. The most important implication of this review is that when a secondary task is added during driving, the neural system re-directs attentional resources away from the primary task, increasing the possibility for car accidents. In addition, even though some studies have not collected RTs and even miss rates for the tracking tasks (e.g., Graydon et al., 2004; Just et al., 2008; Uchiyama et al., 2012; Choi et al., 2017), making difficult to get a reliable effect of the secondary task on driving at both neural and behavioral levels, it appears that distracted driving yields to neural programs that reveal in advance possible behavioral consequences. This can represent a new research line in the understanding of human driving behavior, which usually appears to be highly automated, but also highly modifiable in terms of neural programs. The in-depth analysis of such an issue can help to implement learning driving programs. In this vein, since some behavioral studies revealed that there is a null effect on lane keeping variation with increased cognitive load (for a meta-analysis see Horrey and Wickens, 2006), the neuroimaging studies reviewed in the present paper should be supported by studies aimed at collecting on-road data. That is, the activations during simulated driving not necessarily reflect the exact pattern of activations that would occur in real-world driving conditions. Thus, decreases of activations in critical visuo-spatial areas (e.g., occipital regions) or the absorption of attentional resources in the dual-task condition might be even stronger in real multitasking driving. Future neuroimaging studies should better highlight the relationships between more fine-graded behavioral indexes and neural distracted driving correlates.

Finally, critical variables that might affect neural correlates during distracted driving, such as the type of the distracting task (e.g., passenger conversation and cell phone conversation) should be compared in order to understand the differential impact on neural mechanisms underpinning attentional processes. Despite, some study found no difference between remote (cell phone) and in-person (passenger) conversation in terms of attention performance (Amado and Ulupinar, 2005), it is not possible to exclude changes at neural level according to the type of conversation. Personality (Parr et al., 2016), driving styles (e.g., Lucidi et al., 2010; Giannini et al., 2013; Pierro et al., 2013; Sagberg et al., 2015), gender (Irwin et al., 2011; Cordellieri et al., 2016), age (Thompson et al., 2012; Cordellieri et al., 2016) of the driver, and the amount of driving experience (Klauer et al., 2014) must be also considered to get more reliable results in terms of neural correlates. Yet, emotional factors should have also accounted for. For example, using the static load paradigm while carrying out an emotional conversation task (different questions were presented using a neutral or angry speech tone), Hsieh et al. (2010) revealed by a congress paper that the angry emotional tone enhanced the right fronto-parietal networks and yielded desynchronizing or dampening of the left frontal activity as compared to neural emotional tone. Future research should explore the neural correlates involved in distracted driving considering different mediating factors. This integrated approach will definitively improve the prevention of unsafe driving.

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MP: participated to the bibliography search and to writing. LP, MB, and AG: participated to writing and to define the theoretical implications. FB: participated to writing. PC: participated to bibliography search. RS and UG: participated to define the theoretical implications.

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Driving Style Recognition Based on Electroencephalography Data From a Simulated Driving Experiment

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Driving style is a very important indicator and a crucial measurement of a driver's performance and ability to drive in a safe and protective manner. A dangerous driving style would possibly result in dangerous behaviors. If the driving styles can be recognized by some appropriate classification methods, much attention could be paid to the drivers with dangerous driving styles. The driving style recognition module can be integrated into the advanced driving assistance system (ADAS), which integrates different modules to improve driving automation, safety and comfort, and then the driving safety could be enhanced by pre-warning the drivers or adjusting the vehicle's controlling parameters when the dangerous driving style is detected. In most previous studies, driver's questionnaire data and vehicle's objective driving data were utilized to recognize driving styles. And promising results were obtained. However, these methods were indirect or subjective in driving style evaluation. In this paper a method based on objective driving data and electroencephalography (EEG) data was presented to classify driving styles. A simulated driving system was constructed and the EEG data and the objective driving data were collected synchronously during the simulated driving. The driving style of each participant was classified by clustering the driving data via K-means. Then the EEG data was denoised and the amplitude and the Power Spectral Density (PSD) of four frequency bands were extracted as the EEG features by Fast Fourier transform and Welch. Finally, the EEG features, combined with the classification results of the driving data were used to train a Support Vector Machine (SVM) model and a leave-one-subject-out cross validation was utilized to evaluate the performance. The SVM classification accuracy was about 80.0%. Conservative drivers showed higher PSDs in the parietal and occipital areas in the alpha and beta bands, aggressive drivers showed higher PSD in the temporal area in the delta and theta bands. These results imply that different driving styles were related with different driving strategies and mental states and suggest the feasibility of driving style recognition from EEG patterns.

Keywords: driving style, EEG, driving behavior, driving data, K-means, support vector machine

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INTRODUCTION

Driving style generally refers to the way a driver prefers to or habitually drives the car (Motonori et al., 2007; Martinussen et al., 2014). It is based on a compilation of cognitive, emotional, sensory and motor factors occurring over space and time (Lin et al., 2006a; Yang et al., 2018). Rather than events that happen at any given moment, the driving style, as describe by internal states of the human, seems to be less informative than the measurable driving behaviors. However, the driving style does have some relationship with the driving behaviors. Previous studies have suggested that the driving style can be classified into three types: Aggressive type, Moderate type, and Conservative type (Chu et al., 2017; Deng et al., 2017; Li et al., 2017; Palat et al., 2019). Different driving styles can result in different kinds of behaviors and actions of the drivers and vehicles. The Aggressive driving style is usually associated with faster speed, acceleration, and larger steering wheel rotation angle and angular velocity, whereas a Conservative driving style is usually associated with longer space headway, larger angle of the brake pedal, and longer deceleration. The moderate driver drives with relative steady motions that are neither too conservative nor too aggressive (Lu, 2011; Hooft van Huysduynen et al., 2018; Yang et al., 2018). In general, driving style is affected by personality, and the physical and mental state of the driver, and externally manifested as driving behaviors. It is noted that the driver with dangerous driving styles would not necessarily, but quite possibly, conduct the dangerous driving behaviors, hence the driving style would be a very important indicator and a crucial measurement of a driver's performance and ability to drive in a safe and protective manner. If the driving styles can be recognized by some appropriate classification methods, much attention could be paid to the drivers with dangerous driving styles. The driving style recognition module can be integrated into the advanced driving assistance system (ADAS), which integrates different modules to improve driving automation, safety and comfort, and then the driving safety could be enhanced by pre-warning the drivers or adjusting the vehicle's controlling parameters when the dangerous driving style is detected. Therefore, driving style recognition has been intensively investigated in the field of transportation and automobile safety.

Over the years, researchers have developed a number of driving style recognition methods based on questionnaire data. For example, a quantitative method based on the Driving Behavior Questionnaire (DBQ) was proposed to classify driving styles and investigate the distinction among three aberrational driving behaviors, i.e., violations, errors and lapses. Violations are the intended acts that a person is most likely aware of, such as speeding or running a red light. People know clearly the consequences but still conduct the violations intentionally. Errors are acts that fail at the planned and intended outcome due to misjudgments, such as abrupt braking. Lapses are unintentional behaviors performed because of poor attention or memory deficits, such as missing the motorway exit (Reason et al., 1990). Lajunen and Summala (1995) constructed the Driving Skill Inventory(DSI) to measure the skill and safety-motive dimensions (transient motivational, personality and attitudes toward safety and traffic) in drivers' self-assessments of their driving styles and abilities. Furthermore, Motonori et al. (2007) developed the Driving Style Questionnaire(DSQ) to specifically classify driving styles and demonstrated validity using a car-following experiment. A hybrid model based on DBQ and DSI was proposed to classify drivers into sub-groups based on their driving styles and driving skills (Martinussen et al., 2014). Deng et al. (2018) applied DBQ-based driving styles to curve safety speed model to determine the theoretical curve safe speed, and the results indicated the new model could not only prevent the risks of rollover and sideslip during turning, but also could adapt to the driver's driving style. Although promising results were obtained, the questionnaire investigation was prone to the subjective factors of the researchers and the participants. In addition, this approach could not provide dynamic real-time identification and prevention of dangerous behaviors and hence, is not useful during actual driving.

Objective driving data such as vehicle speed and acceleration were also utilized as the data sources for driving style recognition. In actual driving experiments, these driving data were collected by in-vehicle sensors, transported by the vehicle's Controller Area Network (CAN)-Bus, and then analyzed to identify driving style by using the pattern recognition method (Choi et al., 2007; Ly et al., 2013). Due to the complexity and low repeatability of the actual driving experiment, a number of researchers chose to conduct experiments on simulated driving platforms (Hooft van Huysduynen et al., 2018; Yang et al., 2018). In contrast to the questionnaire studies, driving style recognition based on objective data is not prone to subjectivity, and the online real-time analysis can be achieved. But these objective driving data mostly reflect the behaviors of the vehicle, which are the external or resultant outcome of the driver's driving style. As noted above, dangerous driving styles are more likely to trigger dangerous behaviors, but not necessarily. The purpose of driving style recognition is to evaluate the possibility of the occurrence of dangerous driving behaviors and then introduce prevention measures. It may be insufficient to build up the temporal and causal relationship between driving behavior and driving style only by using objective driving data. More direct and precise evaluation of the driver's state might be helpful.

A number of studies have utilized electroencephalography (EEG) to identify dangerous driving states, such as fatigue and distraction (Chuang et al., 2015; Hajinoroozi et al., 2016; Belakhdar et al., 2018; Guo et al., 2018; Ma et al., 2018), driving behaviors, such as emergency braking (Haufe et al., 2011), speeding (Lutz et al., 2008) and turning (Taghizadeh-Sarabi et al., 2013), and driving styles, such as car-following and obstacle-dodging (Lin et al., 2006b; Yang et al., 2018). Specifically, some researchers classify and assess the driver's behavior and style based on the amplitude and power spectral density information of α, β, δ, and θ bands of EEG signals. For example, Lin et al. (2006b) used the power spectrum analysis to investigate the correlation between driving style and brain activities revealed by EEG, and found power difference at 10 Hz and 20 Hz between aggressive and conservative drivers. Taghizadeh-Sarabi et al. (2013) extracted the absolute power of these four bands by Fast Fourier Transforms (FFT) to assess the driver's cognitive responses when turning left and right. Yang et al. (2018) combined the amplitude and the power spectral density to classify the driver's driving skill and driving style. As mentioned above, driving style is related with cognitive, emotional, sensory and motor factors, and EEG patterns across different brain areas can effectively reflect these factors. Compared with the moderate and conservative drivers, the drivers with the aggressive driving styles had more intensive emotion fluctuations and difficulties in emotion regulation (Trógolo et al., 2014; Zhang et al., 2016), which was associated with the delta and theta power in the temporal area (Knyazev et al., 2008, 2009). The aggressive drivers were more likely to engage in aberrational driving behaviors (Reason et al., 1990; Martinussen et al., 2014; Lee and Jang, 2017), which was resultant from the poor cognitive states and cognitive failures (Wickens et al., 2008) and related with the theta/beta ratio of the EEG signal in the frontal area (Angelidis et al., 2018; Puma et al., 2018). Besides, some studies suggested that high beta power in the parietal area was associated with the pro-active driving state, which was related with a better anticipation and active use of ongoing information, and a more proactive planning of future responses (Tao et al., 2010; Garcia et al., 2017; Getzmann et al., 2018). Compared with the traditional driving data and the questionnaire data, EEG shows several advantages in driving style recognition. Specifically, EEG data has a time resolution of milliseconds, allowing for more accurate real-time classification; EEG can provide physiological data and emotional data, without disturbing driving behaviors (Yang et al., 2018). More importantly, EEG data is not only an objective, but also a direct reflection of the driver's cognitive status, which can be predictive of future unsafe driving behaviors. Therefore, EEG has great potential in driving style recognition.

The aim of this study was to develop a driving style recognition method based on EEG data. A simulated driving system was constructed, the driving data and the EEG data were collected synchronously and then analyzed by machine learning algorithms. Our results demonstrated the strong correlations between driving style as measured by driving data and EEG patterns.

MATERIALS AND METHODS

Experiment and Participants

Participants

Twenty-three healthy participants with a driver's license, 21 males and 2 females, with a mean age of 23.6 ± 1.6 years and average driving experience of 2.9 ± 1.7 years, were recruited and participated in the simulated driving experiment. This study was carried out in accordance with the recommendations of the ethical review committee of Wuhan University of Technology with written informed consent in accordance with the Declaration of Helsinki from all participants. The protocol was approved by the ethical review committee of Wuhan University of Technology.

Driving Scenario and Task

The driving scenario was designed based on Unity 3D (Unity Technologies, USA). Previous studies demonstrated the coupling between turning and driving styles (Ly et al., 2013; Choi et al., 2017; Deng et al., 2018), brain dynamics (Garcia et al., 2017). Hence a seven-kilometer circular road containing two consecutive S-shaped curves, two curved roads with a radius of 20 m and seven other curves in a montanic scenery was applied (**Figure 1A**). There was a left or right turn sign before each curve and some simulated vehicles were placed on the road. Each participant was asked to start a simulated compact car at the starting line and drive along the circular road. Four laps of driving was taken as a driving task and each participant completed two to four tasks. After each task, they took a break for a few minutes to avoid driving fatigue. The participants were asked to pay attention to the traffic signs and the real-time speed of the vehicle, and drive according to their driving habits and styles in daily life. The speed limit was 60 km/h. The driving task was performed using a simulated driving system including a driving simulator (G29, Logitech Inc., Fremont, CA) consisting of a steering wheel, a full-size driving seat, a stick shift and three pedals, and a 50-inch screen (**Figure 1B**). All participants were given at least half an hour to adapt to the simulator and the driving task to ensure they were all proficient in driving in the simulator.

Data Acquisition

When the participants were performing the driving task, their EEG signals as well as the state of the steering wheel were collected. EEG signals were recorded continuously using a 16-channel (Fz, Cz, Pz, T6, T5, C4, C3, F8, T4, T3, O2, O1, P4, P3, Fp1, Fp2) Biopac MP150 system (Biopac, Goleta, USA) with a 10–20 system layout at a sampling rate of 1000 Hz. The left earlobe was used as the reference. A photoelectric encoder was tightly coupled with the steering wheel by a synchronous belt so that the rotation of the steering wheel drove the axle of the photoelectric encoder to rotate synchronously. A circuit based on the photoelectric encoder was developed using Arduino microcontrollers to acquire the steering wheel's angular velocity, rotation angle and angular acceleration at a transmission rate of 128000Bd. During driving, the number of collisions and the number of lane excursions were recorded.

Data Analysis

A driving style recognition schema was proposed (**Figure 2**). The schema contained two sections: driving performance data-based recognition and EEG-based recognition. In section Introduction, the driving data was considered as the measure for classifying the driving style and the participants were divided into different groups. In section Materials And Methods, the EEG data, combined with the classification results of section Introduction as labels, were utilized to establish the Support Vector Machine (SVM) model to recognize the driving styles.

Driving Data Analysis

Seven variables including the steering wheel's rotation angle, angular velocity, angular acceleration, total driving time, vehicle velocity and the number of accidents (collision) and aberrations (lane excursion) were selected as the driving data for further analyses. All participants completed the violation-item and error-item of the DBQ, and were divided them into three

FIGURE 1 | Simulated driving system. **(A)** driving track, **(B)** simulated driving platform. The participant has provided written consent for the publication of this image.

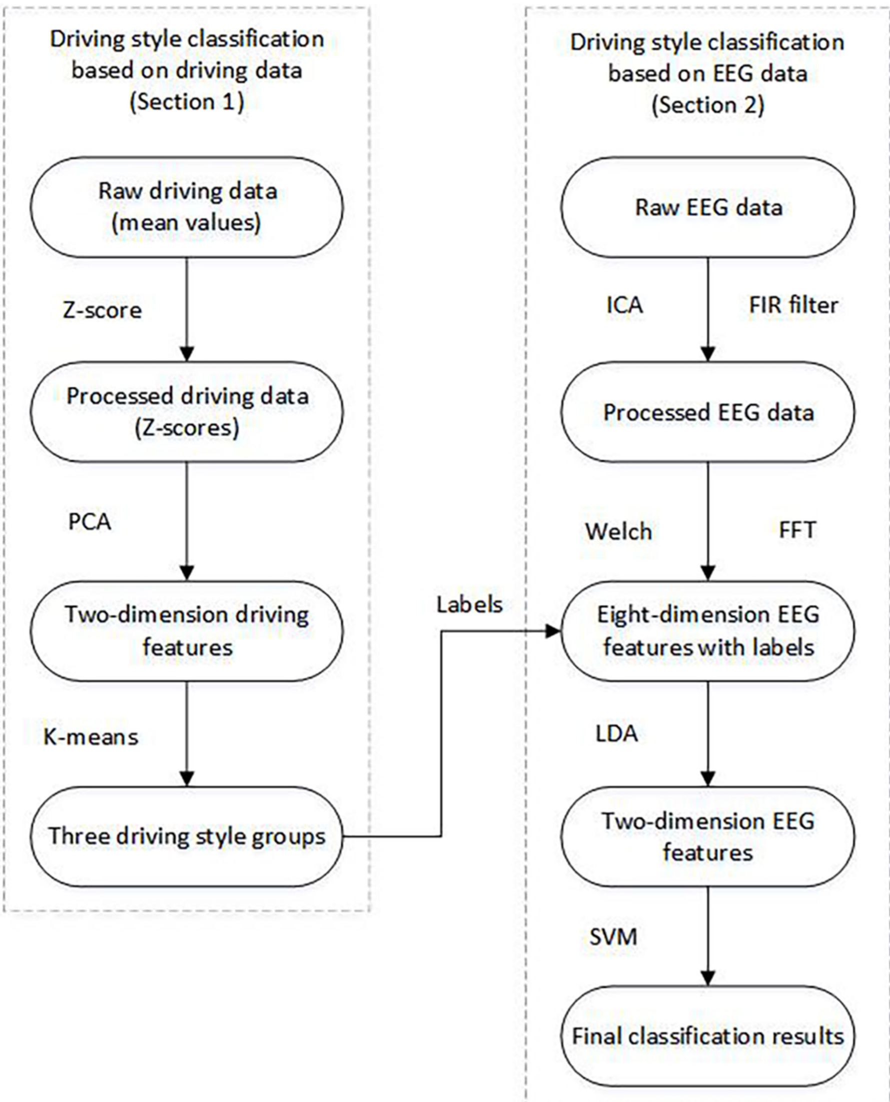

FIGURE 2 | Flow chart of the EEG-based driving style recognition.

driving style groups according to their scores. Firstly, the seven key variables of the 75 tasks were averaged and standardized using the *Z*-score method. These 7-dimension *Z*-scores were reduced to 2-dimensions using Principal Component Analysis (PCA) (Jolliffe and Cadima, 2016). A low-dimensional matrix $\mathbf{M_L}$ ($\mathbf{M_L} \in \mathbf{R}^{75\times 2}$) was obtained and then clustered by the *K*-means clustering method. The K-means algorithm is an unsupervised learning method aiming to classify **n** samples into **K** clusters by minimizing the squared error over all **K** clusters (Bolin et al., 2014; Yang et al., 2018). The K-means algorithm can be formulated as follows.

(1) Initialization. Specify the number of clusters ***K***, form the initial cluster centroids ($\mu_{\mathbf{k}}$ as the centroid for cluster $\mathbf{C_k}$) either by using random selection or through pre-specification of cluster centroids by the researcher, and assign each observation to the nearest cluster.
(2) Calculate the squared Euclidean distance (ESS) (Equation 1) based on the current cluster.

$$\mathbf{ESS} = \sum_{\mathbf{k=1}}^{\mathbf{K}} \sum_{\mathbf{X_i} \in \mathbf{C_k}} \|\mathbf{X_i} - \mu_{\mathbf{k}}\|^{\mathbf{2}} \quad (1)$$

where $\mathbf{X_i}$ is a observation of cluster $\mathbf{C_k}$.

(3) Reassign each observation to the cluster whose centroid is the nearest.
(4) Update the cluster centroids based on the new observation clusters.
(5) Repeat steps 2–4 until there is no further reassignment of the observations (i.e., each observation is in the cluster with the nearest centroid and ESS is minimized).

The number of clusters ***K*** can either be specified according to the experience of the researcher, the priori knowledge of the data, or the clustering quality assessment indicators such as Calinski-Harabasz score (Łukasik et al., 2016), Silhouette Coefficient (Luan et al., 2012), etc. We utilized Calinski-Harabasz score and computed it as follows:

$$\mathbf{s}\,(\mathbf{k}) = \frac{\mathbf{tr}(\mathbf{B_k})}{\mathbf{tr}(\mathbf{W_k})} \frac{\mathbf{m} - \mathbf{k}}{\mathbf{k} - \mathbf{1}}$$

where **m** is the number of training samples, **k** is the number of clusters, $\mathbf{B_k}$ is the covariance matrix between clusters, $\mathbf{W_k}$ is the covariance matrix within a cluster, **tr** is the trace of matrix.

K that maximizes the criterion is chosen.

EEG Data Analysis

Firstly, all EEG data was denoised and preprocessed. Secondly, Fast Fourier transformation (FFT) and the Welch method were utilized to extract the EEG features, and then Linear Discriminant Analysis (LDA) was utilized to generate the core EEG features. These core EEG features were utilized to train the SVM model. Finally, the classification performance was evaluated using a leave-one-subject-out validation method. The detailed procedures are as follows.

(1) EEG data preprocessing

Because EEG signals are weak and easily contaminated by eye movements and muscular tension, it is necessary to remove the noise from the original signals. EEGLAB (Delorme and Makeig, 2004) and MATLAB (v.2016a; MathWorks, USA) were utilized for preprocessing.

The whole EEG data acquired in each task was down-sampled to 512Hz. Because the driver's driving state is closely related to the four EEG frequency bands: delta (δ: 0.5–4 Hz), theta (θ: 4–8 Hz), alpha (α: 8–13 Hz), and beta (β:13–30 Hz) (Khushaba et al., 2011; Li et al., 2012; Lin et al., 2014; Ma et al., 2018), a bandpass Finite Impulse Response (FIR) filter (0.5–30 Hz) was applied to the EEG data and the information in these four frequency bands was retained. Independent Component Analysis (ICA) was utilized to decompose the filtered EEG data into several components and the components caused by artifacts such as eye movements, blinking and muscular tension were identified based on ADJUST (Mognon et al., 2011), an EEGLAB plugin, and then removed (Akhtar et al., 2012; Ma et al., 2018). The bad channels were detected and replaced by the average of the two neighboring channels. Finally, the EEG data was re-referenced to the average reference to reduce the forward model error of each channel and baseline corrections were performed to eliminate the noise caused by spontaneous brain activity.

(2) EEG features extraction

The features of the EEG data in the frequency domain were extracted. The amplitude of the EEG signal in δ, θ, α, and β bands were obtained by using FFT, and the power spectral densities (PSDs) in these four bands were estimated using the Welch's method (Upadhyay et al., 2012).

Each participant's FFT and PSD features were integrated to generate an 8-dimensions feature vector, along with the driving style label. Then, the feature vectors were reduced to 2-dimensions using LDA for simplifying calculations in the next SVM training process and improving the final classification accuracy. Unlike PCA, LDA is a supervised dimension reduction method which needs the labeled information. It projects the original data into a low-dimensional space by maximizing the between-class distance and minimizing the within-class distance (Martinez and Kak, 2001; Yuan and Tao, 2015).

(3) EEG data classification via SVM

SVM is a supervised learning model that is commonly used for pattern recognition, classification, and regression analysis. The core content of SVM is creating hyperplanes that separate the data points of a binary classification problem. Assuming train data in the form of $\{(\mathbf{S_1},\mathbf{y_1}), (\mathbf{S_2},\mathbf{y_2}), \ldots, (\mathbf{S_n},\mathbf{y_n})\}$, where $\mathbf{S_i}$ is a train sample and $\mathbf{y_i}$ is the label of $\mathbf{S_i}$, $\mathbf{y_i} \in \{-\mathbf{1},\mathbf{1}\}$. In this SVM model, all labels were acquired based on the driving data clustering (section Driving Data Analysis), where "**−1**" represented "the Conservative driving style" and "**1**" represented "the Aggressive driving style". The separating hyperplane can be formulized as:

$$\mathbf{W} \cdot \mathbf{S} + \mathbf{b} = \mathbf{0} \quad (2)$$

where **W** is the vector of the separating hyperplane, and $\frac{\mathbf{b}}{\|\mathbf{W}\|}$ is offset of the separating hyperplane from the origin along vector **W**. The linear SVM utilizes two parallel hyperplanes ($\mathbf{W \cdot S + b = \pm 1}$) to divide the train data points into two groups. The train data points in the two parallel hyperplanes are called "support vector." The distance between the two parallel hyperplanes is $\frac{2}{\|\mathbf{W}\|}$, which is called "margin." To search for a best separating hyperplane, the "margin" needs to be maximized, or $\|\mathbf{W}\|^2$ needs to be minimized as follows:

$$\min \quad \frac{1}{2}\|\mathbf{W}\|^2 \tag{3}$$

$$\textbf{subject to} \quad \mathbf{y_i\,(W \cdot S_i + b) \geq 1} \qquad \mathbf{i = 1, 2, \ldots, n} \tag{4}$$

The Lagrange method is utilized to obtain **W** and **b** as the key parameters of the optimal hyperplane. For multi-classification problems, the core idea is to transform a single multiple classification problem into multiple binary classification problems (Duan and Keerthi, 2005), there are two methods: (1) One-Versus-Rest (OVR), Building binary classifiers that distinguish between one of the labels and the rest; (2) One-Versus-One (OVO), Building binary classifiers that distinguish between every pair of classes. In this paper, we used OVO to perform the classification. A leave-one-subject-out cross validation and the F-measure were utilized to evaluate the performance of the classification.

RESULTS

Driving Data Classification Results

No instances of simulator sickness were observed in our experiments. The 23 participants completed 75 driving tasks and hence 75 samples of driving data and EEG data were acquired. The 7-dimension feature vectors of the driving data, i.e., steering wheel rotation angle, angular velocity, angular acceleration, total driving time, vehicle velocity, the number of collisions and the number of lane excursions, were calculated and processed by PCA and reduced to 2-dimensions. The Calinski-Harabasz score was utilized to determine the optimal number of clusters, which was 3 for our dataset (**Figure 3**). In addition, previous studies have suggested that driving style can be classified into Aggressive type, Moderate type, and Conservative type (Chu et al., 2017; Deng et al., 2017; Li et al., 2017; Palat et al., 2019), accordingly in this paper K is 3. Three random samples were selected as the initial clustering centroids and the samples were clustered into three driving style groups via the K-means algorithm (**Figure 4**).

The mean values and standard deviations of the driving data for each group were calculated (**Table 1**) and the three groups were referred to as the Aggressive group, Moderate group and Conservative group. The analysis of variance (ANOVA) indicated that there was significant difference of the driving data among three groups of different driving styles (**Table 1**, all $P < 0.01$). The pairwise differences were all significant. The Aggressive group had the most accidents and aberrations including lane excursion and collision, and the largest rotation angle, angular velocity, angular acceleration of the steering wheel and faster vehicle velocity. The Conservative group had the least number of accidents and aberrations, and the smallest rotation angle, angular velocity, angular acceleration, and the vehicle velocity. The Moderate group had mid-level parameters between the Aggressive and Conservative groups.

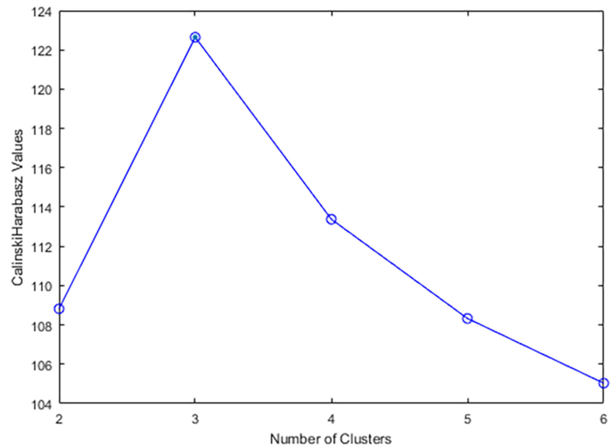

FIGURE 3 | Calinski-Harabasz score corresponding to different number of clusters.

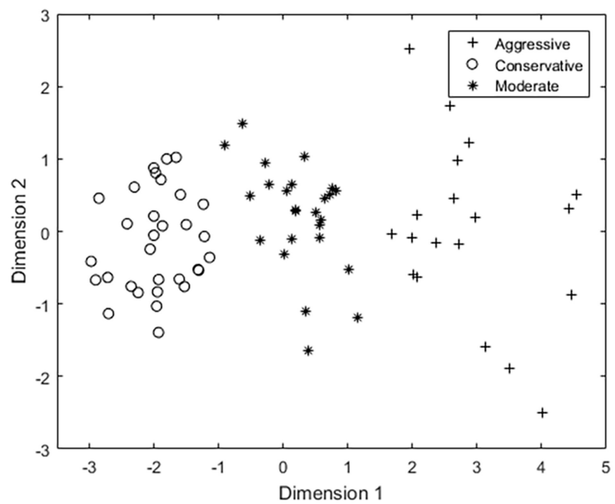

FIGURE 4 | Results of K-means based on the driving data.

We compared the clustering of driving behavior results with the questionnaire results and the driving style labels of 49 samples were consistent with the participants' self-reports, including 11 in the Aggressive group, 18 in the Conservative group and 20 in the Moderate group.

