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# The prevention of road accidents in non-expert drivers: Exploring the influence of Theory of Mind and driving style

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ABSTRACT

*Background:* Drivers consider external and hypothetical behaviours of other drivers, but internal factors also impact road safety.
*Objectives:* This study aims to examine the connection between Cognitive and Affective Theory of Mind (ToM) and Driving Style in road safety. It hypothesizes that a higher level of ToM corresponds to a greater ability to avoid accidents and to assume virtuous driving behaviour. The study investigates how ToM impacts driving behaviour, directly correlating with assessing potential accidents' probability and severity.
*Method:* 207 non-expert drivers, including 164 females, participated in assessing Cognitive and Affective ToM through two tasks. They also completed self-measured questionnaires to assess their driving style and behaviours. In addition, they evaluated 12 videos depicting cars, motorcycles, trucks, and pedestrians to determine the probability of a road accident and the level of danger in each scenario.
*Results:* The results of the mediation models clearly indicate a relationship between ToM and the reduction of road accidents. Specifically, Cognitive ToM plays a crucial role in assessing the probability of risky and dangerous situations related to Risky and Angry Driving Styles. However, it was observed that Cognitive ToM does not significantly affect the prediction of actual driving behaviours.
*Conclusions:* Findings are discussed within the theoretical framework of the Task-Capability Interface Model and the Embodied Simulation Model based on mirror neuron research. Our results suggest the importance of creating drive-assistance systems considering both the Cognitive ToM and Driving Style to reduce road accidents among non-expert drivers.

## 1. Introduction

Road accidents are considered one of the leading causes of death. This is why there is a considerable effort from all governments to prevent accidents. The efforts made in this direction have brought results and, in the last decade, the situation has improved slowly but steadily in Europe and Italy. Focusing on the Italian context, Italy is 11 out of 27 European countries with the lowest fatalities per million inhabitants. Concerning the mortality rate, 40 road fatalities are reported per million inhabitants, which is just below the European average (M = 42). Specifically, 2,395 people were killed in reported traffic accidents in 2020. Since 2001, the mortality rate in Italy has declined at the same pace as the European Union. For the years 2020–2021, it is noteworthy to consider the mobility restrictions imposed by the COVID emergency, which have resulted in fewer accidents in both Italy and Europe (European Commission, 2023; the Italian case: Colonna & Intini, 2020).

However, the European road safety goals of halving the number of fatalities and serious injuries by 2030, compared to the benchmark year

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2019, have already been complicated by the increase in road fatalities recorded in the first six months of 2022 (Istituto Nazionale di Statistica, ISTAT, 2022). Achieving these goals will require dramatically reducing the number of injury accidents in the coming years. There is a worldwide effort to reduce road crashes, such as their economic impact. The estimated economic cost of all traffic crashes in the United States in 2019 is $1,035 for each of 328 million citizens and 1.6 % of the gross domestic product ($21.4 trillion in 2019). The economic costs include insurance premiums, taxes, medical costs, costs related to lost time, congestion costs, and increased environmental impact (Blincoe, et al., 2023). This is particularly relevant for new drivers as driving performance is influenced by experience. Studies have shown that experience plays a significant role in driving behaviours (Pammer & Blink, 2018; Crundall et al., 2014; Pammer et al., 2021). Although it can be difficult to determine the difference between an expert and a non-expert driver, insurance companies typically consider someone an expert driver once they reach age 26 or older. Expert drivers have more detailed and refined driving patterns than non-experts (Pammer et al., 2018; Pammer et al., 2021), making non-expert drivers almost four times more likely to get into accidents (Insurance Institute for Highway Safety, IIHS, 2021). Indeed, many studies (e.g., Regev et al., 2018; Gomes-Franco et al., 2020) indicate that the highest crash rates are observed in the youngest age group, peaking at ages 21–29 and then sharply decreasing until ages 60–69. The largest number of accidents involves cars, heavy vehicles, and motorcycles. Interestingly, many road deaths are caused by accidents that do not involve other vehicles. Frequent accidents arise from excessive speed or driver distraction, such as multitasking while driving (Palmiero et al., 2019). Negligence and carelessness play a significant role as well. Human factors likely have the most profound impact on the severity of accidents (Eboli & Forciniti, 2020). In the Supplemental Material section, you can find the European data about accidents for 2021. This information has been sourced from the European Commission and was last updated in 2023.

## 2. Literature review

Several theoretical frameworks have been proposed to conceptualize driving behaviour to enhance road safety. However, we will focus on the Task-Capability Interface (TCI) model developed by Fuller in 2000. This model emphasizes the significance of comprehending drivers' individual differences to avoid accidents.

### 2.1. The TCI Model

The model indicates that the driver maintains control when the external task demand is low, such as driving on a well-lit street with little traffic, and the driver's ability exceeds the demand. Conversely, the driver may lose control if the external demand increases, such as driving on an unlit road in heavy traffic. The TCI framework takes into account both biological factors, such as the driver's skill, as well as acquired factors, like training and experience. The drivers' ability is determined by their processing capacity and speed, reaction time, physical reach, motor coordination, flexibility, and strength. Knowledge and skills are built upon these characteristics from experience and training. This knowledge comprises formal elements, such as road rules, procedural knowledge, which defines what actions to take under different circumstances, and a representation of the dynamics of road and traffic scenarios. This knowledge enables one to predict how different scenarios will evolve, like an internalized mental video that runs ahead of the observed situation (Kaempf & Klein, 1994). One's ability to control the vehicle and handle challenging situations, such as a skid, is always a part of biological factors. The driving behaviour is, however, susceptible to various human factors (such as attitude, motivation, effort, fatigue, drowsiness, time of day, drugs, distraction, emotions, and stress) that can diminish driver expertise, resulting in a slightly reduced level of ability (Fuller, 2005).

In addition to the TCI model, it is crucial to recognize that driving is not only a mechanical task but also a complex social interaction. Our ability to understand and interact with others on the road relies on both personal experience and ability to understand others' intentions and actions through the capability to empathize with them. Therefore, it is highly beneficial to incorporate the Embodied Simulation Model into our understanding of driving, as it enables drivers to interpret the actions and, therefore, intentions of others accurately. Embodied simulation is crucial in attributing mental states to others (see Gallese, 2007), allows understanding of a visual scene, and is mediated by the activation of mirror neurons (Gallese, 2006).

Researchers have identified various contributing factors, such as demographic characteristics, when considering human factors. For example, young male drivers commit more traffic violations than older individuals and females. The violations include: i) using a cell phone, driving at high speeds, not wearing seat belts, drinking more alcohol, and thinking the risk is lower (Greenberg et al., 2003; McDonald et al., 2014; Navas et al., 2019); ii) personality trait – individuals with a tendency towards high-level sensation seeking, such as heightened levels of general anxiety, show a correlation with unsafe driving behaviours (e.g., Dula et al., 2010; Lucidi et al., 2020); iii) cognitive factors – individuals with increased levels of executive functions demonstrate greater ability to manage complex tasks, such as driving behaviour, by effectively filtering among relevant and irrelevant information (e.g., Walshe, et al., 2017); iv) drivers with a higher level of spatial skills exhibit better driving behaviour (e.g., Nori, et al., 2020); v) driving style encompasses the choices drivers make during regular driving, including speed, level of attention, and adherence to safety measures (e.g., Taubman-Ben-Ari, Mikulincer, & Gillath, 2004; Freuli et al., 2020).

