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Aberrant behaviors of drivers involved in crashes and related injury severity: Are there variations between the major cities in the same country?

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ABSTRACT

Introduction: Crash data analyses based on accident datasets often do not include human-related variables because they can be hard to reconstruct from crash data. However, records of crash circumstances can help for this purpose since crashes can be classified considering aberrant behavior and misconduct of the drivers involved. *Method:* In this case, urban crash data from the 10 largest Italian cities were used to develop four logistic regression models having the driver-related crash circumstance (aberrant behaviors: inattentive driving, illegal maneuvering, wrong interaction with pedestrian and speeding) as dependent variables and the other crash-related factors as predictors (information about the users and the vehicles involved and about road geometry and conditions). Two other models were built to study the influence of the same factors on the injury severity of the occupants of vehicles for which crash circumstances related to driver aberrant behaviors were observed and of the involved pedestrians. The variability between the 10 different cities was considered through a multilevel approach, which revealed a significant variability only for the inattention-related crash circumstance. In the other models, the variability between cities was not significant, indicating quite homogeneous results within the same country. *Results:* The results show several relationships between crash factors (driver, vehicle or road-related) and human-related crash circumstances and severity. Unsignalized intersections were particularly related to the illegal maneuvering crash circumstance, while the night period was clearly related to the speeding-related crash circumstance and to injuries/casualties of vehicle occupants. Cyclists and motorcyclists were shown to suffer more injuries/casualties than car occupants, while the latter were generally those exhibiting more aberrant behaviors. Pedestrian casualties were associated with arterial roads, heavy vehicles, and older pedestrians.

1. Introduction

Road safety analyses should be directed towards Vision Zero (Johansson, 2009; Ecola et al., 2018). The main goal of Vision Zero is to reach zero deaths and to drastically reduce severe injuries due to road crashes (Doctor et al., 2020). This ambitious objective has required an upheaval in the way of conceiving safety assessments. The "Safe System" approach is focused on preventing deaths and serious injuries: on designing roads to reduce human mistakes and anticipate human limitations; on reducing system kinetic energy (resulting in fewer consequences for human bodies in the case of crashes); and, lastly, on sharing responsibilities as well as proactively identifying and addressing risks.

Mainly for these reasons, nowadays, interventions on road infrastructure are planned and prioritized based on road safety, due to the great number of fatalities or injuries brought about by crashes (WHO, 2018). In Europe, 42% of crashes recorded during 2019 happened in the urban environment. Among these crashes, 50% involved vulnerable road users (VRUs; Decae, 2021). Hence, it is crucial to promote specific countermeasures to protect VRUs, and in general all urban users (Bassani et al., 2020; Zegeer and Bushell, 2012). This tendency also finds a practical explanation, that is, the remarkable impact that fatal and injury crashes have on the country's economy (see e.g., Russo & Comi, 2017).

Even though road crashes are random and largely unpredictable events with spatial and temporal fluctuations, they happen for several interacting factors. One of the most common contributing factors for

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crash occurrence is the human one, as widely demonstrated worldwide (see e.g., ISTAT, 2021; Decae, 2021; NHTSA, 2020, for fatal crashes): around 90% of crashes are due to at least one human-related cause (Treat et al., 1979; NHTSA, 2008). This awareness is fundamental since, by knowing the main crash driving factors, specific engineering countermeasures can be designed. Human errors are also related to crash severity, as has generally emerged from previous research; and, generally, the greater the level of misbehavior, the greater is the severity (e.g., Cardamone et al., 2016). Despite the importance of human factors, its mitigation in crash prevention is not always analyzed as an engineering issue, while it should be considered in the road design stage instead (NASEM, 2012). In fact: "*road users cannot be expected to solve either highway design or traffic engineering problems without making mistakes and/or compromising operational efficiency and safety*'' (NASEM, 2012). Driving errors were clustered into the following four categories by NHTSA (2008): recognition, decision, performance, and non-performance errors. Speeding (decision error) and inattention/distraction (recognition error) also fall into these categories, which are among the most important human errors to be mitigated, according to the Safe System (Doctor et al., 2020).

Several studies have attempted to find relationships between distracted behavior and human characteristics, such as sex, age, and driving tasks (Smith et al., 2008; Box, 2009; McCartt et al., 2009; Shell et al., 2015; Cardamone et al., 2016). Despite this, it must also be considered that vehicle, road, and environmental factors can influence each other and contribute to leading to human driving errors or misbehavior and crashes. In this sense, Hauer (2009) found a correlation between speeding, road geometry, and vehicle characteristics. Wang and Qin (2015) tended to relate all human driving behavior not only to psychological factors but also to the external conditions and vehicle characteristics at intersections, aiming to predict the driver error based on the circumstances. Attempts to analyze, understand, and overcome human factor issues based on on-road tests with the help of different technological systems (Dula et al., 2010; Elias et al., 2010; Jun et al., 2011; Isler et al., 2011) and questionnaires (Ossenbruggen et al., 2001; Chen et al., 2016; Useche et al., 2018) can be found in previous research. Moreover, different statistical methods can be used to highlight human-related safety problems; an extensive overview of the most suitable statistical methods was made by Lord and Mannering (2010) for crash frequency analyses and Savolainen et al. (2011) for injury severity analyses. Among the most used statistical approaches, the logit model structure is a candidate for analyzing the likelihood of particular crash types and injury severities (e.g., Dissanayake, 2004; Adanu & Jones, 2017; Eboli & Forciniti, 2020). In this regard, some important findings were noted, such as the major impact of speeding on crash frequency if compared to the disrespect of traffic signs (Penmetsa & Pulugurtha, 2017); the dangerous effect in terms of increased crash risk either of slippery roads (Laapotti et al., 2006) or traffic violations (Zhang et al., 2013); the impact of road types, street lighting conditions and weather on crash occurrence (Híjar et al., 2000); and the strict relation between vehicle type and location with injury severity (Al-Ghamdi, 2002). Recently, logit model structures were also shown to be complementary to other data mining approaches in analyzing crash patterns (Rella Riccardi et al., 2022).

In regression models, crash circumstances are also related to other factors, such as socio-economic factors and technological advances (Factor et al., 2008) or to geographical differences (e.g., Eboli & Forciniti, 2020). The possibility of a geographic variability depending on local factors is, in fact, considered in safety performance analyses (see e.g., the calibration procedures of the safety performance functions proposed by the Highway Safety Manual: AASHTO, 2010 or Geedipally et al., 2017; Shirazi et al., 2017). Different crash rates can be measured in different parts of the same regions or even large cities, depending on characteristics such as terrain, driving population, weather, or other unobserved factors (Geedipally et al., 2017). However, while some studies take the geographic factor into account for crash frequency analyses (see e.g., Aguero-Valverde and Jovanis, 2008; Intini et al., 2019), for macroscopic aggregate analyses (see e.g., Siddiqui et al., 2012; Papadimitriou et al., 2013) or for crash severity analyses (see e.g., Eboli & Forciniti, 2020), this aspect is often overlooked in road safety studies, also conditioned by data availability (Mitra & Washington, 2012).

In detail, some of the attempts to account for the spatial variability in road safety performances were dedicated to predicting an excess of crash frequency at different area levels (e.g., using counties or census zones within a country or state, see Noland & Quddus, 2004a; Aguero-Valverde, 2013; Amoros et al., 2003; Flask & Schneider IV, 2013; municipalities within a province, see Intini et al., 2019, or traffic analysis zones within a large city, see Matkan et al., 2013) or considering the spatial correlation due to geographic proximity between crash data while modeling crash frequencies on road segments (Aguero-Valverde & Jovanis, 2010; El-Basyouny & Sayed, 2009). In these cases, several geographic, socio-economic, land-use and infrastructure-related variables were used to characterize the spatial units (see e.g., Mitra & Washington, 2012; Aguero-Valverde, 2013; Amoros et al., 2003). Moreover, crashes of different severity levels or related to different road users (e.g., motorcycles in Flask & Schneider IV, 2013, or vulnerable road users in Noland & Quddus, 2004b) were used for these types of analyses. However, even if different crash types and severities were investigated, those studies did not consider how different crash circumstances related to driving aberrant behaviors can be affected by spatial variability. Moreover, possible differences between large cities (taken as spatial units) belonging to the same country were not explored.

Hence, the motivation of this study arises from a twofold perspective: (1) human-related variables are often included as predictors in crash frequency analyses, injury severity analyses and driving behavioral studies, but the direct investigation of crash circumstances that are related to driver aberrant behaviors is less frequently explored and linked to other crash-related factors; (2) the spatial variability of driver aberrant behaviors at the country level (that is, for example, between different regions, provinces or cities in the same country) was not studied in detail in previous research. However, according to literature studies, this hypothesis is reasonable given that the geographic variability of different safety performances was already demonstrated in several instances. Moreover, to the authors' knowledge, the specific spatial variability of driver aberrant behaviors observed during crashes, especially within the same country, was not explored. Hence, this is a peculiar research contribution of this study, which was dealt with by using multilevel models (see e.g., Huang & Abdel-Aty, 2010; Dupont et al., 2013; Ziakopoulos at al., 2020) and the 10 largest Italian cities as a testbed.

