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The guilty, the unlucky, or the unaware? Assessing self-reported behavioral contributors and attributions on pedestrian crashes through structural equation modeling and mixed methods

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A B S T R A C T

Introduction: Recent literature suggests that the causation of pedestrians' crashes and the contribution of safety-related behaviors within them may substantially differ compared to other road users. This study aimed to test the effect of individual factors and safety-related road behaviors on the self-reported walking crashes suffered by pedestrians and, complementarily, to analyze the causes that pedestrians attributed to the crashes they suffered as pedestrians during the previous five years. *Method:* For this cross-sectional research performed in Spain, data from a nationwide sample of 2,499 pedestrians from the 17 regions of the country were collected. Participants had a mean age of 31 years. They responded to a questionnaire on demographics, safety-related walking behaviors, and self-reported pedestrian crashes and the causes attributed to them. *Results:* Utilizing Structural Equation Models (SEM), it was found that self-reported walking crashes can be predicted through unintentional risky behaviors (errors). However, violations and positive behaviors remain non-significant predictors, allowing to hypothesize that they might, rather, play a key role in the pedestrian's involvement in pre-crash scenarios (critical situations preceding crashes). Also, categorical analyses allowed to determine that the causes that pedestrians attributed to the walking crashes they had suffered were principally their own errors (44.6%), rather than their own traffic violations (8.5%). Nevertheless, this trend is inverse when they believe the responsibility of the crash weighs on the driver. That is to say, they usually attribute the crash to their traffic violations rather than errors. However, many biases could help explain these attributional findings. *Practical Applications:* The results of this study highlight key differences in behavioral features and crash predictors among pedestrians, with potentially relevant applications in the study and improvement of walking safety from behavioral-based approaches.

1. Introduction

Walking has been proven to have several demonstrable benefits on health and well-being (Hanson & Jones, 2015). However, traffic crashes suffered by pedestrians are still highly prevalent, implying an extensive burden to, for example, economic and healthcare systems, public institutions, and the society as a whole (Shrivastava, Shrivastava, & Ramasamy, 2016; Mader & Zick, 2014; WHO, 2010).

In the European Union alone, about 40% of the almost 10,000 fatal victims of urban traffic crashes in 2018 were pedestrians (ETSC, 2019), and around 350 were Spaniards (DGT, 2019). Whereas in some countries, such as Sweden, pedestrian safety has improved over the years due to systematic actions (Värnild, Larm, & Tillgren, 2019), in many others, it has not. For instance, about 6,000 pedestrians lose their lives in the United States every year, and 80,000 sustain serious injuries (Wells, McClure, Porter, & Schwebel, 2018).

In this regard, recent literature systematically points the preventability of traffic crashes (one of the key reasons to stop calling them "accidents"). They also underline the need to develop further studies and interventive actions in consideration of the specific features of each type of road user (Oviedo-Trespalacios et al., 2019; Shi, Chen, Ren, & Rong, 2007).

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1.1. Behavioral perspectives and safe walking: are risk factors over-generalized?

While it is well-known that traffic crashes are preceded by many possible contributors, there are factors whose explanatory value is usually greater in the existing literature. This is the case of human factors (i.e., road users' behavior), which has shown to be responsible for about 80–90% of road crashes worldwide (Alavi et al., 2017; Gicquel et al., 2017). However, the role of road behavior in traffic crashes should not be generalized, since behavioral repertoires (same as their role in crashes) may substantially vary depending on the type of road user (Yu et al., 2020; Zhang, Yau, & Zhang, 2014).

Additionally, the accumulated empirical evidence is considerably disproportionate if the number of sources available on motor-vehicle drivers' behavior is compared with the scientific findings dealing with non-motorized users. This gap could be due to several factors, among which we can highlight: (*i*) the problematic accessibility to certain study samples; (*ii*) the scarcity of available tools to address each user's behavioral specificities and, unfortunately; (*iii*) the relatively low potentiality of publications of non-significant or "theoretically-unexpected" scientific results (Amrhein, Korner-Nievergelt, & Roth, 2017; Af Wåhlberg, Barraclough & Freeman, 2015; Sümer, 2003). Consequently, whereas walking is the oldest transportation means, scientific studies of pedestrian crashes have produced less empirical evidence than other similar areas. Therefore, more research is needed to reduce crash and injury risk in this area (Yu et al., 2020).

That being said, some key behavior-related insights can be found in the existing literature. For instance, some studies have associated traffic-rule violations with the injuries and fatalities suffered by pedestrians, especially in high-risk urban locations, such as crossings or intersections (Hashemiparast, Negarandeh, & Montazeri, 2017; Cinnamon, Schuurman, & Hameed, 2011). Also, other studies state that risky behaviors may influence traffic crashes as they increase the likelihood of road users being involved in a pre-crash scenario. This can be understood as a 'critical' event or situation immediately prior to the crash (Yu et al., 2020; Özkan & Lajunen, 2005).

1.2. Other "emerging" evidence on road behaviors as crash contributors

Demographic factors such as age and gender indicate that males and young people tend to be considered the most 'risky' profiles of users (Iversen & Rundmo, 2004; Martí-Belda et al., 2019). However, some previous key evidence addressing road behavior should be mentioned here. For instance, recent studies describe how traffic violations (deliberate risky behaviors) are more likely to occur when road users have, for example, a more negative assessment of traffic laws, greater intentions of bypassing the law, lower perception of road risks, or a lower risk perception (Dinh et al., 2020; Yu et al., 2020). Furthermore, pedestrians' violations hold the potential to influence others' road behaviors. This often explains problematic *feedbacks* and road conflicts, potentially endangering safe and healthy walking (Hashemiparast, Negarandeh, & Montazeri, 2017).

On the other hand, walking errors (unintended risky behaviors) have been closely related to walking crashes that: are less frequently reported in official databases and accident records (Dandona et al., 2008; Loo & Tsui, 2007); often remain considerably serious as a result of pedestrians' poor passive safety (Fredriksson, Shin, & Untaroiu, 2011; Helmer et al., 2010); and mainly become explained by observation (up to 44% of them) and planning errors (up to 37%; Thomas, Morris, Talbot, & Fagerlind, 2013).

Also, some studies clearly differentiate the role of errors and violations in crashes. For instance, O'Hern, Stephens, Young, and Koppel (2019) found that errors – albeit not violations – had a significant relationship with self-reported crashes of Australian bicyclists. Also interestingly, Thomas, Morris, Talbot, and Fagerlind (2013) show how errors (especially timing ones) seem to be the most common crash cause among different road users, but especially among pedestrians, where the proportion of crashes related to it could be up to 68%.

In addition, other studies performed on walking behavior using observational methods point out pedestrians' errors as a major contributor to their crash likelihood. They also indicate that – despite several variations amongst crashes – errors of pedestrians might constitute a critical issue requiring attention and prompt action (Deb et al., 2017; Granié, Pannetier, & Guého, 2013).

1.3. Attributions: Do they differ from actual crash causes?

Overall, the attribution theory addresses the processes involved in explaining why events or behaviors take place (Kelley, 1980). In brief, several different attributions may be made in a single event, addressing issues such as "*who is responsible* (*the guilty*)?", "*why did I let something happen* (when culpability is put on oneself)?" and "*has this an actual explanation, or might it be a result of luck or fate*?".

One key insight provided by previous research was finding that, after suffering an adverse event (*e.g.*, a traffic crash), individuals' attributions may substantially differ from the objective causes actually explaining it, especially in a "defensive way." In other words, individuals tend to assign the responsibility of negative events, including the case of traffic crashes, to someone else (Pöllanen et al., 2020; Salminen, 1992; Burger, 1981).