### 2.2. Human factors

The study of driving style has become important for its close relationship with road safety. Indeed, identifying driving style is important to provide personalized driving assistance to reduce dangerous driving behaviours and improve road safety (Taubman-Ben-Ari, Mikulincer, & Gillath, 2004; Astarita et al., 2016; Zhang et al., 2023). For this reason, methods and tools have been developed to classify driving styles and analyze their association with other factors to prevent accidents (e.g., Taubman-Ben-Ari, Mikulincer, & Gillath, 2004; Cordellieri et al., 2016; Eboli, Mazzulla, & Pungillo, 2017; Zhang et al., 2023). Most of the research on driving style is typically based on subjective or objective indexes, such as vehicle microtrajectory-based research (i.e., the detailed depiction of traffic flow useful for traffic management and control applications). Numerous studies have created assessment tools that are centred around specific elements for evaluating driving style through questionnaires and subjective indices (e.g., Reason et al., 1990; Taubman-Ben-Ari, Mikulincer, & Gillath, 2004; Cordellieri, et al., 2016). "The Multidimensional Driving Style Inventory" (MDSI) is the most commonly used questionnaire in the field (Taubman-Ben-Ari, Mikulincer, & Gillath, 2004). It has been developed and revised by researchers from different countries (e.g., Italy: Freuli et al., 2020; Malaysia: Kamaludin et al., 2022; China: Guo, An, & Sun, 2022) to analyze the relationship with driving decision-making style, socio-demographics, and personality characteristics. Specifically, the association between driving styles and some socio-demographics and personality characteristics has been studied for a long time. It is widely recognized that for both younger and more experienced drivers, men display higher scores in risky and angry driving styles compared to women; on the other hand, women display higher scores in patient and careful driving styles (Taubman-Ben-Ari & Skvirsky, 2016; Freuli et al., 2020). Taubman-Ben-Ari and Yehiel (2012) studied how driving style is related to personality. They found that extroverted people tend to be more distracted and hostile while driving. People who experience distress while driving are less conscientious and more neurotic. Careful driving is associated with higher agreeableness, conscientiousness and openness. Furthermore, according to Cordellieri et al. (2019), driving style is associated with the mode of transportation. While motorcyclists and car drivers have similar attitudes towards road safety regulations, motorcyclists appear to be less worried than car drivers about the possibility of a road accident, leading to a higher likelihood of risky driving behaviour than car drivers.

### 2.3. Objective index

Studies on vehicle microtrajectory-based research have identified four methods of trajectory data acquisition. These methods include vehicle-mounted trajectory (e.g., Mohammadnazar et al., 2021), driver simulator simulation trajectory (e.g., Wang et al., 2017), smartphone trajectory (e.g., Mantouka et al., 2019), and computer vision-based trajectory (e.g., Lu et al., 2021). These methods are used to define driving style. However, driving activity does not occur in isolation but requires interaction between drivers using different modes of transport. To avoid accidents and ensure that traffic flows smoothly, drivers rely on both external information and their judgment. This includes considering their surroundings, other vehicles on the road, and adhering to traffic rules. Additionally, drivers must consider the hypothetical driving behaviours of other drivers on the road (e.g., Shimojo et al., 2020; Shimojo et al., 2022).

### 2.4. Theory of Mind

According to the Theory of Mind ability (ToM, Premack & Woodruff, 1978), individuals can comprehend others' thoughts, intentions, and emotions that cannot be directly observed, to determine their actions. It enables perceiving individuals as cognitive beings with their own beliefs, desires, emotions, and intentions. Human beings can understand others' physical actions, goals, and interactions by taking into consideration their mental states. It is crucial to note that recent models have characterized ToM as a complex process with cognitive and affective subcomponents, as outlined by Baron-Cohen and Wheelwright (2004) and Shamay-Tsoory et al. (2010). Cognitive ToM involves making inferences about beliefs and motivations, while affective ToM focuses on inferring another person's emotional state, distinct from emotional empathy (Gillespie, Mitchell, & Abu-Akel, 2017). Furthermore, Shamay-Tsoory et al. (2010) propose that cognitive ToM serves as a foundational skill for affective ToM, which in turn relies on intact empathy processing.

Therefore, it is important to clarify how the cognitive and affective ToM act, to understand how drivers make decisions to reduce road crashes.

### 2.5. Autonomous driving

Autonomous vehicles need to better understand people's current state of mind to ensure safe and confident movement around humans (Verberne et al., 2012; Beggiato & Krems, 2013, Matsubayashi et al., 2020). Unfortunately, autonomous vehicles are not very good at this, as demonstrated by a study of road crashes in California, where over half of the accidents involving autonomous vehicles were caused by rear-ending. This was because human drivers could not comprehend the autonomous vehicle's actions (Chandra et al., 2020). Schwarting et al. (2019) aimed to quantify and predict the social behaviour of other drivers. They categorized driver behaviour into four groups: altruists, who prioritize the enjoyment of others; prosocial drivers, who take actions for the benefit of all; individualists, who focus on their own driving experience; and competitive drivers, who only care about their enjoyment. This enabled them to make more accurate predictions about how the agent would engage and collaborate with others. They calculated the anticipated driving path for each category based on the starting position of other vehicles. The autonomous vehicle was designed to compare the actual drivers' trajectories to the calculated ones and use this information to identify the most probable category for the drivers. The results demonstrate a 25 % error reduction in predicting human movement, significantly improving autonomous performance. Similarly, Chandra et al. (2020) created a Machine Theory of Mind (M−ToM) called StylePredict to infer human drivers' behaviours by observing their vehicles' trajectories. StylePredict uses graph-theoretic techniques, such as spectral analysis and centrality functions, to infer driver's styles by mapping the extracted trajectory of a vehicle in traffic, mimicking human ToM. Moreover, Matsubayashi and colleagues (2020) created a driving model that observes the behaviours of other drivers and makes decisions based on the estimated characteristics of those drivers. The study found that understanding the behaviours of other drivers is crucial for avoiding road crashes, particularly in situations where lanes merge. The success or failure of this understanding directly impacts the probability of avoiding accidents. Even though recent research has emphasized the significance of ToM in comprehending others' driving intentions (Chandra et al., 2020; Matsubayashi et al., 2020; Shimojo et al., 2020), there is a lack of empirical investigation into the influence of cognitive and affective ToM on driving styles and means of transportation.

### 2.6. Objectives of the study

This study investigates the impact of driving styles and cognitive and affective ToM on road safety. Non-expert drivers evaluate different types of vehicle collisions by judging the road accident's risk (probability) and the situation's severity (danger).

