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Use of smartphone and crash risk among cyclists

Abstract
High percentages of cyclists admit using smartphone devices while cycling. Moreover, such use has been found to be associated with near crashes and crashes, representing a risk factor for cyclists. This study examines the relationship between such type of behaviors, comprising both calling and manipulating the screen, and the frequency of near crashes and actual crashes among Italian cyclists. We administered an online survey measuring smartphone specific violations, errors, near crash and crash to Italian cyclists (N=298; age range: 19 – 72). We hypothesized that the relationship between smartphone use and near crashes would be explained by an increase in the number of errors committed, thus increasing the likelihood of being involved in near crashes. Moreover, we hypothesized that near crashes will predict actual crashes. Results of path analysis showed that smartphone specific violations predicted crashes throughout their consecutive effects on errors and near crashes only in the subsample of men. These findings offer an explanation of how smartphone use contributes to incrementing the likelihood of getting involved in near crashes and actual crashes. To our knowledge, the present study is the first in building a path model explaining how smartphone specific violations lead to more near crashes among cyclists.

Keywords: Errors, Near Crashes, Smartphone Specific Violations.

1. Introduction

The high prevalence of smartphone use while cycling reported in previous research conveys a clear message about the generalized presence of such practices.
Goldenbeld, Houtenbos, Ehlers, and Waard [1] reported that 70% of their participants sometimes used a portable electronic device and one out of six of those that were under 35 used it during every trip. Such percentages are of particular interest to traffic safety research given its prominent keenness to understand the factors enhancing road users' proneness to getting involved in dangerous events, such as crashes or near crashes. This way, Ichikawa and Nakahara [2] found mobile phone usage while cycling to be associated with previous crashes and near crashes, thus directly linking such behaviours to critical safety outcomes. Moreover, Goldenbeld et al. [1], using self-reported methods, found the use of portable electronic devices to be a risk factor for cyclists under 35 years old in The Hague (the Netherlands).
Gauld et al. [3] stated that, nowadays, the majority of young drivers own a smartphone and that, given its great potential as a social interactive technology, the majority of them reported to use their smartphone to update their social media status and to text while driving, thus underlining the importance of improving countermeasures, such as public education messages, to prevent this dangerous behavior among youngsters.
Furthermore, He et al. [4] reported abundant evidence demonstrating that texting while driving impairs driving performance and found that concurrent texting impaired driving by increasing the lane deviation. Also, it was shown that driving impaired texting by

increasing texting completion time, texting errors, and key entry time intervals, and reduced key entry speed. Given this mutual interference, it is clear that texting while driving undermines the driver's safety increasing the risk of a crash and also decrease the texting performance, making it definitively not convenient for the user.
Smartphone use while cycling and the risk associated thereto refer to the relationship between human behaviors and safety threatening outcomes, previously pointed out as a key factor in the study of road crashes by Rowe, Roman, McKenna, Barker, and Poulter [5]. In this realm, the Generic Error Modeling System (GEMS) [6] offers a compelling theoretical and empirically driven explanation about how human behavior can lead to safety threatening outcomes, such as near crashes and crashes. It has been widely applied across different types of road users, such as car drives (e.g., [7]), motorcyclists (e.g., [8]) and cyclists (e.g., [9]). GEMS allows for distinction of several types of behaviors and prediction of cycling safety outcomes (e.g., [9]). The model identifies two categories of risky behaviors, namely 'errors' and 'violations', each governed by different psychological mechanisms. Errors have been defined as 'the failure of planned actions to achieve their intended consequences' [10]. Thus, they involve unintentional deviations from safe practices and reflect inadequate skills (e.g., because of inexperience), or temporarily adverse states (e.g., because of fatigue) involving information processing. Violations, on the contrary, are 'deliberate deviations from those practices believed necessary to maintain the safe operation of a potentially hazardous system' [10], for instance, deliberately violating a red light. Therefore, they reflect a person's safety motivation, such as, a trade-off between risk and time lost. In addition, violations do not necessarily imply an infringement of some written rule, but they can also entail breaking an unofficial safety norm [9][10].