Also, Stewart (2005) shows how, regardless of their severity, road users tend to attribute the most responsibility for crashes to others (especially to drivers) than to themselves. On the other hand, external factors (e.g., environmental and weather conditions) can be also cited with a certain frequency. Further, Yu et al. (2020) described how crash-related attributions might vary depending on a range of cognitive, perceptual, and exposure-related factors, including user's age and educational level.

Still, to date, there is not much empirical evidence in this regard among pedestrians, especially studies contrasting crash attributions with other self-reported data, such as road behaviors. This could contribute to further understanding the psychosocial factors influencing walking crashes, how they are attributed, and potential divergences and bias related to pedestrians' road behavior.

1.4. Objectives and hypotheses

The first aim of this study was to test the effect of individual factors and safety-related (both risky and positive) road behaviors on the self-reported walking crashes suffered by pedestrians. Secondly, this study aimed to analyze the causes they attributed to the walking crashes that occurred during the previous five years to compare them with the structural model outcomes.

Four study hypotheses were developed based on the literature on behavioral-based crash prediction and attributions. The first two refer to the quantitative outcomes, while the others are related to the qualitative phase of the study, as follows:

Hypothesis 1 – Risky behaviors (errors and violations) may have a positive effect on self-reported walking crashes, while the effect of positive behaviors should be negative.

Hypothesis 2 – There might be significant differences in the average of risky and positive walking behaviors self-reported by pedestrians having reported walking crashes (higher risky and lesser positive behaviors), compared to the "non-crashed" ones.

Hypothesis 3 – Regarding crash attributions, pedestrians having suffered crashes would interpret them as a result of errors (rather than violations) when they believe they were responsible for their causation.

Hypothesis 4 – Suffered crashes could be interpreted as a result of deliberate behaviors rather than errors when the attributed guilt or responsibility weights on another user.

2. Materials & methods

2.1. Sample

For this cross-sectional research, a convenience (non-probabilistic) sampling method was used to perform an e-survey. This was because mailing list-based e-surveying eases accessing a study population potentially spread across many regions of the country. Hence, the data collection was carried out by means of an online (electronic) questionnaire. The questionnaire was sent through an e-mail invitation to a wide sample of approximately 9,500 subjects contained in a pre-existent mailing list used for research purposes.

The only requirements for participating in the e-survey were: having a basic literacy level (that would allow them to understand the statements and the logic of a self-report survey), and having a mobile device (*i.e.*, smartphone or tablet) or computer with an internet connection. The questionnaire was standardized in a web-based format in order to avoid platform-related gaps or technical limitations preventing its correct filling.

The data used for this study were retrieved from a nationwide sample of n = 2,499 Spanish pedestrians, of which 1,456 (58.3%) participants were females and 1,043 (41.7%) were males. The sample participants were aged between 16 and 79, with a mean value of M = 32.88 (SD = 14.17) years. Regarding the educational level of the participants, less than half of the respondents (45.3%) had an undergraduate degree, 13.8% a post-graduate degree, and 16.6% a technical training (more advanced than a high school diploma, but lower than a university degree); 18.6% only had a high school diploma, and the remaining 5.8% had a maximum educational level of primary studies.

Out of the 2,499 participants, 10.4% stated having suffered at least one walking crash during the last five years. The average self-reported crashes suffered during the last five years was M = 0.17 (SD = 0.61). Further demographic and walking-related sample features of participants are presented in Table 1.

The sample was considerably large, distributed nationwide (covered all 17 Spanish regions), and included individuals from all educational levels. However, it remains dissimilar from the demographic population features in terms of age, gender, and education. This is principally due to the non-probabilistic design and the e-survey data collection method used, which is ineffective to gather data from some population segments (*e.g.*, individuals not commonly using internet devices, needed to respond to the e-form; Tyrer & Heyman, 2016). Therefore, it cannot be considered fully representative of the Spanish population.

2.2. Description of the questionnaire and study variables

The questionnaire, administrated in Spanish, consisted of various sections, described as follows:

The first part (*Section 1*) asked about individual and demographic variables, such as age, gender, education, region of provenance, educational level, and occupation.

For the second part (*Section 2*), self-reported pedestrian behaviors were assessed using the validated version of the Walking Behavior Questionnaire (WBQ) (Useche, Montoro, & Alonso, 2020), which measures both risky (*errors* and *violations*) and protective (or *positive*) walking behaviors.

The WBQ questionnaire is a frequency Likert-based questionnaire of 5 levels [0 = Never – 4 = Almost always] composed of 30 items distributed into three factors and has been found to have high alpha coefficients: Traffic Violations (16 items; α = 0.890; Useche, Hezaveh, Llamazares, & Cherry, 2021); Errors (10 items; α = 0.868); and Positive Behaviors (4 items; α = 0.728).

Table 1
Descriptive data on the walking patterns of the study sample.

Feature	Category	Frequency	Percentage
Main reason for walking	For daily commuting	1,181	47.3%
	For exercise or fitness	273	10.9%
	As part of their job	201	8.0%
	For making a short trip to a specific point in the city	408	16.3%
	For leisure (“go for a walk”)	303	12.1%
	For daily tasks or housework (e.g., go shopping, picking up their children...)	133	5.3%
Type of area	Urban	2,319	92.8%
	Semi-urban	180	7.2%
Hours spent walking per week	<1 h	98	3.9%
	1–5 h	951	38.1%
	6–10 h	884	35.3%
	11–15 h	249	10.1%
	16–20 h	121	4.9%
	>20 h	196	7.5%
Length of the most common walking trip	0–15 min	745	29.8%
	16–30 min	1,105	44.2%
	31–45 min	307	12.2%
	46–60 min	219	8.7%
	>60 min	123	4.8%
Self-reported number of walking crashes (last 5 years)	0	2,237	89.5%
	1	177	7.1%
	2	46	1.8%
	3	23	0.9%
	4	11	0.5%
	5 or more	5	0.2%

Table 2
Definition and operationalization of latent study variables.

Study variable	Data source	Subscale	Definition/Operationalization.
Traffic violations [a]	Self-reported (participant)	WBQ (Factor 1)	Deliberate risky behaviors that contravene traffic laws or safety-related practices e.g., despite being relatively close to the crosswalk, crossing the road among cars.
Errors		WBQ (Factor 2)	Non-deliberate, unplanned or unintended risky behaviors performed while walking, usually related to lack of attention, distraction and/or operational failures; e.g., crossing at a traffic light without realizing it is not green.
Positive behaviors		WBQ (Factor 2)	Intended habits and actions contribute to reducing the risk of suffering a traffic crash; e.g., such as avoiding circulation under adverse weather conditions or low visibility.
Knowledge of traffic laws		RPRS (Factor 1)	The extent to which the individual is aware of traffic laws; e.g., appraising that pedestrian users have priority over drivers in zebra crossings with no traffic light.
Risk perception		RPRS (Factor 2)	The subjective appraisal made in regard to the risk involved in traffic situations; *e.g.,* perceiving greater risks if suffering a crash while walking, than on board a car.

Notes for the Table: [a] Overall, studies following the Behavioral Questionnaire (BQ) paradigm do not understand "violations" as behaviors necessarily "forbidden by law", but also encompass further deliberate risky actions performed by road users endangering road safety, including aggressive expressions and intended reckless behaviors. For further information on this taxonomy, please refer to Reason et al (1990) and Özkan and Lajunen (2005).

It follows the original error/traffic violation factorial structure typical of the Behavioral Questionnaire (BQ) paradigm, widely used and well-validated in questionnaires such as: Reason's et al. (1990) Driving Behavior Questionnaire (DBQ) used for four-wheeled drivers, the Motorcycle Rider Behaviour Questionnaire (MRBQ; Elliott & Baughan, 2004), and the Moped Rider Behaviour Questionnaire (MRQ; Steg & Van Brussel, 2009) used for two-wheeled motorcyclists and moped riders; and the Cycling Behavior Questionnaire (CBQ; Useche, Montoro, Tomas, & Cendales, 2018), the Adolescent Cycling Behavior Questionnaire (ACBQ; Feenstra et al., 2011), and the Bicycle Rider Behavior Questionnaire (BRBQ; Hezaveh, Zavareh, Cherry, & Nordfjærn, 2018), used for bicycle riders' behavioral assessment. All these questionnaires base the distinction between errors and violations on the deliberate/undeliberate character of road behaviors.