Hy 1. Cognitive and affective ToM abilities are linked to an improved capacity to assess the probability of road accidents and the level of danger in any given situation, regardless of the mode of transportation used.

Hy 2. Driving style mediates the ability to predict the probability of a road accident and the level of danger of the situation.

Hy 3. The relationship between cognitive and affective ToM and driving behaviour, measured by violations, errors, and lapses, is mediated by driving style.

## 3. Method

### 3.1. Participants

A power calculation was performed to determine the sample size using G*Power 3.1. (Faul et al., 2007). To perform mediation analyses considering thirteen predictors (cognitive and affective ToM, eight driving styles, and three covariates: age, gender, and driving license) and the following parameters (effect size $f^2 = 0.15$ - medium magnitude; alpha = 0.05; power = 0.95), the sample size required was at least 189 participants. Our sample was composed of 213 participants. The z-test, using the range ± 4.0 *z*-scores for samples larger than 100 (e.g., Giancola, 2022; Mertler & Vannatta, 2005), identified 6 univariate outliers, which were discarded from the dataset. The final sample consisted of 207 young adults (students and workers), whose 164 were female and the remaining 43 were male: mean age = 22.19 ± 2.16 range 18–26; mean educational level = 14.54 ± 1.98; mean of driving license = 4.35 ± 1.92. Participants were excluded if they suffered from some conditions that might cause them difficulty or distress when completing the tasks, such as neurological or psychiatric disorders. The inclusion criterion was to have a driving license. None of the participants was excluded. All participants signed a written consent form before the study began. The local Ethics Committee approved the study (Prot. N. 61,302 of 15/03/2021, University of Bologna).

### 3.2. Materials

*The Short Story Task* (*SST* – Dodell-Feder et al., 2013). SST is used to investigate the cognitive ToM. In the SST, participants read an ambiguous short story about the relationship between two persons and were asked to assess their mental states. The task is composed of three parts: i) Eight questions assessed the understanding of characters' explicit first-order (i.e., inferring the character's beliefs; Why does Marjorie reply, "Oh Nick, please cut it out! Please, please do not be that way!"?) and second-order mental states (i.e., inferring what one-character thinks about another character's beliefs or actions; Why is Nick afraid to look at Marjorie?). For each question, the definitive mental state assessment score ranges from 0 (inaccurate) to 2 (complete understanding). The maximum score is 16. ii) Five questions probed the reader's comprehension of factual story events (non-mental content). For each question, the comprehension score ranges from 0 (inaccurate) to 2 (complete understanding), for a maximum score of 10. iii) One question assessed the reader's comprehension of spontaneous characters' mental states (presence versus absence of a mental state inference produced by participants to the question: "In just a few sentences, how would you summarise the story?"). In this case, the spontaneous mental state inference score ranges between 0 and 1 (presence versus absence of a mental state inference). The total score of the SST was obtained by the sum of detailed mental state assessment (0–16), comprehension answers (0–10), and spontaneous mental state inference (0–1). The maximum score is 27. Questions are open-ended, and the answers provided were analyzed according to the paper guidelines of Dodell-Feder et al. (2013) by two independent judges, unaware of the hypotheses, who carried out the coding with an agreement of 96 %. Any discrepancies in coding were resolved through discussion.

*The Reading the Mind in the Eyes Test* (*RMET* - Baron-Cohen, Wheelwright, Hill, et al., 2001). RMET is used to investigate the affective ToM. In the RMET, participants saw 36 pairs of eyes. Each one had to judge which of four adjectives best described the mental state expressed through the eyes (for example, "jealous, fearful, arrogant, odious"). The score ranges from 0 to 36. Photographs are displayed centrally and the four adjectives (one correct adjective and three distractors) are placed in the four corners of the paper sheet. A single practice trial precedes the 36 experimental trials.

*The Multidimensional Driving Style Inventory (MDSI* – Taubman-Ben-Ari et al., 2004; Freuli et al., 2020). To measure the driving style, we adopted the MDSI, one of the most used questionnaires in literature to assess participants' driving style. The MDSI relies on the idea that the driving style is a multidimensional construct and provides a profile of the different dimensions characterizing the driving style for each driver (Taubman-Ben-Ari et al., 2004). The original version of the MDSI included 44 items aimed to investigate four different domains of driving style (DS) hypothesized by the authors, i.e., "careless and reckless DS"; "anxious DS"; "angry and hostile DS"; "patient and careful DS" (Taubman-Ben-Ari et al., 2004; page 324). The Italian version included 40 items relating to eight DS: 1. *Dissociative DS*, mainly associated with distraction while driving; 2. *Anxious DS*, indicating persons who experience distress while driving; 3. *Risky DS,* identifies persons prone to risk and sensation-seeking while driving; 4. *Angry DS*, characterizing persons who show hostility towards external events or other drivers; 5. *High-velocity DS,* which indicates impatience while driving; 6. *Distress-reduction DS,* describes drivers who usually engage in relaxing activities while driving; 7. *Patient DS,* indicates calm behaviours during driving activity; 8. *Careful DS*, characterizing careful people with good problem-solving and planning abilities while driving. Drivers responded to statements about their feelings, thoughts, and behaviours while driving on a 6-point Likert scale ranging from 1 (*not at all*) to 6 (*very much*). In the original Freuli et al.'s (2020) study, for individual subscales, the analysis showed different reliability indexes: Factor 1 (Dissociative DS) showed moderate reliability indexes (Cronbach's $\alpha = 0.65$); Factor 2 (Anxious DS) showed good reliability indexes (Cronbach's $\alpha = 0.82$), as well as Factor 3 (Risky DS) (Cronbach's $\alpha = 0.80$), Factor 4 (Angry DS) (Cronbach's $\alpha = 0.66$) and Factor 5 (High-velocity DS) (Cronbach's $\alpha = 0.62$), whereas lower levels of reliability were found in factors related to the DS characterized by behaviours aimed to stress-reduction (Factor 6; Cronbach's $\alpha = 0.54$) and the patient DS (Factor 7; Cronbach's $\alpha = 0.46$); whereas Factor 8 (Careful DS) showed acceptable reliability indexes (Cronbach's $\alpha = 0.65$). In the current research, the Cronbach's α was as follows: Dissociative DS = $\alpha$ 0.76, Anxious DS = $\alpha$ 0.52, Risky DS = $\alpha$ 0.85, Angry DS = $\alpha$ 0.76, High-velocity DS = $\alpha$ 0.67, Distress reduction DS = $\alpha$ 0.60, Patient DS = $\alpha$ 0.77, Careful DS = $\alpha$ 0.49, and total MDSI = $\alpha = 0.89$.