According to the previous definitions, smartphone behaviors on the bicycle can be considered violations given that, even if not all the countries' road rules officially ban them, they are deliberate deviations of the safe practice.

Research has also shown the effect that such type of violations might have on attention and information processing, as well as on behaviors based on them. Terzano [11] found differences in unsafe behaviors while performing secondary-tasks and cycling in comparison to those only riding a bicycle. In addition, several authors [12][13][14] have found that operating a smartphone led to reduced cyclist's visual detection and perception, posing a risk for cyclists. Therefore, such findings imply that this type of violations might have an effect on other sort of unsafe behaviors that rely on information processing, that is, they might be leading to increased error occurrence. Given the implied effect of such violations on errors, and thus, their idiosyncrasy, we regard them as a specific type of violations, that is, smartphone specific violations, from now on.

DeWard, Westerhuis, and Lewis-Evans [15], in an observational study, found that cyclists texting used to cycle further from curbs and used to gaze with less frequency at intersections when generally using a phone. Nevertheless, they also reported different compensatory behaviors when using such devices, among which were paying better attention to traffic or wearing a helmet, thus, contradicting the findings by Terzano [11] above mentioned.

Bayer and Campbell [16] further investigate the texting behavior and introduced the concept of automaticity, opposed to mere frequency of past behavior, to better understand why people text while driving. They found that texting while driving behavior may be performed by drivers without awareness, control, attention, and intention regarding their own actions despite of societal norms and individual intentions. Thus, changing the automatic texting behavior of drivers could be very difficult and further research are needed to develop new solutions.

All in all, even though the body of research on bicyclists' smartphone use growing, there is still need for more research to further untangle how – and to what extent – this type of violations affects human error.

Other research studying unsafe cycling behavior from the GEMS perspective has focused on adolescent cycling behavior or particular types of violations. Feenstra, Ruiter, Schepers, Peters, and Kok [17] found that, among adolescents in The Netherlands, boys were more prone to committing errors and violations, and so were older participants for exceptional violations. Moreover, they also reported that errors and violations, classified into common and exceptional, were related to near crashes. Errors were also associated with accident frequency and exceptional violations with accident severity. Moreover, Twisk et al. [9] proposed a mediation model in which risky behaviors were mediating the relationship between psychological determinants (e.g., opinions about alcohol, feeling responsible for one's actions) and safety outcomes (i.e., crashes and near crashes). The authors also found errors to be predicting crashes and near crashes in a subsample of 14 to 16-year-old students, and crashes in a sub-sample of 12 to 13-year-old students. These two main studies [9][17] have focused on adolescent behavior and have investigated them in the context of The Netherlands. Therefore, there is need for further examination of the association of errors and the particular type of smartphone specific violations with near crashes and crashes on adult population and in different countries, such as Italy which, to our knowledge, lacks scientific research on risky cycling behaviors. In addition, since previous research on other road users suggests that there might be gender differences in unsafe behaviors (e.g., [18]), we intend to explore such differences in our study. Furthermore, given the high frequency of smartphone specific violations and the contradictory findings on whether it leads to more unsafe behaviors or to compensatory ones, there is need for clarification of such relationships.

Based on the previously reported findings and the stated need for more research, we establish a hypothesized path model in which smartphone specific violations will be positively associated with errors (hypothesis 1) and near crashes (hypothesis 2). We also hypothesize that errors will be positively associated with near crashes (hypothesis 3).

In the Safety Pyramid model, near misses comprise the lower part of the pyramid, while accidents are at the pinnacle (e.g., [19]). Near misses have been used both to predict accidents and to limit accidents in a broad spectrum of industries, such as rail and air transport sector, medicine, and chemical process industry (e.g., [19][20][21][22][23]). However, in the road safety literature, most studies conceptualized near misses as an outcome in combination with accidents. Thus, although there have been investigations that included near misses, these data were not used to predict the likelihood of crashes.

Indeed, only limited evidence has been presented that investigates the association between near misses and actual driving accidents. One example is the study of Powell et al. [24], in which it was found that near miss sleepy driving accidents predict self-reported actual driving accidents. To address this research gap, we hypothesized that near crashes will predict actual crashes (hypothesis 4).