EEG Characteristics of Three Groups With Different Driving Styles

The averaged PSDs of EEG data in each group are shown in **Figure 5**. Generally, the PSDs in all groups decreased with an increase of the frequency, except for the Conservative group, where there was an obvious bump around 15 Hz. The PSD was the highest in the Aggressive group and lowest in the Conservative group, i.e., Aggressive group > Moderate

TABLE 1 | Driving variables of the three groups.

Driving variable	Aggressive group ($n = 19$)	Moderate group ($n = 25$)	Conservative group ($n = 31$)	F/P/ η^2	Aggressive vs. moderate	Aggressive vs. conservative	Moderate vs. conservative
Velocity(Km/h)**	68.2 ± 4.1	62.2 ± 3.3	51.4 ± 2.1	118.2/0.000/0.77	0.000	0.000	0.000
Total time of driving(s)*	430.3 ± 18.6	428.3 ± 15.2	499.5 ± 9.6	7.0/0.002/0.15	0.598	0.001	0.000
The number of lane excursions**	10.0 ± 4.4	4.8 ± 3.0	1.8 ± 2.1	40.9/0.000/0.53	0.000	0.000	0.000
The number of collisions**	4.6 ± 1.9	2.8 ± 1.5	0.7 ± 0.9	47.6/0.000/0.57	0.001	0.000	0.000
Angular velocity of steering wheel(rad/s)**	1.96 ± 0.38	1.49 ± 0.18	1.15 ± 0.19	61.8/0.000/0.63	0.000	0.000	0.000
Angular acceleration(rad/s^2)**	1001.1 ± 167.5	697.6 ± 148.7	413.5 ± 118.8	101.8/0.000/0.74	0.000	0.000	0.000
Rotation angle of the steering wheel(°)**	48.8 ± 12.6	32.2 ± 5.7	26.2 ± 2.5	57.6/0.000/0.62	0.000	0.000	0.000

*$P < 0.01$ **$P < 0.001$

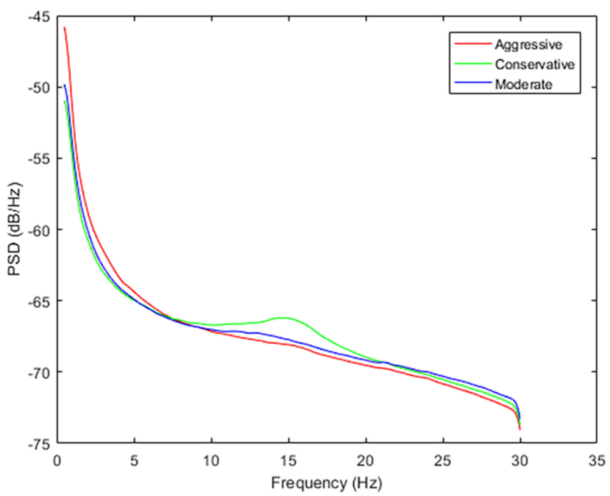

FIGURE 5 | Power spectrum of different driving styles. An obvious bump can be observed in the Conservative group around 15Hz.

group > Conservative group between 0.5–7 Hz (Band 1), and Conservative group > Moderate group > Aggressive group between 7–21 Hz (Band 2), and Moderate group > Conservative group >Aggressive group between 21–30 Hz (Band 3).

The detailed PSD information of all the electrodes in these bands in the three groups are listed in **Table 2** and the scalp topography is shown in **Figure 6**. In Band 1, PSDs were significantly different among the three groups in the parietal (all $P < 0.05$, $\eta^2 > 0.11$), temporal (all $P < 0.05$, $\eta^2 > 0.10$) and left frontal areas ($P < 0.01$, $\eta^2 > 0.37$). The Aggressive group had higher Band 1 power density in the parietal (except C4, all $P < 0.05$), temporal (all $P < 0.05$) and the left frontal areas ($P < 0.01$) compared with Conservative group. There existed PSD difference in the parietal (all $P < 0.05$) and left frontal areas ($P < 0.01$) between the Aggressive and Moderate groups. In Band 2, PSDs were significantly different among the three groups in the parietal (all $P < 0.05$, $\eta^2 > 0.11$) and occipital areas ($P < 0.05$, $\eta^2 > 0.11$). The Conservative group had the significantly highest PSD values. In band 3, PSDs were significantly different among the three groups in left temporal area ($P < 0.01$, $\eta^2 = 0.13$), and the Moderate group clearly had the significantly highest PSD values.

EEG Data Classification Results

The original 8-dimension EEG feature vectors were reduced to 2-dimensions by using the LDA method, and then used as the input data to train the SVM model. The classification performance evaluated by the leave-one-subject-out cross validation approach is listed in **Table 3**. The overall accuracy was 80.0%, the precision and recall for the Aggressive group were 83.3 and 78.9% respectively, for the Moderate group 70.0 and 84.0%, respectively, and for the Conservative group 88.9 and 77.4%, respectively. The F-measures of the Aggressive group, the Moderate group and the Conservative group were 81.0, 76.4, and 82.8% respectively.

We compared the SVM classification results with the questionnaire results. The driving style labels based on SVM of 47 samples were consistent with the participants' self-reports, including 9 in the Aggressive group, 16 in the Conservative group and 22 in the Moderate group.

DISCUSSION

In this study we presented a driving style recognition schema based on a combination of EEG and driving behavioral data. The driving data included the velocity, the total driving time, the number of lane excursion, the number of collision, the rotation angle, the angular velocity and the angular acceleration of the steering wheel, which mainly reflected the driving behavior of the participants. EEG data mainly reflected the cognitive

TABLE 2 | Power spectral densities of three groups in three frequency bands.

Band	Channel	Aggressive (dB) ($\bar{x} \pm s$,n=19)	Moderate (dB) ($\bar{x} \pm s$,n=25)	Conservative (dB) ($\bar{x} \pm s$,n=31)	F/P/η^2	Aggressive vs. moderate	Aggressive vs. conservative	Moderate vs. conservative
Band 1	Fz	−60.7 ± 2.1	−62.6 ± 1.4	−58.1 ± 4.1	1.6/0.20/0.04	-	-	-
	F8	−59.4 ± 2.3	−59.1 ± 3.1	−61.6 ± 1.8	0.7/0.51/0.02	-	-	-
	Cz	−56.9 ± 4.0	−61.8 ± 1.5	−62.6 ± 1.3	13.0/0.00/0.26	0.00	0.00	0.15
	Pz	−59.5 ± 2.7	−61.2 ± 2.5	−57.6 ± 4.1	0.5/0.60/0.01	-	-	-
	T6	−56.3 ± 4.1	−58.7 ± 3.1	−59.7 ± 2.8	2.1/0.14/0.05	-	-	-
	T5	−51.9 ± 5.7	−54.4 ± 4.7	−58.3 ± 2.4	3.7/0.03/0.10	0.27	0.02	0.01
	C4	−53.3 ± 4.8	−56.8 ± 3.9	−54.0 ± 5.1	4.6/0.01/0.11	0.00	0.75	0.31
	C3	−60.1 ± 2.7	−62.9 ± 1.5	−63.2 ± 1.1	9.5/0.00/0.21	0.01	0.00	0.40
	T4	−54.9 ± 3.9	−55.6 ± 4.2	−61.4 ± 1.7	4.3/0.02/0.11	0.84	0.00	0.27
	T3	−54.4 ± 4.7	−55.9 ± 3.3	−60.7 ± 2.3	5.9/0.00/0.14	0.34	0.00	0.01
	O2	−59.8 ± 2.3	−61.9 ± 1.6	−61.9 ± 1.7	1.3/0.28/0.03	-	-	-
	O1	−57.8 ± 2.7	−59.2 ± 1.8	−58.5 ± 3.0	0.6/0.55/0.02	-	-	-
	P4	−59.0 ± 3.3	−62.4 ± 1.9	−63.2 ± 1.4	13.2/0.00/0.27	0.04	0.00	0.19
	P3	−61.4 ± 2.9	−63.9 ± 1.8	−63.7 ± 2.3	4.7/0.01/0.12	0.01	0.02	0.79
	Fp2	−58.0 ± 2.6	−60.0 ± 2.6	−60.3 ± 2.2	1.0/0.38/0.03	-	-	-
	Fp1	−57.0 ± 2.5	−60.5 ± 2.1	−61.4 ± 1.2	21.1/0.00/0.37	0.00	0.00	0.19
Band 2	Fz	−68.5 ± 0.5	−68.6 ± 0.2	−68.2 ± 0.6	1.1/0.34/0.03	-	-	-
	F8	−68.4 ± 0.5	−68.3 ± 0.7	−68.3 ± 0.5	0.2/0.79/0.008	-	-	-
	Cz	−67.0 ± 1.1	−67.4 ± 0.2	−65.8 ± 1.8	5.5/0.01/0.13	0.04	0.11	0.00
	Pz	−67.9 ± 1.3	−65.3 ± 3.0	−60.8 ± 3.5	4.5/0.01/0.11	0.47	0.00	0.00
	T6	−68.7 ± 1.0	−68.6 ± 0.2	−68.3 ± 0.6	2.1/0.13/0.06	-	-	-
	T5	−67.5 ± 1.0	−67.6 ± 0.6	−67.7 ± 0.8	0.8/0.46/0.02	-	-	-
	C4	−68.2 ± 0.9	−65.9 ± 3.1	−67.4 ± 1.9	1.6/0.22/0.04	-	-	-
	C3	−68.2 ± 2.0	−68.6 ± 0.3	−67.5 ± 1.7	1.1/0.35/0.03	-	-	-
	T4	−67.8 ± 1.3	−68.0 ± 1.1	−68.2 ± 0.5	0.8/0.46/0.02	-	-	-
	T3	−67.8 ± 0.6	−66.2 ± 2.0	−67.7 ± 1.4	0.9/0.42/0.02	-	-	-
	O2	−68.1 ± 0.5	−68.1 ± 0.2	−68.0 ± 0.4	0.4/0.64/0.01	-	-	-
	O1	−63.5 ± 3.7	−68.2 ± 0.3	−62.4 ± 3.3	5.2/0.01/0.13	0.26	0.00	0.00
	P4	−69.3 ± 0.5	−69.0 ± 1.2	−66.8 ± 2.7	2.1/0.13/0.06	-	-	-
	P3	−69.2 ± 2.9	−71.9 ± 0.4	−68.1 ± 3.4	1.2/0.29/0.03	-	-	-
	Fp2	−65.4 ± 3.0	−65.2 ± 3.2	−66.2 ± 2.6	0.2/0.84/0.005	-	-	-
	Fp1	−68.3 ± 0.4	−68.4 ± 0.2	−68.2 ± 0.5	1.2/0.32/0.03	-	-	-
Band 3	Fz	−70.8 ± 0.1	−70.7 ± 0.2	−70.5 ± 0.5	5.0/0.01/0.12	0.02	0.01	0.07
	F8	−70.7 ± 0.1	−70.6 ± 0.2	−70.6 ± 0.4	1.2/0.30/0.03	-	-	-
	Cz	−69.9 ± 0.2	−69.8 ± 0.2	−69.3 ± 1.0	7.1/0.00/0.17	0.30	0.01	0.01
	Pz	−70.4 ± 0.7	−70.6 ± 1.2	−70.3 ± 1.5	0.4/0.66/0.01	-	-	-
	T6	−71.7 ± 0.9	−71.4 ± 0.3	−71.3 ± 0.6	2.7/0.08/0.07	-	-	-
	T5	−70.8 ± 0.5	−70.7 ± 0.4	−70.9 ± 0.6	0.5/0.58/0.02	-	-	-
	C4	−71.2 ± 0.5	−70.9 ± 1.1	−71.1 ± 0.8	1.2/0.32/0.03	-	-	-
	C3	−71.5 ± 0.5	−71.6 ± 0.1	−71.3 ± 0.6	2.1/0.13/0.06	-	-	-
	T4	−71.2 ± 0.2	−70.9 ± 0.6	−71.0 ± 0.7	0.5/0.59/0.01	-	-	-
	T3	−69.0 ± 0.4	−66.8 ± 3.4	−68.8 ± 1.9	5.0/0.01/0.13	0.02	0.47	0.03
	O2	−71.1 ± 0.1	−71.0 ± 0.2	−70.9 ± 0.5	1.0/0.37/0.03	-	-	-
	O1	−71.2 ± 0.8	−71.2 ± 0.3	−70.6 ± 1.3	4.7/0.01/0.11	0.76	0.06	0.01
	P4	−72.0 ± 0.1	−71.7 ± 1.0	−71.5 ± 1.0	1.4/0.25/0.04	-	-	-
	P3	−74.9 ± 0.6	−74.9 ± 0.4	−74.4 ± 1.3	3.1/0.04/0.08	0.90	0.10	0.04
	Fp2	−71.0 ± 0.7	−70.7 ± 0.7	−70.8 ± 0.8	0.8/0.45/0.02	-	-	-
	Fp1	−71.4 ± 0.1	−71.4 ± 0.1	−71.3 ± 0.4	0.2/0.81/0.006	-	-	-

ANOVA among the three groups was performed. If P <= 0.05, then the pairwise comparison (LSD) among three groups was performed.

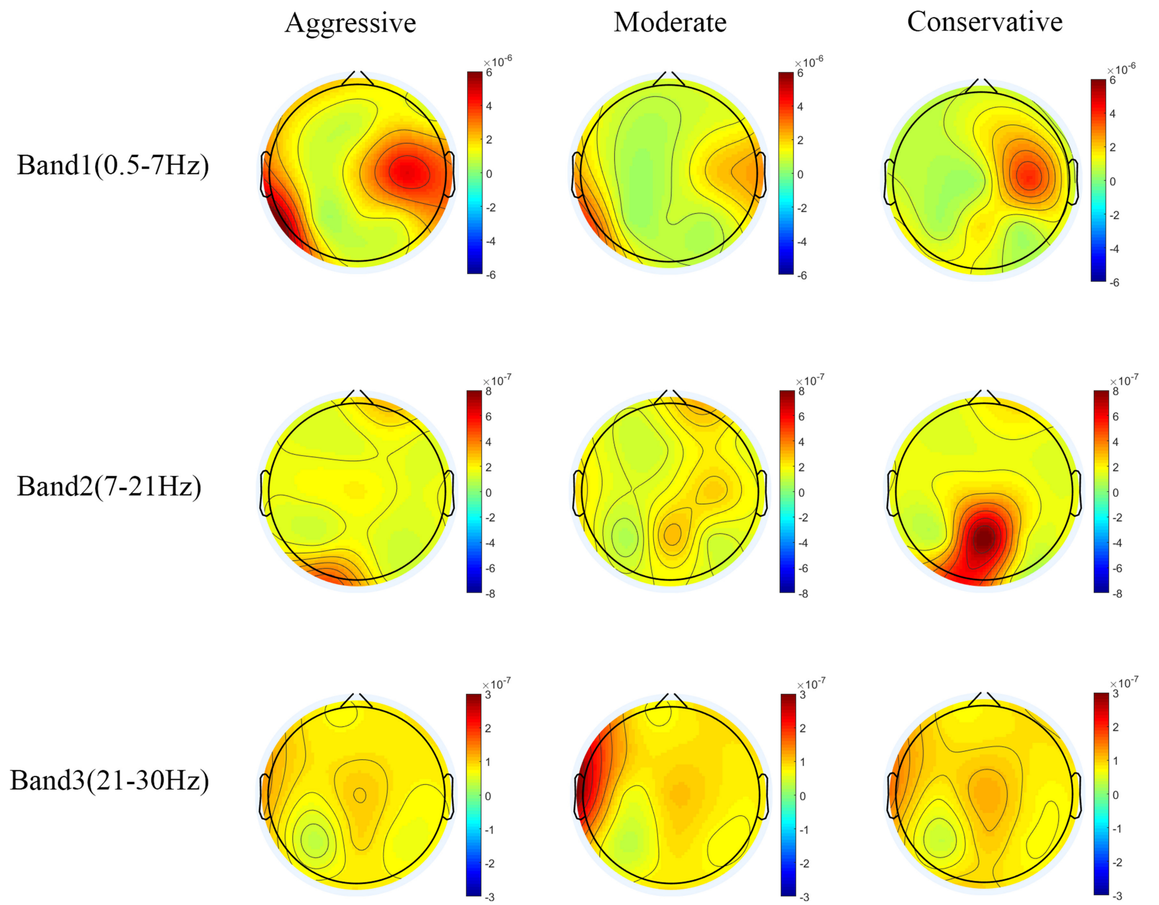

FIGURE 6 | Power topographic maps for the three driving styles in four bands.

TABLE 3 | Confusion matrix of the SVM model.

Accuracy	**80.0%**	**True label**			**Precision**
		Aggressive driving style	**Moderate driving style**	**Conservative driving style**	
Predicted label	Aggressive driving style	**15**	2	1	83.3%
	Moderate driving style	3	**21**	6	70.0%
	Conservative driving style	1	2	**24**	88.9%
Recall		78.9%	84.0%	77.4%	

Bold values indicate that the true label is consistent with the predicted label.

status of the participants during driving. The driving data was clustered into three clusters using the *K*-means algorithm, which corresponded to three driving styles, i.e., Aggressive, Moderate and Conservative. The EEG features in the frequency domain, including the amplitude and the PSDs of the EEG signal in δ, θ, α, and β bands, along with the cluster results of the driving data, were utilized to train the SVM classification model. The leave-one-subject-out cross validation approach showed considerable classification performance of the schema with the total accuracy of 80.0%, the highest precision 88.9% and the highest recall 84.0%. The *F*-measures showed that this classifier was approximately equally sensitive to the three driving styles and the classification performance was balanced. These results suggested a close relationship between EEG and driving style and demonstrated the feasibility of driving style recognition and prediction using EEG data.

Relationship of Driving Behavior and Driving Style

Large mean values of the driving behaviors indicated the driver's preference for speeding and turning sharply and quickly, which meant the driver was inclined to an "Aggressive driving style," whereas small mean values indicated the driver's preference for keeping a low speed and turning the steering wheel conservatively, which meant the driver was inclined to a "Conservative driving style." As shown in **Table 1**, steering wheel rotation angle, angular velocity, angular acceleration, total driving time, vehicle velocity, and number of collisions and number of lane excursions were all the highest in the Aggressive group and lowest in the Conservative group. Moreover, the number of accidents and aberrations increased with the agressiveness of the driving style. Consistent with previous studies (Reason et al., 1990; Martinussen et al., 2014; Lee and Jang, 2017), these results demonstrate the close relationship between driving behavior characteristics and driving styles.

Previous studies have regarded a driver's driving style as fixed and difficult to change (Chen et al., 2013; Shi et al., 2015). However, in this paper, we found that 13 participants maintained the driving style during the whole experiment, 4 participants' driving styles varied between conservative and moderate, 4 participants' driving styles varied between aggressive and moderate, and 2 participants' driving styles varied between aggressive and conservative. These results indicate that a driver's driving style may fluctuate to some extent.

Driving skill refers to how good a person is at handling a car, and it is typically measured by the standard deviation of the driving data, which is negatively correlated with the stability of the driving skill (Lu, 2011; Martinussen et al., 2014). As shown in **Table 1**, the standard deviations for almost all driving variables were Aggressive group > Moderate group > Conservative group, which indicated that driving skill may have a potential relationship with the driving style. The more aggressive the driving style, the more variable the driving skills.

Relationship of EEG Characteristics and Driving Style

In Band 1 (0.5–7 Hz), the Aggressive group had significantly higher PSD values in the left temporal area than the Conservative group (**Figure 6**), which meant more delta and theta power in the temporal gyrus of aggressive drivers, which was related with more emotion fluctuations when driving (Knyazev et al., 2009). As shown in **Figure 5**, in the theta band (4–7 Hz), the Aggressive group had the highest PSD among the three groups. While in the beta band (13–30 Hz), the Aggressive group had the lowest PSD. Moreover, the Aggressive group had the highest PSD in the frontal area in Band 1 (**Figure 6**, **Table 2**). These results indicate that the Aggressive group had highest theta/beta ratio in the frontal area compared with the other two groups, which implies that aggressive drivers had poorer executive cognitive control and attentional control (Angelidis et al., 2016, 2018), and might have greater mental workload (Matthews et al., 2017; Karthaus et al., 2018; Puma et al., 2018). In **Figure 5**, it can be seen that the Conservative group's PSD increased along with an increase of in frequency and was the highest in the alpha band (7–13 Hz), which possibly implies that conservative drivers had a more relaxed mental state (Karthaus et al., 2018). In beta 1 (13–18Hz) and beta 2 (18–21Hz), the Conservative group's PSD was the highest (**Figure 5**) and concentrated over the parietal area which was related with associate sensory function(Tao et al., 2010) (**Figure 6**). It seems that conservative drivers were more inclined to the pro-active driving state (Garcia et al., 2017), which was associated with a better anticipation and active use of ongoing information, and a more proactive planning of future responses (Getzmann et al., 2018). According to the above analysis based on EEG signals, conservative drivers were less likely to have aberrational driving behaviors like "violations" and "errors" (Reason et al., 1990).

Novelty and Limitations of This Study

Prior studies utilized questionnaires and/or objective driving behavior data to recognize driving styles (Ly et al., 2013; Martinussen et al., 2014; Hooft van Huysduynen et al., 2018). Different from these studies, we developed a driving style recognition schema based on the combination of objective driving data and a psychophysiological signal—EEG data. The objective behavior driving data is a direct reflection of the driving behavior, which is associated with the driver's brain activity and cognitive state. The traditional questionnaire is a subjective and indirect reflection of the human cognitive trait. Furthermore, because its measurement would occupy the full attention or interrupt the normal activity of the driver, it can't be applied to evaluate the driver's driving style in real time without interference. In contrast, EEG data is a direct reflection of the underlying cognitive state. Except for the requirement of wearing an electrode cap, there is not much interference with the behavior of the participants. Besides, EEG is the objective evaluation, which is less likely to be affected by the subjective factors of the experimenters and the participants (Taubman-Ben-Ari et al., 2004; Martinussen et al., 2014). Accordingly, the results could be more reliable and comparisons among different studies would be more feasible. EEG has high temporal resolution, which is at the same time scale as the underlying mental activity, so it can be applied on the real-time online occasions in the future. Considering that driving is a time-varying behavior, prediction and intervention of dangerous behaviors requires the system to have high temporal performance. Thus, it is of great practical significance to use EEG to identify the driving style and to warn the drivers of dangerous behaviors. Generally, our schema of simultaneous collecting and unified analysis of the driving and the EEG data from a simulated driving system provided a new method for driving style recognition.

Driving style recognition plays a significant role in the ADAS, which could help to identify the current status of the driver and adjust the vehicle parameters accordingly to ensure safe driving. As shown in **Table 1** and demonstrated by previous studies, drivers with an Aggressive style tend to operate the vehicle intensively and cause more accidents (Yang et al., 2018), so this driving style is regarded as unsafe and should to be avoided. But it is noted that an Aggressive driving style does not inevitably result in dangerous behaviors (Taubman-Ben-Ari et al., 2004; Yang et al., 2018). What is more important, brain activities are the preconditions of the behaviors, and usually precede the actual behaviors. By using our schema, the dangerous driving style related real-time EEG features could be monitored and detected. And then the driving assistance system can initiate a warning procedure immediately by reminding the driver to adjust his/her behavior, or even take over the vehicle by adjusting the controlling parameters of the steering wheel and the accelerator pedal. These actions could avoid the occurrence and diminish the adverse consequences of dangerous driving behaviors.

Driving style recognition methods can also be utilized to improve driving experience and comfort. Previous research suggested that a driver may exhibit different driving styles in different traffic conditions (Yang et al., 2018). This variability was also observed in our results. By integrating our schema with the driving assistance system, multiple sets of driving parameters can be set for different driving styles and individualized for different drivers according to their daily driving behaviors and his/her own preferences. What's more, EEG data can reflect the driver's physiological state, such as fatigue and distraction (Wang et al., 2015; Hajinoroozi et al., 2016; Guo et al., 2018; Ma et al., 2018).

There are some limitations of this study. The traffic scenario was relatively simple without considering multiple driving scenarios, such as traffic jams. The changes of driving style under different driving scenarios should be analyzed in future. The complexity of the scenario would affect the degree of driving difficulty. Specifically the performance of turning was related to different driving styles (Ly et al., 2013; Choi et al., 2017; Deng et al., 2018) and brain dynamics (Garcia et al., 2017). Hence in this study, a curved mountainous road was chosen as the scenario. The participants reported difficulty in driving in this scenario and their performance differed among groups with different driving styles. The cognitive load and simulator related side effects were not considered and this is a limitation of our study. The relationship and differentiation between driving style and driving ability, and the manifestation in EEG signals are worthy of further analysis. Other kinds of scenarios, or the available control scenarios should be studied further. The participants may have been biased because of their young ages and short driving years, and the unbalanced male and female ratio. Because the driving styles were divided based on the task-specific data instead of the subject-specific data, the impact of the demographic characteristics of the participants on the driving styles could not be analyzed by using the current schema, which is worthy of further analysis. During the experiment some participants reported fatigue and expressed their will to terminate the driving tasks. Hence, the number of the tasks performed by each participant varied between two to four. How to improve the experiment and how to diminish the impact of task number inconsistencies among different participants warrant further research. The presented schema was offline, which needs to be improved to fulfill the requirement of online analysis. Its performance under a realtime condition warrants further research. Finally, because of the limitation of the simulated driving experiments, the driver's perception of the surroundings, the vehicles and the roads may be biased, so actual driving experiments need to be conducted in the future studies.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the ethical review committee of Wuhan University of Technology with written informed consent in accordance with the Declaration of Helsinki from all participants. The protocol was approved by the ethical review committee of Wuhan University of Technology.

AUTHOR CONTRIBUTIONS

FY and ML designed the data processing schema and wrote the manuscript. ML, CD, and YW designed the experiment and were involved in the data collection. LY conceived the basic frame of this study and revised the manuscript.

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Behavior Evaluation Based on Electroencephalograph and Personality in a Simulated Driving Experiment

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Assessments and predictions of driving behavior are very important to improve traffic safety. We hypothesized that there were some patterns of driving behaviors, and these patterns had some correlation with cognitive states and personalities. To test this hypothesis, an evaluation of driving status, based on electroencephalography (EEG) and steering behavior in a simulated driving experiment, was designed and performed. Unity 3D was utilized to design the simulated driving scene. A photoelectric encoder fixed on the steering wheel and the corresponding data collection, transmission, and storage device was developed by Arduino, to acquire the rotation direction, angle, angular velocity, and angular acceleration of the steering wheel. Biopac MP 150 was utilized to collect the EEG data simultaneously during driving. A total of 23 subjects (mean age 23.6 ± 1.3 years, driving years: 2.4 ± 1.6 years, 21 males and two females) participated in this study. The Fuzzy C-means algorithm (FCMA) was utilized to extract patterns of driving behavior and the cognitive state within the window width of 20 s. The behaviors were divided into five kinds, i.e., negative, normal, alert, stress, and violent behavior, respectively, based on the standard deviation of steering wheel data. The cognitive states were divided into four kinds, i.e., negative, calm, alert, and tension, respectively, based on the EEG data. The correlation of these data, together with the personality traits evaluated using Cattell 16 Personality Factor Questionnaire (16PF) were analyzed using multiclass logistic regression. Results indicated the significance of the cognitive state and seven personality traits [apprehension (O), rule consciousness (G), reasoning (B), emotional stability (C), liveliness (F), vigilance (L), and perfectionism (Q3)] in predicting driving behaviors, and the prediction accuracy was 80.2%. The negative and alert cognitive states were highly correlated with dangerous driving, including negative and violent behaviors. Personality traits complicate the relationship with driving behaviors, which may vary across different types of subjects and traffic accidents.

Keywords: personality, electroencephalography, steering behavior, simulated driving, prefrontal cortex, cognitive state

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INTRODUCTION

With the development of the auto industry and an advanced driver assistance system, the accident rates caused by car failure has reduced significantly while human factors play a crucial role. About 80% of collision accidents were related to distraction (CDC, 2014), and in a total of 37,133 deaths on American highways in 2017, more than 35% involved drunk driving or distraction (NHTSA, 2018). Unsafe driving behaviors such as drunkenness, fatigue, and distraction could cause serious accidents and lead to enormous loss of life and property. Effective monitoring of the driver's status would be very helpful in maintaining the reliability of driving behavior, thereby reducing the occurrence of traffic accidents caused by human error.

Driving is a complex behavior affected by many factors, either long-term (experience, age, disease and disability, alcoholism, drug abuse; self-evaluation of capabilities, driving habit, accident proneness, personality) or short-term (drowsiness, fatigue, acute alcohol intoxication, acute psychological stress, temporary distraction; psychotropic drugs, motor vehicle crime, suicidal behavior, compulsive acts) (Petridou and Moustaki, 2000). The driver's personality, such as agreeableness, extraversion, and neuroticism, has some correlation with driving accidents (Cellar et al., 2000; Lajunen, 2001; Guo et al., 2016). Drivers with a low score in extraversion, conscientiousness (Guo et al., 2016), and a high score in sensation seeking, driver anger, and normlessness (Brown, 1976) will be more likely related to risky driving behaviors. Young male drivers' personality traits and tendencies play a major role in predicting risky behavior (Taubman-Ben-Ari et al., 2016).

