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**TRAVELLING WITH THE MIND. INTERFERENCE AND DISTRACTION IN
PERFORMING DANGEROUS ACTIVITIES: THE CASE OF DRIVING**

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GENERAL INTRODUCTION

Distracted driving (DD) is a global phenomenon that is associated with an ever-increasing rise in Motor-Vehicle Crashes (MVCs) (Edwards et al., 2019). For instance, in the United States, approximately three thousand fatalities in 2023 were attributed to distracted drivers (NHTSA, 2024). The emerging adults (e.g., 18–29) and older adults (over 65) are frequently defined as the most vulnerable categories of road users, with an elevated risk of incurring in MVCs (Lyon et al., 2021). In England and Wales, different evidence suggests that in-vehicle distraction is a contributing factor in MVCs. It is estimated that approximately 2% of fatal MVCs constitute a conservative estimate (Stevens & Minton, 2001). Research conducted in other countries has indicated a significantly higher prevalence of MVCs attributable to distraction. In the Italian context, the last report of Automobile Club Italia (2025) showed that the DD and the negligence in observing traffic signs were the main causes of MVCs, which together accounted for about 54.7%.

DD can be defined as: *“Diversion of attention from the driving task to secondary activities, driven by perception/response to external stimuli or self-generated internal thoughts”* (p. 8; Lee, Young, & Regan, 2008). Distraction can be classified by perceptual and behavioral modality. A common distinction is between visual, auditory, manual, and cognitive distraction. Visual distraction is defined as eye deviation from the relevant visual stimuli associated with driving, such as the road, mirrors, and the functional dashboard, towards stimuli that are not relevant to driving safety (i.e., reading messages/notification banners on a smartphone or infotainment system; Gershon et al., 2019; Kircher & Ahlstrom, 2012). Auditory distraction concerns the presence of competing auditory streams that necessitate monitoring and decoding, such as loud music, alarms, and conversations (Karthus et al., 2020). This can compromise the identification of critical signals, such as sirens and horns, and the selective reallocation of attention (Millet et al., 2019). Manual distraction is related to the use of one or both hands in actions that are not pertinent to the control of the vehicle, the

alteration of motor input required for steering, the changing of gears, or the signaling (i.e., typing or scrolling with the smartphone) (Li et al., 2020). Finally, cognitive distraction can be defined as a type of inattention that occurs when an individual becomes distracted from their driving task while maintaining focus on other tasks or objects (Strayer et al., 2015). Differently by distraction, inattention refers to “*whenever a driver is delayed in the recognition of information needed to safely accomplish the driving task, because of having chosen to direct his attention elsewhere for some non-compelling reason*” (p. 21) (Treat, 1980).

Beyond the modality-based taxonomy delineated above, it is also important to distinguish driving distraction from driving inattention. In accordance with the previous definition, the term "distracted driving" denotes the act of diverting one's attention from the primary driving task to concurrent activities. This distraction is typically triggered by external factors, such as visual or auditory stimuli. On the other hand, driver inattention is characterized by an inability to allocate and maintain attention on the driving task, regardless of the presence of competing external stimuli (Regan et al., 2011; Kircher & Ahlstrom, 2017). A recent review showed that driver inattention contributes to a substantial proportion of fatal and non-fatal crashes. This proportion is estimated to be no less than 12% of MVCs (Sagberg & Sundfør, 2016).

Within this theoretical framework, Mind-wandering (MW) is conceptualized as an internally generated form of inattention toward the primary task, often resulting in a decoupling of attention from the external environment. It can be either deliberate or spontaneous, which diverts cognitive resources from task-relevant monitoring (Stawarczyk et al., 2011; Smallwood & Schooler, 2016), even when gaze and hands remain apparently engaged in the driving task (looked but failed to see) (Pepin et al., 2021). In light of the above, DD can be defined as a multifaceted construct that can be driven by internal (cognitive/MW) (Gil-Jardiné et al., 2017) and external (visual, auditory, manual) sources (Sorum & Pal, 2022).

To maximize the effectiveness of prevention strategies and countermeasures, it is important to define these dimensions and accurately profile driver distraction.

Driving behavior models: a theoretical framework of the driving context

To better understand the mechanisms underlying the driver's attention and their ability to operate safely in a road environment, several frameworks of human driving behavior have been developed. This paragraph summarizes two driving theoretical models that have a significant influence on psychological studies of DD.

The first refers to the distal and proximal factors included in Sümer's contextual-mediated model of Traffic Accident Involvement (2003). Distal factors are general and stable background factors that do not directly cause MVCs. They represent an individual's predisposition or the general context. These factors refer to personality traits (e.g., sensation seeking, aggression), psychological symptoms, demographic characteristics, habits, values, and cultural factors. Proximal factors are defined as "mediating" factors, which refer to the specific behaviors and choices made by the driver within the driving context. These factors are described as proximal to the MVCs and are those that directly increase the risk. These refer to aberrant driving behaviors (e.g., traffic violations, errors), speeding, and dysfunctional drinking habits.

In light of this, the DD can be conceptualized as a proximal factor (Tinella et al., 2022; 2024). It is not considered a stable personality trait, but rather an aberrant driving behavior associated with the context, similar to the inclusion of violations, errors, and speeding in the model. This conceptualization frames DD as a direct mediator, the mechanism through which more distal influences (e.g., personality, social pressures, cognitive load) are expressed. The act of diverting attention from the driving task is the component that directly compromises

safety and increases the immediate likelihood of MVCs, acting as a direct link in the causal path immediately preceding a potential collision (McManus et al., 2017; Pope et al., 2017).

Figure 1 represents the Sümer model.

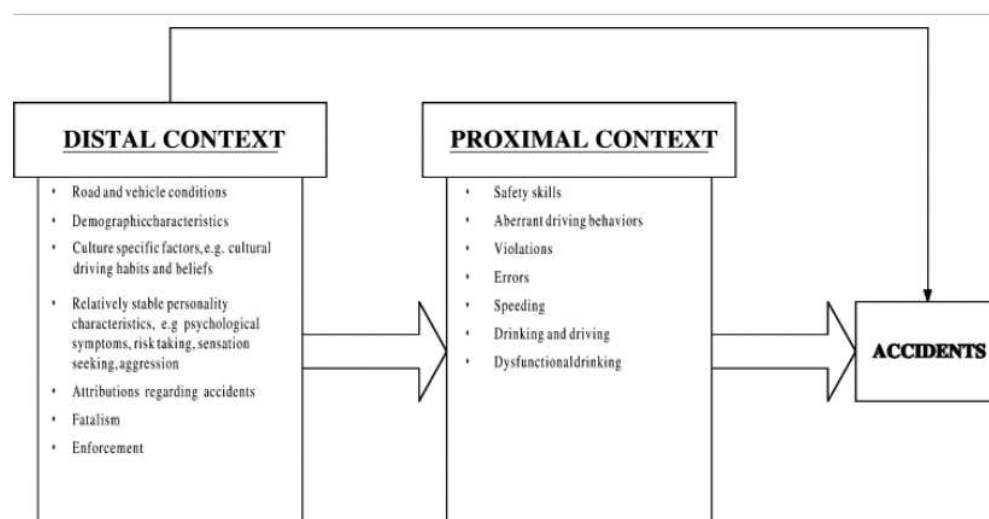


Figure 1. Contextual mediated model (adapted by Sümer, 2003)

A second notable and probably the most important model refers to the hierarchical classification of human tasks interacting with the environment, developed by Michon (1985). This model suggests that human mobility is embedded within a social and technological context. This model functions as a descriptive framework that specifies the fundamental tasks underlying the complex human interaction with the traffic and transport system. From a hierarchical perspective, the individual is defined as an active road user, transportation consumer, social being, and psychobiological organism.

This model categorizes the cognitive demands on drivers into three distinct nested levels: strategic, tactical, and operational. The strategic level is the highest layer and consists of all pre-trip planning and goal setting. At this stage, the driver defines the journey's overarching objectives by selecting the destination, specific route, and mode of transportation.

The driver also evaluates additional factors, such as journey time, costs, and potential risks (Michon, 1985). A key characteristic of this level is that these decisions are typically made in advance, not under the immediate temporal pressure of being on the road. The intermediate tactical level describes the real-time execution of maneuvers necessary to navigate the immediate road and traffic environment. This includes actions such as turning, changing lanes, accepting gaps, or overtaking other vehicles. These decisions are made during the drive and are subject to moderate time pressure. Although these maneuvers are guided by general strategic-level goals (e.g., "stay on route"), Michon (1985) emphasizes that this level is primarily "constrained by actual events." This implies a dynamic relationship: an outcome at the tactical level (e.g., encountering an unexpected road closure) can force an adaptation or modification of the original strategic plan. Finally, the operational level is the lowest and fastest in the hierarchy. It allows the control of the vehicle's moment-to-moment movements. It involves sensorimotor skills and basic cognitive functions, such as perception, visual scanning, reaction times, and attention. These functions are executed under high time pressure to implement maneuvers decided at the tactical level (Michon, 1985). Michon (1985) also distinguishes the processing types associated with these levels. Activities at the tactical level are generally controlled cognitive processes that require conscious effort, while activities at the operational level are largely automatic and require minimal conscious oversight due to extensive practice.

Michon's hierarchical model (1985) is a useful taxonomy for examining the effects of DD (Zhang et al., 2014; Knapper, 2018). Rather than a single error, distraction is a failure that impairs performance, especially at two levels of control: operational and tactical levels. It impairs automatic processes at the operational level, resulting in delayed reaction times and increased lateral deviation (SDLP) (NHTSA, 2017). At the tactical (maneuver) level, distraction causes errors in gap acceptance and overtaking by diverting the cognitive resources

needed for traffic decisions (Brown & Groeger, 2002). Figure 2 shows Michon's hierarchical model.

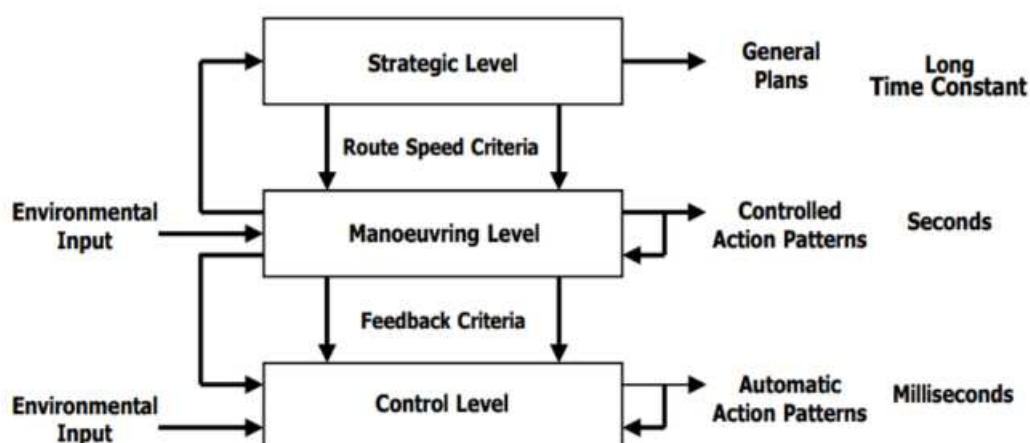


Figure 2. Graphical representation of the Michon's hierarchical model of driving behavior (Michon, 1985). Three coupled levels of skills are required in vehicle control: strategic (planning), tactical (manoeuvring), and operational (control), (adapted by Michon, 1985).

Theoretical model of conscious experience applied to distracted driving: task-relatedness and stimulus-dependency approach.

In light of the above presented model, the construct of DD remains a multifaceted phenomenon that merits further investigation. To this end, the theoretical model developed by Stawarczyk et al. (2011) may be useful, because it delineates Conscious Experience (CE) through two principal domains: task-relatedness (TR) and stimulus dependency (SD). TR evaluates how the thought's content relates to the main task, while SD evaluates how well the content is grounded in the information found in the sensory environment. Crossing these dimensions yields four distinct classes of conscious experience. Attention is successfully engaged with the task and its pertinent cues when thought is both task-related and stimulus-

dependent (TRSD) (the canonical "on-task" state). The task-related but stimulus-independent class refers to thoughts that interfere with the appraisal of the current task. These thoughts may include wondering when the task will end or thoughts about one's overall performance (i.e., task-related interferences; TRSI). Task-unrelated and stimulus-dependent class refers to exteroceptive and interoceptive perception caused by irrelevant stimuli to the current task (i.e., external distractions; TUSD). Finally, the task-unrelated and stimulus-independent (TUSI) class refers to thoughts that are decoupled from the stimuli present in the current environment and unrelated to the activity being carried out at the time of their occurrence. The last class is commonly defined as MW.

The model could be used dynamically even in the driving context. During the driving task the driver's CE shifts between the four classes as the journey goes on, and these shifts are impacted by several variables. These variables include weather, the length of time spent on a task, the degree of automation in the vehicle, individual differences in executive control, traffic complexity, monotony on the road, and motivation (Thiffault & Bergeron, 2003; Körber et al., 2015; Walker & Trick, 2018). This framework could provide a theoretical basis for mechanistic explanations of attention allocation because TR and SD are orthogonal. According to this framework, the allocation of attention is determined by a competition between top-down goal maintenance (e.g., lane keeping, speed regulation, route execution) and bottom-up salience (e.g., roadside events, driver-assistance system alerts, smartphone notifications). When applied to the domain of driving, taxonomy could distinguish between four distinct states. TRSD (task-related, stimulus-dependent) refers to a state of full engagement with the roadway and instruments. TRSI (task-related, stimulus-independent) refers to thoughts concerning the tasks that are decoupled from current input, such as the evaluation of the route or performance. TUSD (task-unrelated, stimulus-dependent) reflects the capture by irrelevant external stimuli, including billboards, device pop-ups, and

smartphone notifications. Finally, TUSI (task-unrelated and stimulus-independent) refers to thoughts that are decoupled from the stimuli present in the current environment and unrelated to the driving task. The theoretical model is shown graphically in Figure 3.

In the following paragraphs, an analysis will be conducted of the different conscious experiences of the TR/SD model within the driving context. The focus will be on the TRSI, TUSD, and TUSI. In particular, DD related to smartphone use, MW propensity, and psychological factors will be investigated in detail.

		Stimulus-dependency	
		Stimulus-dependent	Stimulus-independent
Task-relatedness	Task-related	<i>Being totally focused on the task currently being performed</i>	<i>Thoughts related to the appraisal of the current task</i> <i>(Task-related interferences)</i>
	Task-unrelated	<i>Sensory perceptions/sensations irrelevant to the current task</i> <i>(External distractions)</i>	<i>Mind-wandering</i>

Figure 3. Conceptual division of ongoing conscious experiences occurring during tasks requiring sustained externally driven attention according to their “stimulus-dependency” and “task-relatedness” dimensions (adapted from Stawarczyk et al. 2011).

The external distraction and smartphone use: when road users engage in risky driving behavior.

Several possible external distractions could divert our focus from the road when we are driving (Shinar et al., 2017). Billboards, windows, construction sites that catch our attention, or unforeseen conversations or events in the passenger compartment can all serve as these distractions. Susceptibility to distraction can be influenced by dispositional factors, such as personality. Indeed, different evidence underlying the positive effects of Neuroticism, Extraversion, and Agreeableness on all dimensions of susceptibility to distracted driving (Braitman & Braitman, 2017; Tinella et al., 2024).

These distractions can become so intense that they interfere with our ability to concentrate while driving, which is a risky driving situation (Jazayeri et al., 2021). As mentioned above, external distraction can be driven by visual, auditory, and manual sources (Wu et al., 2024). In light of this, the multimodal nature of smartphone distraction, which engages the visual (looking away from the road to read or look at the display), manual (typing, scrolling, hand-manipulation of the device), and auditory (notifications, ringtones, conversations) channels, makes it a paradigmatic case (Oviedo-Trespalacios et al., 2020). With reference to Stawarczyk's model, the engagement in these episodes can generate task-unrelated thoughts and stimulus-dependent (TUSD).

Concerning the susceptibility to smartphone distraction, literature focuses on two phenomena in particular: No-mobile-phone-phobia (Nomophobia) and Fear of missing out (FOMO). Nomophobia is defined as anxiety and fear experienced when individuals cannot use their technological devices for communication (Bragazzi & Del Puente, 2014). FOMO is defined as a pervasive apprehension that others might be having rewarding experiences from which one is absent (Przybylski et al., 2013). Indeed, nomophobia and FOMO are characterized by diminishing attention span, impaired working memory, persistent

monitoring, and a higher frequency of anticipatory checking (Gezgin et al., 2018; King et al., 2010). In light of this, situations involving smartphone manipulation have the potential to increase the risk of MVCs. Moreover, it has been demonstrated that smartphone use while driving can change eye orientation and information selection (Jing et al., 2021), and decrease visual scanning (Babic et al., 2022), and specular check rates (Basacik et al., 2011). These changes have important effects on proximal safety indices like increased steering angle (Voinea et al., 2023), headway and speed instability (Kita et al., 2022), increased braking reaction times (He et al., 2014) and increased standard deviation of lateral position (SDLP) (Taneja et al., 2024).

Distraction driven by internal source: the role of Mind-Wandering behind the wheel.

As mentioned before, distraction can be driven by internal and external sources. MW is an example of inattention, characterized by a shift of attention away from a task to internal thoughts and images unrelated to the task at hand (Smallwood & Schooler, 2006). According to research on MW, task-related interferences (TRSI) and task-unrelated thoughts (TUSI) are the two main categories into which the contents of off-task thought clusters fall (Stawacrczyk et al., 2011; Walker & Trick, 2018). Between truly off-task mentation and completely on-task focus, TRI exists in a transitional state. They represent an individual's evaluation of the task and are usually triggered by aspects of the ongoing activity or its context (Walker & Trick, 2018). A driver stopped at a light, for instance, may notice that the brakes have started to squeal and briefly consider what that means. However, these reflections do not directly improve performance because they are not focused on the driving task execution. TUT, on the other hand, reflects subjects that are completely unrelated to driving, like making vacation plans while commuting (Gil-Jardiné et al., 2017; Smallwood & Schooler, 2016). The situations of daily life, including ongoing events, future planning, problem solving, and

emotionally charged concerns, are the primary focus of MW (Andrews-Hanna et al., 2014; Smallwood & Schooler, 2015). This mentation frequently contains socially salient themes related to friends, family, and one's own health and well-being (e.g., Buckner, Andrews-Hanna, & Schacter, 2008). Beyond these topics, examples of off-task cognition include daydreaming and rumination. Daydreaming is characterized by the spontaneous generation of vivid mental images, while rumination is characterized by the recurrent formation of negative thought patterns that result in the repetition of unresolved issues (Christoff et al., 2016; Ehring et al., 2021).

These diversions of attention from the task can degrade performance by compromising perceptual encoding (e.g., McVay, Kane, & Kwapil, 2009; Risko et al., 2012) and disrupting the accuracy of time estimation (Schooler et al., 2004; Smallwood et al., 2008). In the driving context, relatively few studies focus on MW behind the wheel, even though inattention while driving could have important consequences (Walker & Trick, 2018). According to simulator-based research, MW behind the wheel is associated with driving time and is more frequent when traveling on familiar roads (Yanko & Spalek, 2013; Burdett et al., 2016). In general, drivers who are engaged in MW do not monitor the environment as effectively as those individuals who are not preoccupied with internal thoughts (Charlton & Starkey, 2011; Martens & Fox, 2007; Van Elslande & Fouquet, 2007). Indeed, during MW episodes, drivers spend less time monitoring side mirrors, engage in less complex eye movements, and experience a general narrowing of horizontal visual scanning (Galéra et al., 2012; He et al., 2011). Moreover, as with external distractions, although to a lesser extent, during MW episodes, there is a tendency to increase the driving speed, increase the SDLP, and decrease the headway distances (Albert et al., 2018; Duncan et al., 1991; Mrazek et al., 2012; Yanko & Spalek, 2013). Indeed, case-control studies also suggest that individuals who have been

engaged in MW are more likely to be judged responsible for a collision (e.g., Galéra et al., 2012).

Psychological factors as precursors of distracted driving

The psychological factors associated with DD are related to the intersection of trait vulnerability and situational factors (Stephens & Groeger, 2009; Regan et al., 2014). On the trait side, different studies show that personality traits, anxiety, sensation seeking, impulsiveness, and anger are associated with risk behaviors and choices that compete with attention maintenance (e.g., smartphone use, inadequate headway) (e.g., Akbari et al., 2019; Tinella et al., 2022; Tinella et al., 2026). This suggests the presence of a profile characterized by low executive control and high stimulus search sensitivity to ego-centric capture (Zhang et al. 2020). On the state side, state anxiety has been demonstrated to further modulate resource allocation. State anxiety has been shown to impair driving performance, as evidenced by delays, micro-errors, and non-optimal control strategies (Hidalgo-Muñoz et al., 2023; Clapp et al., 2011). Furthermore, attempts at self-regulation of anxiety while driving can result in cognitive costs that increase lapses and errors. This phenomenon is referred to as a regulatory paradox, which states that the over-regulation of anxiety can worsen driving safety (Gwyther & Holland, 2012). In this theoretical framework, the spatial dimension of anxiety is especially relevant in the context of navigation tasks. Spatial anxiety (SA), defined as fear related to orientation, wayfinding, and route decisions (Lawton et al., 1994; Geer et al., 2024), has been demonstrated to be associated with diminished navigation performance, the adoption of less efficient strategies, and an increased load in environmental learning tasks (Davis & Veltkamp, 2019; Geer et al. 2024). When SA is triggered in real traffic conditions, it has the potential to divert executive resources from external monitoring, facilitating transitions to lapses and distraction (Nori et al., 2023).

In summary, the phenomenon of DD originates from a complex psychological ecosystem in which traits (e.g., trait-anxiety, sensation seeking) and states (e.g., state-anxiety) interact with the constraints of the road context.

Distracted Driving as a multidimensional construct: how susceptibility to different kinds of distractions impacts driving behavior.

The present work aimed to conduct a comprehensive investigation of the different kinds of distractions that drivers can experience, applying the TR/SD framework (Stawarczyk et al., 2011). In particular, we are interested in understanding how different types of distraction may impact driving performance, using simulated driving tasks. Moreover, another aim is to understand the influence of specific distal factors on DD. We first conducted a theoretical review to summarize the relevant literature on the topic. After this, we developed and validated psychometric instruments to assess distinct distraction profiles for different road users. Finally, we operationalized Stawarczyk's TR/SD model within controlled driving-simulator tasks to test its predictions under experimentally manipulated conditions. To that end, we have conducted six studies (*Chapter I, Chapter II; Chapter III; Chapter IV; Chapter V; Chapter VI*).

Chapter I presents a systematic review of the available evidence on driving-related factors associated with MW behind the wheel. PRISMA guidelines and the PECO's method were applied to screens for eligible studies. Thirty-four studies from Scopus and Web of Science (WoS) met the inclusion criteria.

Chapter II presents a validation study of a new instrument for measuring driver mental state, Questionnaire on Distraction in Driving Activities (QUADRIVIA), following

Stawarczyk's model (2011) related to the TR/SD approach. Validity, factorial (EFA and CFA), and reliability analyses were conducted to establish the psychometric properties of the tool.

Chapter III presents another validation study of a new instrument designed to cross-regionally assess mobile phone use and associated risk-compensating behaviors among cyclists, the Phone Use while Riding Scale (PURS). The PURS was tested using Structural Equation Modeling (SEM) to evaluate its psychometric properties, following a theory-based three-dimensional structure, which assesses cyclists' Visual-Manual Interactions, Risk-Compensating Behaviors, and Hands-Free Auditory Interactions.

Chapter IV presents the Italian adaptation of the Nomophobia Questionnaire (NMP Q), testing a four-factor structure and establishing normative data by age and gender. Data were collected from 1147 participants. Exploratory Structural Equation Modeling (ESEM) assessed different factorial configurations. At the same time, scores were computed for the 1st and the 99th percentile and for each ventile; the 80th and 95th percentiles indicate risk and presence of nomophobia, respectively.

Chapter V presents a driving simulator study to test whether drivers' distraction susceptibility moderates the effects of low vs. high perceptual load on driving performance. 34 participants, divided into high vs. low susceptibility groups via QUADRIVIA, drove a car-following (high-load) and a free-driving (low-load) scenario in counterbalanced order. We recorded speed, SDLP, and steering variability. After this, the content of thoughts online and offline (TRT/TUT) was probed.

Chapter VI presents a study where it was hypothesized that the severity of SA affects risky driving behaviors and that this relationship is mediated by the driver's self-regulation abilities. Self-reported SA symptoms, driving self-regulation abilities, and risky driving behaviors (i.e., errors, violations, and lapses) were examined in 838 Italian drivers. Data were

analyzed through linear regressions and path analysis models, controlling for sociodemographic variables.

Chapter I

DRIVING-RELATED FACTORS AFFECTING MIND-WANDERING BEHIND THE WHEEL: A SYSTEMATIC REVIEW

This chapter is based on: Traficante, S., Tinella, L., Lopez, A., Bosco, A., Koppel, S., E., Ricciardi, Spano, G., Napoletano, R., Caffò, A. Driving-related Factors Affected Mind-Wandering Behind the Wheel: a systematic review. *Transport Review* (10.1080/01441647.2025.2525284)

Introduction

According to the World Health Organization (WHO 2015), road traffic injury is any fatal or non-fatal injury resulting from a collision on a public road involving at least one moving vehicle. Motor-Vehicle Crashes (MVCs) represent one of the highest causes of death and serious injury globally (Chang et. al. 2020).

However, research has established that more than 90% of MVCs are directly or indirectly caused by human factors (Dingus et al. 2016). It is important to acknowledge that the utilization of the term may be considered overly broad. The present study refers to a specific body of literature that delineates how human factors can contribute to road MVCs (Dingus et al., 2016; Petridou & Moustaki, 2000; Bucsuházy et al., 2023). Petridou and Moustaki (2000) delineate human factors in two categories: those that diminish an individual's capacity to respond to traffic contingencies (e.g., advanced age, temporary distraction, drug use, etc.) and those that modulate the risk-taking propensity while driving (e.g., habitual speeding, habitual disregard of traffic laws). Moreover, according to Dingus and colleagues (2016), these human factors can be divided in: compromission (e.g., intoxicated driving, fatigue, drowsiness); driver error performance (e.g., failing to signal; stop/yield sign violation; driving too slowly; making an improper turn); driver judgment error (e.g., illegal passing or following too closely) and driver distraction (e.g., handheld cell dealing, reading/writing). Our aim is not to attribute blame to individual drivers but rather to highlight how specific cognitive and individual characteristics may interact with the road context, influencing MW and driving behavior.

Among these factors, distracted driving (DD) has emerged as the primary cause of incidents (e.g. Young et al., 2007), representing a significant global challenge to road safety. DD is a significant risk to road safety. DD is defined as “*a diversion of attention away from activities critical for safe driving toward a competing activity*” (Lee et al., 2009, p. 34). For example, the National Center for Statistics and Analysis (NCSA) showed that 3.142 people died during 2020 in MVCs caused by

distracted driving in the US; 12% were related to cell phone use. Moreover, the US Census Bureau (2012) reported that 36% of MVCs could potentially be avoided if no distractions were present. In Italy, during 2021, the greatest number of MVCs was partially or uniquely determined by distracted driving (30.478 MVCs: 15.14%), involving especially younger (age 20-24) and adult male drivers (age 45-59; ISTAT 2022). The reported data demonstrates the impact that DD has on public safety, the loss of human lives, and its severe social consequences.

DD can occur due to shifted attention focus from the driving primary task to secondary irrelevant stimulations (e.g., operating with in-vehicle devices, talking with passengers, looking out to advertising signs) or to internal feelings and sensations (i.e., worries, rumination on past moments, etc.). Indeed, shifting attention from the primary task to self-generated thoughts, sensations, and feelings, also known as “Mind-Wandering” (MW), could increase the possibility of risky behavior while driving (Delhomme & Gheorghiu, 2021). More specifically, MW refers to a shift in the contents of thought away from an ongoing task and from events in the external environment to internal and self-generated thoughts, sensations, and feelings (Murray et al. 2020; Smallwood and Schooler 2015; Stawarczyk et al., 2011).

MW can be considered a cognitive state generating interference with the driving task (Pepin et al. 2018). Different studies have shown that MW has significant implications for road safety (Yanko and Spalek, 2013; Geden & Feng, 2015). MW has been linked to risky driving behavior, including increased reaction time (RT), (Yanko and Spalek 2014), elevated speed, shorter headway distance, and decreased visual scanning (He et al., 2011). However, to date, few studies have focused on MW behind the wheel. Although numerous studies have examined the effect of external distractions on driving behavior, there is limited understanding of the influence of MW on driving performance and MVC risk due to the challenges associated with measuring inattention (Galéra et al., 2012; Burdett et al., 2016). In the absence of official data, we should assume that a small proportion of the registered MVCs caused by DD have been attributed to MW. Moreover, it should be noted that there are no

clear and consistent regulations regarding MW while driving across different countries. Consequently, MVCs caused by MW are likely underreported and/or misclassified in national survey reports (Gil-Jardiné et al., 2017). This aspect holds importance considering those studies showing MW as positively associated to aberrant driving behavior, changes in driving performance, and culpability for MVCs (Galera et. al., 2012; Yanko and Spalek, 2014). Similarly, a few devices have been developed, exclusively for experimental purposes, to detect and reduce MW behind the wheel through the recognition of MW-related patterns of eye movements (Beninger et al., 2021).

Overall, MW represents a complex phenomenon with a serious and partially unknown impact on road safety that needs further research efforts to be fully recognized as a part of DD behavior. To date, the limited literature on MW behind the wheel has highlighted a series of environmental and individual factors affecting the occurrence of this phenomenon. Despite institutional interventions to prevent road injuries due to DD, the study of MW behind the wheel remains difficult and represents a matter of debate. This study aimed to systematically review the available evidence on driving-related factors associated with MW behind the wheel, to propose a taxonomy of them by analyzing their occurrence and their interaction in causing MW.

Methods

This review was conducted according to PRISMA guidelines (Page et al., 2021).

Eligibility criteria

Inclusion criteria

The PECO (Participants, Exposure, Comparison, Outcomes) method was used to define the selection criteria for suitable studies. The PECO method facilitates the comparison of heterogeneous studies and increases the transparency of the selection of articles, thus ensuring a rigorous methodological approach. Indeed, it is suitable for cross-sectional studies and useful when assessing exposure to a condition rather than an intervention (Page et al., 2021).

[P] Participants: active drivers with a valid license; no sex, age or health conditions restrictions were applied.

[E] Exposure: the tendency to MW assessed through the probe-caught method; self-caught method; self-reported measures as well as the experience sampling method.

[C] Comparison: conditions or groups of participants (i.e., control group: young male drivers with neutral mood; experimental group: young male drivers with negative mood).

[O] Outcomes: simulated driving, real-world driving, self-reported driving behaviors, police-recorded violations, and MVCs.

Only articles written in English were included without any limitations regarding the year of publication.

Exclusion criteria

Studies were excluded from the review according to the following criteria: a) studies that did not contain empirical data (e.g., literature reviews, editorial, commentaries letter to the editor, etc.); b) studies that did not go through a peer-review process (e.g., dissertation, technical reports, book chapters, etc.); and c) studies that did not investigate the relationship between MW and the above mentioned driving outcomes [O].

Search strategy and study selection

The search was conducted on 28 September 2024 through Scopus and Web of Science (WoS). These databases were used since they are considered the main sources for citation data (Archambault et al. 2009). In addition, the interdisciplinary coverage of these databases is a significant strength for studying and comparing different scientific fields (Archambault et al. 2006). The search strategy was defined using the following syntax terms based on title, abstract, and keywords: “Driv*” OR “Driving” OR “Drive” AND “Mind-Wander*” OR “Mind-Wandering” OR “Mind Wandering” OR “Daydream*” OR “Daydreaming”. Queries adjusted for each database are presented in Table 1.

Bibliographic records were screened through two steps, including title, abstract and keywords, then analyzing full texts. Finally, the bibliographic records matching the eligibility criteria were selected and included in the final sample. Figure 1 shows the diagram of the study selection procedure.

Table 1. Queries adjusted for WoS and Scopus database

Database	Queries
WEB OF SCIENCE	(((((TS=(driv*)) OR TS=(driving)) OR TS=(drive)) AND TS=("mind-wander*")) OR TS=("mind-wandering")) OR TS=("mind wandering")) OR TS=(daydream*) OR TS=(daydreaming)
SCOPUS	(TITLE-ABS-KEY (driv*) OR TITLE-ABS-KEY (driving) OR TITLE-ABS-KEY (drive) AND TITLE-ABS-KEY ("Mind-Wander*") OR TITLE-ABS-KEY ("Mind-Wandering") OR TITLE-ABS-KEY ("Mind Wandering") OR TITLE-ABS-KEY (daydream*) OR TITLE-ABS-KEY (daydreaming)

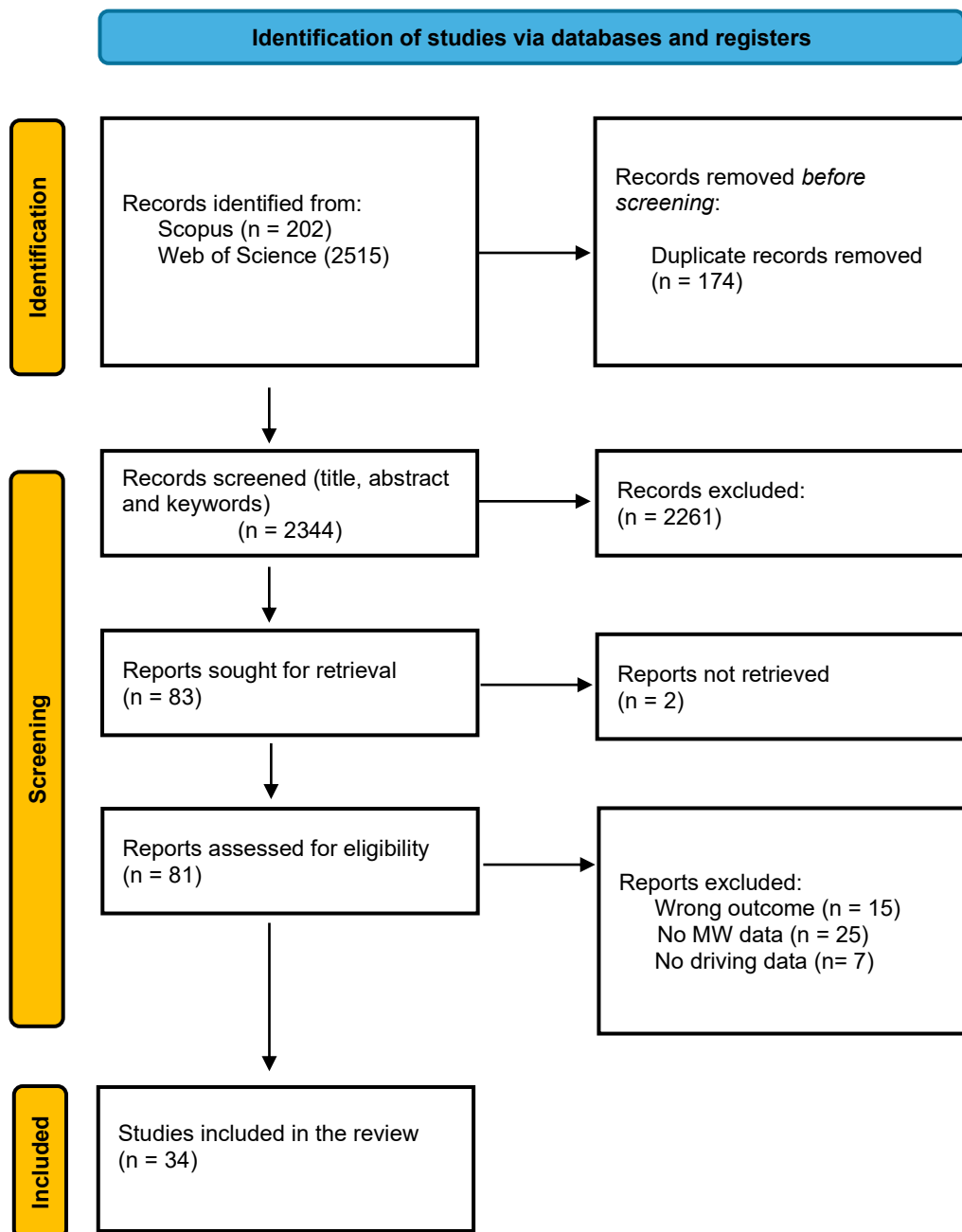


Figure 1. Flowchart for selection process of articles

Quality assessment

For the study of quality assessment, the NHS Critical Appraisal Skills Program (CASP) checklist was used (Critical Appraisal Skills Program 2018). The CASP checklist consists of several guiding questions about the validity, reliability, and the applicability of results of the considered studies (Carroll et al., 2011). The scores range from 0 (low quality) to 6 points (high quality), with

higher values indicating better quality. An independent panel of two expert reviewers assessed all selected studies separately. Fleiss's Kappa was used to determine interrater reliability. Three reviewers (ST, LT and AL) independently provided their quality scores on each study. A value of $K = 0.94$ was found, thus indicating almost perfect agreement between the three reviewers (McHugh, 2012) (Table 2).

Table 2. Fleiss' Kappa

	N. of Studies	rater	statistic	z	p
Fleiss Kappa	34	3	0,943	14,8	< 0,001

Study findings

Study selection

The initial search on both databases identified 2,517 documents (SCOPUS=202; WoS= 2,315). After applying the eligibility criteria: 174 documents were excluded since they were duplicates, 141 documents were excluded since they were not written in English, 386 documents were excluded because they were not research papers (e.g., book chapters, reviews, editorial material, meeting abstract, poetry, conference review, art exhibit review). The screening of titles, abstracts, and keywords resulted in the further exclusion of 1,755 documents because they did not meet the inclusion criteria. The remaining 34 studies underwent full-text screening

Study characteristics

Thirty-four studies were included in the current review. The selected studies were published during the period from 2009 (He et al., 2009) to 2023 (Yoshida et al., 2023). There were 20 cross-sectional studies, 9 retrospective self-report studies, 1 qualitative study, 2 case-control studies, 1 repeated measure study, and 1 study implementing randomized controlled trials design. The study's sample size ranged from 10 (Lin et al., 2016) to 955 (Galéra et al., 2012), and participants' ages

ranged between 18 and 85 years old. Samples were selected from different settings: universities; hospitals and laboratories. The selected studies were conducted in different countries, namely France (8); USA (6); Canada (5); New Zealand (3); Australia (2); China (2); Japan (2); Netherlands (1); Germany (1); United Kingdom (1); Italy (1); Taiwan (1); Iran (1). Further information is available in Table 3.