In a nutshell, we have hypothesized a model (see Figure 1) in which smartphone specific violations and errors predict near crashes. In turn, near crashes were hypothesized to predict actual crashes. Thus, we have posed that smartphone specific violations and errors will indirectly increase the likelihood of actual crashes by raising the likelihood of occurrence of near crashes. Therefore, we hypothesize that near crashes will mediate the effect of smartphone specific violations and errors on actual crashes (hypothesis 5). Moreover, we have also proposed that smartphone specific violations will enhance the probability of committing errors, and this, at the same time will increase the likelihood of being involved in near crashes. In addition, since we have also posed that crashes will be predicted by near crashes, we hypothesize a serial mediation model in which errors will mediate the effect of smartphone specific violations on near crashes, and these will act as a mediator between errors and the occurrence of crashes (hypothesis 6). Figure 1 displays the hypothesized path model.

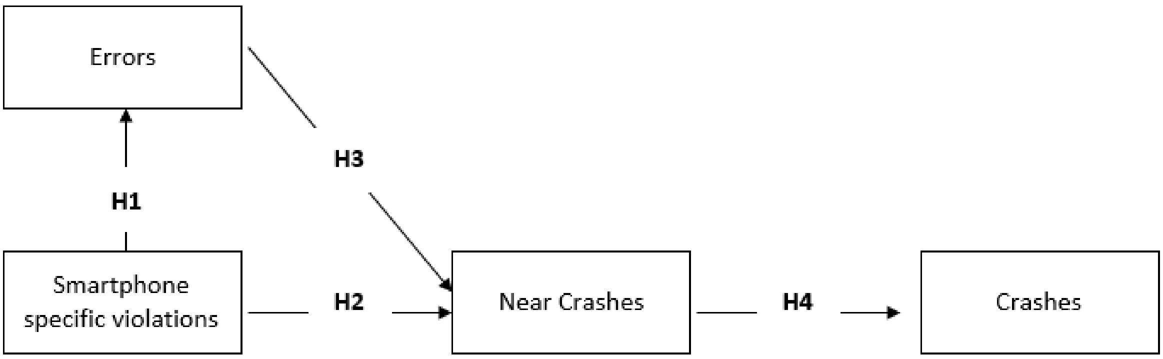

Figure 1. Hypothesized path model. Hypothesis 5 encompasses all the paths between Smartphone specific violations and Crashes (i.e., those of H1, H2, H3 and H4), whereas Hypothesis 6 includes those between Errors and Crashes (i.e., those of H3 and H4).

2. Method

2.1 Procedure

Data were collected from December 10, 2015 to February 29, 2016 through a self-reported online questionnaire. In order to reach a wide variety of participants with different demographics characteristics and from different locations in Italy, the questionnaire was disseminated through the web. We found the cyclist associations' websites, social media groups, and forums using keywords (i.e., "cycling" "bicycle" "cyclists' association"). Social media groups with less than 500 participants were discarded. We contacted in total 45 groups and 29 websites. To reach the selected targets two methods were used: (a) firstly, the link to the questionnaire was directly posted on groups' walls or on websites bulletin boards if available; (b) secondly, an email was written to the website administrators, kindly asking to advertise the questionnaire directly on their website, through their social media channels or inside their newsletter. The second method was the one that ensured more respondents.

2.2 Participants

A total of 455 participants responded the questionnaire. After considering only those participants that had filled out the items for age, sex and that acknowledged to use the bicycle at least once a week, the remaining sample comprised 298 (65.5%) participants. From these, 178 (59.7%) were male, 119 (39.3%) were female and 3 (1.0%) did not feel identified with any of these categories. The age of the participants ranged from 19 to 72 years old. The mean for female was 37.09 (*SD* = 14.39), the mean for male was 45.80 (*SD* = 13.93), whereas the general mean value was 42.46 (*SD* = 14.71).

Among these participants, 34 (11.4%) of them used the bicycle once a week, 34 (11.4%) used it twice, other 35 (11.7%) participants cycled three times a week, 31 (10.4%) did so four times, 45 (15.1%) of them cycled five times a week and the remaining 119 (39.9%) participants used the bicycle six or more times per week. Moreover, regarding the frequency of use in comparison with other means of transportation, 28.2% of the participants reported to use the bicycle as a primary mode of transportation.