*The Manchester Driver Behaviour Questionnaire (MDBQ* - Reason et al., 1990). MDBQ is used to evaluate the driving behaviour of participants. It is a self-report questionnaire, which measures driving behaviour in terms of i) lapses (e.g., How often do you hit something you did not see when you turn around?); ii) errors (e.g., How often do you move without checking mirror?); iii) highway code violations, that is, ordinary violations (e.g., How often do you race away from traffic lights to beat the driver next to you?); and iv) aggressive violations (e.g., How often do you sound your horn to indicate your annoyance to another driver?). Participants were required to indicate, on a six-point scale ranging from "never" (1) to "nearly all the time" (6), how often they committed that specific behaviour while driving. To ensure parsimony, in the current study, a total score of the MDBQ was computed (Driving Behaviour). In our sample, the Cronbach's α was as follows: lapses = $\alpha$ 0.83; errors = $\alpha$ 0.87; ordinary violations = $\alpha$ 0.86; aggressive violations = $\alpha$ 0.71; and the total score (Driving Behaviour) = $\alpha$ 0.93.

*Videos of road crashes.* The Municipal Police provided videos displaying scenes of potential road accidents. Road crashes involved cars, heavy vehicles, motorbikes, and pedestrians. The videos were chosen based on specific criteria. First, no underage individuals were featured in the videos. Second, the video had to give the viewer the impression that they were the vehicle's driver. Third, the videos were filmed during the day. Fourth, at least two people had to be involved in the road crash. Finally, the duration of the videos had to be between 9 and 11 s. Then, the videos were edited to stop a few seconds before the hypothetical crash. The participants then had to determine whether the crash occurred or not. At the beginning, 31 videos were divided into four categories: cars (10), motorcycles (9), heavy vehicles (6), and pedestrians (6), as shown in Fig. 1.

A pre-test study was conducted to select videos that did not differ in valence and arousal. Through the pre-test study, three videos were selected for each category of means of transport, for a total of 12 videos. Details about the pre-test experiment are available in the Supplementary Material section. An example of a video frame that was presented to the participants is shown in Fig. 2.

During the experimental phase, participants were presented with the videos and asked to rate their perceptions of the *probability* of a road crash occurrence and the level of *danger* of the situation depicted in the videos. Participants answered on a Likert scale ranging from 0 (not at all) to 10 (high).

### 3.3. Procedure

The experiment was conducted using the Qualtrics platform (2005, USA). Participants were invited to participate in the experiment via email or social networks. They initially gave informed consent to take part in the study. They were then asked to provide information regarding their demographics (such as gender, age, and education), driving habits (including preferred mode of transportation, duration of their driver's license, frequency of driving, and any history of driving accidents), as well as their overall health to ensure the absence of neurological and psychiatric conditions. Finally, participants were also asked about their habitual use of medication, drugs, or alcohol. Then they completed the tasks, in a randomized order, to measure Cognitive (SST; Dodell-Feder, et al., 2013) and Affective ToM (RMET; Baron-Cohen, et al., 2001), driving styles (MDSI; Taubman-Ben-Ari, et al., 2004, Freuli et al., 2020) and driving behaviour (MDBQ; Reason et al., 1990). At the end, the twelve videos showing possible road crashes were presented, in a randomized order, three for each category (cars,

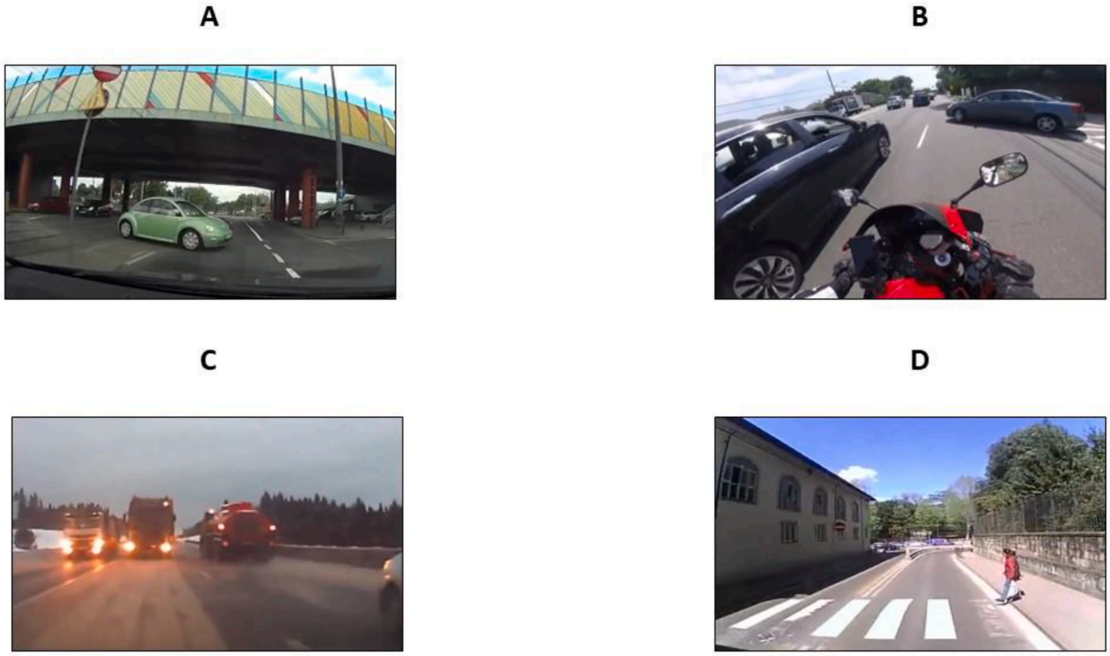


**Fig. 1.** The 4 accident situations involving 3 different means of transport and pedestrians.


**Fig. 2.** An example of the video frames viewed by participants.

motorcycles, heavy vehicles, pedestrians), followed by two questions about the level of probability of the road crash and the level of danger of the situation. The videos were submitted at the end of the experiment to prevent participants' drop-in concentration. The experiment lasted approximately 45 min.

### 3.4. Statistical analysis

Data were analysed using SPSS Statistics version 24 for Windows (IBM Corporation, Armonk, New York, USA). Descriptive statistics were computed to preliminary evaluate the main features of the sample, whereas bivariate correlations were performed to detect the associations among the study variables. Afterward, the mediation analyses were carried out through the PROCESS macro (Model 81) for SPSS version 3.5 (Hayes, 2017).

In the PROCESS procedure, the mediation effect is denoted by a significant 95% confidence interval (CI) bootstrapped based on 5,000 samples. Bootstrapping is a non-parametric approach that bypasses the problem of non-normality and provides an accurate evaluation of the indirect effect, also in small- to medium-sized samples (e.g., Giancola et al., 2022; Giancola et al., 2023). The significance of the results is provided if the range of the bootstrapped CI does not include the value of zero (Preacher & Hayes, 2004). In the bootstrapping approach, the $R^2$ measures the effect size. Finally, all significance in this study was set to $p < .05$. The dataset of the current research is available at the following link: https://osf.io/cn9bs/?view_only = e184be687d9c4253bca3c743ed950497.