Table 3: Study characteristics

N/A= not applicable; MW= mind wandering; N= participants; US= Unites States; UK= United Kingdom; Q.A= quality assessment of the studies

Study	Design	Population	Key Findings	Q.A.
Albert et al. (2018)	Cross-Sectional	Canadian male drivers (N= 30)	MW predicts an increase in driving speed.	4/6
Albert et al. (2022)	Cross-sectional	Canadian young drivers (N=40)	Negative mood leads to more frequent MW in young male drivers.	4/6
Berthié et al. (2015)	Retrospective study	French drivers (N=191)	MW frequently occurs in situations requiring minimal attention	5/6
Burdett et al. (2016)	Retrospective study	New Zealand drivers (N= 502)	MW is common in undemanding conditions and rapidly interrupted by task-requiring effort.	4/6
Burdett et al. (2018)	Retrospective study	New Zealand drivers (N=11)	These findings suggest that in familiar, undemanding situations, drivers are more likely to be found in MW	4/6
Burdett et al. (2019)	Cross-sectional	New Zealand drivers (N= 25)	MW is associated with fatigue, younger age, and familiar roads.	4/6
Farahmand & Boroujerdian (2018)	Cross-sectional	Young Iranian drivers (N= 17)	Diverse road geometry has been demonstrated to enhance vigilance and performance.	3/6
Geden & Feng (2015)	Cross-sectional	US students with a driving license (N=29)	It was observed that high MW levels were present in conditions of low perceptual load.	2/6
Geden et al. (2018)	Cross-sectional	US drivers (N=40)	Driving performance fluctuated greatly over the driving duration when MW	4/6
Galera et al. (2012)	Case-control	French drivers (N=955)	Intense MW linked to responsibility for crashes.	5/6

Gil-Jardiné et al. (2017)	Case-control	French drivers crash-involved (N= N/A)	MW contributes to a 10% crash risk; disruptive thoughts impair engagement with the driving task.	5/6
He et al. (2009)	Cross-sectional	US drivers (N=19)	MW narrows visual scanning, impairing hazard detection.	4/6
He et al. (2011)	Cross-sectional	US drivers with 4+ years' experience (N=18)	MW is lower in challenging wind conditions.	4/6
Körber et al. (2015)	Cross-sectional	German drivers (N=20)	Fatigue occurs without active engagement, linked to automated driving and MW.	3/6
Lemercier et al. (2014)	Retrospective study	French drivers (N= 20)	MW state led to less micro-regulation of both speed and lateral position and altered visual scanning	3/6
Lin et al. (2016)	Cross-sectional	Taiwanese students with a driving license (N=10)	MW tends to occur under low perceptual demands during driving	3/6
Lin et al. (2021)	Retrospective study	Chinese drivers (N=190)	MW varies by age group; triggered by emotional and work-related thoughts.	3/6
Mueller et al. (2022)	Cross-sectional	US drivers using automation (N= 31)	Familiarity with automation affects the attentional strategy	4/6
Nijboer et al. (2016)	Cross-sectional	German drivers (N=48)	MW impairs performance more than radio tasks; driving alone encourages MW.	5/6
Pepin et al. (2018)	Repeated measures	French drivers with 3+ years' experience (N= 20)	MW led to fixed gaze; effort was needed to switch attention back to driving.	5/6
Pepin et al. (2020)	Retrospective study	French drivers (N= 60)	Reduced visual amplitudes and longer reaction times during MW.	5/6
Qu et al. (2015)	Retrospective study	Chinese drivers (N=310)	MW positively correlated with risky behaviors like aggressive or drunk driving.	3/6
Schnebelen et al. (2020)	Cross-sectional	French drivers (N=12)	Frequent gaze shifts are required in automated driving to manage MW and tactical information.	3/6
Steinberger et al. (2016)	Cross-sectional	Australian young male drivers (N=24)	MW associated with boredom in routine drives	2/6
Techer et al. (2017)	Cross-sectional	French drivers (N=33)	Results indicated that anger impacted driving performance and attention.	5/6

Tinella et al. (2022)	Retrospective study	Australian and Italian drivers (N=904)	MW mediates the effects of personality traits like neuroticism and extraversion on driving behavior.	4/6
Walker & Trick, (2018)	Cross-sectional	Canadian drivers (N=40)	Fatigue and task length predict MW during driving.	4/6
Watling & Watling, (2021)	Retrospective study	Australian drivers (N=118)	Sleepiness and poor impulse control linked to MW during driving	3/6
Weaver et al. (2022)	Cross-sectional	US drivers (N=48)	Adaptive cruise control (ACC) reduced MW, improving driving performance	3/6
Yanko & Spalek, (2013)	Cross-sectional	Canadian Students (N=66)	Drivers showed slower reaction times and closer following distances in familiar routes.	6/6
Yanko & Spalek, (2014)	Cross-sectional	Canadian Students (N=49)	MW increased reaction times and speed, reducing forward distance and increasing crash risk.	6/6
Yoshida et al. (2023)	Cross-sectional	Japanese drivers (N=42)	MW correlates with slower brake reaction times.	5/6
Zhang & Kumada, (2017)	Cross-sectional	Japanese drivers (N=40)	Higher workload correlates with less MW, while task time increases MW frequency.	4/6
Zimasa et al. (2019)	Cross-sectional	UK drivers (N=40)	Negative moods increase MW and riskier driving, even with cognitive load disengagement.	4/6

Risk of bias within studies

All 34 studies were rated on the CASP checklist. Nine studies were rated “high quality” (2 studies had a score of 6; 7 studies had a score of 5). Seventeen studies obtained a score of 4, indicating “moderate quality”. Eight studies obtained a score of 3, indicating “poor quality”. Nine studies included self-reported measures to assess MW behind the wheel, mainly through online surveys and paper and pencil questionnaires (Berthié et al., 2015; Burdett et al., 2016; Lin et al., 2021; Qu et al., 2015; Burdett et al., 2018; Lemercier et al., 2014; Pepin et al., 2021; Watling et al., 2021; Tinella et al., 2022). It is well known that self-reported measures include several limitations in terms of reliability and potential risk for response bias.

Age stratification was often lacking, with selected studies including participants with an average age span ranging from 19,23 to 42,46. Indeed, several studies only considered gender as a demographic variable, neglecting age groups (Geden et al., 2015; Burdett et al., 2016). Furthermore, some studies focused on an entirely male sample, limiting the investigation of gender differences in MW frequency (Burdett et al. 2016). Another limitation is related to the reliability of the retrospective recall of MW episodes using self-caught and probe-caught methods (Berthiè et al., 2015; Lin et al., 2014). This may have prompted participants to think about off-task thoughts, likely contributing to an increase in reported episodes of MW. Additionally, several studies were focused on highly selective samples, such as university students, which may not be completely representative of the broader population of drivers (Yanko & Spalek, 2013; Yanko & Spalek, 2014). Finally, only the documents written in English were included. Considering this, publication bias may emerge.

Results of studies

Fifteen studies examined the impact of perceptual load on MW rates. One study examined the relationship between MW and driving environment. Nine studies examined the impact of negative mood (4), socio-demographic factors (3), and personality traits (2) on MW rates behind the wheel. Four studies examined the relationship between automated driving systems and MW rates during driving situations. Five studies examined relationships between the propensity to MW, behavioral consequences, and MVCs risk.

After analyzing the selected articles, three major thematic areas related to MW behind the wheel emerged from the literature: vehicle-related factors (e.g. ADAS), environmental factors (e.g. weather conditions), and human factors (perceptual load, socio-demographic factors and personality traits). Table 4 represents a summary of the results.

Table 4. Summary of key findings on MW behind the wheel.

Category	Findings	References/Example
Perceptual load	Familiarity with the road: Increases MW due to reduced attention demand; associated with slower reaction times.	Yanko & Spalek, 2013; Burdett et al., 2019
	Driving time: Prolonged driving leads to monotony, mental fatigue, and higher MW frequency.	Zhang & Kumada, 2017; Steinberger et al., 2016
Personality Traits	Neuroticism: Positive association with rumination and heightened MW. Extraversion: Associated positively with MW.	Tinella et al., 2022; Walker & Trik, 2018
Socio-demographic factors	Young male drivers: Higher MW propensity than older adults. - Content of MW: Differs by age; younger drivers focus on personal concerns.	Albert et al., 2022; Lin et al., 2021
Vehicle-Related Factors	ADAS systems: Higher MW rates with Level 2 automation; minimal MW increase with Level 1 systems like ACC.	Korber et al., 2015; Mueller et al., 2022
Environmental Factors	Weather conditions: Strong crosswinds reduce MW by increasing perceptual load.	He et al., 2011
Behavioral Outcomes	MW and MVCs: Higher MW propensity is linked to reduced braking performance, lane deviations, and increased collision risk.	Galéra et al., 2012; Yoshida et al., 2023
	Visual scanning: MW causes narrow horizontal scanning and slower responses to hazards.	He et al., 2011; Yanko & Spalek, 2014

Notes: MW= Mind Wandering; MVCs= Motor Vehicle Crashes; ADAS= Advanced driver assistance systems; ACC= Adaptive Cruise Control

Vehicle-related factors

Drawing upon the reviewed literature, the relationship between vehicle-related factors, specifically Advanced Driver-Assistance Systems (ADAS), and MW during driving presents a complex interplay warranting careful consideration (Korber et al., 2015, Schnebelen et al., 2020, Weaver et al., 2022, Mueller et al., 2022). Studies investigating this association have yielded nuanced findings: Adaptive Cruise Control (ACC), a Level 1 automation system, did not demonstrate an

association with increased MW episodes in the study by Weaver et al. (2022). The use of ACC correlated with enhanced safety behaviors, such as greater following distance and reduced speed variability. Conversely, research concerning partial automation (Level 2) suggests the potential for elevated MW. Korber et al. (2015) reported an increase in MW under simulated partial automation, potentially attributable to the reduced perceptual load afforded by such systems, leading drivers to divert attentional resources away from the primary driving task. The impact of familiarity with Level 2 automation on attentional strategies was explored by Mueller et al. (2022). While the study did not find significant effects of familiarity, a correlation emerged between recalling non-critical salient events and higher levels of self-reported MW. In the context of highly automated driving, Schnebelen et al. (2020) investigated the "out-of-the-loop" (OOTL) phenomenon. Their findings indicate that drivers exhibiting lower MW scores displayed more frequent gaze transitions towards driving-relevant areas. In contrast, drivers with higher MW scores tended to fixate on driving-irrelevant regions, with both OOTL and MW appearing to increase throughout automated driving. In general, these studies suggest that the influence of ADAS on MW is not uniform across different levels of automation. While lower levels of assistance like ACC may not exacerbate MW and could even promote safer driving habits, higher levels of automation, particularly when diminishing perceptual load, may inadvertently foster a greater propensity for drivers to engage in task-unrelated thoughts (Korber et al., 2015). This underscores the importance of considering the level of automation and the resultant impact on driver perceptual engagement when evaluating the relationship between vehicle-related factors and the occurrence of MW behind the wheel. Further research is warranted to elucidate this intricate interaction and to develop effective countermeasures for mitigating potential safety risks associated with MW in increasingly automated vehicles (Schnebelen et al., 2020). One study received a score of 4/6 on the CASP checklist (Mueller et al., 2022). Three studies received a score of 3/6 on the CASP checklist (Schnebelen et al., 2020; Korber et al., 2015; Weaver et al., 2022).

Environmental factors

In terms of studies examining environmental factors influencing MW behind the wheel, only one study was identified. He et al. (2011) studied the frequency and correlation of MW while driving. MW episodes were measured through the self-capture method, and drivers were asked to report any time they found themselves MW. For converging evidence of self-report validity of task, the authors evaluated MW levels of eighteen during a simulated driving task under two different weather conditions: with and without a strong crosswind. Participants reported more MW rates during every 15 minutes of driving. MW was less frequent in strong crosswind conditions, and compared with their attentive performance, participants showed few deficits in vehicle control while MW tended to focus visual attention narrowly on the road ahead. The study received a score of 4/6 on the CASP checklist.

Human Factors

Twenty-four studies examined the impact of human factors on MW rates. Of these, fifteen studies examined the impact of perceptual load on MW rates. Additionally, nine studies examined the impact of socio-demographic factors and personality traits on MW rates behind the wheel.

Perceptual load imposed by the driving environment

Fifteen studies were identified that examined the impact of perceptual load on MW behind the wheel from two main perspectives. The first one is familiarity with the road/route. For the sake of clarity, the concept of “familiarity” in this context refers to familiarity with the environment but not necessarily with the specific driving task.

Twelve studies explored this perspective (Yanko & Spalek, 2013; 2014; He et al., 2011; Lemercier et al., 2014; Burdett et al., 2016; 2018; 2019; Berthié et al., 2015; Nijboer et al., 2016; Lin et al., 2016; Geden et al., 2018; Geden & Feng, 2015). Familiarity with the route/road leads to increased levels of MW behind the wheel. Consequently, drivers have longer reaction times for both central and peripheral hazards, and they tend to decrease their following distance (Yanko & Spalek, 2013; Yanko & Spalek, 2014). Additionally, they also have less variability in horizontal gaze and pay

less attention to side mirrors and restricted visual scanning (He et al., 2011; Lemercier et al., 2014). Indeed, in the studies by Burdett et al. (2016; 2018; 2019), most participants reported more task-unrelated thoughts on roads they travel daily. Greater route familiarity decreased attentional and perceptual resources allocated to primary tasks. These findings suggest that drivers are more likely to engage in MW rather than focus on driving on familiar roads, roads with low traffic density, and with low attention demand (Berthié et al., 2015; Nijboer et al., 2016). However, MW tends to be quickly interrupted when driving activities require more intense attention and thus a higher perceptual load (Lin et al. 2016; Geden et al., 2018). On the other hand, three studies (Farahmand & Boroujerdain, 2018; Zhang & Kumada, 2017; Steinberg et al., 2016) explored driving time perspective and its association with MW while driving. These studies observed an increase in MW with prolonged driving duration (Zhang and Kumada 2017). When drivers spend more time engaged in the driving task, the monotony and passive nature of the activity can lead to decreased attention and to a greater likelihood of MW (Farahmand & Boroujerdain, 2018; Steinberg et al., 2016). This phenomenon is evident during long highway drives or in situations where the driving demands are relatively low. The extended periods of focused attention required for driving can result in mental fatigue and a tendency for drivers to divert their attention towards internal thoughts and daydreaming (i.e., MW). Two studies received a score of 2/6 on the CASP checklist (Geden & Feng, 2015; Steinberger et al., 2016). Three studies received a 3/6 score on the CASP checklist (Lemercier et al. 2014; Lin et al. 2016; Farahmand & Boroujerdain, 2018). Six studies received a score of 4/6 on the CASP checklist (He et al. 2009; Burdett et al., 2016; 2018; 2019; Zhang & Kumada, 2017; Geden et al., 2018). Two studies received a score of 5/6 on the CASP checklist (Berthié et al., 2015; Nijboer et al., 2016). Two studies received a score of 6/6 on the CASP checklist (Yanko & Spalek, 2013; 2014).

Personality traits and sociodemographic factors

The influence of human factors in terms of individual differences on MW levels has been investigated in nine studies. These studies have explored how personality traits and sociodemographic

factors can contribute to increased MW rates during driving. Two studies (Walker & Trik, 2018; Tinella et al., 2022) examined how personality traits can influence individuals' tendency to engage in MW behind the wheel. The evidence suggests that certain personality traits may be associated with a higher propensity for MW behind the wheel (Tinella et al., 2022). Individuals with high levels of neuroticism, openness and extraversion, may be more prone to MW than individuals with low levels of these traits. Neuroticism can make individuals more susceptible to worries and rumination, which can interfere with attention during driving (Walker & Trik, 2018). Indeed, the results highlight the positive influence of MW tendency on self-reported aberrant driving behaviors and may indicate its detrimental role by amplifying the positive effects of neuroticism and extraversion while mitigating the effects of conscientiousness (Tinella et al. 2022). On the other hand, openness may also contribute to MW, as individuals may focus on internal thoughts and stimuli rather than the road (Tinella et al. 2022). Four studies (Qu et al., 2015; Techer et al., 2017; Zimasa et al., 2019; Albert et al., 2022) have investigated the relationship between MW behind the wheel and mood. In a randomized control trial, Albert et al. (2022) demonstrated that drivers exposed to negative moods exhibited higher levels of MW. High levels of MW are associated with sad mood and a greater propensity for traffic violations (Qu et al. 2015). The effect of MW on drivers with sad or angry moods is evident both behaviorally and in eye fixation, with a reduction in headway distance, decreased horizontal fixation, and reduced processing of critical information (Techer et al., 2017; Zimasa et al., 2019). Three studies (Albert et al., 2018; Watling & Watling, 2021; Lin et al., 2021) have evaluated the influence of sociodemographic factors on MW. The findings have shown a higher propensity to MW among young male drivers compared to older drivers. Male drivers are more likely to engage in risky and aggressive driving behaviors (Albert et al., 2018; Watling & Watling, 2021). Moreover, the types of task-unrelated thoughts also vary based on the drivers' age. The content of thoughts among older drivers reflects concerns about family and work routines, while younger drivers' task-unrelated thoughts are more focused on personal issues (Lin et al., 2021). Three studies received a score of 3/6 on the CASP checklist (Lin et al., 2021; Watling & Watling, 2021; Qu et al., 2021). Five studies received a score

of 4/6 on the CASP checklist (Albert et al., 2022; Zimasa et al., 2019; Tinella et al., 2022; Albert et al., 2018; Walker et al., 2018). One study received a score of 5/6 on the CASP checklist (Techer et al., 2017).

Behavioral changes and increased MVC risk

Five studies explored the behavioral changes (Yoshida et al. 2023; Pepin et al. 2020; 2018) of MW behind the wheel and the risk of MVCs (Galéra et al., 2012; Gil-Jeardiné et al., 2017).

Two case-control studies investigated the association between MVCs and MW while driving. Galéra et al. (2012) reported that elevated MW rates were significantly associated with driver culpability for MVCs. Similarly, Gil-Jeardiné et al. (2017) found that both MW trait and MW state independently increased the odds of being responsible for an MVC. The behavioral consequences of MW were explored in three additional studies. Yoshida et al. (2023) demonstrated that periods of inattentiveness during driving, indicative of MW, were associated with increased reaction time variability and a significant positive correlation with delayed brake response reaction times, suggesting an impairment in braking performance. Pepin et al. (2020), utilizing EEG, highlighted that MW led to reductions in visual N1 and P3 amplitudes and an increase in reaction time, indicating a disruption in visual information processing. Furthermore, Pepin et al. (2018) observed that both MW and problem-solving thoughts resulted in prolonged gaze fixation, with MW requiring cognitive effort for attentional re-engagement with the driving task. In summary, the evidence presented in this section indicates a clear link between MW while driving and negative behavioral outcomes. These outcomes include impaired hazard perception, delayed reaction times, compromised braking performance, and altered visual attention patterns (Yoshida et al., 2023, Pepin et al., 2020, 2018; Galéra et al., 2012; Gil-Jeardiné et al., 2017).

Four studies received a score of 5/6 on the CASP checklist (Galéra et al., 2012; Gil-Jeardiné et al., 2017; Pepin et al., 2020; Yoshida et al., 2023). One study received a score of 4/6 on the CASP checklist (Pepin et al., 2018).

Discussion

The review of the selected papers suggests that the MW behind the wheel has been studied in relation to three main clusters of factors: vehicle-related factors (i.e., ADAS), environmental factors (i.e., weather as well as road conditions), human factors (i.e., perceptual load, personality traits, and socio-demographic factors), along with its behavioral consequences.

Vehicle-related factors

The main findings indicate that the impact of MW varies according to the level of automation in ADAS systems. While an increase in MW was observed with Level 2 (L2) or higher systems (Korber et al., 2015), the use of Adaptive Cruise Control (ACC), a Level 1 (L1) system, did not show a significant increase in MW (Weaver et al. 2022). These results align with De Winter and colleagues' (2014) suggestion that the perceptual load reduction associated with ACC is minimal compared to that offered by L2 systems. Consequently, the increased responsibility maintained by drivers with ACC may help maintain greater situational awareness, limiting the onset of MW (McKerral et al. 2023). Moreover, the study by Weaver et al. (2022) was conducted on real roads, unlike many previous simulator-based studies. This real-world context may have prompted increased attention to the external environment, particularly under conditions of low familiarity with the automation system. This interpretation aligns with previous literature suggesting that increased familiarity with higher-level automation (L2 and above) can further reduce perceptual load, which may, in turn, lead to increased fatigue and a higher propensity for MW (Schömig et al., 2017). The implications of these results highlight how the introduction of vehicle automation systems does not have a uniform effect on drivers' attention. Systems that significantly reduce perceptual load, such as partial Level 2 and higher automation, may paradoxically increase the risk of inattention. This inattention may reduce alertness and impair the driver's ability to intervene promptly in dangerous situations (McWilliams & Ward, 2021; Lee, 2014).

For the sake of clarity, it has been theorized that the categorization of ADAS as a vehicle factor represents an intrinsic technological component of the vehicle that directly influences the visual and auditory environment within the cabin. While the driver's mental model is a human factor, the system's architecture, such as the frequency of alerts, the interface complexity, and the reliability of sensors, can constitute a vehicle-related source of perceptual load (Lavie, 2005). Therefore, ADAS is included here as a vehicle factor because its technical specifications define the objective amount of information that the driver's sensory system must process, regardless of the driver's prior experience or trust. Therefore, the way in which the vehicle presents information (visual and audible alarms, haptic feedback) is a structural feature of the vehicle.

Environmental factors

Only one study was identified that examined MW rates behind the wheel in different weather conditions (He et al., 2011). The results of this study suggest that drivers exposed to cross-wind conditions in simulated driving tasks self-reported low MW rates behind the wheel. He supports the notion that perceptual load plays a critical role in driving attention (Green & Murphy, 2017) and aligns with evidence indicating that increased road geometric variety can enhance driver alertness. In light of this, it can be inferred that heavy weather conditions increase driving difficulty and lead drivers to pay more attention to environmental driving. Unfortunately, to date, there are no sufficient studies that have investigated how environmental factors (weather conditions, road geometry) influence MW behind the wheel. Some evidence has shown how drivers respond to road geometry. Indeed, increased road geometric variety reduces vigilance impairment compared to monotonous scenarios (Farahmand & Boroujerdian, 2018). Consequently, the introduction of horizontal curves in road design can increase the driver's perceptual load under low-stimulus conditions (Thiffault & Bergeron, 2003). Further work should improve and increase the research on environmental factors and their impact on MW behind the wheel, understanding the role of road geometry and weather conditions.

Human Factors

Twenty-four studies examined the impact of human factors on MW. Fifteen studies investigated the effect of perceptual load on MW rates behind the wheel. Nine studies explored the impact of socio-demographic factors and personality traits on MW rates behind the wheel.

Perceptual load imposed by the driving environment

Overall, the studies' findings suggest that MW increases in situations characterized by low attentional demand. For example, the studies have explored the perceptual load according to two perspectives: 1) familiarity with the road environment and 2) driving time.

Regarding familiarity with the road environment, previous research has shown an increased incidence of MW when a task becomes more automatic or when drivers become more familiar with a route (Mason et al., 2006; Martens & Fox, 2007). Indeed, a consistent part of the literature suggests that drivers on familiar roads may exhibit dangerous driving behaviors, increasing the risk of MVCs (Gil-Jardiné et al., 2017). Additionally, driving time can increase the MW rates behind the wheel, presumably because perceptual load increases with driving time (Zhang et al., 2017). This finding is consistent with Smallwood and Schooler's (2015) study, which confirmed that as perceptual load increases over time, our brains self-regulate to increase spontaneous MW to relieve the brain's perceptual load.

In line with this, our results support the existing literature showing that drivers can be more prone to MW when fatigue and perceptual load increase during the task (Trutschel et al., 2012). This result could provide a theoretical foundation for the phenomenon of MW during protracted driving tasks and its subsequent impact on driver performance, attentiveness, and the response to critical events (Trick et al., 2004). Indeed, especially under fatigue, the executive-control is compromised, and this causes an inability to perform (McVay & Kane, 2010). Given these findings it is important to develop several road-level solutions to reduce the impact of familiarity road and driving time on MW susceptibility. These solutions could include awareness campaigns as well as driver education.

While educational interventions alone are not sufficient, they are especially relevant in this context, as MW is difficult to detect in real-time and no agile, in-vehicle monitoring technologies are currently available (Zhang & Kumada, 2018). Therefore, making drivers aware of this phenomenon is a better modality to mitigate their risky behavior in MW situations (Koppel et al., 2018).

Personality traits and socio-demographic factors

The results suggest that inclination to MW behind the wheel can be influenced by personality traits and sociodemographic factors. These findings align with the literature that suggests neuroticism and extraversion appear to increase the propensity to MW (Robinson et al., 2017). Specifically, neuroticism, characterized by emotional instability and ruminative thinking (Costa & McCrae, 1985), has been associated with reduced executive functioning and increased self-focused cognition, both of which can facilitate MW (Williams et al., 2009). Considering extraversion, the findings of previous studies are in line with our results. Indeed, Pereira et al. (2020) demonstrated that low levels of extraversion are linked to high MW levels. Extraversion has been shown previously to be positively associated with risky behavior tendency, such as aggressive driving and alcohol use (Dahlen et al., 2012; Cooper et al., 2000). Moreover, extraverted individuals tend to engage in positive, affective, and emotional experiences (Dauvier et al., 2019).

About socio-demographic factors, age has been demonstrated to influence the propensity for MW while driving. Specifically, young male drivers are more susceptible to MW compared to older drivers (Albert et al., 2022). Following the literature, MW could be attributed to age-related changes in environmental dependency (Maillet & Schacter, 2016; Carciofo et al., 2016). It has been suggested that older individuals may allocate a greater proportion of their cognitive resources to driving tasks or external stimuli, resulting in a reduced capacity for task-unrelated thoughts (Maillet & Rajah, 2013). Concerning the differences in MW rates between male and female drivers, current research has not found significant differences. However, earlier studies have indicated gender disparities in aberrant driving behaviors, with male drivers demonstrating a propensity to assume greater risk and

exhibit elevated rates of motor vehicle crash (MVC) involvement (Butters et al., 2012; Ventsislavova et al., 2021). Further research should examine gender differences in MW, considering current inconsistencies.

Overall, the results suggest that different personality traits and socio-demographic factors can influence aberrant driving behaviors. It may be useful to develop and evaluate programs for driver personality assessment and targeted interventions (such as mindfulness) to reduce MW and improve road safety (Koppel et al., 2019). The authors suggest that the practice of mindfulness, defined as the act of paying attention to the present moment (Kabat-Zinn 2003), may be particularly useful to mitigate DD (Kass et al., 2011) and, consequently, MW behind the wheel (Koppel et al., 2018). Indeed, a body of research has demonstrated that lack of mindful attention and awareness can also predict engagement in tasks that involve a conscious decision to engage, divided attention, and lower levels of risk perception (Koppel et al., 2019). Anyway, with limited and low-quality evidence regarding mindfulness-based interventions, few conclusions can be drawn regarding applicability (Koppel, 2018). Therefore, it seems that further research is needed to understand the relationship between mindfulness and safer driving practices.

Behavioral changes and increased MVCs risk

Several studies have highlighted the behavioral changes related to MW behind the wheel and their impact on MVCs (Galéra et al., 2012; Gil Jeardiné et al., 2017). Indeed, MW propensity is associated with MVC risk. As demonstrated in the studies conducted by Galéra et al. (2014), this phenomenon can be attributed to the presence of a risky decoupling of attention from online perception. This dynamic has been shown to have a significant impact on drivers' behavior, decreasing reaction time, increasing eye blink rate, and horizontal narrowing of visual scanning (Marquart et al., 2015; Jeong & Liu, 2019).

In addition, MW is associated with shifts in lane position, decreased distance from the head vehicle, decreased variability of vehicle speed, and increased steering variability (He et al., 2011;

Pepin et al., 2020). Recent studies have demonstrated how MW disrupts processing in the left visual field (Kam et al., 2014). This finding has shown that MW can lead drivers to respond in a dysfunctional way to risk-driving situations, increasing MVC's susceptibility. However, it is important to acknowledge that drivers frequently compensate for errors or lapses in attention. Despite this, research has demonstrated that MW could reduce the safety margin and the capacity to rectify errors on time, particularly in critical scenarios (Yanko & Spalek, 2014; Yoshida et al., 2023). Reduced attention and diminished reaction times have been shown to decrease the probability of effective correction, thus increasing the probability of incurring an MVC.

Limitations

There are some limitations to note. In particular, the inclusion of predominantly cross-sectional studies restricts the ability to make inferences about temporal relationships between variables. It may be difficult to fully identify or understand fluctuations or changes over time. Therefore, future studies should concentrate on longitudinal measurements to identify possible temporal associations between MW and other intervening variables. Another important consideration is that several studies assessed driving behavior in simulated environments, which may not accurately reflect real-world driving situations. Future studies should use objective measures to identify MW behind the wheel, such as new devices that can identify whether a driver is in a MW state or not by tracking their eye movements (Lee et al., 2021). Finally, another limitation is associated with the in-vehicle system to detect MW behind the wheel. Indeed, there is an absence of road-level strategies or in-vehicle systems capable of reliably detecting MW in real time (Baldwin et al., 2017). This technological and operational discrepancy limits the feasibility of implementing direct interventions targeting MW during driving. In light of this, the implementation of awareness campaigns could be a provisional approach, aimed at increasing drivers' understanding of MW and its potential impact on road safety (Koppel et al., 2018). While acknowledging the limitations of educational strategies in altering behaviors, we

recognize their potential as a viable means to influence driver attitudes and risk perception, particularly in contexts where detection and mitigation solutions are not yet available.

Conclusion

In conclusion, this study indicates that MW behind the wheel can be a determining factor in road safety due to its association with human, vehicle-related, and environmental elements. The review determined that human factors, particularly low perceptual load from route familiarity and prolonged driving (Burdett et al., 2019), along with certain personality traits (e.g., neuroticism, extraversion) (e.g. Tinella et al., 2022) and socio-demographics (younger male drivers) (e.g. Albert et al., 2018), could increase MW propensity. In addition, higher levels of vehicle automation (ADAS Level 2+) are linked to increased MW, whereas lower levels (ADAS Level 1) show less impact (Korber et al., 2015; Weaver et al., 2022). While less studied, environmental factors suggest that increased perceptual load (e.g., strong crosswinds) can reduce MW (He et al., 2011). Finally, MW has behavioral consequences, including lane deviations, reduced visual scanning, and slower reaction times, thus elevating the risk of MVCs (Yanko & Spalek, 2014).

Future research directions

Future research should continue to explore the interactions among these factors and work toward developing comprehensive interventions to address them. This effort could also contribute to building a taxonomy that explains the mechanisms underlying MW behind the wheel. Moreover, while current studies predominantly rely on self-report methods such as experience sampling and questionnaires, these approaches, despite their usefulness, present certain limitations when applied to naturalistic driving contexts. Therefore, there is a need to develop and integrate more objective and scalable methodologies to improve the detection of MW in real-world conditions. A promising direction for future research involves the combination of self-report with complementary techniques, such as eye-tracking and probe-caught methods, which could allow real-time assessment of MW and enhance the robustness of findings through methodological triangulation. According to the literature,

MW is associated with changes in gaze patterns (Albert et al., 2018). The advent of L2 automation vehicles could lead to the potential implementation of technology designed to detect and alert drivers to the presence of MW.

Chapter II

THE QUESTIONNAIRE ON DISTRACTION IN DRIVING ACTIVITIES (QUADRIVIA): MEASURING TASK-RELATEDNESS AND STIMULUS DEPENDENCY IN THE CONTEXT OF DRIVING

This chapter is based on: Traficante, S. Tinella, S., Lopez, A., Useche, S.A, ... R., Bosco, A., Caffò. A.O. The QUestionnAire on distraction in DRIVIng Activities (QUADRIVIA): Measuring Task-Relatedness and Stimulus Dependency in the context of Driving [in preparation].

Introduction

Theoretical definitions of driving distraction

Road safety is a matter of global importance, with a high number of crashes resulting in significant death and injury every year. According to World Health Organization (WHO) estimates, motor vehicle crashes (MVCs) are among the leading causes of death and disability worldwide and are expected to become the fifth leading cause of death worldwide by 2030 (WHO, 2011). Among the contributing factors, Distracted Driving (DD) emerges as one of the most significant and dangerous causes of road crashes (Regan et al. 2022) by representing a growing risk to the driver's health and safety. Indeed, according to Naumann and Dellinger (2013), collisions caused by DD are more likely to result in fatalities or serious injuries, an assertion supported by empirical data. According to a report by the National Highway Traffic Safety Administration (NHTSA, 2022), in the USA, approximately 3,308 people were killed by DD every year.

DD can be defined as the diversion of attention from critical activities to safe driving to a competing activity (Lee, 2014). Driving distractions can be categorized into four primary categories: manual distractions, auditory distractions, visual distractions, and cognitive distractions (Liang & Lee, 2010; Strayer et al., 2015). Manual distractions occur when a driver takes their hands off the steering wheel to interact with another object or perform a secondary activity (Fernández et al., 2016). A prime example of this is the act of composing or sending text messages (e.g., SMS, WhatsApp) or interacting with in-vehicle devices (such as the radio or the navigation system). Auditory distraction arises from concurrent sound sources, such as loud music, warning signals, or speech, that demand cognitive effort for processing and monitoring (Karthaus et al., 2020). Visual distractions occur when the driver takes their eyes off the road and surroundings to focus on another activity or stimulus (Crundall & Underwood, 2011). This can include looking at a smartphone device, a satellite navigation system, or a particularly visually

striking billboard. Cognitive distractions, on the other hand, can manifest in various forms, originating from sources within the driver (internal) as well as from task-unrelated stimuli (external) (Lavie, 2010; Yanko & Spalek, 2014). Examples of external distractions include talking with passengers in the car, while examples of internal distractions include Mind Wandering (MW), which can be characterized as a self-generated or spontaneous stream of thoughts that is unrelated to the current task (Smallwood & Scholer, 2015).

The consequences of DD can be severe, impairing the driver's ability to perceive traffic signals, maintain vehicle trajectory, and react promptly to unexpected situations, increasing the risk of crashes (Stavrinos et al., 2013). Indeed, the background literature shows increased driving errors, including lane deviations, failure to maintain a safe distance, and misjudging distances and speeds of other vehicles (Tinella et al., 2021). Reaction times are also delayed due to distraction, increasing the risk of failing to promptly respond to unexpected events while driving. DD can compromise a driver's control over the vehicle, as it affects the ability to maintain a stable trajectory and control speed (Dingus et al., 2016). It also reduces situational awareness, making it harder to anticipate hazards and react properly (Ma & Kaber, 2005). Additionally, the existing literature suggests that these effects can be modulated by socio-demographic factors (Stavrinos et al., 2020). For instance, a higher level of education has been shown to reduce the likelihood of aggressive driving and risky behavior among both male and female drivers (Turner & McClure, 2003). Additionally, male drivers with extensive driving experience often overestimate their driving performance. Moreover, the interplay between gender and the impact of distraction while driving is discernible in the driving behaviors exhibited by male drivers (Fountas et al., 2019; Öztürk et al., 2023).

The TR/SD framework and conscious experiences

To better understand the varied nature of mental states that can influence driving, including distraction, it is useful to refer to theoretical models that attempt to categorize and explain different types of conscious experiences. In this context, the Stawarczyk and colleagues' model (2011) is

based on two dimensions characterizing the conscious experiences during the execution of complex tasks: the “task-relatedness” (TR) (e.g., involvement with the task) and the “stimulus-dependency” (SD) (e.g., dependence on external stimuli). According to this model, conscious experiences can be conceptualized as occurring in a two-dimensional space defined by how focused thoughts are on the task at hand (task-related vs. task-unrelated) and how anchored they are to perceptual stimulus (stimulus-dependent vs. stimulus-independent). Applying this model to the driving context, a state of full attention to the ongoing task would be classified as TR and SD. In this case, the driver is focused on the task, and their attention is primarily directed toward information from the road environment (i.e., signs, other vehicles, pedestrians, etc.). The second type of conscious experiences reflects thoughts that can interfere with the current task, TR and SI. They represent an individual's evaluation of the task and are usually triggered by aspects of the ongoing activity or its context (Walker & Trick, 2018). A driver stopped at a light, for instance, may notice that the brakes have started to squeal and briefly consider what that means. However, these reflections do not directly improve performance because they are not focused on the driving task execution. External distractions, such as being interrupted by a phone notification or a sudden event on the road, would be classified as TU but SD, in that attention is captured by an external stimulus that is not directly relevant to the primary driving task. Finally, the mind's wandering to thoughts unrelated to the current task and stimulus independent would be classified as TU and SI (Kucyi et al., 2021). The validity of this model is supported by neuroscientific studies that have shown how different regions of the Default Mode Network (DMN) appear to show increased activity when thoughts are both task-unrelated and independent of external stimuli. These findings suggest a role in these areas in the cognitive processes underlying MW (Poerio et al., 2017; Taruffi et al., 2017).

		Stimulus-dependency	
		Stimulus-dependent	Stimulus-independent
Task-relatedness	Task-related	<i>Being totally focused on the task currently being performed</i>	<i>Thoughts related to the appraisal of the current task</i> <i>(Task-related interferences)</i>
	Task-unrelated	<i>Sensory perceptions/sensations irrelevant to the current task</i> <i>(External distractions)</i>	<i>Mind-wandering</i>

Figure 1.: Conceptual division of ongoing conscious experiences (Figure 1, Adapted from Stawarczyk et al. 2011)

DD has been mainly investigated using general measures of driving behavior (errors, deviations, reaction times) or self-report questionnaires that assess the frequency of distracting behaviors or general cognitive characteristics (e.g., 4-FMW or CFQ for cognitive errors) (Lopez et al., 2023). While these measures are important for quantifying driving performance and identifying common distraction patterns, they often do not provide an accurate understanding of the specific mental state that the driver is experiencing behind the wheel. Indeed, many questionnaires assess general cognitive tendencies (e.g., susceptibility to distraction) rather than focusing on the specific mental states experienced while driving. This can limit their ability to capture the dynamic interplay between driving demands and different types of distractions.

The present study

To overcome this limitation, the present study aims to validate a new instrument for measuring driver conscious experience, the Questionnaire on Distraction in Driving Activities (QUADRIVIA), following TR and SD dimensions of Stawarczyk's model (2011). It is suggested that this instrument can facilitate a more profound understanding of the cognitive factors that influence road safety. The aim is to develop a reliable and valid self-reported instrument with good psychometric properties that can discriminate between different driving distraction profiles, including distractions driven by external stimuli and distractions driven by self-generated thoughts.

Therefore, for theoretical reasons, the focus was directed towards the three quadrants of the model that define distractions from the primary task, with the exclusion of the TRSD conscious experience (task-related/stimulus-dependent; "fully focused"). This is because we aimed to assess driver-distraction profiles, and TRSD can be defined as the theoretical antithesis of distraction. The inclusion of TRSD dimension would introduce construct-irrelevant variance and inflate inter-factor correlations. Therefore, TRSD was chosen as the reference state of possible conscious experiences, and models were developed for states in which attention deviates from this ideal dimension. These models include the decoupling of stimuli or the driving task (TRSI; TUSD; TUSI), aligning with commonly accepted definitions of distraction as attention diverted from the driving task (Lee, Young & Regan, 2008; Regan et al., 2011).

Materials and Methods

Descriptive Data

A power analysis was conducted to estimate the adequate sample size, employing G*Power 3.1 (Faul et al., 2009) using the following parameters: a p -level of 0.05, a conservative low effect size (0.12), and a power of 0.80. Results indicated that a sample size of 240 participants would provide an 80% chance of correctly rejecting the null hypothesis. The study involved a total of

1147 Italian drivers, including 657 females ($M \pm SD: 40.41 \pm 19.25$) and 490 males ($M \pm SD: 46.90 \pm 19.03$), with an age range from 18 to 85 years. The sample was divided into three age categories: emerging adults (18-29 years), adults (30-59 years), and older adults (60-85 years).

This division in age categories is in accordance with established developmental and international standards. According to Arnett's (2000) framework of extended identity exploration and cognitive maturation, the 18-29 age group is considered emerging adulthood. Adults aged 30-59 represent the peak of driving experience and stable cognitive performance (WHO, 2021). Older adults aged 60-85 meet the criteria for monitoring age-related shifts in health and cognitive functions as defined by the UN (2019). Moreover, this categorization allows for the analysis of the invariance of the measure. It is needed to investigate whether QUADRIVIA measures the same construct in an identical way between gender and age categories.

All participants were required to: (a) Hold a valid, current driver's license, provisional or above; (b) Have normal or corrected to normal vision; (c) Being in a good psychological health (Beck Depression Inventory II < 17); (d) Have driven more than one time within the last month; (e) Not be or have been a professional driver (e.g., taxi driver, truck driver, transporter on delivery, etc.); and (f) Have Italian as their mother tongue. Descriptive statistics are reported in Table 1. Participants were recruited through the help of proxy informants, typically undergraduate students and trainees, and were unaware of the study hypothesis. All participants provided written informed consent before enrolment in the study, which was approved by the Ethical Committee of the host institution (ET-23-23). The study was conducted following the Helsinki Declaration and its subsequent amendments.