In detail, several crash-related factors are used in this study to explain the occurrence of aberrant behaviors and the related vehicle occupant and pedestrian injury severity in the crash reports of the largest Italian cities. We consider four types of aberrant behavior: speeding, inattentive driving, illegal maneuvering, and wrong interaction with pedestrians. Since the analysis relies on a country-wide urban crash dataset including the 10 largest cities in Italy, the possibility of estimating city-specific model parameters was explored, in order to inquire into the within-country variability of the relationships between crash circumstances/severity and other factors. For this reason, a grouped (by city) random parameter approach was applied, where relevant (see Sarwar et al., 2017; Cai et al., 2018; Fountas et al., 2018; Eker et al., 2019; Heydari et al., 2018; Pantangi et al., 2019, Intini et al., 2020).

The methods used in this study are described in next section. The results are then presented and discussed in light of previous research. Finally, conclusions from this study are drawn, by also focusing on possible applications.

2. Methods

The crash dataset used and the statistical analyses performed are presented and described as follows.

2.1. Database

The crash dataset used, related to a recent three-year period (2016–2018), is available online from ISTAT (Italian Institute of Statistics). This dataset only includes fatal and injury crashes, in which at least one motor vehicle was involved. Given the aims of this study, the database was filtered to include only fatal and injury crashes that occurred in the urban environment, in the 10 major Italian cities (having more than 300,000 inhabitants): Roma, Milano, Napoli, Torino, Palermo, Genova, Bologna, Firenze, Bari, Catania (listed in descending order according to their population). Except from Roma -with a population of almost 3 million inhabitants- and Miliano, all other cities have less than 1 million inhabitants.

2.1.1. Variability between the major Italian cities

The main characteristics of the investigated cities (highlighted in Fig. 1) are summarized in Table 1. The large differences between the considered geographic and socio-economic indicators of the 10 most populated Italian cities are evident.

In particular, population density is largely variable between a minimum of 1.64 inhabitants per km^2 (Catania) and a maximum of 7.65 inhabitants per km^2 (Napoli), revealing different levels of urban sprawl, which can have different impacts on crash frequency and severity (Ewing et al., 2016). Most of large Italian city areas (6 out of 10) start from the sea level and have an average rainfall height smaller than 600 mm (except than Genova, Firenze and Bologna). However, a very high variability of the terrain elevation can be noted for Palermo and Genova, in which there is a difference of more than 1000 m between the highest and the lowest point in the city area. Besides absolute population numbers, the distribution into age classes (which may be related to different crash risks, see Aguero-Valverde & Jovanis, 2006) is mostly uniform across cities, even if slightly more 0–14 years old inhabitants (and less 65 + years old inhabitants) can be found in the most Southern cities (Napoli, Palermo, and Catania) with respect to the other cities. Income is largely variable, showing again a high difference between the most Southern cities (with average annual income smaller than or equal to 20 k€) and the highest-income city (Milano, more than 30 k€). This is another source of variability between the major Italian cities that can affect safety performances. For example, Noland and Quddus (2004a) found that the most deprived areas of a country (United Kingdom in that case) are associated with more casualties, especially if non-motorized. Motorization rate, which can be associated to traffic exposure, is largely variable as well from a minimum of about 0.50 (e.g., Milano, which has one of the most widespread public transport networks in Italy) to a maximum of 0.78 (Catania, which means almost one vehicle per inhabitant).

Hence, most of the considered geographic and socio-economic variables were associated with a variability in crash frequencies and severities and they largely vary between the 10 most populated Italian cities. Thus, it is likely possible that the relationships between crash circumstances related to driver aberrant behaviors and other crash factors can vary across different Italian cities. This occurrence is investigated here.

2.1.2. Crash data

The dataset of urban crashes in the 10 largest Italian cities (2016–2018) includes 112,592 fatal and injury -FI- crashes in which 202,591 vehicles were involved (1.80 per crash on average).

The variables present in the dataset (see Table 2) are related to: general crash-specific context variables (date and time, road type, pavement, road signs and type of crash), and vehicle- and driver-specific variables (age, sex and crash circumstances associated to the drivers involved).

The dataset includes the driver-related crash circumstance for each involved vehicle. The circumstances are drawn from a list of 67 different possible maneuvers or conducts undertaken by the driver.[1] These 67 codes were further classified into more parsimonious general classes: moving forward regularly, distracted (or uncertain) driving (henceforth referred to as inattentive driving), generally illegal maneuver/conduct (i.e., illegal turning, overtaking or inadequate distance between vehicles), speeding, generally regular maneuver, wrong interaction with pedestrian, other. Among those classes, the driver-related crash circumstances that were deemed useful for the aims of this study are those in which aberrant behaviors corresponding to traffic violations were documented by the officers who completed the crash reports. In particular, these classes of circumstances are: inattentive driving, illegal maneuvering, speeding, and wrong interaction with pedestrians. It is important to note that these four classes are not mutually exclusive and independent. However, this research is based on data corresponding to standardized crash reports provided by ISTAT (2018), which includes just one aberrant behavior per involved vehicle. In those reports, it is not explicitly specified how the possible condition of multiple concurrent aberrant behaviors is treated (e.g., speeding and illegal maneuvering). Thus, we assume that the reported behavior is the one that has contributed most to the occurrence of the crash. The "speeding" circumstance was kept separate from other illegal maneuvers/conducts, such as illegal turning, overtaking or inadequate safety distance; to focus on this specific behavior which, especially in the urban environment, should be particularly studied and mitigated (Doctor et al., 2020), given the possible influence on severity and on the safety of vulnerable road users. The "wrong interaction with pedestrian" behavior only includes driver-related circumstances (e.g., failing to give way to pedestrians at crossings) not covered by the other three types of aberrant behavior (i.e., inattentive driving, illegal maneuvering, speeding). Moreover, independently on the number of vehicles involved in the crash (there could be more than two involved vehicles), the standardized crash dataset includes the main driver-related crash circumstance for the first and the second involved vehicles only. Given that it cannot be certainly excluded that drivers in the other crashed vehicles may have exhibited aberrant behaviors, crashes with more than two involved vehicles were removed from the initial dataset. In this way, it is possible to assign a crash circumstance to each vehicle involved in the crash.

The classification of all vehicles involved in crashes according to different circumstances for the 10 largest Italian cities is reported in Fig. 2. Even if absolute numbers are often disproportionate between cities, by considering the percentage split it is already evident how there are remarkable differences between cities. For example, about 40% of crashed vehicles on average were identified in the major Italian cities as "regularly driving," but these were about 50% in Roma and about 30% in Genova. As expected, a chi-square test of independence showed that there is a significant association between crash circumstances and cities, $\chi^2(270, 134994) = 21800$, $p < .001$.

The other crash-related variables elaborated from the source dataset are: day type (classified as weekday or weekend/holidays), day period (arranged in five classes, in which the morning and afternoon peak periods according to average Italian working hours, and the night period are separated from the other times), year period (four trimesters per year, grossly corresponding to the four different seasons), road type (city-managed roads or other urban roads managed at higher

[1] For crashes involving pedestrians, the crash circumstance includes additional information about the behavior of the pedestrian. Such information is not used in this study as the focus is on the behavior of drivers. However, clearly, the behavior of the pedestrians involved in a crash affects the possibility of the driver interacting with them correctly. This influence should be analyzed in future studies.

Fig. 1. Location of major Italian cities in terms of population (>300,000 inhabitants) on the left and their area width on the right (highlighted in red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of geographic and socio-economic data for the ten most populated Italian cities.

Cities	Population (million inhab.)	Area (km^2)	Density (10^3inh./ km^2)	Mean elevation (m)	Min.-max. elevation (m)	Average rainfall height (mm) and yearly days	Population by age (%)			Average Annual Income (k€)	Motorization rate (vehicles/ inh.)
							0–14 years old	15–64 years old	>65 years old		
Roma	2.75	1287	2.14	66	0–380	514 (77)	12.7	64.5	22.8	25.99	0.62
Milano	1.35	182	7.42	122	100–147	588 (77)	12.8	64.1	23.1	33.70	0.49
Napoli	0.91	119	7.65	100	0–453	559 (81)	14.5	65.9	19.7	20.32	0.57
Torino	0.84	130	6.46	266	205–706	439 (73)	11.9	61.9	26.3	24.43	0.64
Palermo	0.63	161	3.91	183	0–1050	534 (74)	13.9	63.6	22.5	19.98	0.60
Genova	0.56	240	2.33	277	0–1182	601 (74)	10.7	60.2	29.1	22.95	0.47
Bologna	0.39	141	2.77	84	31–392	831 (79)	12.1	63.1	24.7	26.49	0.53
Firenze	0.36	102	3.53	84	29–336	739 (83)	11.9	62.2	26.0	24.77	0.54
Bari	0.32	117	2.74	36	0–130	480 (74)	12.5	64.3	23.3	21.40	0.57
Catania	0.30	183	1.64	34	0–379	459 (n.d.)	14.2	64.2	21.6	19.05	0.73

Note: Population, and population by age data source is: ISTAT (2022). Area data source is ISTAT (2020). Elevation data source is ISTAT (2011). Income data source is the Italian Ministry of Economics and Finance (2022). Motorization rate data source is Legambiente (2020). Rainfall data source is the Italian Ministry of Agriculture, food and forest (2017) and ISTAT (2002–2016) for average rainy days.

administrative levels, e.g., by the State, Region or Province), road element type (arranged in the following classes to avoid an excessively fragmented classification: ordinary or critical segment, signalized or unsignalized intersection or crossing), road conditions (dry or not), road signs/markings (present or not), vehicle type, crash type (grouped in six elementary classes from more detailed definitions: fixed-object including run-off-road, head-on, angle, sideswipe, rear-end, crash with pedestrians), age classes (clustered in the four classes; young, adult, middle-aged and senior), and sex. For what concerns road type, we clarify that the adopted classification does not precisely reflect posted speed limits, which are not specified for each crash in the dataset. However, while the speed limit in the urban environment is generally posted to 50 km/h, some city-managed roads may have lower speed limits (i.e., typically 30 km/h in restricted traffic zones). The different crash types were not considered as predictors of a particular crash circumstance since different crash types may rather be a consequence of specific driving-related circumstances in the chain of events.