Thirdly (*Section 3*), the Risk Perception and Regulation Scale (RPRS; Useche et al., 2018) was used to measure the pedestrians' risk perception and knowledge of traffic laws. The RPRS is a generic Likert scale composed of 12 items (7 for risk perception; 5 for assessing general traffic laws among non-motorized users). The degree of perceived risk and self-reported knowledge of generic road rules are assessed on a scale from 0 (no knowledge/risk perceived) to 4 (highest knowledge/risk perceived). The whole set of latent study variables assessed in sections 2 and 3 of the questionnaire and their operationalization is depicted in Table 2.

Finally, we included a set of questions about participants' walking habits and patterns, including the rough number of hours walking a week and the average length of their most common journeys. In addition, participants were asked to self-report their walking traffic crashes suffered during the previous five years. This was excluding pedestrian-to-pedestrian bumps and slight tripping because these types of incidents are quite common, hardly retained by pedestrians, and significantly underreported as a consequence of social desirability, underestimation, or memory biases when self-reported (Af Wåhlberg, 2011). Therefore, the variable *number of crashes* can be understood in this study as "the total amount of self-reported traffic *accidents/crashes* suffered while circulating as a pedestrian during the last five years." Pedestrians affirmatively responding to the latter were asked to indicate (*i*) their attributed guilt for each crash (*i.e.*, their own fault, other road users, the infrastructure or environment, or other) and (*ii*) the most likely cause to which they ascribed the crash.

2.3. Ethics

During the design phase, the research proposal was submitted to the Research Ethics Committee of the University of Valencia, in order to verify that this study followed the general ethical principles and the Declaration of Helsinki, obtaining a favorable assessment (IRB approval number H1535548125595).

An informed consent statement containing ethical principles and data treatment details was used for all participants, explaining the study aim, the average duration of the survey, the treatment of personal data, and the voluntary participation. This form was always provided before participants answered the questionnaire. Personal and/or confidential data were not used and the form was anonymous, implying no potential risks for the integrity of our participants.

2.4. Data processing

2.4.1. Quantitative analyses

After careful data curation (i.e., organizing, cleaning, and coding observations), descriptive analyses were performed in order to score the scales used in the study.

Bivariate correlation analyses were performed to establish potential relationships among the variables of the study (as presented in Table 3). Spearman's *rho* (or r_s), considering their robustness over Pearson's (r) correlations, were used when ordinal values were measured (Liu et al., 2016; Mukaka, 2012). Apart from the correlational analysis (that is merely bivariate), the relationships among deliberate (traffic violations), non-deliberate (errors) risky behaviors, and the number of self-reported walking crashes suffered along the last five years were modeled and assessed through 3D graphical analyses.

Furthermore, after testing basic parameters, the association between risk perception, knowledge of traffic laws, risky (errors and violations) and positive road behaviors, and self-reported walking crashes suffered during the previous five years was tested using Structural Equation Modeling (SEM). The model controlled for age and trip length in order to minimize their impact on the results, and the possible statistical mediations made by risky road behaviors. Overall, SEM models aim at assessing both direct and indirect/non-linear effects among study variables, defined by:

$$\eta = \beta\eta + \Gamma\xi + \zeta \quad (1)$$

where η is a vector ($p \times 1$) of latent endogenous variables. ξ is a vector ($q \times 1$) of latent exogenous variables. Γ is a matrix ($p \times q$) of coefficients $\gamma_{i\ j}$ that relate the latent variables exogenous with endogenous. β represents a ($q \times p$) matrix of coefficients that relate the endogenous latent variables to each other. ζ is a vector ($q \times 1$) of errors or "disturbance terms." They indicate that endogenous variables are not perfectly predicted by structural equations (Lara, 2014).

The model fit was evaluated through Chi-square (χ^2), Confirmatory Fit Index (CFI), Normed Fit Index (NFI), Tucker-Lewis Index (TLI), Incremental Fit Index (IFI), and Root Mean Square Error of

Table 3
Results of the measurement model.

Variable	Component	Descriptive statistics		Standardized factor loadings[3]			Reliability measures		
		M[1]	SD[2]	λ[4]	SE[5]	CR[6]	CRI[7]	Cronbach's Alpha	McDonald's Omega
Traffic violations	WBQ1	1.96	0.97	0.612	0.029	26.852	0.992	0.897	0.899
	WBQ2	1.86	1.00	0.646	0.041	26.916			
	WBQ3	1.25	0.98	0.497	0.038	21.762			
	WBQ4	1.34	1.05	0.606	0.042	25.629			
	WBQ5	1.78	1.16	0.664	0.047	27.509			
	WBQ6	1.91	1.20	0.606	0.048	25.610			
	WBQ7	1.06	0.98	0.448	0.037	19.920			
	WBQ8	0.67	0.92	0.482	0.036	21.200			
	WBQ9	1.86	1.24	0.582	0.049	24.802			
	WBQ10	1.03	1.14	0.567	0.045	24.297			
	WBQ11	1.76	1.48	0.571	0.059	24.426			
	WBQ12	1.49	1.20	0.685	0.05	28.158			
	WBQ13	1.87	1.20	0.742	0.05	29.825			
	WBQ14	2.08	1.04	0.600	0.042	25.408			
	WBQ15	1.04	0.98	0.571	0.039	24.434			
	WBQ16	1.68	1.19	0.644	0.048	26.852			
Errors	WBQ17	0.45	0.70	0.718	0.034	29.538	0.992	0.887	0.887
	WBQ18	0.54	0.73	0.761	0.031	35.902			
	WBQ19	0.49	0.70	0.759	0.030	35.810			
	WBQ20	0.56	0.80	0.565	0.034	26.724			
	WBQ21	1.13	0.86	0.598	0.036	28.310			
	WBQ22	0.73	0.79	0.678	0.033	32.040			
	WBQ23	0.75	0.90	0.675	0.038	31.931			
	WBQ24	0.75	0.88	0.656	0.037	31.027			
	WBQ25	1.04	0.87	0.640	0.036	3.291			
	WBQ26	0.63	0.80	0.624	0.034	29.538			
Positive behaviors	WBQ27	2.66	1.19	0.490	0.032	21.273	0.966	0.745	0.747
	WBQ28	1.84	1.15	0.762	0.071	21.241			
	WBQ29	1.99	1.23	0.576	0.064	19.006			
	WBQ30	1.88	1.12	0.780	0.070	21.273			
Risk perception	RPRS1	3.25	0.98	0.734	0.024	36.439	0.990	0.851	0.854
	RPRS2	2.04	1.25	0.438	0.037	20.681			
	RPRS3	3.10	1.00	0.782	0.030	37.121			
	RPRS4	2.71	1.07	0.676	0.031	32.090			
	RPRS5	3.02	1.27	0.607	0.037	28.779			
	RPRS6	3.03	1.08	0.774	0.032	36.727			
	RPRS7	2.86	1.09	0.768	0.032	36.439			
Knowledge of traffic laws	RPRS8	3.21	0.97	0.848	0.019	47.669	0.991	0.846	0.853
	RPRS9	2.98	1.02	0.877	0.02	53.492			
	RPRS10	2.39	1.23	0.383	0.03	19.023			
	RPRS11	3.05	1.00	0.793	0.021	46.36			
	RPRS12	2.81	1.12	0.808	0.023	47.669			

Notes for the Table: [1]M = Arithmetic mean; [2]SD = Standard Deviation; [3]All p <.0001; [4]Factor Loading (Lambda / λ); [5]SE = Standard Error; [6]CR = Critical Ratio; [7]CRI = Composite Reliability Index.