Table 1. Descriptives information

	GEN	N	<i>M</i>	SE	SD	Skewness	SE	Kurtosis	SE
AGE	F	657	40.41	0.751	19.25	0.364	0.094	-1.207	0.190
	M	490	46.90	0.860	19.03	0.006	0.110	-1.260	0.220
EDU	F	657	13.60	0.154	3.96	-0.375	0.095	0.316	0.190
	M	490	12.57	0.182	4.00	0.099	0.110	0.567	0.220
DR_F	F	657	2.46	0.059	1.50	0.547	0.095	-1.156	0.190
	M	490	1.59	0.048	1.07	1.890	0.110	2.753	0.220

Note: *M*= mean; *SD*= standard deviation; *S.E.*= standard error; **GEN**: gender; **F**= female; **M**= male; **DR_F**= driving frequency (each week); **EDU**= years of schooling

Material and Procedure

Participants had to be in a good general state of physical and psychological health. All participants were enrolled between October and December 2023. A brief interview was administered by supervised trainees in neuropsychological assessment to collect demographic information, to exclude neurodegenerative and vision/hearing disorders, and to gather information about participants' driving habits and years of license. After the interview, all participants completed a survey with the following self-report questionnaire.

Questionnaire on Distraction in Driving Activities (QUADRIVIA)

The QUADRIVIA was developed to assess the different types of conscious experiences associated with driving contexts, following the Stawarczyk et al. (2011) model. The questionnaire evaluates conscious experiences following two specific domains: Task Relatedness (TR) and Stimulus Dependency (SD). According to Stawarczyk's model (2011), these domains can categorize four different conscious experiences: Task-Related Stimulus Dependent (TRSD) (e.g. While driving, I keep the vehicle steadily within the lane), Task-Related Stimulus Independent (TRSI)(e.g. While driving, I consider the potential risks involved in driving), Task-Unrelated Stimulus Dependent (TUSD)(e.g. While driving, I sometimes pay attention to the billboards along

the road), and Task-Unrelated Stimulus Independent (TUSI) (e.g. While driving, I start to daydream). As mentioned before, we have excluded the TRSD conscious experience for theoretical reasons. Figure 1 offers a visual representation of the model.

The scale included 21 items. These items are rated on a 5-point Likert scale, with 1 “Never” and 5 “Almost always”. The score for each subscale is calculated by summing the responses to each subscale item (TRSI 6-30, TUSD 8-40, TUSI 7-35), resulting in total scores ranging from 21-105, with higher scores corresponding to greater susceptibility to distracted driving. The English and Italian translations (forward and backward) of the items are shown in Table 2, in the appendix I.

Driving Behavior Questionnaire (DBQ)

The Italian 28-item version of the Driver Behavior Questionnaire (DBQ), developed by Reason et al. (1990) and adapted to the Italian context by Lucidi et al. (2010), was utilized to measure self-reported aberrant driving behaviors. The instrument has three subscales: (a) errors, misjudgments, or failures of observation that could be hazardous to others (e.g., failure to check mirrors, not seeing a pedestrian crossing); (b) lapses, absent-minded behaviors which may be frustrating or have negative consequences for the driver responsible; (c) violations, deliberate contraventions of legally regulated or socially accepted behaviors associated with safe vehicle operation (e.g., speeding, poor lane discipline, close following of another vehicle). The questionnaire is rated on a six-point scale, from 0 (Never) to 5 (Almost always). Scores of this scale indicate the frequency of aberrant behaviors during driving activities, with higher scores showing a higher frequency of such behaviors. The questionnaire shows good psychometric properties (DBQ Violation, $\alpha=.80$; DBQ Errors, $\alpha=.77$; DBQ Lapses, $\alpha=.76$).

Beck Depression Inventory II

The 21-item Italian version of the Beck Depression Inventory-II (BDI) (Maggi et al., 2023) is a psychometric tool designed to assess the severity of depressive symptoms. The scale includes somatic, cognitive, and affective symptoms. The scale covers somatic and cognitive-affective symptoms, and each item is scaled from 0 to 3, reflecting the patient's feelings over the past two weeks. The total score derived from all 21 items assesses depressive symptoms. A score of 14 or above is indicative of depressive symptoms. The symptoms were categorized as follows: minimal to moderate depressive symptoms (14-19), moderate to severe depressive symptoms (20-29), and severe depressive symptoms (30-63). The instrument presents good psychometric properties (BDI total scale, $\alpha=.88$).

QUADRIVIA Development and Content Validity

The development of QUADRIVIA was conducted using a rigorous two-phase methodology, aligning with established practices in scale construction. Phase one entails item generation, informed by a comprehensive review of pertinent literature, identifying key factors associated with DD. The item formulation employed both situational and behavioral approaches, incorporating specific driving scenarios. The item pool underwent rigorous review and refinement by the research team, with linguistic validation provided by experts in transportation research.

The study's authors, all holding doctoral degrees and specializing in fields such as traffic psychology, cognitive psychology, and psychometrics, established content validity through expert evaluation. A preliminary set of 40 items underwent a rigorous evaluation process, in which each item was assessed individually by ten experts based on its dimensional significance (i.e., TRSI, TUSD, TUSI). Items that attained an average rating of 70% or higher were retained, resulting in a final questionnaire comprising a total of 21 items. These items were distributed across three distinct conscious experience domains (6 items for TRSI; 8 for TUSD, and 7 for TUSI), reflecting

the multidimensional nature of the construct under investigation. This process yielded a comprehensive questionnaire encompassing diverse thematic areas pertinent to conscious experience while driving. Phase two comprised pilot testing with a volunteer sample, utilizing paper-based questionnaire administration. This approach facilitated monitoring of the completion process and identification of potential ambiguities in instructions, item content, or response scales. Participants were encouraged to provide feedback, leading to minor revisions based on their suggestions. Subsequently, the refined questionnaire was administered to a larger sample, enabling comprehensive psychometric analysis and validation.

Statistical Analysis

Exploratory Factor Analysis

An Exploratory factor analysis (EFA) was conducted to investigate the factorial configuration of QUADRIVIA, using Jamovi (2.6.44). To determine the suitability of the data for factor analysis, both Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were examined. The EFA was performed with Maximum Likelihood (ML) estimation to Oblimin rotations, identifying the latent factors and interrelationships among the items. This analytical approach was adopted to determine the dimensional composition of the scale and to provide insights into the relationships between the measured variables (Marsh et al. 2009).

Confirmatory Factor Analysis

In light of the aforementioned considerations, the factorial configuration of the model was investigated using Confirmatory Factor Analysis (CFA). This analysis involved the investigation of a range of goodness-of-fit indices, including the chi-square statistic (χ^2), the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Standardized Root Mean Square Residual (SRMR), the Root Mean Square Error of Approximation (RMSEA), the Akaike Information

Criterion (AIC), and Bayesian Information Criterion (BIC). The model was deemed to have an adequate fit when CFI and TLI values exceeded .90, RMSEA and SRMR values were below .08, and AIC and BIC values were comparatively lower, indicating a parsimonious model with optimal fit (e.g. Marsh et al., 2004; Vrieze, 2012). The model's appropriateness was assessed through the magnitude and consistency of parameter estimates, as well as the absence of substantial or unwarranted modification indices. To mitigate potential bias, a Monte Carlo parametric bootstrapping procedure was implemented using SPSS software (version 26.0), a resampling technique that iteratively tests and re-estimates the model using numerous randomly generated subsamples of equivalent size. This allowed to correct standardized coefficients under optimal reliability assumptions and to obtain 95% confidence intervals for them, this minimizing the risk for Type I or Type II statistical errors (Fornell & Larcker, 1981; Gilleland, 2020).

Reliability and Internal Consistency

To examine potential demographic differences in QUADRIVIA scores, independent sample T-tests were employed for gender comparisons, while analyses of variance (ANOVA) were conducted for age groups. The reliability and internal consistency of the scale were evaluated using Cronbach's alpha (α), McDonald's omega (ω), and the Composite Reliability Index (CRI). Cronbach's alpha and McDonald's omega provide estimates of internal consistency, with higher values indicating greater reliability. CRI, based on lambda coefficients, residuals, and critical ratios of subscales, offers a robust assessment of reliability (Jenkins & Taber, 1977). The use of these three coefficients, all measured on a 0-1 range, facilitates direct comparison and straightforward interpretation. High McDonald's omega and Cronbach's alpha values ($>.70$) signify strong reliability and internal consistency (Hayes & Coutts, 2020). Finally, an assessment of the invariances of the measure by gender and age categories was conducted (R Studio, 4.4.1).

Validity Analysis

The construct validity of the QUADRIVIA was evaluated through a series of psychometric analyses, the aim of which was to ensure the scale accurately captured the intended constructs and demonstrated theoretical relevance in measuring conscious experiences during driving. Convergent validity, divergent validity, and inter-factor correlations were assessed. The assessment of convergent validity was conducted using the Driving Behavior Questionnaire (DBQ), while the assessment of divergent validity was conducted through the administration of the Beck Depression Inventory II (BDI). Pearson's correlation coefficient was employed to examine inter-factor correlations and convergent validity. This analysis investigated the relationships between the three QUADRIVIA dimensions, confirming their distinctiveness while maintaining theoretical interconnectedness. Correlation coefficients were interpreted by established psychometric guidelines, ensuring that factors retain conceptual independence while contributing to the overarching Stawarczyk's construct (2011).

Results

Explorative Factor Analysis

An Exploratory Factor Analysis (EFA) revealed a three-factor structure, as detailed in Table 3. The identified factors were: (1) Task-Related Stimulus Independent (TRSI), demonstrating that experiences of task-related cognitions, which are decoupled from immediate sensory input, have the potential to interfere with driving performance. Examples of such CE include ruminations about route planning, traffic-related obligations, the state of the vehicle, or anticipated traffic conditions. While these cognitions are task-related, they do not directly pertain to the ongoing driving scenario. (2) Task-Unrelated Stimulus Dependent (TUSD): the driver's attention is diverted by environmental stimuli unrelated to the driving task. This includes exteroceptive distractions, such as advertising signs, external noises, distractions related to smartphone use (texting, answering the phone), and interoceptive distractions, such as physical

discomfort or fatigue. Finally, (3) Task-Unrelated Stimulus Independent (TUSI), where the driver's attention is disengaged from immediate driving stimuli and environmental distractions, resulting in internally generated thoughts unrelated to the driving task. Examples of internally generated thoughts include recollections of past events, anticipations of future activities, or thoughts about personal relationships, leading to a state of MW.

The variance explained by each factor was as follows: Factor 1 (TRSI) accounted for 12.33% of the item variance (eigenvalue of 4.27), Factor 2 (TUSD) for 12.25% (eigenvalue of 3.81), and Factor 3 (TUSI) for 8.3% (eigenvalue of 2.73), cumulatively explaining 32% of the total variance. The findings indicate that the QUADRIVIA scale encompasses multiple dimensions. Even though the total cumulative variance explained by these factors was 32%, this level is considered acceptable in the exploratory stages of scale development within the social and behavioral sciences (30-50% of total variance). This is because complex latent constructs often involve a high degree of variability (Hair et al., 2019; Williams et al., 2010). Table 2 presents the cumulative variance explained, the variance explained by each factor, and the corresponding eigenvalues. To assess the factorability of the correlation matrix, Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were employed. Bartlett's test yielded a statistically significant result ($\chi^2 = 7770$, $df = 300$, $p < .001$), rejecting the null hypothesis of an identity matrix with zero correlations. The KMO index was .901, indicating excellent sampling adequacy. These findings confirmed the appropriateness of factor analysis for the data (Kaiser & Rice, 1974). Table 4 presents the factor loadings (λ) for each item on its respective factor, with a cut-off criterion of $\lambda = .400$.

Table 2. Factor statistics summary

Factor	Eigenvalues	% of Variance	Cumulative %
1	4.276	12.577	12.577
2	3.812	11.212	23.789
3	2.733	8.038	31.827

Table 4. Item and factor composition of the three-factor structural model of the QUADRIVIA: CFA.

			QUADRIVIA three-factor structure										
	M ^a	SD ^b	Reliability/ Consistency	λ^c	U.E. ^d	S.E. ^e	C.R	p^g	Bootstrap bias-corrected values ^h				
									S.E. ^d	Bias ⁱ	95% Ci ^j	p	
TRSI													
TRSI_1	2.29	1.37	CRI=.968 α^l =.701 ω^m =.704	.434	.596	.051	11.458	<.001	.070	.012	.781	1.12	.014
TRSI_2	2.87	1.26		.457	.578	.047	10.872	<.001	.095	.000	.796	1.09	.014
TRSI_3	3.28	.99		.471	.470	.038	11.214	<.001	.070	.000	.864	1.11	.014
TRSI_4	3.06	1.07		.426	.437	.041	10.556	<.001	.090	.008	.787	1.09	.014
TRSI_5	2.80	1.26		.572	.720	.047	11.000	<.001	.090	.007	.592	.901	.019
TRSI_6	3.04	1.32		.541	.716	.049	10.214	<.001	.094	.009	.544	.916	.012
TUSD													
TUSD_1	2.15	1.02	CRI=.989 α^l =.806 ω^m =.810	.652	.653	.029	19.393	<.001	.074	.008	1.19	1.44	.006
TUSD_2	1.85	.99		.583	.580	.029	16.657	<.001	.073	.002	.968	1.20	.009
TUSD_3	2.60	1.09		.591	.648	.033	15.871	<.001	.057	.000	.955	1.14	.006
TUSD_4	2.51	1.01		.563	.569	.030	16.462	<.001	.068	.002	.968	1.19	.010
TUSD_5	1.86	.99		.565	.562	.030	15.592	<.001	.056	.001	.813	.998	.007
TUSD_6	2.03	.88		.557	.493	.026	13.393	<.001	.054	.007	.816	1.01	.019
TUSD_7	2.34	1.00		.492	.493	.030	18.541	<.001	.070	.000	.845	.995	.006
TUSD_8	1.41	.74		.664	.541	.023	18.239	<.001	.087	.003	1.20	1.50	.009
TUSI													
TUSI_1	1.43	.73	CRI=.992 α^l =.840 ω^m =.846	.717	.527	.020	18.505	<.001	.037	.000	.712	.833	.012
TUSI_2	1.70	.88		.755	.670	.024	17.113	<.001	.059	.002	.848	1.04	.008
TUSI_3	1.67	.91		.659	.600	.025	18.304	<.001	.052	.004	.807	.981	.014
TUSI_4	1.52	.85		.621	.533	.024	19.467	<.001	.035	.000	.776	.943	.008
TUSI_5	1.83	.99		.567	.564	.029	20.689	<.001	.043	.002	.800	.950	.009
TUSI_6	1.41	.74		.658	.489	.022	21.038	<.001	.059	.004	.981	1.17	.018
TUSI_7	1.84	.98		.700	.689	.027	20.447	<.001	.060	.000	1.04	1.25	.009

Notes: ^a Arithmetic Mean – scale [1-5]; ^b Standard Deviation; ^c Standardized factor loading; ^d Unstandardized estimates; ^e Standard Error; ^f All p -values were lower than .001 – all p -values in bootstrap were statistically significant / p -values lower than .050; ^g Bootstrapped (bias-corrected) model; ^h Bias identified (and corrected) in the item; ⁱ Confidence Interval at the level 95% (lower bound – left; upper bound – right); ^j Composite Reliability Index; ^k Cronbach's alpha; ^l McDonald's omega.

Confirmatory Factor Analysis

Different Confirmatory Factor Analyses (CFA) were conducted to competitively evaluate the factor structure of the QUADRIVIA, specifically examining alternative factorial configurations. This involved testing a one-factor model, a two-factor model, and a three-factor model. Different two-factor models were assessed. Firstly, comprising TRSI (Factor 1) and TUSD (Factor 2); secondly, comprising TRSI (Factor 1) and TUSI (Factor 3), and finally, comprising TUSD (Factor 2) and TUSI (Factor 3). Subsequently, a three-factor model, differentiating TRSI (Factor 1), TUSD (Factor 2), and TUSI (Factor 3), was evaluated. Comparative analysis revealed that the three-factor solution demonstrated superior model fit indices (CFI= .931; TLI= .921; RMSEA= .047; SRMR= .049) and alignment with the theoretical conceptualization of the scale, rendering other factorial configurations less adequate. Table 4 provides a comprehensive overview of the fit indices for each of the tested models. Figure 2 illustrates the three-factor model and presents standardized parameter estimates for each item. A detailed examination of the initial three-factor model identified significant modification indices, indicating potential relationships between specific items and their residuals. Following these adjustments, a refined three-factor constrained model demonstrated improved data fit, as evidenced by the key fit indices presented in Table 5.

Table 5. Goodness of fit indices for different structure models.

Model	χ^2	df ¹	p	RMSEA ²	90% CI ³		SRMR ⁴	AIC ⁵	BIC ⁶	TLI ⁷	CFI ⁸
					Lower	Upper					
<i>Baseline models</i>											
One-factor structure	1959.665	190	<.001	.090	.087	.094	.076	6330	6362	.707	.736
Two-factor structure (TRSI+TUSD vs. TUSI)	1484.001	189	<.001	.078	.074	.081	.068	6281	6315	.784	.807
Two-factor structure (TRSI+TUSI vs. TUSD)	1548.794	188	<.001	.076	.083	.091	.071	6284	6321	.773	.797
Two-factor Structure (TUSD+TUSI vs. TRSI)	1357.219	188	<.001	.074	.070	.077	.058	6270	6302	.805	.826
Three-factor structure	904.958	186	<.001	.058	.054	.062	.049	6225	6258	.879	.893
<i>Adjusted model</i>											
Three-factor adjusted structure	639.757	181	<.001	.047	.043	.051	.047	6199	6235	.921	.931

Notes: ¹df= Degrees of freedom; ²RMSEA= Root Mean Square Error of Approximation; ³Confidence Interval for RMSEA ($\alpha = .010$); ⁴SRMR= Standardized Root Mean Square Residual; ⁵AIC=Akaike Information Criterion; ⁶BIC= Bayesian Information Criterion; ⁷TLI= Tucker-Lewis Index; ⁸CFI= Confirmatory Fit Index.

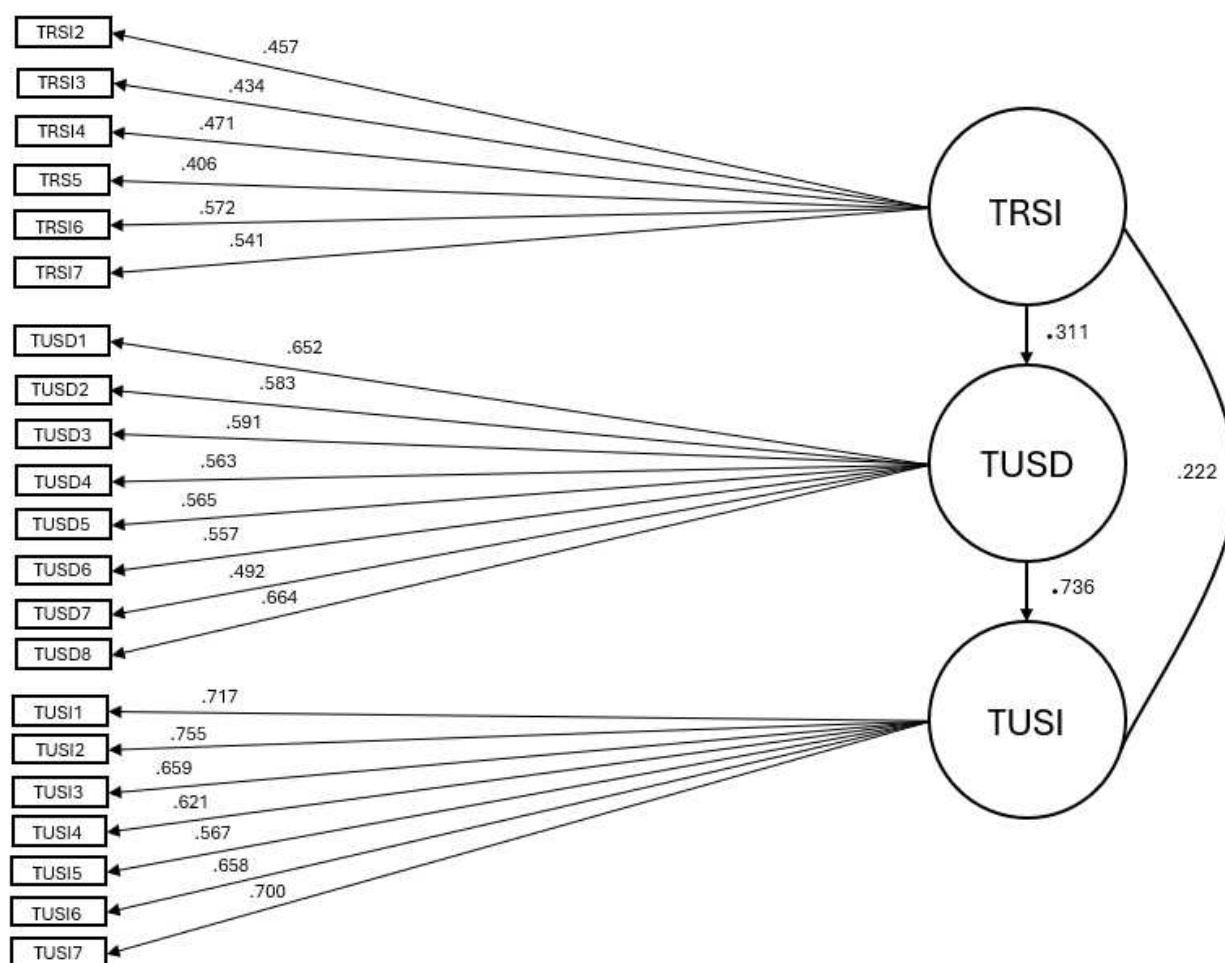


Figure 2. Three-factor model and standardized parameter estimates (λ) for each item

Reliability and Internal Consistency

The three-factor configuration of QUADRIVIA shows good reliability and internal consistency, with Cronbach's alpha coefficient exceeding .70 for each subscale and for the overall scale (α = .70; .80; .84; α total score = .83). Table 3 shows Cronbach's alpha, McDonald's omega, and CRI for each scale. Indeed, they served as a valuable complementary assessment tool, demonstrating optimal reliability levels for all latent constructs measured by QUADRIVIA. Specifically, the CRI for Factor 1 (TRSI) was .968, for Factor 3 (TUSD) it was .989, and for Factor 4 (TUSI) it was .992. These results indicate high internal consistency within each factor.

Construct Validity

To evaluate the construct validity of the QUADRIVIA, Pearson correlation coefficients (σ) were calculated to assess the associations between QUADRIVIA scores and the dimensions of the Driving Behavior Questionnaire (DBQ) for the convergent validity, and the Beck Depression Inventory II (Reason et al., 1990, Lucidi et al., 2010; Beck et al., 1988) for the divergent validity. The findings showed significant positive correlations between the DBQ subscales (violations, errors, and lapses) and the QUADRIVIA dimensions (TRSI, TUSD, and TUSI). However, no statistically significant correlation was found between the QUADRIVIA dimensions and the Beck Depression Inventory II scores. This outcome validates the distinct validity of the measure.

The statistically significant intercorrelations among the three factors of QUADRIVIA provide further evidence for the internal coherence of the scale, indicating that while these dimensions are conceptually distinct, they exhibit significant interrelationships. DBQ demonstrated a positive relationship between QUADRIVIA scores and self-reported driving lapses ($\sigma = .264$) and driving errors ($\sigma = .367$). Moreover, the Beck Depression Inventory II demonstrated a non-significant relationship with the QUADRIVIA dimensions. This result aligns with established psychometric criteria, demonstrating that each QUADRIVIA dimension maintains sufficient independence from the others while collectively contributing to a robust measurement model. A comprehensive overview of the inter-factor correlations is presented in Table 6.

Table 6. Parametric partial correlation matrix controlled for age and gender

		TRSI_TOT	TUSD_TOT	TUSI_TOT	DBQ_V	DBQ_L	DBQ_E	BDI_TOT
TRSI_TOT	Pearson's r	—						
	p-value	—						
TUSD_TOT	Pearson's r	0.240 ***	—					
	p-value	< .001	—					
TUSI_TOT	Pearson's r	0.187 ***	0.612 ***	—				
	p-value	< .001	< .001	—				
DBQ_V	Pearson's r	0.061 *	0.400 ***	0.330 ***	—			
	p-value	0.038	< .001	< .001	—			
DBQ_L	Pearson's r	0.105 ***	0.353 ***	0.264 ***	0.357 ***	—		
	p-value	< .001	< .001	< .001	< .001	—		
DBQ_E	Pearson's r	0.082 **	0.421 ***	0.367 ***	0.521 ***	0.569 ***	—	
	p-value	0.005	< .001	< .001	< .001	< .001	—	
BDI_TOT	Pearson's r	0.006	0.014	-0.019	-0.006	0.023	0.005	—
	p-value	0.835	0.644	0.519	0.828	0.437	0.876	—

Note: controlling for Age and Gender; **TRSI_TOT**= Task-related/Stimulus-independent; **TUSD_TOT**= Task-unrelated/Stimulus-dependent; **TUSI**= Task-unrelated/Stimulus-independent; **DBQ_V**= Driving violations; **DBQ_L**= Driving lapses; **DBQ_E**= Driving errors; **BDI**= Beck Depression Inventory

* $p < .05$, ** $p < .01$, *** $p < .001$

Multi-group gender and age invariances

Multigroup invariance analysis was conducted on separate sub-groups defined by gender and age categories. The baseline model, assessing configural invariance, demonstrated a good fit to the data ($S-B\chi^2 = 1034.2$, $RMSEA = .058$, $CFI = .902$). This indicates that the instrument's structure was similar across both gender groups. The next level of invariance, metric invariance, was assessed. The results showed that the metric invariance model fit the data adequately ($S-B\chi^2 = 1049.1$, $RMSEA = .058$, $CFI = .890$). The non-significant change in χ^2 ($\Delta\chi^2 = 12.85$) and negligible changes in CFI ($\Delta CFI = <.001$) suggest that the factor loadings were largely equivalent across gender. Finally, the most restrictive level of invariance, scalar invariance, which assesses the equivalence of intercepts, was also examined. The scalar invariance model also demonstrated a “borderline” fit ($S-B\chi^2 = 197.7$, $RMSEA = .062$, $CFI = .861$); moreover, the significant change in χ^2 ($\Delta\chi^2 = 137.466$, $p < .001$) suggests that full scalar invariance was not supported.

The investigation of measurement invariance across age categories followed a consistent procedure. To compare Emerging Adults versus Adults, the configural model, which tested for equivalence in the form of the factor structure, demonstrated acceptable fit: $S-B\chi^2 = 842.02$, $RMSEA = .063$, $CFI = .900$. This finding suggests that the latent factors underlying the observed variables are comparable across both age groups. The metric invariance model also demonstrated an acceptable fit: $S-B\chi^2 = 852.49$; $RMSEA = .062$, $CFI = .891$. However, the scalar invariance model revealed a statistically significant change in chi-square ($\Delta\chi^2 = 86.992$, $p < .001$), indicating a lack of full scalar invariance.

In the case of the comparison between Adults and Older Adults, the configural model demonstrated an acceptable fit: $S-B\chi^2 = 792.2$; $RMSEA = .061$, $CFI = .900$. The metric invariance model also exhibited an acceptable fit: $S-B\chi^2 = 809.64$, $p < .001$; $RMSEA = .059$, $CFI = .880$. The change in chi-square was not statistically significant, $\Delta\chi^2 = 13.2$, and the negligible changes

in CFI ($\Delta\text{CFI} = .001$) suggest that the factor loadings are largely equivalent across these age groups. However, the scalar invariance model indicated a statistically significant change in chi-square ($\Delta\chi^2 = 86.992$, $p = .005$), suggesting a lack of full scalar invariance.

Finally, we tested the invariance measure between Emerging Adults and Older Adults. The configural model demonstrated acceptable fit, as evidenced by the following indices: $\text{S-B}\chi^2 = 846.6$; $\text{RMSEA} = .066$, $\text{CFI} = .901$. Similarly, the metric invariance model exhibited adequate fit: $\text{S-B}\chi^2 = 878.2$; $\text{RMSEA} = .062$, $\text{CFI} = .895$. The change in chi-square ($\Delta\chi^2 = 23.81$, $p = .070$) was not statistically significant, and the negligible change in the Comparative Fit Index ($\Delta\text{CFI} = .004$) indicates that the factor loadings are largely equivalent across the compared age groups. However, the scalar invariance model revealed a statistically significant change in chi-square ($\Delta\chi^2 = 144.4$, $p = .005$), suggesting a deviation from full scalar invariance. Table 7 shows the invariance comparison for age and gender.

Therefore, despite the robust configural and metric invariance, the results indicated a lack of full scalar invariance across gender and age groups ($\Delta\chi^2$ significant at $p < .001$). This finding indicates that the item intercepts demonstrate considerable variation across groups. Consequently, when conducting group comparisons of latent means, a cautious interpretation is suggested.

Table 7. Invariances of the measures

Model	df	S-Bχ^2	RMSEA	CFI	Diff. χ^2	ΔCFI
<u>Gender</u>						
Configural Invariance	334	1034.206	.060	.902	-	-
Metric Invariance	351	1049.105	.058	.890	12.851	.001
Scalar Invariance	368	1241.095	.064	.861	197.785***	-.030
<u>Age</u>						
<u>Eme.Adults vs. Adults</u>						
Configural Invariance	298	842.015	.063	.900	-	-
Metric Invariance	314	852.490	.062	.891	8.866	.001
Scalar Invariance	330	938.602	.064	.861	86.992***	-.015
<u>Adults vs. Older Adults</u>						
Configural Invariance	334	792.240	.061	.900	-	-
Metric Invariance	351	809.640	.059	.880	13.124	.001
Scalar Invariance	368	842.470	.073	.875	33.014*	-.003
<u>Eme.Adults vs. Old.Adults</u>						
Configural Invariance	334	846.602	.067	.901	-	-
Metric Invariance	351	878.203	.066	.895	23.810	.004
Scalar Invariance	368	1018.665	.072	.874	144.454***	-.035

Note: **S-B χ^2** = Satorra-Bentler; **df** = Degrees of freedom; **RMSEA** =Root Mean Square Error of Approximation; **CFI**: Comparative Fit Index; **Diff. χ^2** = Chi-square difference; **Δ CFI**= Delta-Comparative Fit Index ***p<.001

General discussion

The present study aims to develop and validate a new instrument for measuring driver mental state, Questionnaire on Distraction in Driving Activities (QUADRIVIA), following Stawarczyk's model (2011) related to the TR and SD dimensions. The study aimed to provide evidence on a reliable and valid instrument with good psychometric properties that can discriminate between different conscious experiences behind the wheel, including moments of task-related interferences, external distractions, and MW. The results of EFA and CFA provided empirical support for a three-factor structure of the QUADRIVIA: Task-Related Stimulus-Independent (TRSI), which includes thoughts related to driving but generated internally; Task-Unrelated Stimulus-Dependent (TUSD), which refers to thoughts unrelated to driving but triggered by external stimuli; and Task-Unrelated Stimulus-Independent (TUSI), which captures the MW phenomenon, that is, thoughts unrelated to the driving task and not triggered by the environment. The reliability analysis indicated moderate to good internal consistency for each subscale.

The adoption of Stawarczyk's TR/SD model (2011) represents a potentially significant step in the assessment of driver distraction. As previously discussed, this theoretical approach aims to provide a more detailed and accurate understanding of the different types of distraction profiles, trying to overcome the limitations of more generic measures that often fail to distinguish between different forms of inattention that can affect driving performance and crash risk. For instance, the model allows for the distinction between task-unrelated thoughts triggered by external events (TUSD) (e.g., a billboard) and task-unrelated thoughts independent of stimuli (TUSI), a critical distinction for understanding the conscious experience that affects the driver's performance. Several self-reported measures of distraction and mental states utilize questionnaires, such as the Mindful Attention Awareness Scale (MAAS) and the Cognitive Failures Questionnaire (CFQ), in the driving context (Brown et al., 2003; Bridger et al., 2013). Burdett et al. (2016) utilized these

instruments, just as Welburn et al. (2010) developed the Questionnaire Assessing Distracted Driving (QUADD). The QUADRIVIA is potentially different in its specific focus on the TRSD framework applied to the driving context, allowing for a more detailed and theoretically robust measure than broader measures of general attention or cognitive failures. As a result, validation of the QUADRIVIA may provide a more focused tool for investigating various facets of distraction behind the wheel.

This is supported by the QUADRIVIA subscale's positive correlations with the DBQ errors and lapses dimensions, which point to a strong construct validity. Indeed, the literature showed that high MW levels are associated with a higher frequency of lapses and errors while driving (Burdett et al., 2019; Traficante et al., 2025). The TUSD dimension has demonstrated similar trends. According to the literature, external distractions are associated with an increased probability of engaging in risky driving behaviors, with an increase in errors and violations behind the wheel (Gershon et al., 2017; Jazayeri et al., 2021; Arevalo-Tamara et al., 2022). This finding further confirms the robustness of the measure, as it demonstrates that an elevated susceptibility to these distractions is associated with an increased tendency to engage in risky driving behaviors, as is supported by existing literature in this domain (Vassallo et al., 2007).

Despite the promising results, the present study has some limitations. For instance, while the study population was composed of Italian drivers, despite the acceptable invariances of the measure found in the sample, further research is needed to investigate the generalizability and cross-cultural invariance of the instrument across different populations and driving contexts. Second, the study did not directly explore the relationship between QUADRIVIA scores and objective measures of driving performance (e.g., driving simulator data or data from actual driving events), which would limit the understanding of its criterion validity, therefore, its predictive power on actual driving behavior and crash risk. Future studies that investigate the criterion validity of the instrument are necessary.

Conclusion

The present study aimed to validate a new instrument for measuring driver conscious experience, following the TR/SD model (Stawarczyk et al., 2011). The intent was to develop a reliable and valid instrument with good psychometric properties that can discriminate between different mental states behind the wheel, including moments of distraction driven by external and internal stimuli. This instrument could have important practical implications. Developing a reliable and valid instrument for assessing a driver's conscious experiences can facilitate a more detailed understanding of the cognitive factors that influence road safety. The QUADRIVIA tool has the potential to be utilized in research settings for the study of the prevalence and characteristics of MW and distractions in various driving conditions, demographics, and age groups. Furthermore, it could be utilized to assess the efficacy of interventions designed to mitigate distraction and increase driver awareness. Indeed, the distinction provided by QUADRIVIA between different types of conscious driving experiences could contribute to a more accurate definition of DD, overcoming more generic definitions and developing more targeted and effective prevention strategies. In summary, the capacity to differentiate between different conscious experiences, as outlined by Stawarczyk's (2011) model, is important in light of the potential cognitive and behavioral ramifications these phenomena may have on driving performance.

Chapter III

THE PHONE USE WHILE RIDING SCALE (PURS): A 44-COUNTRY CROSS-REGIONAL VALIDATION

This chapter is based on: Useche, S. Alonso, F. Tinella, L. Traficante, S.....Oviedo-Trespalacios. Phone Use while Riding Scale (PURS): A cross-regional validation in 44 countries and associations with crashes (under review on Accident Analyses and Prevention).

Introduction

The use of mobile phones while cycling has become increasingly common, raising concerns about road safety (Jiang et al., 2021; Terzano, 2013). Decades of accumulated research support that mobile phone distraction can reduce situational awareness, delay reaction times, and impair motor control (De Waard et al., 2010; Oviedo-Trespalacios et al., 2016), increasing the likelihood of crashes and near-misses (Talbot et al., 2013; Useche, Alonso, et al., 2018). While this issue remains largely underexplored in cycling research, safety concerns persist. For instance, although the European Union recorded a 23% decline in overall road fatalities and severe injuries between 2010 and 2019, cycling-related incidents still account for approximately 9% of these cases (European Commission, 2021, 2023).

In addition to the significant safety risks faced by cyclists, recent studies highlight the rise of the so-called ‘technology era’ in which communication and information systems increasingly shape daily life. However, while extensive research has documented the negative impact of mobile phone distraction among drivers and pedestrians (Arafat et al., 2023; Jiang et al., 2021; Rahmillah et al., 2023), fewer studies have examined its effects on cyclists, a particularly vulnerable group.

Overall, these studies on drivers have shown that mobile phone use leads to cognitive overload, slower reaction times, and an increased risk of MVCs (Strayer et al., 2015; Strayer & Drews, 2007). Similar effects have been observed in cycling, where mobile phone use (but especially texting) impairs steering control, lane maintenance, and a rider’s ability to maintain a stable trajectory, react to environmental stimuli, and respond to complex –and sometimes unpredictable– traffic demands (Caird et al., 2018; De Waard et al., 2014). Thus, investigating whether cyclists engage in ‘technological’ risky behaviors and risk-compensating patterns has been systematically claimed as a relevant step for designing more effective safety policies and interventions.

Mobile phones and riding safety in the digital era

The emergence of social networks, real-time communication platforms, and adaptive technologies designed to enhance the cycling experience has increased the likelihood of mobile phone use during cycling activities (Garber et al., 2019; Useche, Alonso, Oviedo-Trespalacios, et al., 2024; Yang et al., 2022). As a general consequence, smartphone use while cycling has been linked to cognitive (De Waard et al., 2010), visual (Ahlstrom et al., 2016), and auditory distractions (Møller, Berghoefer, et al., 2024; Møller, Useche, et al., 2024), reducing cyclists' ability to focus on the primary task and predicting subsequent errors and crashes (Terzano, 2013; Useche, Alonso, et al., 2018).

Importantly, research suggests that this issue is not merely a matter of unawareness. Cyclists who use mobile phones exhibit greater speed variability, delayed braking responses, and an increased likelihood of failing to perceive critical road hazards – despite being aware of the potential risks associated with technological misuse (De Waard et al., 2010, 2015; Stavrinou et al., 2018). Moreover, surveys conducted in urban settings indicate that many cyclists admit to using mobile phones or earphones while riding (De Waard et al., 2011; Stelling-Konczak et al., 2017).

In other words, existing research supports the idea that a considerable proportion of risky cycling behaviors is technology-induced. However, these trends may be highly dynamic. For example, a study by Santos-Reyes et al. (2022) found that 31.4% of participants engaged in risky behaviors while cycling, including mobile phone use. Similarly, De Waard et al. (2014, 2015) observed a decline in the proportion of cyclists making calls in 2013 compared to 2008, yet a simultaneous increase in texting and typing while riding. In this context, recent studies suggest that both regular steering and emergency maneuvers become increasingly difficult and pose greater safety risks in such situations (De Waard et al., 2010; Jiang et al., 2021).

Regarding auditory distraction, a study by De Waard et al. (2010) found that 8% of cyclists listened to music while riding, which can obstruct critical auditory cues such as car horns and emergency sirens, potentially impairing hazard perception and reaction times (Nygårdhs et al., 2018). In line with this, a substantial body of research indicates that visual-manual and auditory distractions from mobile phone use increase cognitive workload, delay responses to road stimuli, impair balance, reduce lateral control, and prolong reaction times to auditory cues (De Waard et al., 2010, 2011, 2014).

Risk compensation, technology, and cycling behavior

Beyond the direct risks associated with mobile phone use while cycling, it is also relevant to consider the behaviors that cyclists adopt to mitigate these risks (Huemer et al., 2022; Nygårdhs et al., 2018). Risk-compensating behaviors refer to adaptive strategies that individuals employ to offset perceived increases in risk when engaging in potentially hazardous maneuvers (Choudhary & Velaga, 2017), which also influence their subsequent valuation of the ‘compensated’ risk (Flügel et al., 2019; Messiah et al., 2012). In the case of cyclists, these behaviors may include adjustments in riding style, increased environmental scanning, or strategic decision-making aimed at minimizing the dangers linked to mobile phone use (Nygårdhs et al., 2018).