Fundamentally, driving behavior is controlled by the underlying cognitive process of the human brain. It can be considered as the output of the underlying executive function which regulates thoughts and behaviors including attention, problem solving, decision making, action monitoring, and evaluation (Miller et al., 2016). This cognitive process is affected by many factors, such as consciousness states (attention, alertness, distraction, fatigue) and emotion states (depression, nervousness). Consciousness is the state of awareness of the external or internal object. Attention is the ability to focus and filter relevant stimuli from irrelevant stimuli, and can be selective, divided, or sustained (Miller et al., 2016). Distracted, decreased, or lost attention results in distraction or fatigue. Drivers' attentional states are very crucial for traffic safety. Previous studies found that drivers with attention deficit hyperactivity disorder such as an impairment in selective attention (Corbett and Stanczak, 1999; Lovejoy et al., 1999; Dinn et al., 2001), divided attention (Tucha et al., 2008), flexibility/set shifting (Hollingsworth et al., 2001; Rohlf et al., 2012), and vigilance/sustained attention (Epstein et al., 2001) may have a higher likelihood to cause or, at least, be involved in traffic accidents. Emotion states such as depression could affect the selective attention of subjects (Joormann and Quinn, 2014) and driving performance such as standard deviation of lateral position of driving (SDLP) (van der Sluiszen et al., 2017). Cognitive processes, which are collective effects on the human brain, of complex factors from external environment and physiological states of drivers, could finally affect normal driving behaviors and stress reactions related to the traffic safety.

Several indexes, such as percent eyelid closure (PERCLOS) (Liu et al., 2008), pupil diameter (Xiong, 2013), or displacement of the driver's head (Aykent et al., 2014), were utilized to identify cognitive states. Fatigue and high recognition accuracy was mostly obtained. But these indexes could neither directly reflect the mental state nor be applied for direct control of driving behavior. Additionally, fatigue was just one of the factors affecting the cognitive processes that cause traffic accidents and accounted for a small ratio in all traffic accidents, for example, in some countryies like Japan, it accounted only for 1.0–1.5% (Gu, 2009). Prediction of the driver's cognitive states based on electroencephalography (EEG) signals has been an active area of research in cognitive ergonomics (Sonnleitner et al., 2014; Xiaoling et al., 2016; Hajinoroozi et al., 2017; Lacko et al., 2017). Researchers used EEG to explore the differences of driving behaviors between young and old people and found that older drivers preferred either a rather proactive and alert driving strategy, or a rather reactive strategy (Karthaus et al., 2018). EEG signals contain plentiful information about the underlying cognitive function and can be applied to study the complex information processing procedure (She et al., 2012). Larger 10- to 11-Hz alpha desynchronization at occipital areas was found to relate with compound limb motor imagery task (Yi et al., 2014). EEG has the millisecond-rang temporal resolution, and can objectively and directly reflect the driver's complicated cognitive function.

During driving, the drivers received a large amount of information. They should adjust their attention, evaluate the behavior of him/herself and the vehicle, balance the risk of traffic accidents and the benefit of driving fast, make decisions, and act accordingly. The frontal gyrus of the human brain plays a crucial role in cognition function including attention (Hsieh et al., 2009), decision-making, executive control, and emotions (Volz et al., 2006), which are all important procedures in driving. The activities of the frontal gyrus will be a good indicator to reveal cognitive states of drivers and, hence, to evaluate the safety of driving behavior.

We hypothesized that there were some patterns of driving behaviors, and these patterns had some correlation with cognitive states and personalities. To test this hypothesis, an evaluation of driving status based on EEG and steering behavior in a simulated driving experiment was designed and performed. Unity 3D was utilized to design the simulated driving scene. A photoelectric encoder fixed on the steering wheel and the corresponding data collection, transmission, and storage device were developed by Arduino to acquire the rotation direction, angle, angular velocity, and angular acceleration of the steering wheel. Biopac MP 150 (Biopac, United States) was utilized to collect the EEG data simultaneously during driving. A total of 23 subjects participated in this study. Their personality traits, evaluated using Cattell 16 Personality Factor Questionnaire (16PF), together with the EEG data near the frontal area, and the steering wheel data were analyzed by using fuzzy C-means algorithm (FCMA) and multiclass logistic regression.

Results indicated the significance of cognitive state and seven personality traits in predicting the driving behaviors, and the prediction accuracy was 80.2%. Our work might be helpful for driving behavior prediction and precaution by using EEG and personality traits.

MATERIALS AND METHODS

Method Overview

The workflow of the whole study is shown in **Figure 1**. The following steps were included: (i) simulated driving environment design; (ii) driving data, EEG data acquisition, and personality evaluation; (iii) clustering by FCMA; and (iv) multiclass logistic regression analysis.

Experiment Design

Simulated Driving System Designed by Using Unity 3D

We established a simulated driving system using Unity 3D (Unity Technologies, Denmark) and Logitech G29 (Logitech, Switzerland). A circular track with total length about 8.5 km was designed containing two consecutive S-shaped curves, two large curved roads with a radius of 20 m, and seven other curves (**Figure 2A**). The models such as road sign, rock, or vehicle from opposite lane in the resource library of Unity 3D were utilized to simulate the reality world and signs of turning direction before each curve was set to inform the drivers to prepare for the coming turning (**Figure 2B**). Logitech G29 simulator is the controller of the simulated driving system with force feedback steering wheel, brakes, and clutch.

Driving Task

Each driving task contained four rounds of the track. The subjects were instructed to keep their attention on driving and completed two or three driving tasks with a speed limit of 60 km/h. Before the experiment, the subject had enough time (at least 20 min) to get familiar with the acceleration torque of the car, the sensitivity of the steering wheel and the seat, in preparation for the experiment. After each task, the subjects would rest for at least 5 min. The total driving time for every subject was above 30 min. The errors that the driver made during the experiment, including driving out of the lane, colliding with obstacles in the opposite lane, and losing control of the vehicle, were recorded. Subjects with the lowest accident rates would receive extra rewards including a free haircut coupon and a free and expensive meal. We introduced this incentive mechanism to make sure that the subjects would drive as seriously as in their normal states.

A total of 23 subjects (mean age 23.6 ± 1.3 years, driving years: 2.4 ± 1.6 years, 21 males and two females) were recruited in this study. All subjects had driving licenses and reported no neurological or psychiatric problems. All subjects provided prior written informed consent. The study was approved by the ethical review committee of Wuhan University of Technology.

Data Acquisition

A driving data acquisition device was developed using Arduino Mega 2560 and a photoelectric encoder, which was fastened tightly to the steering wheel using a synchronous belt. The movement of the steering wheel would trigger the rotation of the encoder simultaneously, and the signal would be transmitted to the computer by the serial port at a transmission rate of 128,000 Bd. Subjects' EEG data were collected by MP 150 with a sampling rate at 1,000 Hz. A total of 16 electrodes covered by Ag/AgCl with a 10–20 system layout (Fz, F8, Cz, Pz, T6, T5, C4, C3, T4, T3, O2, O1, P4, P3, Fp1, and Fp2) were mounted on a recording cap, and one earlobe electrode was taken as the reference electrode (**Figure 2C**). After the driving experiment, each subject was asked to complete the 16PF Questionnaire.

Data Processing

Definition and Extraction of the Feature Vectors

The rotation angle data were restored using linear interpolation. The transient speed and acceleration were calculated accordingly. Then, these driving data were segmented using 20 s as the window width. The mean and standard deviation of each segment was calculated as feature vectors of driving behavior.

Four channels of EEG data acquired around the frontal area (Fz, F8, Fp1, and Fp2) were first aligned temporally with the behavior data, normalized using the *Z*-score method, and then segmented using 20 s as the window width. The mean and standard deviation of each segment was calculated as EEG feature vectors. MATLAB (R2017a, MathWorks, Natick, United States) was utilized to process the data.

Clustering of the Behavioral and EEG Features

Fuzzy C-means algorithm was utilized to cluster the driving feature vectors and EEG features. FCMA uses the fuzzy theory to model the data and divide the data (*n* samples) into *K* clusters (m_j as the cluster center, $j \in \{1,2...k\}$). Each sample x_i is evaluated using *K* membership functions $\mu_j(x_i)$, and an objective function embodying the similarity within the same cluster and dissimilarity between different clusters is constructed as follows:

$$J_f = \sum_{j=1}^{k} \sum_{i=1}^{n} [\mu_j(x_i)]^b \parallel x_i - m_j \parallel^2$$

where *b* is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. By optimizing the objective function, an optimal clustering of the data and the membership of each sample was acquired. The number of clusters can be determined by some *a priori* information or using cluster validity procedures such as the "elbow method" (Ketchen and Shook, 1996) or Bayesian information criteria (Neath and Cavanaugh, 2012).

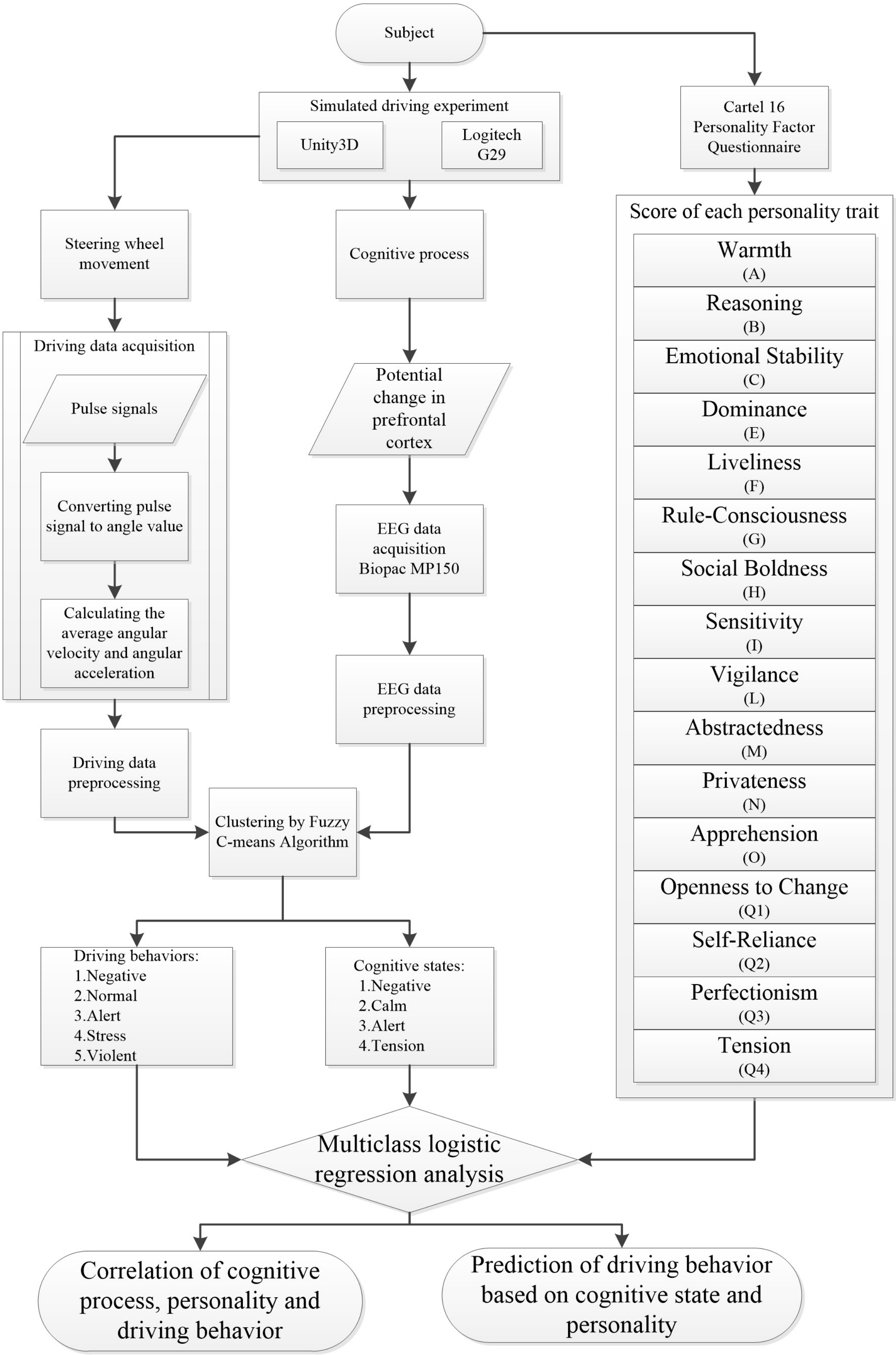

FIGURE 1 | Research flow chart.

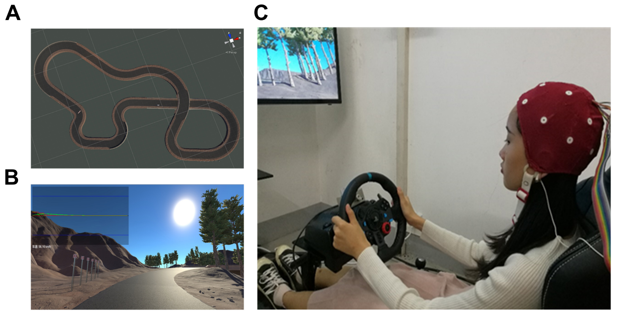

FIGURE 2 | Simulated driving system. **(A)** Driving track, **(B)** driving scenario, and **(C)** simulated driving platform. The subject has provided written consent for the publication of this image.

Multiclass Stepwise Logistic Regression Analysis

Multiclass forward stepwise logistic regression analysis was performed to determine the correlation between driving behavior and EEG features, by taking the clustering result of the driving features as a dependent variable, the clustering result of EEG features as an independent variable, and scores of the 16PF traits as the covariates. This analysis was performed using SPSS 22.0 (IBM, United States).

RESULTS

A total of 1,630 samples from 23 subjects were clustered. The driving data were clustered into five categories and EEG data into four categories. Each dimension of the feature vector of the clusters was sorted. The one with the largest value had five votes, and the one with the smallest value had one vote. The total vote of each cluster was obtained by summing these votes together, and the clusters were ordered accordingly. The driving behavior clusters were ordered and termed as "Negative," "Normal," "Alert," "Stress," and "Violent," respectively. The EEG clusters were ordered and termed as "Negative," "Calm," "Alert," and "Tension," respectively. The details listed in **Tables 1**, **2**.

Model Fitting Information

The result of multiclass logistic regression analysis is shown in **Table 3**. The EEG factor and seven personality traits in all 16PF [apprehension (O), rule consciousness (G), reasoning (B), emotional stability (C), liveliness (F), vigilance (L), and perfectionism (Q3)] were significant ($P < 0.05$). The model fitting test indicated −2 times log likelihood of intercept only; the final models were 2,735.193 and 714.291, respectively, and the model was significant ($\chi^2 = 2{,}020.902$, $df = 40$, $P = 0.000$).

Parameter Estimation

Normal driving behavior and Tension cognitive state in EEG were taken as the reference category. The estimated parameters for Negative, Alert, Stress, and Violent driving behavior using multiclass logistic regression are shown in **Figure 3** and **Supplementary Table S1**.

Negative behavior had a significant correlation with Negative cognitive state [Exp(B) = 15.922 P = 0.000], apprehension (O) [Exp(B) = 8.929, P = 0.000], rule consciousness (G) [Exp(B) = 8.389, P = 0.000], reasoning (B) [Exp(B) = 0.195, P = 0.000], emotional stability (C) [Exp(B) = 3.855, P = 0.000], liveliness (F) [Exp(B) = 1.574, P = 0.000], vigilance (L) [Exp(B) = 2.637, P = 0.000], and perfectionism (Q3) [Exp(B) = 4.605, P = 0.000]. Alert behavior had a significant correlation with Negative [Exp(B) = 0.000, P = 4.305] and Alert [Exp(B) = 1.996, P = 0.024] cognitive state, apprehension (O) [Exp(B) = 1.935, P = 0.000], rule consciousness (G) [Exp(B) = 0.590, P = 0.000], emotional stability (C) [Exp(B) = 2.424, P = 0.000], liveliness (F) [Exp(B) = 0.732, P = 0.000],vigilance (L) [Exp(B) = 1.581, P = 0.000], and perfectionism (Q3) [Exp(B) = 3.383, P = 0.000]. Violent driving behavior had a significant correlation with Alert cognitive state [Exp(B) = 14.128, P = 0.0232] apprehension (O) [Exp(B) = 17.471, P = 0.000], rule consciousness (G) [Exp(B) = 9.149, P = 0.000], liveliness (F) [Exp(B) = 11.626, P = 0.000], vigilance (L) [Exp(B) = 0.176, P = 0.000], and perfectionism (Q3) [Exp(B) = 0.188, P = 0.000]. Stress behavior had no significant correlation with the cognitive states and personality traits.

Model Prediction

Table 4 shows the predicted results of driving behavior using the regression model. Of 676 samples in the Negative category, 624 were correctly predicted and the correct rate was 92.3%; of 297 samples in the Normal category, 228 were correctly predicted and the correct rate was 76.8%; of 568 samples in the Alert category, 382 were correctly predicted and the correct rate was also 67.3%; of the seven samples in the Stress category, 0 were correctly predicted and the correct rate was 0%; of 82 samples in the Violent category, 74 were correctly predicted and the correct rate was 90.2%. Of all the 1,630 samples in the

TABLE 1 | Original cluster centers of cognitive states.

Clusters	Fz	F8	Fp2	Fp1	Total votes
Tension	0.1080	0.1050	0.1020	0.0998	15
Alert	0.1030	0.0948	0.1040	0.0368	13
Calm	0.0583	0.0557	0.0944	0.0329	8
Negative	0.0213	0.0212	0.0301	0.0201	4

TABLE 2 | Original cluster centers of driving behaviors.

Clusters	Angle	Angular speed	Angular acceleration	Total votes
Violent	0.6570	0.40500	0.60	11
Stress	0.0253	0.02170	10.30	10
Alert	0.0562	0.00515	1.49	9
Normal	0.0507	0.00723	1.19	8
Negative	0.0495	0.00432	1.71	7

TABLE 3 | Likelihood ratio test results of the regression model.

Effect	Model-fitting criteria	Likelihood ratio test		
	−2 log-likelihood value of the simplified model	Chi-square	df	*P*
Intercept	714.291[a]	0.000	0	.
Cognitive state	10,223.281[b]	9,508.991	12	0.000
Apprehension (O)	1,078.625	364.334	4	0.000
Rule consciousness (G)	1,410.471	696.181	4	0.000
Reasoning (B)	1,089.280	374.990	4	0.000
Emotional stability (C)	797.754	83.463	4	0.000
Liveliness (F)	956.240	241.949	4	0.000
Vigilance (L)	867.224[c]	152.933	4	0.000
Perfectionism (Q3)	1,029.613[c]	315.322	4	0.000

[a]*This reduced model is equivalent to the final model because omitting the effect does not increase the degrees of freedom.* [b]*The log-likelihood value cannot be further increased after maximum number of step-halving.* [c]*There are singularities in the Hessian matrix.*

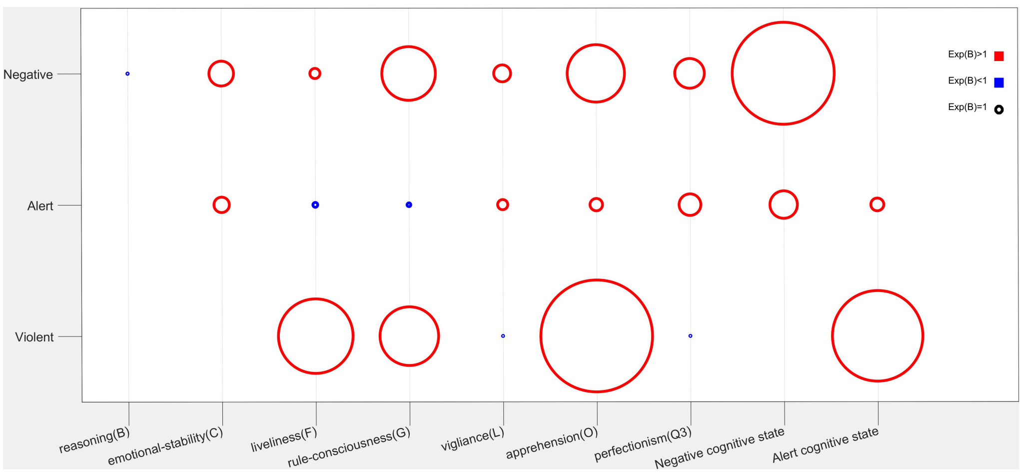

FIGURE 3 | Exp(*B*) (radius of the circle) of the estimated significant parameters in the regression model. The circle with radius equaling 1 was shown in black.

five categories, 1,308 were correctly predicted and the correct rate was 80.2%.

DISCUSSION

In this study, we designed steering wheel acquisition equipment with Arduino Mega 2560 and set up the simulated driving experiment environment using the Unity 3D platform and Logitec G29. A total of 23 subjects participated in the study. The steering wheel data and EEG data were acquired simultaneously, and were clustered using the fuzzy C-clustering algorithm. The driving behavior was divided into five kinds of patterns, and EEG data around the frontal area were divided into four kinds of patterns. A multiclass forward stepwise logistic regression analysis was performed to explore the correlation between driving behavior and EEG patterns, as well as personality traits. The likelihood ratio test indicated the significance of the EEG pattern and seven personality traits in the regression model (**Table 3**). The total prediction accuracy of the regression model was 80.2% (**Table 4**).

Correlation Among Driving Behavior, Cognitive State, and Personality

Driving Behavior and Cognitive State Classification

Steering wheel movement has a direct effect on automobile behaviors and driving safety. Emergency steering evasion (ESE) is a typical phenomenon in collision avoidance. There were two typical abnormal steering wheel movements with relatively the largest lane deviation during ESE, one with the largest first peak values of the steering angle, fast steering speed, over steering, and large fluctuations of steering wheel angle and the other with low steering speed and insufficient steering angle to avoid collision (Zhao et al., 2018). The mean and standard deviation of the movement data of the steering wheel were demonstrated to be the robust and consistent with characterization (Das et al., 2012). Some researchers used the sudden correction of the steering wheel within a period of time (window width = 60 s) as indicators to measure the degree of driver's fatigue (Zhang et al., 2010). In our work, we differentiated the steering wheel data based on the standard deviation. The steering wheel data within a 20-s window width, with relatively the highest standard

TABLE 4 | Model prediction results.

Observation value	Predictive value					
	Negative	**Normal**	**Alert**	**Stress**	**Violent**	**Percentage correction**
Negative	624	1	51	0	0	92.3%
Normal	20	228	46	0	3	76.8%
Alert	113	73	382	0	0	67.3%
Stress	5	0	2	0	0	0.0%
Violent	5	1	2	0	74	90.2%
Total percentage	47.1%	18.6%	29.6%	0.0%	4.7%	80.2%

deviation of angle, angular speed, and acceleration was classified as violent driving behavior, which corresponds to the most radical driving or ESE, represented the intensive modulation of the steering wheel, and was closely related with accidents. The cluster with the relatively lowest standard deviation of angle, angular speed, and acceleration was classified as negative driving behavior, which represented the lowest activity of steering wheel, maintained the steering wheel in a specific state for a relatively long time, and revealed insufficient control of the steering wheel. Normal driving behavior represented the normal, smooth, and safe driving behaviors with moderate modulations of the steering wheel. Stress driving behavior represented the behaviors happening before traffic accidents or emergency corrections of the steering wheel when the drivers realized their errors. Alert driving behavior represented vigilant driving behavior when drivers were alert to the potential danger of the environment. The movements of the steering wheel were adjusted more aggressively than in normal conditions, which can show how to improve driving safety or may also become the precursor of stress driving behavior.

A previous study on epileptic seizures found that the standard deviation of EEG signals at different frequency bands of EEG helps to predict ictal brain activity (during a seizure), which differs from normal brain activity, and their model prediction accuracy of epileptic states was 96.7% (Samanwoy et al., 2007). Similarly, we used the standard deviation of a segment of EEG signals near the frontal area as the indicator of the activation degree or efficiency level of the human brain. Through the voting algorithm, the feature vectors of the cluster center were compared; the four EEG categories were sorted according to the overall activation degrees and termed as Negative, Calm, Alert, and Tension, respectively. A negative cognitive state represented decision-making behavior with the lowest self-awareness of the value system (Volz et al., 2006) and was related with the temporary physiological behavior of attention loss caused by fatigue, distraction, or chemical factors like drugs and alcohol (Dinn et al., 2001; Epstein et al., 2001; Rohlf et al., 2012). An alert cognitive state represented the decision-making behavior with the second highest self-awareness of the value system and alertness. Its occurrence was usually accompanied by highly focused attention caused by threatening information or stimuli (Fox et al., 2001, 2002; Ohman et al., 2001). A calm cognitive state represented decision-making with the third highest self-awareness of the value system and the third highest alertness. Its occurrence was usually companied by accustomed behavior like driving in a familiar road which could be completed due to frequent repetition (Volz et al., 2006). A tension cognitive state represented the decision-making with the highest self-awareness of system value and the highest alertness. Its occurrence was usually accompanied with significant mood swings caused by unexpected threats or emergency like oncoming vehicles or lane intrusion (Fox et al., 2001, 2002).

The Regression Model of Driving Behavior

Electroencephalography clusters and seven personality traits [apprehension (O), rule consciousness (G), reasoning (B), emotional stability (C), liveliness (F), vigilance (L), and perfectionism (Q3)] were significant factors (**Table 3**) in the final significant regression model (χ^2 = 2020.902, *df* = 40, *P* = 0.000). In the 17 initial independent variables, eight were significant, which implied that as a very complicated behavior, driving does get affected by many factors including both cognitive states and different profiles of personalities.

From **Table 4**, it can be seen that, in all 1,630 samples, negative behavior appeared 676 times and the frequency was 41.4%, normal behavior appeared 297 times (18.2%), alert behavior appeared 382 times (23.4%), stress behavior appeared seven times (0.4%), and violent behavior appeared 84 times (5.1%). If predicting according to the frequency based on the current data, the rates of correct prediction of the driving behaviors would be 41.4, 18.2, 23.4, 0.4, and 5.1%, respectively. Now, by using the multiclass logistic regression analysis, the correct rates for the five kinds of driving behaviors were 92.3, 76.8, 67.3, 0, and 90.2% and increased by 50.9, 58.6, 43.9, −0.4, and 85.1%, respectively. If there is no extra information, the predicted probability for each driving behavior should be 1/5, and the total predicted accuracy is 20%. Instead of using the regression model, the rate of correct prediction of whole samples has been increased by 60.2 to 80.2%. The prediction accuracy for negative and alert behavior was larger than 90%; while for normal and alert it was about 70%. The regression parameters for stress behavior were not significant, and hence, the prediction for stress was low (0%). This meant that the model cannot explain stress behavior well, but it appeared only seven times and did not have much influence on the total prediction accuracy. In general, these results indicated that the regression model can significantly increase the prediction accuracy.

Detecting the patterns of the driving behavior and using the driver's personality and cognitive state to predict these patterns is the main purpose of this study. The regression model revealed the complicated relationship between behavior, personality, and EEG features, which will be elaborated in the following section.

Correlation Between Cognitive State and Driving Behavior

The likelihood ratio test indicated that the cognitive state was a significant factor ($\chi^2 = 9508.991$, $P = 0.000$; **Table 3**). The estimated regression parameters of cognitive states for each driving behavior listed in **Supplementary Table S1** revealed that negative behavior had a significant positive correlation with the negative cognitive state [Exp(B) = 15.922, $P = 0.000$]; alert behavior had a significant positive correlation with the negative [Exp(B) = 4.305, $P = 0.000$] and alert [Exp(B) = 1.996, $P = 0.024$] cognitive states; violent behavior had a significant positive correlation with the alert cognitive state [Exp(B) = 14.128, $P = 0.023$].

A negative cognitive state was possibly accompanied by temporary physiological behavior of attention loss caused by fatigue, distraction, or chemical factors like drugs and alcohol, which was potentially related with the lesion or dysfunction of the frontal lobe (Dinn et al., 2001; Epstein et al., 2001; Rohlf et al., 2012). There were many curves with different curvatures in the lane, used in the simulated driving experiments, and the acceleration of the virtual vehicle was different compared to real driving, which made the whole driving task challenging. Drivers needed to be highly focussed, pay full attention to the environment and the vehicle, and frequently modulate their behaviors. Drivers under a negative cognitive status had the lowest cognitive decision-making efficiency. They more easily made mistakes in environment sensing or movement selection and performance. These little mistakes accumulate and may finally cause traffic accidents. An alert cognitive state was related with highly focused attention to threatening information or stimuli (Fox et al., 2001, 2002; Ohman et al., 2001). Drivers under the alert state had high decision-making efficiency, and they more easily to realized and corrected mistakes during driving. A alert cognitive state would also occur when a driver had already been involved in traffic accidents due to the negative emotions such as fear (Ohman et al., 2001) and threat-related stimuli (Fox et al., 2001).

Negative driving behavior always occured when the driver was drowsy or even drunk, when there was the lowest movement or even no movement of the steering wheel at all (Das et al., 2012). Alert, stress, and violent driving behaviors usually occured before traffic accidents or during an emergency correction of the steering wheel when drivers realized their driving errors and the underlying risk of an accident (Zhao et al., 2018). When trying to avoid obstacles or correcting the driving trajectory, different drivers had different strategies. Some had a steady strategy with a relatively small steering wheel angle and smooth angular velocity, whereas some turned the steering wheel sharply with a large angle and an angular velocity. The steady drivers usually had a prediction or a calculation of the best turning trajectory, and the latter changed the trajectory sharply which would potentially increase the driving risks such as slipping or losing control. According to the intensity of the movement, alert behaviors represented the steady steering wheel modulation strategy, violent behaviors represented the sharp modulation strategy, and stress seemed to mediate between them (Zhao et al., 2018).