After having excluded crashes for which some of these variables were not recorded, the final dataset analyzed includes 78,323 fatal and injury crashes in which 131,898 vehicles were involved (1.68 vehicles per crash on average). Most of these crashes are multi-vehicle crashes with two vehicles involved (81%). In two-vehicle crashes, it is possible to observe cases in which one of the two vehicles is not associated with any injury or casualty. Differently, in single-vehicle crashes, there was at least one injury or casualty because of the crash (according to the ISTAT dataset definition). This difference was also used to study the influence of the different variables on the severity (i.e., vehicle occupants who suffered from injuries/casualties or not).

Table 2
Descriptive statistics of the variables extracted from the crash dataset.

General information	Modalities	Vehicles count	Percentage
Number of vehicles	Vehicles involved in single-vehicle crashes	24,748	18.8%
	Vehicles involved in two-vehicle crashes	107,150	81.2%
Vehicle occupant injury severity	No injury	46,512	35.3%
	Injury	84,726	64.2%
	Fatal	660	0.5%
Pedestrian injury severity*	Injury	5,332	98.4%
	Fatal	84	1.6%
Crash circumstances	**Modalities**	**Vehicles count**	**Percentage**
Inattentive driving	No (reference)	113,220	85.8%
	Yes	18,678	14.2%
Illegal maneuvering	No (reference)	101,861	77.2%
	Yes	30,037	22.8%
Speeding	No (reference)	121,038	91.8%
	Yes	10,860	8.2%
Wrong interaction with pedestrian*	No (reference)	126,482	95.9%
	Yes	5,416	4.1%
Crash variables	**Modalities**	**Vehicles count**	**Percentage**
Day type	Weekday: Monday to Friday (reference)	102,923	78.0%
	Weekend	28,975	22.0%
Day period	7 a.m.- 9 a.m. (morning peak - reference)	16,932	12.8%
	1 a.m.- 6 a.m. (night)	10,778	8.2%
	10 a.m.- 4p.m. (day)	55,959	42.4%
	5p.m.- 7p.m. (afternoon peak)	25,516	19.3%
	8p.m.- 0 a.m. (evening)	22,713	17.2%
Year period	January-March (winter - reference)	30,345	23.0%
	April-June (spring)	36,314	27.5%
	July-September (summer)	30,954	23.5%
	October-December (autumn)	34,285	26.0%
Road type	City-managed road (reference)	130,604	99.0%
	Other urban roads	1,294	1.0%
Element type	Ordinary road segment (reference)	55,803	42.3%
	Crossing	23,541	17.8%
	Unsignalized intersection	21,055	16.0%
	Signalized intersection	23,739	18.0%
	Segments with horizontal/vertical issues, tunnels	7,760	5.9%
Pavement	Dry (reference)	113,328	85.9%
	Wet/icy	18,570	14.1%
Road signs/markings	Horizontal, vertical or both (reference)	123,591	93.7%
	Absent	8,307	6.3%
Vehicle type	Car (reference)	78,201	59.3%
	Heavy vehicle/public transport	8,013	6.1%
	Bicycle	5,455	4.1%
	Light motorcycle	4,461	3.4%
	Motorcycle	35,768	27.1%
Crash type	Fixed object/Run-off (reference)	17,673	13.4%
	Head-on	5,328	4.0%
	Angle	55,486	42.1%
	Sideswipe	22,092	16.7%

(*continued on next page*)

Table 2 (*continued*)

General information	Modalities	Vehicles count	Percentage
	Rear-endWith pedestrians (for single-vehicle crashes only)	17,532	13.3%
	*	13,787	10.5%
Driver age	Adult (30–54, reference)	67,956	51.5%
	Young (<30 years)	31,878	24.2%
	Middle-aged (55–64)	17,149	13.0%
	Senior (>64 years)	14,915	11.3%
Pedestrian age	Adult (30–54, reference)Young	1,596	29.5%
	(<30 years)Middle-aged	1,298	24.0%
	(55–64)Senior	706	13.0%
	(>64 years)	1,573	29.0%
	More than 1 pedestrian involved in different age classes	206	3.8%
Driver sex	Male (reference)	100,375	76.1%
	Female	31,523	23.9%
Pedestrian sex	Male (reference)	2,150	39.7%
	Female	3,041	56.1%
	More than 1 pedestrian involved of different sex	225	4.2%

*The pedestrian injury severity analysis refers to those single-vehicle crashes in which the crash circumstance reported for the driver is: "wrong interaction with pedestrian", coherently with the definitions used in the crash circumstance analysis. Hence, the "vehicle count" column refers to the number of crashed vehicles in which drivers reported pedestrian-related aberrant behaviors. Note that the number of these crashes does not coincide with the total number of pedestrian hit crashes because, in several cases, another circumstance was attributed to the driver, such as e.g., "regularly travelling".

However, due to the initial source dataset not including property-damage-only crashes, it is important to highlight that the analysis of driver-related aberrant behaviors is based on crashes in which, as a direct consequence, there was at least one injured person. Hence, the analysis may provide only a partial portrait of the overall phenomenon. This is a very common condition in road safety studies based on crash datasets that often include only fatal + injury crashes (especially in Europe). Wang et al. (2019) studied the relationships between aberrant driving behaviors and crash risk based on surveys submitted to taxi drivers in China. They have found that "reckless driving" (which includes running red lights, speeding and using mobile phone while driving) and "aggressive behavior" (which includes overtaking without using turn lights, aggressive driving and accelerating at yellow light) were predictors of both property-damage-only and injury crashes, as a result of a bivariate model. This confirms that driver-related aberrant behaviors could be also found as recurrent crash circumstances in non-injury crashes, as expected. Nevertheless, Shaon and Qin (2020) highlighted that crash circumstances associated with driver errors increase the probability of having more severe crashes (i.e., fatal + injury) compared to crash circumstances in which no driver errors were reported. The driver errors considered in the cited study are: decision (including speeding and illegal maneuvering), performance (which include errors possibly resulting in outcomes related to illegal maneuvering and wrong interaction with pedestrians), non-performance and recognition (which include inattentive driving) errors, and their combinations. This means that all the driver-related aberrant behaviors considered in this study were also related to an increase in the likelihood of injury severity with respect to non-injury crashes. Moreover, results from the study by Duddu et al. (2018) revealed that speeding and aggressive driving crash circumstances were related to an increase in severe injuries with respect to the reference violation included as crash circumstance "disregarding signs, signals or markings," for both at-fault and not at-fault drivers. Hence, the unavailability of property-damage-only crashes may surely hide a portion of the problem, but it is likely that, by analyzing fatal + injury crashes, the most urgent part is taken into account, especially for what concerns speeding and aggressive driving-related (e.g., illegal maneuvering) crash circumstances.

2.2. Statistical methods

Two types of analyses in the urban environment were conducted in this study:

- the influence of the crash, driver, and vehicle-related variables on driver-related crash circumstances,

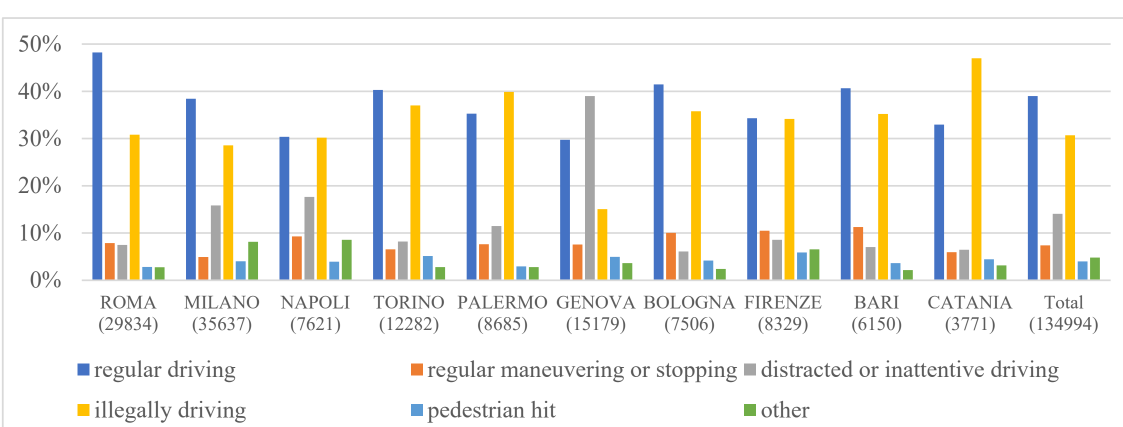

Fig. 2. Distribution of the crash circumstances for each of the 10 largest Italian cities.

- the influence of the crash, driver, and vehicle-related variables on the injury severity of both the occupants of crashed vehicles for which driver aberrant behaviors were reported and the involved pedestrians.