From an empirical standpoint, some studies suggest that cyclists, aware of the potential impairment caused by distraction, may consciously reduce their speed, increase their following distance from other road users, or limit their phone interactions to moments of lower traffic density (Ahlstrom et al., 2016; Kircher et al., 2015). These compensatory strategies align conceptually with risk homeostasis theory, which proposes that individuals maintain a personally acceptable level of risk by adjusting their behavior in response to external road hazards (Kita et al., 2022; Wilde, 1988).

However, the extent to which cyclists successfully compensate for distraction remains an open question. While some may effectively adapt their behavior to mitigate risk, others might overestimate

their ability to do so (Schleinitz et al., 2018; Lardelli-Claret et al., 2003; Wilde, 1988). For instance, a cyclist who slows down to text may still be too distracted to react appropriately to sudden changes in traffic or unexpected obstacles. How cyclists respond to perceived risks likely depends on several factors, including age, level of experience, confidence, risk perception, and perceived control over their environment (Chaurand & Delhomme, 2013; Useche et al., 2025).

Although risk compensation has been extensively studied in the context of driving (Chen, 2007; Choudhary & Velaga, 2017; Fitch et al., 2014), its role in cycling remains comparatively underexplored. Given the unique challenges cyclists face—such as balance requirements, exposure to environmental conditions, and heightened vulnerability in traffic—the authors of this study consider that further research is needed to determine whether these compensatory behaviors genuinely enhance safety or merely create a false sense of security.

Study aims and hypotheses

Aiming to bridge the aforementioned gaps, the core objective of this validation study was to develop and assess the Phone Use while Riding Scale (PURS) as a tool for measuring three key dimensions of mobile phone use among an extensive sample of cyclists across five continents.

Grounded in theoretical and empirical insights from previous research on mobile phone usage in urban cycling, four literature-based hypotheses were formulated:

Hypothesis 1: The PURS was expected to show a well-defined factorial structure, with medium-to-high factor loadings, as well as adequate reliability and internal consistency indices.

Hypothesis 2: The PURS was hypothesized to demonstrate good validity insights, showing significant and consistent associations between its scale scores and criterion variables identified in previous literature, along with a suitable percentage of average variance explained, supporting discriminant validity.

Hypothesis 3: This study aimed to provide evidence for the cross-regional validity of the scale, postulating that the PURS has a good psychometric fit across the five geographical regions where it was tested (Europe, the Americas, Oceania, Africa, and Asia).

Hypothesis 4: Regarding its relevance to crash prevention, we expected to find statistical insights endorsing the idea that the PURS has predictive value in explaining cyclists' crash figures.

Methods

Study Sample

This cross-sectional study was conducted using data from 15,532 bicycle riders, with 38.4% identifying as female, 61.8% as male, and .7% as non-binary. Participants ranged in age from 16 to 83 years ($M \pm SD = 37.24 \pm 16.83$). The research covered a total of 44 countries across five continents. Detailed age distributions and gender proportions for each country, as well as for the full sample, are presented in Table 1.

Procedure

The data collection of this macro-study was conducted through a multi-national electronic survey, as part of the Bike-Barometer II project, which explores emerging factors and phenomena that relate to the safety and well-being of urban cyclists. The study data were collected between the years 2023 and 2024. The survey methodology was based on an online questionnaire translated into the most widely spoken language(s) of each participating country. While the survey design remained uniform, the platforms used for data collection varied across certain countries. This variation was primarily due to institutional recommendations favoring specific pre-paid survey platforms in some collaborating universities/research centers, or platform restrictions in certain regions (e.g., Google Forms is banned in China).

Regarding recruitment strategies, a combination of approaches was used to ensure broad participation across all countries. These included social media advertising, collective questionnaire

distribution, mailing lists, and collaboration with national cycling federations. Finally, no economic incentives were offered to participants in this research.

Questionnaire Characteristics

After enrolling in the study and providing informed consent, participants completed a comprehensive electronic questionnaire on cycling-related matters. The survey covered self-reported behavioral issues, risk perception, cycling patterns, habits, and safety-related outcomes. The questionnaire followed a block-based structure, consisting of the following sections:

The first block included sociodemographic characteristics such as age, gender, and educational level, used for descriptive and statistical control purposes. However, the gender category “non-binary/other”, which accounted for approximately 1% of the sample, was used exclusively for descriptive purposes due to its low representation.

Phone Use while Riding Scale (PURS)

The PURS is a self-reported Likert-type scale designed to assess cyclists’ interactions with mobile phones, categorizing tasks into: Visual-Manual Interactions (VMI – F1); Risk-Compensating Behaviors (RCB – F2); and Hands-Free Auditory Interactions (HAI – F3).

The scale evaluates risks associated with prolonged engagement (*Example item: “You looked continually at the phone for more than two seconds”*), immediate responses to notifications (*Example item: “You reacted without delay to a ringing phone”*), and various content-related activities such as social media use and GPS navigation (*Example items: “You posted on social media apps”; “You used your phone as a GPS/Maps device”*).

Additionally, the questionnaire assesses risk-compensating behaviors cyclists may adopt to enhance their safety while using a phone (*Example item: “You reduced your speed while using your phone to prevent a crash”*). This allows for a better understanding of how cyclists balance connectivity and safety.

The initial version of the PURS included 11 items, rated on a five-point Likert scale, ranging from 0 (Never) to 4 (Very often). Total scores were calculated by averaging responses across items, resulting in dimensional scores ranging from 0 to 4, with higher scores indicating greater exposure to mobile phone-related tasks while cycling.

Cycling Behavior Questionnaire (CBQ)

The CBQ is a 29-item, cross-culturally validated scale that measures self-reported risky (violations and errors) and protective behaviors while cycling (Useche et al., 2018, 2022). Responses were recorded on a five-point Likert scale ranging [0–4], where 0 = Never; 4 = Almost always. The CBQ is one of the most widely used behavioral assessment tools for cyclists worldwide.

The CBQ is based on the Behavioral Questionnaire (BQ) paradigm, which follows Reason's framework on Errors (E) and Violations (V) (Reason et al., 1990). Specifically, the CBQ evaluates three factors: Deliberate risky behaviors (Traffic Violations – F1); Undeliberate risky behaviors (Riding Errors – F2); and Protective behaviors (F3) – a novel addition to cycling research based on the use of positive behavioral issues, pioneered by Özkan & Lajunen in driving populations (Özkan & Lajunen, 2005), and by Useche et al. among cyclists and pedestrians (Useche et al., 2020; Useche, Montoro, et al., 2018).

To date, the Cycling Behavior Questionnaire has been cross-culturally validated in 13 languages, showing adequate internal consistency (Cronbach's α ranging [.603–.920]; McDonald's ω ranging [.770–.932] and reliability (Composite Reliability Index [CRI] ranging [.980–.995] (Li et al., 2022; Useche et al., 2021, 2022).

Cyclists' Risk Perception and Regulation Scale (RPRS)

The RPRS is a 12-item Likert-type scale that measures cyclists' risk perception and understanding of traffic regulations (Useche et al., 2019). It includes seven items assessing risk perception and five items evaluating knowledge of cycling-related traffic rules.

Responses were recorded on a five-point Likert scale, ranging [0–4], where 0 = Total disagreement; 4 = Total agreement. Overall, the RPRS has shown adequate-to-satisfactory internal consistency indexes, with Cronbach’s alpha coefficients ranging from [.66 – .72], and a systematically worthy performance as a criterion validity measure in previous studies addressing cycling populations (Useche, 2025; Useche et al., 2022).

Self-Reported Crash Data

To assess cycling crash involvement, participants were asked whether they had experienced any non-fatal cycling crashes (regardless of severity) in the past five years. Those who responded affirmatively were then asked to specify the number of crashes, which was used as a continuous indicator of cycling safety incidents.

PURS Development

The development of the PURS questionnaire followed a two-stage process, aligned with established literature on scale development and item-response theory in the field of social, behavioral, and transport sciences (Boateng et al., 2018; DeVellis & Thorpe, 2022; Ledesma et al., 2021; Morgado et al., 2018). In the initial phase, items were proposed based on a comprehensive review of previous research addressing mobile phone usage in different transport modalities, including cycling, driving, walking, and e-scooting, identifying key behavioral patterns associated with mobile phone use while cycling (Choudhary & Velaga, 2017; Oviedo-Trespalacios & Scott-Parker, 2017; Simmons et al., 2020; Useche, Alonso, Faus, et al., 2024).

This process focused on characterizing visual-manual and auditory interactions, as well as risk-compensating behaviors, ensuring that the scale reflected both specific cycling scenarios and common behavioral responses. Items were formulated using a situational approach, depicting real-life situations encountered by cyclists (e.g., “*You looked continually at the phone for more than two seconds*”), and a behavioral approach, emphasizing adaptive responses to distractions (e.g., “*You*

increased your distance from the vehicle/bike in front while using the phone to prevent a crash”). Given that the questionnaire targeted urban cyclists, the item pool underwent a rigorous review and refinement process, where language adjustments were made in consultation with an expert in stress and transportation research before proceeding with content validity assessment.

To establish content validity, the questionnaire was evaluated by the study’s authors, all of whom hold doctoral degrees and possess expertise in transport psychology, psychometrics, and behavioral assessment. Each item was assessed for dimensional relevance, with only those receiving an average rating of at least 70% being retained. This double-checking process helped to ensure that the final questionnaire incorporated a diverse yet theoretically grounded selection of items, covering key thematic areas, patterns, and facets directly related to mobile phone use while cycling.

The second phase involved pilot testing, where the questionnaire was initially administered in paper format to a volunteer sample. This phase allowed for real-time monitoring of the response process, enabling the identification of potential ambiguities in instructions, item wording, and response scales. Participants were encouraged to provide qualitative feedback, which was subsequently analyzed to refine the instrument. Although the majority of respondents reported no major concerns, minor revisions (e.g., wording adjustments and the inclusion of specific behavioral examples) were implemented to improve the clarity of the questions, if pertinent. Following these modifications, the revised version was administered online to a larger sample, facilitating psychometric analysis and validation while maintaining consistency across diverse linguistic and cultural contexts.

Table 1. Descriptive statistics of age and gender distribution among study participants (n = 15,532), along with data collection details across the 44 participating countries.

Country	Frequency	Percent	Age		Gender			Language/s
			Mean	SD	Female	Male	Other ¹	
Australia	1280	8.8%	53.30	13.39	23.4%	75.8%	.8%	English
Bangladesh	400	2.8%	23.89	3.99	22.8%	77.3%	<.1%	Bengali
Bolivia	200	1.4%	37.19	12.34	41.5%	58.0%	.5%	Spanish
Bosnia & Herzegovina	169	1.2%	30.75	11.95	34.9%	65.1%	<.1%	Bosnian
Brazil	331	2.3%	40.61	12.49	27.2%	71.9%	.9%	Portuguese
Chile	103	.3%	41.37	11.35	30.4%	69.0%	.6%	Spanish
China	779	5.4%	30.96	11.63	29.3%	70.6%	.1%	Chinese
Colombia	449	3.1%	29.19	11.35	53.5%	46.3%	.2%	Spanish
Croatia	148	1.0%	30.15	11.70	49.3%	50.0%	.7%	Croatian
Cuba	316	2.2%	28.87	11.76	49.7%	50.3%	<.1%	Spanish
Ecuador	203	1.4%	38.02	11.63	24.8%	75.2%	<.1%	Spanish
Finland	262	1.8%	46.92	12.33	40.5%	56.1%	3.4%	Finnish
France	139	1.0%	22.51	5.99	80.6%	18.0%	1.4%	French
Germany	507	3.5%	37.57	17.83	69.0%	29.5%	1.5%	German
Ghana	65	.4%	28.71	7.98	23.1%	76.9%	<.1%	English
Greece	833	5.8%	34.09	14.37	38.2%	61.1%	.7%	Greek
Indonesia	194	1.3%	30.01	13.28	50.5%	49.5%	<.1%	Basha/English
Italy	156	1.1%	33.62	13.73	28.8%	70.5%	.6%	Italian
Japan	691	4.8%	54.77	13.57	25.3%	74.7%	<.1%	Japanese

Latvia	299	2.1%	32.19	14.09	41.5%	57.9%	.7%	Latvian
Malaysia	214	1.5%	40.10	9.99	12.1%	87.9%	<.1%	Malay
Mexico	156	1.1%	41.55	11.64	29.5%	70.5%	<.1%	Spanish
Nepal	143	1.0%	35.61	12.04	18.9%	81.1%	<.1%	Nepali/English
New Zealand	896	6.2%	46.76	14.55	39.4%	58.5%	2.1%	English
Nigeria	102	.4%	25.29	5.61	34.3%	65.7%	<.1%	English
Norway	311	2.1%	33.37	11.12	65.3%	34.7%	<.1%	Norwegian
Panama	238	1.6%	27.27	10.57	44.1%	55.9%	<.1%	Spanish
Pakistan	226	1.6%	21.81	6.91	52.2%	47.8%	<.1%	Urdu/English
Philippines	51	.4%	25.98	6.96	2.0%	96.1%	2.0%	Tagalog/English
Poland	76	.5%	30.55	10.30	13.8%	86.2%	<.1%	English; Polish
Portugal	43	.3%	40.28	10.37	23.3%	76.7%	<.1%	Portuguese
Romania	297	2.1%	38.42	11.67	23.9%	75.1%	1.0%	Romanian
Russia	404	2.8%	24.75	9.12	31.0%	67.6%	1.4%	Russian
Serbia	294	2.0%	34.32	14.88	42.5%	56.8%	.7%	Serbian
Slovakia	225	1.6%	32.92	11.49	39.9%	60.1%	<.1%	Slovak
Spain	560	3.9%	28.48	14.94	41.8%	57.9%	.3%	Spanish
South Africa	131	.9%	46.66	13.91	22.1%	77.9%	<.1%	English
Sweden	303	2.1%	49.82	12.36	58.6%	39.4%	2.0%	Swedish
Switzerland	535	3.7%	46.35	17.51	59.6%	40.2%	.2%	Swiss
Turkey	359	2.5%	33.25	11.45	41.8%	57.1%	1.1%	Turkish
Ukraine	430	3.0%	33.77	14.62	44.0%	55.1%	.9%	Ukrainian
Uruguay	100	.7%	39.15	11.31	30.0%	70.0%	<.1%	Spanish

United States of America	302	2.1%	50.39	15.91	35.8%	62.3%	2.0%	English
Uzbekistan	548	3.8%	24.03	8.79	20.3%	79.7%	<.1%	Uzbek/Russian
Total	15,532	100%	36.60	16.70	38.4%	61.0%	.7%	--

Statistical Analysis

Descriptive Data

An initial descriptive analysis was conducted to examine the sociodemographic characteristics of participants, which were quantified, categorized, and labeled accordingly. Following a careful data curation process, key scale and subscale scores, including those for the CBQ and RPRS factors, were computed in line with their respective scoring guidelines.

Exploratory Factor Analysis

To assess the factorial structure of the PURS, an initial Exploratory Factor Analysis (EFA) was conducted using Robust Maximum Likelihood (MLR) estimation with Oblimin rotations. ML estimation is preferred for its ability to provide unbiased parameter estimates and standard errors, even in cases of multivariate non-normality (Costello & Osborne, 2005; Fabrigar et al., 1999). The choice of Oblimin rotation, an oblique method, was justified by the assumption that the underlying factors of the PURS are correlated rather than orthogonal, aligning with psychometric best practices (Russell, 2002).

To determine the suitability of the data for factor analysis, both Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy were examined. While the first (Bartlett's test) assesses whether the correlation matrix is significantly different from an identity matrix, indicating that factor analysis is appropriate, the second (KMO) evaluates the proportion of variance among variables that might be caused by underlying factors, with values $> .800$ generally considered meritorious, allowing to meet the necessary conditions for a reliable factor extraction (Tabachnick & Fidell, 2013).

Factor extraction criteria consisted of eigenvalues > 1.00 , in addition to the theoretical interpretability of the exploratory factors (Henson & Roberts, 2006). Subsequently, one item (GPS usage) with a low factor loading ($< .400$) and high cross-loadings was scrutinized for

removal to optimize the clarity and construct validity of the scale. The resulting factor structure, suggesting 10 items, was subsequently tested through Confirmatory Factor Analysis (CFA) to validate the dimensionality identified in the exploratory phase, as suggested in expert literature focused on road behavioral assessment from psychometric approaches (Ledesma et al., 2021).

Confirmatory Factor Analysis

Following the aforementioned EFA outcomes and literature-based insights, Structural Equation Modeling (SEM) was conducted to assess the factor composition of the PURS using Confirmatory Factor Analysis (CFA). Several goodness-of-fit indices were employed to evaluate model adequacy, including chi-square value (χ^2), Comparative Fit Index (CFI), Normed Fit Index (NFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The criteria for acceptable model fit were set at CFI/TLI > .900 and RMSEA < .080, while lower AIC and BIC values indicated a more parsimonious model (Kuha, 2004; Ruiz-Hernández et al., 2020; Marsh et al., 2004).

The model adequacy was evaluated based on parameter estimates, factor loadings, and modification indices, ensuring that no large or unnecessary modifications were introduced. Following the advice of expert literature, a Monte Carlo parametric bootstrapping procedure was applied, generating 3,000 subsamples to assess model stability and correct for bias through iterative testing (Andrews & Buchinsky, 2000). This allowed to correct standardized coefficients under optimal reliability assumptions and to obtain 95% confidence intervals for them, this minimizing the risk for Type I or Type II statistical errors (Fornell & Larcker, 1981; Gilleland, 2020).

Reliability and Internal Consistency Analysis

Internal consistency and reliability were assessed using Cronbach's alpha (α) and McDonald's omega (ω) for both the full scale and individual subscales. Cronbach's alpha remains one of the most widely used measures of internal consistency, with values above .700 generally considered acceptable for psychological scales (Tavakol & Dennick, 2011). However, alpha is sensitive to the number of scale items and may underestimate reliability in cases of heterogeneous constructs (Peterson & Kim, 2013). To complement this, McDonald's omega (ω) was calculated, as it provides a more robust estimation of internal consistency, particularly when factor loadings vary across items (Dunn et al., 2014).

Additionally, the Composite Reliability Index (CRI) was computed, incorporating lambda coefficients, residuals, and critical ratios. This index offers an alternative approach to assessing reliability, as it is less prone to bias than traditional internal consistency measures, particularly when used in isolation (Padilla & Divers, 2016; Stensen & Lydersen, 2022).

The advantage of these three indices is that they are measured on the same [0–1] scale, which facilitates direct comparison and straightforward interpretation. Alpha/omega/CRI values over .700 are typically indicative of adequate reliability or consistency, while values exceeding .800 suggest a 'highly reliable' construct (Raykov, 2009).

Validity Analysis

The construct validity of the PURS was evaluated using multiple psychometric properties, including convergent validity, factor correlations, and discriminant validity (via AVE scores). In a first step, Pearson correlations (σ) were used to assess inter-factor correlations, ensuring that the three PURS dimensions were adequately distinct yet theoretically related. Correlation coefficients were interpreted based on psychometric guidelines, confirming whether

the factors retained conceptual independence while simultaneously contributing to a unified construct of mobile phone use while cycling.

Subsequently, the discriminant validity of the PURS was assessed using the Average Variance Extracted method. From a theoretical standpoint, the ‘rules of thumb’ state that an AVE value of .500 or higher is generally considered acceptable, as it indicates that the construct captures at least 50% of the variance in its indicators, reducing the influence of measurement error (Fornell & Larcker, 1981). Values above .600 are typically deemed as strong evidence of convergent validity, while values below .500 suggest that the construct may not be adequately represented by its indicators, potentially requiring model adjustments or item refinement (Cheung et al., 2024; Hair Jr & Sarstedt, 2019).

Path Analysis

To assess the predictive validity of the PURS, a Structural Equation Model (SEM)-based Path Analysis was conducted, examining whether the scale could predict self-reported cycling crashes in the past five years. The model controlled for cyclists’ age and riding exposure to isolate the predictive role of PURS dimensions.

The analysis aimed to determine whether the latent constructs of the PURS –representing visual-manual interactions, auditory interactions, and risk-compensating behaviors– could significantly predict the frequency of self-reported cycling crashes. This approach provided a robust assessment of the questionnaire’s predictive ability, moving beyond simple correlational analyses to a structured, theoretically driven model. Apart from using bootstrapped coefficients, the model for cyclists’ age and exposure aiming to minimize confounding effects, which improves the accuracy and reliability of the inter-variable relationships established.

Study Ethics

Ethical approval for this study was obtained from the Research Ethics Committee at the Research Institute on Traffic and Road Safety (INTRAS), University of Valencia, Spain (HE0002210423), in accordance with the Declaration of Helsinki.

Given its technical features and the data collection procedure characteristics, the study was classified as minimal risk, as it involved the collection of anonymous demographic data and adhered to established safety protocols. All our participants provided informed consent before responding to the questionnaire, but after receiving comprehensive information about the study purpose, methodology, and data management parameters, emphasizing the merely scientific value of the data provided.

Results

Exploratory Factor Analysis

The Exploratory Factor Analysis (EFA) suggested a three-factor structure. Together, these three factors explained 64% of the variance, with the following distribution: (F1) Visual-Manual Interactions (5 items; 25.8% of variance explained); (F2) Risk-Compensating Behaviors (3 items; 18.9% of variance explained); and (F3) Hands-Free Auditory Interactions (3 items; 18.9% of variance explained). The third factor consists of behaviors related to hands-free phone conversations and listening to music via hands-free devices. Although this factor includes a relatively small number of items, they keep a strong internal correlation, indicating a cohesive underlying construct.

To assess the factorability of the matrix, Bartlett's test of sphericity was performed to examine both partial and bivariate correlations, while the Kaiser-Meyer-Olkin (KMO) measure was used to evaluate sampling adequacy. Bartlett's test yielded significant results ($\chi^2 = 5011$, $df = 26$; $p < .001$), rejecting the null hypothesis that the correlation matrix is an identity matrix with zero correlations

(Goretzko et al., 2021). Regarding sampling adequacy, the KMO index was .916, indicating that the dataset was highly suitable for factor analysis (Kaiser & Rice, 1974).

However, the item related to using a phone as a GPS or maps device (Item 11) was excluded from the final model due to its low factor loading ($\lambda < .400$) across all dimensions and weak correlation with other behaviors. In other words, it suggests that it represents a distinct type of mobile interaction rather than fitting within the identified factor structure, making it advisable to dismiss the item from an expert literature-based approach (Costello & Osborne, 2005; Ledesma et al., 2021).

Confirmatory Factor Analysis

As previously described, theory-based Confirmatory Factor Analyses (CFA) were conducted to assess the factor structure of the PURS, comparing multiple alternative factorial configurations. Specifically, one-factor, two-factor, and three-factor models were tested to determine the most statistically and theoretically appropriate solution.

First, a two-factor model was tested, grouping Visual-Manual Interactions (F1) and Hands-Free Auditory Interactions (F3) into a single construct. Next, a three-factor solution was examined, distinguishing between Visual-Manual Interactions (F1), Risk-Compensating Behaviors (F2), and Hands-Free Auditory Interactions (F3). The three-factor model suggested a superior fit, both in terms of goodness-of-fit indices and its alignment with theoretical expectations of the scale. In contrast, the alternative configurations displayed notably poorer fit, reinforcing the adequacy of the three-factor structure. Table 2 presents the comparative fit indices for the tested models, while Figure 1 illustrates the standardized item estimations within the retained three-factor configuration.

Table 2. Goodness of fit indices of the competitively analyzed PURS structural solutions.

Model	c^2	df ¹	p	RMSEA ²	90% CI ³		NFI ⁴	RFI ⁵	IFI ⁶	TLI ⁷	CFI ⁸
					Lower	Upper					
<i>Baseline models</i>											
One-factor structure	1007,735	35	<.001	.194	.192	.197	.833	.765	.833	.765	.833
Bifactorial structure	899,920	34	<.001	.137	.135	.140	.919	.882	.919	.883	.919
Three-factor baseline structure	270,358	32	<.001	.074	.071	.76	.974	.956	.975	.956	.975
<i>Adjusted model</i>											
Three-factor adjusted structure	31,678	16	<.001	.035	.032	.38	.997	.992	.997	.992	.997

Notes: ¹df= Degrees of freedom; ²RMSEA= Root Mean Square Error of Approximation; ³Confidence Interval for RMSEA ($\alpha = .010$); ⁴NFI= Normed Fit Index (Delta1); ⁵RFI= Relative Fit Index (rho1); ⁶IFI= Incremental Fit Index (Delta2); ⁷TLI= Tucker-Lewis Index (rho2); ⁸CFI= Confirmatory Fit Index.

Table 3. Item/factor composition and key coefficients of the final three-factor structural model of the Phone Use While Riding Scale (PURS).

PURS three-factor structure														
Item	Item Content	M ^a	SD ^b	Reliability/ Consistency	λ^c	U.E. ^d	S.E. ^e	C.R. ^f	p^g	Bootstrap bias-corrected values ^h				
										S.E. ^d	Bias ⁱ	95% Ci ^j	p	
Factor 1: Visual-Manual Interactions														
PURS1	You looked continually at the phone for more than two seconds	3.95	1.10	CRI=.997; α^l =.913; ω^m =.915	.854	1.000	.007	130.291	<.001	.001	.000	.772	.777	.012
PURS2	You reacted without delay (e.g., searched, reached or picked up mobile phone) to a ringing phone (audio or vibration)	3.52	1.17		.852	.985	.008	130.190	<.001	.002	.000	.652	.659	.011
PURS3	You performed a visual-manual task on your mobile phone (e.g., texting, browsing, or emailing)	3.96	1.15		.875	.966	.007	136.874	<.001	.002	.000	.647	.655	.025
PURS4	You posted on social media apps (e.g. Facebook, Twitter, Snapchat, etc.)	3.53	1.20		.730	.760	.007	102.517	<.001	.001	.000	.772	.777	.009
PURS5	You had a phone conversation using your hands	3.92	1.15		.803	.897	.008	118.614	<.001	.001	.000	.724	.730	.015
Factor 2: Risk Compensating Behaviors														
PURS6	You increased your distance from the vehicle/bike in front while using the phone to prevent a crash	3.42	1.19	CRI=.998; α^l =.907; ω^m =.910	.845	1.000	.007	130.174	<.001	.002	.000	.775	.781	.009
PURS7	You reduce your speed while using your phone to prevent a crash	3.45	1.27		.934	1.190	.008	144.921	<.001	.002	.000	.727	.733	.014
PURS8	You frequently looked up at the road while riding your bike to avoid potential hazards when using the pone	3.34	1.25		.857	1.143	.009	129.852	<.001	.002	.000	.622	.629	.007
Factor 3: Hands-Free Auditory Interactions														
PURS9	You had a phone conversation without using your hands (hands-free device, earphones, etc.)	3.37	1.16	CRI=.992; α^l =.780;	.906	1.000	.008	122.746	<.001	.001	.000	.897	.901	.012
PURS10	You listened to music using a hands-free device/earphone	3.39	1.15	ω^m =.781	.709	.906	.011	81.704	<.001	.001	.000	.806	.812	.012

Notes: ^a Arithmetic Mean – scale [0-4]; ^b Standard Deviation; ^c Standardized factor loading; ^d Unstandardized estimates; ^e Standard Error; ^f Composite Reliability Indexes; ^g All p -values were lower than .001 – all p -values in bootstrap were statistically significant / p -values lower than .050; ^h Bootstrapped (bias-corrected) model; ⁱ Bias identified (and corrected) in the item; ^j Confidence Interval at the level 95% (lower bound – left; upper bound – right); ^k Composite Reliability Index; ^l Cronbach's alpha; ^m McDonald's omega.

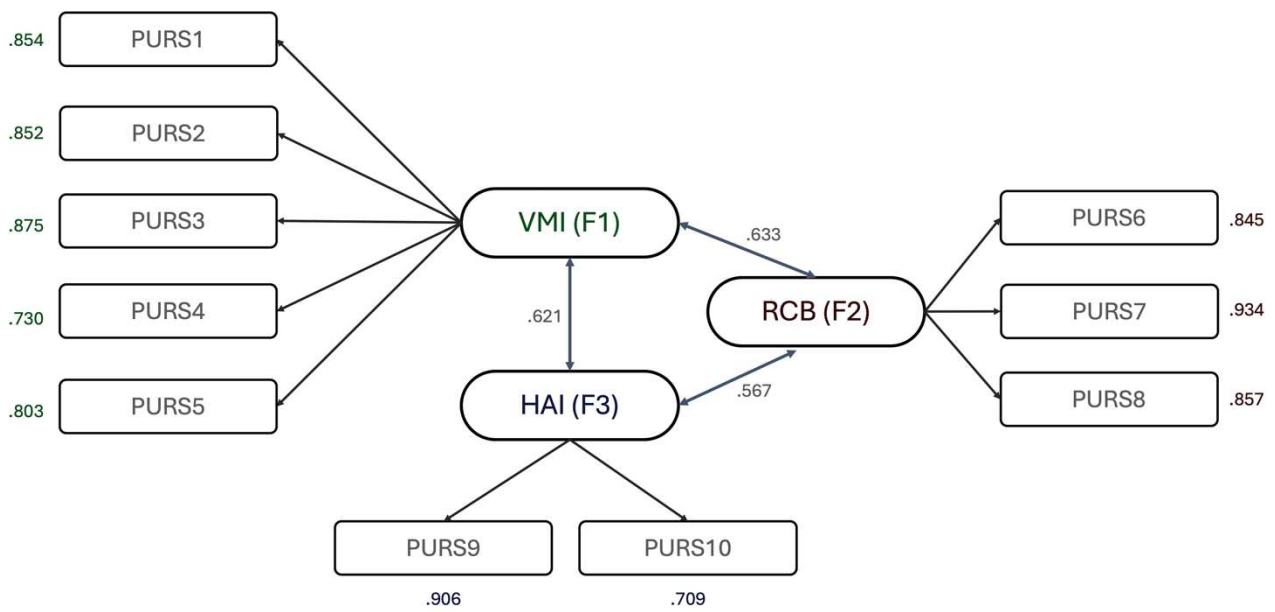


Figure 1. Configurational structure and standardized coefficients (l) for each item regarding their final factor. All bootstrapped standardized estimates were $p < .001$.

A closer examination of the initial three-factor model revealed a small set of large modification indices (over .030), indicating associations between certain items and residuals. After applying the targeted adjustments, the refined three-factor constrained model yielded a more satisfactory fit, with the final indices reported in Table 2.

Reliability and Internal Consistency

The three-factor structure of the PURS suggests strong reliability and internal consistency, as reflected by a full-scale Cronbach's alpha ($\alpha = .929$) and McDonald's omega ($\omega = .931$), both exceeding the commonly accepted .700 threshold (Arrojo et al., 2024; Pina et al., 2022; Stensen & Lydersen, 2022). At the subscale level, reliability coefficients were also consistently high, with F1 (Visual-Manual Interactions) $\alpha = .913$, $\omega = .914$; F2 (Risk-Compensating Behaviors) $\alpha = .907$, $\omega = .906$; and F3 (Hands-Free Auditory Interactions) $\alpha = .780$, $\omega = .781$.

Table 4 details Cronbach's alpha (α) and McDonald's omega (ω) values if individual items were removed, if a unifactorial composition of the scale is used. Given that the removal of any item would result in lower internal consistency coefficients, it can be inferred that each retained item contributes meaningfully to the overall reliability of the scale.

Table 4. Scale's Cronbach's alpha (α) and McDonald's omega (ω) coefficients if an item is removed from the full (unifactorial) item solution.

Item		Scale coefficients after deletion	
		Cronbach's α	McDonald's ω
PURS1	You looked continually at the phone for more than two seconds	.888	.889
PURS2	You reacted without delay (e.g., searched, reached or picked up mobile phone) to a ringing phone (audio or vibration)	.893	.894
PURS3	You performed a visual-manual task on your mobile phone (e.g., texting, browsing, or emailing)	.894	.895
PURS4	You posted on social media apps (e.g. Facebook, Twitter, Snapchat, etc.)	.888	.890
PURS5	You had a phone conversation using your hands	.892	.894
PURS6	You increased your distance from the vehicle/bike in front while using the phone to prevent a crash	.886	.888
PURS7	You reduce your speed while using your phone to prevent a crash	.889	.891
PURS8	You frequently looked up at the road while riding your bike to avoid potential hazards when using the phone	.888	.890
PURS9	You had a phone conversation without using your hands (hands-free device, earphones, etc.)	.889	.891
PURS10	You listened to music using a hands-free device/earphone	.897	.898

Moreover, the Composite Reliability Indexes (CRI) were calculated alongside traditional reliability measures, following expert literature recommendations that highlight the limitations of basic indices such as Cronbach's alpha (Padilla & Divers, 2016; Peterson & Kim, 2013). Overall, the results suggest high internal consistency for both the full-scale PURS and its three latent constructs. Specifically, the CRI for the full scale, treated as a unifactorial solution, was .997, while the CRI for F1, F2, and F3 reached .997, .998, and .992, respectively. These findings reinforce the psychometric

robustness of the PURS, as all standardized factor loadings were positive and statistically significant across their respective dimensions.

Construct and discriminant validity

To assess construct validity, Pearson correlation coefficients (σ) were computed to examine the associations between PURS scores and CBQ dimensions (Useche et al., 2018, 2022). The results suggest a strong positive correlation between CBQ subscales (Traffic Violations, Riding Errors, and Positive Behaviors) and PURS dimensions (Visual-Manual Interactions, Risk-Compensating Behaviors, and Hands-Free Auditory Interactions).

The significant inter-correlations among the three PURS factors ($\sigma_{(VMI \leftrightarrow RCB)} = .568$, $\sigma_{(VMI \leftrightarrow HAI)} = .542$) further support the internal coherence of the scale, suggesting that while these dimensions are theoretically distinct, they are interrelated. Additionally, the CBQ showed a moderate positive relationship between PURS scores, cycling errors ($\sigma = .454$), and deliberate violations ($\sigma = .421$). A smaller yet significant positive correlation was observed between PURS scores and self-reported cycling crashes over the past five years ($\sigma = .185$). The full set of inter-factor correlations is presented in Table 5.

Finally, to investigate discriminant validity, the Average Variance Extracted (AVE) score was calculated. The obtained value exceeded the commonly used ‘acceptable’ threshold of .500, with a final score of .558, suggesting good discriminant validity (Cheung et al., 2024; Spector, 2006). This outcome aligns with the pre-defined psychometric standards (see 2.5 Statistical Analysis Strategy), suggesting that each PURS dimension retains sufficient independence from the others while still contributing to a cohesive measurement model.

Table 5. Correlation matrix for each PURS subscale of self-reported cycling behaviors, risk perception, and cycling crashes.

Variable	Parameter	2	3	4	5	6	7	8	9	
PURS Factors										
1	PURS F1 (VMI)	<i>r</i> ^a	.568**	.542**	.883**	-.113**	.504**	.482**	-.103**	.181**
		Sig.	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
2	PURS F2 (RCB)	<i>r</i>	--	.494**	.846**	.056**	.280**	.250**	.072**	.155**
		Sig.		<.001	<.001	<.001	<.001	<.001	<.001	<.001
3	PURS F3 (HAI)	<i>r</i>		--	.744**	-.027	.307**	.283**	.009	.106**
		Sig.			<.001	.002	<.001	<.001	.327	<.001
4	PURS FULL	<i>r</i>			--	-.038	.454**	.421**	-.017	.185**
		Sig.				<.001	<.001	<.001	.057	<.001
Risk Perception and Cycling Behaviors										
5	Risk Perception	<i>r</i>					-.163**	-.189**	.435**	-.050
		Sig.					<.001	<.001	<.001	<.001
6	CBQ Errors	<i>r</i>						.737**	-.159**	.193**
		Sig.						<.001	<.001	<.001
7	CBQ Violations	<i>r</i>							-.144**	.196**
		Sig.							<.001	<.001
8	CBQ Positive Behaviors	<i>r</i>								-.092**
		Sig.								<.001
Self-Reported Safety Outcomes										
9	Cycling Crashes (5 years)	<i>r</i>								--
		Sig.								

Notes: ^a Parametric partial correlation coefficients, controlling for cyclists' age and gender; ** The correlation is significant at the level $p = <.001$.

Cross-regional validity and descriptive outcomes

A two-step process was conducted to assess the cross-regional validity of the PURS and analyze its descriptive outcomes. First, the factorial structure of the validated model was tested using a region-based approach, evaluating how well the data from each region of reference fit (or not) the cross-regional model. Second, given that cycling behavior may vary significantly across countries, even within the same region, descriptive scores for each country were computed, as shown in Table 6.

Regarding the first step, the results suggest that the factorial structure of the PURS aligns well across all regions included in the study. However, it is worth noting that the RMSEA value for the African sample was .096, which is slightly above the optimal threshold of .080. Despite this, all other fit indices fell within acceptable ranges, reinforcing the overall suitability of the model, as shown in a column-based format in Table 7.

Remarkably, the Confirmatory Fit Index (CFI) and the Tucker-Lewis Index (TLI) —the two ordinal indices commonly used to evaluate model fit in three-factor solutions—both exceeded .900. Moreover, the Δ CFI values remained below the commonly recommended cut-off point of .010, suggesting that configural, metric, and scalar invariance were achieved (Chen, 2007). All in sum, these results suggest that, besides its general contents translatable to all these regions, the PURS factorial structure remains stable across different cultural contexts, allowing for valid cross-regional measurements and comparisons.

Anyway, regarding the descriptive outcomes, the study reveals significant heterogeneities in sample sizes and age across countries. Specifically, Australia represents the largest subsample but also the second-oldest population on average. This demographic skew is critical for PURS validation, as mobile phone use while riding is strongly age-dependent. For this reason, the numerical dominance of an older Australian cohort may have influenced the global mean scores, potentially reflecting more

conservative habits than those of younger, more technologically active populations. These differences should be considered in more detail when interpreting the cross-regional comparisons. Indeed, we have added this information as a limitation of the study.

Table 6. Descriptive PURS factor scores (VMI, RCB, and HAI) in the 44 different countries covered by the study.