In terms of the movement intensity alert behavior intermediate between negative and violent behaviors, it is interesting that alert behavior was affected by both the specific cognitive states closely related with negative and violent behaviors, respectively, i.e., a negative and alert cognitive state (**Supplementary Table S1**). Once a negative cognitive state was detected, both negative and alert behaviors would occur, and the former had a higher odds ratio [Exp(B) = 15.922 vs. 4.305]; once an alert cognitive state was detected, both violent and alert behaviors would occur, and the former had higher odds ratio [Exp(B) = 14.128 vs. 1.996]. Hence, when negative and alert cognitive states were detected, high attention should be paid to the resultant behavior. If it is alert behavior, the current driving is safe; otherwise, either negative or violent behavior would be closely related with risky driving, and some precaution and prevention measures should be taken to avoid possible accidents.

Correlation Between Personalities and Driving Behavior

The likelihood ratio test indicated that seven 16PF personality traits, i.e., apprehension (O), rule consciousness (G), reasoning (B), emotional stability (C), liveliness (F), vigilance (L), and perfectionism (Q3) were significant factors (χ^2 = 364.334, 696.181, 374.990, 83.463, 241.949, 152.933, 315.322, respectively, all $P = 0.000$, **Table 3**).

According to the regression parameters in **Figure 3** and **Supplementary Table S1**, negative driving behavior had a positive correlation with these personality traits except for reasoning (B) [Exp(B) = 0.195]. Alert driving behavior had a positive correlation with these personality traits except for liveliness (F) [Exp(B) = 0.732], rule consciousness (G) [Exp(B) = 0.590], and reasoning (B) ($P = 0.238$, not significant). Violent driving behavior had a positive correlation with these personality traits except for vigilance (L) [Exp(B) = 0.176], perfectionism (Q3) [Exp(B) = 0.788], reasoning (B) ($P = 0.124$, not significant), and emotional stability (C) ($P = 0.564$, not significant). Stress behavior had no significant correlation with the personality traits.

16PF research on the accident drivers and safety drivers indicated that tension (Q4) and perfectionism (Q3) were positively correlated with safe driving, while apprehension (O), openness to change (Q1), self-reliance (Q2), and abstractedness (M) were positively correlated with risky driving (Suhr, 1953; Brown, 1976; Hilakivi et al., 1989; Zhang et al., 2009). Research conducted in China found that drivers with higher scores in self-reliance (Q2), emotional stability (C), warmth

(A), dominance (E), liveliness (F), social boldness (H) and lower scores in vigilance (L), and self-reliance(Q2) would be more likely to have a traffic violation than safe drivers (Meng and Lian, 2004).

The highly positive correlation of apprehension (O) with negative and violent behaviors, which were classified as dangerous behaviors, was in accordance with previous research. Though apprehension (O) was also positively related with alert behavior, the odds ratio for alert behavior (Exp(B) = 1.935) was much smaller compared with those for negative [Exp(B) = 8.929] and violent [Exp(B) = 17.471] behaviors. People with a high apprehension (O) score tend to be guilt-prone, worrying, insecure, self-reproaching, and anxious, who were prone to negative emotions such as anxiety and depression and some trivial little things (Brown, 1976). Liveliness (F) and rule consciousness (G) had a positive correlation with negative and violent behaviors, and a negative correlation with alert behavior. These results imply that liveliness (F) and rule consciousness (G) are risk factors for dangerous driving. People with a high liveliness (F) score tend to be highly energetic, carefree, and extraverted but lack restraint and self-control (Conn and Rieke, 1994), which may cause such drivers to ignore traffic regulations and to decrease their alertness and effectiveness in an emergency. And it has been revealed that accident drivers tended to have higher liveliness (F) score (Meng and Lian, 2004). People with high rule-consciousness (G) score tend to be dutiful, staid, and rule-bound. Its positive correlation with dangerous driving behavior seemed unreasonable. Rule consciousness may prevent drivers from drinking or over-speeding, but it may not effectively affect their behavior caused by emergency or emotion fluctuation. The extreme rule consciousness would make people to be compulsive, or become the workaholics or perfectionists (Carter et al., 2016). Under emergency when there was no enough preparation time, these people might act inflexibly or panicky, which may result in negative or violent behavior, respectively. These results also implied that different kinds of traffic events demanded different abilities, such as emotion control, flexibility, self-control, and rule consciousness. Because of the complexity of the personality and driving behavior, there existed some inconsistence in the role of personality traits in driving, such as sensitivity (I), which was the protective factor for safe driving in Brown and Hilakivi's researches (Brown, 1976; Hilakivi et al., 1989), but the risk factor for dangerous driving in Zhang's research (Suhr, 1953; Zhang et al., 2009). This inconsistence may relate with the studied subjects and the types of the traffic accidents.

Vigilance (L) and perfectionism (Q3) were positively correlated with negative and alert behaviors, but negatively correlated with violent behavior. People with high vigilance (L) score tend to be suspicious and independent. People with high perfectionism (Q3) score tend to be perfectionistic, self-disciplined, organized, and self-sentimental (Conn and Rieke, 1994). There were no consistent results about their roles in safe or dangerous driving. But it seemed that the drivers with these personality traits can be prevented from modulating the steering wheel too intensively.

Driving Simulation and Experiment Design

Customization of the Simulated Driving Environment

Simulating real driving as similar as possible might ensure the physiological response of the subjects is as normal as during real driving. Driving scenario and automobile operation had the most direct effect on the intuitive feelings of the subjects for the simulated driving experiment. The track model was modified by placing warning signs before every turn, and the number of obstacles such as huge rocks and retrograde vehicles was increased to induce different driving behaviors and the cognitive states of the drivers. Vehicle parameters, such as weight (1.5 t) and suspension vibration frequency (1 Hz), were adjusted according to a normal family car. Maximum torque and real-time torque of the car were set according to the principles of automotive dynamics in real driving. Instead of applying the differential physical model to calculate the angle of wheels based on the real inner and outer wheel angle of the car, the inner steering wheel control program of Unity 3D used the average angle, which made the simulated car more likely to slip and thus increasing the accident risk compared to real driving. Hence, we decreased the maximum angle of the steering wheel to 30° to reduce the occurrence of tire slipping and to improve the operability and comfort of simulated driving. There was no physical feedback from the facilities of the simulation platform, which would greatly affect the feeling and thus the decision-making process of subjects. To address this problem, the slip ratio and vibration of the suspension, as well as the current speed, were displayed on the screen. The high deviation of the slip ratio and vibration of suspension from the baseline, implied the high possibility of losing control. The subjects were instructed to take note of these data and to modulate their behavior accordingly.

Incentive Mechanisms

The incentive mechanisms were introduced to encourage a better driving performance. In our experiment, we assumed the difficulty of driving as safely as possible was not much more difficult than driving less carefully. We also offered the driver with the least number of accidents an additional reward (a free and expensive meal at a fine dining restaurant, and a hairdressing coupon) to lure the driver to balance the risk of every behavior during experiments. Like driving license suspension, which is a non-monetary sanction to incapacitate dangerous individuals and deter most drivers from infringing the law (Bourgeon and Picard, 2007), the subjects were told that their driving data would be abandoned if there were too many accidents. Reward-based associative learning had a great effect on driving behavior (Behrens et al., 2008). Both positive effects (highly focused) and negative effects (anxious, ashamed, and angry when making mistakes) were observed in the subjects.

Data Processing

Brain Area Selection

The human brain is a complex organization of information reception, processing, integration, and transmission. Driving is a complicated behavior which should be fulfilled by multiple sensory and cognitive functions of different brain regions. The external information about the environment and the vehicle is censored, decisions are made, and then the corresponding movements of the body are made. During this procedure, several areas should cooperate with each other. Information from the spatial senses converges within the parietal cortex, and is then fed forward to the premotor cortex and integrated with information from the frontal cortex, about action goals and contexts, before the final motor output is sent to the motor areas such as the sensorimotor cortex and primary motor cortex, relayed *via* the corticospinal tracts, and modulated by the cerebellum and basal ganglia (Ball et al., 2008; Gallivan et al., 2013).

The functions of the frontal cortex in cognitive processes has been explored in many studies (Christoff and Gabrieli, 2000). The frontal cortex sub-serves executive control, that is, the ability to select actions or thoughts in relation to internal goals (Koechlin and Summerfield, 2007). During distracted driving, brain activation shifts dramatically from the posterior, visual, and spatial areas to the frontal cortex (Li et al., 2009). Frontal activation is also involved in alerting responses to adapt to challenges in the environment (Richard et al., 2004). As we intended to study the related factors of attention and decision-making in driving, and as the frontal lobe is considered as the control center, we focused on the EEG signal acquired near the frontal lobe (Fz, F8, Fp1, and Fp2).

Data Analysis Method

The temporal window width for data analysis was 20 s, and the steering wheel and EEG data within this window were clustered; hence, both the behavior and the cognitive states were described in terms of patterns in a period of time instead of the real-time activities. Some detailed information within this window was filtered. The quantitative effect of the window width on the results, and accuracy of the multiclass regression analysis is worth further researching. Additionally, the application of a moving window on the signal might increase the real-time capability of the schema.

Novelty and Limitations

In this study, the driving behavior, neuroimaging data, and the personality data were analyzed in a unified schema, which provided a new viewpoint to monitor the driving behavior and predict the dangerous behaviors based on the cognitive states and personality traits of the subjects. Most driving safety research utilized self-report tools (Schultheis et al., 2002; Arnedt et al., 2005; Kass et al., 2010) to evaluate subjects' physiological and psychological states like drowsiness, drunkenness, or distraction, which may possibly induce negative observer-expectancy (Sackett, 1979) and subject-expectancy (Clifford and Maisto, 2000) effects. We utilized the relatively objective indicators extracted from EEG data to depict the different cognitive states, and from the movement of the steering wheel to depict the different behaviors of the subjects. The application of these indicators can avoid the subjectivity of those performing the experiment and the subjects, resulting in more robust and accurate predictions, which are exhibited in our model prediction results (**Table 4**).

The present study is limited principally by the relatively small sample size, unbalanced gender proportion, and concentrated age of the subject samples. Previous research revealed that age (Aartsen et al., 2002), gender (Rhodes and Pivik, 2011), and education background (Salthouse, 2009) were significant factors affecting human's cognitive functions and cognitive abilities like inductive reasoning, spatial visualization, episodic memory, and perceptual speed. Our results need to be replicated in a much larger sample size and general population. In this study, the related factors of attention and decision-making in driving was the primary focus, and hence, the EEG signal acquired near the frontal lobe (Fz, F8, Fp1, and Fp2) was analyzed. Including more areas with sensory and motor functions in the analysis might help to further our understanding of driving behavior. We chose the mean and standard deviation of behavioral and EEG segments as the feature vector, which reflected the characteristics of the dataset in the time domain. Other features in the frequency domain may also contain important information of human cognitive states (Elif et al., 2006; Kisley and Cornwell, 2006; Kanayama et al., 2010). Finding the optimal feature vectors based on multiple characteristics of the dataset might be helpful to optimize the prediction model. Additionally, the method to cluster driving behaviors and cognitive states was FCMA, which is susceptible to the local extremum. Using the fuzzy neural network algorithm by imitating the brain functions such as learning, association, identification, and information processing as the prediction model, may help to solve this problem. The long-term goal of this research is to construct a real-time monitoring system of driving safety, which is dependent on an effective and flexible hardware and software platform, including data acquisition devices, real-time data analysis methods, and executive equipment. The CPU clock speed and serial port baud rate of the driving data acquisition device need to be optimized, and the offline clustering and regression methods should be modified and improved in order to supply real-time serial analysis results.

CONCLUSION

The EEG and steering wheel movement data was acquired simultaneously in a simulated driving experiment. Based on the EEG data, the cognitive states of the driver were divided into four clusters, i.e., negative, calm, alert, and tension; based on the steering wheel data, the driving behaviors were divided into five clusters, i.e., negative, normal, alert, stress, and violent. The cognitive state and seven personality traits [apprehension (O), rule consciousness (G), reasoning (B), emotional stability (C), liveliness (F), vigilance (L), and perfectionism (Q3)] were significant factors in predicting driving behaviors. The regression model was significant, and the prediction accuracy was 80.2%. Negative and alert cognitive states were highly correlated with dangerous driving, including negative and violent behaviors. Personality traits showed a complicated relationship with driving behaviors, which may vary across different types of subjects and traffic accidents.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the ethical review committee of Wuhan University of Technology with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by Wuhan University of Technology.

AUTHOR CONTRIBUTIONS

LY and FY was awarded the grant that supported the manuscript. CD designed the data acquisition device and simulated the driving experiment. CD, YW, and ML obtained the data set. CD and LY analyzed the data and wrote the manuscript.

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SUPPLEMENTARY MATERIAL

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Driving as a Travel Option for Older Adults: Findings From the Irish Longitudinal Study on Aging

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The role of transport in the health and wellbeing of older people is increasingly recognized: driving is the main form of personal transportation across the adult life-span. Patterns of changed mobility and driving cessation are an important focus of research. We investigated cross-sectional changes in driving as the main form of transportation and the frequency of such driving. The impact of Gender and Marital Status on Driver Status was also examined along with the reasons cited for ceasing driving. The impact that Driver Status had on Quality of Life and Loneliness was also assessed. Questionnaire based data from the Irish longitudinal study on aging (TILDA), a stratified clustered sample of 8163 individuals representative of the community dwelling population aged 50 years and over between 2009 and 2011 were examined. Driving oneself was identified by 76.1% as their most frequently used form of transport. Only for 80+ participants in Rural and Urban non-Dublin was it the second most popular option, being replaced by Being driven by someone else. Less women identified Driving oneself as their most frequently used option and they experienced an almost linear decline in uptake with Age. The uptake reported by men remained high up to 69 and only after this point did it begin to decline. A greater proportion of men were Current drivers with a similar pattern being shown by women in relation to Never drivers. Irrespective of Gender, married participants were more likely to drive. A greater proportion of women cited a reason other than health for giving up driving. Three reasons for giving up were impacted by Age category of which Physical incapacity was not one. Driving status impacted positively on Quality of Life and Loneliness. The results are discussed in light of the advantages to society of older drivers continuing to drive.

Keywords: older drivers, driving cessation, driving status, travel options, driving frequency

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INTRODUCTION

One of the most striking trends in the fields of transport, health and aging has been a shift from a previous misplaced emphasis on the safety of older drivers to a realization that a lack of transport access and equity is likely to be a significant threat to well-being and health in later life (O'Neill, 2015). We now know that older drivers are not only a safe group of drivers, but also that their crash rates and fatalities continue to decline (Cicchino and McCartt, 2014) even despite the higher levels of fragility that increases the risk of fatality compared to younger people for a crash of a given severity.

An early indicator of the challenge to transport access and equity was the finding by Foley et al. (2002) that older men and women aged from 70 to 74 could expect not to be driving and would be dependent on alternative transportation for the last 7 and 10 years of their life, respectively. The impacts of driving cessation are well recognized in terms of depression, premature admission to nursing home and mortality (Chihuri et al., 2016). In addition, the association of better health and well-being is recognized with increased life-space mobility, a standard measure of mobility and transport mobility (Portegijs et al., 2016): this is of significance as not driving a car is associated with restricted life-space mobility for older people (Tsuji et al., 2018). The use of the personal car as driver is a key element, not only because it is the primary mode of personal vehicular transport, even in countries with well-developed public transport, but its use as a passenger as opposed to a driver is associated with life-space restriction.

Therefore, there is a strong imperative to understand and interrogate the changes and transitions in late-life transport mobility so as to plan and develop policies and strategies which facilitate the least possible restriction on life-space mobility. One United States cross-sectional study confirmed the gendered decline in daily trips and personal driving with advancing age, but showed that while older women had less daily drips as a driver, they were more likely to travel as a passenger and underwent longer journeys than older men (Shen et al., 2017). There are still many knowledge gaps relating to the transition from driving to non-driving, with factors including health, confidence, comfort and input from family and peers (Dickerson et al., 2017). Among the unresolved issues are the use of multi-modality in transport, as well as how and by whom alternative modes of transport are provided, as well as the impact of higher levels of public transport options in jurisdictions outside the United States.

Longitudinal studies on aging represent an important source of data for exploring driving and transport mobility, although to date many such studies have not included significant data on driving (Bartley and O'Neill, 2010). The Irish Longitudinal Study on Aging (TILDA) offered the opportunity to investigate the travel choices of older Irish adults within the constraints of the questions that were posed by the original survey (Kearney et al., 2011). Issues addressed here in this exploratory analysis cover five main issues. Firstly, which modes of transport were most commonly used and whether location and age impacted on these choices. Secondly, since driving oneself is universally the most common travel choice for older people it is important to determine just how dominant it is in Ireland and whether reliance on it is affected by age and gender. Thirdly, to look at the proportions who have ceased driving or never drove in the first place, and establish the extent to which these are affected by gender. Fourthly, to investigate the reasons cited for giving up and the impact that gender might have on these. And finally, since the ability to drive impacts positively on quality of life and felt loneliness, how being able to drive oneself impacts on these.

MATERIALS AND METHODS

TILDA was designed to collect data on a comprehensive set of variables relating to health, economic and social circumstances from participants aged 50 and over. Data collection occurred every 2 years and the first trench were collected between 2009 and 2011, and this trench only was selected for analysis here since it contained the largest sample of participants, with each participant being sampled only once during this time period. These data were collected using Computer-Aided Personal Interview (CAPI), a self-complete questionnaire and physical assessment. Only a very small subset of these data are relevant to the analysis conducted here. The data relating to travel were collected using CAPI. Fifteen questions were posed relating to travel choices, behavior and experiences. Quality of life was measured using the Quality of Life Scale (CASP-19) which measures four domains (control, autonomy, pleasure and self-realization) with Cronbach's alphas between 0.6 and 0.8 (Hyde et al., 2003) and the data were collected during the CAPI session. Loneliness was measured using the University of California, Los Angeles Loneliness Scale which is a global bipolar factor with Cronbach's alpha ranging from 0.89 to 0.94 (Russell, 1996). These data were collected during the self-complete questionnaire session.

Participants

The target population for this research was anyone in the Republic of Ireland, aged over 49, who lived in the community. Postal addresses in Ireland were stratified by socioeconomic status and geographical location, assigned to clusters and then a sample of these clusters were selected. Subsequently 25600 addresses were identified and visited by an interviewer of which 22321 were occupied. Of these, 9818 had a person over 49 and successful interviews were conducted in 6279, leading to a response rate of 62% and a final sample of 8163 (Kenny et al., 2010). As can be seen from **Table 1**, the sample had slightly more females (54.2%) and an average age of 63.68 (9.16). The three levels of highest education were fairly evenly distributed with Secondary being the most common at 40%. The majority of the sample were married (69%) and rural location was the most common domicile location. In terms of self-rated physical health, 76.8% rated themselves as good or better.

RESULTS

Transport Options Most Frequently Used

Participants were asked a single question relating to which of 12[1] categories of transport options they used most often. For simplicity, these 12 categories were collapsed across the five presented in **Figure 1**. Driving oneself was by far the most prevalent with 76.1% compared to the next most popular of Been driven my someone else at 17.5%. Slightly different patterns emerged when the data were broken down across Age and

[1]The original question relating to transport options provided participants with 12 options to select from and these were subsequently collapsed to 5, e.g., the three categories Driven as passenger by family, Driven as passenger by friends and Taxi/hackney were collapsed to Driven by someone else.

TABLE 1 | Sample characteristics.

		Women	Men	Overall
n		4423 (54.2%)	3740 (45.8%)	8163 (100%)
Mean age		63.41 (9.22)	63.68 (9.08)	63.68 (9.16)
HLoE* – Primary		1247 (28.2%)	1245 (33.3%)	2492 (30.5%)
HLoE – Secondary		1807 (40.8%)	1454 (38.9%)	3261 (40%)
HLoE – Tertiary		1359 (30.8%)	1038 (27.8%)	2397 (29.4%)
Married/living together		2847 (64.4%)	2784 (74.4%)	5631 (69%)
Never married		346 (7.8%)	444 (11.9%)	790 (9.7%)
Separated/divorced		342 (7.7%)	209 (5.6%)	551 (6.7%)
Widowed		888 (20.1%)	303 (8.1%)	1191 (14.6%)
Live in Dublin – city/county		1074 (24.3%)	858 (22.9%)	1932 (23.7%)
Live in town/city – not Dublin		1249 (28.2%)	1059 (28.3%)	2308 (28.3%)
Live rurally – not Dublin		2095 (47.4%)	1816 (48.6%)	3911 (47.9%)
Self-rated physical health	Excellent	729 (16.5%)	543 (14.5%)	1272 (15.6%)
	Very good	1245 (28.1%)	1087 (29.1%)	2332 (28.6%)
	Good	1432 (32.4%)	1227 (32.8%)	2659 (32.6%)
	Fair	788 (17.8%)	694 (18.6%)	1482 (18.2%)
	Poor	229 (5.2%)	188 (5%)	417 (5.1%)

**HLoE, Highest level of education.*

Location as depicted in **Figure 1**. The dominance of Driving oneself remained such that even for the 65–79 cohort the smallest advantage it has over the second most common option was 49% in Dublin where the bus was most popular after Driving oneself. Only in the case of the 80+ participants in Rural and Urban non-Dublin where Driving oneself dropped to 41.7 and 33.9% was been Driven by someone else more popular with 50.5 and 57.9%, respectively. Also of note is the fact that in Dublin the least favorite option was Bicycle/motorbike replacing Rail which occupied this status within the other two regions.

Driving Oneself

Due to the pre-eminence of Driving oneself, it is important to look at these data alone and determine how they break down across Age and Gender, as presented in **Figure 2**. For males, there is a non-linear decline in Driving oneself as the dominant mode in that prevalence remains above 80% until the 65–69 category and then begins to gradually decline such that at 80–84 it becomes 68.4% and only drops below 50% to 21.4% for the oldest category. For women, however, Age brings about an almost linear decline in the dominance of Driving oneself, starting from 76.9% among 50–54 year-olds, dropping below 50% for the 75–79 (42.7%) and reducing to 29% for the 80–84 s. Thereafter the decline became more pronounced reducing to only 2.9% in the 90+.

In addition to the categorical dominance of Driving oneself, it is important to look at how frequently such driving is engaged in. Of the 5840 identified drivers (classified as such if they had driven at least twice in the last 12 months), 86.9% drove between 5 and 7 days per week. **Figure 3** shows the percentage of drivers in each Age/Gender cohort that drove with this frequency. It indicates there was little or no impact of Gender on the slow reduction in this level of driving with 50–54 males starting at 95.1% and dropping to 75.6 for the 80–84 cohort. The equivalent drop in women was of a similar magnitude and rate going from 90.1 to 68.7%. Thereafter the data appear somewhat anomalous (male level increases to 80.9% and female 90+ goes to zero) which is likely to be a by-product of the small numbers remaining driving in these cohorts.

Driving Status

Current drivers (within the last 12 months drove themselves more than twice) made up 76.1% of the sample, with Ceased drivers (self-identified as having driven in the past, but not more than twice within the last 12 months) and Never drivers making up 7.3 and 16.6%, respectively. A chi-square test of independence indicated that there was a significant relationship between Gender and Driving Status, $\chi^2(2, n = 8163) = 535.98$, $p < 0.001$. **Table 2** below shows the biggest deviations from the expected values came from the fact that a larger proportion of women never learned to drive, 25.2% (SR = 14.1) compared to 6.4% (SR = −15.3) for men. In addition, a greater proportion of men were Current drivers, 86.7% (SR = 7.4) as opposed to 67.1% (SR = −6.8) for women. Although the proportions of Males (7%) and Females (7.6%) who gave up driving are remarkedly similar it is nevertheless informative to investigate potential differences between these two groups in terms of reasons for giving up. Note since there were no data available relating to age at which they gave up driving, comparing the age of Males and Females who had given up is uninformative.

Impact of Marital Status on Driver Status

The fact that Gender impacted on Driver status could be explained by the fact that in marriage, males may be more likely to do the driving (Wilkins et al., 1999). Therefore, it is important to consider how Marital Status impacts on Driver Status and since Driver Status is different across males and females it is important to conduct this analysis separately for both genders. As can be seen from **Table 3**, Gender had little impact on how Driver Status

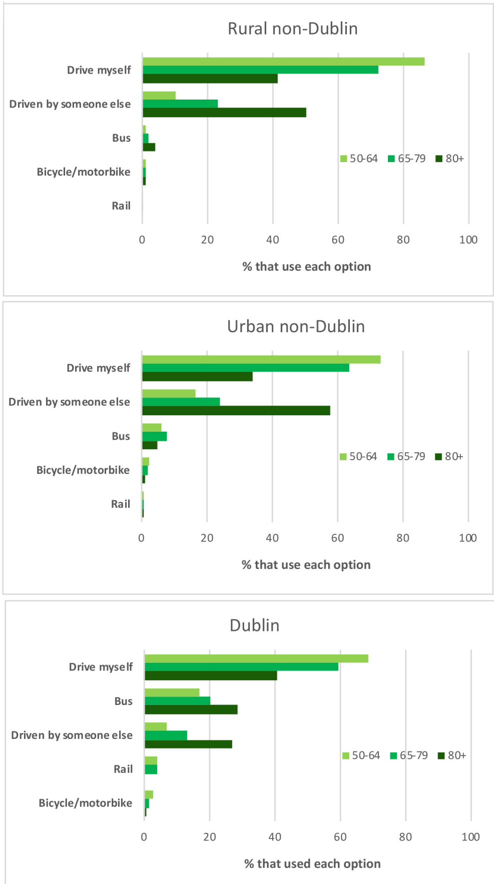

FIGURE 1 | Modes of transport most commonly used across Location and Age[2].

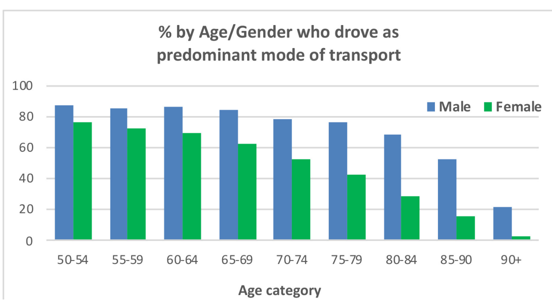

FIGURE 2 | Percentage of participants across Age and Gender who drove themselves as their predominant mode of transport.

was distributed across Married participants. For Married Males there was a higher than expected number of Drivers (SR = 2.9) and a lower than expected number of Ceased (SR = −4.9) and Never Drivers (SR = −5.6). For Married Females the pattern was very similar although the proportion of Drivers was higher

[2] For ease of interpretation the number of Age categories was reduced to three with the first two spanning 15 years.

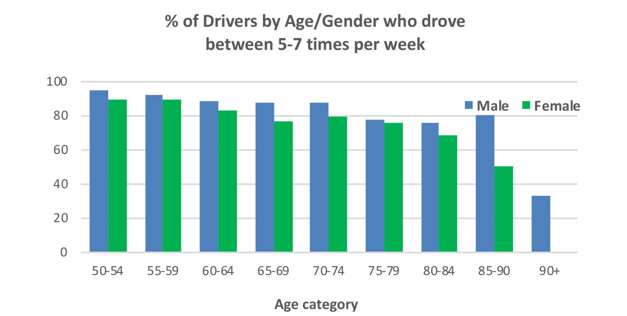

FIGURE 3 | Percentage of Drivers across Age and Gender who drove between 5 and 7 times per week.

TABLE 2 | Crosstabulation of gender by driving status.

		Current drivers	Ceased driving	Never drivers	Total
Male	Count	3241	260	239	3740
	Gender%	86.7%	7.0%	6.4%	100%
	SR	7.4	−0.8	−15.3	
Female	Count	2970	337	1116	4423
	Gender%	67.1%	7.6%	25.2%	100%
	SR	−6.8	0.8	14.1	
Total	Count	6211	597	1355	8163
	Gender%	76.1%	7.3%	16.6%	100%

SR, standardized residual.

(SR = 3.9) and the proportion of Ceased Drivers was not as low (SR = −2.2). For those who were Never Married, Gender did impact on Driver Status. For Males, the proportion of Drivers was lower than expected (SR = −5.2) and the proportions of Ceased (SR = 6.5) and Never Drivers (SR = 12.5) were higher than expected with the latter representing the most extreme value in the table. A very different pattern emerged for Females in that the distribution of Driver Status was remarkably close to expectation across all 3 levels of Driver Status with −0.3 (for Ceased Driving) being the most extreme value. Being separated or divorced had little impact on the distribution of Driver Status across both Males and Females. The only standardized residual to exceed a magnitude of 2 came from Males who ceased driving, having a value of 3. Being widowed seemed to negatively impact on driving with negative SRs for Current Drivers, −7.3 in the case of Females, and positive SRs for having ceased or never driven with SRs being generally more extreme for Females.