Both analyses were conducted considering multilevel models and the within-country variability of those relationships between the different Italian cities analyzed. For this aim, general linear mixed models were used. Logistic regressions with a logit link function were specified for each model. In detail, four models were developed for the first type of analyses (crash circumstances) and two additional models for the second type of analyses (injury severity). It is specified that, differently than crash circumstances which are driver-related, the injury severity is determined at the vehicle level, thus it is classified according to the most severe outcome recorded among the vehicle occupants (i.e., the driver and the eventual passengers).

The binary dependent variables of these models are listed as follows:

- driver-related crash circumstance: inattentive driving (yes or no)
- driver-related crash circumstance: illegal maneuvering (yes or no)
- driver-related crash circumstance: speeding (yes or no)
- driver-related crash circumstance: wrong interaction with pedestrian (yes or no)
- vehicle occupant injury severity (fatal/injury or no injuries)
- pedestrian injury severity (fatal or injury).

The first four models (for crash circumstances) were based on the entire dataset of vehicles involved in crashes. The models for vehicle occupant injury severity uses only vehicles ($n = 51{,}557$) involved in two-vehicle crashes where aberrant behavior was reported for at least one driver ($n = 46{,}475$), since the data source does not include single vehicle crashes with no injuries. Casualties and injuries were not further differentiated in this case since only one injury severity level is present (i.e., with no differentiation between severe and light injuries) and fatal outcomes are extremely rare in the urban environment (in this dataset: 660 out of 131,898 vehicles, about 0.5%). The vehicle occupant injury severity analysis was limited to the vehicles in which driver-related aberrant behaviors were reported, given the specific focus of this study. Given that, as previously specified, only two-vehicle crashes are used for this purpose, the circumstance "wrong interaction with pedestrian" is not present because it is only associated to single-vehicle crashes (including crashes with pedestrians). For this reason, in order to analyze the pedestrian injury severity as well, another model was specified. It uses only vehicles ($n = 5{,}416$) that were involved in formally defined "single-vehicle" crashes, in which the circumstance "wrong interaction with pedestrian" was recorded coherently with the crash circumstance analysis. In those cases, the driver exhibits the aberrant behavior related to one or more pedestrians involved in the crashes (e.g., not giving way to the pedestrian). Since all pedestrians involved in this sample of crashes suffer at least injuries and the percentage of fatal outcomes is significant, a binary outcome is considered in this case: injured or killed pedestrian.

For each model estimation, the following procedure was applied:

- estimate the Intra-Class Correlation coefficient (ICC; Dupont et al., 2013; Sommet & Morselli, 2017) considering the different cities as the grouping variable with respect to an intercept-only model;
- based on the computed ICC, decide whether to pursue a multilevel mixed model with city as a grouping variable or to run a more parsimonious fixed-effects logit model;
- perform the model selection stage by retaining the predictor variable in the model if there is at least one statistically significant coefficient related to a specific modality of the predictor, having assumed a baseline reference modality for the same predictor (in the case of mixed models, also select which predictors reveal city-specific effects);
- estimate the model coefficients (fixed in the case of fixed-effects logit models or random, and grouped for each city in the dataset, in the case of mixed logit models).

The mixed logit model structure used is reported as follows (Washington & Karlaftis, 2003):

$$V_{a,v} = \ln\left[\frac{P_v(a_1)}{P_v(a_0)}\right] = \beta_{0,c} + \sum_{i=1}^{X_a} \beta_i X_{a,v} + \sum_{i=1}^{Z_a} \beta_{i,c} Z_{a,v} \quad (1)$$

Where:

$V_{a,v}$ = systematic component of the likelihood of observing a given vehicle-related crash attribute (driver-related crash circumstance or vehicle occupant/pedestrian injury severity) a for the vehicle unit v;

$P_v(a_1)$ = probability of observing the crash attribute (circumstance or severity) a_1 for the vehicle unit v;

$P_v(a_0)$ = probability of observing the reference crash attribute (circumstance or severity) a_0 for the vehicle v;

$\beta_{0,c}$ = estimate for the intercept (generally city-specific: $\beta_{0,c} = \beta_0 + \varepsilon_{0,c}$, but which may also be fixed: β_0);

$\boldsymbol{X_a}$ = vector of explanatory variables for different crash attributes a;

$X_{a,v}$ = generic explanatory variable for different crash attributes a, for the vehicle unit v;

β_i = coefficient estimated for each explanatory variable (fixed);

$\boldsymbol{Z_a}$ = vector of explanatory variables (for which city-specific coefficients were estimated) for different crash attributes a;

$Z_{a,v}$ = generic explanatory variable (for which city-specific coefficients were estimated) for different crash attributes a, for the vehicle unit v;

$\beta_{i,c}$ = coefficient estimated for each explanatory variable, grouped for each city c.

Fixed-effects logit model is estimated if the ICC does not indicate variations between cities. The use of mixed models could identify variations in the effects of the other predictors, an interesting research question but beyond the scope of this paper (also in consideration of the computational effort such estimation would require for such a large dataset). The fixed-effects logit model is obtained by simplifying Equation (1) into the following (where all the terms have the same meaning as explained above):

$$V_a = \ln\left[\frac{P(a_1)}{P(a_0)}\right] = \beta_0 + \sum_{i=1}^{X_a} \beta_i X_a \quad (2)$$

The Intra-Class Correlation coefficient ICC_c (considering cities c as classes) is computed as follows. It varies between 0 and 1 and it quantifies how the outcome is homogeneous within the groups of observations (Dupont et al., 2013; Sommet & Morselli, 2017), cities in this case:

$$ICC_c = \frac{\sigma^2(\varepsilon_{0,c})}{\sigma^2(\varepsilon_{0,c}) + \left(\frac{\pi^2}{3}\right)} \quad (3)$$

An ICC value less than 0.5 is generally considered as poor (Liljequist et al., 2019). However, an ICC of 0.1 was used as a minimum threshold value to further inquire into the city variability in this study (i.e., inquiring into differences between cities if more than 10% of chances of exhibiting a given driver-related crash circumstance or injury severity level is explained by between-cities variability).

Table 3
Intra-class correlation coefficients for crash circumstances (ICC > 0.10 in bold).

Crash circumstance	ICC (group = city)
Inattentive driving	**0.121**
Illegal maneuvering	0.048
Speeding	0.033
Wrong interaction with pedestrian	0.015

Table 4
Inattentive driving predictors (mixed logit model).

Explanatory variable	Coeff. est.	OR	Std. dev.	Std. error	z value	p-value
(Intercept)	−2.067	0.127	*	0.242	−8.535	<0.001
Day period: night (ref.: morning peak)	**0.279**	**1.322**	**0.191**	**0.077**	**3.629**	**<0.001**
Day period: day (ref.: morning peak)	0.051	1.052	0.131	0.053	0.957	0.339
Day period: afternoon peak (ref.: morning peak)	−0.002	0.998	0.159	0.064	−0.034	0.973
Day period: evening (ref.: morning peak)	−0.024	0.976	0.057	0.041	−0.601	0.548
Year period: spring (ref.: winter)	**0.085**	**1.089**	**0.057**	**0.033**	**2.605**	**0.009**
Year period: summer (ref.: winter)	**0.078**	**1.081**	**0.035**	**0.028**	**2.758**	**0.006**
Year period: autumn (ref.: winter)	0.059	1.061	0.161	0.060	0.987	0.324
Element type: crossing (ref.: ordinary segment)	**−0.638**	**0.528**	**0.432**	**0.144**	**−4.408**	**<0.001**
Element type: unsignalized intersection (ref.: ordinary segment)	**−0.554**	**0.575**	**0.539**	**0.180**	**−3.076**	**0.002**
Element type: signalized intersection (ref.: ordinary segment)	**−0.317**	**0.728**	**0.385**	**0.132**	**−2.398**	**0.016**
Element type: segment with issues/tunnel (ref.: ordinary segment)	**0.336**	**1.399**	**0.062**	**0.050**	**6.661**	**<0.001**
Pavement: wet/icy (ref.: dry)	**0.056**	**1.058**	**–**	**0.024**	**2.348**	**0.019**
Vehicle type: heavy vehicle (ref.: car)	0.087	1.091	0.126	0.069	1.262	0.207
Vehicle type: bicycle (ref.: car)	**0.368**	**1.445**	**0.231**	**0.096**	**3.827**	**<0.001**
Vehicle type: light motorcycle (ref.: car)	**0.340**	**1.405**	**0.242**	**0.092**	**3.676**	**<0.001**
Vehicle type: motorcycle (ref.: car)	**0.137**	**1.147**	**0.162**	**0.059**	**2.325**	**0.020**
Driver Age: young (ref.: adult)	**0.057**	**1.059**	**–**	**0.021**	**2.755**	**0.006**
Driver Age: middle-aged (ref.: adult)	−0.021	0.979	–	0.026	−0.821	0.412
Driver Age: senior (ref.: adult)	**0.055**	**1.057**	**–**	**0.028**	**1.996**	**0.046**
Driver Sex: female (ref.: male)	**0.053**	**1.054**	**–**	**0.020**	**2.651**	**0.008**

Likelihood ratio test (reference: random intercept only model): $\chi^2(74) = 1819.2$, p-value < 0.001

*Different std. dev. are estimated for the intercept, for each explanatory variable for which random parameters were estimated.