Country	N	Visual-Manual Interactions (VMI)				Risk Compensating Behavior (RCB)				Hands-Free Auditory Interactions (HAI)			
		M	SD	95% CI		M	SD	95% CI		M	SD	95% CI	
				LB	UB ^a			LB	UB			LB	UB
Australia	1280	.344	.471	.319	.370	.744	1.139	.682	.806	.860	1.095	.800	.919
Bangladesh	400	1.446	1.094	1.338	1.553	1.801	1.232	1.680	1.922	1.586	1.180	1.470	1.702
Bolivia	200	.909	.955	.775	.1.042	1.685	1.353	1.496	1.873	1.685	1.309	1.502	1.867
Bosnia & Herzegovina	169	1.382	1.115	1.219	1.551	2.051	1.445	1.831	2.270	1.393	1.301	1.195	1.591
Brazil	331	.712	.843	.621	.803	1.381	1.438	1.226	1.537	1.086	1.125	.964	1.207
Chile	103	.809	.891	.635	.984	1.647	1.415	1.370	1.923	1.616	1.297	1.363	1.870
China	779	2.616	.907	2.616	2.740	3.442	.989	3.374	3.510	2.915	1.007	2.841	2.980
Colombia	449	1.021	1.088	.920	1.122	1.754	1.394	1.625	1.883	2.025	1.320	1.903	2.148
Croatia	148	1.475	.978	1.316	1.634	1.970	1.273	1.763	2.177	.8953	.948	.741	1.049
Cuba	316	.121	.406	.076	.166	.204	.634	.134	.274	.466	.886	.368	.564
Ecuador	203	.905	1.043	.761	1.049	1.665	1.455	1.463	1.866	1.598	1.315	1.416	1.780
Finland	262	.596	.659	.518	.674	1.467	1.441	1.296	1.638	1.110	1.177	.970	1.250
France	139	.653	.847	.512	.795	1.625	1.299	1.408	1.843	1.172	1.224	.967	.1,378
Germany	507	.514	.670	.456	.573	1.216	1.251	1.107	1.325	1.142	1.204	1.036	1.247
Ghana	65	1.384	1.088	1.115	1.654	1.902	1.232	1.597	2.208	1.892	1.260	1.577	2.204
Greece	833	.723	.736	.673	.774	1.299	1.354	1.207	1.391	1.477	1.312	1.388	1.566
Indonesia	194	.8536	.930	.721	.985	1.709	1.420	1.508	1.910	1.466	1.219	1.293	1.639
Italy	156	.661	.793	.536	.787	1.666	1.440	1.438	1.894	1.267	1.309	1.267	1.681
Japan	691	.314	.579	.271	.358	.242	.580	.198	.285	.298	.689	.246	.349
Latvia	299	1.200	1.037	1.081	1.318	1.658	1.363	1.503	1.814	1.764	1.351	1.610	1.918
Malaysia	214	1.128	1.080	.982	1.273	2.277	1.366	2.093	2.461	1.630	1.362	1.447	1.814
Mexico	156	.815	.843	.682	.948	1.786	1.499	1.549	2.023	1.439	1.301	1.233	1.645

Nepal	143	1.507	1.141	1.319	1.696	—	2.097	1.316	1.880	2.315	1.674	1.309	1.458	1.891
New Zealand	896	.359	.505	.326	.392		.961	1.330	.874	.1.048	.801	1.041	.733	0.87
Nigeria	102	1.560	1.215	1.315	1.806		1.849	1.386	1.577	2.122	1.946	1.367	1.677	2.214
Norway	311	.516	.683	.440	.592		.832	1.226	.696	.969	.901	1.137	.775	1.028
Panama	238	1.037	1.127	.892	1.181		1.649	1.410	1.469	1.830	1.630	1.307	1.463	1.797
Pakistan	226	1.500	1.081	1.359	1.642		2.005	1.218	1.846	2.165	1.811	1.262	1.646	1.977
Philippines	51	1.207	.950	.950	1.465		2.627	1.485	2.209	3.045	1.549	1.335	1.173	1.924
Poland	76	1.100	1.041	.862	1.337		2.100	1.482	1.762	2.438	1.605	1.400	1.285	1.925
Portugal	43	.493	.620	.302	.684		1.124	1.487	.663	1.580	1.002	1.118	.655	1.344
Romania	297	.653	.731	.569	.736		2.104	1.496	1.933	2.275	1.338	1.319	1.187	1.489
Russia	404	.939	.1.084	.833	1.045		1.710	1.462	1.567	1.853	1.427	1.297	1.300	1.553
Serbia	294	.957	1.014	.847	1.073		1.661	1.423	1.497	1.824	1.215	1.290	1.103	1.399
Slovakia	225	1.056	.914	.935	1.176		1.985	1.342	1.808	2.161	1.288	1.292	1.119	1.458
Spain	560	.667	.880	.549	.740		1.394	1.345	1.282	1.505	1.257	1.229	1.155	1.359
South Africa	131	.455	.678	.337	.572		.867	1.136	.671	1.064	.782	1.004	.608	.956
Sweden	303	.590	.631	.516	.664		1.576	1.399	1.412	1.740	1.302	1.200	1.161	1.443
Switzerland	535	.369	.627	.315	.422		.810	1.191	.708	.911	.830	1.073	.739	.922
Turkey	359	.901	.793	.820	.982		2.116	1.276	1.986	2.246	1.296	1.152	1.179	1.414
Ukraine	430	1.714	.835	1.634	1.793		2.772	.805	2.695	2.848	1.570	1.123	1.464	1.677
Uruguay	100	.834	.884	.658	.1.010		1.706	1.436	1.421	1.991	1.405	1.232	1.160	1.649
United States of America	302	.536	.658	.461	.611		.867	1.211	.867	1.141	1.149	1.194	1.013	1.284
Uzbekistan	548	1.488	1.166	1.390	1.586		1.537	1.201	1.436	1.637	1.591	1.191	1.491	1.691
Full sample	15.332	.888	1.022	.871	.904		1.506	1.454	1.482	1.529	1.322	1.299	1.301	1.343

Notes: ^aM= Mean; ^bSD= Standard deviation; ^c95% CI= Confidence interval at the level 95%; ^dLB= Lower Bound; ^eUB= Upper Bound.

Table 7. Fit indexes (PURS) for the general confirmatory model across all regions covered by the validation study.

Region	χ^2	df ¹	p	RMSEA ²	90% CI (Lower)	90% CI (Upper)	AIC ³	BIC ⁴	TLI ⁵	CFI ⁶
Full Sample	316	16	<.001	.035	.032	.038	2766	2777	.992	.997
Europe	921	29	<.001	.071	.067	.071	16568	19692	.945	.964
Americas	552	28	<.001	.085	.082	.094	62434	62658	.931	.957
Asia	658	30	<.001	.076	.071	.083	83133	83349	.969	.980
Africa	134	30	<.001	.096	.084	.122	6862	6995	.945	.965
Oceania	521	29	<.001	.085	.082	.095	55561	55756	.901	.922

Notes: ¹df= Degrees of freedom; ²RMSEA= Root Mean Square Error of Approximation; Confidence Interval for RMSEA; ³AIC= Akaike Information Criterion; ⁴BIC = Bayesian Information Criterion; ⁵TLI= Tucker-Lewis Index; ⁶CFI= Confirmatory Fit Index

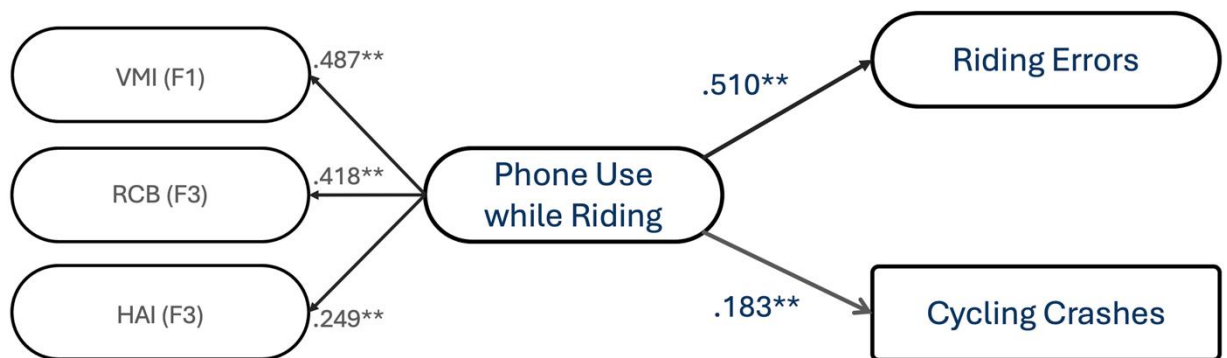
Predictive value of the PURS: Path analysis

Finally, to examine the predictive value of the PURS, a Structural Equation Model (SEM)-based Path Analysis was performed. The structural model controlled for cyclists' age, education, and exposure, allowing for a focused assessment of the impact of mobile phone use while cycling (as measured by the PURS) on both cycling errors (unintentional risky road behaviors) and self-reported cycling crashes. Regarding the distribution of crash involvement, the data showed a clear positive skewness (Skewness = 2.61), indicating that the distribution was significantly right-skewed. This outcome aligns with the findings in road safety research, where the number of reported incidents is typically low. The mean number of crashes was 1.06 (SD = 1.75), with values ranging from 0 to 11. To address this non-normal distribution and its potential impact on the path model, as indicated in the statistical analysis strategy section (page 88), we employed Robust Maximum Likelihood (MLR) estimation. This approach provides parameter estimates and standard errors that are robust to non-normality and skewness, ensuring

that the relationships between PURS scores and crash involvement are accurately estimated without inflating the Type I error rate.

Grounded in the theoretical framework of this study (see Section 1) and the correlation results shown in Table 4, it was hypothesized that higher PURS scores would significantly predict both cycling errors and self-reported crashes. The resulting Structural Equation Model provided strong fit indices ($\chi^2 = 342.581, p < .001$; NFI = .964; CFI = .964; IFI = .964; RMSEA = .066, 90% CI: [.061–.072]), accounting for the covariances between age, weekly cycling intensity, and PURS scores.

Overall, the Path Analysis results support the assumption that the Phone Use while Riding Scale (PURS) serves as a significant predictor of cyclists' safety-related outcomes. Specifically, the two predictive paths tested were found to be significant and positively associated with increased scores in both risky cycling errors ($b_{(PURS \rightarrow Errors)} = .510; p < .001$) and self-reported cycling crashes ($b_{(PURS \rightarrow Crashes)} = .183; p < .001$).



Notes: ** Paths were $p < .001$; Ellipses represent latent variables; Rectangles denote observed factors.

Figure 2. Path analysis of the predictive relationships among PURS scores, riding errors, and cycling crash involvement.

Discussion

This research aimed to cross-regionally validate the Phone Use while Riding Scale (PURS), examining its properties, reliability indexes, validity insights, and descriptive scores in a large sample from 44 countries and on five continents: Europe, the Americas, Asia, Africa, and Oceania.

Approaching the PURS from a psychometric perspective, the outcomes of this study provide insightful information on its dimensional structure, reliability, and validity as a self-report questionnaire for assessing cycling safety from a technology-behavioral perspective. Next, we will discuss these fundamental points considering previous evidence (including some applications of the PURS worldwide), underlying theories, psychometric findings and descriptive outcomes of the current study.

The PURS dimensionality

Overall, the dimensional structure of the Phone Use while Riding Scale (PURS) was assessed through exploratory and confirmatory factor analyses, in order to test the assumptions of Hypothesis 1. The results suggest a three-factor structure, which aligns with the theoretical framework guiding the scale development. Specifically, the identified dimensions include: (1) Visual-Manual Interactions (F1), encompassing behaviors such as instant phone reaction, continuous viewing, texting, browsing, emailing, and social media posting; (2) Risk-Compensating Behaviors (F2), involving strategies like increasing distance from vehicles, reducing speed, and frequently checking the road while using the phone; and (3) Hands-Free Auditory Interactions (F3), referring to hands-free phone conversations and listening to music via earphones.

This structure is supported by both the EFA and CFA procedures. First, Exploratory Factor Analysis (EFA) indicated that Factor 1 accounted for 25.8% of the variance, Factor 2

for 18.9%, and Factor 3 for 18.9%, totaling 64% of the explained variance, in line with the stipulated by specialized literature (Brown, 2015; Van Prooijen & Van Der Kloot, 2001). Moreover, the factorability of the matrix was supported by Bartlett's test of sphericity ($\chi^2 = 5011; p < .001$) and the Kaiser-Meyer-Olkin (KMO) index of .916, indicating a strong sampling adequacy. Second, Confirmatory Factor Analysis (CFA) further supported this three-factor structure, demonstrating superior model fit compared to alternative configurations (CFI = .997, TLI = .992, RMSEA = .035). Standardized factor loading exceeded the recommended cutoff ($\lambda = .400$), except for an item related to the use of a phone as a GPS or mapping device, which was removed due to low factor loadings and weak inter-item correlations.

On a theoretical level, these findings align with previous research on mobile phone use in transportation contexts, where distinct behavioral components have been observed among cyclists, pedestrians, and drivers. For instance, studies on mobile phone-related distractions among cyclists indicate that visual-manual tasks pose a substantial risk by diverting attention from the riding task, whereas auditory tasks, such as hands-free conversations, appear to have a moderate but significant influence on attentional resources (Gené-Sampedro et al., 2024; Jiang et al., 2021). Similarly, studies on pedestrian and driver distraction suggest that risk-compensating behaviors tend to arise as an adaptive response to counterbalance cognitive workload and perceived threats (Oviedo-Trespalacios et al., 2016; Simmons et al., 2020).

The inter-correlations among the three PURS dimensions further reinforce its internal coherence, as seen in moderate-to-strong associations between F1 and F2 ($r = .568$) and F1 and F3 ($r = .542$). In other words, these theoretically coherent and statistically significant associations suggest that while these dimensions are distinct, they are functionally related in influencing cyclists' interactions with mobile devices while riding.

Bearing in mind the aforementioned considerations (see *Hypothesis 1*), the present findings support the theoretical relevance and psychometric robustness of the PURS as a multidimensional measure of mobile phone use among cyclists, aligning with broader research trends emphasizing the need to consider task complexity, attentional demand, and behavioral adaptation in the assessment of mobile technology use while riding (Stelling-Konczak et al., 2017; Useche, Alonso, et al., 2018).

PURS reliability and consistency indexes

A second step of this validation study involved assessing the reliability and internal consistency of Phone Use while Riding Scale (PURS) using multiple psychometric indicators, including Cronbach's alpha (α), McDonald's omega (ω), and Composite Reliability Indexes (CRIs), in order to provide a rigorous approach to *Hypothesis 2*. The results suggest that the PURS exhibits strong internal reliability across all subscales, reinforcing its measurement stability and suitability for assessing mobile phone use behaviors among cyclists.

The Cronbach's alpha coefficients for each PURS dimension exceeded the widely accepted bound of .700, supporting their internal consistency (Stensen & Lydersen, 2022; Tavakol & Dennick, 2011). Specifically, the Visual-Manual Interactions (F1) subscale presented an alpha of .913, the Risk-Compensating Behaviors (F2) subscale reported .907, and the Hands-Free Auditory Interactions (F3) subscale reached .780. The overall scale reliability was also considerably high ($\alpha = .921$).

In addition to Cronbach's alpha, McDonald's omega coefficients were calculated to address some of the known limitations of alpha in reliability assessments (Peterson & Kim,

2013). The omega values were comparable to the alpha coefficients, with all exceeding .780, confirming the robust internal consistency of the scale. These findings align with previous research using omega for scale validation in traffic psychology and human factors research (Møller & Haustein, 2017; Stensen & Lydersen, 2022)

Moreover, the Composite Reliability Indexes (CRIs) –which provide a latent variable-based reliability estimate superior to classical test theory approaches– showed optimal values across all three PURS dimensions. Specifically, the CRIs were .997 for F1, .998 for F2, and .992 for F3. This is particularly relevant as CRI accounts for item-factor correlations and residual variances, making it a preferred metric in structural equation modeling applications (Hair & Alamer, 2022; Hair Jr & Sarstedt, 2019). Additionally, previous studies assessing risky and distracted behavior in cycling and driving have reported similar alpha and omega values, indicating consistent psychometric properties across transport safety measures (Møller & Haustein, 2017; Oviedo-Trespalacios et al., 2021; Oviedo-Trespalacios & Scott-Parker, 2017; Useche, Alonso, Boyko, et al., 2024).

Taken together, these results reinforce the reliability and internal consistency of the PURS, supporting its use as a robust tool for assessing mobile phone-related risks and adaptive behaviors among cyclists. These findings align with prior research on reliability assessments of transport behavior scales, where multi-indicator reliability coefficients have been used to ensure measurement precision across diverse populations (Useche et al., 2022; McIlroy et al., 2022).

Validity insights of the scale

The third step, related to *Hypothesis 3*, involved assessing the construct validity of the Phone Using While Riding Scale. To this end, we evaluated several criteria, including convergent validity, factor correlations, and the Average Variance Extracted (AVE). These analyses aimed to ensure that the scale accurately captures the intended constructs, reinforcing its theoretical relevance in assessing phone use while riding.

Convergent Validity and Factor Correlations

A key indicator of convergent validity is the magnitude and significance of inter-factor correlations, which should align with theoretical expectations (Fornell & Larcker, 1981). The results indicate statistically significant correlations between the three PURS dimensions. Specifically, Visual-Manual Interactions (F1) and Risk-Compensating Behaviors (F2) were positively associated ($\sigma = .568$; $p < .001$), while F1 and Hands-Free Auditory Interactions (F3) also showed a strong correlation ($\sigma = .542$; $p < .001$). These findings suggest that while each factor captures a distinct behavioral aspect, they remain interrelated, aligning with theoretical expectations regarding different manifestations of phone use while cycling.

From a theoretical standpoint, these results further support the PURS' convergent validity, as they indicate that the scale's factors maintain significant associations while preserving their conceptual distinctions (Fornell & Larcker, 1981). This pattern aligns with previous research in transport psychology, which has shown that risky and compensatory behaviors tend to be significantly intercorrelated yet theoretically independent (De Waard et al., 2010; Jiang et al., 2021; Useche et al., 2022).

Additionally, studies on driver distraction and pedestrian safety have reported similar patterns, where technology-mediated interactions influence risk perception and behavioral adaptation (Oviedo-Trespalacios et al., 2016; Simmons et al., 2020). All in sum, these findings

suggest that while cyclists may attempt to compensate for risks associated with mobile phone use, such behaviors remain linked to potentially hazardous outcomes.

Average Variance Extracted (AVE) and Discriminant Validity

In this study, the AVE scores of the PURS were calculated to assess the proportion of variance explained by each factor relative to measurement error. Overall, the PURS dimensions exceeded the recommended AVE lower threshold of .500, with a general AVE score of .558, supporting adequate discriminant validity (Hair et al., 2019). This suggests that the PURS dimensions are sufficiently distinct from one another, reinforcing the robustness of the proposed three-factorial structure of the PURS.

These explained variance rates, which can be considered as average-high in comparison with preceding literature addressing similar risk-related road behavioral topics (Khattak et al., 2024; Nguyen-Phuoc et al., 2020), add insights to the coherent correlations described in the previous section. Moreover, it theoretically aligns with previous research on distraction and risky behavior in transport psychology, where measures of AVE have been used to validate the independence of behavioral constructs across different populations (Useche et al., 2018; Oviedo-Trespalacios & Scott-Parker, 2017).

Validity in the Context of Crash Risk Prevention

Bearing in mind the insights provided by the validity-related analyses, our results indicate that the PURS validity measures are consistent with findings from broader transport safety research, emphasizing that mobile phone use while cycling constitutes a complex and closely attention-related behavior involving both deliberate and compensatory actions. This is also highlighted in previous research on distraction, risky road behavior (especially technology-induced errors), and safety outcomes. For instance, prior studies such as Jiang et al. (2021) and Oviedo-Trespalacios et al. (2016) claim that different forms of phone use –manual, auditory,

and compensatory– are present in cycling, driving, and pedestrian contexts, with varying degrees of risk. On a practical level, the validity analyses support the theoretical soundness of the PURS, positioning it as a psychometrically solid instrument for assessing mobile phone use behaviors among cyclists.

Path analysis: Does the PURS predict cyclists' safety outcomes?

Finally, regarding *Hypothesis 4*, the predictive validity of the Phone Use while Riding Scale (PURS) was tested using a Structural Equation Modeling (SEM)-based Path Analysis, which examined whether the scale effectively predicts self-reported cycling errors and crash involvement. The structural model controlled for key demographic variables, including age, education, and cycling exposure, to ensure that the associations identified between PURS scores, risky cycling behaviors, and crash rates were not merely artifacts of individual differences.

Regarding the predictive paths between Phone Use while Riding (measured through the PURS) and cycling safety variables, there were consistently positive and significant associations for both riding errors (bootstrapped $\beta = .510$; $p < .001$) and self-reported crashes ($\beta = .183$; $p < .001$). This methodologically supports the robustness of the PURS in predicting cyclists' safety-related outcomes, as previous studies have similarly found strong predictive relationships between self-reported mobile phone use and cycling risk indicators (Oviedo-Trespalacios et al., 2016; Useche, Alonso, et al., 2018; Møller, Berghoefer, et al., 2024).

From a theoretical standpoint, these findings align with previous research on safety-related transport behavior, which has associated mobile phone use while cycling, driving, or walking with increased attentional demand, risk compensation strategies, and greater exposure to traffic hazards (Simmons et al., 2020; Zhou et al., 2012). recent literature on 'slow mobility' users (e.g., pedestrians and cyclists) suggests that distraction sources in these groups are often

linked to crash-related outcomes through the statistical mediation of risky road behaviors, particularly unintentional errors. This pattern has been emphasized in causal studies on these specific road users, reinforcing the idea that distraction impacts safety not only directly but also through behavioral mechanisms. Notably, in contrast to previous studies on motor vehicle drivers, non-deliberate risk assumptions (i.e., errors) represent the most significant dimension of risky behavior among non-motorized road users. (Useche, Alonso, et al., 2018; Useche & Llamazares, 2022; Yue et al., 2020).

Additionally, studies on distracted driving and pedestrian behavior have shown that mobile device engagement consistently predicts errors and near-miss incidents (Jiang et al., 2021; Oviedo-Trespalacios & Scott-Parker, 2017). However, to the best of our knowledge, the specific influence of technological distractions on risky cycling behaviors and self-reported crashes had not been systematically examined until this study. Thus, this research represents a pioneering effort in addressing and assessing technological distractions in cycling safety through a behavioral questionnaire approach, providing a structured framework for further investigation and policy considerations.

Limitations

The PURS scale has some limitations that should be noted despite its promising psychometric qualities. First, only self-report measures were used to collect the data, which could be prone to retrospective recall errors or social desirability bias about driving behavior.

A more specific limitation is related to the demographic composition of the cross-cultural sample. While the study benefited from a significant global reach, the Australian subsample, which constituted the largest portion of the total participants, was characterized by being the second-oldest population on average. This demographic distribution is relevant for

validating a scale focused on technology use. A comparison of smartphone interaction patterns among older riders and riders with those of younger generations reveals distinct tendencies. Older riders tend to exhibit lower engagement with mobile devices while in motion. As the Australian data significantly influences the overall findings, the results might reflect the habits and perceptions of an older population, potentially underestimating the prevalence or variety of phone-related distractions common among younger users. Finally, the use of non-probabilistic convenience sampling may limit the generalizability of the results to the broader global population. Future studies should aim to validate the PURS using more balanced age distributions across different countries and incorporate naturalistic driving observations or simulator-based studies to cross-verify if self-reported phone use aligns with actual behavioral frequency and its impact on riding safety.

Conclusions

This study presented the cross-regional validation process of Phone Use while Riding Scale (PURS), a tool designed to assess mobile phone use behaviors and their associated risk-compensating strategies among cyclists. In line with the literature-based hypotheses, the findings suggest that the PURS has a robust psychometric structure, showing adequate factor loadings, strong reliability and internal consistency indices, and an appropriate model fit across both unifactorial and three-dimensional configurations. Moreover, the validity analyses further support its theoretical coherence, as the scale scores showed significant and meaningful associations with key external measures, reinforcing their relevance for behavioral research in cycling safety.

Regarding the multi-country character of this study, its optimal properties across different regions and its ability to maintain measurement invariance across them suggest that it

is a suitable tool for cross-regional comparisons, an increasingly relevant aspect in transport psychology and safety research.

Finally, beyond its psychometric properties, the results indicate that measuring mobile phone use through the PURS provides valuable insights into its implications for safety. In other words, its ability to predict risky cycling behaviors and self-reported crash involvement highlights its potential for research and intervention development.

Practical applications

From an applied perspective, the PURS offers several contributions that may be valuable for researchers, policymakers, and practitioners aiming to address cycling safety in the context of mobile phone use. While previous research has focused extensively on driver and pedestrian distraction, the PURS provides a structured approach to studying mobile phone use among cyclists, a growing but often overlooked issue in road safety.

The scale allows for differentiating between visual-manual interactions, hands-free auditory interactions, and risk-compensating behaviors, offering a more nuanced understanding of how cyclists engage with mobile devices while riding. By identifying the most prevalent and risky forms of mobile phone use while cycling, the PURS may help guide evidence-based policy recommendations, awareness campaigns, and targeted interventions aimed at reducing cycling distractions and enhancing road safety. Taken together, these findings reinforce the importance of addressing cyclist distraction as a behavioral and safety-related issue. The PURS may serve as a valuable tool for furthering knowledge on how mobile phone use influences cycling safety, ultimately supporting strategies aimed at promoting safer and more sustainable urban mobility.

Chapter IV

ITALIAN ADAPTATION OF NO-MOBILE-PHONE-PHOBIA QUESTIONNAIRE: FACTORIAL VALIDITY WITH ESEM TECHNIQUE AND POPULATION-BASED CUT-OFF SCORES

This chapter is based on: Traficante, S. Tinella, S., Lopez, A., Useche, S.A...Bosco, A., Caffò. A.O. Italian adaptation of No-Mobile-Phone-Phobia Questionnaire: factorial validity with ESEM technique and population-based cut-off scores across the lifespan, *European Journal of Investigation in Health, Psychology and Education*; (<https://doi.org/10.3390/ejihpe15080166>).

Introduction

The evolution of information and communication technologies (ICTs) has significantly reshaped how individuals communicate and access information, amplifying the dynamics of the ‘digital age’ in everyday life (Aceto et al., 2018; Hamelink et al., 1997). However, the pervasive use of mobile phones for communication, information retrieval, and social interaction has led to increased reliance on these devices, with psychological consequences when they become unavailable (see Jahrami et al., 2021, 2022). This technological revolution has also contributed to the emergence of new phobias and threats for mental health (Hodkinson, 2019; A. L. S. King et al., 2013). Among these, a particular condition has gained increasing attention: “NO-mobile-phone-phobia,” or Nomophobia, which describes the anxiety and fear experienced when individuals cannot use their technological devices for communication (Bhattacharya et al., 2019; Bragazzi & Del Puente, 2014; Gonçalves et al., 2020; Kaviani et al., 2020).

On a practical level, nomophobia has been linked to several ‘typical’ symptoms, including anxiety or panic when the phone is misplaced, runs out of battery, or has no network coverage (AlMarzooqi et al., 2022; Farchakh et al., 2021). Individuals may experience obsessive thoughts about checking their phone and staying connected, leading to restlessness or irritability if unable to do so. Physical symptoms can include sweating, trembling, and a rapid heartbeat (Bulut & Sengul, 2024). The condition can also affect daily activities, causing distraction, reduced productivity, and negative impacts on social interactions and mental health (Aguilera-Manrique et al., 2018).

Among its typical psychological expressions and correlates, nomophobia has been demonstrated to diminish attention span, impair working memory, and diminish cognitive performance during complex tasks that require concentration, such as problem-solving or project management (Gezgin et al., 2018; A. L. S. King et al., 2010). Additionally, it has been linked to increased anxiety, an inclination towards procrastination, and a reduction in the

capacity for critical and creative thinking (Cheever et al., 2014). As mobile phones have become integral to daily life, this phenomenon has become increasingly prevalent, and related by previous studies with a so-called ‘sense of urgency’ (Useche et al., 2024). Furthermore, the prevalence and severity of nomophobia have been growingly associated with demographic factors, especially gender and age (e.g. Gezgin & Çakir, 2018; Kaviani et al., 2020; Buctot et al., 2023).

Gendered and age-defined: Nomophobia and socio-demographic factors

Previous studies show that the prevalence and severity of nomophobia are not uniformly distributed. In fact, it varies between 6% and 73% across different populations, with significant associations to demographic factors, particularly gender and age (León-Mejía et al., 2021a). Specific studies further suggest that these factors are key in shaping an individual’s reliance on mobile devices and their susceptibility to anxiety when deprived of mobile connectivity (León-Mejía et al., 2021a). In other words, gender differences are clear across literature, with research indicating that women may experience higher levels of nomophobia than men, potentially due to different social and communication needs (Arpaci, 2022; Arpaci et al., 2017).

Regarding these gender differences, women often use mobile phones for social communication, increasing their dependence on these devices and their anxiety when they are unavailable (Bian & Leung, 2015). Furthermore, women are typically more sensitive to social and emotional cues, which can heighten the distress related to being out of touch through mobile communication (Arpaci, 2022). In contrast, men tend to use mobile phones for more utilitarian purposes, such as information retrieval and gaming, leading to a different dependency pattern (León-Mejía et al., 2021a; Notara et al., 2021). Additionally, cultural and social expectations related to gender roles may contribute to these differences. Women are often expected to maintain close social and emotional connections, which are facilitated through mobile phone

use (Walker et al., 2015). Consequently, the disruption of this ‘communication network’ can lead to greater psychological discomfort.

Moreover, as suggested by the limited available literature, age appears to be a clear differentiating factor in nomophobia. Younger individuals, particularly adolescents and young adults, are generally more susceptible, often reporting higher scores and experiencing greater discomfort when disconnected (Gurbuz & Ozkan, 2020). This vulnerability is attributed to their extensive use of smartphones for social networking, academic activities, and entertainment (Moreno-Guerrero et al., 2020). The pervasive integration of mobile technology into their everyday lives fosters strong dependence, increasing their anxiety when disconnected. In contrast, middle-aged and older adults tend to show lower levels of nomophobia, which is related to less frequent use of technology compared to younger individuals. In addition, previous studies have systematically shown how older adults often have difficulty interacting with technological devices in several spheres, compared to younger generations (Lijarcio et al., 2019; Vaportzis et al., 2017). However, it is noteworthy that the gap is narrowing as mobile technology becomes more ubiquitous and integral across all age groups (Fox & Connolly, 2018).

Assessment of Nomophobia: Present and future tools and practices

In recent years, various instruments have been developed to assess the problematic use of technology and nomophobia. Particularly, the Mobile Phone Involvement Questionnaire (MPI-Q) (Walsh et al., 2010) and the Problematic Mobile Phone Use Questionnaire (PMPU-Q) (Billieux et al., 2008) have gained prominence as accurate and valid questionnaires in this pursuit. Overall, these scales are designed to assess different aspects of mobile phone usage and potential dependency.

The MPI-Q assesses the degree of an individual's involvement with their mobile phone, covering dimensions such as frequency of use, emotional attachment, and the extent to which phone use interferes with daily activities. It helps identify users who may display problematic behaviors (Walsh, White, & Young, 2010).

In contrast, the PMPU-Q focuses on the problematic aspects of mobile phone use, including addiction symptoms such as withdrawal, tolerance, and the negative consequences of phone use on daily life (Billieux et al., 2008). It provides a broader view of mobile phone dependency and its adverse effects. While both questionnaires offer valuable insights into mobile phone use and dependency, they lack specific items that address the emotional and psychological responses linked to the absence of a mobile phone, which is important for screening possible cases of nomophobia.

At a practical level, and given the rising prevalence of nomophobia, there has been a clear need to identify and develop tools to assess this condition. Yildirim & Correia (2015) validated a new psychometric tool, the Nomophobia Questionnaire (NMP-Q), for the identification of the levels of nomophobia. The NMP-Q comprises 20 items and four sub-scale that investigate four nomophobia dimensions: “not being able to access information”, “giving up convenience”, “not being able to communicate, and losing connectedness”. To date, the NMP-Q has been translated and validated in different countries, including China (Gao et al., 2020), Spain (Gutiérrez-Puertas et al., 2019), Portugal (Galhardo et al., 2020), Mexico (Caba-Machado et al., 2024) and Italy (Adawi et al., 2018).

In each of these validations, the original four-factor structure was retained, with the exception of the Italian validation, which proposed a three-factor structure as more appropriate. The psychometric properties of the Italian version of the NMP-Q (Adawi et al., 2018), particularly its factor structure, remain open to debate. This version suggested a three-factor

model (Adawi et al., 2018), which may not fully cover the complexity of nomophobia compared to Yildirim & Correia (2015), supporting the rather literature-based original model. Moreover, Adawi et al. (2018) did not conduct Confirmatory Factor Analysis (CFA) procedures to assess the fit of the factorial model with the empirical data, nor did they establish normative data population-based for identifying different levels of nomophobia.

The present study

Given these limitations, we are interested in contributing further to the validation of the tool, including the reproducibility of the proposed results and models. Therefore, the aim of this study was twofold: first, the aim is to examine which of the two models (3 or 4 factors) fits our data better. We are interested in providing further input into the validation of the tool, including the replicability of the proposed results and models. Second, to establish empirically supported cut-off points for identifying different levels of nomophobia in the Italian population.

Regarding the first objective, several studies have introduced a second-order factor to explain the four dimensions of nomophobia (Caba-Machado et al., 2024; Galhardo et al., 2020; A. León-Mejía et al., 2021b). However, the relationships between each indicator and the higher-order factors are indirect, mediated by first-order factors. This assumption is somewhat rigid and often lacks empirical support (Gignac & Kretzschmar, 2017). Consequently, several studies advocate for the use of Bifactorial Exploratory Structural Equation Modeling (B-ESEM) as a more effective approach to evaluating the factorial structure of multidimensional constructs (Marsh et al., 2014; Morin et al., 2016).

This method separates the total item covariance into a global component (the G factor), which accounts for the variance shared across all items, and specific factors (S factors) that explain the covariance within subsets of items not captured by the global component. It directly explains the relationship between each indicator (specific factor S) and the higher-order factors

(general factor G) (Valenti et al., 2024). Interestingly, the literature has demonstrated that the B-ESEM approach most effectively represents the complexity of the nomophobia construct, yielding optimal fit indices (Valenti et al., 2024).

Regarding the second aim, the results of this validation study are expected to provide researchers and clinicians with a reliable tool for measuring nomophobia in the Italian context. In other words, it is expected that a more accurate factor structure will improve the identification of individuals at risk of nomophobia and inform targeted interventions.

Methods

Study setting

This study employed a cross-sectional, questionnaire-based design. Data collection followed a convenience (pseudo-probabilistic) sampling approach, focusing on the general population. Participants were screened to ensure they were in good physical and psychological health, using a set of inclusion/exclusion criteria prior to participation. A group of supervised trainees conducted brief neuropsychological assessments, gathering demographic information, excluding individuals with neurodegenerative, vision, or hearing disorders (3 participants were excluded from the study), and collecting details about participants' smartphone usage and technological habits. Data were collected between October and December 2023 as part of a larger research project at the University of Bari (Italy), focused on studying driving distractions, including the use of technological devices by drivers.

The NMP-Q used in this study was the Italian translation by Adawi et al. (2018). The scale items were translated using the “backward and forward” method, following the steps outlined in both specialized literature and previous adaptations of scales addressing similar topics (Adawi et al., 2018; Peters & Passchier, 2006).

Ethical Issues

We recognize the significance of a more comprehensive ethical analysis in addition to the official ethics committee approval and the implementation of common safeguards (such as anonymity and informed consent). According to Petousi and Sifaki (2020), identifying possible contextual harm, like over-pathologizing commonplace behaviors or fostering digital stigma, is another aspect of ethical integrity in research. Therefore, to reinforce a preventive and awareness-raising framework, our study was designed to minimize interpretive bias, respect participants' autonomy, and avoid any labeling or diagnostic implications. Indeed, the research was conducted following the principles set out in the Declaration of Helsinki and approved by the local ethics committees (ET-23-23). Finally, informed consent was obtained from all patients to participate in the study

Study sample

A total of 1,147 participants took part in the study, including 658 females (age: $M \pm SD = 40.40 \pm 19.30$) and 489 males (age: $M \pm SD = 47 \pm 19$), with ages ranging from 18 to 85 years. The sample was designed to cover the entire lifespan to enhance the reliability and representativeness of the study findings. Given its size and diversity, the sample coverage was considered satisfactory, with a N/k ratio adequate (number of participants/number of items = $1147/21 = 54.35$ (Kline, 2023) for conducting factorial analysis. The participants of the study were exclusively Italian and white. Information regarding the educational level and other demographic characteristics of the study sample is described in detail in Table 1.

Table 1. Descriptive statistics

	Gender	N	M	SD	Skewness		Kurtosis	
					Skewness	S.E.	Kurtosis	S.E.
NMPQ_TOT	F	658	68.8	25.18	.118	.095	-.509	.190
	M	489	59.7	24.89	.371	.110	-.357	.220
AGE	F	658	40.4	19.26	.366	.095	-.206	.190
	M	489	47.0	19.01	.002	.110	-.258	.220
EDU	F	657	13.6	3.96	-.372	.095	.322	.190
	M	488	12.6	4.04	.103	.110	.568	.221

Statistical Analysis

To assess the factorial validity of the Italian version of the NMP-Q, an Exploratory Structural Equation Modeling (ESEM) was conducted using R Studio (version 4.4.1, 2024). This method was employed to identify the underlying relationships among the measured variables.

The model was evaluated using several goodness-of-fit criteria: chi-square value (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). Different ESEM models were tested to confirm the optimal factorial configuration for the instrument. The thresholds for CFI and TLI were set at $> .900$, SRMR and RMSEA at $< .080$ (Kuha, 2004; Ruiz-Hernández et al., 2020; Marsh et al., 2004). In addition, three cut-off points were established to categorize different levels of nomophobia across age categories and divided by gender.

For comparative analyses, analysis of variance (ANOVA) was used to assess age differences, and t-tests for independent samples were conducted to examine gender differences,

if any. Internal consistencies were assessed by calculating Cronbach's alpha and McDonald's omega coefficients for the overall scale (approached as an unifactorial construct) and each subscale, following the literature-based hypnotizable composition of the scale. Finally, measurement invariance was assessed by gender (male vs. female) and age categories (young adults vs. adults; adults vs. older adults).

Results

Results of comparison models with ESEM approach

Overall, the ESEM outcomes confirm the suitability of a four-factors configuration. The four-factors identified are the same as those of the first validation: (1) Not being able to communicate; (2) Losing connectedness; (3) Not being able to access information; (4) Giving up convenience (Yildirim & Correia, 2015). Factor 1 explains the 17.9% of item variance; Factor 2 explains the 14.9% of item variance; Factor 3 explains the 11.8% of item variance and Factor 4 explains the 10 % of item variance. To further examine the factorability of the matrix, Bartlett's test of sphericity was employed to analyze both partial and bivariate correlations. Additionally, the Kaiser-Meyer-Olkin (KMO) measure was used to evaluate sampling adequacy. Bartlett's test of sphericity yielded significant results ($\chi^2 = 17831$, $df = 190$; $p < .01$), rejecting the null hypothesis that the correlation matrix was an identity matrix with zero off-diagonal correlations (Williams et al., 2010). Regarding sampling adequacy, the KMO index was .955. Consequently, these findings confirmed that factor analysis was adequate for the data (Kaiser & Rice, 1974).

In order to examine different possible compositions of the NMP-Q, different ESEM models were tested. We evaluated one factor, combinations of two and three factors from different factor solutions, and four factors to test the EFA results. Additionally, we evaluated the bifactor model with a four-factor solution (B-ESEM). We chose to test this factorial

configuration because, in the B-ESEM solution, the associations between general and specific factors are direct. This means that all indicators load onto both a general factor (Factor G) and specific factors (Factor S). The variance of the items is divided into three sources: (a) the specific factor, (b) the general factor, and (c) measurement error. For these reasons, it has been suggested that unless there is a strong theoretical justification for a higher-order representation, bifactor models should be preferred (Marsh et al., 2014; Valenti et al., 2024).

The main results of comparisons between models are shown in Table 2. The best-fitting model was Model 1, which featured the anticipated B-ESEM solution. All fit indices were satisfactory, with both the CFI and the TLI exceeding .900 SRMR, and RMSEA less than or equal to .080 (Byrne, 2001). These indices, which are considered less sensitive to sample size, indicate a good fit between the models. Considering the ESEM findings and the indices, the B-ESEM model with four-factor results in the best factorial configuration, with CFI, TLI, SRMR, and RMSEA satisfactory (CFI: .960; TLI: .940; SRMR: .03; RMSEA: .060). Finally, all standard estimations are significant ($<.001$). The comparison between the models makes it clear that the other factorial configurations are not adequate. Indeed, the chi-square difference tends to increase from Model 1 ($\Delta\chi^2=426$; $p < .001$) to Model 13 ($\Delta\chi^2=3463$; $p < .001$). Furthermore, alternative models failed to adequately fit the data, rendering these solutions unacceptable. Therefore, the conclusion is that the four-factor solution using items in the Italian language is the optimal choice, aligning well with the original factorial configuration (Yildirim & Correia, 2015). The Bifactor Exploratory Structural Equation Modeling with four factors (B-ESEM) plot with standard estimates (λ) is shown in Figure 1.

Table 2: Results of ESEM comparison models (Model 13 to Model 1).