## 4. Results

### 4.1. Preliminary analysis

Kolmogorov-Smirnov Test indicated that all continuous variables were not normally distributed except for Affective ToM, High-velocity DS, and Distress-reduction DS. In addition, Harman's single-factor test (Podsakoff et al., 2012) revealed that the variance explained by a single-factor exploratory model was 21.20 %, suggesting no common method bias problems (test critical threshold ≥ 50 %). Furthermore, the preliminary correlational analysis (Table 1) indicated that Cognitive ToM was positively correlated with Affective ToM, Patient DS, estimation of Crash probability vehicles, and Danger of the situation vehicles, as well as negatively with Risky DS and Angry DS. In addition, Risky DS and Angry DS were positively correlated with Driving behaviour and negatively correlated with estimation of Crash probability vehicles and of Danger of the situation vehicles. Finally, Patient DS was positively correlated with Affective ToM, estimation of Crash probability vehicles, and of Danger of the situation vehicles.

### 4.2. Mediation analysis

Three mediation models (Model A, Model B, and Model C) were advanced based on correlations. Model A comprises Cognitive ToM as the independent variable and Affective ToM, Risky DS, and Angry DS as the mediators. Model B and Model C include Cognitive ToM as the independent variable and Affective ToM, Risky DS, Angry DS, and Patient DS as the mediators. Driving Behaviour, Crash probability vehicles, and Danger of the situation vehicles were entered in PROCESS one by one as the dependent variables. Finally, Age, Gender, and Driving license were used as covariates in all models (Fig. 3).

For the Model A, results from the mediation analysis indicated that Risky DS ($B$ = -0.355, $BootSE$ = 0.148, $BootCI$ 95 % = [-0.668, −0.090]) and Angry DS ($B$ = -0.326, $BootSE$ = 0.122, $BootCI$ 95 % = [-0.568, −0.082]) mediated the association between Cognitive ToM and Driving Behaviour (Table 2). In addition, the direct effect of Cognitive ToM on Driving Behaviour was not significant ($B$ = -0.03, $p > .05$). Finally, the total effect was significant ($B$ = -0.77, $SE$ = 0.21 $t$ = -3.53, $CI$ 95 % = [-1.194, −0.338]), and the $R^2$ for the entire model was 0.47 [$F(8,198)$ = 25.24, $p < .001$] (Fig. 4).

For the Model B, results revealed that the association between Cognitive ToM and Crash probability vehicles was mediated by the effect of Risky DS ($B$ = 0.070, $BootSE$ = 0.028, $BootCI$ 95 % = [0.017, 0.127]) and Patient DS ($B$ = 0.034, $BootSE$ = 0.020, $BootCI$ 95 % = [0.001, 0.079]) (Table 2). Also, the analysis indicated that the direct effect of cCgnitive ToM on Crash probability vehicles was not significant ($B$ = 0.04, $p > .05$), while the total effect was significant ($B$ = 0.15, $SE$ = 0.06, $t$ = 2.48, $CI$ 95 % = [0.030, 0.268]). The $R^2$ for the entire model was 0.17 [$F(8,198)$ = 5.13, $p < .001$] (Fig. 5).

When performing the mediation analysis for Model C, findings mirrored the evidence reported in Model B. Specifically, results revealed that Risky DS ($B$ = 0.091, $BootSE$ = 0.034, $BootCI$ 95 % = [0.025, 0.159]) and Patient DS ($B$ = 0.046, $BootSE$ = 0.024, $BootCI$ 95 % = [0.005, 0.097]) mediated the interplay between Cognitive ToM and Danger Vehicles (Table 2), while the direct effect of Cognitive ToM on Danger vehicles was not significant ($B$ = 0.00, $p > 0.05$). The total effect was significant ($B$ = 0.16, $SE$ = 0.06, $t$ = 2.51, $CI$ 95 % = [0.034, 0.284]), and the $R^2$ for the entire model was 0.28 [$F(8,198)$ = 9.78, $p < .001$] (Fig. 6).

### 4.3. Post hoc power analysis

A post hoc power analysis was performed to evaluate the power obtained from the collected data. The power values of the models ranged from 0.99 to 1.00, satisfying the recommended cut-off value of 0.80 (Cohen, 1992): the sample of 207 was appropriate to test the study's hypotheses.

## 5. Discussion

Driving behaviour is shaped by many rules that follow a form of "if-then" reasoning (for example, if the light is red, then I have to stop) taught by driver handbooks and instructors. However, most rules are learned from real-life situations, which help drivers make better choices over time (Fuller, 2000). Here, we focused on analyzing situations where a driver's abilities are tested, requiring them to make quick decisions with limited information to prevent road accidents. This allows assessing the driver's actual capabilities in critical moments.

The present study adopted a driver-centred approach based on the TCI model (Fuller, 2000), especially its skill to understand the intentions of others (i.e., ToM). Specifically, our purpose was to explore the impact of Cognitive and Affective ToM ability and Driving Styles on road safety. We conducted the study with non-expert drivers who were asked to evaluate different types of vehicle collisions, by estimating the probability of an accident and the level of danger associated with each situation, corresponding to the severity of the potential road accident. We recruited new drivers to learn more about their thinking skills while driving instead of focusing on their driving experience. This is because novice drivers are significantly more prone to accidents than experienced drivers. We formulated three hypotheses: i) Better Cognitive and Affective ToM improve the ability to estimate the probability and danger of a potential road accident, regardless of the vehicle involved; ii) Driving Style mediates the ability to predict the probability and the level of danger of a road accident. iii) The link between Cognitive and Affective ToM and driving behaviour, as measured by violations, errors, and lapses, is influenced by driving style.

Hypothesis 1 is partially supported, showing that only the Cognitive component of the ToM is crucial in predicting road accidents, especially when other drivers are involved. In the context of driving competition, this ability is crucial in understanding the intentions of other drivers based on their driving behaviours (Gillespie, et al., 2017). A typical example in everyday life, while driving, it is common to change lanes to merge onto the main road. When this happens, the driver who has to merge must make a quick decision by interpreting the behaviour of other drivers to determine whether they can merge before or after the oncoming car. When drivers face decisions similar to these, they must predict and interpret intentions. Therefore, Affective ToM is not involved in this process.

Concerning Hypothesis 2, the drivers' ability to understand other's intentions (Cognitive ToM) is influenced by their Driving Style, which can either be risky or patient. For instance, when two vehicles are travelling side-by-side, one driver may speed up and overtake the other vehicle in a risky manner. In contrast, another driver may be patient and let the other vehicle through safely without endangering anyone. On the other hand, each driver has a unique Driving Style that can be predicted, to some extent, by their ToM. Drivers with low Cognitive ToM tend to have a risky and angry driving style, while those with high Cognitive ToM tend to be more patient while driving. However, it is important to note that only drivers with a combination of risky and patient driving styles have a higher probability of correctly predicting a potential road crash. A lack of empathy and understanding towards others' behaviours predicts a risky and aggressive Driving Style, consistent with other