Approximation (RMSEA). Goodness-of-fit was based on the cut-off criteria expanded in the literature (Kline, 2011; Miles & Shevlin, 2007; Hu & Bentler, 1999). Therefore, the model fit was based on the following cut-off standards: RMSEA < 0.080, CFI/NFI/TLI/IFI > 0.900, were indicative of an adequate model fit (Marsh, Hau, & Wen, 2004). Significance of parameters was established at differential levels of p <.001, p <.010, and p <.050.

Bootstrap-based robust maximum likelihood estimations (i.e., 10,000 bootstrap samples and 95% confidence intervals) were performed in order to handle non-normality issues. This was because most of the study variables did not meet the basic assumption of univariate normality, and multivariate normality was not met either, as usually happens in self-report based studies (Brown et al., 2015; Byrne, 2010).

The indirect (or mediated) effects of the model, their confidence intervals (at the level 95%), and significance levels were calculated following the bootstrap method, specifically through a Monte Carlo (parametric) procedure. This method constitutes a reasonable alternative to estimation methods such as Satorra-Bentler or Weighted Least Square Mean and Variance adjusted (WLSMV), as it favors estimates bias-correction, avoiding type I errors (*false positives*) in regression paths.

With the aim of testing *Hypothesis 1* about the effect of study variables on the traffic crashes suffered by pedestrians and the potential mediating role of both risky (errors and violations) and positive self-reported behaviors, a three-step Structural Equation Model (SEM) was built according to the empirical directions and hypothesized paths described in the introduction.

Overall, the exogenous variables included in the model were tested as predictors of errors, violations, and positive road behaviors. Pedestrians' age has significant paths going to walking errors, traffic violations, and positive road behaviors. The effect of the exogenous variables was tested in relation to walking crashes, drawing paths between *(i)* errors, *(ii)* traffic violations, and *(iii)* positive behaviors and self-reported walking crashes (endogenous variable).

For this purpose, individual factors (*i.e.*, age, walking trip length, rule knowledge, and risk perception) were used as independent variables; traffic violations, errors, and positive behaviors were used as mediators; and the dependent or endogenous variable was the number of self-reported walking crashes. This initial *a priori* model did not fit the data completely well: $x^2(6) = 1090.702$, p <.001; NFI = 0.731; CFI = 0.730; IFI = 0.732; RMSEA = 0.249, 90% CI [0.237–0.262]. Therefore, key modifications were made according to the theoretically parsimonious modification indexes. Firstly, the covariances between the variables contained in the first step (*i.e.*, age, trip length, rule knowledge, and risk perception) were drawn. Secondly, two non-significant and very low paths from trip length and rule knowledge to walking crashes were set to zero. Finally, a very large Modification Index (MI) that pointed out a relevant relationship between errors and violations was included. With these three modifications, which made the model even more parsimonious, the model fit resulted adequate: $x^2(6) = 49.512$, $p < .001$; NFI = 0.988; CFI = 0.989; TLI = 0.949; IFI = 0.989; RMSEA = 0.054, 90% CI [0.041–0.068].

To test *Hypothesis 2*, a comparative analysis on the dimensional scores of the WBQ was carried out through Welch's comparative analyses. Welch robust tests are Student's t-based non-parametric statistical test entailing a considerable set of advantages over parametric tests such as ANOVA, especially if variances are predominantly imbalanced and/or the compared group sizes are disproportionate. This is the case in the present study, where <11% of pedestrians reported having suffered at least one walking crash during the last five years.

2.5. Categorical analysis

Finally, and with the aim of testing *Hypotheses 3* and *4,* the data from a total of 262 self-reported crashes described by pedestrians were analyzed through a categorical strategy. Two qualified researchers performed data coding on social research and data analysis with the PhD formation and previous publications on the matter, jointly analyzing the qualitative data retrieved in the study. Content analysis was used for assigning different categories to the transcribed data, allowing researchers to nominalize the participants' information, such as hierarchical organization and quantifications, to develop further analyses (Bergin, 2018).

Categories were created on the basis of the crash description provided by respondents, which contained a minimum of three key issues asked from the respondents: the *what*, the *who*, and the *why*. These main categories corresponded to: (*i – what?*) the type of crash(es) they suffered and what kind of user was the crash-partner; (*ii – who?*) the user to whom the responsibility for the crash was attributed; and (*iii – why?*) the most probable cause of the crash (i.e., error; violation; vehicle fail-infrastructure; other; undeterminable).

Also, it could happen that as a crash attribution may be related to various potential causes: for example, a traffic violation (mobile phone use) enhances an error (not seeing a car) that ends up in a crash. To uniformly avoid confusions in this regard, the more immediate attributed cause of the crash was taken into account for data categorization, in order to respect and coherently keep the logic of the theoretical model followed by the study (see Fig. 2).

Detailed crash-related information was accessible for 262 crashes out of 415 reported by participants. 204 (78%) of these 262 crashes involved a second road user or *crash partner*. The parties most commonly involved were: a motor vehicle (94 crashes), a bicycle (71 crashes), an e-scooter (32 crashes), or another type of vehicle (*e.g.*, utility trailers/bulldozers; 7 crashes). On the other hand, the remaining 58 (22%) crashes occurred between pedestrians and fixed objects (including serious falls), with no crash partner.

2.6. Data processing software

3D graphical modeling and analyses were performed in Sigma Plot software, version 12.0 (2019). All other statistical analyses were performed using ©IBM SPSS (Statistical Package for Social Sciences), version 26.0 (2020); SEMs were estimated in ©IBM SPSS AMOS, version 26.0 (2020).

3. Results

3.1. The measurement model

The measurement model assesses how good a certain set of applied items and variables of factors fit together, and to what extent they may be considered as representative of a construct of interest.

As previously described, a set of validity and reliability indicators was obtained for each latent variable included in the study (i.e., traffic violations, errors, positive behaviors, risk perception, and knowledge of traffic laws), as shown in Table 3.

The validity of the measures was assessed through standardized factor loadings (λ coefficients), and reliability and consistency of each latent variable were assessed using both Composite Reliability Indexes (CRIs), Cronbach's alphas (α), and McDonald's omega coefficients.

All latent variables had adequate internal reliability and consistency indexes, with: (*i*) high Composite Reliability Indexes (CRIs) ranging between [0.966–0.992]; (*ii*) good Cronbach's alphas, all between [0.745–0.897]; and (*iii*) similarly high McDonald's omega coefficients, ranging between [0.747–0.899].

Regarding scale composition, standardized factor loadings were all $\lambda > 0.383$, significant at the cut-off point $p < .001$ for all the latent variables measured. Table 3 also shows item-based descriptive data, following the questionnaires' structure (please see section "*2.2 Description of the questionnaire*" for more information).

3.2. Descriptive statistics and correlation analysis

Descriptive statistics (means and standard deviations) obtained for the study variables are summarized in Table 4, along with bivariate (Spearman) correlation analyses that showed significant correlations between demographic and walking-related variables included in the study. Specifically, the average length of walking trips was positively related to risk perception, traffic violations, and positive behaviors. The knowledge of traffic laws was associated with risk perception, protective behaviors, and (negatively) errors.

Errors and violations keep a significant correlation, and positive behaviors are negatively correlated to both errors and traffic violations, even though the magnitude of the correlation was lower for errors. Risk perception is also negatively associated with errors and traffic violations and consistently related to positive road behaviors.

Finally, the number of self-reported walking crashes suffered during a period of five years was significantly correlated to errors, but not to traffic violations nor to positive behaviors (see Table 4 for the full summary of σ coefficients and significance levels).