Model Type	MODEL	χ^2	df	<i>p</i>	CFI	TLI	SRMR	RMSEA	Model Comparision	$\Delta\chi^2$	df	<i>p</i>
M13	1 factor-configuration	5001	170	.001	0.72	0.68	.09	.15	M13-M1	3463	6	.001
M12	2 factors (1+2)(3+4)	4355	169	.001	0.75	0.72	.09	.14	M12-M1	2817	5	.001
M11	2 factors (1+3)(2+4)	4161	169	.001	0.76	0.74	.09	.14	M11-M1	2624	5	.001
M 10	2 factors (1+4)(2+3)	3494	169	.001	0.80	0.78	.09	.13	M10-M1	1956	5	.001
M9	3 factors (3+4), 2, 1	3812	167	.001	0.79	0.76	.08	.13	M9-M1	2274	3	.001
M8	3 factors (1+2), 3, 4	3812	167	.001	0.79	0.76	.08	.13	M8-M1	2274	3	.001
M7	3 factors (1+3), 2, 4	3049	167	.001	0.83	0.81	.09	.12	M7-M1	1511	3	.001
M6	3 factors (2+3), 1, 4	2825	167	.001	0.84	0.82	.07	.11	M6-M1	1288	3	.001
M5	3 factors (2+4), 1, 3	2662	167	.001	0.85	0.83	.07	.11	M5-M1	1124	3	.001
M4	3 factors (1+4), 2, 3	2231	167	.001	0.88	0.86	.07	.10	M4-M1	694	3	.001
M3	4 factors (1+2+3+4)	1538	164	.001	0.92	0.91	.06	.08	M3-M1	604	24	.001
M2	Bifactor model with 3 factors	1261	144	.001	0.93	0.92	.06	.08	M2-M1	426	4	.001
M1	Bifactor model with 4 factors	835	140	.001	0.96	0.94	.03	.06				

Notes: χ^2 = chi-square; df= degrees of freedom; CFI= Confirmative Fit Index; TLI= Tucker-Lewis Index; SRMR= Standardized Root Mean Square Residual; RMSEA= Root Mean Square Error of Approximation; $\Delta\chi^2$ = delta chi-square; *p*= *p*-value. The highlighted sections in grey show the best-fitting models (M1 and M2) with the B-ESEM solution.

Reliability and Internal Consistency

The four-factor configuration of the NMP-Q shows good internal consistency, with Cronbach's and McDonald's alpha coefficients exceeding .800 for each subscale and for the overall scale ($\alpha/\omega \approx [.850 - .930]$; overall $\alpha/\omega \approx .950$), suggesting an adequate level of internal consistency for both the questionnaire appraised from an unifactorial perspective and its four specific and psychometrically-endorsed subscales.

Table 3 presents Cronbach's alpha and McDonald's omega values if an item is deleted. Based on the results, each item can be considered indispensable, as removing any item from an NMP-Q subscale either decreases or maintains the Cronbach's alpha and McDonald's omega values, according to the four-factor composition shown in Figure 1.

Table 3. Results of ESEM and Reliability analyses of the full scale and its subscales.

Items	λ	Cronbach's alpha if item deleted	McDonald's omega if item deleted	Cronbach's alpha	McDonald's omega
Factor 1 (Not being able to communicate)					
13	0.934	0.911	0.912	0.932	0.931
11	0.902	0.919	0.919		
10	0.767	0.916	0.917		
12	0.630	0.919	0.919		
14	0.616	0.921	0.922		
15	0.567	0.930	0.930		
Factor 2 (Losing connectedness)					
18	0.876	0.849	0.859	0.895	0.902
17	0.913	0.854	0.861		
16	0.799	0.865	0.875		
19	0.601	0.892	0.901		
20	0.410	0.895	0.902		
Factor 3 (Not being able to access information)					
2	0.941	0.824	0.826	0.879	0.880
4	0.731	0.840	0.841		
1	0.605	0.857	0.859		
3	0.590	0.824	0.860		
Factor 4 (Giving up convenience)					
6	0.784	0.817	0.817	0.853	0.855
5	0.642	0.818	0.822		
7	0.615	0.815	0.817		
8	0.532	0.828	0.831		
9	0.470	0.838	0.840		
Full scale (Unifactorial composition)				0.951	0.952

Notes: λ = Lambda factor loadings / standardized estimates

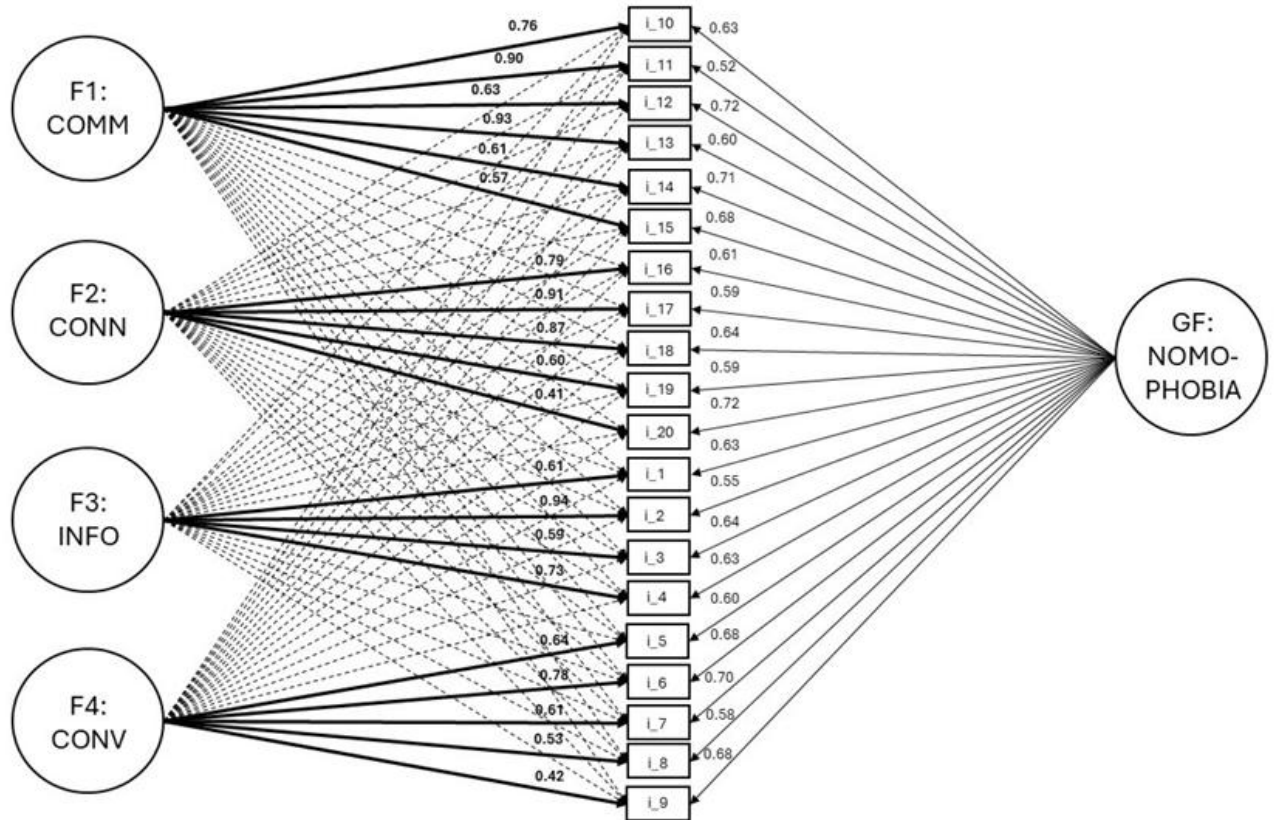


Figure 1. Bifactor Exploratory Structural Equation Modeling with four factors (B-ESEM) with standard estimates. *Notes:* **GF: NOMOPHOBIA**= general factor of nomophobia; **F1: COMM**= Not being able to communicate; **F2: CONN**= Losing connectedness; **F3: INFO**= Not being able to access information; **F4: CONV**= Giving up convenience.

Cut-off points of Italian version of NMP-Q for age and gender

Cut-off points for different age categories were established: young adults (18-29 years old), adults (30-64 years old), and older adults (65+ years old). The mean and standard deviation of the NMP-Q for females was 68.8 ($SD = 25.2$), while for males it was 59.7 ($SD = 24.9$). We have identified significant differences between age and gender in the total score of NMP-Q. The sex differences have been observed through a t-test for independent samples ($t = 6.13$; $df = 1145$; Cohen's $d = .366$; $p < .001$), while the age differences have been observed in all three age categories through a one-way ANOVA ($F = 59.5$; $p < .001$).

Moreover, the post-hoc tests showed the significant difference between young adults and adults (M differences= -14.8; $p < .001$), young adults and older adults (M differences= 25.7; $p < .001$) and adults and older adults (M differences= 10.9; $p < .001$). Three cut-off points have been identified, corresponding to the 80th and 95th percentiles, for males and females and for each of three age categories. The two percentiles correspond to the following categories, respectively: risk of nomophobia, and nomophobia.

Such cut-off points have been established following the existing literature on the topic. Indeed, the León-Mejía study (2021b) and the González-Cabrera (2017) study have identified these three cut-off points in line with other technological contexts, such as gaming disorders, pathological gambling, and problematic use of the technology. In light of this, we have adapted the nomophobia construct to these categories, as done by León-Mejía (2021b) and González-Cabrera (2017). Table 4 presents the percentile scores for each age category, split by gender.

Table 4. Cut-off scores split by age and gender

Percentile	Male			Female		
	Young Adults (18-29) n= 140	Adults (30-64) n= 248	Older Adults (65-85) n= 102	Young Adults (18-29) n= 280	Adults (30-64) n=287	Older Adults (65-85) n= 92
1th	20	20	20	29	20	20
5th	33	25	20	42	28	20
10th	40	29	20	49	36	20
15th	43	33	20	55	40	21
20th	47	36	20	59	43	25
25th	52	40	25	65	48	29
30th	55	43	28	69	51	33
35th	59	46	34	72	53	38.
40th	61	49	39	74	56	40
45th	65	53	42	76	60	41
50th	69	57	46	79	62	43

55th	71	61	50	83	66	46
60th	74	63	54	87	68	53
65th	78	66	59	90	71	60
70th	79	72	65	93	74	65
75th	81	75	67	96	78	73
80th	87	79	71	100	82	76
85th	92	83	79	106	89	80
90th	95	89	89	110	93	83
95th	108	102	96	120	105	97
99th	127	119	100	135	118	97
M	68.0	58.5	49.1	80.1	63.7	50.2
SD	22.3	9.6	24.8	22.8	22.3	24.1

Notes: Bold rows indicate the 80th. and 95th percentiles. The two percentiles correspond to the following categories, respectively: risk of nomophobia (80th) and nomophobia (95th). Such cut-off points have been established following the existing literature on the topic.

Multi-group gender and age invariances

Multi-group invariance analysis was conducted on subgroups defined by gender and age categories. The baseline model, assessing configural invariance, demonstrated a good fit to the data ($S-B\chi^2 = 1768.938$, $df = 328$, $RMSEA = .055$, $CFI = .916$), suggesting that the structure of the instrument was similar across both gender groups.

Next, metric invariance was assessed. The results showed that the metric invariance model fit the data well ($S-B\chi^2 = 1776.627$; $df = 344$, $RMSEA = .062$; $CFI = .916$). The non-significant change in χ^2 ($\Delta\chi^2 = 7.689$; $p > .050$) and negligible changes in CFI ($\Delta CFI = .001$) and RMSEA ($\Delta RMSEA = .001$) suggest that factor loadings were largely equivalent across gender. Moreover, scalar invariance (the most restrictive level, assessing the equivalence of intercepts) was also examined in detail. While the scalar invariance model showed an acceptable fit ($S-B\chi^2 = 1829.497$; $df = 364$; $RMSEA = .080$; $CFI = .912$), the significant change

in χ^2 ($\Delta\chi^2 = 52.870$; $p < .001$) and notable changes in CFI ($\Delta\text{CFI} = .010$) and RMSEA ($\Delta\text{RMSEA} = .011$) suggest that full scalar invariance was not supported.

A similar procedure was followed to investigate variations by age categories. The configural model, testing for equivalence in the factorial structure's form, demonstrated acceptable fit ($S\text{-}B\chi^2(492) = 1437.301$; $p < .001$; $\text{RMSEA} = .070$; $\text{CFI} = .912$), suggesting that the same latent factors underlie the observed variables in both groups. The metric invariance model also showed an acceptable fit ($S\text{-}B\chi^2(524) = 1468.825$; $p < .001$; $\text{RMSEA} = .075$; $\text{CFI} = .910$). The non-significant change in χ^2 ($\Delta\chi^2(32) = 31.524$; $p = .69$) and minimal changes in CFI ($\Delta\text{CFI} = .003$) and RMSEA ($\Delta\text{RMSEA} = .005$) indicate that the relationships between the items and their respective factors were largely equivalent across Young Adults and Adults.

The scalar invariance model, however, showed a statistically significant change in χ^2 ($\Delta\chi^2(40) = 156.926$; $p < .001$), suggesting a lack of full scalar invariance. Also, the changes in CFI ($\Delta\text{CFI} = .013$) and RMSEA ($\Delta\text{RMSEA} = .009$) indicate that scalar invariance was not supported. Finally, the configural model exhibited acceptable fit for adults and older adults: $S\text{-}B\chi^2(328) = 1347.900$; $p < .001$; $\text{RMSEA} = .078$; $\text{CFI} = .924$. The metric invariance model also showed a considerably acceptable fit: $S\text{-}B\chi^2(343) = 1380.758$; $p < .001$; $\text{RMSEA} = .080$; $\text{CFI} = .911$, as shown in detail in Table 5. While the change in χ^2 was statistically significant ($\Delta\chi^2(15) = 32.841$; $p < .010$), the small changes in CFI ($\Delta\text{CFI} = .006$) and RMSEA ($\Delta\text{RMSEA} = .002$) suggest that factor loadings remained equivalent across these age groups. However, the scalar invariance model revealed a statistically significant change in χ^2 ($\Delta\chi^2(17) = 38.584$; $p < .010$), indicating a lack of scalar invariance. Also, as in the previous case, the changes in CFI ($\Delta\text{CFI} = .009$) and RMSEA ($\Delta\text{RMSEA} = .006$) indicate that the scalar invariance was not supported.

Table 5. Multi-group gender and age invariances of NMP-Q scores.

Model	df	S-Bχ^2	RMSEA	CFI	Diff. χ^2	ΔCFI
<u>Gender</u>						
Configural Invariance	328	1768.938	.055	.916	-	-
Metric Invariance	344	1776.627	.062	.916	7.689	.000
Scalar Invariance	364	1829.497	.080	.912	52.870***	.005
<u>Age</u>						
Young Adults vs. Adults						
Configural Invariance	492	1437.301	.070	.912	-	-
Metric Invariance	524	1468.825	.075	.910	31.524	.003
Scalar Invariance	564	1624.332	.079	.901	156.926***	.011
Adults vs. Older Adults						
Configural Invariance	328	1347.900	.078	.924	-	-
Metric Invariance	343	1380.758	.080	.911	32.841**	.009
Scalar Invariance	360	1419.302	.086	.903	38.584**	.009

Notes: S-B χ^2 = Satorra-Bentler Chi-square; df = Degrees of freedom; RMSEA = Root Mean Square Error of Approximation; CFI: Comparative Fit Index; Diff. χ^2 = Chi-square difference; Δ CFI = differences in Comparative Fit Index; ** $p < .010$; *** $p < .001$

Discussion

The present study aimed to validate an Italian version of the NMP-Q and to provide relevant insights into the measurement of nomophobia. Approaching the NMP-Q from a psychometric perspective, the findings of this study offer valuable insights into its dimensional structure, reliability, and population-based cut-off points as a self-report tool for assessing nomophobia under optimal methodological assumptions.

The following section discusses these key aspects in light of previous research, relevant theoretical frameworks, psychometric results, descriptive findings, and practical implications from the present study.

Three or four? How does the NMP-Q fit the best?

The first aim of this study was to evaluate the psychometric properties of the NMP-Q and to determine whether a four-factor model offers a more accurate representation of the nomophobia construct with respect to a previously validated three-factor model. The results of the B-ESEM support the superiority of the four-factors model, consistently to the concluded by (Valenti et al., 2024). Particularly, the B-ESEM model with four factors, including a general factor (G) and four specific factors (S), demonstrated a significantly better fit than alternative models.

From a psychometric approach, this is supported by the ordinal and error-related fit indices obtained in the retained model, where both the CFI and TLI both exceeded the threshold of .900, and the RMSEA was below .080 (Hu & Bentler, 1999). These indices suggest that the four-factor B-ESEM model aligns well with the data, consistent with the theoretical framework proposed by Yildirim & Correia (2015). Furthermore, chi-square tests reinforced the inadequacy of alternative factorial configurations, further substantiating the robustness of the four-factor solution (see León-Mejía et al., 2021).

Considering previous research, this factorial structure appears to be more aligned with a four-factor version of the NMP-Q globally. For example, the Chinese validation of the instrument supports a four-factor model (Gao et al., 2020), as does the Mexican validation, which includes the same factors identified in Yildirim and Correia's original model and incorporates a second-order factor explaining the relationships among the four dimensions of nomophobia (Caba-Machado et al., 2024).

The same theoretical structure has been found in the Spanish and Portuguese validations (Galhardo et al., 2020; León-Mejía et al., 2021). Once examined both these studies and the present outcomes, it seems obvious that a four-factors configuration provides a more

comprehensive representation of the multidimensional nature and psychological correlation and expressions of nomophobia. Moreover, following the methodological approach proposed by Valenti et al. (2024), we employed a B-ESEM model capable of explicitly capturing the relationships between the specific factors (S) and the higher-order general factor (G). In other words, this modeling approach seems to enhance the structural clarity of the NMP-Q, reinforcing the validity of the four-factors configuration over a three-dimensional approach.

Finally, an important finding of this study is the divergence from the previously validated three-factor Italian structure proposed by Adawi et al. (2018). The preliminary validation indicated a three-dimensional model that lost the distinction between “Loss of communication” and “Giving up convenience.” On the other hand, our findings support the original four-factor structure. The precision of the current adaptation represents methodological advancement for several reasons. In contrast to the PCA approach used in the previous Italian study, we employed ESEM. This technique is more robust because it accounts for cross-loadings, reducing the risk of inflated factor correlations often found in traditional CFA models (Asparouhov & Muthén, 2009). Moreover, the ESEM approach offers a more multidimensional representation of the psychological construct of nomophobia, acknowledging that specific behaviors (e.g., item 7 regarding battery life or item 15 regarding constant connection) may share variance across dimensions (Marsh et al., 2014). Preserving the four-factor structure of the model offers higher diagnostic sensitivity and theoretical alignment with the international literature, providing a more reliable tool for clinical screening in the Italian population.

Gender and Age-Based Cut-Off Scores: Examining Nomophobia Variability

Regarding the second aim of this study, we identified different cut-off scores for males and females. Overall, these thresholds differ from those proposed by León-Mejía (2021b) and González-Cabrera (2017) but follow a similar pattern. Additionally, our results indicate that

females consistently report higher levels of nomophobia than males across all age categories, a trend widely documented in the literature, which often highlights greater technology affinity and related concerns among female individuals (Gezgin et al., 2018; O'Hern et al., 2025).

Regarding age differences, these findings align with previous findings suggesting that younger individuals are more susceptible to nomophobia (Dasgupta et al., 2017), with levels peaking during adolescence and early adulthood (King et al., 2017). Conversely, the cut-off points for older adults were considerably lower than those observed in younger groups, reinforcing the literature-supported idea that nomophobia and problematic technology use tend to be less prevalent among older individuals (Gurbuz & Ozkan, 2020).

In addition to identifying cut-off points, the internal consistency of the NMP-Q was evaluated using Cronbach's alpha and McDonald's omega, adopted as complementarily reliable indicators of the scale's internal consistency. Looking at the numbers, both unifactorial coefficients approached .950, while subscale alphas ranged between .850 and .930, all exceeding conventional reliability thresholds. In other words, these results indicate a strong internal consistency, confirming that the items within each subscale effectively measure their respective constructs. The robustness of these reliability indices further supports the validity of the four-factor structure and highlights the NMP-Q's suitability for assessing nomophobia across different demographic groups.

While the current study provides strong evidence for the validity and reliability of the 4-factor model, it is not without limitations. The use of a convenience sample may limit the generalizability of the findings. However, future research should aim to replicate these results in more diverse and representative samples to improve the generalizability of the findings, including adolescents (Leon-Mejia et al., 2020; Gonzalez-Cabrera, 2017). Additionally, longitudinal studies are needed to examine the stability of the factor structure over time and to

explore the causal relationships between nomophobia and its psychological and behavioral correlates.

Conclusion

This study proposed a validation of the four-factors structure of the No-Mobile-Phone-Phobia Questionnaire in Italian population, confirming its reliability and utility as a self-report tool for assessing nomophobia. Its core conclusions, raised in accordance with the study aims and their practical implications, are summarized below:

First, the findings of this research support the psychometric suitability of the NMP-Q, as well as its applicability in both research and clinical screening contexts, facilitating the identification of individuals at higher risk and informing targeted interventions.

Second, this study identifies sensitive gender and age differences in nomophobia levels. Females consistently report higher nomophobia scores across age groups, while younger individuals exhibit greater susceptibility compared to older adults. These patterns reinforce the need for age- and gender-sensitive approaches in future research and intervention strategies.

On a practical level, the robust metric properties of the Italian NMP-Q make it a valuable instrument for investigating nomophobia in both academic and applied settings. Moreover, the alignment of the Italian version with the original factorial structure, composed of four literature-coherent dimensions, enhances its potential for cross-regional comparisons following the same theoretical approach.

In summary, this study has adapted a new factorial configuration with superior fit and robust psychometric properties. Nevertheless, future research should focus on more diverse and representative samples, including adolescents, and explore the stability of the factor structure over time.

Chapter V

“HEAD ON THE ROAD, MIND ELSEWHERE: THE MODERATING ROLE OF
GENDER AND DISTRACTION SUSCEPTIBILITY ON DRIVING PERFORMANCE
UNDER DIFFERENT PERCEPTUAL LOAD CONDITIONS”.

This chapter is based on: Traficante, S., Tinella, L., Lopez, A., Koppel, S., Ricciardi, E.,
Napoletano, R., ... & Caffò, A. O. (2024). “Head on the Road, Mind Elsewhere”: The
Moderating Role of Gender and Distraction Susceptibility on Driving Performance under
Different Perceptual Load Conditions”. [in preparation].

Introduction

Distracted driving is a major contributor to motor-vehicle crashes (MVCs). In the United States, about three thousand fatalities in 2023 involved distracted drivers (NHTSA, 2024), with younger adults (e.g., 18–29) frequently reported at elevated risk (Freeman et al., 2012). Furthermore, the recent increase in MVCs and injuries, especially in several high-income countries, highlights the need for more targeted prevention strategies (Curry et al., 2021; Fridman, 2021). According to the literature, Distracted Driving (DD) can be defined as the diversion of attention from the primary driving task to secondary activities driven by perception/response to external stimuli or self-generated internal thoughts (Lee, Young, and Regan, 2008). DD is often categorized by modality, typically into visual, auditory, motor, and cognitive forms (Neyens & Boyle, 2007). Considering mobile-phone use while driving as an illustration: visual distraction means shifting your gaze from the traffic scenario to the phone's screen; auditory distraction is attending to the caller's voice; manual distraction involves dialing or texting; and cognitive distraction is mentally processing the conversation (Sundfør et al., 2019). Looking away from the roadway is one clear visual hazard, but all the aforementioned types of distractions can contribute to MVCs, resulting in injury and fatalities.

For the sake of clarity, another important distinction must be considered between distraction and inattention. As mentioned before, DD involves an attentional shift to concurrent activities usually linked to stimuli from external sources (e.g., visual, auditory). However, Driver Inattention (DI) can be defined as the failure to invest attention in the driving task (Regan et al., 2011). Indeed, a recent review concluded that DI accounts for a substantial proportion of MVCs, fatal and non-fatal alike, with a lower-bound estimate of about 12% of all the registered MVCs (Sagberg & Sundfør, 2016). In this theoretical framework, the phenomenon of Mind-Wandering (MW) can be included (Smallwood & Schooler, 2014). In light of this, MW behind the wheel is defined as a shift of attention to internal mentation (Traficante et al., 2025).

Stawarczyk et al. (2011) defined MW as a specific conscious experience characterized by a series of thoughts that are not related to the task at hand and are not dependent on external stimulation.

Moreover, different studies defined it variously, but one of the most famous formulations associated with MW is “look but failed to see” (Herslund & Jørgensen, 2003). The term is usually used to describe a phenomenon known as inattention blindness, which occurs when an individual fails to perceive a visible stimulus because their attention is directed elsewhere (Charlton & Starkey, 2013). In such situations, drivers maintain a firm grip on the steering wheel and maintain their gaze on the road ahead. However, they do not allocate cognitive resources to the driving task (e.g., Kimura et al., 2022).

The previous literature showed different factors that affected MW during driving activities, including human factors (e.g., susceptibility to distraction, personality characteristics, etc.) (Tinella et al., 2022, 2024), environmental factors (e.g., weather conditions or road geometry; Burdett et al., 2017), and vehicle-related factors (e.g., advanced driver assistance systems, ADAS) (Traficante et al., 2025). While all these factors influence MW while driving, the most frequently mentioned factor in the literature is that related to perceptual load. Indeed, a substantial body of research, including studies by Geden et al. (2018) and Yanko and Spalek (2014), has identified a specific association between susceptibility to perceptual load and two distinct conditions: driving time and road familiarity. Indeed, extant research has demonstrated that MW at the wheel often occurs near the driver's place of residence or the immediate neighborhood (Burdett et al., 2017). This suggests the crucial role of familiarity with the driving environment, as a low perceptual-load condition, in influencing MW. On the other hand, the literature has demonstrated that under high perceptual load conditions, participants' minds wandered less often (Geden et al., 2018), focusing more attention on the driving task and producing more task-related thoughts (TRT) (Walker & Trick, 2018). He et al. (2011) showed

in their study that brief gusts of crosswind increased the demand for control (steering corrections to stay in lane). During/immediately after these disturbances, drivers reported fewer irrelevant thoughts. Crosswind, therefore, acted as an attentional anchor, increasing the perceptual load: greater task demand and less attentional decoupling.

Literature shows that when drivers are in a low perceptual load condition, they are more likely to engage in Task-Unrelated Thoughts (TUT) (e.g. Lemerrier et al., 2014; Özbozdağı, 2021). Furthermore, some studies have shown that these situations were associated with a deterioration in driving performance, observing that MW was associated with a reduction in driving distance (Yanko & Spalek, 2014), higher average speed (Burdett et al. 2019), and an increase in the standard deviation of the lateral position (SLDP: quantitative measure of the car's lateral movement, showing how consistently a driver stays within lane lines) (He et al., 2011; Baldwin et al., 2017). About the time factor, a study by Zhang & Kumada (2017) demonstrated that the frequency of MW increased significantly with driving time. This phenomenon is associated with driving fatigue, which increases the driver's cognitive load and impairs executive control, thereby increasing the likelihood of MW episodes.

Moreover, it is important to recognize that the impact of distraction and cognitive load on driving performance varies significantly among all drivers. Gender represents a significant demographic variable that has been demonstrated to influence driving behavior and distract driving susceptibility, as evidenced by numerous studies in the extant literature (e.g., Billah et al., 2022; Barr et al., 2015; Öztürk et al., 2023). A substantial body of research indicates that male drivers, particularly among the younger individuals, show a propensity to underestimate risk, a high level of sensation seeking, and overestimate their abilities (Fountas et al., 2019; Ulleberg & Rundmo, 2003). This cognitive bias has been associated with an increased likelihood of speeding and engaging in other hazardous behaviors (Ulleberg & Rundmo, 2003).

Conversely, female drivers tend to employ more cautious driving behaviors, showing an increased level of driving self-regulation (Kostyniuk & Molnar, 2008).

Despite considerable progress, some critical issues remain. First, although it is clear that perceptual load has an influence, there is a lack of literature on whether individual susceptibility to distraction amplifies or attenuates its impact on driving performance. Second, most studies examine only one cognitive aspect, and relatively few studies simultaneously assess TUT and TRT under systematically manipulated perceptual load. This limits the ability to provide a detailed description of how thought content changes with contextual demands. Third, the interaction between gender and other individual predispositions, such as susceptibility to distraction, in regulating driving performance under specific perceptual load conditions, remains to be fully clarified.

The present study

To address this gap, the present study aims to investigate the impact of distracted driving susceptibility and perceptual load on various behavioral patterns in a simulated driving task. To this end, a high-fidelity driving simulator was employed to measure moment-by-moment changes in steering, speed, and response to hazards. Moreover, we probed the participants' thoughts both online (during the task) and offline to investigate the frequency of TRT and TUT during the experimental conditions. Our hypotheses are formulated as follows:

H1: Participants with low susceptibility to distracted driving should maintain stable performance across different perceptual load conditions.

H2: Participants with high susceptibility to distracted driving should be more likely to worsen their driving performance in low perceptual load conditions.

H3: Participants should be more likely to incur TRT in the high perceptual load condition.

H4: Participants should be more likely to incur TUT in the low perceptual load condition.

Materials and Methods

Design

We aimed to understand how susceptibility to distracted driving and different levels of perceptual load, as predictors, interact together, influencing the conscious experience related to TRT and TUT. We have included gender as a covariate and three independent variables: perceptual load levels, susceptibility to distracted driving, and driving time. The first variable involved a within-subjects comparison of a high perceptual load condition and a low perceptual load condition. The second variable involved a between-subject comparison. Driving time was considered only in terms of the time points (3, 6, 9). We divided the sample into two groups based on high or low susceptibility to distraction. Groups were formed based on the results of the QUADRIVIA questionnaire, which detects different types of conscious experience related to distraction. Participants with a score equal to or below the 25th percentile were included in the low susceptibility group. Participants with a score equal to or above the 75th percentile were included in the high susceptibility group. Susceptibility groups were also balanced for gender. We then measured how these variables affected different behavioral patterns in a simulated driving task, including driving speed (meters per second, m/s), standard deviation of lateral position (SLDP) (meters, m), and steering angle (degrees °).

Participants

We recruited 34 undergraduate students in clinical psychology, comprising 24 females and 10 males (High Susceptibility Group: $M \pm SD = 21.82 \pm 2.06$; Low Susceptibility Group: $M \pm SD = 20.64 \pm 1.96$) from the University of Bari Aldo Moro. They were unaware of the study hypothesis. All participants were required to: (a) hold a valid, current driver's license, provisional or above; (b) have normal or corrected to normal vision; (c) have driven more than

one time within the last month; and (d) not be or have been a professional driver (e.g., taxi driver, truck driver, transporter on delivery, etc.). Descriptive statistics are reported in Table 1. All participants provided written informed consent before enrolment in the study, which was approved by the Ethical Committee of the host institution (ET-23-23). The study was conducted following the Helsinki Declaration and its subsequent amendments.

Table 1. Participants' information was split for gender and groups

	Gen	Groups	N	Mean	SE	SD
Age	F	H	12	21.75	0.60	2.09
		L	12	20.25	0.35	1.21
	M	H	5	22.00	1.00	2.23
		L	5	21.60	1.40	3.13
Edu	F	H	12	15.50	0.65	2.27
		L	12	14.91	0.46	1.62
	M	H	5	16.20	0.86	1.92
		L	5	13.80	0.49	1.09

Notes: Gen= gender; Edu= years of schooling; N= number of participants; SE= standard errors; SD= standard deviation; H= high susceptibility to distraction; L= low susceptibility to distraction

Self-Report measurements

The QUestionnAire on distraction in DRIVIng Activities (QUADRIVIA)

The QUADRIVIA was developed to assess the different types of conscious experiences associated with driving contexts, following the Stawarczyk et al. (2011) model. The questionnaire evaluates conscious experiences following two specific domains: Task Relatedness (TR) and Stimulus Dependency (SD). As discussed in Chapter II, we have opted to categorize these domains for three conscious experiences, driven by theoretical considerations: Task-Related Stimulus Independent (TRSI) (e.g. While driving, I consider the potential risks involved in driving), Task-Unrelated Stimulus Dependent (TUSD)(e.g. While

driving, I pay attention to noises or stimuli outside the vehicle [e.g. the noise of an airplane or a train passing by]), and Task-Unrelated Stimulus Independent (TUSI) (e.g. While driving, I start to daydream). The scale included 21 items. These items are rated on a 5-point Likert scale, with 1 “Never” and 5 “Almost always”. The score for each subscale is calculated by summing the responses to each subscale item (TRSI 6-30, TUSD 8-40, TUSI 7-35), resulting in total scores ranging from 21-105, with higher scores corresponding to greater susceptibility to distracted driving. Participants with a score equal to or below 51 (25th percentile) were included in the low susceptibility group. Participants with a score equal to or above 78 (75th percentile) were included in the high susceptibility group

Dundee Stress State Questionnaire (DSSQ)

The Dundee Stress State Questionnaire (DSSQ) (Matthews et al., 2002) is a multidimensional tool designed to measure transient states of stress, distinguishing them from stable personality traits. The questionnaire has 90 items and analyzes three main second-order factors: (1) Task Engagement, which reflects levels of energy, motivation, and concentration; (2) Distress, which measures feelings of tension, unhappiness, and low confidence in controlling the situation; and (3) Worry, which assesses self-reported cognitive interference and task-related self-esteem. Participants were asked to rate their current condition on a 5-point Likert scale (from 0 = ‘not at all’ to 4 = ‘extremely’). For a theoretical reason, we decided to use only 16 items related to the content of thoughts (Worry), TRT and TUT.

Simulator Sickness Questionnaire (SSQ)

To monitor the onset of symptoms related to simulator sickness, the Simulator Sickness Questionnaire (SSQ) (Kennedy et al., 1993; Biondi, 2018) was administered. The tool consists

of a checklist of 16 symptoms (e.g., general fatigue, headache, sweating, nausea) that the participant rates on a 4-point scale (0 = 'none', 1 = 'mild', 2 = 'moderate', 3 = 'severe'). The raw scores are processed using specific weighting formulas to obtain three diagnostic subscales: (1) Nausea (gastrointestinal and autonomic symptoms), (2) Oculomotor (visual fatigue and headache), and (3) Disorientation (dizziness and vestibular disorders). The questionnaire was administered in the post-exposure phase to quantify the impact of the simulation.

Apparatus and Stimuli

The simulation software employed in this study is a commercially available model manufactured by CarnetSoft BV, located in Groningen, Netherlands. The simulator's hardware consists of a computer (CPU Intel Core i7-11700K), three rendering monitors (HP V27i G5 FHD, 16:9), a steering wheel, pedals, and a gear shift (Logitech G29), as shown in Figure 1. The monitors were equipped with a 27" diagonal display and a 100-Hz refresh rate. They were positioned on laboratory tables at eye level in front of a black shroud, which obscured the laboratory room. The pedals and driver's seat were adjusted individually to ensure optimal comfort. The steering wheel, seat, pedals, and gear shift were positioned at the midpoint between the center and the left edge of the middle screen, thereby replicating the driver's position in a real car.



Figure 1: Our experimental setting using the CarneSoft software simulator (CarnetSoft® BV, Groningen, Netherlands). The image included three rendering monitors, a steering wheel, pedals, and a gear shift.

We adopted rural driving scenarios with daylight, one lane for each direction of traffic. The road's design was relatively simple, with road geometry and environmental details that were identical for both experimental conditions. By maintaining constant environmental conditions, any observed variation in driving performance metrics could be directly attributed to the effect of task duration and the presence of TUT, rather than to external factors related to road geometry. In the high perceptual load condition, the driving scenario entailed a car following task. In this task, the participant was required to follow the vehicle in front without overtaking and maintaining a safe distance, while the other lane was occupied with regular traffic moving in the opposite direction. In the low perceptual load condition, the driving scenario is identical to the other condition, but it is not a car-following task, and no traffic is shown in the opposite lane. We asked people to drive safely and follow the road rules. The driving scenarios are presented in Figures 2 and 3.

Driving performance was measured during all tasks, including average speed: variability of vehicle speed over time. Standard Deviation of Lateral Position (SDLP): standard deviation of vehicle position in the lane (lateral oscillations). Finally, steering angle: variability in steering wheel movements (measured as angular deviation or frequency of adjustments).



Figure 2. Driving scenario in the high perceptual load condition (CarnetSoft demonstration)



Figure 3. Driving scenario in the low perceptual load condition (CarnetSoft demonstration)

Procedure

Upon arrival, participants were asked to read and sign the informed consent form and were informed that they may experience symptoms typical of simulator sickness (e.g., nausea, dizziness, eye pain). Once the consent form had been signed, participants were invited to proceed to the simulator area, where they were greeted by the simulator operator and given instructions regarding the driving portion of the experiment. In particular, they were encouraged to drive safely, to observe all driving rules, and to always stay in the right lane. They were also informed that they would periodically hear the researcher inquiring about their thoughts during driving tasks. Following that, participants completed a 5-minute practice drive, which allowed them to become accustomed to the feeling of being in a driving simulator and to become familiar with the controls of the car.

Participants then completed the two experimental conditions, each lasting 10 minutes, and the order of which was counterbalanced across participants. Additionally, MW probes were used to determine whether the drivers were thinking about driving online and after completing the task. At five different times (1-3-6-8-9) during each driving condition, the researcher asked: "Are you thinking about anything right now?" If they said "No" or "Nothing," they kept driving. If they said "Yes", they were asked about the content of their thoughts. That means they were asked if their thoughts were task-related (TRT) or task-unrelated (TUT).

At the conclusion of each drive, participants were invited to complete the offline probing post-task and share their thoughts through the DSSQ (Matthews et al., 1991). For a theoretical reason, we decided to use only the 16 items related to the content of thoughts, TRT, and TUT. In light of this, we performed Cronbach's alpha and McDonald's omega for each subscale (TRT $\alpha=.817$; TRT $\omega=.844$; TUT $\alpha=.702$; TUT $\omega=.724$). The theoretical rationale for utilizing the Worry factor lies in its ability to capture the comprehensive spectrum of cognitive interference during the driving task. While TUTs (e.g., personal issues) and TRTs (e.g., concerns about

driving performance) have different origins, they both function as "competitors" for limited executive resources (Smallwood et al., 2003). By incorporating a factor that integrates both, we can assess the combined impact of intrusive thoughts on attentional decoupling. Specifically, Worry can reflect a state where the driver is not only distracted by internal life concerns (TUT) but is also cognitively overloaded by the evaluation of the task itself (TRT). In a simulated environment, this measure can provide a more ecologically valid representation of how a driver's internal distractions, regardless of their focus, deplete the working memory capacity necessary for maintaining optimal reaction times and situational awareness.

Finally, the SSQ (Biondi et al. 2018) was administered. Following the conclusion of the experiment, the participants were provided with a debriefing sheet and expressed their gratitude for their involvement. The entire experimental procedure lasted approximately 35 minutes.

Statistical Analysis

In the following sections, we present two sets of analyses. The initial investigation involved an analysis of variance (ANOVA), in which the effects of time on tasks (3, 6, and 9 time blocks), perceptual load levels, and susceptibility to distraction on driving performance were examined. This was conducted using repeated measures analysis of variance, one for each driving outcome. The second set of analyses involved a goodness-of-fit chi-square between the frequency distribution of different conscious experiences (TRT/TUT) detected online in high and low load conditions. Moreover, a paired sample t-test was performed to compare the mean values of TRT and TUT for the probing post-task.

Results

Analysis of Variance

Driving Speed

The analysis of variance on speed revealed a significant two-way interaction between Time and Load ($F(2, 60) = 13,420, p < .001; \eta^2p = .306$). However, the most interesting results emerge from higher-order interactions. Specifically, a post-hoc Time $\times$ Load $\times$ Gender analysis ($F(2, 60) = 4,588, p = .014; \eta^2p = .133$) demonstrated that the interaction between time and load was moderated by gender. Subsequent post hoc analysis revealed that, while the general trend demonstrated an increase in speed over time under Low Load conditions, this effect was more evident in male participants. Nevertheless, direct comparison between load levels at the final time point (Time 9) confirmed that the speed difference between Low Load and High Load was robust and statistically significant for both genders (for females, $p = .008$; for males, $p = .003$).