3. Results

Results from the modeling stage are reported as follows, dividing the section into two sub-sections dedicated to crash circumstances and injury severity.

3.1. Crash circumstances

Four models were developed, one for each driver-related crash circumstance. The results of the preliminary search for intra-class correlations are developed in the first instance. A multilevel model was developed only for the dependent variable "inattentive driving," given the results shown in Table 3 (only in this case was an ICC > 0.1 found, that is more than 10% probability of exhibiting the inattentive driving crash circumstance was explained by between-cities variability). This confirms the high variability that was already qualitatively shown in Fig. 2. Hence, results concerning the mixed model having the "inattentive driving" crash circumstance as dependent variable are reported in Table 4. Results concerning the other fixed parameters model having the "illegal maneuvering," "speeding," and "wrong interaction with pedestrian" crash circumstances as dependent variable are reported in Table 5.

The odds of exhibiting inattentive driving for drivers involved in crashes was higher: at night than in the morning peak hours; during spring and summer versus winter; on segments with demanding horizontal and vertical alignments or tunnels than ordinary segments; on wet/icy than dry road surface; with cyclists and motorcyclists versus car drivers; for female over male drivers. The same odds were lower at all intersections than on ordinary segments.

However, given the random parameter approach used in this case and the obtained individual city coefficients, it is important to note that the effect of day period, year period, element type, and vehicle type is variable across the 10 considered cities (i.e., these effects can be positively or negatively related to inattentive driving as based on crash reports). The tendencies in contrast with the average national data are analyzed in the discussion section.

The odds of having recorded the illegal maneuvering crash circumstance for drivers involved in crashes was higher: on road types different than city-managed urban roads; at intersections than ordinary segments (OR > 4 for crossings and unsignalized intersections); for young than adult drivers. On the other hand, the same odds were lower: for all other periods than morning peak hours; on segments with issues/tunnels than ordinary segments, wet/icy than dry road surfaces; for heavy vehicle drivers, cyclists, and motorcyclists (in this latter case: OR < 0.5) than car drivers.

The odds of having recorded the speeding crash circumstance for drivers involved in crashes were higher: on weekends than weekdays; during late hours (evening and night, especially night) versus morning peak hours; on road types different than city-managed roads; on segments with issues/tunnels versus ordinary segments; on wet/icy pavements than dry pavements; for young compared to adult drivers. On the other hand, the same odds were lower: on intersections compared to ordinary segments; for other drivers than car drivers; for middle-aged and senior versus adult drivers; and for female compared to male drivers.

The odds of having recorded the wrong interaction with pedestrian crash circumstance for drivers involved in crashes were higher: during the afternoon peak than during the morning peak hours; during autumn compared to winter; at unsignalized intersections versus ordinary segments; on wet/icy than dry road surfaces; and for middle-aged/senior than adult drivers. The same odds were lower: on weekends than weekdays; at night than morning peak hours (OR < 0.25); during spring and summer than winter; on road types different than city-managed roads (OR < 0.25); at crossings, signalized intersections and segments with issues/tunnels than ordinary segments; on roads with signs/markings; for all drivers who are not car drivers (in particular motorcyclists: OR < 0.5 and cyclists: OR < 0.25); for young than adult drivers; and for female versus male drivers.

3.2. Injury severity analysis

Additional models were developed for the study of the injury severity of vehicle occupants and pedestrians, given the previously presented hypotheses. In both cases the ICC coefficient is less than 0.02: that is less than 2% probability of having a different severity outcome explained by between-cities variability. Hence, fixed-effects logit models were developed (see Tables 6 and 7).

The odds of suffering injuries/casualties as an occupant of a crashed

Table 5
Predictors of illegal maneuvering, speeding and wrong interaction with pedestrians.

Explanatory variable	Coeff. estimate	OR	Std. error	z value	p-value
Dependent variable: Illegal maneuvering (reference: no)					
(Intercept)	−1.889	0.151	0.025	−76.699	<0.001
Day period: night (ref.: morning peak)	**−0.095**	**0.909**	**0.031**	**−3.088**	**0.002**
Day period: day (ref.: morning peak)	**−0.053**	**0.948**	**0.022**	**−2.387**	**0.017**
Day period: afternoon peak (ref.: morning peak)	**−0.076**	**0.927**	**0.025**	**−3.011**	**0.003**
Day period: evening (ref.: morning peak)	**−0.057**	**0.945**	**0.026**	**−2.218**	**0.027**
Road type: other urban road (ref.: City-managed road)	**0.323**	**1.381**	**0.070**	**4.599**	**<0.001**
Element type: crossing (ref.: ordinary segment)	**1.625**	**5.078**	**0.020**	**82.994**	**<0.001**
Element type: unsignalized intersection (ref.: ordinary segment)	**1.516**	**4.554**	**0.020**	**74.618**	**<0.001**
Element type: signalized intersection (ref.: ordinary segment)	**1.355**	**3.877**	**0.020**	**67.735**	**<0.001**
Element type: segment with issues/tunnel (ref.: ordinary segment)	**−0.084**	**0.919**	**0.041**	**−2.016**	**0.044**
Road surface: wet/icy (ref.: dry)	**−0.215**	**0.807**	**0.021**	**−10.273**	**<0.001**
Vehicle type: heavy vehicle (ref.: car)	**−0.214**	**0.807**	**0.030**	**−7.208**	**<0.001**
Vehicle type: bicycle (ref.: car)	**−0.434**	**0.648**	**0.037**	**−11.768**	**<0.001**
Vehicle type: light motorcycle (ref.: car)	**−0.616**	**0.54**	**0.042**	**−14.611**	**<0.001**
Vehicle type: motorcycle (ref.: car)	**−0.750**	**0.472**	**0.018**	**−41.890**	**<0.001**
Driver Age: young (ref.: adult)	**0.158**	**1.171**	**0.017**	**9.174**	**<0.001**
Driver Age: middle-aged (ref.: adult)	−0.015	0.985	0.022	−0.666	0.505
Driver Age: senior (ref.: adult)	0.027	1.027	0.023	1.177	0.239
Likelihood ratio test (reference: null model): $\chi^2(18) = 55{,}369$, p-value < 0.001					
Dependent variable: Speeding (reference: no)					
(Intercept)	−2.226	0.108	0.035	−63.031	<0.001
Day: weekend (ref.: weekday)	**0.139**	**1.149**	**0.024**	**5.806**	**<0.001**
Day period: night (ref.: morning peak)	**0.743**	**2.102**	**0.041**	**17.912**	**<0.001**
Day period: day (ref.: morning peak)	−0.053	0.948	0.034	−1.560	0.119
Day period: afternoon peak (ref.: morning peak)	−0.071	0.931	0.038	−1.866	0.062
Day period: evening (ref.: morning peak)	**0.123**	**1.131**	**0.038**	**3.221**	**0.001**
Road type: other urban road (ref.: City-managed road)	**0.179**	**1.196**	**0.089**	**2.010**	**0.045**
Element type: crossing (ref.: ordinary segment)	**−0.587**	**0.556**	**0.031**	**−18.888**	**<0.001**
Element type: unsignalized intersection (ref.: ordinary segment)	**−0.546**	**0.579**	**0.033**	**−16.734**	**<0.001**
Element type: signalized intersection (ref.: ordinary segment)	**−0.493**	**0.611**	**0.030**	**−16.554**	**<0.001**
Element type: segment with issues/tunnel (ref.: ordinary segment)	**0.312**	**1.366**	**0.037**	**8.542**	**<0.001**
Pavement: wet/icy (ref.: dry)	**0.118**	**1.125**	**0.028**	**4.246**	**<0.001**
Vehicle type: heavy vehicle (ref.: car)	**−0.099**	**0.906**	**0.045**	**−2.206**	**0.027**
Vehicle type: bicycle (ref.: car)	**−0.553**	**0.575**	**0.064**	**−8.685**	**<0.001**
Vehicle type: light motorcycle (ref.: car)	**−0.236**	**0.79**	**0.060**	**−3.948**	**<0.001**
Vehicle type: motorcycle (ref.: car)	**−0.134**	**0.875**	**0.024**	**−5.515**	**<0.001**
Driver Age: young (ref.: adult)	**0.225**	**1.252**	**0.024**	**9.349**	**<0.001**
Driver Age: middle-aged (ref.: adult)	**−0.146**	**0.864**	**0.034**	**−4.305**	**<0.001**
Driver Age: senior (ref.: adult)	**−0.076**	**0.927**	**0.036**	**−2.129**	**0.033**
Driver Sex: female (ref.: male)	**−0.226**	**0.798**	**0.026**	**−8.819**	**<0.001**
Likelihood ratio test (reference: null model): $\chi^2(20) = 109944$, p-value < 0.001					
Dependent variable: Wrong interaction with pedestrian (reference: no)					
(Intercept)	−2.707	0.067	0.053	−51.112	<0.001
Day: weekend (ref.: weekday)	**−0.313**	**0.731**	**0.038**	**−8.161**	**<0.001**
Day period: night (ref.: morning peak)	**−1.406**	**0.245**	**0.110**	**−12.769**	**<0.001**
Day period: day (ref.: morning peak)	−0.044	0.957	0.044	−0.993	0.321
Day period: afternoon peak (ref.: morning peak)	**0.276**	**1.318**	**0.048**	**5.755**	**<0.001**
Day period: evening (ref.: morning peak)	0.083	1.087	0.051	1.617	0.106
Year period: spring (ref.: winter)	**−0.294**	**0.745**	**0.040**	**−7.385**	**<0.001**
Year period: summer (ref.: winter)	**−0.332**	**0.717**	**0.043**	**−7.738**	**<0.001**
Year period: autumn (ref.: winter)	0.033	1.034	0.037	0.896	0.370
Road type: other urban road (ref.: City-managed road)	**−1.529**	**0.217**	**0.280**	**−5.467**	**<0.001**
Element type: crossing (ref.: ordinary segment)	**−0.201**	**0.818**	**0.040**	**−5.002**	**<0.001**
Element type: unsignalized intersection (ref.: ordinary segment)	**0.112**	**1.119**	**0.038**	**2.972**	**0.003**
Element type: signalized intersection (ref.: ordinary segment)	**−0.468**	**0.626**	**0.044**	**−10.653**	**<0.001**
Element type: segment with issues/tunnel (ref.: ord. segment)	**−0.555**	**0.574**	**0.074**	**−7.513**	**<0.001**
Pavement: wet/icy (ref.: dry)	**0.366**	**1.442**	**0.037**	**9.973**	**<0.001**
Road markings: yes (ref.: no)	**−0.631**	**0.532**	**0.072**	**−8.717**	**<0.001**
Vehicle type: heavy vehicle (ref.: car)	−0.029	0.971	0.056	−0.512	0.608
Vehicle type: bicycle (ref.: car)	**−2.116**	**0.121**	**0.166**	**−12.749**	**<0.001**
Vehicle type: light motorcycle (ref.: car)	**−0.775**	**0.461**	**0.098**	**−7.899**	**<0.001**
Vehicle type: motorcycle (ref.: car)	**−0.710**	**0.492**	**0.038**	**−18.639**	**<0.001**
Driver Age: young (ref.: adult)	**−0.155**	**0.856**	**0.040**	**−3.831**	**<0.001**
Driver Age: middle-aged (ref.: adult)	**0.301**	**1.351**	**0.040**	**7.444**	**<0.001**
Driver Age: senior (ref.: adult)	**0.631**	**1.879**	**0.038**	**16.412**	**<0.001**
Driver Sex: female (ref.: male)	**−0.160**	**0.852**	**0.034**	**−4.672**	**<0.001**
Likelihood ratio test (reference: null model): $\chi^2(24) = 140{,}023$, p-value < 0.001					