Furthermore, the 3D-based graphical analysis of the multivariant relationships amongst intentional (traffic violations) and unintentional (errors) risky behaviors in regard to the self-reported number of walking crashes is available in Fig. 1. Overall, it shows that pedestrians self-reporting higher numbers of crashes also tend to report higher scores in errors, although not necessarily in traffic violations (see Fig. 1's quadrants *X*:[1-2]; *Y*:[3-4]; *Z*:[5-15]). In other words, and although there is a small conglomerate for high-violation scores (see quadrant *X*:[2-3]; *Y*:[2-3]; *Z*:[0-5]), higher crash rates are largely clustered in higher error-scored intercepts combined with average traffic violation rates.

3.3. Structural equation modeling (SEM)

The retained structural equation model and its standardized and bias-corrected parameter estimates are presented in Table 5

Table 4
Means, standard deviations and bivariate correlations (Spearman's *rho*) between study variables.

	Study variable	Mean	SD	1	2	3	4	5	6	7
1	Age (Years)	32.88	14.17	–						
2	Most common trip (Length - minutes)	29.26	20.54	0.219**	–					
3	Knowledge of Traffic Laws	2.89	0.84	−0.053**	−0.004	–				
4	Risk Perception	2.85	0.80	0.108**	0.051*	0.463**	–			
5	Errors[1]	0.77	0.56	−0.163**	−0.030	−0.161**	−0.093**	–		
6	Traffic Violations[1]	1.54	0.70	−0.548**	−0.154**	0.034	−0.100**	0.521**	–	
7	Positive Behaviors[1]	2.09	0.88	0.076**	0.071*	0.183**	0.222**	−0.079**	−0.139**	–
8	Self-reported Walking Crashes (5 years)	0.17	0.61	0.017	0.030	−0.047	−0.038	0.106**	0.048	−0.057*

Notes: ** Correlation is significant at p <.001 level (2-tailed); * Correlation is significant at p <.050 level (2-tailed): [1]Scale = 0–4.

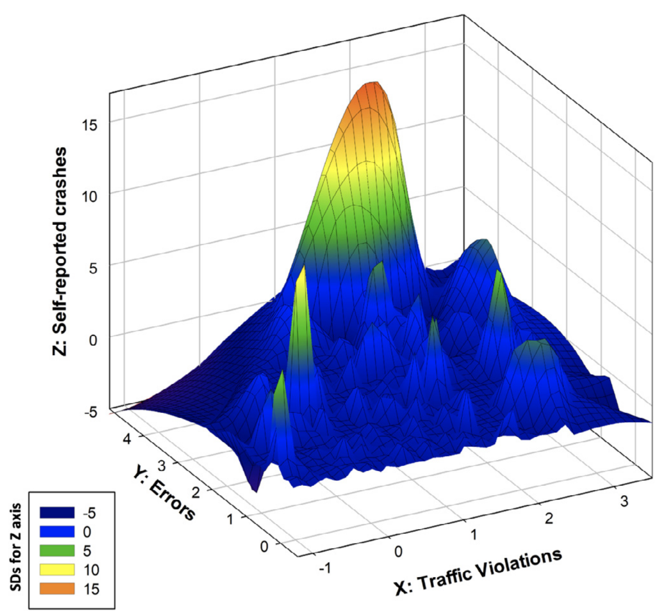

Fig. 1. Three-axis graph for assessing the linear relationships among traffic violations (X-axis), errors (Y-axis) and self-reported walking crashes by Spanish pedestrians in a period of 5 years (Z-axis). *Note:* All axis scores correspond to standardized variable values, where each number represents one Standard Deviation (SD).

(detailed coefficients) and Fig. 2. The solid lines or arrows indicate significant predictive relationships between variables.

Regarding **direct effects** over self-reported walking crashes, three significant links were found, specifically from risk perception, errors, and positive behaviors. However, neither traffic violations nor positive behaviors had a direct effect on self-reported walking crashes. However, traffic violations had, indeed, a significant effect on errors.

As for **indirect effects**, errors fully mediate the relationships between age, knowledge of traffic laws, traffic violations, and the dependent variable (self-reported walking crashes). Similarly, positive behaviors exert a full mediation between age, knowledge of traffic laws, and self-reported crashes, and also a partial mediation between risk perception and the latter. Moreover, age shows to be the strongest contributor to the mediating variables (errors, violations, and positive behaviors), being also correlated to both trip length and risk perception.

The observed relationships among modeled variables suggest that errors (undeliberate risky walking behaviors) have a predictive (and positive) link with the number of crashes suffered by pedestrians. Also, errors fully mediate the link between traffic violations and self-reported number of walking crashes.

On the other hand, the predictive link between positive behaviors and crashes is negative, whereas pedestrians' risk perception directly influences their walking crashes. Overall, these results endorse the assumptions of *Hypothesis 1*. That is to say, risky behaviors (although only errors) have a positive effect on self-reported walking crashes. In contrast, the effect of positive behaviors is negative.

Table 5
Variables included in the model, estimates, significance levels and bootstrap bias-corrected values of the SEM paths for predicting self-reported walking crashes (5 years).

Study variable			SPC[a]	S.E.[b]	C.R.[c]	p[d]	Bootstrap bias-corrected values[e]				
							Est[f]	S.E.[b]	95% CI[g]		p[d]
Age	→	Errors	−0.158	0.001	−7.702	***	−0.006	0.001	−0.008	−0.005	*
Age	→	Traffic Violations	−0.553	0.001	−32.008	***	−0.027	0.001	−0.028	−0.026	*
Age	→	Positive Behaviors	0.094	0.001	4.718	***	0.006	0.001	0.004	0.008	*
Trip Length	→	Errors	−0.017	0.001	−0.839	0.402	0.000	0.001	−0.001	0.001	0.347
Trip Length	→	Traffic Violations	−0.037	0.001	−2.166	*	−0.001	0.001	−0.002	−0.001	*
Trip Length	→	Positive Behaviors	0.045	0.001	2.252	*	0.002	0.001	0.001	0.004	*
Knowledge of Traffic Laws	→	Traffic Violations	0.026	0.018	1.219	0.223	0.022	0.02	−0.011	0.055	0.233
Knowledge of Traffic Laws	→	Errors	−0.118	0.017	−4.581	***	−0.079	0.019	−0.109	−0.048	**
Knowledge of Traffic Laws	→	Positive Behaviors	0.126	0.026	5.041	***	0.132	0.028	0.08	0.175	**
Risk Perception	→	Errors	0.038	0.018	1.486	0.137	0.027	0.018	−0.003	0.058	0.144
Risk Perception	→	Traffic Violations	0.004	0.019	0.174	0.862	0.003	0.02	−0.03	0.032	0.807
Risk Perception	→	Positive Behaviors	0.193	0.027	7.715	***	0.211	0.03	0.153	0.257	*
Traffic Violations	→	Errors	0.695	0.016	35.941	***	0.562	0.015	0.535	0.589	*
Risk Perception	→	Self-reported Crashes	−0.068	0.020	−2.576	**	−0.051	0.02	−0.083	−0.014	*
Knowledge of Traffic Laws	→	Self-reported Crashes	−0.026	0.019	−1.008	0.314	−0.019	0.018	−0.049	0.010	0.284
Trip Length	→	Self-reported Crashes	0.022	0.001	1.098	0.272	0.001	0.001	−0.001	0.001	0.360
Errors	→	Self-reported Crashes	0.120	0.026	4.983	***	0.129	0.025	0.09	0.175	**
Traffic Violations	→	Self-reported Crashes	−0.028	0.021	−1.154	0.248	−0.024	0.022	−0.066	0.010	0.220
Positive Behaviors	→	Self-reported Crashes	−0.041	0.014	−1.965	*	−0.028	0.014	−0.052	−0.007	*

Notes: [a] SPC = Standardized Path Coefficients (can be interpreted as b-linear regression weights); [b] S.E. = Standard Error; [c] CR = Critical Ratio; [d] p-value: *significant at the level p <.050; **significant at the level p <.010; ***significant at the level p <.001; [e] Bootstrapped (bias-corrected) model; [f] Unstandardized estimates; [g] Confidence Interval at the level 95% (lower bound – left; upper bound – right).