Additionally, a second three-way interaction Time $\times$ Group $\times$ Gender ($F(2, 60) = 4.613, p = .014; \eta^2p = .133$), suggests that levels of distraction susceptibility, in combination with gender, also modulate the evolution of speed over time. The post hoc analysis indicated a significant increase in speed from time 3 to time 6 for the high-susceptibility females ($p = .010$ and $p = .022$, respectively). Conversely, the speed of the low-susceptibility females remained consistently stable for the entire driving task. In contrast, males who demonstrated a high susceptibility to distraction showed a higher and more consistent speed compared to males with low susceptibility to distraction ($p = .005$) (Table 2, Figure 4, and Figure 5).

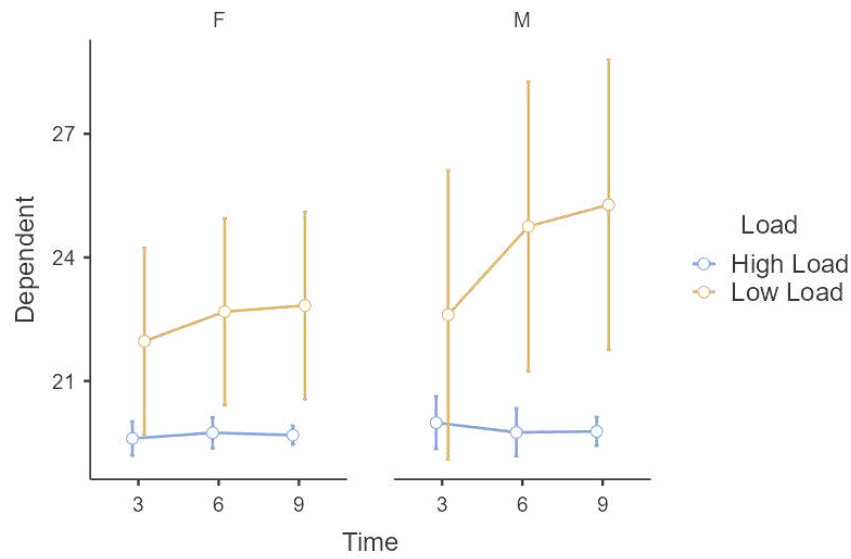


Table 2. Analysis of Variance of Speed

	Sum of Squares	df	Mean Square	F	p	η^2	η^2_p
Time	23.122	2	11.561	11.416	<.001	0.004	0.276
Time * Groups	0.630	2	0.315	0.311	0.734	0.000	0.010
Time * Gender	4.246	2	2.123	2.096	0.132	0.001	0.065
Time * Groups * Gender	9.343	2	4.671	4.613	0.014	0.001	0.133
Residual	60.763	60	1.013				
Load	547.634	1	547.634	13.225	0.001	0.084	0.306
Load * Groups	159.694	1	159.694	3.856	0.059	0.024	0.114
Load * Gender	25.723	1	25.723	0.621	0.437	0.004	0.020
Load * Groups * Gender	12.901	1	12.901	0.312	0.581	0.002	0.010
Residual	1242.279	30	41.409				
Time * Load	26.699	2	13.349	13.420	<.001	0.004	0.309
Time * Load * Groups	2.624	2	1.312	1.319	0.275	0.000	0.042
Time * Load * Gender	9.127	2	4.564	4.588	0.014	0.001	0.133
Time * Load * Groups * Gender	4.273	2	2.136	2.148	0.126	0.001	0.067
Residual	59.686	60	0.995				

Figure 4. Interaction effect between Time x Load x Gender

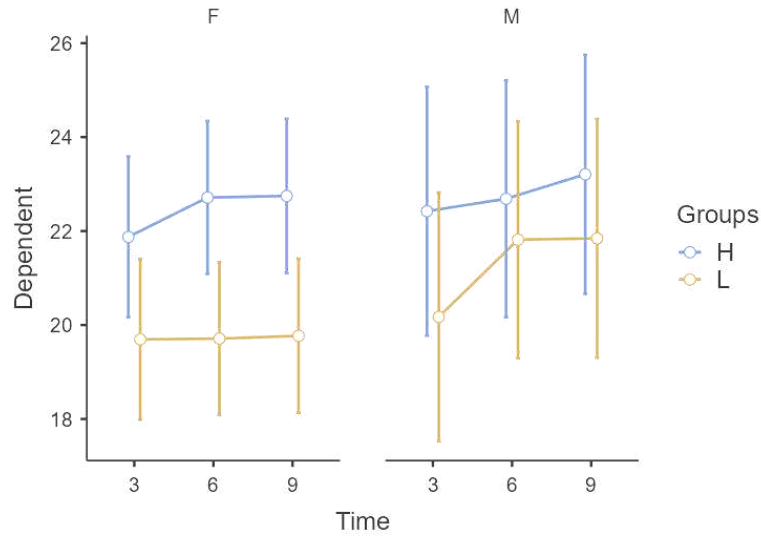


Figure 5. Interaction effect between Time x Groups x Gender (H= high susceptibility to distraction; L= low susceptibility to distraction; M= Male; F= Female).

Standard deviation of Lateral Position

The analysis revealed a statistically significant principal effect of the time factor, indicating that the SDLP of the participants within the lane changed during the test ($F(2, 60) = 4,427, p = .016, \eta^2_p = .129$). The analysis revealed no significant interactions between factors within subjects (Table 3). Considering the factors between subjects (Table 4), a statistically significant overall difference was observed between males and females in the maintenance of lateral position ($F(1, 30) = 4,711, p = .038; \eta^2_p = .136$). The absence of significant interactions suggests that these effects are constant. The difference between genders does not change as time or load varies, and the effect of time is the same for all participants, regardless of their susceptibility group, gender, or imposed cognitive load.

Table 3. Analysis of Variance of SLDP

	Sum of Squares	df	Mean Square	F	p	η^2	η^2_p
Load	0.063	1	0.063	3.243	0.082	0.017	0.098
Load * Gender	0.013	1	0.013	0.650	0.426	0.003	0.021
Load * Groups	0.066	1	0.066	3.375	0.076	0.018	0.101
Load * Gender * Groups	0.004	1	0.004	0.219	0.643	0.001	0.007

Table 3. Analysis of Variance of SLDP

	Sum of Squares	df	Mean Square	F	p	η^2	η^2_p
Residual	0.585	30	0.020				
Time	0.018	2	0.009	4.427	0.016	0.005	0.129
Time * Gender	0.004	2	0.002	1.016	0.368	0.001	0.033
Time * Groups	0.008	2	0.004	1.888	0.160	0.002	0.059
Time * Gender * Groups	0.006	2	0.003	1.361	0.264	0.002	0.043
Residual	0.123	60	0.002				
Load * Time	0.001	2	0.001	0.290	0.749	0.000	0.010
Load * Time * Gender	0.001	2	0.001	0.336	0.716	0.000	0.011
Load * Time * Groups	0.002	2	0.001	0.384	0.682	0.000	0.013
Load * Time * Gender * Groups	0.001	2	0.001	0.343	0.711	0.000	0.011
Residual	0.120	60	0.002				

Table 4. Between-Subjects Effects SLPD

	Sum of Squares	df	Mean Square	F	p	η^2	η^2_p
Gender	0.132	1	0.132	4.711	0.038	0.036	0.136
Groups	0.007	1	0.007	0.236	0.630	0.002	0.008
Gender * Groups	0.002	1	0.002	0.076	0.785	0.001	0.003
Residual	0.841	30	0.028				

Steering wheel angle

Statistically significant main effects emerged for both the Time ($F(2, 60) = 39,574$, $p < .001$; $\eta^2_p = .569$) and the Load ($F(1, 30) = 8,009$, $p = .008$, $\eta^2_p = .211$). These effects are qualified by a significant two-way interaction Load $\times$ Time ($F(2, 60) = 13,515$, $p < .001$). In this case, it was determined that the participants decreased the steering angle up to block 6 in the high-load condition and then increased it significantly in block 9. In the low-load condition, participants showed a wider steering angle throughout the task.

The three-way higher-order interaction Time $\times$ Gender $\times$ Groups ($F(2, 60) = 3.217$, $p = .047$; $\eta^2p = .097$) was significant. Post-hoc analysis showed that females with low susceptibility to distraction exhibited a significant change in steering angle between the initial and intermediate phases of driving (time 3 vs. time 6; $p < .001$). The males of this group also demonstrated a marked evolution, with significant differences both between the initial and final phase (time 3 vs. time 9; $p = .002$) and between the intermediate and final phase (time 6 vs. time 9; $p < .001$). In the high susceptibility group, a significant change in steering behavior was observed between the intermediate and final phases of the task (time 6 vs. time 9; $p < .001$). A similar pattern was observed in the male participants, who also demonstrated a significant change between the intermediate and final phases (time 6 vs. time 9; $p < .001$). (Table 5, Figure 6).

Table 5. Analysis of Variance of Steering Angle

	Sum of Squares	df	Mean Square	F	p	η^2	η^2p
Load	37.144	1	37.144	8.009	0.008	0.046	0.211
Load * Gender	1.168	1	1.168	0.252	0.619	0.001	0.008
Load * Groups	14.778	1	14.778	3.186	0.084	0.018	0.096
Load * Gender * Groups	0.048	1	0.048	0.010	0.920	0.000	0.000
Residual	139.139	30	4.638				
Time	24.966	2	12.483	39.574	<.001	0.031	0.569
Time * Gender	1.164	2	0.582	1.845	0.167	0.001	0.058
Time * Groups	0.680	2	0.340	1.078	0.347	0.001	0.035
Time * Gender * Groups	2.029	2	1.015	3.217	0.047	0.003	0.097
Residual	18.926	60	0.315				
Load * Time	7.970	2	3.985	13.515	<.001	0.010	0.311
Load * Time * Gender	0.860	2	0.430	1.459	0.241	0.001	0.046
Load * Time * Groups	0.249	2	0.124	0.421	0.658	0.000	0.014
Load * Time * Gender * Groups	1.010	2	0.505	1.713	0.189	0.001	0.054
Residual	17.690	60	0.295				

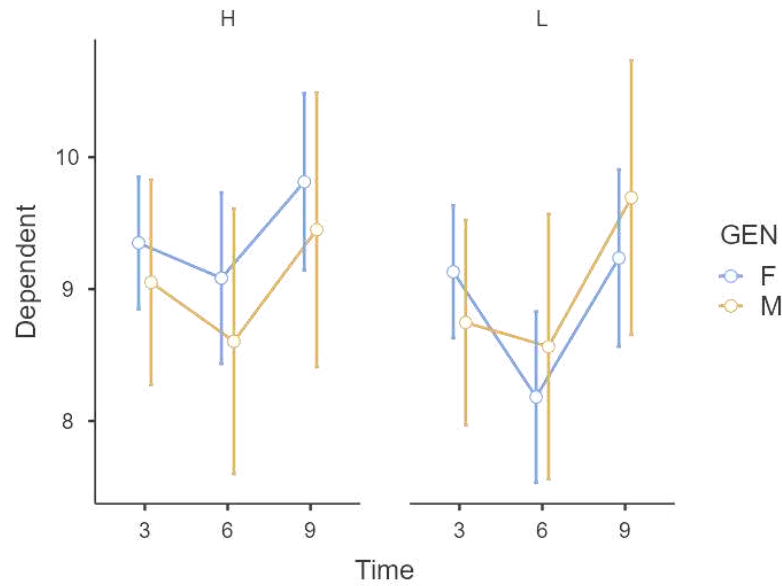


Figure 6. Interaction effect between Time x Groups x Gender (H= high susceptibility to distraction; L= low susceptibility to distraction; M= Male; F= Female).

Probing analyses online

We performed goodness-of-fit chi-squared tests between the frequency distributions of various types of conscious experience in high and low-load conditions, one for each detection of thought content during the task. The results of the study indicated that the chi-squared tests were all significant. The analysis of the standardized residues revealed a substantial difference in the frequencies of TRT in favor of the high-load condition, as well as a considerable difference in the frequencies of TUT in favor of the low-load condition ($z_{ij}=-2.01$; $-2,41$; $-2,49$; $-3,30$; $-2,46$). More information is included in the following tables: Table 6, Table 7, Table 8; Table 9, Table 10.

Table 6. First detection in high load vs. low load condition (1 min).

Level		Count	Proportion
TRT	HL	25	0.735
	LL	18	0.529
TUT	HL	1	0.029

Table 6. First detection in high load vs. low load condition (1 min).

Level		Count	Proportion	χ^2 Goodness of Fit		
				χ^2	df	p
NO	LL	6	0.176	7.289	2	0.026
	HL	8	0.235			
	LL	10	0.294			

Note: **HL**= High load; **LL**= Load Load; **TRT**= task-related thoughts;
TUT= task-unrelated thoughts; **NO**=No thoughts; **df**= degree of freedom

Table 7. Second detection in high load vs. low load condition (3 min).

Level		Count	Proportion	χ^2 Goodness of Fit		
				χ^2	df	p
TRT	HL	23	0.676	10.660	2	0.005
	LL	19	0.559			
TUT	HL	3	0.088			
	LL	11	0.324			
NO	HL	8	0.235			
	LL	4	0.118			

Note: **HL**= High load; **LL**= Load Load; **TRT**= task-related thoughts;
TUT= task-unrelated thoughts; **NO**=No thoughts; **df**= degree of freedom

Level		Count	Proportion	χ^2 Goodness of Fit		
				χ^2	df	p
TRT	HL	21	0.618	10.993	2	0.004
	LL	16	0.471			
TUT	HL	4	0.118			
	LL	13	0.382			
NO	HL	9	0.265			
	LL	5	0.147			

Note: **HL**= High load; **LL**= Load Load; **TRT**= task-related thoughts;
TUT= task-unrelated thoughts; **NO**=No thoughts; **df**= degree of freedom

Table 9. Fourth detection in high load vs. low load condition (8 min).

Level		Count	Proportion			
TRT	HL	19	0.559			
	LL	10	0.294			
TUT	HL	4	0.118			
	LL	18	0.529			
NO	HL	11	0.324			
	LL	6	0.176			

χ^2 Goodness of Fit		
χ^2	df	p
23.156	2	< .001

Note: **HL**= High load; **LL**= Load Load; **TRT**= task-related thoughts;
TUT= task-unrelated thoughts; **NO**=No thoughts; **df**= degree of freedom

Table 10. Fifth detection in high load vs. low load condition (9 min).

Level		Count	Proportion			
TRT	HL	19	0.559			
	LL	6	0.176			
TUT	HL	9	0.265			
	LL	20	0.588			
NO	HL	6	0.176			
	LL	8	0.235			

χ^2 Goodness of Fit		
χ^2	df	p
34.717	2	< .001

Note: **HL**= High load; **LL**= Load Load; **TRT**= task-related thoughts;
TUT= task-unrelated thoughts; **NO**=No thoughts; **df**= degree of freedom

Probing analyses post-task

A two-paired sample t-test was conducted to investigate the effect of cognitive load on the nature of participants' thoughts, detected post-task through DSSQ. The analysis compared the frequency of TRT and TUT between high-load and low-load conditions. The first t-test compared the frequency of TRT between the two load conditions. The results showed a statistically significant difference ($t(33) = 3.308$, $p = .002$). The analysis of the mean difference (Mean Difference = -3.853) indicates that participants reported significantly more TRT during the high-load condition than during the low-load condition. The effect size found was medium (Cohen's $d = 0.567$), underlining the robustness of this result. The second t-test examined the

frequency of TUT under the same conditions. A statistically significant difference emerged, $t(33) = 4.423$, $p < .001$. Mirroring what was observed for TRT thoughts, participants reported significantly fewer TUT episodes during the high-load condition compared to the low-load condition (Mean Difference = 3.500). The effect size was large (Cohen's $d = 0.859$) (Table 11, Figure 7, Figure 8).

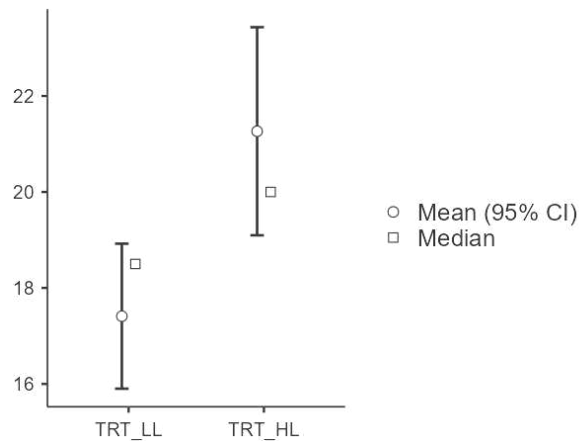
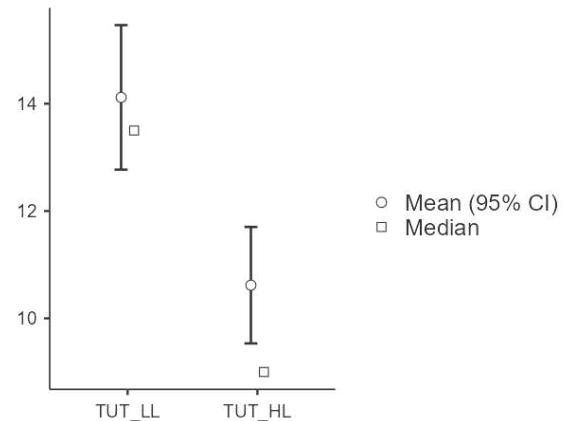
Table 11. Paired samples t-test

			statistic	df	p	Mean difference	SE difference		Effect Size
TRT_LL	TRT_HL	Student's t	-3.308	33.000	0.002	-3.853	1.165	Cohen's d	-0.567
TUT_LL	TUT_HL	Student's t	4.423	33.000	< .001	3.500	0.791	Cohen's d	0.859

Table 11. Paired samples t-test

	statistic	df	p	Mean difference	SE difference	Effect Size
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Note. $H_a: \mu \text{ Measure 1} - \text{Measure 2} \neq 0$; **TRT_HL**= task-related thoughts in high load condition; **TRT_LL**= task-related thoughts in low load condition; **TUT_HL**= task-unrelated thoughts in high load condition; **TUT_LL**= task-unrelated thoughts in low load condition.

**Figure 7.** TRT in HL vs LL condition**Figure 8.** TUT in HL vs LL condition

Discussion

This study aimed to investigate the impact of perceptual load manipulation and individual susceptibility to distraction on participants' driving performance and conscious experience in a driving simulation task. In order to provide a more comprehensive framework of the effects of attention on driving, the study measured behavioral parameters (speed, SDLP, and steering angle). It analyzed thinking contents (TRT and TUT). The findings support some of the existing literature and demonstrate the complex relationships that necessitate further investigation.

Driving Speed

A detailed analysis of driving speed revealed three-way interactions that were found to be subordinate to the influence of gender. The Time $\times$ Load $\times$ Gender interaction demonstrated that under low load conditions, male participants showed a significant increase in speed over time then to female participants. This could be indicative of an increased inclination towards risk-taking behavior or a heightened perception of confidence in navigating conditions that are perceived as simple (Özkan et al., 2006; De Craen et al., 2011). This finding aligns with the extant literature, which frequently associates male drivers with an overestimation of their abilities and an elevated overconfidence (Mynttinen et al., 2009; Wohleber et al., 2016). As driving duration and confidence in performing the task increase, this tendency can potentially result in an increased probability of engaging in risky driving behaviors (e.g. Fuller et al., 2008).

A particularly salient finding was the Time $\times$ Group $\times$ Gender interaction. The post-hoc data suggest that females with high susceptibility demonstrated a progressive increase in speed until the first temporal block, after which the rate of change in speed stabilized until the conclusion of the task. In contrast, females with low susceptibility exhibited the opposite pattern, demonstrating stable speed over time. This phenomenon could be interpreted as a compensatory strategy adopted to address a perceived attention deficit (Sörqvist & Rönnerberg, 2014), or it may be associated with higher levels of self-regulation (Wandtner et al., 2016). In order to males, the driving behavior shown by male drivers with a low susceptibility can be interpreted as a process of risk adaptation and calibration. The initial increase in speed is in accordance with literature on adapting to a new environment, such as a simulated driving environment (Reed & Green, 1999). In this phase, the driver becomes familiar with the vehicle dynamics and the virtual environment, increasing his confidence (e.g. Sportillo et al. 2018). Subsequent speed stabilization suggests that these participants rapidly attain a perceived optimal level of performance, balancing speed with maintaining safety. This behavior is

suggestive of an effective self-regulation process, in which the driver adapts his behavior to the minimum demands of the task and then maintains that level of performance, avoiding the taking of unnecessary risks, once a "set-point" of comfort and safety has been attained (Ang et al., 2019).

Standard Deviation of Lateral Position (SDLP)

An analysis of variance was conducted, which revealed a statistically significant main effect of the Time factor on SDLP. This result suggests that the variability in maintaining the vehicle's position within the lane has changed significantly as the driving task has advanced. This finding aligns with a well-established phenomenon in literature, known as the time on task effect and the relative decrease in vigilance (Zanesco et al., 2024; Zeller, 2022). The extant literature demonstrates a consistent pattern: over time, the ability to maintain an optimal level of attention decreases, resulting in increased driver fatigue. A body of research has demonstrated a correlation between fatigue and a temporary decline in executive functions, which are responsible for monitoring and adapting behavior. In different cases, executive control is compromised, resulting in deficits in task execution (e.g., Zhang & Kumada, 2017). On the other hand, the increase in SDLP can be interpreted as an indication of skill development and task automation in a stable and predictable environment (Saffarian et al., 2012). Drivers adopt a less demanding approach after becoming aware that continuous control is not required to complete the task efficiently (Müller et al., 2021). In summary, the principal impact of time on SDLP can be attributed to two factors: a decline in attentiveness and a shift in control strategy. The adoption of automation for monotonous tasks and the reallocation of cognitive resources are indicative of these changes. As a consequence, the vehicle's position within the lane may become more variable.

Steering Wheel Angle

The steering angle analysis revealed a significant three-way interaction between Time, Gender, and Susceptibility Group. In this scenario, the trend can be interpreted as a behavioral manifestation of the decline in vigilance. The primary conclusion of this result is that this decline is not experienced equally by all drivers. In contrast to drivers with low susceptibility, who demonstrate more consistent performance over time, participants with a high susceptibility to distraction show a faster decline in their attention threshold. This finding suggests that their executive control systems are inherently less effective at mitigating external and internal interferences. The Attentive Resource Theory can explain this vulnerability (Kahneman, 1973). This model suggests that individuals' cognitive resources are limited. High-susceptibility drivers are defined as individuals who require a greater proportion of these resources to effectively mitigate distractions and maintain concentration (Broadbent et al., 2023; Zhu et al., 2024). In comparison to low-susceptibility drivers, who possess the capacity to maintain their attention for extended periods, this sustained and active effort results in a more rapid depletion of resources in a monotonous task (Ma et al., 2018). This interpretation is supported by the extant literature on executive control. Research has demonstrated a correlation between variations in executive function efficiency, including working memory capacity, and individual differences in susceptibility to distraction (Kane & Engle, 2003). Individuals showing poorer executive control are not only more susceptible to distractions but also manifest a marked decline in performance on sustained attention tasks (e.g. Hawkins et al., 2021).

Probing online and post-task

Another aim of this study was to directly measure the driver's thoughts, to confirm our theories regarding how perceptual load and susceptibility to distraction can affect conscious experience. The manifestation of TRTs is more frequently observed in circumstances

characterized by high perceptual load, while TUTs are more frequently observed in low perceptual load scenarios. These results were confirmed in the probing online and post-task.

These findings are consistent with previous research, particularly with Lavie and colleagues' (1994) perceptual load theory. This theory posits that the capacity for attentional processing is finite. A primary task that is perceptually demanding utilizes all the attentional resources that are available. As a result, no resources remain to process irrelevant stimuli or to generate and maintain a flow of internal thoughts not pertinent to the task. The task, in this case, functions as a "hook" that facilitates sustained engagement with the external environment. Our findings are consistent with those of other studies that employed analogous manipulations. This includes the work of He et al. (2011), who utilized wind gusts as an attentional anchor, and Geden et al. (2018), who increased traffic complexity. Moreover, other research has shown that driving in high perceptual load scenarios is associated with an increase in TRTs and a decrease in MW (Burdett et al., 2019; Yanko & Spalek, 2014; Lemercier et al., 2014).

Additionally, this outcome is consistent with Resource-Control Theory (Smallwood & Schooler, 2015; Randall et al., 2014). This viewpoint suggests that MW occurs when executive control systems are inadequate in maintaining focus on the primary task's aims. This failure is characterized by its inability to sustain executive monitoring, which renders it more likely to manifest in contexts where the task is considered easy (Thomson et al., 2015). The internal cognitive processes of individuals can result in the allocation of executive resources, which are not subject to external constraints or limitations. On the other hand, a high-load task needs constant executive control activation, which actively works to suppress internal distractions and maintain driving focus (Gutteleing et al., 2021).

Limitations

While the study offers positive findings, several limitations should be considered. One of these relates to the sample size, as there were only 34 participants; the other is related to the drivers' average age of 21 years. This limitation precludes the possibility of generalizing these findings to include groups of drivers with differing ages and backgrounds. Secondly, the study utilized self-report measures to detect thought contents and classify participants into susceptibility groups. However, it must be recognized that these measures may be susceptible to limitations in terms of introspective accuracy or the presence of social desirability bias (Grimm, 2010). Furthermore, it is possible that the verbal and invasive nature of "online" thought probes influenced the participants' mental states at the time of detection. In order to create a more comprehensive and reliable theoretical framework for understanding the mechanisms underlying cognition in distracted driving, future research should integrate objective indicators of attentional status (e.g., eye-tracking and neurophysiological data) with self-report measures to replicate these findings on larger and more diverse samples.

Conclusion

The present study aimed to investigate the impact of distracted driving susceptibility and perceptual load on various behavioral patterns in a simulated driving task. To this end, a high-fidelity driving simulator was employed to measure moment-by-moment changes in steering, speed, and response to hazards. Moreover, we probed the participants' thoughts both online (during the task) and offline to investigate the frequency of TRT and TUT during the experimental conditions. The most significant contribution of the work is its demonstration of the irregularity of these mental states' behavioral manifestation. The analysis identified complex three-way interactions, indicating that driving performance, particularly speed and steering control, derives from a multifaceted interaction between task demands, driving duration, and the driver's demographic characteristics, including gender and distraction susceptibility. To

corroborate these hypotheses, it is recommended that this experimental paradigm be extended to road studies or the analysis of naturalistic driving data. Finally, the study's identification of distinct risk profiles facilitates the development of customized training programs and the design and validation of ADAS systems capable of adapting their warnings or interventions not only in response to road conditions but also to a driver's profile, which includes factors such as gender and distraction susceptibility.

Finally, this highlights the need to progress beyond unidimensional models of distraction, focusing research and interventions on a more tailored and multifaceted approach to identifying and mitigating potential risky driving behaviors.

Chapter VI

“REGULATING MY ANXIETY WORSENS THE SAFETY OF MY DRIVING”: THE SYNERGISTIC INFLUENCE OF SPATIAL ANXIETY AND SELF-REGULATION ON DRIVING BEHAVIOR

This chapter is based on: Traficante, S., Tinella, L., Lopez, A., Koppel, S., Ricciardi, E.,
Napoletano, R., ... & Caffò, A. O. (2024). “Regulating my anxiety worsens the safety of
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Introduction

Spatial mental representation of the environment and spatial navigation play a crucial role for the execution of various daily activities (Lopez et al., 2020; Lopez et al., 2021). Spatial mental representation refers to the cognitive maps and mental models that individuals construct to understand and navigate their environment (McNamara, 1986; Tversky et al., 1993), whereas spatial navigation refers to the ability to move through physical space, to understand directions, and to reach specific destinations (Darken et al., 2002; Epstein et al., 2017; Caffò et al., 2020). These abilities can influence the performance in spatial tasks, including driving performance. Drivers create mental representations of familiar routes, including landmarks, intersections, and turns (Charlton et al., 2017). These representations help them in anticipating upcoming actions and making informed decisions (e.g. Kunishige et al., 2020; Tinella et al., 2020). Moreover, knowing where they are relative to their position or destination allows drivers to adjust their driving behavior accordingly, moving through physical space, understanding directions, and reaching specific destinations. Furthermore, spatial mental representations aid memory recall, helping drivers remember critical details about their route (e.g. Taylor et al., 1992; Von Stülpnagel & Steffens, 2012). Drivers mentally plan their routes by considering distances, turns, and landmarks. Effective spatial navigation ensures efficient and safe travel. For example, when faced with road closures, detours, or unexpected obstacles, spatial navigation skills allow drivers to find alternative routes. Drivers use spatial cues (such as road signs, buildings, and natural features) to stay oriented and avoid getting lost, maintaining their awareness of surroundings. Precise spatial awareness is crucial for parking, merging lanes, and navigating tight spaces. Drivers must constantly monitor the vehicle's position relative to the road, other vehicles, and surrounding obstacles, using both direct visual information and mental representations of space (Anstey et al., 2012; Meneghetti et al., 2021). Considering all of this,

driving represents a complex spatial activity involving perception, attention, sensory and navigational abilities (Ranney et al., 1994; Tinella et al., 2021).

SA is a multi-faceted, domain-specific type of anxiety that influences navigation, and the performance of spatial tasks (e.g., navigation, wayfinding, mentally manipulating or rotating objects, perspective taking; Lawton, 1994; Ramirez et al., 2012). It is a form of fear or apprehension that an individual experiences while processing environmental information contained in one's geographical space (Lawton et al., 1994). Indeed, previous research has shown that spatial tasks can be challenging for individuals, causing uncomfortable internal sensations, and producing SA (Lawton et al., 1994; Lyons et al., 2018).

SA has been found to relate to problems with everyday activities, including driving behavior. SA creates a state of increased stress and arousal (e.g., Nori et al., 2023). This can impair a driver's ability to think clearly and make rational decisions. Attention becomes fixated on navigating complex situations, leading to a narrowed focus (Wickens et al., 2020). This can cause drivers to miss crucial information like traffic signals or pedestrians. Moreover, SA can influence decision making, leading to hesitation and indecisiveness. This indecisiveness can cause delayed reactions or impulsive maneuvers to avoid perceived threats (e.g. Bishop et al., 2018). Furthermore, SA can increase risk taking such as speeding to get through intersections or challenging areas faster, making sudden lane changes without proper checks, disregarding traffic rules due to a desire to reach the destination quickly (e.g., Clapp et al., 2011; Nori et al., 2020; Gwyther & Holland, 2012). On one hand, all these behaviors can involve driving risks with dangerous consequences for the individual. On the other hand, SA can lead to avoidance behaviors especially on unfamiliar routes or during peak traffic hours (Stephens et al., 2020). In light of this, SA might lead to modifications in driving behavior to avoid challenging situations, as a form of driving self-regulation (Molnar et al., 2013; Molnar et al., 2014). Individuals may exhibit self-regulatory behaviors to cope with their discomfort. In situations of

anger, stress, sleepiness, and anxiety, drivers often need to use self-regulatory strategies to reduce the probability of engaging in risky driving behaviors and motor vehicle crashes (e.g. Watling et al., 2016; Love et al., 2023). Indeed, driving self-regulation is an important road safety strategy because drivers can recognize a possible danger, avoiding driving situations they find difficult (e.g., driving only in familiar environment, avoiding rush hours and night driving), reducing crash involvement (Baldock et al., 2006; Molnar et al., 2013; Lazuras et al., 2022). While several studies have examined the relationship between anxiety and self-regulation (Gwyther & Holland, 2012), there is limited research that has focused on the potentially dangerous role that self-regulation can play in drivers with SA. In light of above, it was hypothesized that drivers who are anxious and lack confidence may be at a higher risk of self-regulation which could affect the driving behavior.

The focus of the present study was to investigate the relationships between SA, driving self-regulation, and risky driving behaviors. While previous research has examined SA in various contexts, there remains a gap in understanding its relationship to driving behaviors. Based on the previous literature, it was hypothesized that the severity of SA may influence risky driving behavior (i.e., violations, errors, and lapses), with the relationship mediated by a driver's self-regulation abilities. Based on previous literature and the gaps identified in the current research, the present study aims to investigate the relationships between Spatial Anxiety (SA), driving self-regulation, and risky driving behaviors (i.e., violations, errors, and lapses). The following hypotheses are proposed: (1) Drivers who experience higher levels of Spatial Anxiety (SA) will report more frequent risky driving behaviors, including violations, errors, and lapses. Research indicates that SA increases stress and arousal, impairing clear thinking and decision-making in drivers, leading to missed traffic signals, delayed reactions, and impulsive maneuvers. Elevated SA has been associated with higher rates of navigational and timing errors in spatial tasks (Hund & Minarik, 2006). (2) Driving self-regulation mediates the

relationship between SA and driving lapses. SA may lead to avoidance behaviors as a form of self-regulation to cope with discomfort in driving situations. This maladaptive self-regulation could result in lapses due to over-regulation and cognitive interference from anxiety (Gwyther & Holland, 2012). (3) Driving self-regulation mediates the relationship between SA and driving errors. In this case, while high self-regulation levels generally improve road safety (Molnar and Eby, 2008; Auzoult et al., 2015), over-regulation due to anxiety could impair attentional control and decision-making, leading to errors (e.g. Derryberry & Reed, 2002). Finally, the last hypothesis tries to explore if the (4) driving self-regulation mediates the relationship between SA and driving violations. Although SA is linked to unintentional errors and lapses, its role in deliberate violations is less clear. Self-regulation strategies might influence the frequency of violations, especially in drivers with high SA.

Material and Methods

Participants

A power analysis was conducted to estimate the sample size using G*Power 3.1 (Faul et al., 2009), with the following parameters: a p level of 0.05, a cautious low effect size (0.12), and a power of 0.80. Results indicated that a sample size of 113 participants was sufficient to warrant an 80% chance of correctly rejecting the null hypothesis. Eight hundred and thirty-eight participants, 375 females (F) (age: $M \pm SD = 43,76 \pm 17,03$; Years of schooling: $M \pm SD = 13,40 \pm 3,82$) and 463 males (M) (age: $M \pm SD = 39,67 \pm 19,59$; Years of schooling: $M \pm SD = 13,06 \pm 3,34$) between 18 and 85 years of age, took part in the study. All participants were required to: (a) hold a valid current driver's license, provisional or above; (b) have normal or corrected to normal vision; (c) have driven more than one time within the last month; and not be or had been a professional driver (e.g., taxi driver, truck driver, transporter on delivery, etc.). Descriptive statistics for categorical variable (gender) and correlation matrix for continuous

variable (age, years of schooling, driving behaviors; driving self-regulation and SA) are reported in Table 1. No correlation coefficient between age, years of schooling, gender and SA was higher than 0.75, suggesting that there were no issues of multicollinearity among the predictors. The participants, blind to the hypothesis of the study, were volunteers recruited with the support of a proxy informant, generally undergraduate and graduate students, and trainees. All participants signed their informed consent prior to the enrolment in the study. The Ethical Committee of the Department of Education, Psychology, and Communication approved the study protocol, and the whole study was performed following the Helsinki Declaration and its later amendments.

Table 1. Mean (M), standard deviation (SD) and correlation matrix for age, gender, years of schooling, driving lapses, driving errors, driving violations, driving self-regulation and spatial anxiety.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

		AGE	YSC		LAPSES		ERRORS		VIOL		DMQ		QAS		MALE		FEMALE	
															M	SD	M	SD
AGE		—													39.67	19.59	43.76	17.03
YSC		- ***	—												13.06	3.34	13.40	3.82
LAPSES		0.474 - ***	0.139	***	—										7.25	4.94	7.45	4.37
ERRORS		0.232 - ***	0.063		0.571	***	—								4.11	3.60	3.37	3.33
VIOL		0.134 - ***	0.032		0.372	***	0.557	***	—						12.15	8.06	9.28	7.50
DMQ		0.202 - ***		***	0.173	***	0.079	*	- **	—					32.22	13.98	36.99	12.82
QAS		0.055 - **	0.130		0.320	***	0.168	***	0.100 -		0.329	***	—		20.94	8.25	23.18	7.63
GEN		0.097 0.127	***	0.146	***	0.190	***	0.034	0.017 -		-	***	0.035	—	—	—	—	—
									0.075		0.197							

YSC= years of schooling; LAPSES= driving behavior questionnaire (lapses); ERRORS driving behavior questionnaire (errors); VIOL= driving behavior questionnaire (violation); DMQ-A= driving mobility questionnaire (total score); QAS= spatial anxiety questionnaire (total score); GEN= gender; p= p value

Material and Procedure

Participants had to be in a good general state of physical and psychological health. All participants were enrolled between October and December 2023. A brief interview was administered by supervised trainees in neuropsychological assessment to collect demographic information, to exclude neurodegenerative and vision/hearing disorders, and to gather

information about participant's driving habits and years of license. After completing the interview, all participants completed a survey with the following self-report questionnaires.

Driving Behavior Questionnaire (DBQ)

The Italian 28-item version of Driver Behavior Questionnaire (DBQ), developed by Reason et al. (1990), and adapted to the Italian context by Lucidi et al. (2010), was used to measure self-reported aberrant driving behaviors. The instrument includes three subscales: (a) *errors*, misjudgments or failures of observation that could be hazardous to others (e.g., failure to check mirrors, not seeing a pedestrian crossing); (b) *lapses*, absent-minded behaviors which may be frustrating or have negative consequences for the driver responsible, but generally do not pose a threat to anyone's safety (e.g., taking the wrong exit); and (c) *violations*, deliberate contraventions of legally regulated or socially accepted behaviors associated with safe vehicle operation (e.g., speeding, poor lane discipline, close following of another vehicle). Each item in the questionnaire is rated on a six point-scale, ranging from 0 (Never) to 5 (Almost always). In this scale, higher score indicated a higher frequency of aberrant behaviors during driving activities. The questionnaire presented good psychometrics properties (Lucidi et al., 2010) (Cronbach's α violations = .78; Cronbach's α errors = .80; Cronbach's α lapses = .75; Cronbach's α overall scale = .77).

Driving Mobility Questionnaire (DMQ-A)

The 21-item version of Driving Mobility Questionnaire (Extended DMQ-A) developed by Wong et al. (2015), and validated for Italian drivers (Spano et al., 2019), was used to measure the frequency with which drivers avoided driving (i.e., driving self-restriction) in certain conditions (i.e., at night, in the rain, or in foggy conditions). According to Spano and colleagues (2019), this questionnaire includes two factors: External Driving Environment (EDE) and Internal Driving Environment (IDE). Each item in the questionnaire is rated on five-point scale,

ranging from 1 (Never avoid) to 5 (Always avoid). In this scale, higher scores indicate a higher level of self-restriction. The questionnaire presented good psychometrics properties (Spano et al., 2019) (Cronbach's α EDE = .84; Cronbach's IDE = .79; Cronbach's α overall scale = .73).

Spatial Anxiety Questionnaire (QAS)

The Spatial Anxiety Questionnaire (De Beni et al., 2014) measures the level of anxiety in environmental tasks. The questionnaire comprises 8 items, and each item is rated on a six point-scale, ranging from 1 (Never) to 6 (Always). In this scale, higher scores indicated a higher level of SA in specific situations and environmental tasks. The questionnaire presented good psychometrics properties (De Beni et al., 2014) (Cronbach's α = .80).