**Table 1**
Means, standard deviations, and inter-correlations amongst all variables.

| | *M* | *SD* | 1. | 2. | 3. | 4. | 5. | 6. | 7. | 8. | 9. | 10. | 11. | 12. | 13. | 14. | 15. | 16. | 17. | 18. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Age | 22.19 | 2.16 | 1 | | | | | | | | | | | | | | | | | |
| 2. Gender | | | −0.02 | 1 | | | | | | | | | | | | | | | | |
| 3. Driving licence (years) | 4.35 | 1.92 | 0.68** | 0.08 | 1 | | | | | | | | | | | | | | | |
| 4. Cognitive ToM | 13.34 | 4.85 | 0.26** | −0.08 | 0.24** | 1 | | | | | | | | | | | | | | |
| 5. Affective ToM | 25.00 | 4.16 | 0.23** | −0.15* | 0.19** | 0.19** | 1 | | | | | | | | | | | | | |
| 6. Dissociative DS | 13.00 | 4.56 | 0.04 | −0.08 | −0.01 | −0.06 | 0.05 | 1 | | | | | | | | | | | | |
| 7. Anxious DS | 17.95 | 4.58 | 0.27** | −0.15* | 0.04 | 0.07 | 0.07 | 0.31** | 1 | | | | | | | | | | | |
| 8. Risky DS | 5.02 | 2.24 | 0.02 | 0.17* | −0.01 | −0.15* | −0.10 | 0.30** | −0.03 | 1 | | | | | | | | | | |
| 9. Angry DS | 9.28 | 3.92 | 0.13 | 0.10 | 0.08 | −0.14* | −0.05 | 0.48** | 0.28** | 0.36** | 1 | | | | | | | | | |
| 10. High-velocity DS | 12.35 | 4.20 | 0.19 | 0.12 | 0.15* | −0.02 | 0.00 | 0.56** | 0.23** | 0.40** | 0.65** | 1 | | | | | | | | |
| 11. Distress-reduction DS | 9.69 | 3.60 | 0.07 | −0.01 | 0.03 | 0.00 | 0.09 | 0.32** | 0.25** | 0.21** | 0.30** | 0.35** | 1 | | | | | | | |
| 12. Patient DS | 16.73 | 5.20 | 0.17* | −0.22 | 0.04 | 0.19** | 0.23** | 0.06 | 0.37** | −0.27** | −0.03 | 0.02 | 0.28** | 1 | | | | | | |
| 13. Careful DS | 10.27 | 2.71 | 0.01 | −0.19** | −0.08 | 0.04 | 0.10 | 0.02 | 0.43** | −0.24** | −0.08 | −0.04 | 0.26** | 0.55** | 1 | | | | | |
| 14. Driving behaviour | 47.86 | 14.82 | 0.11 | 0.09 | 0.08 | −0.10 | −0.02 | 0.68** | 0.25** | 0.42** | 0.63** | 0.72** | 0.32** | −0.02 | −0.08 | 1 | | | | |
| 15. Crash probability vehicles | 24.25 | 4.08 | 0.10 | −0.06 | −0.01 | 0.15* | 0.09 | −0.14* | 0.12 | −0.29** | −0.17* | −0.14* | 0.09 | 0.24** | 0.24** | 0.23** | 1 | | | |
| 16. Crash probability pedestrian | 7.53 | 1.87 | 0.05 | −0.07 | −0.02 | −0.01 | −0.03 | −0.07 | 0.05 | −0.07 | −0.02 | −0.08 | 0.01 | −0.04 | 0.09 | −0.06 | 0.18* | 1 | | |
| 17. Danger of the situation vehicles | 24.61 | 4.37 | 0.01 | −0.27** | −0.06 | 0.15* | 0.10 | −0.14* | 0.07 | −0.36** | −0.24** | −0.23** | 0.06 | 0.37** | 0.34** | −0.30** | 0.76** | 0.14 | 1 | |
| 18. Danger of the situation pedestrian | 8.61 | 1.67 | 0.10 | 0.02 | 0.01 | 0.02 | −0.02 | −0.06 | 0.12 | −0.08 | −0.02 | −0.05 | 0.12 | 0.12 | 0.19** | −0.05 | 0.27** | 0.66** | 0.21** | 1 |

*Note.* N = 207, gender was dummy coded (0 = F; 1 = M), ToM = Theory of mind; DS = Driving style. *$p < .05$ (two tailed); ** $p < .01$ (two tailed).

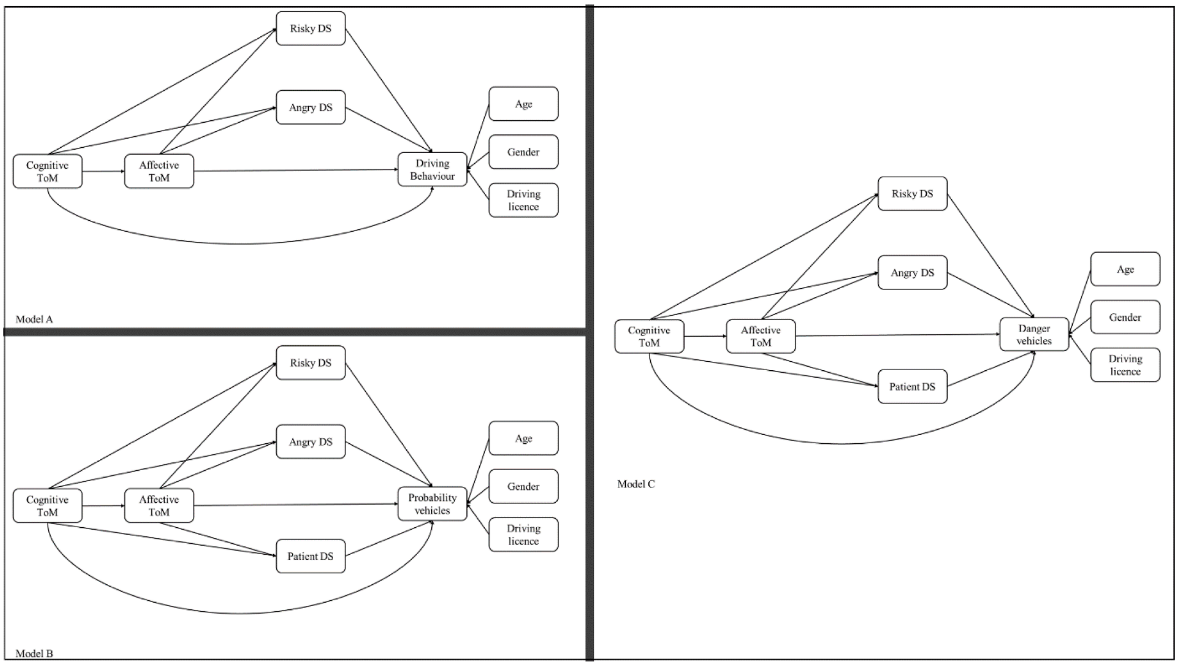


**Fig. 3.** The theoretical models (Model A, Model B, and Model C) advanced in the current research. Note. ToM = Theory of Mind; DS = Driving Style.

works in the literature in which these styles have been found associated with unsafe driving (e.g., Deffenbacher et al., 2003; Dahlen et al., 2005; Schwebel et al., 2006). However, these Driving Styles accurately predict the probability of a road accident. It is plausible that these driving styles can even more reliably identify the behaviours (such as risky or patient) exhibited by other drivers, enabling a better understanding of the probability of an accident and the ability to adjust one's behaviour accordingly. Different Driving Styles can significantly impact drivers' ability to assess potential dangers. This factor remains consistent across various vehicle types, such as cars, heavy vehicles, and motorcycles, but not for pedestrians.