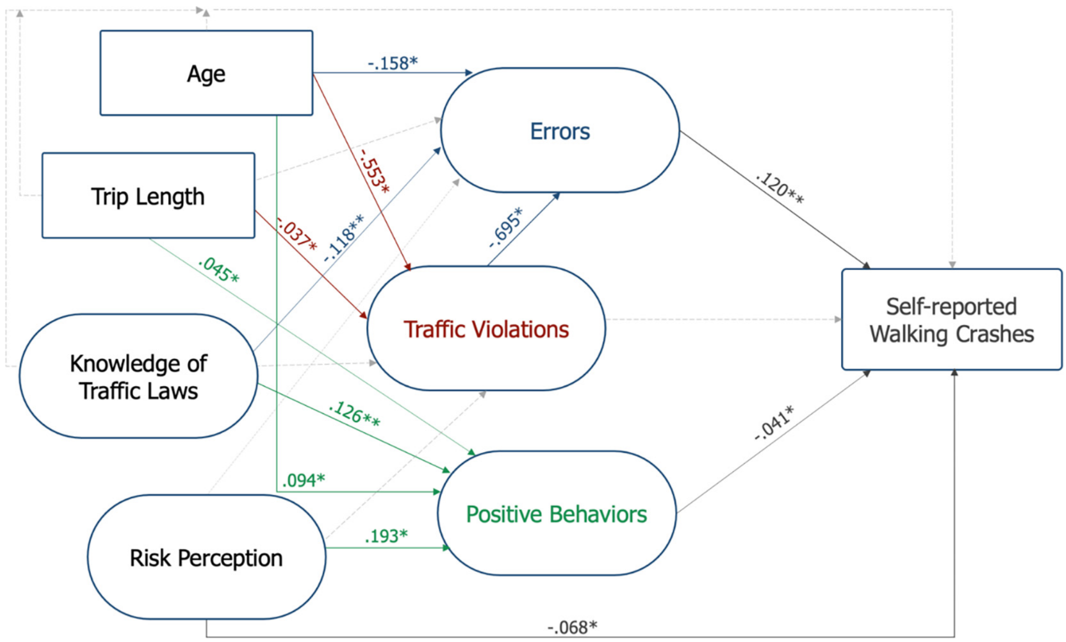

Fig. 2. Standardized parameter estimates. Solid lines represent significant paths, boxes denote observable (non-inferred) variables, and ellipses represent latent variables. Note: All listed estimates in solid lines are significant (as shown in Table 5).

3.4. Mean differences in risky and positive behaviors: crashed versus non-crashed users

The second hypothesis of this study assumed that differences might exist in both risky and positive walking behaviors of pedestrians who self-reported walking crashes. In this regard, higher risky and lesser positive behaviors were observed, compared with the "non-crashed" ones, as shown in Table 6. This finding endorses the assumptions of *Hypothesis 2*.

3.5. Causes attributed to walking crashes

For this step, traffic crashes reported by $n = 262$ participants were assessed; these participants provided further information on their most clearly recalled/accessible crash, that is, if they suffered at least one. Since there could be a few "multi-crashed" participants, which might have a consistent attributional trend and bias results, this decision might help prevent overrepresenting the sample. The walking crash features inquired were: (*i*) the type of crash they suffered and (if available) the kind of user who was the crash-partner; (*ii*) the attributable culpability (user or factor responsible for the crash); and (*iii*) the most probable cause.

These crashes were analyzed using an excluding category-based strategy (only one main/most probable cause and user were accounted for per crash). The aim of this analysis was to assess participants' attributed causes to these crashes: own behavior, the behavior of other user(s), or infrastructural/environmental factor(s), and (in cases being attributed to others) inquiring if it occurred because of an error or a violation. Summarizing the results (the full flow-chart including both absolute and relative frequencies is available in Fig. 3), it was found that:

- The culpability of about half the traffic crashes suffered by pedestrians (117 crashes; 44.6% of the total) was self-attributed, endorsing the assumptions of *Hypothesis 3*. Also, and specifically, within the 44.6% of walking crashes in which pedestrians assume their behavior was the most probable cause of the crash, 89.7% were attributed to errors. However, only 8.5% relate them to traffic violations, mainly walking under the influence of alcohol (60% within sub-category).
- Within the crashes attributed to ones' own distracted walking, 63% corresponded to generic/non-specific distractions, and 32% (1 out of 3) were related to walking while distracted by a cellphone (whether texting, talking, or watching media contents).
- When the pedestrian crash responsibility was attributed to a third parties (*i.e.*, drivers, motorcyclists, or cyclists), 60.6% of them were attributed to a traffic violation committed by them, while 27.8% were attributed to potential driving errors, supporting *Hypothesis 4.*

Table 6
Descriptive data and Welch's robust mean comparisons. Categorical factor: Crash history (dichotomized).

Variable	Group	Mean	SD	Statistic [a]	df1	df2	Sig.
Errors	Crashed	0.98	0.68	28.554	1	300.474	***
	Non-crashed	0.74	0.55				
Violations	Crashed	1.65	0.79	5.712	1	307.534	*
	Non-crashed	1.53	0.69				
Positive Behaviors	Crashed	1.96	0.88	6.701	1	323.548	**
	Non-crashed	2.11	0.88				

Notes for the Table: [a] Asymptotically F distributed; *significant at the level p <.050; **significant at the level p <.010; ***significant at the level p <.001