Statistical Analyses

Statistical Analyses were conducted using the software Jamovi, version 2.3.28 (The Jamovi Project, 2023). Independent samples t-tests were conducted to investigate differences in self-reported measures between gender groups. In order to assess theoretical mediation assumptions, three multiple regression analyses were performed considering demographic variables (i.e., age group, gender, and years of schooling), and SA (i.e., QAS) as predictors of different facets of aberrant driving behavior (i.e., DBQ errors, lapses, and violations), considered as outcomes. We have followed the theoretical assumptions of statistical mediation as highlighted by Baron and Kenny (1986) and by Gallucci and Leone (2017). These assumptions indicate that predictors (QAS) should significantly affect the mediator (DMQ); predictors should have a significant effect on the outcome (DBQ); the outcome should be predicted by the mediator. If there is not a significant effect between predictor and dependent variable, the mediation assumption is violated. In light of this, path models were tested, estimating the direct, indirect and total effects (through driving self-regulation, i.e. DMQ-A) of SA on driving errors and driving lapses.

Results

The independent samples t-test revealed significant gender differences across several variables. A significant difference in age was observed between genders, with males being, on average, younger than females (AGE: Welch's $t = -3.233$; $df = 832$; $p = 0.001$; Cohen's $d = -0.223$). This indicates a small effect size. Males reported a significantly higher number of driving violations compared to females (DBQ_VIOL= Welch's $t = 5.329$; $df = 820$; $p < 0.001$; Cohen's $d = 0.368$), corresponding to a moderate effect size. Additionally, males were found to have committed more driving errors than females (DBQ_ERRORS = Welch's $t = 3.087$; $df = 821$; $p = 0.002$ Cohen's $d = 0.213$), indicating a small effect size. Female participants exhibited significantly higher levels of driving self-regulation than male participants (DMQ_TOT = Welch's $t = -5.144$; $df = 823$; $p < 0.001$; Cohen's $d = -0.355$) with a moderate effect size. Additionally, females exhibited higher levels of spatial anxiety compared to males (QAS_TOT = Welch's $t = -4.067$; $df = 821$; $p < 0.001$; Cohen's $d = -0.2814$), indicating a small to moderate effect size. We chose to adopt the Welch's t-test because the Levine's test resulted significant ($p < 0.05$), assuming a violation of equal variances. Moreover, the multiple regression analyses as well as the path models performed for each driving outcome are summarized below.

Driving Behaviors: multiple regression analyses

The first multiple regression analysis was performed on driving violations. Significant and non-significant effects are reported in Table 3. Explained variance (R^2) for the main effect model was equal to 0.0786 (adj. $R^2 = 0.0731$). Significant results were found for the effects of age group ($\beta = -0.099$; $p < 0.001$), gender ($\beta = 2.1425$; $p < 0.001$), years of schooling ($\beta = -0.191$; $p = 0.027$), and overall driving self-regulation ($\beta = -0.062$; $p < 0.001$). No significant differences were found for the effects of SA ($\beta = 0.0176$; $p = 0.616$).

The second multiple regression analysis was performed on driving lapses. Significant and non-significant effects are reported in Table 4. R^2 for the main effect model was equal to 0.150 (adj. $R^2 = 0.145$). The first-order effects model showed significant effects between driving lapses and age group, ($\beta = -0.0431$; $p < 0.001$), driving self-regulation ($\beta = 0.0286$; $p = 0.017$) and SA ($\beta = 0.161$; $p < 0.001$). No significant differences were found for the effects of gender ($\beta = -0.149$; $p = 0.632$) and years of schooling ($\beta = 0.077$; $p = 0.115$). The third multiple regression analysis was performed on driving errors. Significant and non-significant effects are reported in Table 5. R^2 for the main effect model was equal to 0.0577 (adj. $R^2 = 0.0520$). Significant results were found for the effects of age group ($\beta = -0.016$; $p = 0.023$), gender ($\beta = -0.892$; $p < 0.001$) and SA ($\beta = 0.069$ $p < 0.001$). No significant differences were found for the effects of driving self-regulation ($\beta = 0.0119$; $p = 0.207$) and education ($\beta = 0.0256$; $p = 0.507$).

Table 2. Linear regressions of driving VIOLATIONS; LAPSES and ERRORS: standardized estimates (Estimate), standard errors (SE), t scores and p value for each outcome.

VIOLATIONS				
Predictor	Estimate	SE	t	p
Intercept	20.2056	1.9215	10.516	< .001
AGE	-0.0990	0.0166	-5.971	< .001
GEN	-2.1450	0.5515	-3.889	< .001
YSC	-0.1910	0.0865	-2.210	0.027
DMQ-A	-0.0620	0.0211	-2.937	0.003
QAS	0.0176	0.0351	0.502	0.616

LAPSES				
Predictor	Estimate	SE	t	p
Intercept	3.6656	1.08970	3.364	< .001
AGE	-0.0431	0.00940	-4.581	< .001
GEN	-0.1498	0.31278	-0.479	0.632
YSC	0.0773	0.04903	1.576	0.115
DMQ-A	0.0286	0.01198	2.388	0.017
QAS	0.1608	0.01988	8.088	< .001

ERRORS				
Predictor	Estimate	SE	t	p
Intercept	2.5973	0.85606	3.034	0.002
AGE	-0.0168	0.00739	-2.279	0.023
GEN	-0.8925	0.24572	-3.632	< .001

YSC	0.0256	0.03852	0.664	0.507
DMQ-A	0.0119	0.00941	1.264	0.207
QAS	0.0698	0.01562	4.468	<.001

VIOLATIONS= driving behavior violations; LAPSES= driving behavior lapses; ERRORS= driving behaviors errors; GEN= gender; YSC= years of schooling; DMQ-A= driving-mobility questionnaire (total score); QAS= spatial anxiety questionnaire (total score).

Path model predicting Driving Lapses and Driving Errors

The path model testing the direct effect between SA and driving violations was not significant and therefore was not tested. This choice is corroborated by Baron and Kenny (1986) and Gallucci and Leone (2017). According to the authors, if there is not a significance effect between predictor (QAS) and dependent variables (DBQ_VIOL), the mediation assumption is violated. However, path models were tested between SA and two other driving outcomes, lapses and errors. The relationship between SA (QAS) and driving lapses was found to be significantly and totally mediated by driving self-regulation. The direct effect ($\beta=0.295$; $p < 0.001$), indirect effect ($\beta=0.0250$; $p < 0.05$) and total effect ($\beta=0.320$; $p < 0.001$) were significant. In other words, SA significantly and positively affected driving self-regulation which in turn affected significantly and positively driving lapses.

Conversely, the second path model showed that driving self-regulation was not a significant mediator for the relationship between total SA (QAS) and driving errors. The path model found significant direct ($\beta=-0.170$; $p < 0.001$), indirect ($\beta=-0.012$; $p = 0.039$), and total ($\beta=-0.183$; $p < 0.001$) effects of age on driving lapses. Additionally, significant indirect effects of years of schooling ($\beta=-0.018$; $p = 0.026$) and gender ($\beta=0.013$; $p = 0.031$) on driving lapses were found. Moreover, significant direct ($\beta = -0.089$; $p = 0.022$) and total effects ($\beta=-0.096$; $p = 0.013$) of age and gender ($\beta=-0.126$; $p < 0.001$; $\beta = -0.119$; $p < 0.001$) on driving errors were found. The findings on driving lapses and errors are described in Table 3, Figure 1 and Figure 2.

Table 3. Direct, indirect, and total effects of predictor and covariates on driving lapses and errors. * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

Effect	Direct Effect	Indirect effect	Total Effect	R squared
<i>On Lapses</i>				0.145
of QAS	0.276***	0.025*	0.301***	
of AGE	-0.170***	-0.012*	-0.183***	
of YSC	0.058	-0.018*	0.040	
of GEN	-0.015	0.013*	-0.002	
<i>On Errors</i>				0.055
of QAS	0.160*	0.014	0.174***	
of AGE	-0.089*	-0.006	-0.096*	
of YSC	0.026	-0.010	0.015	
of GEN	-0.126***	0.007	-0.119***	

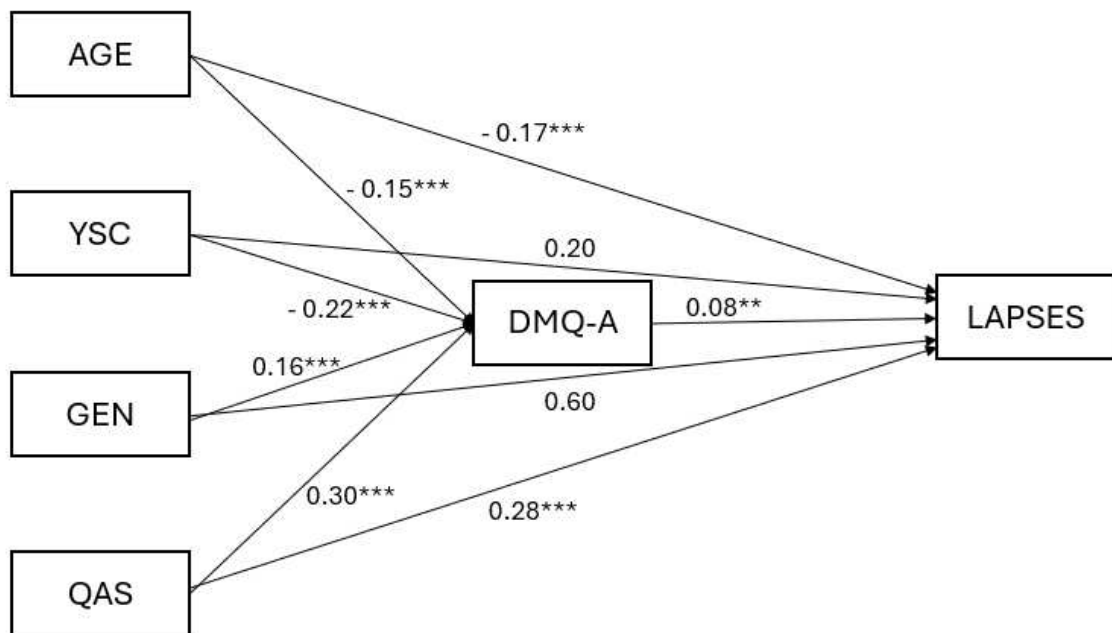


Figure 1. Model tested on DBQ_LAPSES. Coefficients are reported for each regression path. * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

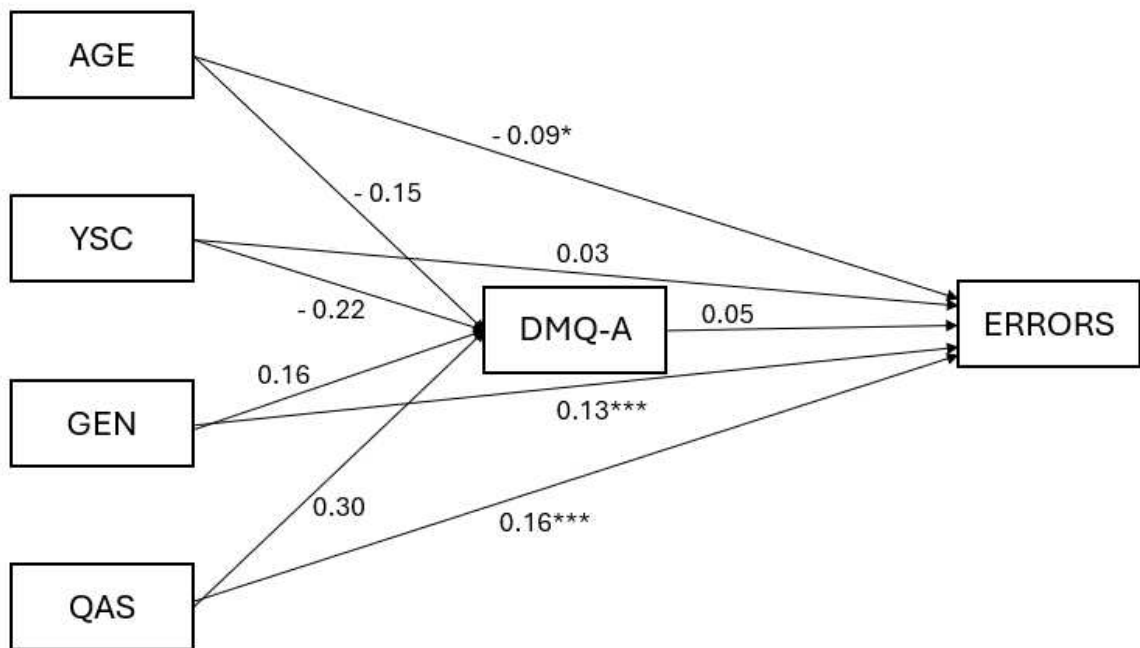


Figure 2. Model tested on DBQ_ERRORS. Coefficients are reported for each regression path. * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$.

Discussion

The present study aimed to investigate the relationships between SA and aberrant driving behaviors by examining the mediation role of driving self-regulation in a sample of 838 active drivers. The results showed that (1) SA negatively impacts on driving errors and lapses; (2) driving self-regulation mediates the relationship between SA and driving lapses; (3) driving self-regulation does not mediate the effect of SA on driving errors, and (4) There is no significant relationship between SA and driving violations.

The mediation models have demonstrated a significant impact of gender on driving lapses and errors. Research suggests that female drivers exhibit higher levels of driving self-regulation (Gwyther et al., 2012; D'Ambrosio et al., 2008). In general, women report higher levels of SA, or anxiety about environmental navigation, than men (Geer et al., 2019; Geer et al., 2024; Lawton 1994). This aspect is corroborated by literature indicating that women tend

to use simple spatial navigation strategies more frequently than men (Munion et al., 2019). For example, different studies have highlighted as women were more likely use a route strategy (attending to instructions on how to get from place to place), whereas men were more likely to use an orientation strategy (maintaining a sense of their own position in relation to environmental reference points). The route spatial navigation strategy is associated with higher levels of SA.

On the other hand, in light of the mediation models results, age appears to influence susceptibility to SA, with older drivers make less driving errors and lapses compared to younger drivers. This finding is consistent with the current literature, which attributes the lower error rates of older drivers to their adoption of more effective driving coping strategies to compensate for age-related declines in reaction times (e.g. Charlton et al., 2006). Conversely, younger drivers tend to exhibit riskier driving behaviors and may underestimate potential risks (e.g., Hatfield & Fernandes, 2009). Moreover, older drivers are more inclined towards self-regulation in driving, as indicated by Bauer et al. (2003), who noted that as people get older, they are more likely to avoid driving at night, during peak hours, on long journeys, and when alone. This can be an explanation of the significant mediation role of the driving-self regulation on the relationship between age and driving lapses.

Spatial Anxiety and driving behavior

The multiple regression models have shown that SA has an impact on driving behavior, specifically on lapses. Generally, drivers with elevated SA are more prone to commit driving errors, such as entering a side street without noticing pedestrians crossing, and driving lapses, such as starting in third gear from a traffic light. These findings are consistent with the existing literature (Hund & Minarik, 2006; Walkowiak et al., 2015), which associates SA with higher rates of navigational and timing errors in route selection. Research has found that drivers with

higher levels of anxiety are worse at detecting specific signals among other distractors and may take longer to brake at crosswalks (Morton & White, 2013). Moreover, drivers with higher anxiety levels show evidence of visual tunneling (Briggs et al., 2011).

Nori et al. (2020) showed that individuals with a spatial cognitive style that favors surveying and have the ability to memorize landmarks, spatial relationships, and distances between landmarks and navigation targets are better equipped to develop an accurate mental representation that facilitates good driving skills with less errors and lapses. Drivers with poor visuospatial skills and elevated SA tend to explore less new environments and often drive on the same roads. This behavior limits their representation of the city to the places they usually visit. Environmental avoidance theory (Berman et al., 2010) suggests that drivers avoid new driving situations and routes due to the emotions and anxiety caused by the fear of getting lost. Therefore, avoiding these situations is associated with an increase of SA and a reduction in the opportunity to improve spatial skills. In this case, a cyclical response may occur in which poor spatial skills lead to increased SA, which leads to increased avoidance of driving situation, and which ultimately leads to minimized opportunities for improvement in spatial skills (Berman et al., 2010; Geer et al., 2019; Geer et al., 2024).

In light of this, the higher the spatial strategy that is used, the lower the number of lapses and errors in the driving process (Nori et al., 2020). Additionally, the literature shows that poor visuospatial orientation skills are associated with deliberate violations (Nori et al., 2020). However, the present study did not find a significant relationship between SA and driving violations. The results may be explained by the poor perception and confidence in drivers' spatial abilities. Indeed, driving violations refer to deliberate and intentional risky behaviors taken by drivers. In other words, driving behavior is influenced by attitudes, subjective norms, and perceived behavioral control. These factors shape an individual's intentions to engage in

specific aberrant driving behaviors (Reason et al., 1990; Ajzen, 1991; Khanpour et al., 2023). On the other hand, lapses and errors are characterized by unintentional and inadvertent mistakes made while driving (Reason et al., 1990). For instance, ordinary violations may be more likely to occur due to overconfidence in spatial ability (Schlehofer et al., 2010). However, if the belief is not associated with actual ability, confident individuals with low spatial ability are more likely to commit violations than those who lack confidence and have low spatial ability (Nori & Piccardi, 2015; Nori et al., 2020). This behavior may be due to low confidence in their spatial abilities and high levels of SA. This can lead drivers to avoid potentially dangerous road situations, such as running stop signs or red lights.

The mediation role of driving self-regulation.

While existing literature suggests a relationship between SA and risky driving behaviors, the role of self-regulation as a mediator requires further empirical exploration and theoretical insight.

Results presented here showed that driving self-regulation was a significant mediator for the relationship between SA and driving lapses. Driving lapses refer to brief moments of inattention or unconsciousness that can occur while driving (e.g. Trick et al., 2004). They can occur due to various factors, including fatigue, distraction, stress, or cognitive overload. The significant direct effect suggests that higher levels of SA are associated with more frequent driving lapses, which aligns with expectations (e.g. Nori et al., 2020). Moreover, the significant indirect effect indicates that driving self-regulation partially accounts for the relationship between SA and driving lapses. In other words, individuals with higher SA may have poorer driving self-regulation skills, which in turn contribute to an increased likelihood of driving lapses. Together, these findings suggest that while SA directly influences driving lapses, a portion of this influence is also mediated by the individual's level of driving self-regulation.

This result might appear initially counterintuitive given that several studies highlighted that high driving self-regulation levels improve road safety by reducing the occurrence of aberrant behaviors (Oviedo-Trespalacios et al., 2017; Ang et al., 2019). Several studies have highlighted that successful self-regulation depends on executive functions such as inhibiting impulsive behavior, shifting attention between tasks, and updating working memory (Hofmann et al., 2012; Dohle et al., 2018). Despite the above, the literature also has shown that over-regulation behind the wheel may be dangerous for driving tasks. Gwyther and Holland (2012) indicate that anxious drivers may be more prone to over-regulation. Over-regulation could be considered a maladaptive response related to driving anxiety, namely the unnecessary avoidance of certain behaviors. These findings indicate that drivers with high scores for self-regulation and SA cope with the worries and stressors of driving by disconnecting from the driving task.

Another possible explanation of the result could be due to the cognitive interference of SA, that could impair an individual's ability to concentrate and make effective decisions while driving (e.g. Barnard et al., 2016; Nori et al., 2020). This interference can disrupt the cognitive processes involved in self-regulation, such as attentional control, impulse regulation, and decision-making (e.g. Taubman-Ben-Ari et al., 2004; Gugliotta et al., 2017; Shi et al., 2019). As a result, individuals with higher SA may struggle to regulate their driving behavior effectively, increasing the likelihood of lapses such as missing traffic signs or failing to check blind spots.

Finally, driving self-regulation does not mediate the relationship between SA and driving errors. This means that the level of driving self-regulation (the ability to control one's driving behavior) does not act as an intermediary factor in such a relationship. In other words, even if someone has good driving self-regulation skills, it doesn't necessarily mean that their

SA won't affect their likelihood of making driving errors. So, regardless of how well someone can regulate their driving behavior, if they experience SA, it may still directly contribute to an increase in driving errors without being mitigated or influenced by their level of driving self-regulation (Lazuras et al., 2019; Meng and Siren, 2012).

This concept is important in understanding the complex interplay between psychological factors (like anxiety) and driving performance, highlighting that simply having good self-regulation skills may not be enough to counteract the negative effects of SA on driving behavior. Probably other factors that we should have taken into consideration might explain the lack of the effect, including driving inexperience. It might undermine the effectiveness of driving self-regulation as a mediator between SA and driving errors by limiting the development of self-regulation skills, increasing vulnerability to anxiety, impeding the adoption of coping mechanisms, and reducing confidence on the road safety (e.g. Gotardi et al., 2019; Bowen et al., 2020; Sheykhfard et al., 2022). Moreover, novice drivers typically experience higher cognitive loads while driving as they must simultaneously process a wide array of information, such as traffic signals, road signs, and the actions of other drivers (Mourant et al., 1972; Paxion et al., 2015). This cognitive load may interfere with their ability to effectively regulate their driving behavior, making it difficult to mitigate the impact of SA on their performance (e.g. Matthews et al., 1996). Furthermore, inexperienced drivers may lack the coping strategies necessary to manage SA effectively (e.g. Kontogiannis et al., 2006). While self-regulation theoretically involves the ability to adapt one's behavior in response to internal and external factors (e.g. Molnar et al., 2013), novice drivers may not yet have developed the repertoire of strategies needed to mitigate the effects of anxiety on their driving performance (Xiang et al., 2024). Finally, individual differences in neurobiological factors, such as stress response mechanisms, may also play a role in shaping the relationship between SA, driving self-regulation, and the occurrence of driving errors in inexperienced drivers. Some individuals

may be more predisposed to experiencing heightened anxiety in spatially demanding situations, which could further exacerbate their susceptibility to making errors behind the wheel (e.g., Taylor et al., 2007; Taubman-Ben-Ari et al., 2012).

Study limitations

Some limitations of the present study should be noted. Firstly, the study used only self-report questionnaires, which, although validated and widely used, may not provide the most accurate objective representation of driving behavior. Indeed, they can be influenced by different limitations such as self-deception, recall bias, subjective interpretation, and the emotional state of respondents. Despite these issues, they are valuable in cross-sectional studies for providing preliminary evidence on variable relationships. Combining these with objective measures, like physiological assessments and biofeedback, and neurofeedback, can improve data quality and reliability, offering a more comprehensive understanding of SA levels and driving self-regulation behaviors. In addition, the study's measure of self-regulation was limited to avoidance behaviors, which is consistent with previous literature in the field (e.g. Sullivan et al., 2011; Molnar et al., 2013).

Furthermore, other factors should be taken into account, such as individual differences, coping capacities, or the level of familiarity with driving performance. Future studies should replicate these findings using objective measures, such as a driving simulator, which can provide a more ecologically valid assessment of risky scenarios. Another important aspect to consider is the driving frequency and its potential impact on SA and self-regulatory behaviors. Unfortunately, we had not information available on this aspect as well as on numbers of motor vehicle crashes. Moreover, no state or trait anxiety scores were examined. This could be considered a limitation of our study. Nevertheless, the literature has shown that general anxiety

doesn't affect spatial navigation (Thoresen et al., 2016). Indeed, people with high trait and state anxiety scores do not necessarily have high SA scores (Walkowiak et al. 2015).

Finally, employing a Structural Equation Model (SEM) would have allowed the inclusion of heterogeneity effects within the model through the Multi-Group Analysis (MG). Anyway, the size of our sample did not allow for testing structural equation models. Indeed, the number of observed variables/variables is slightly greater than 13 ($838/60 = 13,9$) but is more less to 20, as defined by Kline (2023). For this reason, we didn't employ SEM. Future research should adopt a sample size more representative to provide a more comprehensive view.

Conclusion

This study has highlighted that SA is related to risky driving behaviors and that driving self-regulation mediates this relationship. Considering our findings, SA is associated with higher rates of navigational and timing errors in route selection (Hund et al., 2006; Lawton, 1996). In general, drivers with elevated SA had higher levels of self-reported driving errors and lapses. The more interesting result is related to the mediating role of driving self-regulation between SA and driving lapses. This suggests that anxious and less confident drivers may be at greater risk of over-regulation, as an anxious driving style and a negative affective attitude were significant predictors of self-regulation. Moreover, the findings indicate that drivers with high scores of self-regulation and SA cope with the worries and stressors of driving by disconnecting from the driving task (Gwyther and Holland, 2012).

The results of this study suggest the potential benefits of developing tailored training programs to reduce SA. One promising avenue of exploration is the integration of mindfulness-based anxiety reduction techniques. By incorporating mindfulness practices into training programs, individuals may develop a more awareness of their thoughts and emotions associated with SA. This increased awareness may enable them to effectively manage anxious situations

while navigating through space during the driving task (Koppel et al., 2019). In addition, drivers with poorer spatial navigation strategies could be trained to improve their spatial skills using virtual reality programs or game-based learning interventions (Rupp et al., 2012). Game-based interventions can reduce SA symptoms behind the wheel by providing gamified tasks with realistic simulations of traffic situations, immediate feedback on driver performance as well as on their arousal while driving (e.g. Dunwell et al., 2014; Hulme et al., 2021). These interventions can help drivers develop stress management and spatial navigation strategies in a controlled and safe environment. (e.g. Xie et al., 2016; Khan et al., 2021; Chen et al., 2023).

In addition, the study of these aspects can be considered a key area for future research. It is of great importance to investigate detailed planning through driving simulators and virtual reality, to integrate advanced driver assistance systems (ADAS), and to develop personalized interventions that consider individual differences in spatial anxiety. Longitudinal studies are recommended to assess the long-term effectiveness of the proposed interventions. Furthermore, research should be expanded to encompass a wider range of populations to gain a deeper understanding of and more effective means of managing SA. Policy makers and road safety authorities should consider these findings to develop policies and campaigns promoting traffic safety and mindful driving to mitigate SA.

GENERAL DISCUSSION AND CONCLUSION

The need to address the complex issue of DD through a multifaceted approach led to the research path taken in this doctoral thesis. Despite the extensive nature of the existing literature, current evidence often presents a fragmented perspective on the topic of distraction. These studies tend to analyze specific risk factors or use general metrics that do not fully capture the complexity of the driver's conscious experience. Therefore, this doctoral thesis aimed to develop a more comprehensive framework of DD, adopting the TR/SD model as a theoretical reference. This model delineates conscious experiences along the orthogonal dimensions of task-relatedness (TR) and stimulus-dependency (SD). This work, divided into six studies, has advanced the research topic in several ways. First, it has helped transition from a theoretical synthesis of literature to the development and validation of new psychometric tools capable of detecting different distractions in the driving context, whether driven by external or internal sources. Second, it has supported the objective investigation of the interaction between environmental factors and individual differences that can influence the DD. The integration of the results from these six studies showed that the impact of distraction on driving performance is not a homogeneous effect but is dynamically moderated by an interplay of factors. These factors can include individual (e.g., age, gender), cognitive (e.g., susceptibility to distraction), psychological (e.g., spatial anxiety), and environmental characteristics (e.g., traffic conditions). Therefore, this concluding section provides a summary of the studies presented in preceding chapters and the findings detailed in previous paragraphs.

In *Chapter I*, the first study was presented. The aim was to conduct a systematic review of the available evidence on driving-related factors associated with MW behind the wheel. The literature review suggests that the MW behind the wheel has been studied in relation to four main clusters of factors: vehicle-related factors (i.e., ADAS), environmental factors (i.e., weather as well as road conditions), human factors (i.e., perceptual load,

personality traits, and socio-demographic factors), and behavioral consequences. The novel aspect of this literature review was the identification of the crucial role that human factors play in increasing the propensity of MW. Specifically, the study identified perceptual load, specific personality traits (e.g., neuroticism, extraversion), and socio-demographics (e.g., younger male drivers) as potential factors that contribute to MW while driving. In addition, higher levels of vehicle automation are linked to increased MW, while lower levels show less impact. The study's findings provide support for the implementation of focused training techniques, such as mindfulness, to assist drivers in more effectively managing their inattentional states. The development of preventive strategies that target specific high-risk situations is possible through the identification of these situations, such as driving on well-known routes or for extended periods of time. Finally, the study highlights the importance of developing device systems capable of monitoring attention, thereby transitioning from awareness-based prevention to active technological support.

In *Chapter II*, a validation of a new psychometric instrument for measuring driver conscious experience associated with DD was conducted. The study aimed to develop a reliable and valid self-reported instrument with good psychometric properties that can discriminate between different driving distraction profiles, including distractions driven by external stimuli and distractions driven by self-generated thoughts. The TR/SD theoretical model was followed. In light of the results obtained, this instrument could have important practical implications. Indeed, the QUADRIVIA tool has the potential to be used in research settings for the study of the prevalence and characteristics of internal and external distractions in various driving conditions, demographics, and age groups. Furthermore, it could be used to assess the efficacy of interventions designed to mitigate distraction and increase driver awareness. Indeed, the distinction provided by QUADRIVIA between several types of conscious driving experiences could contribute to a more accurate

definition of DD, overcoming more generic definitions and developing more targeted and effective prevention strategies. In summary, the capacity to differentiate between different conscious experiences is important in light of the potential cognitive and behavioral ramifications these phenomena may have on driving performance.

At the same time, the thesis expanded his psychometric contributions to include other groups of road users. In *Chapter III*, an innovative cross-regional validation study was conducted on an extensive scale, encompassing over 15,000 cyclists from 44 countries. This study focused on the Phone Use While Riding Scale (PURS). This work provides a considerable methodological and theoretical significance, not only confirming the transcultural validity of a three-dimensional structure (i.e., visual-manual interactions, risk compensation behaviors, and auditory interactions) but also showing the scale's predictive power with respect to self-reported incidents. The PURS novelty was to offer a standardized instrument for global research on the security of a category of vulnerable users, whose interaction with technology was, until now, little quantifiable in a systematic way. Moreover, from an applied perspective, PURS offers several contributions that may be valuable for researchers, policymakers, and practitioners aiming to address cycling safety in the context of distraction associated with mobile phone use. While previous research has focused extensively on driver and pedestrian distraction, PURS provides a structured approach to studying the distraction associated with mobile phone use among cyclists and motorcyclists, a growing but often overlooked issue in road safety.

Chapter IV provided validation for the Italian version of the NMP-Q by addressing the construct of nomophobia and further extending the study of psychological factors associated with technology. The novelty of this study was double. Firstly, the findings of this research support the psychometric validity of the NMP-Q, as well as its applicability in both research and clinical screening contexts. The establishment of normative data can help

to identify individuals at higher risk of nomophobia and inform targeted interventions in the Italian context. Secondly, this study identifies sensitive gender and age differences in nomophobia levels. Females consistently report higher nomophobia scores across age groups, while younger individuals show greater susceptibility compared to older adults. These patterns reinforce the need for age and gender sensitive approaches in future research and intervention strategies.

Chapter V tried to investigate the impact of DD susceptibility and perceptual load on different behavioral patterns in a simulated driving task, with the aim of operationalizing the two conscious experiences related to the stimulus-independence domain of Stawarczyk's model: task-related stimulus-independent thoughts (TRSI) and task-unrelated stimulus-independent (TUSI) thoughts. To this end, a high-fidelity driving simulator was employed to measure moment-by-moment changes in steering, speed, and SDLP. Moreover, the participants' thoughts both online (during the task) and offline were probed to investigate the frequency of TRSI and TUSI during the experimental conditions. The novelty of this study lies in its exploration of the limitations of conventional analyses of the effects of distraction. It shows that driving performance is influenced by a multifaceted interaction between several factors, including individual factors such as gender and susceptibility to distraction, and contextual factors (perceptual load conditions). The study offers new insights by exploring how drivers with different distraction profiles adopt specific driving strategies in response to the same load conditions. Concurrently, it provides a substantial contribution to the field by offering a comprehensive analysis of the type of thought associated with different perceptual load conditions. Regarding practical implications, the study's identification of distinct risk profiles can facilitate the development of customized training programs and the design and validation of ADAS systems capable of adapting their

warnings or interventions not only in response to road conditions but also to a driver's profile.

In order to provide a comprehensive overview of individual differences, *Chapter VI* investigated an additional psychological factor, likely associated with driving distraction: spatial anxiety. The study aimed to understand how the severity of SA affects risky driving behaviors and whether this relationship is mediated by the driver's self-regulation abilities. The more interesting result is related to the mediating role of driving self-regulation between SA and driving lapses. This suggests that anxious and less confident drivers may be at greater risk of over-regulation, as an anxious driving style and a negative affective attitude were significant predictors of self-regulation. Moreover, the findings indicate that drivers with high scores of self-regulation and SA cope with the worries and stressors of driving by disconnecting from the driving task. Therefore, these results confirmed that SA has the potential to lead the drivers to divert executive resources from external monitoring, facilitating transitions to lapses and distraction.

Limitations of the current studies and future directions

This thesis presents some limitations. The first limitation refers to the convenience sampling method. Indeed, it is a method that presents several disadvantages. In particular, biases related to convenience sampling are, for example, the lack of variety in the sample. This potential limitation may reduce the reliability and validity of the findings. A second limitation concerns the use of self-report questionnaires, which are subject to several potential biases. One is social desirability, in which participants may have reported being better drivers than their actual abilities. Another aspect that merits consideration is the potentially limited introspective accuracy of participants in reporting their conscious experiences. A third limitation pertains to the low sample size of the study presented in the

Chapter V. This increases the difficulty of generalizing the results. Indeed, the behaviors manifested by young drivers may not be indicative of similar behaviors observed in middle-aged or older drivers.

In conclusion, this thesis aimed to provide a more accurate and comprehensive theoretical framework for DD, focusing on the interplay between several factors that influence this phenomenon. In light of the limitations explained above, future research on this topic should be conducted with a longitudinal study design in which the drivers are profiled according to their susceptibility to distraction. This would help to understand how driving behavior changes over time after specific interventions tailored to improve awareness and vigilance behind the wheel. Moreover, the research should try to conduct new studies based on driving real world (i.e. real-world/simulator driving, Caffò et al., 2020) to increase the ecological validity and reliability of the findings. On the other hand, the implementation of in-car devices could be useful to detect different types of distractions through eye-tracking systems. Moreover, considering the increasing levels of automated driving (ADAS), the utilization of specialized in-car devices has the potential to contribute to the development of algorithms for driver monitoring systems capable of detecting various forms of distraction in real time. This could help the drivers to be more oriented to the driving task and decrease the propensity to engage in concurrent activities.

Take-home messages: who might find this work useful?

This doctoral work provides an updated theoretical framework, new validated psychometric tools, and experimental data on the interplay between environmental and individual factors. These contributions may be especially helpful for researchers in the field of road safety. This research can be used by road safety stakeholders and policymakers to guide laws, awareness campaigns, and preventative measures that target the most

vulnerable groups and newly identified risk factors. In particular, this work can facilitate the development of targeted awareness campaigns and individualized educational programs, enabling the identification of driver profiles that are particularly susceptible to various forms of distraction, including cognitive, visual and manual distractions. Furthermore, the findings concerning the association between anxiety, self-regulation, and risky driving behaviors provide significant evidence in support of the integration of psychological testing and training into programs for driver licensing or rehabilitation. As automated driving becomes more prevalent, this knowledge about attentional processes becomes relevant to ADAS developers, who can use it to create driver monitoring systems capable of identifying internal distractions and promoting safety. Additionally, driving schools can enhance their instructional methods by incorporating the scientific basis of this phenomenon into their curricula, thereby providing new drivers with a comprehensive understanding of less evident hazards, such as MW, and the psychological impact of domain-specific anxiety. While clinical psychologists develop the skills and knowledge to establish connections between psychological disorders (e.g., spatial anxiety and nomophobia) and road safety, and assess interventions such as mindfulness, public health organizations can facilitate more effective prevention by considering DD as a health concern. Finally, the development of risk models and the design of infrastructure by insurance companies and urban planners/transport engineers, respectively, can be improved to mitigate the impact of familiarity and monotony of MW behind the wheel.

Appendix I.

QUADRIVIA items list (Chapter II)

Italian	English	Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Almost always (5)
1) Mi capita di pensare allo stato del veicolo mentre guido (p.e.; la pressione degli pneumatici, la funzionalità dei tergicristalli) (TRSI_01)	1) I sometimes think about the condition of the vehicle while driving (e.g. tyre pressure, windscreen wiper functionality). (TRSI_01)					
2) Mentre sono alla guida, mi chiedo se sono in regola con gli adempimenti legati alla circolazione (e.g. bollo, assicurazione, tagliando, revisione).	2) While driving, I find myself wondering whether I'm up to date with the vehicle's legal and maintenance requirements (e.g., vehicle tax, insurance, scheduled servicing, roadworthiness inspection) (TRSI_02)					
3) Mentre sono alla guida, mi capita di riflettere sulle condizioni della strada.	3) While driving, I reflect on the road condition (TRSI_03)					
4) Mentre sono alla guida, penso al punto del tragitto in cui mi trovo	4) While I am driving, I think about where I am on my route (TRSI_04)					
5) Mentre sono alla guida, penso quanto il guidare possa essere pericoloso	5) While I'm driving, I think about how dangerous driving can be (TRSI_05)					
6) Mentre sono al volante, penso agli effetti della mia guida sui passeggeri	6) While I am driving, I think about the effects of my driving on my passengers (TRSI_06)					
7) Mentre sono alla guida, mi accorgo di guardare edifici o la natura circostante senza uno scopo preciso.	7) While driving, I find myself looking at buildings or the surrounding nature without any particular purpose (TUSD_01)					
8) Mentre sono alla guida, mi concentro sui veicoli accanto a me, soprattutto se mi piace la marca o il modello.	8) While driving, I focus on the vehicles next to me, especially if I like the car model (TUSD_02).					

9) Mentre sono alla guida, osservo il paesaggio, le montagne o il mare.	9) While driving, I often find myself looking at the landscape, the mountains, or the sea (TUSD_03)					
10) Mentre sono alla guida, mi capita di essere attratto dallo scenario di un incidente e/o dei lavori stradali presenti. (TUSD_04)	10) While driving, I am often drawn to the scene of an accident and/or roadworks (TUSD_04)					
11) Mi capita di utilizzare il telefono cellulare quando sono alla guida (TUSD_05)	11) I use my mobile phone while driving (TUSD_05)					
12) Durante l'attività di guida mi capita di prestare attenzione ai cartelloni pubblicitari lungo la strada (TUSD_06)	12) While driving, I sometimes pay attention to the billboards along the road (TUSD_06)					
13) Durante l'attività di guida mi capita di distrarmi dai discorsi degli altri passeggeri. (TUSD_07)	13) While driving, I sometimes get distracted by the conversations of other passengers (TUSD_07)					
14) Mentre sono alla guida, mi distraigo guardando un negozio o un ristorante. (TUSD_08)	14) While driving, I get distracted by looking at a shop or restaurant (TUSD_08)					
15) Mentre sono alla guida, pianifico una festa o un evento speciale. (TUSI_01)	15) While I'm driving, I plan a party or special event (TUSI_01)					
16) Mentre sono alla guida, pianifico cosa fare nel fine settimana. (TUSI_02)	16) While I'm driving, I plan what to do at the weekend (TUSI_02)					
17) Mentre sono alla guida, rifletto su eventi storici o fatti interessanti. (TUSI_03)	17) While driving, I reflect on historical events or interesting facts (TUSI_03)					
18) Mentre sono alla guida di un veicolo inizio a sognare ad occhi aperti. (TUSI_04)	18) While driving a vehicle, I start daydreaming (TUSI_04)					
19) Mentre sono alla guida, fantastico su cosa mangiare al mio ristorante preferito. (TUSI_05)	19) While I'm driving, I wonder what to have for lunch/dinner (TUSI_05)					

20) Mentre sono alla guida, mi capita di andare oltre il luogo che volevo raggiungere perché penso ad altro (es. andare oltre un certo negozio, superare la via che si voleva imboccare). (TUSI_06)	20) When I'm driving, I sometimes end up driving past my destination because I'm thinking about something else (e.g., passing a certain shop, or missing the turn onto the street I wanted to take) (TUSI_06)					
21) Mi ritrovo a pensare a una vacanza o eventi futuri durante la guida (TUSI_07)	21) While driving, I think about a vacation or future events (TUSI_07)					

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