Reasons for Ceasing Driving

Overall the top three cited reasons for giving up driving were Don't want to anymore (27.5%), Reason not related to health (26.3%) and Physical incapacity (20.9%). **Figure 4** presents the percentage of drivers by Gender who agreed that their stopping driving was related to the specified option, with participants being allowed to select as many options as they deemed relevant. Women deviated from the overall trend in that Reason not related to health was most widely cited at 31.8% and this proportion along with the corresponding 19.2% for men produced a

TABLE 3 | Crosstabulation of martial status by driving status for both genders separately.

Gender	Driver Status	χ^2 stats	Marital status			
			Married	Never married	Separated/Divorced	Widowed
Male	Current driver	Count	2556	282	169	234
		%	78.9%	8.7%	5.2%	7.2%
		SR	2.9	−5.2	−0.9	−1.8
	Ceased driving	Count	125	67	26	42
		%	48.1%	25.8%	10.0%	16.2%
		SR	−4.9	6.5	3.0	4.6
	Never driver	Count	103	95	14	27
		%	43.1%	39.7%	5.9%	11.3%
		SR	−5.6	12.5	0.2	1.7
Female	Current driver	Count	2082	234	237	417
		%	70.1%	7.9%	8.0%	14.0%
		SR	3.9	0.1	0.5	−7.3
	Ceased driving	Count	185	25	28	99
		%	54.9%	7.4%	8.3%	29.4%
		SR	−2.2	−0.3	0.4	3.8
	Never driver	Count	580	87	77	372
		%	52.0%	7.8%	6.9%	33.3%
		SR	−5.2	0.0	−1.0	9.9

SR, standardized residual.

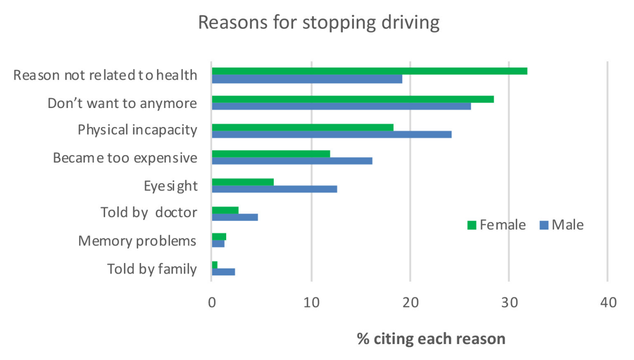

FIGURE 4 | Percentage of participants by Gender who identified each reason for them giving up driving.

significant impact of Gender on identifying this as a reason, $\chi^2(1, n = 597) = 11.87$, $p < 0.001$. The only other reason to produce a significant difference was Problems with eyesight with 12.7% of men citing it as opposed to 6.2% for women, $\chi^2(1, n = 597) = 7.45$, $p = 0.006$*[3].

In light of the impact of age on health it is important to look at its impact on Reasons for ceasing driving. The same analysis as for Gender was conducted with Age (50–64, 65–79, 80+) replacing Gender and the results are presented in **Table 4**.

Only three reasons were impacted by Age category and perhaps surprisingly Physical incapacity was not one of them. Becoming too expensive was more frequently cited than expected by the youngest (50–64) group (SR = 1.9) and less frequently by the oldest (80+, SR = −2.7). Visual impairment increased with age with the youngest group citing it less than expected (SR = −2.4) and the oldest group citing it more (SR = 3.6). Being Told by family increased across the age categories and the greatest deviation from the expected frequency came for the oldest group where the standardized residual was 2.8. It is worth noting no such pattern emerged with being Told by doctor where the result was clearly non-significant.

To determine the impact of Driver Status on Quality of Life a three-way factorial ANOVA was conducted with Gender and Age[4] also included as between groups variables. All three variables produced significant results as presented in **Table 5**, while all two-way and three-way interactions were non-significant. However, the significant results should be interpreted in light of the effect sizes produced. Partial eta squared for both Gender and Age were almost negligible whereas there was a small impact of Driving Status of 0.024. Tukey *post hoc* tests indicated that the Drivers' mean score of 44.92 (7.34) was significantly higher than that for Ceased drivers (41.99, SD = 8.77) and Never drivers (41.77, *SD* = 8.48), while the difference between Ceased Drivers and Never drivers was not significant.

A similar three-way ANOVA was also conducted on Loneliness. Again all three variables produced significant results, but as presented in **Table 6**, only Driver Status produced an effect size of any magnitude (0.015) with Drivers being less lonely that the other two groups. In addition there was an interaction

[3]With eight comparisons the new critical alpha level when a Bonferroni conversion is applied becomes 0.00625. The other six analyses were non-significant at the standard alpha level of 0.05.

[4]To make the numbers in each age group as comparable as possible the age bands chosen were 50–59, 60–69, and 70+.

TABLE 4 | Key results from chi-square goodness of fit for age category by reason for ceasing.

Reason for ceasing	Overall% citing reason	χ^2 prob	χ^2 stats	50–64	65–79	80+
Don't want to anymore	27.5	0.0688	Count	63	66	35
			%	38.4	40.2	21.4
			SR	−0.2	−0.3	0.7
Not related to health	26.3	0.256	Count	65	69	23
			%	41.4	43.9	14.6
			SR	0.4	0.4	−1.3
Physical incapacity	20.9	0.728	Count	49	55	21
			%	39.2	44	16.8
			SR	0.0	0.4	−0.6
Became too expensive	13.7	0.002	Count	43	34	5
			%	52.4	41.5	6.1
			SR	1.9	0.0	−2.7
Visual impairment	9	<0.001	Count	10	22	22
			%	18.5	40.7	40.7
			SR	−2.4	−0.1	3.6
Told by doctor	3.5	0.798	Count	7	9	5
			%	33.3	42.9	23.8
			SR	−0.4	0.1	0.5
Told by family	1.3	0.006	Count	2	1	5
			%	25	12.5	62.5
			SR	−0.6	−1.3	2.8
Memory problems	1.3	0.794	Count	4	3	1
			%	50	37.5	12.5
			SR	0.5	−0.2	−0.4

All 3 significant results remain significant at the Bonferroni adjusted alpha level of 0.00625.

TABLE 5 | Main effect results for the three between groups variables on quality of life.

Variable	*F*	*df*	*p*	η_p^2
Gender	18.523	1,5861	<0.001	0.003
Age	11.479	2,5861	<0.001	0.004
Driving status	71.606	2,5861	<0.001	0.024

TABLE 6 | Significant results for the three between groups variables on loneliness.

Variable	*F*	*df*	*p*	η_p^2
Gender	6.33	1,6659	=0.012	0.001
Age	4.243	2, 6659	=0.014	0.001
Driving status	51.623	2, 6659	<0.001	0.015
Gender * Driv Stat	6.043	2, 6659	=0.002	0.002

between Gender and Driver Status such that for Ceased drivers the differences between males (2.8, $SD = 2.57$) and females (2.37, $SD = 2.46$) tended toward significance ($p = 0.072$) suggesting men were more lonely.

DISCUSSION

The pre-eminence of the car as the most often used mode of transport is confirmed by the fact that when Driving oneself and being Driven by someone else are combined, 93.6% of the sample choose either of these two options. Driving oneself at 76.1% for the sample overall was the most popular travel option and even within the 65–79 is was clearly more prevalent mirroring results from other jurisdictions (e.g., Hjorthol et al., 2010). Only among the 80+ cohort within Rural and Urban non-Dublin was its dominance replaced by being Driven by someone else. These data clearly demonstrate that older Irish adults rely upon driving oneself as their most popular form of transport and given the benefits of this it is important to ensure that access to driving is not unnecessarily hindered, e.g., by unwarranted medical screening of older drivers (O'Neill, 2012), while facilitating access to alternative transportation using private or hired cars such as through the creative ITNAmerica system (Bird et al., 2017). With the increase in the level of automation within cars, driving may increasingly become easier and safer making it arguably even more attractive to older people (Harper et al., 2016). Given the advantages of maintaining driving status for older people it is imperative that manufacturers of such cars take into consideration the characteristics and needs of the older driver to ensure that this cohort is not excluded from such advances in technology. In Dublin, the bus was the second most common travel option, so obviously where there is access to appropriate public transport older people will avail of it, but it is important to acknowledge that public transport may not be accessible or adequate for social inclusion once the older person is no longer driving (Hine and Mitchell, 2017). In addition, there are safety concerns for older people in terms of non-collision injuries (O'Neill, 2016).

The usual finding of men driving more than women (Li et al., 2012) is confirmed here in that across all age cohorts men drove more than women (a higher percentage identified it as their most frequently used mode of transport). In addition, these data show how Gender impacts on the decline of the prevalence of driving with Age. For women there is an almost linear decline whereas for men prevalence remains almost static up to 69 years of age and an obvious decline is only seen after 79. The reason for this greater rate of decline needs further investigation. Some diseases vary in prevalence between men and women, e.g., in the TILDA study, hypertension, angina, and stroke are more common in men while osteoporosis, arthritis and high cholesterol are more common in women. Although women report far greater "fear of falling," no difference in falls prevalence is observed between older men and women (Barrett et al., 2011). Other factors may also play a role, such as pain and urinary incontinence, both of which are more common in women in TILDA. It is also possible the reason may be psychological in nature relating to something like confidence and as yet undetected by the research literature. When looking at the frequency of driving, the previous advantage enjoyed by men is considerably reduced suggesting that when women do choose to drive, they do so just as frequently as men. Only when it comes to the two oldest age categories is there an obvious greater frequency of driving among men.

Following on from the prevalence of driving as the most popular travel option, it is perhaps not surprising to find that Gender and Driver Status are related to each other. When these variables were cross tabulated the biggest deviation from the expected values came from the higher proportion of women who never learned to drive as opposed to the lower proportion of men. Presumably when this cohort was entering early adulthood it was more important for men to learn to drive. Correspondingly a higher than expected proportion of men and a lower than expected proportion of women were Current drivers. Interestingly the proportions of each gender who ceased driving were remarkably similar. Irrespective of Gender, Married participants were more likely to be Drivers with Females being slightly more so, less likely to have ceased driving, with Men slightly less so and less likely to have never driven. It is as if the ability to drive confers an advantage to becoming married, or being married requires development of driving skills and requires this skill to be maintained irrespective of Gender. Arguably, having children may require this skill (Scheiner and Holz-Rau, 2017) and subsequently having grandchildren may necessitate its maintenance into older age. This interpretation is somewhat supported when those who never married are considered. Males who never married are less likely to be a Current Driver and more likely to have ceased driving or to have been a never driver with the latter category providing the most extreme value of this analysis ($SR = -12.5$). This supports the idea that marriage is selective for driving and without the consequences of marriage, never married males are more likely to give up driving. However, this argument is somewhat negated by the fact that never having been married would appear to have no influence on the distribution of Driver Status across Females. This leads to the interpretation that Driver Status is selective for Marriage in Males only, or at least in the era when this sample was getting married, but once married it is selective for developing and maintaining driving skills irrespective of Gender. Being widowed has a negative impact on driving, consistent with other studies (Isherwood et al., 2017): possible interpretations include less practice and attachment to driving by female widows, poor health, increased age and a more realistic sense of driving abilities (Hjorthol et al., 2010).

With respect to Reasons for stopping driving it is important to note that physical incapacity was only the third most cited reason and second for men, further reinforcing the complexity of the process of driving cessation as not just one of health and physical status. The two reasons which produced significantly different proportions in men and women were Reasons not related to health, which was more prevalent among women and Problems with eyesight, which were more prevalent among men. Taken in conjunction with the above noted greater rate of decline in driving among women with age, it would seem that the reasons why women give up driving quicker than men are poorly understood and need more investigation (Dickerson et al., 2017). Three Reasons for ceasing driving were impacted by Age category. Becoming too expensive was cited more frequently than expected by the youngest group and less so by the oldest group. Presumably the youngest group may still have financial dependents and concerns relating to issues such as mortgages while the oldest group are likely to no longer have such concerns. Visual impairment, consistent with previous research, was impacted by Age category with it being less prevalent than expected among the younger group and more prevalent among the oldest group. Being Told by family was higher than expected in the oldest group suggesting that family members become more concerned with age. But the legitimacy of these concerns needs to be questioned given that the same pattern does not emerge for doctors, although it is likely in some cases doctors may not discuss or advise on driving (e.g., Puvanachandra et al., 2008). The fact that the frequency of Physical incapacity being cited as a reason was not impacted by Age category was somewhat surprising but may reflect the fact that subjective appreciation of health related status may not reflect reality (Schneider et al., 2004).

Looking at the impact of Age, Gender and Driving Status on Quality of Life and Loneliness it is clear given the effect sizes that only Driver Status had a meaningful impact on these with being a Current driver conferring an advantage over having ceased driving or never haven driven. Although these are simplistic models it does give an indication of the advantages that are experienced by drivers. Obviously, there are other variables that might be conferring this advantage, and these would need to be teased apart through the use of more sophisticated statistical models.

An interesting area of research relates to exploring the heterogeneity of transport profiles associated with increased heterogeneity and inter-individual variability of later life. One overview of existing studies suggested segmenting older peoples' transport profiles into four generic segments: (1) an active car-oriented segment; (2) a car-dependent segment, restricted in mobility; (3) a mobile multi-modal segment; (4) and a segment depending on public transport and other services (Haustein and Siren, 2015). The current data did not lend themselves to such an analysis but future research may benefit from ensuring such profiles can be identified should they exist.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the Faculty of Health Sciences Research Ethics Committee at Trinity College Dublin with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the Faculty of Health Sciences Research Ethics Committee at Trinity College Dublin.

AUTHOR CONTRIBUTIONS

MG conducted the analysis and wrote the Materials and Methods, Results, and Discussion. DO wrote the Introduction and contributed to the Discussion.

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Impulsive and Self-Regulatory Processes in Risky Driving Among Young People: A Dual Process Model

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The present study empirically examined a novel dual process model of self-reported aberrant driving behavior in young and novice drivers that incorporates both impulsive and self-regulatory processes. Four hundred and nine participants aged 18–25 years (*M* age = 21.18 years, *SD* = 2.12; 65.5% females) completed online questionnaires on impulsivity, normlessness, sensation seeking, emotion and self-regulation, and attitudes toward driving safety. Path analysis showed that motor impulsivity was associated with self-reported driving violations, errors, and lapses, whereas sensation seeking was uniquely directly associated with self-reported errors. Non-planning impulsivity, normlessness and sensation seeking had significant indirect effects on self-reported errors, via self-regulation. Finally, motor impulsivity and normlessness had a significant indirect effect on self-reported violations, errors and lapses, via attitudes to driving safety. Based on our findings we suggest that a dual-process approach is relevant to the study of aberrant driving behavior in young and novice drivers, and the results of the present study have important implications for initiatives to promote driving safety in this population.

Keywords: risky driving, young drivers, impulsivity, attitudes, self-regulation, driving violations, driving errors

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INTRODUCTION

According to the 2016 World Health Organization report on road safety, over a million people die in road traffic crashes (RTCs) each year, and traffic crash-related injuries represent the leading cause of death among young people aged between 15 and 29 years (World Health Organisation, 2016). In the United Kingdom alone, 29,081 people were killed or seriously injured in 2017 in traffic crashes, with an estimated cost of ∼£16 billion p.a. for reported crashes to the United Kingdom economy (Department for Transport [DFT], 2018). Novice drivers are overrepresented in road traffic casualties, with the per-mile crash rate for teenage drivers being 10 times higher than that of more experienced and older drivers (Mayhew et al., 2003; McKnight and McKnight, 2003). The Decade of Action for Road Safety (DARS) 2011–2020 represents a United Nations initiative that aims to improve road safety and reduce by 50% the number of deaths attributed to traffic injuries and RTCs, especially among young drivers. One of the key action areas of the global plan to achieve the DARS 2011–2020 goals is road user behavior, according to the UN Road Safety Collaboration (World Health Organisation, 2019). Accordingly, a recent evaluation of actual RTC data showed that driver behavior was a main risk factor in 90% of the observed crashes (Dingus et al., 2016).

Better understanding the driver-related risk factors for RTCs can help in further promoting road safety in young drivers.

So far, a large body of research has shown that crash involvement has been independently associated with specific types of self-reported aberrant driving behavior, such as intentionally violating traffic rules (e.g., speeding), and unintentional driving errors and lapses (e.g., getting into the wrong lane when entering a roundabout or a junction) while driving (Lajunen et al., 2004; de Winter and Dodou, 2010). Early research suggested that lapses may have consequences for the driver but not for other road users, errors and violations are often hazardous to others, but only self-reported violations were associated with crash involvement (Parker et al., 1995). However, a recent meta-analysis (de Winter et al., 2015) showed that the average correlation coefficient between self-reported violations and crash involvement was 0.13 (based on 67 studies), and the respective correlation with self-reported errors was 0.09 (based on 56 studies), suggesting that both types of self-reported aberrant driving represent risk factors for self-reported RTCs. Previous research has shown that although self-reported violations and errors represent distinct facets of aberrant driving behavior (Lajunen et al., 2004), the correlation between them can be as high as 0.70 (de Winter and Dodou, 2010). Further research into the psychological factors associated with errors and violations is needed in order to identify if similar mechanisms are implicated in the prediction of these two types of self-reported aberrant driving.

Direct and Indirect Effects of Personality on Risky Driving

One of the most prolific research areas in the psychological study of aberrant driving behavior is concerned with the influence of personality. Different studies have found that emotion-related traits, such as altruism, sensation and excitement-seeking, and hostility were associated with riskier self-reported driving behavior and higher self-reported crash involvement among young and novice drivers (e.g., Ulleberg, 2001; Oltedal and Rundmo, 2006; Machin and Sankey, 2008; Lucidi et al., 2010). Other research has shown that trait impulsivity is particularly relevant to self-reported risky driving in young and/or novice drivers. Impulsivity reflects people's tendency to act spontaneously and without premeditation and forethought, in response to environmental cues or other triggers, and with a preference for short-term and immediate gratification over long-term and delayed rewards (Moeller et al., 2001). According to Barratt's three-factor model, trait impulsivity reflects three main characteristics: greater motor activation (motor impulsivity), such as acting at the spur of the moment; less attention to the task at hand (attention impulsivity); and a reduced ability to plan actions (non-planning impulsivity; Patton et al., 1995; Stanford et al., 2009).

Constantinou et al. (2011) used Barratt's three-dimensional model of impulsivity (Patton et al., 1995; Stanford et al., 2009) to study the associations between motor, attentional, and non-planning dimensions of impulsivity with self-reported risky driving in young drivers. They found that non-planning impulsivity was positively associated with ordinary driving violations. Another study (Hatfield et al., 2017) used both self-reported and lab-based objective measures of trait impulsivity and showed that higher speeding and "riskier" responses (e.g., overtaking, driving through orange lights, not attending to cyclists on the road) in a computerized driving simulation task were positively associated with poorer performance in impulse control tasks (i.e., more errors in a Go/No Go task), but not with self-reported measures of trait impulsivity. Another study found that impulsivity was associated with driving errors (Pearson et al., 2013). Bıçaksız and Özkan (2016) reviewed 38 studies that included measures of trait impulsivity and different self-reported and police-recorded driving outcomes, including driving errors, lapses, violations, driving under the influence, and speeding. They found that, in most studies, aberrant driving outcomes were significantly associated with impulsivity dimensions: "Among the 38 studies reviewed here, impulsivity failed to relate significantly to the driving related measure in any analyses conducted in that study in only four studies" (p. 215).

Previous research has supported the idea that impulsivity and related personality traits are indirectly associated with risky driving outcomes. Sümer (2003) suggested that psychological characteristics, including risk-taking propensity, aggression/hostility and sensation-seeking, create the tendency for aberrant driving behavior (e.g., driving under the influence, speeding, committing errors and violations) which, in turn, can lead to actual crash involvement. The hypotheses derived from Sümer's (2003) model have been supported by research using self-reported measures of risky driving in young people (e.g., Constantinou et al., 2011). Ulleberg and Rundmo (2003) proposed an alternative model that takes a social cognitive approach and emphasizes the role of safe driving attitudes as a mediator between personality traits and self-reported aberrant driving behavior. According to this model, personality traits related to impulsive behavior and risk-taking, such as sensation seeking, hostility/aggression, and normlessness (i.e., believing that socially unacceptable behaviors are sometimes needed to achieve certain goals), increase the likelihood for aberrant driving (e.g., speeding). On the other hand, traits such as altruism are expected to have a negative correlation with self-reported risky driving and a positive correlation with attitudes toward traffic safety. Ulleberg and Rundmo (2003) further argued that personality traits are likely to have an indirect (vs. a direct) effect on risky driving outcomes, and their model recognizes attitudes to safe driving as a key variable that mediates the association between personality traits and aberrant driving behavior. Their model has been empirically supported by subsequent research studying older (Lucidi et al., 2014) and professional drivers (Mallia et al., 2015). The type of traits associated with self-reported risky driving, and the effect sizes of the direct and indirect associations between personality, attitudes to safe driving, and risky driving indicators (i.e., driving violations, errors, and lapses at wheel) have varied from study to study.

A Dual-Process Model of Aberrant Driving Behavior

A large body of psychological research has shown that human behavior is not always the product of careful planning, premeditation, and self-regulation of thought and action (Evans, 2008; Evans and Stanovich, 2013; Strack and Deutsch, 2015; Melnikoff and Bargh, 2018b). Rather, automatically activated processes, triggered by apparently mundane environmental cues, can elicit a wide range of unplanned and spontaneous behavioral responses, spanning biased information-processing and social judgments, normative behavior, stereotyping, interpersonal violence and hostility, and risk-taking (Aarts and Dijksterhuis, 2003; Bargh et al., 2012; Rivis and Sheeran, 2013; Sheeran et al., 2013; Melnikoff and Bargh, 2018a). Using the terms coined by Stanovich and West (2000), dual process theorists have categorized automatically activated and consciously controlled higher order cognitive processes into System 1 and System 2 respectively (Evans, 2008). According to this classification, System 1 reflects action driven by impulses, intuition, heuristics, and low mental effort, whereas System 2 is characterized by higher cognitive effort, reflective, and analytic thinking, and is associated with our capacity to control impulses (e.g., inhibitory control), and to regulate our thoughts, emotional arousal, and actions - metaphorically, some scholars have respectively likened System 1 and System 2 processes to "hot" and "cold" reasoning and decision-making (Evans, 2008; Strack and Deutsch, 2015). Although dual process theories were originally developed to account for variations in human reasoning and decision-making processes, the "dualism" concept has found useful applications in other domains, such as understanding health and risk-taking behaviors, and developing relevant interventions to change them (Wills et al., 2011; Hollands et al., 2016; Maher and Conroy, 2016).

The dual process paradigm is highly relevant to understanding (and preventing) aberrant driving behavior in young and novice drivers for the following reasons. Recent developmental neuroscience and neurobiology perspectives posit that neural networks located in the prefrontal cortex (PFC) do not mature until early adulthood, and thus, adolescents and young adults can lack sufficient inhibitory control to resist risk-taking, such as antisocial behavior, substance use/abuse, unsafe sexual activity, and reckless driving (e.g., Kuhn, 2006; Steinberg, 2007; Pharo et al., 2011). This is unsurprising given that the PFC has been described as the "command center" of multiple self-regulatory functions such as inhibitory control, working memory, attentional control and planning, and task switching – collectively known as Executive Functions (EFs) – which are necessary for safe and self-regulated driving (Mäntylä et al., 2009). In addition to neurodevelopmental changes, adolescence and young adulthood are characterized by greater autonomy/independence and spending more time with peers. According to Steinberg (2007, 2010) the still "immature" executive control network cannot sufficiently inhibit impulses and actions driven by the highly active socio-emotional network, which can result in higher risk-taking in the presence of peers. Chein et al. (2011) demonstrated that adolescents, but not adults, committed more errors in a driving-related impulse control (Go/No Go) task when they were tested in the presence of peers, but the amount of errors was not statistically significant between age groups when they were tested alone. Furthermore, in the peer condition, adolescents exhibited greater activation in the brain regions associated with reward valuation (e.g., ventral striatum, orbitofrontal cortex or OFC), and less activation of executive control areas, as compared to adults, and this pattern of activation was significantly associated with greater risk-taking (Chein et al., 2011; Albert et al., 2013).

Other studies using driving simulators have examined the association between EF and driving behavior. One study found that young adults with weaker working memory (updating component) performed worse in a lane changing task during a low-fidelity driving simulation (Mäntylä et al., 2009), and another study found that lower response inhibition was associated with more collisions and slower reaction times to hazards in a medium fidelity driving simulation task (Ross et al., 2015). More recently, Ross et al. (2016) extended their previous research by using a dual process paradigm. They assessed the effects of peer presence on driving performance, and its interaction with executive functions, such as inhibitory control. They found that the presence of peers was associated with greater traffic violations in a driving simulation task - a finding that corroborates previous research on the association between the presence of same-age peer passengers and actual RTCs among young and novice drivers (e.g., Simons-Morton et al., 2011). Ross et al. (2016) further demonstrated that driving violations (e.g., speeding) in the peer presence condition were higher among drivers with lower inhibitory control. To date, the studies by Ross et al. (2015, 2016) are the only ones that have explicitly used a dual system approach to evaluate risky driving in young people using driving simulation tasks. Ross et al. (2016) manipulated peer presence as a primary means to resemble System 1 processes. Peer presence, however, represents the (social) stimuli that may elicit System 1 responses, such as increased risk-taking, and does not necessarily reflect System 1 responses *per se*. Another study showed that neural activity in brain areas involved in response inhibition and cognitive control (i.e., System 2) buffered the effects of peer presence on impulsive risk-taking (System 1) in driving simulation tasks among recently licensed teenage drivers (Cascio et al., 2015). This suggests that System 2 processes play an important role in the way System 1 processes may influence (simulated) driving behavior.

The distinction between System 1 and System 2 may also provide a useful framework on which to model the cognitive bases of driving errors, such as getting into the wrong lane, while driving. Many aspects of car control are likely to rely on the more automatic processes of System 1. However, the avoidance of errors (or lapses) may often require intervention from System 2 at key choice points, in order protect behavior from following the most frequently applied routines in the current situation (Reason, 1990). Impulsivity, and its often identified correlate, inattention, may impinge on System 2 input of this sort.

The Present Study

Previous research has indicated that a dual process paradigm can be used to better understand the psychological factors associated with RTCs in young and novice drivers (Mäntylä et al., 2009; Ross et al., 2015, 2016). In the present study we propose a dual process model of aberrant driving behavior in young and novice drivers that is differentiated from previous dual process studies of risky driving (i.e., Ross et al., 2016) in terms of methodology and theoretical framework. Specifically, unlike Ross et al. (2016) who utilized a driving simulator, in the present study we assessed aberrant driving behavior with the Driving Behavior Questionnaire (DBQ; Lajunen et al., 2004), a self-reported measure of aberrant driving that has been found to be reliably and validly associated with RTC risk (e.g., near crashes), and self-reported traffic crashes in different cultures and age groups (for a meta-analysis see de Winter and Dodou, 2010; de Winter et al., 2015), and with driver performance in studies using driving simulation tasks (Helman and Reed, 2015). Furthermore, our theoretical proposition is that a dual process paradigm of risky driving in young and novice drivers should take into consideration individual differences that are implicated in System 1 and System 2 processes. These may include impulsivity and related traits (System 1), and self-regulatory capacities (System 2; e.g., emotion and self-regulation).

Our dual-process model is based on three key premises. The first premise is that System 1 (hot) processes are reflected in individual differences in impulsivity, sensation-seeking and normlessness, which have been previously associated with self-reported aberrant driving behavior (Ulleberg and Rundmo, 2003; Constantinou et al., 2011; Bachoo et al., 2013; Berdoulat et al., 2013; Sullman and Stephens, 2013). Accordingly, System 2 (cold) processes are reflected in individual differences in self-regulation (i.e., the capacity to consciously control behavior and restrain impulsive action, Carver and Scheier, 2016), emotion regulation (i.e., the capacity to regulate emotional responses in order to achieve a certain goal), and attitudes toward driving safety, which have been previously associated with lower scores in self-reported aberrant driving (Iversen and Rundmo, 2004; Sani et al., 2017). The second premise of our model is that the distinction between System 1 and System 2 processes respectively resembles the distinction between risk and protective psychological factors for RTCs. This implies that "hot" input from System 1 processes is likely to increase the risk for RTCs, whereas "cold" self-regulatory System 2 processes can mitigate that risk. The third and final premise purports that the effects of impulsivity traits on driving behavior may be mediated by individual differences in self-regulation (see Cascio et al., 2015).To illustrate, young and novice drivers with higher scores in impulsivity and related traits (e.g., sensation-seeking) may respond more emotionally to an environmental cue (e.g., being overtaken) while driving. Whether this emotional response will predict aberrant driving behavior (e.g., driving violations and/or errors) and actual crash involvement will be determined by the driver's capacity to regulate their thoughts, emotions, and actions and by their attitude toward driving safety - which is hypothesized to be lower in individuals with higher scores in personality traits and characteristics pertaining to System 1, such as impulsivity. With this example the dual-process model of risky driving proposed in the present study explains how impulsivity and impulsiveness-like traits (System 1) are associated with risky driving, and how their effects can be "overtaken" by self-regulatory and reflective processes (System 2). The premises of our model are partly derived from previous theories of self-regulation and impulse control, which purported that self-regulatory failure emerges when the impulsive urges and emotions originating in subcortical structures (i.e., nucleus accumbens/NAcc) cannot be effectively regulated because of diminished self-regulation (i.e., prefrontal activity) due to decision fatigue/ego depletion, negative moods and other influences (e.g., cue exposure; Heatherton and Wagner, 2011).