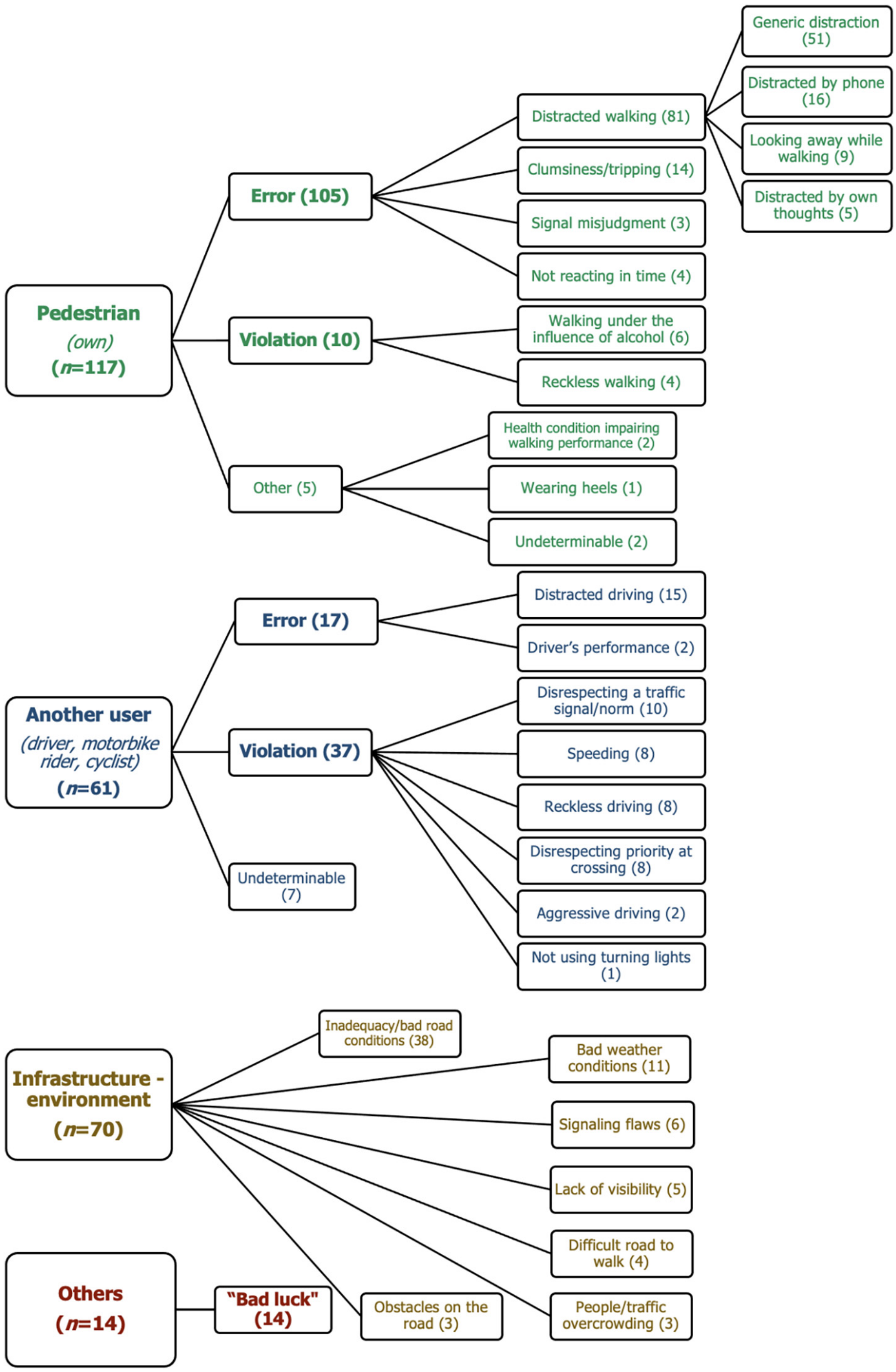

Fig. 3. Pedestrian's attributed culpability (left column) and main cause (second to fourth columns) for the self-reported walking crashes they suffered along the last five years (N = 262 self-reported crashes).

- Infrastructural or environmental factors were assumed to be the causing factor in 26.7% of cases, principally related to the inadequacy of the infrastructure or poor road conditions (54.2%), bad weather conditions at the moment of the crash (15.7%), and bad signaling (8.6%).
- Interestingly, a minor percentage (n = 14; 5.3%) of the crashes suffered by pedestrians were attributed to their "bad luck" instead of a concrete road actor or factor (*please see* last horizontal row of Fig. 3).

4. Discussion

The first aim of this study was to assess the effects of pedestrian-related factors and safety-related road behaviors (both risky and positive) on the walking crashes suffered by pedestrians. Overall, the results of the first (quantitative and structural equation-based) part of this study suggest that walking errors and positive behaviors (o a lesser extent) are significant predictors of self-reported pedestrian crashes, supporting what is stated by *Hypothesis 1*. Some key points in this regard follow:

4.1. Structural models for assessing road behaviors in relation to self-reported crashes of pedestrians

Do errors account for walking crashes more than violations?

The first structural finding to discuss is that, from this SEM perspective, errors are the most relevant behavioral contributors to self-reported walking crashes. Although in first sight, this contrasts with literature dealing with motor-vehicle drivers, recent studies stress that potential behavioral repertories (i.e., possible violations and errors) might substantially differ among users. Also, there are key differences in their nature, frequency, acceptance, and influence on possible pre-crash or crash scenarios (Elliot, Baughan, & Sexton, 2007; D'Elia, Newstead, & Cameron, 2007; Elliott & Baughan, 2004).

For instance, the average speed at which a driver circulates is several times higher than cyclists and pedestrians, influencing possible critical behaviors, and crash likelikood and severity. This might contribute to explaining that certain misbehaviors such as speeding might generally be more crash-involving among drivers (Benhood & Mannering, 2017).

In other words, while in DBQ (driver-based) studies the absence of a great predictive value for traffic violations would not be the *expectable* result (Af Wåhlberg, Barraclough, & Freeman, 2015; Af Wåhlberg & Dorn, 2015), this study contributes to depict a key user-based difference. However, this is coherent with a few previous studies using non-motorized road user data, where errors seem to have a major role in explaining their crashes and crash attributions (Wood et al., 2009).

Also, the most relevant studies suggest that certain road users remain "understudied" compared to drivers, allowing the possibility of an invisible effect of dissemination bias, strengthened by many unpublished results when not aligned with the theoretical budgets provided by studies on motor drivers. Also, the often problematic practice of indiscriminately merging errors and violations as a single dimension (overall "risky behaviors") has been highlighted in the research. This makes it difficult to taxonomically differentiate the actual causes of self-reported crashes (Af Wåhlberg, Barraclough, & Freeman, 2015; Sümer, 2003).

4.2. What other facts could help to understand these differences?

Both the root assumptions of this study and the careful analysis of its quantitative data allow us to believe that errors' predominancy is not a casual or biased result, but rather that it obeys the clear differences between contexts, task dynamics, and specific risk factors and crash scenarios of pedestrians. Some feasible hypotheses in this regard may be that:

- Pedestrians report lower rates of traffic violations as a result of a lower degree of information on traffic rules. Unlike drivers who attend a driving school for licensing, pedestrian information sources such as road safety campaigns and school education are difficult to appraise.
- Enforcement and control strategies are clearly dissimilar among users: in the case of this study, none of the 2,499 participants had received a traffic fine (as a pedestrian), at least over the last five years. Regarding official figures, out of the 3 million traffic fines imposed in Spain during 2018 (the latest statistical report available to date), more than 90% of them sanctioned motor-vehicle drivers (DGT, 2019). In other words, pedestrians are only exceptionally fined compared to drivers, a gap that could contribute to normalizing some usual risky behaviors otherwise conceivable as traffic violations.
- Finally, it is relevant to consider pedestrians less responsible for their accidents, rather than focusing on the pre-crash scenario. The recent in-depth investigation of $n = 142$ walking crashes performed by Yue et al. (2020) revealed that: (*i*) the most frequent vehicle–pedestrian pre-crash scenario for pedestrians (51% of times) involves a crossing pedestrian that gets injured due to driver's distraction (27%) or misjudgment (24).

It might be reasonable to assume that pedestrian crashes may heavily be due to errors (*e.g.,* not noticing an approaching car or crossing while distracted) rather than deliberate traffic violations, which might be more involved in the constitution of the pre-crash scenario.

The root theories (back to the case of evidence retrieved from driver populations) endorse the assumption that positive behaviors (PB) might help to avoid crashes in all trip modalities. However, it is worth mentioning that the literature on pedestrian protective behaviors is considerably scarce. This limits our capacity to draw further attributions to the role of PBs on road crashes. (Yue et al., 2020; Hashemiparast, Negarandeh, & Montazeri, 2017; Cinnamon, Schuurman, & Hameed, 2011; Shi, Chen, Ren, & Rong, 2007).

4.3. The role of errors in self-reported crashes: Could it be getting worse?

Hypothesis 2 proposed that there would be significant self-reported behavioral differences between pedestrians having and not having suffered walking crashes in (the last) five years. In this regard, robust tests allowed to find significant mean differences in all three WBQ factors (i.e., both risky (errors and violations) and positive (or protective) behaviors).

Therefore, another interesting implication of this study could be that behavioral improvements might be a suitable need in pedestrians' road safety planning and policymaking. Coherently, different studies endorse the need to strengthen road training, awareness, and decision-making in risk scenarios as ways to decrease error-based crash likelihood (Maillot, Dommes, Dang, & Vienne, 2017; Demetre et al., 1992).