Note: lines reported in bold are associated to statistically significant coefficient estimates (p-value < 0.05).

Table 6
Vehicle occupant injury severity predictors.

Explanatory variable	Coeff. estimate	OR	Std. error	z value	p-value
Dependent variable: Injuries/casualties (reference: no injury/casualty)					
(Intercept)	−1.564	0.209	0.071	−22.089	<0.001
Day: weekend (ref.: weekday)	**0.261**	**1.298**	**0.026**	**9.956**	**<0.001**
Day period: night (ref.: morning peak)	**0.711**	**2.036**	**0.048**	**14.747**	**<0.001**
Day period: day (ref.: morning peak)	0.017	1.017	0.037	0.463	0.643
Day period: afternoon peak (ref.: morning peak)	**−0.125**	**0.882**	**0.042**	**−2.984**	**0.003**
Day period: evening (ref.: morning peak)	0.069	1.071	0.042	1.649	0.099
Year period: spring (ref.: winter)	**−0.062**	**0.940**	**0.031**	**−1.964**	**0.050**
Year period: summer (ref.: winter)	−0.036	0.965	0.033	−1.087	0.277
Year period: autumn (ref.: winter)	**−0.073**	**0.930**	**0.032**	**−2.292**	**0.022**
Road type: other urban road (ref.: City-managed road)	**0.710**	**2.034**	**0.107**	**6.665**	**<0.001**
Element type: crossing (ref.: ordinary segment)	−0.058	0.944	0.035	−1tpgoto ".671	0.095
Element type: unsignalized intersection (ref.: ordinary segment)	**−0.292**	**0.747**	**0.036**	**−7.994**	**<0.001**
Element type: signalized intersection (ref.: ordinary segment)	**0.163**	**1.177**	**0.034**	**4.811**	**<0.001**
Element type: segment with issues/tunnel (ref.: ordinary segment)	**0.191**	**1.210**	**0.059**	**3.229**	**0.001**
Pavement: wet/icy (ref.: dry)	**0.169**	**1.184**	**0.033**	**5.085**	**<0.001**
Road markings: yes (ref.: no)	**0.125**	**1.133**	**0.047**	**2.643**	**0.008**
Crash type: head-on (ref.: fixed object/run-off)	**0.609**	**1.839**	**0.076**	**8.047**	**<0.001**
Crash type: angle (ref.: fixed object/run-off)	**0.517**	**1.677**	**0.060**	**8.593**	**<0.001**
Crash type: sideswipe (ref.: fixed object/run-off)	0.009	1.009	0.063	0.144	0.885
Crash type: rear-end (ref.: fixed object/run-off)	**0.237**	**1.267**	**0.062**	**3.834**	**<0.001**
Vehicle type: heavy vehicle (ref.: car)	**−0.443**	**0.642**	**0.048**	**−9.248**	**<0.001**
Vehicle type: bicycle (ref.: car)	**4.157**	**63.880**	**0.119**	**35.031**	**<0.001**
Vehicle type: light motorcycle (ref.: car)	**3.474**	**32.266**	**0.100**	**34.607**	**<0.001**
Vehicle type: motorcycle (ref.: car)	**3.846**	**46.805**	**0.044**	**87.856**	**<0.001**
Crash circumstance: illegal maneuvering (ref.: inattentive driving)	**0.169**	**1.184**	**0.029**	**5.882**	**<0.001**
Crash circumstance: speeding (ref.: inattentive driving)	**0.612**	**1.844**	**0.038**	**16.193**	**<0.001**
Driver Age: young (ref.: adult)	**0.171**	**1.186**	**0.027**	**6.284**	**<0.001**
Driver Age: middle-aged (ref.: adult)	**−0.212**	**0.809**	**0.036**	**−5.901**	**<0.001**
Driver Age: senior (ref.: adult)	**−0.219**	**0.803**	**0.037**	**−5.876**	**<0.001**
Driver Sex: female (ref.: male)	**0.430**	**1.537**	**0.025**	**17.024**	**<0.001**
Likelihood ratio test (reference: null model): $\chi^2(31) = 21{,}885$, p-value < 0.001					

Note: lines reported in bold are associated to statistically significant coefficient estimates (p-value < 0.05). Crash circumstance: wrong interaction with pedestrian is not present because the injury severity model regards only multi-vehicle crashes (while the pedestrian crash type is recorded as a single vehicle crash involving a pedestrian).

vehicle for which aberrant behaviors were reported rather than being uninjured is higher: on weekends than weekdays; at night than morning peak hours (OR > 2); on road types different than city-managed roads (OR > 2); at signalized intersections and segments with issues/tunnels than ordinary segments; on wet/icy than dry road surfaces; on roads with signs/markings; for cyclists and motorcyclists than car occupants (OR > 4); while drivers are young with respect to adult drivers; and while drivers are female with respect to male drivers. On the other hand, the odds of suffering injuries/casualties are lower: at afternoon peaks than morning peaks; during spring and autumn than winter; at unsignalized intersections versus ordinary segments; and for heavy vehicle than car occupants. Moreover, in this model, both crash types and circumstances were included as predictor variables of injuries/casualties. Based on the results, the odds of suffering injuries/casualties are higher if vehicles are involved in head-on, angle and rear-end crashes with respect to run-off crashes and if drivers crashed while undertaking illegal maneuvering and speeding with respect to inattentive driving.

The odds of being killed rather than injured as a pedestrian struck by a vehicle in which a pedestrian-related aberrant behavior was recorded is higher: on urban roads different than city-managed roads (OR > 4); in case of heavy vehicle with respect to light vehicles (OR > 2); and for middle-aged and senior pedestrians with respect to adult pedestrians (in both cases: OR > 4). On the other hand, the odds of being killed are lower: during the day than morning peak hours (OR < 0.25); at unsignalized intersections with respect to segments (OR < 0.5); on wet than dry pavements (OR < 0.5); and for female than male pedestrians (OR < 0.5). In this model, crash types and circumstances were not included as predictors since there is only one crash type (pedestrian hit) and one crash circumstance (wrong interaction with pedestrian).

4. Discussion

According to the results shown, it is possible to discuss, in the first place, the importance of the different variables considered and then to analyze the variability of their effects between the different cities in the case of the inattentive driving-related crashes, for which a mixed model was run.

4.1. The influence of specific factors on crash circumstances and injury severity

The results from the statistical analyses provide ground for analyzing specific crash factors and understanding their influence on particular driver-related circumstances and injury severity. In this regard, our results are summarized in Table 8 and further discussed.

Considering the period in which crashes occur, the likelihood of having injured/killed vehicle occupants increase during weekends with respect to weekdays (coherently with Christoforou et al., 2010). The likelihood of crashes with speeding recorded increases as well during weekends, while wrong interactions with pedestrian decrease. This can be explained by less congestion on weekends, which can foster free flowing traffic (as noted by Yu & Abdel-Aty, 2013, who compared weekend and weekday crashes) and then also speeding. The decrease in wrong interactions with pedestrian can also be related to scarce exposure related to reduced working activities at weekends. No particular influence of the week period on the likelihood of crashes related to inattention and illegal maneuvers was found here. In another study (Lyon et al., 2021) weekends were related to reduced distraction, but only in a sample consisting of fatal crashes.