Based on the aforementioned premises, the following hypotheses were formed.

H1: Trait impulsivity (motor, executive, and planning dimensions), sensation seeking, and normlessness (System 1) will be positively associated with self-reported aberrant driving behavior. Accordingly, self-regulation, emotion regulation and attitudes toward driving safety (System 2) will be negatively associated with aberrant driving behavior.

H2: Emotion, self-regulation, and attitudes to driving safety (System 2) will significantly mediate the association between trait impulsivity dimensions, sensation seeking, normlessness (System 1) and aberrant driving behavior.

MATERIALS AND METHODS

Participants

Overall, 409 students from three Universities in North and South-East England participated in the study. They were aged between 18 and 25 years (*M* age = 21.18, *SD* = 2.12). 65.5% of them identified themselves as females, 87.5% identified themselves as having English/Welsh/Scottish/Norther Irish or British background, their average (median) mileage per week was 20 miles, and the average (mean) time since obtaining their driving license was 7.6 years (*SD* = 2.07).

Measures

System 1 Measures

Impulsivity was measured with the Abbreviated Impulsiveness Scale (ABIS; Coutlee et al., 2014). The ABIS is an 11-item measure of trait impulsivity and consists of three subscales that reflect attentional (e.g., "*I don't pay attention*"), motor (e.g., "*I say things without thinking*"), and non-planning (e.g., "*I am future oriented*" reverse scored item) impulsivity. Responses are coded on a 4-point Likert scale (1 = *rarely/never*, 4 = *almost always/always*). Following reverse scoring of 8 items, a mean score is computed for each subscale and higher scores indicate higher impulsiveness. In the present study, the internal consistency reliability coefficient (Cronbach's α) for each ABIS subscale was acceptable (ABIS non-planning α = 0.71; ABIS motor α = 0.71; ABIS attention α = 0.71).

Sensation-seeking was assessed with the mean of five items based on the NEO Personality Inventory (Costa and McCrae, 1992). Responses were recorded on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*), and higher scores reflected higher sensation-seeking. Two items ("*I act in a direct way*" and "*I would never go hang gliding or bungee jumping*") were deleted to improve the internal reliability of the measure, and the final 3-item measure had satisfactory reliability (α = 0.66).

Normlessness was measured with the mean score of three items (e.g., "It is ok to get round laws and rules as long as you do not break them directly" and "If something works, it is less important whether it is right or wrong") based on Kohn and Schooler (1983) normlessness scale, and adapted from Chen (2009) who used this measure in the study of aberrant driving behaviors. Responses were recorded on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), and higher scores reflected normlessness. Internal consistency reliability for this measure was satisfactory (α = 0.73).

System 2 Measures

Emotion regulation was assessed with the Emotion Regulation Questionnaire (ERQ; Gross and John, 2003). The ERQ is a 10-item self-reported survey that measures individual differences in emotion regulation strategies. It comprises two subscales that reflect expressive suppression (e.g., "*I control my emotions by not expressing them*") and cognitive reappraisal (e.g., "*When I want to feel positive emotion (such as joy or amusement), I change what I'm thinking about*"). Responses are given on 7-point scale (1 = *strongly disagree*, 7 = *strongly agree*), and a mean score is computed for each scale with higher scores reflecting higher emotion regulation in each dimension. The reliability and validity of the ERQ have been reported in previous studies (Gross and John, 2003), and the internal consistency reliability for the ERQ subscales in the present study was high (Cognitive reappraisal α = 0.87; Expressive suppression α = 0.75).

Self-regulation was assessed with the 31-item Short Self-Regulation Questionnaire (SSRQ; Carey et al., 2004). The SSRQ reflects different aspects of self-regulation, such as goal-setting and monitoring (e.g., "*I set goals for myself and keep track of my progress*"), deliberate thinking/reasoning of actions (e.g., "*I usually think before I act*"), and self-control (e.g., "*I am able to resist temptation*"). Responses were recorded on a 5-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*), and a sum score was generated with higher scores indicating greater self-regulatory capacity. The reliability of the SSRQ in the present study was high (α = 0.91).

Attitudes to driving safety were assessed with the respective measure developed by Iversen (2004). This is a 16-item self-reported questionnaire of attitudes toward traffic violations (e.g., "*Many traffic rules must be ignored to ensure traffic flow*"), careless driving of others (e.g., "*It's OK to ride with someone who speeds if others do*"), and driving under the influence (e.g., "*I would never drive after drinking alcohol*"). Responses were recorded on a 5-point Likert scale (1 = *strongly agree*, 5 = *strongly disagree*) and a mean score was computed with higher scores denoting more positive attitudes toward driving safety. The internal consistency reliability of the measure was high (α = 0.81).

Driving Behavior Measure

Aberrant driving behavior was assessed with the 27-item version of the Manchester Driver Behavior Questionnaire (DBQ; Lajunen et al., 2004), which measured driving violations (11 items, of which 8 items assessed ordinary violations and 3 items assessed aggressive violations), driving errors (e.g., "*On turning left nearly hit a cyclist who has come up on your inside*" - 8 items) and lapses (e.g., "*Misread the signs and exit from a roundabout on the wrong road*" - 8 items). For driving violations, ordinary (e.g., "*disregard the speed limit on a motorway*") and aggressive violations (e.g., "*Sound your horn to indicate your annoyance to another road user*") were combined into a single score of "total violations" based on previous research showing that these dimensions could reflect a single factor (e.g., Lajunen et al., 2004), and that aggressive violations do not predict crash involvement independently from ordinary violations (Rowe et al., 2015). Respondents were asked to indicate how often they themselves do each of the violations and errors when driving over the last 12 months or since passing their driving test if that was less than 12 months. Responses were recorded on a six-point scale from "Never" to "Nearly all the time." Composite scores were computed for each subscale, and higher scores denoted more frequent engagement in each type of aberrant driving behavior. Internal consistency reliability was satisfactory for total violations (α = 0.82), errors (α = 0.76), and lapses (α = 0.72).

Design/Procedure

A cross-sectional, survey-based design was used to assess the association between System 1 (impulsivity, sensation-seeking, and normlessness), System 2 (emotion regulation, self-regulation, and attitudes to driving safety) and aberrant driving behavior. Participants were contacted either in-person by a trained research associate in University premises, or online through email lists for research participation, and were asked to access and complete an online Qualtrics survey about driving attitudes and behavior. No time restrictions were posed for survey completion and participants took approximately 15 min to complete the online survey. In line with the research ethics guidelines of the British Psychological Society, participants gave their informed consent for participation in the study (by selecting an option in the online survey indicating their agreement to proceed with the study before starting the questionnaire), they were duly informed about the aims and purposes of the study and were given the right to withdraw from it at any point without giving explanations and without any ensuing negative consequences. They were also informed about the anonymity and confidentiality of their responses and were given the opportunity to resolve any questions they had prior to completing the survey. Ethics approval was obtained by the respective ethics review board of the University of Sheffield.

Data Analysis

Initial inter-correlations (Pearson's *r*) among study variables were calculated in SPSS v. 24 (IBM Corp., Armonk, NY, United States).

Following this a path model was estimated in AMOS v. 24 (IBM Corp., Armonk, NY, United States) to test the study hypotheses, featuring the variables that significantly correlated with the outcome variables (i.e., lapses, errors, and violations). The path model included System 1 traits as exogenous predictors, System 2 traits as potential mediators, and the three outcome variables and modeled the regression parameters simultaneously. Error terms for all endogenous variables were permitted to correlate. Given that the outcome variables were correlated, average effects of each of the predictors on the three outcomes were estimated, as well as the differences in the size of these effects using AMOS custom estimands. Bootstrapping (10,000 resamples; Wood, 2005) was used to estimate the significance of coefficients in the path model (Hayes and Scharkow, 2013). Bootstrapping is incompatible with missing data, so a complete case analysis was conducted ($n = 307$).

RESULTS

Descriptive statistics and inter-correlations among the study variables are presented in **Table 1**. The observed correlations were in the expected direction for all measures, thus, supporting the construct validity of the measures used in the study. Taking System 1 measures as an example, sensation seeking was positively correlated with normlessness ($r = 0.24$, $p < 0.001$), attentional ($r = 0.17$, $p < 0.005$), motor ($r = 0.30$, $p < 0.001$), and non-planning ($r = 0.20$, $p < 0.001$) impulsivity. Age was not statistically related to any outcome variable, nor were the emotion regulation variables, and thus these variables were omitted from further analyses.

The results of the path model are in **Table 2**. This model fit the data well, $\chi^2(2) = 0.027$, $p = 0.986$, CFI = 1.00, RMSEA = 0.00, $p = 0.994$, and this set of predictors explained 17%, 25%, and 42% of variance in the three outcomes, lapses, errors, and violations, respectively. Of the System 1 traits, motor impulsivity was significantly directly associated with all three outcomes with coefficients of a similar magnitude, while sensation seeking was statistically uniquely directly associated with self-reported driving errors. Of the System 2 traits, attitudes was significantly negatively directly associated with all outcome variables, but with a statistically meaningful stronger association with violations than either errors or lapses.

Of the indirect (mediation) effects of System 1 traits via System 2 traits on driving outcomes, non-planning, normlessness, and sensation-seeking all had a significant indirect effect on reported driving errors via self-regulation, and these effects were statistically stronger than the same indirect effects on reported driving violations. Motor impulsivity and normlessness both had significant indirect effects on all outcomes via attitudes, and these effects were statistically stronger for reported driving violations than errors or lapses.

DISCUSSION

The present study purported the idea that a dual process paradigm is relevant and useful to the study of the psychological risk factors for RTCs in young and novice drivers - an idea that has started to gain prominence in risky driving research over the last 5 years (see Lambert et al., 2014). We used the System 1/ System 2 distinction (Evans, 2008) to classify impulsivity and impulsiveness traits (i.e., normlessness, and sensation seeking), and self-regulatory capacity (i.e., emotion and self-regulation, and attitudes toward driving safety) respectively, as independent psychological correlates of self-reported driving violations, driving errors and lapses. Accordingly, we hypothesized that self-reported aberrant driving behavior will be positively associated with System 1 and negatively associated with System 2 psychological factors. Our second hypothesis was that the association between System 1 psychological factors (i.e., impulsivity, sensation seeking and normlessness) and self-reported driving behavior (i.e., errors, lapses, and violations) would mediated by self-regulation and attitudes to safe driving, which pertain to System 2 processes. Overall, the results of the study have largely supported our hypotheses in the following ways.

First of all, motor impulsivity was associated with all three indicators of aberrant driving (i.e., self-reported violations, driving errors and lapses). Motor impulsivity reflects behavioral disinhibition (e.g., acting without thinking) and has been associated with impaired inhibitory control (Caswell et al., 2013). Impaired inhibitory control, in turn, has been associated with greater influence of peers on risk-taking in driving simulation tasks among young novice drivers (Ross et al., 2016). Our study corroborates previous findings and indicates that motor impulsivity (behavioral disinhibition) is more relevant to aberrant driving behavior in young and novice drivers, than other dimensions such as executive (non-planning) and cognitive impulsiveness. However, our findings are in contrast with Constantinou et al. (2011) who found that non-planning impulsivity was the only significant correlate of driving violations. A possible explanation is that the association between non-planning impulsivity and self-reported aberrant driving in Constantinou et al. (2011) was attenuated by the inclusion of other predictors, such as sensitivity to punishment/reward and different measures of sensation seeking. Another explanation pertains to the methodological approach used by Constantinou et al. (2011). Specifically, although the zero-order correlations between motor impulsivity and the three dimensions of self-reported aberrant driving were statistically significant (Pearson's r ~0.17 to 0.27) and comparable to those of non-planning impulsivity (Pearson's r ~0.09 to 0.22), the authors decided to include only non-planning impulsivity in their path model.

Furthermore, in the present study, the observed effect sizes in the zero-order correlations between sensation seeking and normlessness are in line with those reported in previous research in the context of risky driving in young people (e.g., Lucidi et al., 2010); sensation seeking was associated with driving errors, and normlessness and sensation seeking both had significant indirect effects, via self-regulation, on driving errors. Higher scores in sensation seeking may predispose young drivers to seek excitement in driving, which may, in turn be associated with more driving errors (e.g., braking too quickly on a slippery road) or other risky driving indicators, such as speeding (Machin

TABLE 1 | Descriptive statistics and inter-correlations among the study variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
(1) *Violations*	–	0.55***	0.38***	0.06	−0.14**	0.16***	0.36***	0.17**	0.21***	0.40***	0.15*	−0.06	0.04	−0.16**	−0.56***
(2) Errors		–	0.56***	−0.01	−0.01	0.04	0.31***	0.13*	0.23***	0.21***	−0.04	−0.05	0.06	−0.24***	−0.36***
(3) Lapses			–	0.01	0.11*	0.04	0.27***	0.13*	0.25***	0.12*	0.11*	−0.08	−0.08	−0.20***	−0.21***
(4) Age				–	0.06	0.08	−0.02	−0.02	−0.09	−0.03	−0.14*	0.10	−0.11*	0.11*	−0.03
(5) Sex					–	0.00	−0.11*	−0.14*	0.02	−0.15*	−0.07	0.05	−0.27***	0.07	0.25***
(6) Mileage						–	0.02	−0.06	−0.02	0.15*	0.02	−0.01	0.04	0.05	−0.02
(7) Motor impulsivity							–	0.30***	0.44***	0.21***	0.30***	0.03	−0.02	−0.23***	−0.29***
(8) Planning impulsivity								–	0.50***	0.15*	0.20***	−0.14*	0.00	−0.40***	−0.19***
(9) Attentional impulsivity									–	0.18***	0.17**	−0.23***	−0.05	−0.57***	−0.23***
(10) Normlessness										–	0.24***	0.06	0.22***	−0.25***	−0.50***
(11) Sensation seeking											–	0.16**	0.05	−0.04	−0.16**
(12) Reappraisal												–	−0.00	0.31***	0.06
(13) Suppression													–	−0.15*	−0.19***
(14) Self-regulation														–	0.28***
(15) Attitudes															–
Mean	1.85	1.54	2.18	21.18	–	54.24	1.95	1.95	1.99	2.51	3.54	4.69	3.89	108.23	3.69
SD	0.59	0.42	0.58	2.12	–	89.57	0.54	0.61	0.50	0.88	0.74	1.12	1.23	16.55	0.56

****$p \leq 0.001$; **$p \leq 0.005$; *$p \leq 0.05$.*

TABLE 2 | Path model results for the direct and indirect effects of system 1 traits on self-reported aberrant driving behavior.

	(A) Lapses. R^2 = 0.17, p = 0.010			(B) Errors. R^2 = 0.25, p = 0.012			(C) Violations. R^2 = 0.42, p = 0.006			Average effect			
Direct effects	β	BCa 95% CI		β	BCa 95% CI		β	BCa 95% CI		β	BCa 95% CI		
		LO	HI		LO	HI		LO	HI		LO	HI	DIFF
Gender	0.19**	0.08	0.30	0.09	−0.03	0.20	0.02	−0.08	0.11	0.10*	0.01	0.18	A > C
Mileage	0.11	−0.04	0.24	0.04	−0.05	0.14	0.17**	0.06	0.27	0.11*	0.01	0.20	B < C
(1) Motor impulsivity	0.20**	0.06	0.34	0.26***	0.11	0.41	0.22**	0.10	0.35	0.23***	0.11	0.35	
(2) Attention	0.06	−0.10	0.22	−0.01	−0.17	0.14	0.00	−0.14	0.14	0.02	−0.10	0.14	
(3) Non-planning	0.00	−0.13	0.14	0.00	−0.11	0.11	0.02	−0.09	0.13	0.01	−0.09	0.10	
(4) Normlessness	−0.04	−0.18	0.09	0.02	−0.13	0.16	0.12†	−0.01	0.23	0.03	−0.08	0.14	A < C
(5) Sensation-seeking	0.03	−0.10	0.15	−0.17*	−0.30	−0.04	−0.03	−0.15	0.08	−0.06	−0.17	0.05	A | C < B
(6) Self-regulation	−0.10	−0.24	0.04	−0.13†	−0.26	0.00	0.04	−0.07	0.16	−0.06	−0.16	0.04	B > C
(7) Attitudes	−0.20**	−0.32	−0.07	−0.32***	−0.47	−0.16	−0.46***	−0.57	−0.34	−0.32***	−0.43	−0.21	A | B < C
Indirect effects[a]													
(1)→(6)	0.00	−0.02	0.01	0.00	−0.02	0.01	0.00	0.00	0.01	0.00	−0.01	0.01	
(2)→(6)	0.05	−0.02	0.14	0.07†	0.00	0.15	−0.02	−0.09	0.04	0.03	−0.02	0.09	B > C
(3)→(6)	0.01†	0.00	0.05	0.02*	0.00	0.05	−0.01	−0.03	0.01	0.01	0.00	0.03	A | B > C
(4)→(6)	0.02	−0.01	0.05	0.02*	0.00	0.05	−0.01	−0.03	0.01	0.01	−0.01	0.03	B > C
(5)→(6)	−0.01	−0.04	0.00	−0.02*	−0.05	0.00	0.01	−0.01	0.03	−0.01	−0.03	0.00	B > C
(1)→(7)	0.03**	0.01	0.07	0.05**	0.01	0.10	0.07**	0.02	0.13	0.05**	0.01	0.10	A | B < C
(2)→(7)	0.02†	0.00	0.05	0.03	−0.01	0.07	0.04	−0.01	0.10	0.03	−0.01	0.07	
(3)→(7)	0.01	−0.02	0.03	0.01	−0.03	0.05	0.02	−0.04	0.07	0.01	−0.03	0.05	
(4)→(7)	0.09**	0.03	0.15	0.14***	0.07	0.22	0.20***	0.14	0.27	0.14***	0.08	0.20	A | B < C
(5)→(7)	0.00	−0.03	0.02	−0.01	−0.05	0.03	−0.01	−0.06	0.04	−0.01	−0.04	0.03	
Total effects[a]													
(1)	0.23**	0.09	0.36	0.31***	0.16	0.44	0.30***	0.16	0.42	0.28***	0.16	0.39	
(2)	0.13†	−0.01	0.26	0.09	−0.04	0.21	0.02	−0.11	0.14	0.08	−0.03	0.18	
(3)	0.02	−0.11	0.15	0.03	−0.08	0.14	0.03	−0.09	0.14	0.03	−0.07	0.12	
(4)	0.06	−0.06	0.18	0.17**	0.06	0.28	0.31***	0.19	0.40	0.18***	0.09	0.26	A < B < C
(5)	0.01	−0.11	0.14	−0.20**	−0.32	−0.07	−0.03	−0.16	0.09	−0.07	−0.18	0.03	A | C < B

*N = 307. $\chi^2(2)$ = 0.027, p = 0.986, CFI = 1.00, RMSEA = 0.00, p = 0.994. [a]Analyses control for the effects of gender on the mediators and DVs, and mileage on the DV. BCa 95% CI = Bias-corrected and accelerated bootstrap confidence intervals (10,000 resamples). DIFF = Tests of equivalence between parameters for DV (A), (B), and (C). or = parameters are significantly different at $p < 0.05$. | = parameters are not significantly different at $p < 0.05$. Bootstrapped significance tests are based on standardized coefficients. ***$p < 0.001$. **$p < 0.01$. *$p < 0.05$. †$p < 0.10$.*

and Sankey, 2008). Previous research has shown that sensation (or thrill) seeking is associated with both driving violations and driving errors (Jonah, 1997; Wishart et al., 2017). In line with a recent meta-analysis (Zhang et al., 2019), in the present study sensation seeking had a significant but weak correlation with self-reported violations. It is possible that the correlation between sensation-seeking and aberrant driving behavior turns non-significant when a multivariate model is examined that accounts for the effects of other predictors.

We further hypothesized that the effects of impulsivity and related traits (normlessness and sensation seeking) on aberrant driving behavior will be mediated by System 2 self-regulatory processes. The results supported this hypothesis. Specifically, attitudes toward driving safety mediated the associations of motor impulsivity and normlessness with self-reported driving errors, lapses and violations. Accordingly, self-regulation mediated the associations of motor impulsivity, normlessness and sensation seeking with driving errors. Our findings further extend previous research by highlighting the roles of safe driving attitudes and trait self-regulation in mitigating the risk for aberrant driving among young drivers with higher scores in behavioral disinhibition (motor impulsivity). In particular the mediation results would suggest that those with higher System 1 traits are likely to have lower scores in characteristics and traits pertaining to System 2 that would function to regulate their driving behavior.

Self-regulated driving has been mostly studied in the context of older drivers and in association with age-related risk-avoidance and cognitive failure (e.g., Sullivan et al., 2011; Meng and Siren, 2012). To the authors' knowledge, our study is among the first to report on the effects of self-regulation on self-reported aberrant driving behavior among young and novice drivers. The present findings indicate a protective effect of self-regulation against driving errors, and further showed that the potential risk for traffic crashes that may be posed by impulsive driving can be mitigated by higher scores in driving safety attitudes and self-regulation. It is noteworthy that self-regulation and impulsivity may be related but they represent distinct psychological constructs that have separate functions, neural pathways and developmental trajectories (Hofmann et al., 2012; Nigg, 2017; Steinberg et al., 2018). Furthermore, our findings corroborate past research where better executive functions were associated with reduced risk-taking and risky driving in driving simulation tasks (Mäntylä et al., 2009; Ross et al., 2015). Executive functions play an important role in self-regulatory capacity (Hofmann et al., 2012; Nigg, 2017), and researchers have argued that executive functions allow people to pursue goal-directed behaviors and self-regulate their actions (Dohle et al., 2018). Accordingly, on the basis of the present findings we suggest that self-regulation may be an important explanatory factor in the association between executive functions and driving behavior (e.g., Mäntylä et al., 2009; Ross et al., 2015). It is also possible that the effects of impulsivity on driving behavior are influenced by individual differences in executive functions and self-regulation (Hofmann et al., 2012). However, these hypotheses require further empirical investigation.

The present study is not free of limitations. First of all, we used self-reported measures for impulsivity and aberrant driving behavior. Although self-reported aberrant driving may be subject to socially desirable responses, a large body of research has shown that the DBQ has been significantly associated with self-reported traffic crashes driving behavior in studies using driving simulators (de Winter et al., 2015). Furthermore, significant associations were observed between certain impulsivity dimensions (i.e., motor impulsivity/behavioral disinhibition) and self-reported aberrant driving behavior, and these associations could be examined further with the use of lab-based measures of impulsivity, and more objective measures of risky driving (e.g., valid observations/reports of traffic crashes). Secondly, our study assessed mostly personality traits that reflect System 1 (i.e., impulsive/hot) and System 2 (i.e., controlled/cold) processes. Future studies should incorporate more expansive measures that reflect broader System 1 (e.g., attentional bias to emotional stimuli) and System 2 reasoning and decision-making processes, such as risk perceptions. This will improve our understanding of automatic and reflective traits and processes involved in aberrant driving behavior, and will also lend further support to the idea that a dual process paradigm is needed in order to better understand and more effectively prevent risky driving among young and novice drivers (see Lambert et al., 2014). Also, in our study we used general measures of emotion and self-regulation and the observed effects could be stronger if driving-specific measures were used. Future studies, therefore, may consider the development of driving-specific measures of emotion and self-regulation (e.g., measures that will reflect how well drivers regulate their aggressive thoughts, emotions and action while driving). Finally, we used a cross-sectional design and this poses the inherent problem of reverse causality. Future studies should incorporate a longitudinal design to determine the developmental trajectories of the associations observed in the present study.

With respect to the practical implications of our findings, researchers have recently emphasized the need to reduce health risk-taking by addressing both reflective and automatic processes in reasoning and decision-making (Marteau et al., 2012). We further argue that the time is ripe to consider a dual system approach to risky driving and, accordingly, inform driving safety interventions. Our study showed that the effects of impulsive action can be mitigated by safe driving attitudes and self-regulation. Although future studies are needed to further validate our findings, interventions for driving safety should consider emphasizing the importance of driving safety attitudes, impulse control and self-regulation in mitigating the risks for RTCs among young and novice drivers.

ETHICS STATEMENT

The study reported in the manuscript was approved by the Ethics Review Board of the Department of Psychology, The University of Sheffield with the registration number 130125783, and approval date: 25/11/2016.

AUTHOR CONTRIBUTIONS

All authors have contributed equally to the study design and managed the data collection. LL led the writing up of the manuscript. DP, AY, PP, and RR contributed to the editing and revision of the final version of the manuscript. PP performed the statistical analysis.

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frontiers in Psychology

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Correlation Among Behavior, Personality, and Electroencephalography Revealed by a Simulated Driving Experiment

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Drivers play the most important role in the human-vehicle-environment system and driving behaviors are significantly influenced by the cognitive state of the driver and his/her personality. In this paper, we aimed to explore the correlation among driving behaviors, personality and electroencephalography (EEG) using a simulated driving experiment. A total of 36 healthy subjects participated in the study. The 64-channel EEG data and the driving data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed were acquired simultaneously during driving. The Cattell 16 Personality Factor Questionnaire (16PF) was utilized to evaluate the personalities of subjects. Through hierarchical clustering of the 16PF personality traits, the subjects were divided into four groups, i.e., the Inapprehension group, Insensitivity group, Apprehension group and the Unreasoning group, named after their representative personality trait. Their driving performance and turning behaviors were compared and EEG preprocessing, source reconstruction and the comparisons among the four groups were performed using Statistical Parameter Mapping (SPM). The turning process of the subjects can be formulated into two steps, rotating the steering wheel toward the turning direction and entering the turn, and then rotating the steering wheel back and leaving the turn. The bilateral frontal gyrus was found to be activated when turning left and right, which might be associated with its function in attention, decision-making and executive control functions in visual-spatial and visual-motor processes. The Unreasoning group had the worst driving performance with highest rates of car collision and the most intensive driving action, which was related to a higher load of visual spatial attention and decision making, when the occipital and superior frontal areas played a very important role. Apprehension (O) and Tension (Q4) had a positive correlation, and Reasoning (B) had a negative correlation with dangerous driving behaviors. Our results demonstrated the close correlation among driving behaviors, personality and EEG and may be taken as a reference for the prediction and precaution of dangerous driving behaviors in people with specific personality traits.

Keywords: personality, electroencephalography, driving behavior, source reconstruction, clustering analysis, simulated driving

INTRODUCTION

With the increasing number of motor vehicles, the incidence of related traffic accidents is also increasing. The World Health Organization (WHO) released the Global status report on road safety in 2018 and indicated that 1.35 million people worldwide died from road traffic accidents and 50 million people were injured every year (WHO, 2018). The report of the National Bureau of Statistics of China (NBSC), indicated that in 2017, 0.203 million traffic accidents occurred in roads and 0.0638 million traffic accidents caused casualties (National Bureau of Statistics of China, 2018). Traffic accidents have become a global problem resulting in deaths, physical injuries, psychological problems and financial losses. Traffic safety research is of critical importance for individuals, families and society.

As the sensory and controlling center, humans play the most important role in the human-vehicle-environment system, and with the development of advanced driver assistance systems, humans have become the primary factor in traffic accidents (Petridou and Moustaki, 2000), accounting for 45–75% (Wierwille et al., 2002), or even up to 95% (Rumar, 1990) of road accidents. Many dangerous driving behaviors, such as drunk driving (Krüger, 2013), motor vehicle retrograde (Zhao et al., 2009), speeding (Chung and Wong, 2010), fatigue driving (Zhang et al., 2016), and distracted driving (Lansdown et al., 2015) can directly lead to accidents. Many efforts are being made to eliminate human factor related accidents worldwide such as the "Human Factors in Connected Vehicles" initiative of the National Highway Traffic Safety Administration (Lerner et al., 2014) and the "Adaptive Integrated Driver-vehicle Interface" initiative in Europe (Amditis et al., 2005).

Driving is a complex and multifaceted behavioral process, which is affected by psychological, physiological and physical factors. Ample evidence has demonstrated the influence of the cognitive state of a driver (Renner and Anderle, 2000; Lajunen, 2001) and his/her personality, on driving behavior. The relationship between personality and driving is usually explored using a questionnaire investigation. According to Eysenck's Personality Questionnaire (EPQ, classifying personality as extraversion, neuroticism, psychoticism) (Eysenck and Eysenck, 1965) investigation, an extroverted personality was positively correlated with traffic accidents (Lajunen, 2001), driving error (Ben-Ari et al., 2016) and illegal behavior (Guo et al., 2016). Neuroticism was associated with aggressive, offensive driving (Jovanović et al., 2011), and was more likely to induce driving fatigue (Šeibokaité et al., 2014) and risky driving behaviors (Booth-Kewley and Vickers, 1994). Psychoticism was found to significantly correlate with driving skills (Alavi et al., 2017), but not significantly with driving accidents (Renner and Anderle, 2000). According to the five factor model (FFM, classifying the personality as Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness) (Digman, 1990) investigation, neuroticism and extraversion were positively correlated with risky driving (Mallia et al., 2015) and aggressive driving (Dahlen and White, 2006), the personality traits of conscientiousness and agreeableness were negatively correlated with risky driving (Cellar et al., 2000). Openness was reported to be the best predictors of aggressive driving (Mallia et al., 2015). Many researchers utilized the 16 Personality Factor Questionnaire (16PF) (Zhang et al., 2009; Manglam et al., 2013) to explore the relationship between drivers' personality traits and driving. The 16PF is a comprehensive measurement of normal adult personality in terms of the 16 personality dimensions, classifying personality as Warmth (A), Reasoning (B), Emotional Stability (C), Dominance (E), Liveliness (F), Rule-Consciousness (G), Social Boldness (H), Sensitivity (I), Vigilance (L), Abstractedness (M), Privateness (N), Apprehension (O), Openness to Change (Q1), Self-Reliance (Q2), Perfectionism (Q3), and Tension (Q4). There were significant differences in personality traits between drivers with no accident history and accident-prone drivers or chronic violators. Sensitivity (I), Tension (Q4), and Perfectionism (Q3) were related to safe driving, and Openness to Change (Q1) and Abstractedness (M) were related to dangerous driving behavior (Suhr, 1953; Brown, 1976; Hilakivi et al., 1989; Manglam et al., 2013). Drivers with higher scores in Emotional Stability (C), Liveliness (F), Warmth (A), Social-boldness (H) and Dominance (E) and lower scores in Vigilance (L), Apprehension (O), and Self-Reliance (Q2), had a higher accident incidence (Zhang et al., 2009).