2.3 Measures

Smartphone specific violations

In order to measure smartphone specific violations, we used a 5-item self-reported scale based on Chataway, Kaplan, Nielsen and Prato's [25] scale on distracted cycling. We asked participants to state the perceived frequency with which they undertook behaviors, such as checking the phone while cycling or texting messages. The frequency was expressed by using a 5-point Likert-type scale (ranging from 1 = *never* to 5 = *always;* assuming that ''always'' entails ''as long as there is the possibility to do so'' and not ''continuously and all the time''). Table 1 shows the item and subscale structure of the questionnaire, as well as some descriptive and reliability values.

Errors

To measure errors, we administered a 7-item scale based on those featured in the Driver Behavior Questionnaire (DBQ) [8] and the Adolescent Cycling Behavior Questionnaire (ACBQ) [14], adapting the former ones to the context of cycling. This scale had been previously used by Marín Puchades, Pietrantoni, Fraboni, De Angelis and Prati [26]. The items asked participants to state the frequency with which they undertook such behaviors by using a 5-point Likert-type scale (ranging from 1 = *never* to 5 = *always*). Table 1 shows the seven items and subscale structure of the questionnaire, as well as some descriptive and reliability values.

Near crashes and crashes

To obtain a measure of near crashes and crashes, we used two items. Regarding the item measuring near crashes: 'In this past year, have you been about to get involved in an accident (either with other road users or a single crash) while you were using your bike?' (*0=No, it never happened to me,* 1=*Once,* 2=*Twice,* 3=*Three times,* 4=*Four or more*). The item measuring crashes was: 'In your whole life, have you ever had an accident (either with other road users or a single crash) while you were driving your bike?' (1=*No, it never happened to me,* 2=*Yes, but I did not get hurt,* 3=*Yes, I got injured and I went to emergency services to get checked,* 4=*Yes, I got injured and after being checked I got hospitalized*). To finally obtain three categories, the last two replies were merged into one category that represented accidents involving injuries.

2.4 Statistical Analysis

We conducted the analyses using SPSS version 23 and AMOS. Analysis of the data was split into several stages. First, correlation coefficients among the key variables were calculated. The magnitude of effect sizes of correlation coefficients was evaluated according to Cohen's [27] guidelines for interpreting the magnitude of correlation coefficients. Specifically, correlation coefficients of .10 are "small," correlation coefficients of .30 are "medium," and correlation coefficients of .50 are "large" in terms of magnitude of effect sizes. Second, we employed path analysis to test mediations, as well as direct effects, because it allowed us to estimate a model that constrains several direct effects to zero (e.g., an eventual direct effect of smartphone specific violations on crashes), thereby, letting us test our hypotheses without the need of testing a saturated model [28]. Provided that two endogenous variables of our model (i.e., near crashes and crashes) are ordinal, we applied Bayesian estimation, AMOS' approach to addressing ordered-categorical data in SEM models [29][30]. This type of analysis allows us to estimate the lower and upper values (also known as Credibility Intervals) within which, with a pre-defined probability, the parameter can be found given the observed data [31]. In other words, once the parameter and the credibility intervals are obtained, one can state that there is an established probability that such parameter is comprised within the credibility interval.

3. Results

The participants that had not been involved in any bicycle crash were 119 (39.9%), whereas 117 (39.3%) suffered at least one accident but did not get injured, and 60 (20.1%) of them had been involved in a bicycle accident in which they got injured. The number of participants that had not suffered a near crash was 110 (36.9%), and 80 (26.8%) of them had indeed been involved in one. Of those that had been involved in more than one near crash, 49 (16.4%) participants had suffered two, 21 (7%) three, and 38 (12.8%) of them suffered four or more.

Twelve (4.03%) cases had at least one missing value, and 17 (0.38%) values were missing among all the variables measured. Since the percentage of missing values is not higher of 5%, it can be considered as irrelevant [32]. Table 1 displays the subscale items of the unsafe cycling behaviors questionnaire along with their mean and standard deviation values. As it can be seen, the smartphone specific violation and error reported as most frequent were “Use the cell/Smartphone to respond a call” and “Abruptly break in order to avoid /dodge a vehicle” respectively.