It appears that individuals who drive cars often struggle to comprehend the intentions of non-drivers, perhaps due to a disparity in the signals they are accustomed to. Those who primarily navigate their way through the world by driving (by any mode of transportation) seldom venture on foot as pedestrians, limiting their understanding of signal utilization in hazardous situations, which makes it less discernible for them. This interpretation aligns with the Embodied Simulation Theory, founded on extensive research on Mirror Neurons (MNs) (for a comprehensive review, refer to Bonini et al., 2022). From this perspective, the comprehension of action results from a series of rapid cognitive processes that involve comparing past experiences with the current visual stimuli (e.g., Casile et al., 2011). In particular, the observer's motor system (MNs) plays a key role in understanding actions, resulting in a close relationship between action perception and production (e.g., Liberman & Mattingly, 1985; Jeannerod, 1997; Prinz, 1997; Rizzolatti et al., 2001). The motor system is involved in different ways, such as when a person perceives auditory cues associated with familiar actions (Kohler et al., 2002) or views acting on a screen in 2D dimension (Caggiano et al., 2016) and even actions that are partially occluded but can still be inferred from their initial motion path (Umiltà et al., 2001). Furthermore, in familiar environments, MNs can encode others' suppressed actions, becoming active even in the absence of observed movement (Bonini, et al., 2014), and demonstrate the ability to anticipate others' actions, even in varied and uncertain circumstances (Bonini, et al., 2010; Maranesi, et al., 2014), to support the idea that MNs can represent potential actions at a high level of abstraction (Maranesi et al., 2014). The MN system is important for representing actions based on sensory input and predicting actions based on context (Gerbella et al., 2013). Our hypothesis is confirmed: drivers can anticipate unsafe others' behaviours based on their experience with driving styles and their ability to simulate and predict future actions.

Regarding Hypothesis 3, which explores the connection between ToM and Driving Styles in predicting individuals' tendency to commit traffic violations, findings are consistent with previous research on risky and aggressive driving styles. Driving behaviour cannot be directly predicted by ToM alone and requires mediation by Driving Styles. ToM measures others' behaviour, intentions, and emotions, and it is less connected to one's behaviour. The patterns of results obtained suggest that individuals with more dangerous driving behaviours are more prone to engage in unsafe driving practices such as violations, aggressive violations, driving errors, or lapses. This association emphasizes that those Driving Styles that pose a greater risk are also the ones that best indicate the likelihood of these behaviours (e.g., Taubman-Ben-Ari & Yehiel, 2012).

It is worth noting that driving transgression behaviours are interconnected. Therefore, a driver who commits a traffic violation, often engages in other driving behaviours that endanger others.

In conclusion, this study is the first ever attempt to analyse how Cognitive and Affective ToM and Driving Style contribute to predicting the probability and severity of accidents, as well as individuals' perception of their unsafe driving behaviour. It is important to distinguish Affective and Cognitive ToM because only the latter plays a role in enhancing road safety, being closely linked to Driving Style but not to driving behaviour.

## 6. Limitations and future research

Our study yields consequential insights for scientific and applied research, but it is not without limitations. First, it relied on self-reports of Driving Style and unsafe driving behaviours and thus may suffer from self-serving biases. However, it is important to note that Sullman and Taylor (2010) found driving self-reports to be unbiased by social desirability. Secondly, it should be interesting to include people of different ages and with different driving expertise. Thirdly, a more balanced distribution between males and females in the sample would allow us to better understand a possible relationship among gender, ToM, and Driving Style. The fourth limitation is not having considered

**Table 2**
The indirect effects of the three models advanced in the current study.

| Path | Effect | SE | BootLLCI | BootULCI |
|---|---|---|---|---|
| Model A | | | | |
| Cognitive ToM → Affective ToM → Driving Behaviour | −0.009 | 0.029 | −0.082 | 0.042 |
| Cognitive ToM → Risky DS → Driving Behaviour | −0.355 | 0.148 | −0.668 | −0.090 |
| Cognitive ToM → Angry DS → Driving Behaviour | −0.326 | 0.122 | −0.568 | −0.082 |
| Cognitive ToM → Affective ToM → Risky DS → Driving Behaviour | −0.029 | 0.029 | −0.104 | 0.005 |
| Cognitive ToM → Affective ToM → Angry DS → Driving Behaviour | −0.020 | 0.023 | −0.083 | 0.006 |
| Model B | | | | |
| Cognitive ToM → Affective ToM → Probability vehicles | 0.001 | 0.010 | −0.024 | 0.020 |
| Cognitive ToM → Risky DS → Probability vehicles | 0.070 | 0.028 | 0.017 | 0.127 |
| Cognitive ToM → Angry DS → Probability vehicles | −0.001 | 0.014 | −0.030 | 0.031 |
| Cognitive ToM → Patient DS → Probability vehicles | 0.034 | 0.020 | 0.001 | 0.079 |
| Cognitive ToM → Affective ToM → Risky DS → Probability vehicles | 0.005 | 0.006 | −0.001 | 0.022 |
| Cognitive ToM → Affective ToM → Angry DS → Probability vehicles | 0.001 | 0.001 | −0.003 | 0.002 |
| Cognitive ToM → Affective ToM → Patient DS → Probability vehicles | 0.003 | 0.003 | −0.001 | 0.013 |
| Model C | | | | |
| Cognitive ToM → Affective ToM → Danger vehicles | −0.001 | 0.010 | −0.027 | 0.014 |
| Cognitive ToM → Risky DS → Danger vehicles | 0.091 | 0.034 | 0.025 | 0.159 |
| Cognitive ToM → Angry DS → Danger vehicles | 0.014 | 0.015 | −0.013 | 0.048 |
| Cognitive ToM → Patient DS → Danger vehicles | 0.046 | 0.024 | 0.005 | 0.097 |
| Cognitive ToM → Affective ToM → Risky DS → Danger vehicles | 0.007 | 0.008 | −0.001 | 0.028 |
| Cognitive ToM → Affective ToM → Angry DS → Danger vehicles | 0.001 | 0.001 | −0.001 | 0.005 |
| Cognitive ToM → Affective ToM → Patient DS → Danger vehicles | 0.005 | 0.004 | −0.001 | 0.017 |

*Note.* N = 207, SE = Standard Error, LLCI = Lower Limit of the 95 % Confidence Interval, ULCI = Upper Limit of the 95 % Confidence Interval, ToM = Theory of mind, DS = Driving style. *** $p < .001$.