Table 7
Pedestrian injury severity predictors.

Explanatory variable	Coeff. estimate	OR	Std. error	z value	p-value
Dependent variable: Casualties (reference: only injuries)					
(Intercept)	−4.855	0.008	0.567	−8.564	<0.001
Day period: night (ref.: morning peak)	0.290	1.336	0.836	0.347	0.729
Day period: day (ref.: morning peak)	**−1.413**	**0.243**	**0.364**	**−3.882**	**<0.001**
Day period: afternoon peak (ref.: morning peak)	−0.122	0.885	0.340	−0.358	0.720
Day period: evening (ref.: morning peak)	0.046	1.047	0.382	0.119	0.905
Road type: other urban road (ref.: City-managed road)	**4.631**	**102.617**	**0.745**	**6.218**	**<0.001**
Element type: crossing (ref.: ordinary segment)	−0.376	0.687	0.336	−1.119	0.263
Element type: unsignalized intersection (ref.: ordinary segment)	**−0.936**	**0.392**	**0.376**	**−2.487**	**0.013**
Element type: signalized intersection (ref.: ordinary segment)	−0.756	0.47	0.414	−1.285	0.068
Element type: segment with issues/tunnel (ref.: ordinary segment)	−0.158	0.854	0.503	0.313	0.754
Pavement: wet/icy (ref.: dry)	**−0.983**	**0.374**	**0.390**	**−2.520**	**0.012**
Vehicle type: heavy vehicle (ref.: car)	**0.794**	**2.212**	**0.349**	**2.274**	**0.023**
Vehicle type: bicycle (ref.: car)	0.856	2.354	1.056	0.810	0.418
Vehicle type: light motorcycle (ref.: car)	−0.272	0.762	0.750	−0.363	0.717
Vehicle type: motorcycle (ref.: car)	−0.209	0.811	0.329	−0.637	0.524
Pedestrian Age: young (ref.: adult)	0.585	1.795	0.610	0.958	0.338
Pedestrian Age: middle-aged (ref.: adult)	**1.976**	**7.214**	**0.569**	**3.472**	**0.001**
Pedestrian Age: senior (ref.: adult)	**3.003**	**20.146**	**0.508**	**5.917**	**<0.001**
Pedestrian Age: mixed (ref.: adult)	−12.339	0.000	>2.00	−0.019	0.985
Pedestrian Sex: female (ref.: male)	**−0.868**	**0.420**	**0.239**	**−3.629**	**<0.001**
Pedestrian Sex: mixed (ref.: male)	−15.189	0.000	>2.00	−0.025	0.980
Likelihood ratio test (reference: null model): $\chi^2(21) = 6{,}774$, p-value < 0.001					

Note: lines reported in bold are associated to statistically significant coefficient estimates (p-value < 0.05).

A notably increased likelihood of having speeding-related crashes can be noted at night, in comparison with morning peak hours. This result is in line with the illuminance-speeding inverse relationship found by de Bellis et al. (2018) and previous remarks about driving behavior under free-flowing conditions. Note that speeding-related crashes are also more likely in the evening with respect to morning hours. On the other hand, also in this case wrong interactions with pedestrians are notably less likely at night, given the dramatically reduced exposure (scarce pedestrian traffic at night), while they are higher during the afternoon than the morning peak hours. This is expected since pedestrian exposure during the afternoon peak hours is high, while visibility conditions may be worse than in the morning. In fact, the considered afternoon peaks range from 5 to 7p.m. which, especially during autumn and winter, is a period including dark hours with respect to the daylight in morning peak hours from 7 to 9 a.m. Note however, that the likelihood of pedestrian casualties is higher during the morning peak than in the other daylight hours, possibly related to the higher impact speeds. Crashes having illegal maneuvering as the main circumstance are instead higher during morning peak hours with respect to all the other periods of the day. This can be explained with the possible increase in illegal evasive maneuvers or the disrespect of road rules in morning traffic jam (see also Li et al., 2021). Moreover, it is much more likely to observe vehicle occupant injuries/casualties at night than in the morning, similarly to other studies (e.g., Huang et al., 2008; Ackaah et al., 2020). By combining this result with the increased likelihood of the speeding crash circumstance at night and the other evidence that, among the considered circumstances, speeding leads to more injuries/casualties than inattentive driving (also considering the well-known general speeding-severity relationship, see e.g., Aarts & van Schagen, 2006); it can be argued that speeding can be a significant contributory factor to the increased likelihood of vehicle occupant injuries/casualties in night crashes. Interestingly, vehicle occupant injuries/casualties during afternoon peak hours seem slightly less likely than during morning peak hours. In this case, a role can be played by the already discussed tendency to illegal maneuvering in the morning, which could also lead to more injuries/casualties.

Seasonal effects can be noted only for inattentive driving and wrong interactions with pedestrian, while it seems that illegal maneuvering and speeding crash circumstances are not affected by the particular period of the year. There is a greater likelihood of inattentive driving during spring and summer than during winter. In another study, Lyon et al. (2021) found that distracted driving implies an increased likelihood of fatal crashes in summer months with respect to all other seasons. A possible interpretation is provided as follows: when weather conditions improve (such as especially during summer), distraction may increase since the environment could be less demanding and drivers may be less focused on the driving task. On the other hand, wrong interactions with pedestrians decrease during spring and summer, while are greater in autumn than in winter. As more people may walk during these months, due to better weather conditions, the increased presence of pedestrians may induce safer behavior in drivers (a sort of "safety in numbers" effect, see Elvik & Bjørnskau, 2017). However, this effect should be further verified, since during autumn the opposite tendency is noted, even if pedestrian exposure may be still higher than in the colder winter months. Interestingly, Sherony and Zhang (2015) found that the annual peak of pedestrian injury crashes in the United States is during the month of November. As far as severity is concerned, injuries/casualties to vehicle occupants are less likely during spring and autumn than in winter months. In this regard, Yu and Abdel-Aty (2014) found that crashes with injuries/casualties are less likely to occur during the snow season, while at the same time low temperatures increase the probability of crashes with injuries/casualties (results obtained on a sample of mountainous freeways).

It is more likely to observe crashes in which the driver conducted speeding or illegal maneuvering on other road types different from city-managed roads but still in an urban environment (i.e., typically multilane two-way roads, also divided, belonging to the state/provincial/regional network, see also Montella et al., 2011). This is clearly explained by the different function of these roads, which may be arterials, thus allowing for higher speeds and maneuvers such as overtaking, which are impeded on, for example, single-lane urban streets (similar results were obtained by Shaon et al., 2018 for drivers' decision errors in urban crashes on one-way roads). This may also lead to the observed greater likelihood of vehicle occupant injuries/casualties, which was already previously related to speeding. The result for wrong interactions with pedestrian is the opposite: it is less likely to observe them on other

Table 8
Summary of results obtained from the statistical analyses.

	Inattentive driving	Illegal maneuvering	Speeding	Wrong interaction with pedestrian	Injury/fatal outcome for vehicle occupants	Fatal outcome for pedestrians
Day: weekday	–	–	ref.	ref.	ref.	ref.
Weekend	–	–	↑	↓	↑	–
Day period: morning peak hours	ref.	ref.	ref.	ref.	ref.	ref.
Night	↑	↓	↑↑	↓↓↓	↑↑	↔
Day	↔	↓	↔	↔	↔	↓↓↓
Afternoon peak	↔	↓	↔	↑	↓	↔
Evening	↔	↓	↑	↔	↔	↔
Year period: Winter	ref.	–	–	ref.	ref.	ref.
Spring	↑	–	–	↓	↓	–
Summer	↑	–	–	↓	↔	–
Autumn	↔	–	–	↑	↓	–
Road type: City-managed road	–	ref.	ref.	ref.	ref.	ref.
Other urban roads	–	↑	↑	↓↓↓	↑↑	↑↑↑
Element type: Ordinary segments	ref.	ref.	ref.	ref.	ref.	ref.
Crossing	↓	↑↑↑	↓	↓	↔	↔
Unsignalized intersection	↓	↑↑↑	↓	↑	↓	↓↓
Signalized intersection	↓	↑↑	↓	↓	↑	↔
Segment with issues/tunnels	↑	↓	↑	↓	↑	↔
Road surface: Dry	ref.	ref.	ref.	ref.	ref.	ref.
Wet/icy	↑	↓	↑	↑	↑	↓↓
Markings: No	–	–	–	ref.	ref.	ref.
Yes	–	–	–	↓	↑	–
Vehicle type: Car	ref.	ref.	ref.	ref.	ref.	ref.
Heavy vehicle	↔	↓	↓	↓	↓	↑↑
Bicycle	↑	↓	↓	↓↓↓	↑↑↑	↔
Light motorcycle	↑	↓	↓	↓↓	↑↑↑	↔
Motorcycle	↑	↓↓	↓	↓↓	↑↑↑	↔
Driver Age: Adult	ref.	ref.	ref.	ref.	ref.	ref.
Young	↑	↑	↑	↓	↑	–
Middle-aged	↔	↔	↓	↑	↓	–
Senior	↑	↔	↓	↑	↓	–
Driver Sex: Male	ref.	–	ref.	ref.	ref.	ref.
Female	↑	–	↓	↓	↑	–
Pedestrian Age: Adult	-	-	-	-	-	ref.
Young	-	-	-	-	-	↔
Middle-aged	-	-	-	-	-	↑↑↑
Senior	-	-	-	-	-	↑↑↑
Mixed	-	-	-	-	-	↔
Pedestrian Sex: Male	-	-	-	-	-	ref.
Female	-	-	-	-	-	↓↓
Mixed	-	-	-	-	-	↔
Crash type: Run-off/fixed object	–	–	–	–	ref.	–
Head-on	–	–	–	–	↑	–
Angle	–	–	–	–	↑	–
Sideswipe	–	–	–	–	↔	–
Rear-end	–	–	–	–	↑	–
Crash circumstance: Inattentive driving	–	–	–	–	ref.	–
Illegal maneuvering	–	–	–	–	↑	–
Speeding	–	–	–	–	↑	–