Besides personality, the cognitive state greatly and directly affects driving behavior. Many researches indicated the influence of the cognitive state on driving such as the attentional state (alertness, distraction, fatigue) and the emotional state (depression, anxiety, compulsion). Fatigue driving would impair the drivers' physical characteristics, such as heart rate, time deviation of speed anticipation, systolic blood pressure, time for dark adaption, eyesight, dynamic visual acuity, reaction time to sound and reaction time to light (Zhang et al., 2014). Anxiety would ingest the cognitive resources of drivers (Eysenck and Byrne, 1992) and cause an augmented reporting of dangerous driving behaviors (Dula et al., 2010). Depression may also affect driving skills and behaviors (Nnjjm et al., 2017) and its severity was positively correlated with a standard deviation of the lateral position (Wingen et al., 2006). Traditionally, the cognitive state was measured by questionnaires such as the Fatigue Assessment Scale (Michielsen et al., 2003), the Hamilton Anxiety Scale (Maier et al., 1988) and the Hamilton Depression Rating Scale (Williams, 1988). Recently, with the development of the physiological and psychological perception techniques, the cognitive state of subjects can be measured in a more objective and quantitative manner. Among these techniques, electroencephalography (EEG) is a reliable and significant method of measuring neurophysiological activity in the human brain and the psychological state of drivers when driving. Using advanced data mining techniques, the EEG signal can be utilized to identify a driver's alertness (Chuang et al., 2015), to predict the distraction (Wang et al., 2015), to study a driver's perception of signal lights (Wang et al., 2008), to monitor a driver's driving states (Peng and Wu, 2009), and to predict a driver's intention to emergency brake (Kim et al., 2014).

Currently, the potential correlation of cognitive function and personality and its effect on driving behavior is complicated and remains unclear. In this paper, we tried to explore the correlation between driving behavior, personality and EEG using a simulated driving task and the corresponding data analysis. Thirty-six healthy subjects participated in the study. The 64-channel EEG data and the driving data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed were acquired simultaneously during driving. The Cattell 16 Personality Factor Questionnaire (16PF) was utilized to evaluate the personalities of subjects. Through hierarchical clustering of the 16PF personality traits, subjects were divided into four groups. The EEG difference and driving behaviors between the four groups were compared. The results indicated a correlation between driving behavior, personality traits and EEG, which might be helpful to improve the integrated human-vehicle-environment model as well as traffic safety.

MATERIALS AND METHODS

Method Overview

The processing schema is shown in **Figure 1**. The following steps were included: (i) clustering analysis, to classify subjects into different groups according to their personality traits; (ii) preprocessing of EEG data and driving data; (iii) driving data analysis; (iv) EEG source reconstruction; (v) the second level group analysis, to explore the correlation between driving behavior, personality and EEG.

Subjects and Experiment Design

Thirty-six healthy subjects (21–46 years old, mean age 27.0 ± 7.8 years, driving years: 5.2 ± 8.4 years, 27 males and nine females) were recruited. All subjects have a driving license and have real driving experience, driving in their daily life. Subjects reported no neurological or psychiatric problems and were all right-handed. Written informed consent was provided by all subjects and the data were anonymized. The study was approved by the ethical review committee of the Wuhan University of Technology.

Subjects were instructed to sit comfortably wearing EEG caps and to drive on a driving simulator platform (**Figure 2**). The platform consisted of a driving simulator (G29, Logitech, Switzerland) and a screen. The Logitech playseat consisted of a highly simulated steering wheel, a full-size driving seat, gears, accelerator and brakes. Unity 3D software (Unity Technologies, America) was employed to design the simulated driving scenario, which consisted of a 7 km circular runway with three left and four right turns. The subjects were instructed to keep their attention on driving and completed two to four driving sessions with a speed limit of 70 km/h. Each session contained four rounds and was accomplished in approximately 7 min. After each session the subjects took a break for a few minutes to avoid driving fatigue. Each subject completed three sessions. The actions of the left and right turning were marked as events when the driver noticed the roadside direction board at the beginning of the curve and made the specific actions. We videotaped the subject's driving behavior simultaneously. Errors including driving out of the road and car collisions were recorded by the researchers.

Data Acquisition

The driving data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed, were acquired using C# scripts based on Unity 3D. Subjects' brain activities were collected at 1000 Hz using the actiCHamp Amplifier (Brain Products GambH, Gilching, Germany) with 64 surface Ag/AgCl electrodes fixed on a recording cap, consistent with the international 10–20 system referenced to the Fz electrode during the driving experiment. All the subjects filled the 16PF questionnaire in after the driving experiment.

Clustering of 16PF Scores and Subject Grouping

In 16PF, all personality traits are evaluated using a score from 1 (low) to 10 (high), where 3 and below are considered low scores, while eight and above are considered high scores. The 36 subjects were divided into different groups according to their personality traits using the agglomerative hierarchical clustering algorithm (SPSS 22.0, IBM, United States). Hierarchical clustering seeks to form a hierarchy of clusters, either by a "bottom up" agglomerative approach (the clusters would merge if their Euclidean distances were small) or by a "top down" divisive approach (a cluster would split if its scope was too large) (Rokach and Maimon, 2005). First, the 16 personality traits were divided into several categories using Euclidean distances and Ward's method. Then the most representative personality traits were picked out, based on which the subjects were hierarchically clustered into different groups. We utilized the least-significant difference method (Atkinson, 2002) for multiple comparisons between groups to explore the relationship of the selected personality traits and aberrant driving behaviors between groups.

Analysis of the Driving Data

The steering wheel angle data with a peri-stimulus window of 0–10 s for all left and right turns of all the subjects were extracted. The relative increment of the steering wheel angle to the first angle at time 0 were calculated and the mean curves of each group of subjects under left and right turning conditions were then obtained. The least square estimate was performed to estimate the slope of two segments of the curves as an angular velocity for each group. Their characteristics were analyzed.

Analysis of EEG Data

The EEG signals were preprocessed with MATLAB (R2018a, MathWorks, American) and SPM12.[1] The preprocessed process included conversion, montage, filter, downsample, epoch, merge, removing artifacts and averaging. First, the raw EEG data were converted to the format available for Statistical Parameter Mapping (SPM). Then all channels of the data were re-referenced by subtracting from the reference channel (Fz). Next, the EEG signals were band-pass filtered in the range of 0.1–30 Hz, to selectively eliminate noise and down sampled to 200 Hz to reduce the sample size. Then, the EEG epochs with a peri-stimulus window of −100 to 1000 ms were extracted. Time 0 denoted the

[1] http://www.fil.ion.ucl.ac.uk/spm

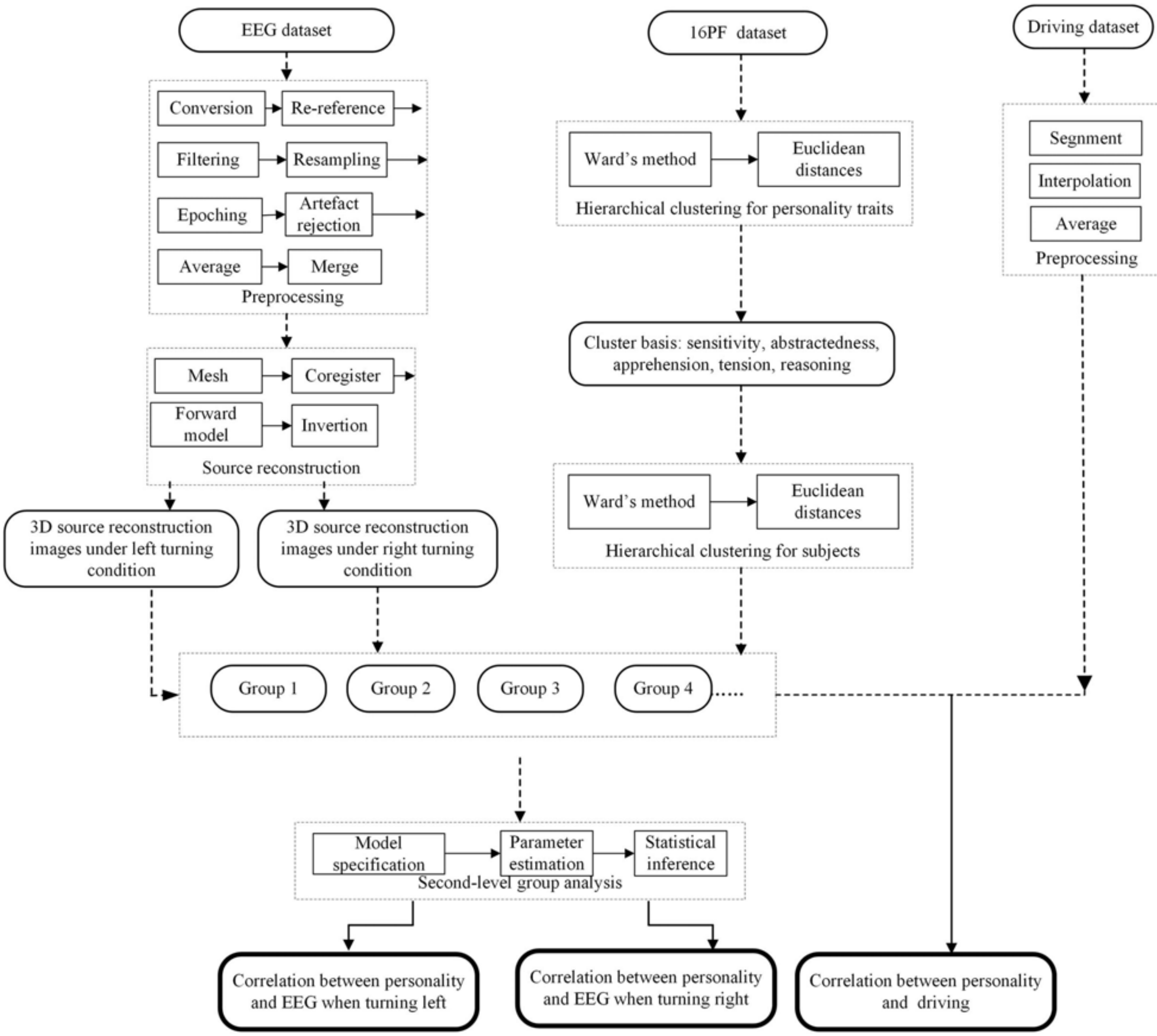

FIGURE 1 | Flow diagrams showing the processing steps for correlation analysis. The flow in the dashed line indicates the preprocessing procedure, the flow in black indicates the procedure of correlation analysis, and bold frames indicate output.

moment the subjects began to turn, which was determined by the time that the vehicle passed by the direction board. The artifacts were removed with the threshold for eye movements or muscular activity exceeding 100 μV. The threshold was set at 0.2 for the bad channel, which would be excluded in the processing which followed. Robust averaging was performed to produce an event related potential (ERP) under two driving conditions (turning left and turning right), respectively.

The ERPs were utilized for source reconstruction, which was conducted to project 2D sensor data into a 3D brain space, to locate the exact anatomical structures of the brain activity (Litvak et al., 2011). Source space modeling, data co-registration, forward computation using the Boundary Element Method (BEM) (Jatoi et al., 2015), and inverse reconstruction using the Multiple Sparse Priors (MSP) algorithm, were performed. The time window of inversion was set as −100 to 1000 ms, which was based on an empirical Bayesian approach. Finally, 3D images containing root mean square (RMS, unsigned) source estimates corresponding to two driving conditions (turning left and turning right) for each subject were obtained and then compared between the different groups using one-way analysis of variance (ANOVA, $P < 0.05$, family wise error (FWE) correction, extent threshold $k > 70$). Age, driving years and gender were utilized as the covariates.

RESULTS

Personality Traits and Clustering Results

Sixteen personality traits of all the subjects were all within the normal range and they were divided into three clusters

FIGURE 2 | Simulated driving platform. The subject has provided written consent for the publication of this image.

(**Figure 3A**), which were (i) Rule-Consciousness, Perfectionism, Emotional Stability, Social Boldness and Liveliness; (ii) Dominance, Privateness, Vigilance, Openness to Change, Self-Reliance and Warmth; (iii) Sensitivity, Abstractedness, Apprehension, Tension and Reasoning. The Euclidean distance between cluster (ii) and (iii) was the smallest, therefore, the personality traits in these two clusters were utilized to conduct the second hierarchical clustering of the subjects. The subjects were divided into four groups according to the five personality traits in cluster (iii) (**Figure 3B**). Four groups had extremely significant differences in personality of Reasoning ($F = 18.852$, $P < 0.0005$), Apprehension ($F = 21.856$, $P < 0.0005$), and Sensitivity ($F = 7.092$, $P < 0.001$). Four groups had significant differences in personality of Emotional Stability ($F = 4.203$, $P = 0.013$), Dominance ($F = 2.934$, $P = 0.048$), Abstractedness ($F = 3.554$, $P = 0.025$), Perfectionism ($F = 6.144$, $P = 0.002$), and Tension ($F = 3.424$, $P = 0.029$, **Table 1**). The subjects were also divided the into four groups according to the six personality traits in cluster (ii), but the ANOVA analysis revealed no significant difference between these groups. Accordingly, the subjects were grouped based on personality traits in cluster (iii). The pairwise comparison was conducted for these five personality traits between the four groups (LSD-*t* test, $P < 0.05$, **Table 2**). The group with significantly lower scores in Apprehension (O), Sensitivity (I), or Reasoning (B) than the other three groups was named as the Inapprehension group, Insensitivity group and Unreasoning group, respectively. The group with the highest scores in Apprehension (O) and who also had a significant difference to the Inapprehension group and Insensitivity group was named as the Apprehension group. As for the driving performance, the number of car collisions were significantly different between the four groups (ANOVA, $P < 0.05$) and the pairwise comparison indicated that the Unreasoning group had significantly more car collisions than the other three groups (LSD-*t* test, $P < 0.05$). The number of times driving out of the road between four groups were not significantly different, but the Unreasoning group drove out of the road

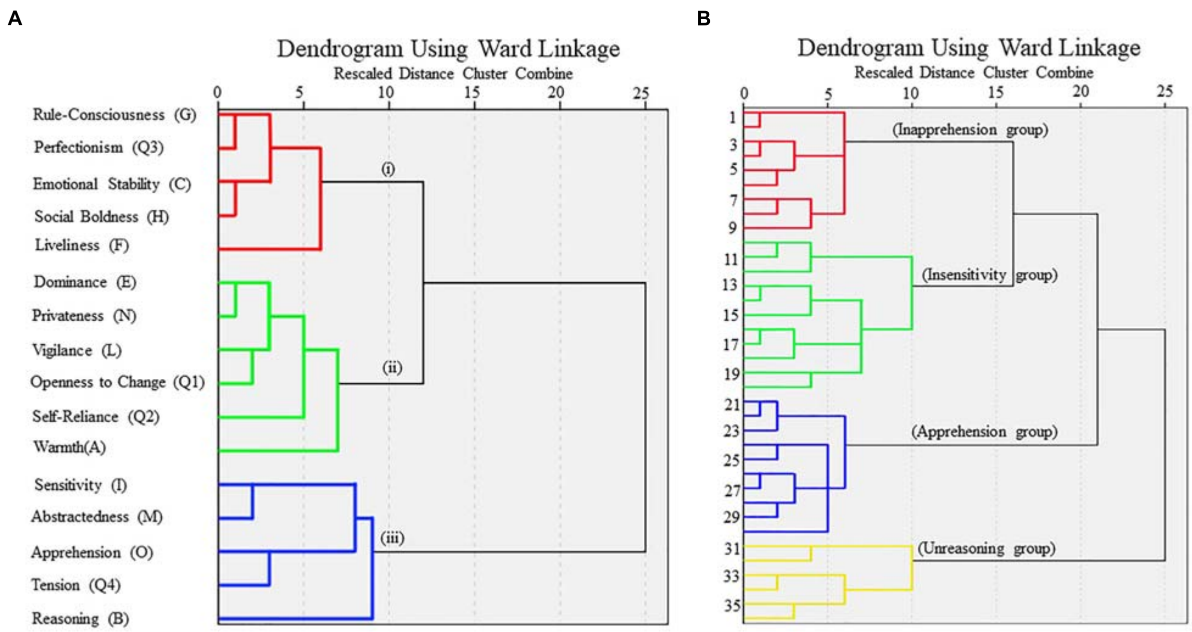

FIGURE 3 | Dendrograms from Hierarchical Clustering (Ward's method, Euclidean distance, SPSS 22.0). **(A)** Dendrogram from Hierarchical Clustering of Cattell 16 personality factors. **(B)** Dendrograms from Hierarchical Clustering of the subjects based on five personality traits [Sensitivity (I), Abstractedness (M), Apprehension (O), Tension (Q4), Reasoning (B)]. 36 subjects were clustered into four groups, from top to bottom, Inapprehension group, Insensitivity group, Apprehension group, and Unreasoning group.

TABLE 1 | The normalized 16PF personality traits and aberrant driving behaviors of the four groups of subjects ($\bar{x} \pm s$).

Feature	Total (n = 36)	Inapprehension group (n = 9)	Insensitivity group (n = 11)	Apprehension group (n = 10)	Unreasoning group (n = 6)	F	P
Warmth (A)	4.72 ± 1.86	5.67 ± 3.73	3.73 ± 1.49	4.70 ± 1.83	5.17 ± 2.14	2.121	0.117
Reasoning (B)	6.17 ± 2.20	7.67 ± 5.82	5.82 ± 1.66	7.30 ± 0.67	2.67 ± 1.86	18.852**	< 0.0005
Emotional Stability (C)	5.19 ± 1.58	5.11 ± 6.36	6.36 ± 1.43	4.30 ± 1.64	4.67 ± 1.37	4.203*	0.013
Dominance (E)	4.36 ± 1.38	4.56 ± 4.64	4.64 ± 0.92	3.40 ± 0.84	5.17 ± 1.47	2.934*	0.048
Liveliness (F)	5.78 ± 1.49	6.22 ± 5.73	5.73 ± 1.68	5.20 ± 1.62	6.17 ± 0.98	0.894	0.455
Rule-Consciousness (G)	5.19 ± 1.58	5.89 ± 5.64	5.64 ± 1.63	4.40 ± 1.51	4.67 ± 1.03	2.110	0.119
Social Boldness (H)	5.00 ± 1.33	5.44 ± 5.45	5.45 ± 1.21	4.30 ± 1.16	4.67 ± 1.63	1.958	0.140
Sensitivity (I)	6.44 ± 1.27	7.22 ± 5.27	5.27 ± 1.27	6.80 ± 1.03	6.83 ± 0.75	7.092**	< 0.001
Vigilance (L)	4.17 ± 1.18	3.89 ± 3.91	3.91 ± 1.38	4.40 ± 1.17	4.67 ± 0.52	0.813	0.496
Abstractedness (M)	7.08 ± 1.44	7.67 ± 6.18	6.18 ± 1.33	7.80 ± 1.32	6.67 ± 1.63	3.554*	0.025
Privateness (N)	4.42 ± 1.36	4.67 ± 3.91	3.91 ± 1.51	4.50 ± 1.27	4.83 ± 0.98	0.798	0.504
Apprehension (O)	6.64 ± 1.69	4.78 ± 6.09	6.09 ± 0.94	8.20 ± 0.92	7.83 ± 1.17	21.856**	< 0.0005
Openness to Change (Q1)	4.78 ± 1.24	5.11 ± 4.64	4.64 ± 1.29	4.50 ± 0.97	5.00 ± 1.79	0.470	0.705
Self-Reliance (Q2)	4.97 ± 1.59	5.44 ± 4.64	4.64 ± 1.36	5.40 ± 2.01	4.17 ± 1.47	1.196	0.327
Perfectionism (Q3)	5.86 ± 1.36	6.89 ± 6.27	6.27 ± 1.1	4.90 ± 0.74	5.17 ± 1.33	6.144**	0.002
Tension (Q4)	5.89 ± 1.62	5.33 ± 5.09	5.09 ± 1.58	6.60 ± 1.26	7.00 ± 2.10	3.424*	0.029
Times of driving out of the road	5.17 ± 6.55	3.33 ± 3.74	4.64 ± 3.78	3.10 ± 3.07	8.17 ± 5.78	2.374	0.089
Times of car collision	5.86 ± 4.48	4.11 ± 2.37	5.09 ± 4.74	5.50 ± 5.28	10.33 ± 2.16	3.049*	0.043
Driving Time (s)	416.24 ± 53.47	420.13 ± 51.96	430.18 ± 46.38	405.08 ± 43.60	403.40 ± 84.11	0.503	0.683

*$P < 0.05$, **$P < 0.01$.*

TABLE 2 | Multiple Comparisons of five personality traits and aberrant driving behaviors between groups.

Feature	Group	Insensitivity group	Apprehension group	Unreasoning group
Reasoning (B)	Inapprehension group	0.006**	0.568	0.000**
	Insensitivity group	–	0.020*	0.000**
	Apprehension group	–	–	0.000**
Sensitivity (I)	Inapprehension group	0.000**	0.380	0.480
	Insensitivity group	–	0.002**	0.006**
	Apprehension group	–	–	0.951
Abstractedness (M)	Inapprehension group	0.017*	0.826	0.156
	Insensitivity group	–	0.008**	0.470
	Apprehension group	–	–	0.103
Apprehension (O)	Inapprehension group	0.007**	0.000**	0.000**
	Insensitivity group	–	0.000**	0.002**
	Apprehension group	–	–	0.489
Tension (Q4)	Inapprehension group	0.716	0.070	0.039*
	Insensitivity group	–	0.025*	0.016*
	Apprehension group	–	–	0.602
Times of driving out of the road	Inapprehension group	0.471	0.899	0.028*
	Insensitivity group	–	0.383	0.090
	Apprehension group	–	–	0.019*
Times of car collision	Inapprehension group	0.601	0.469	0.007**
	Insensitivity group	–	0.822	0.017*
	Apprehension group	–	–	0.030*

*LSD-t test. *$P < 0.05$, **$P < 0.01$.*

significantly more times than the Inapprehension and Apprehension group (LSD-t test, $P < 0.05$). The other comparisons revealed no significance. There was no significant difference in driving time between the four groups.

Driving Features

The steering angles of four groups are shown in **Figure 4** and the detailed data are listed in **Table 3**. There seemed to be two obvious peaks in each curve and the least square estimate was performed to estimate the slope of two segments of the curves, which represented the mean angular velocities. The turning process can be formulated in two steps, i.e., (i) rotating the steering wheel toward the turning direction, modulating the head direction and entering the turn and then (ii) rotating the steering wheel back and leaving the turn.

In the first step, under a left turning condition, the absolute angular velocity was Unreasoning group > Apprehension group > Inapprehension group > Insensitivity group; the absolute angular velocity was Unreasoning group > Inapprehension group > Apprehension group > Insensitivity group. In the second step, under the left turning condition, the absolute rotation angle was Unreasoning group > Apprehension group > Inapprehension group > Insensitivity group; the absolute angular velocity was Unreasoning group > Apprehension group > Insensitivity group > Inapprehension group.

In the first step, under the right turning condition, the absolute angular velocity was Unreasoning group > Apprehension group > Inapprehension group > Insensitivity group; the absolute angular velocity was Unreasoning group > Insensitivity group > Inapprehension group > Apprehension group. In the second step, under the right turning condition, the absolute rotation angle was Insensitivity group > Apprehension group > Unreasoning group > Inapprehension group; the absolute angular velocity was Unreasoning group > Inapprehension group > Apprehension group > Insensitivity group. Under the left turning condition, the two times needed to finish the two steps of turning were Inapprehension group > Apprehension group > Insensitivity group > Unreasoning group; under the right turning condition, the two times needed to finish the two steps of turning were Apprehension group > Inapprehension group > Unreasoning group > Insensitivity group.

EEG Features

EEG Source Reconstruction Results of All Subjects

Electroencephalography source reconstruction results of all the subjects under the two driving conditions are shown in **Figure 5** and the details are listed in **Table 4**. Under the left turning condition, the bilateral temporal gyrus, frontal gyrus and the occipital gyrus were activated. Under the right turning condition, the bilateral temporal gyrus and frontal gyrus were activated. No different activation was found between the two conditions.

EEG Source Reconstruction Results of Four Groups

The EEG source reconstruction results of the four groups are shown in **Figure 6** and the details are listed in **Table 5**. When turning left, in the Inapprehension group, the left inferior occipital gyrus, and right middle temporal gyrus, inferior temporal gyrus, precuneus, middle frontal gyrus and the precentral gyrus were activated; in he Insensitivity group, the left middle occipital gyrus, middle frontal gyrus, inferior frontal gyrus, calcarine and right middle frontal gyrus and the inferior frontal gyrus were activated; in the Apprehension group, the left superior parietal gyrus, middle temporal gyrus, middle frontal gyrus, and right superior frontal gyrus, supramarginal gyrus and the middle temporal gyrus were activated; in the Unreasoning group, the left postcentral gyrus, superior temporal gyrus, middle temporal gyrus, rolandic operculum, and right precentral gyrus, inferior occipital gyrus, calcarine, middle frontal gyrus and the postcentral gyrus were activated.

When turning right, in the Inapprehension group, the left and right superior frontal gyrus were activated; in the Insensitivity group, the left middle and inferior temporal gyrus, superior frontal gyrus, supplementary motor area, and right middle, inferior and superior frontal gyrus were activated; in the Apprehension group, the left and right inferior, middle and superior frontal gyrus, and the left middle temporal gyrus were activated; in the Unreasoning group, the left postcentral gyrus, paracentral gyrus, precentral gyrus, and right superior frontal gyrus, supplementary motor area, paracentral gyrus, and the precentral gyrus were activated.

Intra- and Inter-Group Comparison of EEG Source Reconstruction Results

An Intra-group comparison of the EEG source reconstruction indicated that there was a right turning > left turning activation difference in the left precentral gyrus (peak voxel at [−36 −8 50], $t = 5.14$, 479 voxels) in the Unreasoning group. There was no other intra-group activation difference between the two conditions.

Results of the inter-group comparison are shown in **Figure 7** and the details are listed in **Table 6**. Under the left turning condition, the Inapprehension group had stronger activity in the left inferior occipital gyrus compared to the Apprehension group. The Unreasoning group had stronger activity in the left superior temporal gyrus compared to the Insensitivity group, and in the right occipital pole and left central operculum compared to the Apprehension group.

Under the right turning condition, the Unreasoning group had stronger activity in the left postcentral gyrus, precentral gyrus, paracentral lobule, and right precentral gyrus, superior frontal gyrus, and the supplementary motor area compared to the Insensitivity group, and in the left postcentral gyrus, precentral gyrus, paracentral lobule, and right superior frontal gyrus, precentral gyrus and the paracentral lobule compared to the Apprehension group, and in the left postcentral and postcentral gyrus compared to the Inapprehension group, the Apprehension group had stronger activity in the left superior temporal gyrus compared to the Insensitivity group.

DISCUSSION

In this study, 36 healthy subjects participated in a simulated driving experiment. The 64-channel EEG data and the driving

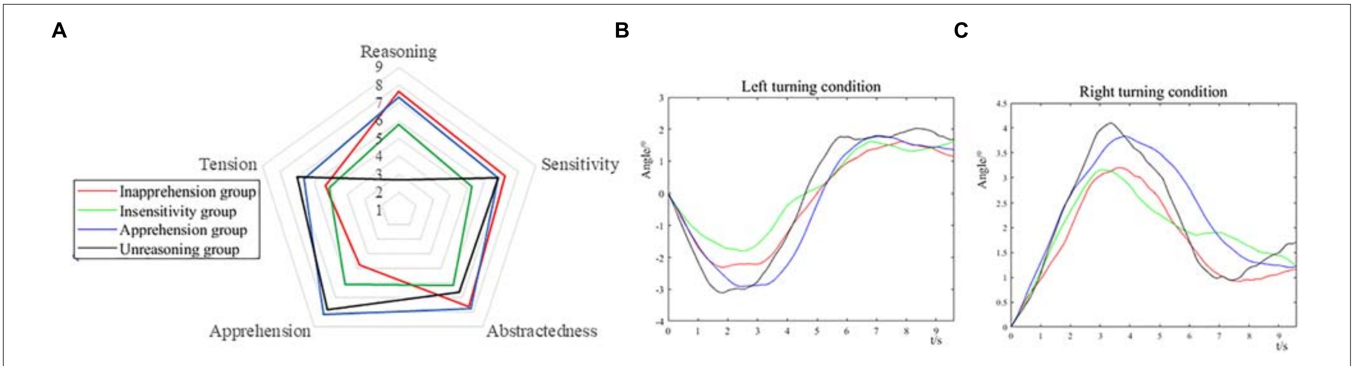

FIGURE 4 | (A) Five selected personality traits of 16PF, averaged over subjects in each group. **(B)** The steering angle of the four groups under the left turning condition. **(C)** The steering angle of the four groups under the right turning condition. Decreasing angle corresponds to counterclockwise rotation, increasing angle corresponds to clockwise rotation.