external risk factors: in our work we mainly focused on the internal risk components (perceived by the driver and closely linked to the driver's skill), whereas future works, should also look more closely to the external risk aspects linked to the road situation and to road rules that affect the driver's behaviour. Future studies must integrate these aspects by utilizing the model developed by Colonna and Berloco (2011), which considers at the same time the effects of two types of risk (i.e., internal and external risks). For instance, travelling one kilometre by motorcycle poses a higher risk of accidents than travelling the same distance by car. Moreover, we overlooked the impact of familiarity with the environment on how people perceive risk in our study. Individuals are more inclined to take risks in familiar surroundings (Intini et al., 2019). Being well-acquainted with the environment enhances people's sense of competence and security from a spatial cognition standpoint (Nori & Piccardi, 2011; Nori et al., 2023); and this familiarity contributes to a stronger inclination to take risks, as demonstrated in Nori et al.'s (2022) research. In the current study, participants solely assessed the perception of risk and the level of danger in unfamiliar environments. Therefore, it would be compelling for future studies to explore and compare these assessments in familiar and non-familiar environments. Finally,

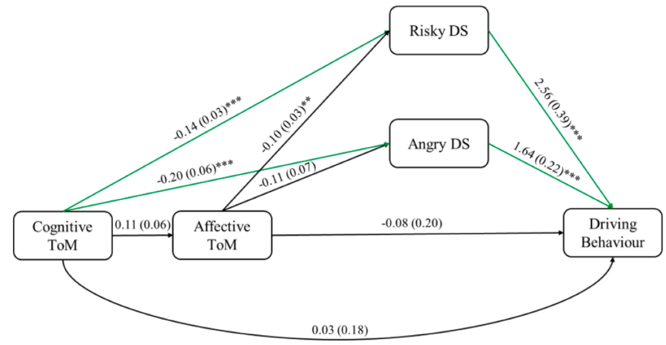


**Fig. 4.** The significant indirect effects (in green) of Cognitive ToM on Driving Behaviour (Model A).*Note. Path values are unstandardised coefficients and standard errors are shown in parentheses. Covariates are omitted for presentation purposes. **p <.01, *** p <.001.* The indirect effect of cognitive ToM on Driving Behaviour through risky DS (*B* = -0.355, *BootSE* = 0.148, *BootCI* 95 % = [-0.668, −0.090]) and angry DS (*B* = -0.326, *BootSE* = 0.122, *BootCI* 95 % = [-0.568, −0.082]). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

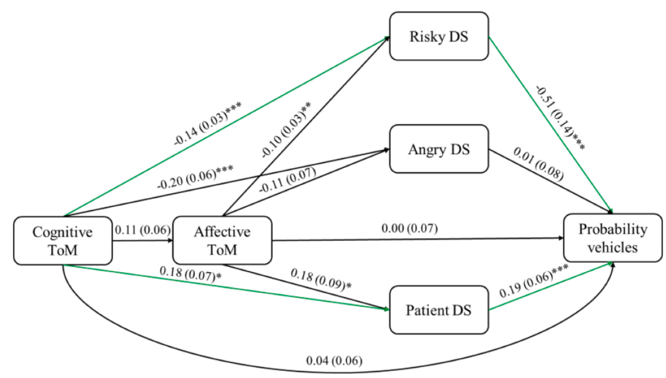


**Fig. 5.** The significant indirect effects (in green) of Cognitive ToM on crash probability vehicles (Model B). *Note.* Path values are unstandardized coefficients, and standard errors are shown in parentheses. Covariates are omitted for presentation purposes. *$p$ <.05, **$p$ <.01, *** $p$ <.001. The indirect effect of cognitive ToM on probability vehicles through risky DS (*B* = 0.070, *BootSE* = 0.028, *BootCI* 95 % = [0.017, 0.127]) and patient DS (*B* = 0.034, *BootSE* = 0.020, *BootCI* 95 % = [0.001, 0.079]). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Cronbach's alpha values for three subscales (i.e., Anxious DS, Distress reduction DS, and Careful DS) were relatively low ($\alpha \leq 0.60$). While this scenario could suggest an internal consistency issue, the value of the total MDSI was good ($\alpha = 0.89$), showing good overall reliability. It is noteworthy that interpreting the values of the three subscales requires a nuanced understanding of the relationship between alpha and the number of items. In particular, since the reduced number of items on a scale negatively affects the alpha size (Komorita & Graham, 1965; Vaske et al., 2017), in the current research, the lower Cronbach alpha values could be attributed to fewer items in the three subscales. Accordingly, future research should confirm our findings by providing a more comprehensive approach, considering multiple measures and ecological assessment of DS.

Despite the limitations, this work clearly showcases the urgency of updating drive-assistance systems. It emphasizes the need to thoroughly consider the drivers' capabilities and the intricate nature of their cognitive abilities. By considering Cognitive ToM and Driving Style as crucial cognitive factors, drive assistance can be optimized to effectively assist non-expert drivers in reducing road accidents.

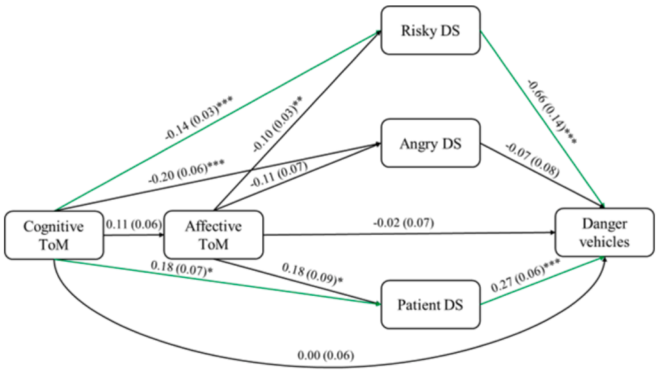


**Fig. 6.** The significant indirect effects (in green) of Cognitive ToM on danger of the situation vehicles (Model C). *Note. Path values are unstandardized coefficients, and standard errors are shown in parentheses. Covariates are omitted for presentation purposes. *p <.05, **p <.01, *** p <.001.* The indirect effect of cognitive ToM on danger vehicles through risky DS (*B* = 0.091, *BootSE* = 0.034, *BootCI* 95 % = [0.025, 0.159]) and patient DS (*B* = 0.046, *BootSE* = 0.024, *BootCI* 95 % = [0.005, 0.097]). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

## CRediT authorship contribution statement

**Raffaella Nori:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Micaela Maria Zucchelli:** Writing – review & editing, Methodology, Investigation, Data curation. **Pierluigi Cordellieri:** Writing – review & editing, Resources, Methodology, Investigation. **Alessandro Quaglieri:** Writing – review & editing, Resources, Methodology, Investigation. **Massimiliano Palmiero:** Writing – review & editing, Methodology, Investigation. **Paola Guariglia:** Writing – review & editing, Methodology, Investigation. **Marco Giancola:** Writing – review & editing, Formal analysis, Data curation. **Anna Maria Giannini:** Writing – review & editing, Methodology. **Laura Piccardi:** Writing – review & editing, Methodology, Conceptualization.

## Declaration of competing interest

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

## Data availability

Data set is available at the following link: https://osf.io/cn9bs/?view_only=e184be687d9c4253bca3c743ed950497

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssci.2024.106516.

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