Table 1. Descriptive Statistics of the Unsafe Cycling Behaviors

Subscales	M	SD	Med	α
Smartphone specific violations				.881
Use a Smartphone to look for information or itineraries on the internet.	1.51	0.88	1	
Use a Smartphone to send text messages.	1.41	0.80	1	
Use a Smartphone to read text messages.	1.60	0.88	1	
Use the Smartphone to respond a call.	1.93	0.97	2	
Use the Smartphone to call someone.	1.76	0.95	1	
Errors				.671
Abruptly brake in order to avoid/dodge a vehicle.	2.58	0.90	3	
Abruptly swerve to avoid a bus or truck that turns right.	1.71	0.84	2	
Be grazed or hit by a scooter or motorbike.	1.09	0.32	1	
Almost hit a pedestrian while you were turning right.	1.53	0.73	1	
Not sight a vehicle merging from a next street.	1.92	0.73	2	
Realize late that you have neglected a traffic red light.	1.35	0.61	1	
Doubt about who has preference in a roundabout.	1.35	0.67	1	

NOTE: “M”=mean; “SD”=standard deviation; “Med”=median.

3.1 Unsafe Cycling Behaviors Effect on Near Crashes and Crashes

Table 2 displays the Spearman bivariate correlations between the key variables studied as well as the descriptive statistics. We employed Spearman’s rho due after the Shapiro-Wilk test results suggested the non-normal distribution (i.e., $p<.001$) of all the variables in the model. Errors correlated with smartphone specific violations ($p<.01$) and with near crashes ($p<.01$). According to Cohen’s [27] guidelines, the effect size of these correlation coefficients was small and medium in magnitude, respectively. Moreover, near crashes also correlated with crashes ($p<.01$) and according to Cohen’s [27] guidelines the effect size of this correlation coefficient was small-to-medium in magnitude. This allows us to continue to test the hypothesized model.

Table 2. Descriptive Statistics and Variable Intercorrelations

	M	*SD*	Range	1	2	3	4
1. Errors	1.65	0.41	1-5	-	.19**	.32**	-.00
2.Smartphone specific Violations	1.64	0.74	1-5		-	.06	-.07
3. Near Crashes	1.32	1.37	-			-	.25**
4. Crashes	0.80	0.75	-				-

Note. * Correlations are significant at p<.05 (2-tailed). **Correlations are significant at p<.01 (2-tailed).

Regarding the hypothesized model, Figure 2 shows the Bayesian estimates for each path. Smartphone specific violations predicted errors (hypothesis 1) but not near crashes (hypothesis 2), whereas errors did predict near crashes (hypothesis 3). In turn, near crashes predicted actual crashes (hypothesis 4). Mediation analysis showed that near crashes were mediating the effect of errors on crashes (Bayesian estimate= 0.085, 95% CI 0.043 – 0.134; hypothesis 5). Furthermore, Smartphone specific violations predicted crashes throughout its consecutive effects on errors and near crashes (Bayesian estimate= 0.013, 95% CI 0.003 – 0.026; hypothesis 6).

We performed a gender comparison of the path model and found differences between males and females. The subsamples of male and female participants were of 178 and 117 participants respectively. Whereas the path estimates found in the general sample were confirmed for the subsample of male participants, we found that in the female subsample, smartphone specific violations did not predict errors (Bayesian estimate=0.044, 95% CI -0.056 – 0.145), and near crashes did not predict crashes (Bayesian estimate=0.100, 95% CI -0.012 – 0.212). Moreover, we also found that the estimate of the path between errors and near crashes is lower for females (Bayesian estimate=0.671, 95% CI 0.182 - 1.156) than for males (Bayesian estimate=1.582, 95% CI 1.050 - 2.111). We give possible explanations for this in the discussion.