TABLE 3 | Driving feature of the four groups under the left turning and right turning conditions.

Task	Group	First step			Second step			Total time (s)
		Rotation angle (°)	Angular velocity (°/s)	Time (s)	Rotation angle (°)	Angular velocity (°/s)	Time (s)	
Turning left	Inapprehension group	−2.2994	−1.3501	1.8653	1.6087	0.8264	5.9474	7.8127
	Insensitivity group	−1.7948	−0.7109	2.4376	1.6079	0.8331	4.3304	6.7680
	Apprehension group	−2.9016	−1.2506	2.3969	1.7668	1.3112	4.5966	6.9935
	Unreasoning group	−3.1045	−1.8599	1.8039	1.7705	1.4134	3.9998	5.8037
Turning right	Inapprehension group	3.1981	0.9666	3.645	0.9218	−0.6762	4.0448	7.6898
	Insensitivity group	3.1531	1.1263	3.0507	1.8565	−0.4698	3.2049	6.2556
	Apprehension group	3.8346	1.0625	3.8502	1.2045	−0.5894	5.5171	9.3673
	Unreasoning group	4.0992	1.3732	3.3372	0.9489	−0.9293	4.0661	7.4033

data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed were acquired simultaneously during driving. Through hierarchical clustering of the 16PF personality traits, the subjects were divided into four groups, i.e., the Inapprehension group, Insensitivity group, Apprehension group and the Unreasoning group, named after their representative personality trait. The driving data, the occurrence of aberrant driving behaviors and EEG source reconstruction results were compared between the four groups. The Unreasoning group had the highest occurrence of car collisions and the highest angular velocity during turning. For the subjects as a whole, the bilateral frontal and temporal gyrus were activated under the left turning and right turning conditions and no difference was detected between the two conditions. An intra-group comparison of the EEG source reconstruction indicated right turning > left turning activation in the left precentral gyrus in the Unreasoning group. An inter-group comparison indicated stronger activation of the temporal gyrus under the left turning condition and motor areas under the right turning condition in the Unreasoning group. Several other areas were also detected in the inter-group comparison, such as the inferior occipital gyrus (Inapprehension group > Apprehension group) and the superior temporal gyrus (Apprehension group > Insensitivity group).

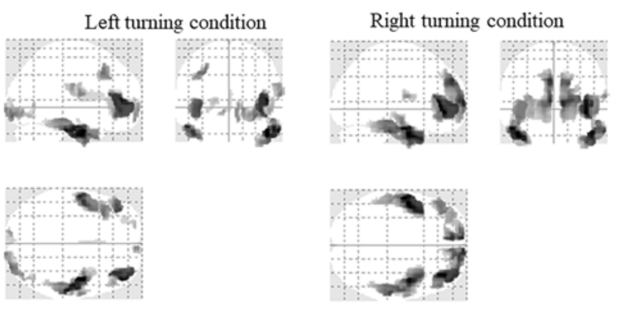

FIGURE 5 | Activation of all the subjects under the two driving conditions (SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$).

Correlation Between Personality and Driving

As shown in **Tables 1–3**, the number of car collisions were significantly different between four groups and were the highest in the Unreasoning group. The number of times driving out of the road were not significantly different between the four groups but were also the highest in the Unreasoning group. As for the performance in turning (**Figure 4** and **Table 3**), the whole turn could be formulated into two steps, i.e., rotating the steering wheel toward the turning direction, modulating the head direction and entering the turn, and then rotating the steering

TABLE 4 | Activation of all the subjects under the left turning and right turning conditions.

Task	Anatomy	Peak location			t	Cluster size (Voxels)
		x	y	z		
Turning left	Inferior temporal gyrus	46	−6	−32	7.58	827
	Middle frontal gyrus	46	46	6	7.12	733
	Middle temporal gyrus	−54	−8	−26	6.90	508
	Inferior frontal gyrus, triangle part	−40	40	−2	6.43	220
	Inferior frontal gyrus, orbital part	−40	40	−4	6.39	156
	Inferior occipital gyrus	30	−94	−12	5.89	369
	Middle frontal gyrus	−36	22	40	5.85	169
	Rolandic operculum	62	−6	14	5.55	247
	Supramarginal gyrus	60	−18	24	5.26	95
Turning right	Middle temporal gyrus	−54	−8	−26	8.48	881
	Inferior frontal gyrus, triangle part	38	40	−4	8.20	708
	Inferior frontal gyrus, triangle part	40	34	8	7.79	399
	Superior frontal gyrus, medial part	−6	52	32	7.43	984
	Superior frontal gyrus, medial part	12	66	6	7.33	528
	Middle temporal gyrus	50	−4	−26	7.09	435
	Superior frontal gyrus	18	60	6	6.74	221
	Inferior frontal gyrus, orbital part	−46	38	−10	6.18	339
	Rolandic operculum	62	−6	14	5.77	81
	Frontal gyrus, orbital part	12	62	−8	5.52	86

SPM12, ANOVA, $P < 0.05$, FWE-corrected for the left turning and right turning, extent threshold $k > 70$. The location is in MNI coordinates.

wheel back and leaving the turn, which was in accordance with previous research (Xiong, 2010; Vesel, 2015). The Unreasoning group had the greatest absolute angular velocity in the two turning steps under the two driving conditions and the greatest rotation angle of the steering wheel in most circumstances (except in the second step of right turning). The total time of left turning of the Unreasoning group was the shortest, and second shortest in right (longer than Insensitivity group). Generally speaking, the greater rotation angle and higher angular velocity in turning corresponded to the more intensive modulation of the steering wheel, and were closely related with accidents (Vesel, 2015). These results indicated the worst driving performance and the most intensive driving action for the Unreasoning group. In the other three groups, the Inapprehension group had the lowest, but not significantly different, number of times of driving out of the road and there seemed to be no obvious difference in the turning performance between them.

People with a high Reasoning (B) score are intelligent, good at abstract thinking, and can learn quickly and correctly (Hilakivi et al., 1989; Manglam et al., 2013), while those with a low Reasoning (B) score are less intelligent, unable to handle abstract problems, think slowly and are suitable for trivial works (Hilakivi et al., 1989; Manglam et al., 2013). People with a high Sensitivity (I) score are sensitive, aesthetic, careful, dependent and lack confidence, while those with a low Sensitivity (I) score are utilitarian, objective, unsentimental, tough minded, careless, independent, realistic, decisive and confident, mature and are able to face reality (Zhang et al., 2009; Shi et al., 2017). People with a high Abstractedness (M) score are abstract, imaginative, absent minded, impractical, absorbed in ideas, imaginative, inattentive to things and careless, while those with a low Abstractedness (M) score are grounded, practical, prosaic, solution oriented, steady, conventional and serious (Zhang et al., 2009; Shi et al., 2017). People with a high Apprehension (O) score are apprehensive, self-doubting, worried, guilt prone and insecure, while those with a low Apprehension (O) score are confident, pretentious, smug and easily adapt to the environment (Brown, 1976; Hilakivi et al., 1989). People with a high Tension (Q4) score are tensive, highly energetic, impatient, driven, frustrated, over wrought, nervous, frustrated and often in a passive situation, while those with a low Tension (Q4) score are relaxed, placid, tranquil, torpid,

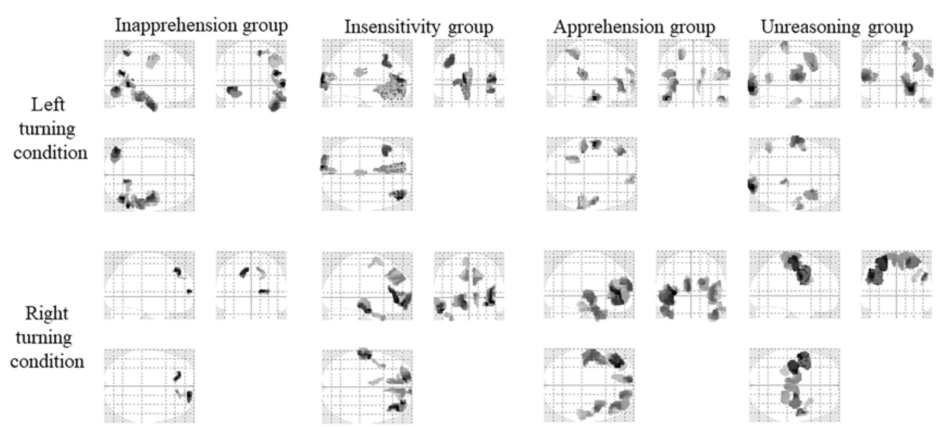

FIGURE 6 | Activation of the four groups under the two conditions (SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$). The names of the groups are shown in the upside. The driving conditions are shown in the left side.

TABLE 5 | Activation of the four groups under the left turning and right turning conditions.

Task	Group	Anatomy	Peak location			*t*	Cluster size (Voxels)
			x	***y***	***z***		
Turning left	Inapprehension group	Middle temporal gyrus	46	−68	20	6.46	468
		Inferior occipital gyrus	−42	−80	−6	6.33	572
		Inferior temporal gyrus	46	−16	−36	5.81	771
		Precuneus	14	−60	60	5.81	623
		Middle frontal gyrus	46	0	54	4.89	75
		Precentral gyrus	56	−2	46	4.67	134
	Insensitivity group	Middle occipital gyrus	−12	−102	8	5.70	639
		Middle frontal gyrus	46	48	6	5.47	383
		Middle frontal gyrus	−36	20	46	5.26	380
		Inferior frontal gyrus, orbital part	42	44	−12	5.16	305
		Calcarine	−8	−102	−2	5.03	314
		Middle frontal gyrus, orbital part	−2	54	−4	4.85	663
	Apprehension group	Middle temporal gyrus	−54	−10	−26	6.40	354
		Middle temporal	52	−14	−24	5.55	214
		Parietal operculum	−38	−32	18	5.52	323
		Middle frontal gyrus	−34	40	2	5.43	439
		Superior frontal gyrus, medial part	12	60	4	5.20	284
		Supramarginal gyrus	46	−40	26	5.15	489
		Superior parietal gyrus	−28	−44	48	5.15	435
	Unreasoning group	Inferior occipital gyrus	26	−98	−8	6.84	610
		Calcarine	18	−104	0	6.04	548
		Postcentral gyrus	−60	−12	14	6.01	466
		Superior temporal gyrus	−60	−12	12	6.00	477
		Middle frontal gyrus	32	18	36	5.90	885
		Postcentral gyrus	12	−32	76	5.45	366
		Rolandic operculum	−64	−4	8	5.27	70
		Middle temporal gyrus	−44	−62	8	5.08	322
		Precentral gyrus	48	−6	−28	4.71	71
Turning right	Inapprehension group	Superior frontal gyrus	18	60	10	5.15	137
		Superior frontal gyrus	−12	36	48	5.02	148
		Superior frontal gyrus	12	38	48	4.63	80
	Insensitivity group	Middle temporal gyrus	−52	−14	−24	6.00	192
		Middle frontal gyrus, orbital part	32	52	−14	5.93	445
		Superior frontal gyrus, orbital part	−12	56	−8	5.81	300
		Inferior frontal gyrus, triangle part	40	36	8	5.67	404
		Inferior temporal gyrus	−60	−30	−18	5.54	607
		Superior frontal gyrus, medial part	−6	44	34	5.00	550
		Superior frontal gyrus, medial part	12	54	32	5.00	621
		Superior frontal gyrus	16	52	32	4.95	81
		Supplementary motor area	−4	−8	58	4.59	190
	Apprehension group	Inferior frontal gyrus, triangle part	−34	40	4	8.07	649
		Middle frontal gyrus, orbital part	−38	44	−4	7.39	750
		Inferior frontal gyrus, triangle part	−40	32	10	7.35	927
		Superior frontal gyrus, medial part	−6	64	14	6.73	988
		Middle temporal	−46	−20	−4	6.49	333
		Middle frontal	44	40	6	6.41	700
		Inferior frontal gyrus, triangle part	40	34	10	6.38	569
		Middle frontal gyrus, orbital part	40	44	−6	6.36	461
		Superior frontal gyrus	16	52	22	6.05	142

(Continued)

TABLE 5 | Continued

Task	Group	Anatomy	Peak location			t	Cluster size (Voxels)
			x	y	z		
	Unreasoning group	Postcentral gyrus	−54	−6	46	7.09	916
		Precentral gyrus	−50	−4	32	6.83	350
		Precentral gyrus	−24	−14	68	6.83	816
		Superior frontal gyrus	22	−12	62	6.30	561
		Precentral gyrus	52	0	36	6.14	716
		Paracentral lobule	−6	−24	60	5.41	242
		Paracentral lobule	4	−30	58	5.31	576
		Supplementary motor area	8	−12	68	5.19	75

SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$. The location is in MNI coordinates.

patient, insensitive and sometimes unresponsive (Manglam et al., 2013; Yan, 2016). Previous 16PF research indicated that Social Boldness (H), Perfectionism (Q3), Dominance (E), Emotional Stability (C), Warmth (A) and Liveliness (F) were protective factors related to safe driving (Zhang et al., 2009; Sun, 2013; Yan, 2016; Shi et al., 2017), while Tension (Q4), Openness to Change (Q1) Abstractedness (M), Vigilance (L), Apprehension (O), Self-reliance (Q2), and Sensitivity (I) were risk factors related to dangerous driving behaviors (Suhr, 1953; Zhang et al., 2009; Shi et al., 2017).

The Unreasoning group had higher Tension (Q4) and Apprehension (O) scores and lower Reasoning (B) scores (**Table 2**), and were tense, highly energetic, impatient, less intelligent and were unable to handle abstract problems (Manglam et al., 2013; Yan, 2016). According to our results, together with the driving performance of the four groups, we speculated the positive correlation of Apprehension (O) and Tension (Q4) with dangerous driving and a negative correlation of Reasoning (B) with dangerous driving.

Correlation Between EEG and Driving

We first analyzed the source reconstruction results of all the subjects. Under the left turning condition, the bilateral temporal gyrus, frontal and the occipital gyrus were activated. Under the right turning condition, the bilateral temporal gyrus and frontal gyrus were activated. No different activations were found between the two conditions. Then, the source reconstruction results of each group of subjects were analyzed and activation in the frontal gyrus was found in all groups. The temporal gyrus was detected in most groups and motor areas (precentral gyrus and postcentral gyrus) were strongly activated in the Unreasoning group. The occipital gyrus was activated in the Inapprehension group, Apprehension group and the Unreasoning group under the left turning condition. The activation of the Inapprehension group under right turning condition was restricted in the superior frontal gyrus.

To fulfill the turning behavior, the subjects needed to notice the turning sign, decide the turning direction and then to manipulate the steering wheel, which consisted of a series of visual-spatial and visual-motor processes. The brain regions related with vision, attention and motion, including the pre-supplementary motor area, the superior parietal and lateral occipital cortices and the cerebellum would be activated (Spiers and Maguire, 2007; Calhoun and Pearlson, 2012). The frontal gyrus was considered as an important area for visual attention (Corbetta and Shulman, 2002; Konen et al., 2004), decision-making (Volz et al., 2006; Glimcher et al., 2009), executive control (Christoff and Gabrieli, 2000; Koechlin and Summerfield, 2007; Posner et al., 2007), performance monitoring and adjustments (Ridderinkhof et al., 2004; Euston et al., 2012). The common activation of the bilateral frontal gyrus when turning left and right (**Table 4** and **Figures 5**, **6**) might be associated with these cognitive procedures. The occipital gyrus was activated in most groups only under the left turning condition. No significant difference was detected in the activations between the two turning conditions (FWE-corrected, $P < 0.05$, extent threshold $k > 70$). But if we applied a less conservative test ($P < 0.01$, uncorrected, extent threshold $k > 70$), left turning > right turning activation could be detected in the superior frontal (peak voxel at [−6 62 10], $t = 3.14$, 254 voxels; **Supplementary Figure S1**). As we described above, the frontal gyrus was involved in decision-making, executive control, performance monitoring and adjustments. The occipital gyrus played the important role in visual function (Lauritzen et al., 2009). Since motorists drive on the right-side in China, drivers are presumably accustomed to watching for traffic from both directions while turning left, which requires considerably stronger brain activity than with right turning (Schweizer et al., 2013; Oka et al., 2015). We speculated that the load of attention and visual information processing was more in left turning than right turning. It had been found that the superior temporal gyrus was an important structure in the pathway consisting of the prefrontal cortex and amygdala, which are all associated with social cognitive processes (Amanda et al., 2004; Callaghan et al., 2017). The stronger activation of the motor and sensorimotor areas in the Unreasoning group may relate with their more intensive movements, i.e., the greatest rotation angle and absolute angular velocity in turning (**Tables 2**, **3**).

Some simulated driving studies investigated the underlying neural mechanisms of driving (Spiers and Maguire, 2007;

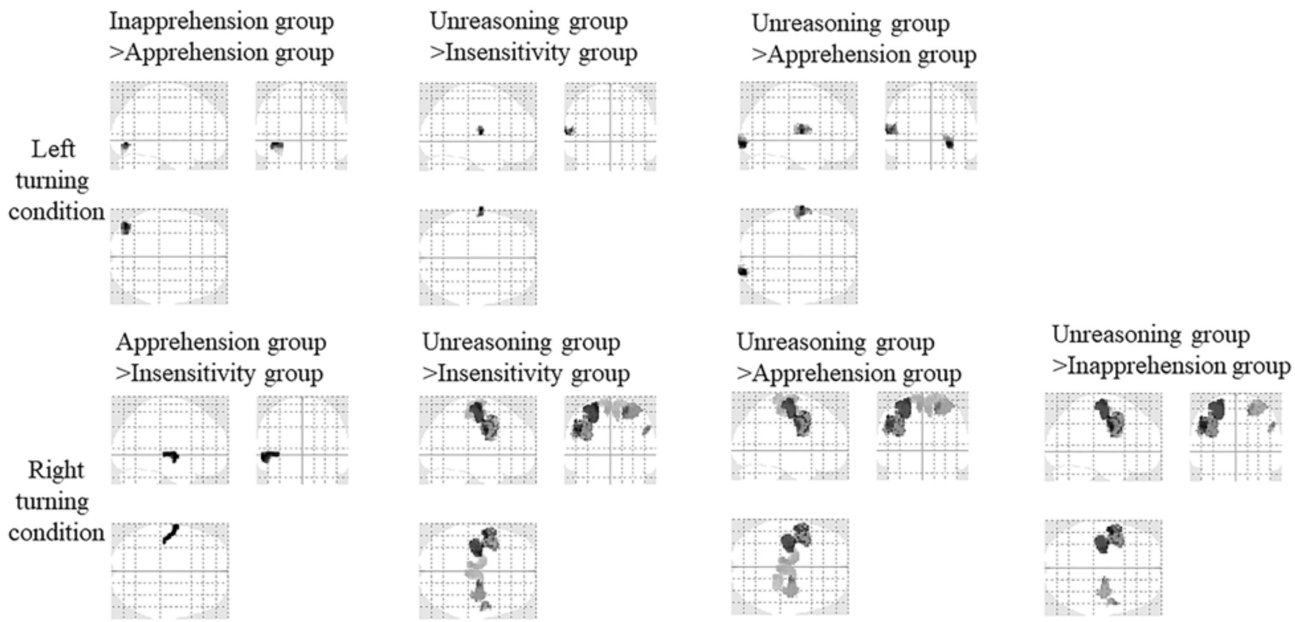

FIGURE 7 | Activation comparison of the four groups under the two conditions (SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$). The driving conditions are shown in left side.

TABLE 6 | Activation comparison among the four groups.

Task	Inter-group comparison	Anatomy	Peak location			t	Cluster size (Voxels)
			x	y	z		
Turning left	Inapprehension group > Apprehension group	Inferior occipital gyrus	−40	−80	−6	4.97	220
	Unreasoning group > Insensitivity group	Superior temporal gyrus	−66	−12	10	4.68	96
	Unreasoning group > Apprehension group	Inferior occipital gyrus	24	−96	−8	5.24	256
		Superior temporal gyrus	−66	−12	10	5.12	336
Turning right	Unreasoning group > Insensitivity group	Postcentral gyrus	−54	−6	46	6.11	555
		Precentral gyrus	−52	−6	34	5.94	981
		Superior frontal gyrus	34	−6	62	4.92	71
		Paracentral lobule	−6	−24	60	4.75	388
		Supplementary motor area	4	−30	56	4.67	379
	Unreasoning group > Apprehension group	Postcentral gyrus	−54	−6	46	6.65	618
		Precentral gyrus	−34	−8	48	6.18	1075
		Paracentral lobule	−8	−24	60	4.97	497
		Superior frontal gyrus	22	−12	62	5.40	548
		Precentral gyrus	34	−24	68	4.88	252
		Paracentral lobule	6	−32	54	4.86	465
	Apprehension group > Insensitivity group	Superior temporal gyrus	−56	−8	−2	4.71	224
	Unreasoning group > Inapprehension group	Postcentral gyrus	−54	−6	46	6.20	595
		Precentral gyrus	−24	−14	66	5.68	982

SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$. The location is in MNI coordinates.

Calhoun and Pearlson, 2012; Schweizer et al., 2013; Oka et al., 2015). The brain regions related with goal direction, attention and motor planning, including the frontal gyrus (Spiers and Maguire, 2007), the superior parietal cortex and lateral occipital cortex (Oka et al., 2015), pre-supplementary motor area and the cerebellum (Calhoun and Pearlson, 2012) were activated. The higher activation of bilateral parietal lobe were positively correlated with good driving performance (Uchiyama et al., 2012), while the activity of the anterior cingulate were negatively correlated with good driving performance and was involved in driving errors (Kan, 2011; Bledsoe et al., 2013). The inter-group comparison indicated that, under the left turning condition, the left superior temporal gyrus (Unreasoning group > Insensitivity group and Apprehension group) and right inferior occipital gyrus (Unreasoning group > Apprehension group) was detected (**Figure 5** and **Table 6**). The superior temporal gyrus is an important area in the pathway consisting of the prefrontal cortex and amygdala, which are all associated with social cognitive processes (Amanda et al., 2004; Callaghan et al., 2017). The occipital gyrus is mainly involved in visual information processing (Lauritzen et al., 2009) and was found to be coupled with the parietal gyrus in sustained attention (Lauritzen et al., 2009) and spatial attention (Garg et al., 2007; Weaver and Stevens, 2007). The Unreasoning group had the greatest absolute angular velocity in the two turning steps under the two driving conditions and the greatest rotation angle of the steering wheel under most circumstances. The total time of left turning in the Unreasoning group was the shortest, and of right turning the second shortest (longer than the Insensitivity group). Their driving style seemed to be the most intensive and more easily made errors. To fulfill the same turning task, the time of the Unreasoning group was generally shorter than the other groups, which meant that they needed to process the same amount of information but in a shorter time. From this viewpoint, we think that the cognitive load of the Unreasoning group to process the turning information was higher.

The cognitive load could affect driving negatively, undermining drivers' driving performance (Lee et al., 2007; Wijayanto et al., 2018). The increased cognitive load was associated with a common network comprising occipital cortices and parietal, thalamus, and the cerebellum (Tomasi et al., 2007). Among these areas, the occipital and parietal cortex are crucial in visual spatial attention functioning (Garg et al., 2007; Weaver and Stevens, 2007; Lauritzen et al., 2009). Visual spatial attention is a kind of attention, including a series of cognitive activities, such as visual searching, spatial area selection, attention switching and selective visual information processing in the useful field of view (Richardson and Marottoli, 2003; Wijayanto et al., 2018). Researches indicated that visual attention played an important role in predicting driving task performance, which is associated with a threefold increase in the risk of driving errors (Richardson and Marottoli, 2003). A higher load of visual spatial attention would diminish the sensitivity to the environment during driving and increase the risk of aberrant driving (Richardson and Marottoli, 2003; Lee et al., 2007), which is consistent with our results that the Unreasoning group are more likely to make errors and have poorer driving performance. Therefore, we speculated that the high occurrence of the aberrant driving behaviors and the intensive driving style in the Unreasoning group, were related with the higher load of visual spatial attention, when occipital areas played an important role.

Under the right turning condition, the Unreasoning group had stronger activity mainly in the bilateral postcentral gyrus, precentral gyrus and the paracentral gyrus compared to the other three groups (**Figure 7** and **Table 6**). The stronger activation of these motor and sensorimotor areas may relate with the more intense movement of the Unreasoning group, i.e., the greatest rotation angle and absolute angular velocity in turning (Haseeb et al., 2007). Besides these areas, the superior frontal gyrus was also detected when comparing the Unreasoning group with the Insensitivity and Apprehension group. Considering the important role of the frontal gyrus in decision-making, executive control, performance monitoring and adjustments, its stronger activation here implied a higher load in these cognitive processes in the Unreasoning group compared to the other three groups. The Unreasoning group had the highest number of car collision with higher Apprehension (O) and Tension (Q4) scores and lower Reasoning (B) scores. We speculated that higher Apprehension (O) and Tension (Q4) and lower Reasoning (B) scores may cause dangerous driving and the superior frontal gyrus might play a very important role.

Limitations of the Study

There are some limitations that should be considered in future studies. First, the samples were biased in gender, age and driving years. A previous study found that age (Callaghan et al., 2017), gender (Adenzato et al., 2017) and driving years (Pekkanen et al., 2018) were significant factors affecting a human's cognitive and perceptive, decision making and spatial attention (Akamatsu et al., 2006). There were more male (75%) than female drivers in this study. The participant pool had relatively few and small personality differences. We compared the 16PF scores of the studied subjects and the national norm (Zhu and Dai, 1988) and found that the studied subjects had significantly different scores in Sensitivity (I), Abstractedness (M), Apprehension (O), perfectionism (Q3), Warmth (A), Dominance (E), Social Boldness (H), Vigilance (L), Privateness (N), and Openness to Change (Q1) (**Supplementary Table S1**). Second, the driving scenario was relatively complicated. The environment around the turns, and the parameters of the turns such as the radius and the length, were not exactly the same, which would affect the subjects' reaction and brain activity to some extent. A simpler and more comparable scenario might be helpful in a quantitative analysis and comparison. Third, different to real driving, simulated driving cannot induce exactly the same experience and performance of the subjects since there was no real risk of a collision or actual injury. Under these circumstances, the underlying cognitive process and behavior may be distorted to some extent. Additionally, one subject failed to accomplish the driving tasks due to driving sickness. How to transplant the experiment and analysis schema safely and effectively to the real driving, is worth studying further. The ERPs utilized for resource reconstruction were acquired throughout the whole driving process, therefore, the effect of driving duration could not be detected using our current schema, which is another limitation of this study. Generally, driving duration had a close relationship with driving behaviors (Otmani et al., 2005; Geden et al., 2018) and EEG features (Puspasari et al., 2017). The influence of driving duration on personality, EEG and driving behaviors warrants further research.

Our study is currently, to some extent, an exploratory work. All the subjects were clustered into four groups based on their personality traits and then a *post hoc* comparison of their driving behaviors and EEG characteristics were conducted. We hoped to, and we did find a relationship between EEG, behavior and personality. If we could develop a large-scale study based on a larger sample size or if we could obtain the original data of the national norm, we might be able to extract all the typical and representative categories of the population, which can be applied as the standard and the new subjects could be classified based on this standard.

CONCLUSION

In this paper, we explored the correlation between driving behavior, personality and EEG using a simulated driving experiment. The subjects were clustered into four groups, i.e., the Inapprehension group, Insensitivity group, Apprehension group and the Unreasoning group, according to their personality traits, using the hierarchical clustering method. The turning process of the subjects can be formulated into two steps, rotating the steering wheel toward the turning direction and entering the turn, and then rotating the steering wheel back and leaving the turn. The bilateral frontal gyrus was found to be activated when turning left and right which might be associated with its function in attention, decision-making and executive control functions in visual-spatial and visual-motor processes. The Unreasoning group had the worst driving performance with highest number of car collisions and the most intensive driving action, which was related to a higher load of visual spatial attention and decision making, when the occipital and superior frontal areas played a very important role. Apprehension (O) and Tension (Q4) had a positive correlation, and Reasoning (B) had a negative correlation with dangerous driving behaviors. Our results demonstrate the close correlation between driving behavior, personality and EEG.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the "Ethical Review Committee of the Wuhan University of Technology" with written informed consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the "Ethical Review Committee of the Wuhan University of Technology." In this paper, we aimed to explore the relationship among personality traits, EEG and driving behavior, thus we needed to collect the electroencephalography signals of drivers during driving process. The whole experiment was completely harmless to the subjects.

AUTHOR CONTRIBUTIONS

FY and KG designed the data processing schema. YW, CD, and ML carried out the experiment. YW analyzed the data. LY and YW wrote the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2019.01524/full#supplementary-material

FIGURE S1 | Activation of all subjects under left turning > right turning condition (SPM12, ANOVA, $p < 0.01$, uncorrected, extent threshold $k > 70$).

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