It is worth mentioning that the correlation and predictive paths between errors and self-reported walking crashes are, although significant, considerably modest in magnitude (explaining between 10.6% and 12% of the variance, respectively). Therefore, further evidence might be needed to endorse this statistical relationship. Also, there remains pending need to assess the specific effect of secondary and potentially distractive tasks, as studies growingly argue for concerns in the cases of cellphone use as well as critical locations of urban areas (such as zebra crossings and intersections; Hou et al., 2021; Alonso et al., 2021; Oviedo-Trespalacios et al., 2019; Alsaleh, Sayed & Zaki, 2018). Therefore, assessing the specific effect of secondary and potentially distractive tasks, as observed in those studies, is yet to be done.

4.4. Do SEM outcomes match with pedestrians' crash attributions?

The second aim of this study was to compare the causes that pedestrians attributed to their pedestrian crashes suffered in the last five years to the multivariate statistical model outcomes. In this regard, *Hypotheses 3* and *4* were developed.

Previously, a few studies addressed similar research questions, especially regarding the lack of consistency between the assumptions and expectations of different road users (including pedestrians) and their safety-related perceptions, behaviors, and practices (Hoekstra et al., 2018; King et al., 2012). Also, previous behavioral assessments by third users problematize the lack of awareness of drivers (in simulated tasks) and non-motorized users over the frequency, self-assessment, and safety implications of their risky behaviors (Alonso et al., 2021; Dixit, Harrison, & Rutström, 2014).

Regarding the actual data collected in this study, the comparison of qualitative and quantitative data sources shows a certain concordance, and errors remain the most relevant issue in what concerns own road behaviors as a crash cause. However, it is worth mentioning that retrospective study designs as the present remain prone to be subjectively biased. Af Wåhlberg (2011) offers good empirical insights on the strong distortion of self-reported crash data. For instance, it is remarked that the number of crashes reported by road users tends to decline in numbers for every year passed, but are hitting a record high in recent years.

These data also show that those pedestrians who suffered crashes attribute the crash to their own walking error (89.7%), while 77.1% of these errors are related to unawareness/lack of attention. Accordingly, the major statistical contributor to self-reported crashes from both sources were undeliberate risky road behaviors (*i.e.,* errors), supporting *Hypothesis 3*.

Secondly, it is attention-worthy that, when attributing the pedestrian-crash culpability to another user (driver, motorcyclist, or cyclist), 60.6% of the time the involved pedestrian states that the causing behavior is associated with a third party's traffic violation. On the other hand, errors (27.8%) take second place with a substantially lower percentage, as expected, thus endorsing the assumptions of *Hypothesis 4* regarding other users' responsibility for their walking crashes.

4.5. Always "better intentioned" than others?... or could our attributions be biased?

Although the attributional findings result coherent with the theoretical assumptions of this study, bias sources should be kept in mind in order to appraise these outcomes. Same as questionnaire data, blame and responsibility attributions remain prone to be whether genuinely (deliberately) or indirectly biased (Holden, 2009). Common bias such as the "fundamental attribution error" (i.e., our inclination to overestimate dispositional and underestimate situational causes of third persons' behaviors) might play an implicit role in these appraisals (Brown, Houghton, Sherples, & Morley, 2015).

Also interestingly, the so-called "theory of blame" remarks how studies addressing causality, responsibility, and blameworthiness over negative events might be considered to differentiate these terms. This is because, for instance, behavioral self-blame could be interpreted as, rather, a self-attribution of causality in most cases, as stated by specialized literature in social psychology (Shaver & Drown, 1986).

Even with this in mind, it makes sense to consider two potential compatible scenarios to interpret the present findings, if they are assumed as unbiased:

- *Scenario 1*: that many of vehicle–pedestrian crashes could be, indeed, preceded by traffic violations when the responsibility is attributed to the driver of a motor vehicle, and by errors (especially preceded by distracted walking) when the pedestrians could be assumed to be responsible for the crash, as implicitly suggested in some analytic studies (Oviedo-Trespalacios et al., 2021; Ralph & Girardeau, 2020).
- *Scenario 2*: that problematic interactions between drivers and pedestrians in critical scenarios explain a "hazardous formula" for many of these traffic crashes (e.g., adding a a distracted pedestrian to a driver not respecting right-of-way). This is also important considering that pedestrians are, morally and causally, equally responsible for being involved in crashes at high-risk locations (Al-Ghamdi, 2002).

Finally, it is worth remembering that the nature of mixed methods is not analytical par excellence, so these theories and assumptions remain needing empirical validation (e.g., experimental designs or naturalistic observations). In addition, a certain accordance between the two data sources used does not allow to validate potential crash prediction causes.

Rather, one of the key points of this second part of the study is to remark how, besides statistical models, crash-related attributions seem to help depict cognitive trends present among pedestrians. This would be useful to address intervention programs and educational strategies. Concretely: (*i*) Risky behavioral attributions about other road users magnify their responsibility when they are involved in crashes (*the Guilty*); (*ii*) Against almost any prognosis, a small (but not negligible) part of them believe that luck is the best explanation for their walking crashes (*the Unlucky*); and (*iii*) Among all self-reported causes of these crashes, distractions remain a pervasive issue, and everything seems to indicate that sources of distraction (including handheld devices) are here to stay (*the Unaware*).

5. Conclusion

The findings of this research suggest, in regard to the first study aim, that errors and (to a lesser extent) positive behaviors, rather than violations, may constitute significant predictors of self-reported walking crashes in a period of five years. Given its predictive path to errors, it is hypothesized that traffic violations may play a more significant role in the pedestrians' involvement in a pre-crash scenario (*i.e.*, a critical event o situation immediately prior to the crash) rather than in walking crashes themselves through an indirect effect. However, more evidence is needed to further develop this idea.

As for the second aim, and with considerable coherence with the first one, the causes that pedestrians attributed to the crashes they suffered are mainly their own errors (44.6%), not traffic violations (8.5%). However, the attribution trend is inverse when the culpability is attributed to third road users, essentially those driving a vehicle. Half of the crashes (60.6%) are attributed to drivers' violations, while about a third of them (27.8%) are causally linked to an error.

6. Limitations and further research

Although this study used a considerably sizeable nationwide sample, it cannot be considered representative of the Spanish population. Apart from not being proportional in terms of age, gender, and education, data collection was founded on a convenience (non-probabilistic) sampling method. Also, it is worth mentioning that convenience sampling-based designs entail shortcomings as for representativeness, especially in cases of online-based recruitment studies. In the case of this research, certain segments of the population remain underrepresented, such as the case of older adults and people less likely to use online devices. Therefore, generalizing the data without considering these shortcomings might be potentially problematic (Kelfve et al., 2013).

Although anonymous and rigorously analyzed, this method is prone to be influenced by common method biases and common method variance (Af Wåhlberg & Dorn, 2015). Therefore, it does not necessarily replace the need to objectively analyze the crashes suffered by pedestrians and other road users. Furthermore, the analysis of settings such as the crash typology, severity, and pre-crash scenario might contribute to more discriminatory findings in regard to, for example, the specific behaviors predicting different crash severity levels.

Furthermore, the sample of $n = 262$ self-reported crashes analyzed, although relatively high in raw numbers, has two essential flaws: (a) it cannot be considered as fully representative in statistical terms; and (b) the reported responsibility and causes correspond to individual attributions, rather than to objective crash ("accident") reports, and is also highly dependent on the information that could be recalled by subjects (Af Wåhlberg, 2011). In other words, participants' understanding of critical events and the potential influence of possible memory failures on the study outcomes. For example, regardless of research protocols and explanations, a single event may constitute a "severe" crash for some individuals while remaining "slight" for others (Kelfve et al., 2013; Loftus & Loftus, 1980).

Therefore, it is suggested to perform more research on this topic through non-necessarily incompatible (but rather complementary) tools, such as objective crash records and in-depth interviews, in order to develop further insights about key crash-related issues among pedestrians.

Conflicts of interest

The authors declare no competing interests.

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