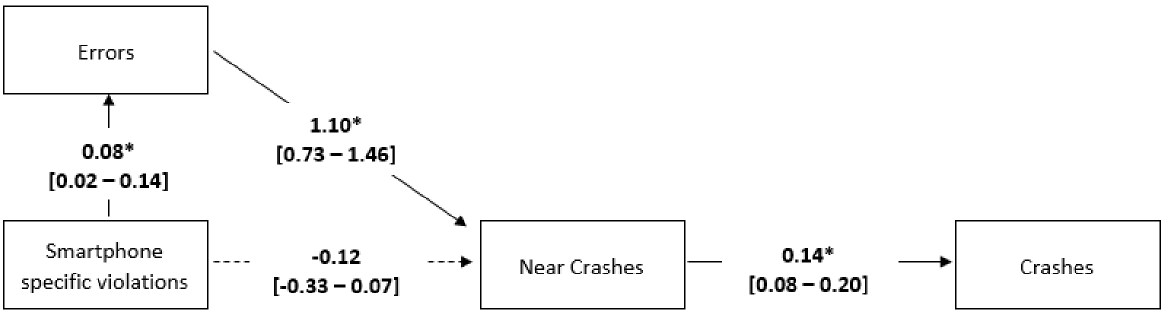

Figure 2. Path model with Bayesian Estimates

4. Discussion

The aims of the current study were to examine the impact of smartphone specific violations and errors on the likelihood of near crashes as well as the indirect effect of such behaviors on actual crashes among Italian cyclists. Moreover, it also aimed to unveil any gender differences in the relationships between the unsafe behaviors (i.e., smartphone specific violations and errors) and the hazardous outcomes (i.e., near crashes and crashes).

It is important to note that, differently from previous studies, our findings focused on smartphone specific violations as a distinct type of violation, whereas other research had differentiated between more common and exceptional violations (e.g., [17]). The rationale for this was that, as previously explained, such type of violations was thought to increase error occurrence by its effect on visual detection and perception. In addition, we wanted to examine whether such behaviors were indeed predicting errors and near crashes or, due to eventual compensatory behaviors [1], they were not associated.

Path analyses confirmed all the hypotheses except for hypothesis 2, that is, smartphone specific violations did not directly predict near crashes. Nevertheless, it did predict errors (hypothesis 1) in the general sample, thus bringing about the point that smartphone specific violations may indeed involve more unsafe behaviors dependent on information processing, instead of leading to more compensatory behaviors. Nevertheless, there is still the need to explore whether this relationship between smartphone specific violations and errors is also due to a confounding variable such as cyclist's safety concerns. This way, cyclists less concerned about safety could be both committing more errors and using more frequently the smartphone while cycling. Errors predicted near crashes, and these, crashes. Our data only partially supported hypothesis 5 since there was no direct effect from smartphone specific violations on near crashes, impeding an indirect effect of the former on crashes unless considering the role of errors. Moreover, the results confirm a mediation effect proposed in hypothesis 6, which explains the effect of smartphone specific violations on crashes throughout errors and near crashes. These findings differ from those of Feenstra et al. [17] according to which both errors and violations (common and exceptional) were directly predicting near crashes. In our study, only errors predicted near crash frequency. Moreover, they found exceptional violations to predict accident severity and errors to predict accident frequency, whereas we did not find significant correlations between any unsafe cycling behaviors (i.e., errors and smartphone specific violations) and crashes. Twisk et al. [9] found errors, but not violations themselves, to predict crashes, thus concurring with our findings. Nevertheless, it is worth noting two main differences between these previous studies and our research. First, we conducted the study among adults and not adolescents, thus, age differences could be explaining some of the differences in findings. And secondly, our study was set in Italy whereas theirs were carried out in The Netherlands.

Moreover, we have found gender differences in the effects of smartphone specific violations on errors and that of near crashes on crashes. That is, the results found in the general sample were confirmed for men, whereas smartphone specific violations did not predict errors and neither near crashes did predict crashes in the female subsample. Smartphone specific violations not predicting errors in the female subsample could be due to gender differences in perception and attention. We offer two possible sets of explanations next: one theoretical and another one concerning statistical artefact. On the one hand, previous research in psychology of individual differences has found that women are quicker in identifying and discriminating objects visually, have a wider peripheral vision, and are more likely to estimate situations as risky [33]. Moreover, Feenstra et al. [17] found that boys tended to engage in riskier behaviors, thus suggesting that women might adopt a less risky approach to cycling and, therefore, might undertake compensatory behaviors while committing smartphone specific violations. This could diminish the effect of using smartphone while cycling on the errors committed. A possible explanation for the fact that near crashes did not predict crashes in the female subsample can be found in the smaller prediction of near crashes by errors. This can be interpreted as near crashes being more dependent on variables other than human error in women. Thus, the frequency of hazardous outcomes such as near crashes, and crashes by extension, is not related to human error, perhaps due to women's eventual less risky approach to cycling derived from their higher likelihood of estimating a situation as risky in comparison to men [33]. Less risk-taking behaviors could be reducing the cyclists' own influence on their crash frequency, leaving it up to other road users' behaviors, and therefore conditioning the occurrence of near crashes and crashes to eventual and more random encounters with other distracted or irresponsible road users. On the other hand, a possible explanation to the lack of association in the female subsample could be due to a lack of statistical power provided a not big enough subsample size. Even though there is no single answer about whether a sample is large enough to conduct Structural Equation Modeling, a common rule of thumb is that there should be 20 observations per parameter that needs to be estimated in the model [34]. Therefore, with 12 parameters to be estimated in our model, both subsample sizes are too small to obtain adequate statistical power. Thus, not finding an association between smartphone specific violations and errors, and near crashes and crashes could be due to the relatively small subsample size. Thus, more research with bigger samples is needed to clarify whether these differences exist or are due to statistical artifact.

This study has several theoretical and practical implications from which we have drawn future research needs. To begin with, we have introduced smartphone specific violations in the model and conceptualized them as a type of violation that is affecting the occurrence of unsafe behaviors relying on information processing (i.e., errors) in men, but not in women. Moreover, for men, we have found them to predict near crashes and crashes through an indirect effect. This entails that smartphone specific violations might have an effect on other unsafe behaviors and, therefore, offers a broader understanding of how such behaviors end up leading to eventual crashes. That notwithstanding, there might be some confounding variables that could explain the effect of smartphone specific violations on errors such as cyclist's safety concerns. This way, further research on this would benefit from controlling for such variable or exploring the eventual effect it might have on both errors and smartphone specific violations. In addition, given the high frequency of smartphone use reported in several studies (e.g., [1][2]), we want to emphasize the importance of future study of these types of unsafe behaviors and how they might be contributing to error and safety outcomes occurrence. Future research could address this issue in two ways: (1) with naturalistic cycling studies that account for the time of phone use as well as errors and near crashes; and (2) with studies based on a one-day diary [35] investigating the occurrence of near misses and the conditions under which these occurred. Moreover, adopting the Safety Pyramid model, we found near crashes to predict crashes among men. This provides further knowledge about how crash events might unfold and should be considered in future research. Moreover, future research should also address the lack of prediction of smartphone specific violations in order to unveil whether it could be due to gender differences in perception, compensatory behaviors or other variables

There are some limitations to this study. On the one hand, we used a self-reported questionnaire to measure both unsafe cycling behaviors and safety outcomes (i.e., near crashes and crashes). This entails two limitations: (1) memories of crashes and near crashes (e.g., [36]), as well as those of unsafe behaviors that do not depend on conscious control (i.e., errors), may not be accurate according to previous findings [9][37]. Previous research suggests that an estimated 80% of the near crashes may be forgotten after two weeks of the event [36]; Moreover, (2) Common Method Variance (CMV), which refers to the amount of variance attributable to the use of the same method to measure related variables [38], constitutes a limitation to our study given that we measured all the variables using self-reported questionnaires. On the other hand, online surveys advertised on websites might involve self-selection bias and, therefore, the resulting sample might not be representative of the whole population of Italian cyclists.

Our findings suggest that smartphone specific violations appear to contribute to the frequency of errors while cycling among men. Furthermore, both errors and smartphone specific violations predict crashes throughout an indirect effect on near crashes. Finally, these findings contribute to examine possible gender factors that can moderate the relationship between unsafe cycling behaviors and crash risk.

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