Note: ↑ indicates an increase (Odds Ratio -OR- included between 1 and 2) in the crash circumstance/injury severity due to the factor indicated in the row, ↑↑ increase with OR between 2 and 4, ↑↑↑ increase with OR greater than 4. ↓ indicates a decrease (Odds Ratio -OR- included between 1 and 0.5) in crash circumstance/injury severity due to the factor indicated in the row, ↓↓ decrease with OR included between 0.5 and 0.25, ↓↓↓ decrease with OR lower than 0.25. ↔ indicates that, even if the modality in the corresponding row belongs to a predictor which was included in the model, that specific modality is not associated to an increase/decrease in the crash circumstance/injury severity. – indicates that the modality in the corresponding row belongs to a predictor which was not included in the model.

road types. This explanation is straightforward as well since pedestrian exposure on urban arterials (which in the Italian context are often located in neighborhoods rather than in the city center) may be limited. Note, however, that this condition is peculiar and cannot be transferred to other contexts where city centers are normally provided with multi-lane arterials (see e.g., Alawadi, 2017; Ewing & Dumbaugh, 2009). On the other hand, while the vehicle–pedestrian conflict may be less frequent on arterial *peri*-urban roads, it was associated to a notable increase in the likelihood of pedestrian casualties, which can be again explained by the higher impact speeds than on city-managed roads.

As far as the type of road section is concerned, there is a strong indication for an increase in illegal maneuvering crash circumstances at unsignalized intersections and, to a lesser extent, at signalized intersections, with respect to ordinary segments. This is evidently related to the disrespect of give-way/stop horizontal/vertical signs and red lights, which may be prevalent with respect to aberrant behavior on ordinary segments, such as, for example, overtaking where not allowed or parking-related illegal maneuvers. The result concerning urban crossings/unsignalized intersections poses questions on the effectiveness and clarity of traffic signs and on the need for more binding controls. Note, however, that there is no evident relationship between this aspect and injury severity since the likelihood of injuries/casualties to vehicle occupants and pedestrian casualties at unsignalized intersections is lower than on ordinary segments. In summary, the numerous illegal maneuvers at unsignalized intersections may not result in more injuries/casualties, also due to the decreased conflict speeds (unsignalized intersections are more common on local streets, where speeds are lower than on arterial streets). This is not valid for signalized intersections, where the likelihood of vehicle occupant injuries/casualties increases with respect to ordinary segments. Inattentive driving and speeding crash circumstances are instead consistently reduced at all intersections with respect to ordinary segments. Clearly, whatever the form of intersection traffic control is, it may contrast speeding and drivers' distraction more effectively than the less constraining environment of a road segment (see e.g., Wong & Huang, 2013, for a detailed discussion about attention patterns at intersections). The likelihood of wrong interactions with pedestrian is higher at unsignalized intersections with respect to ordinary segments, while it is lower in all other section types. Unsignalized intersections may be the worst condition for pedestrian crossings since they are not regulated by traffic lights while pedestrian volumes may be relevant. In this regard, Aghabayk et al. (2021) noted that conflicts with pedestrians were significantly higher at crossings without traffic lights than those with traffic lights. The increased likelihood of inattention and speeding-related crash circumstances may seem surprising for segments with particular horizontal/vertical alignments and tunnels, even if they may be considered direct causes of crashes on these demanding segments with respect to ordinary segments, where crashes could have been more easily avoided even in the case of distraction or speeding. In this regard, route familiarity can be another factor to account for vehicle–pedestrian interactions (Angioi & Bassani, 2022).

Wet/icy conditions result in a decrease of observing illegal maneuvering-related crash circumstances. This can be clearly explained by Italian urban drivers who may be more prudent on non-dry surfaces and thus less likely to perform illegal maneuvering. On the other hand, wet/icy road surface conditions result in an increase in observing inattentive driving, speeding and wrong interactions with pedestrians crash circumstances. However, considering that the average annual rainy days in the major Italian cities are relatively few (e.g., values in Table 1 are much smaller than some other Norther European cities), it could be again argued that it is less likely that non-dry pavements may foster those aberrant behaviors. A possible explanation may be that the environment can be less forgiving in case of drivers performing speeding, inattention or wrong interactions with pedestrians on wet pavements, mainly due to an increase in the required stopping distance. Interestingly, Shaon et al. (2018) have found that drivers' decision and performance errors in urban crashes (including speeding and illegal maneuvering) are higher on wet than on dry roads, so also in this case results may be region-specific (e.g., depending on the annual frequency of rainy days). Mixed results emerge instead for the injury severity: there is a higher likelihood of injuries/casualties for vehicle occupants on wet pavements than on dry roads (which can be again explained by higher speeds following a failed complete deceleration), while a decreased likelihood of pedestrian casualties (with respect to sole injuries).

The effect of road markings is marginal: it is noticed only for wrong interactions with pedestrians, for which the likelihood is decreased when markings are present. This can be a confirmation that pedestrian crossings with traffic lights can be useful to prevent pedestrian crashes. The increased likelihood of vehicle occupant injuries/casualties when markings are present seems surprising and worth further investigation, especially because it cannot be related to other particular crash circumstances. Interestingly, other studies conducted in Italy linked visible road markings to an increase in urban crash frequency (Canale et al., 2005, for three-legged stop control intersections; and Intini et al., 2021, for two-way segments) and the matter is worthy of further investigation.

Cyclists and motorcyclists seem more prone to be involved in crashes while being inattentive. It may be concluded that the inattentive driving condition is clearly less forgiving for two-wheel vehicle drivers in critical near-crash situations as long as there is no direct evidence of cyclists and motorcyclists being generally more inattentive than other drivers. However, there is also evidence of a significant share of inattentive driving for cyclists (see e.g., Wolfe et al., 2016). On the other hand, a decreased likelihood of illegal maneuvering and speeding-related crash circumstances consistently emerges for all drivers other than car drivers in the urban environment. Car drivers seem the most prone to be involved in crashes while involved in aberrant behavior (similar results were found by Zhang et al., 2013, for passenger and good vehicle drivers with respect to motorcyclists). Moreover, the same result can be noted for wrong interactions with pedestrians. In this case, the notably decreased likelihood of having bicycles involved in pedestrian crashes is clearly related to the scarcity of bicycle-pedestrian crashes leading to at least one injured person (condition of the dataset used for the analyses). In agreement with previous research (see e.g., Shinar, 2012; Vanlaar et al., 2016), cyclists and motorcyclists involved in urban crashes are far more prone to suffer injuries or casualties from traffic crashes than other drivers. Considering that this study is based on a relatively recent dataset of urban crashes in the 10 largest Italian cities, the need for improving urban safety conditions of vulnerable road users is thus compelling. In particular, note that the odds of suffering from injuries or dying in traffic crashes is about 60 times higher for cyclists than for car occupants. Moreover, for what concerns pedestrians, it is logical to observe an increased likelihood of fatalities when hit by heavy vehicles than by cars (see also Pokorny et al., 2017 for a discussion about conflicts between heavy vehicles and vulnerable road users, in that case bicyclists).

Young and senior drivers seem to be more prone to inattention-related crash circumstances than the reference adult drivers. As pointed out by Cao et al. (2020), even if limited to cellphone distracted driving, distraction is actually closely related to crashes for young drivers, while it is less frequent for older drivers but can still significantly increase their crash risk. Note that the inattention category also includes the "uncertain" driving so defined in the Italian crash recording system, which may also be relevant for senior drivers. Young drivers also seem more prone to crash while speeding and illegally maneuvering than adult drivers, while on the other hand middle-aged and senior drivers are less prone to crash while speeding than adult drivers. This could be explained by the average aversion to speeding with increased age in the general population (apart from direct involvement in crashes), see for example Perez et al. (2021) and, on the other hand, to a greater attitude to traffic violations for young drivers (Vardaki & Yannis, 2013). The likelihood of wrong interaction with pedestrians seems to increase with age: higher for middle-aged and senior (see also Ulfarsson et al., 2010, for 75+ years senior drivers), lower for young drivers. This may be related to more rapid reactions to avoid hitting pedestrians for younger drivers. On the other hand, injuries/casualties to vehicle occupants follow an opposite tendency, decreasing with the driver age, such as speeding-related crashes. In this case as well, a relationship between speeding and severity seems to exist. Moreover, as expected, the likelihood of casualties is higher for pedestrians more than 55 years old with respect to younger adults (see also Lalika et al., 2022).

For female drivers involved in crashes, speeding and wrong interactions with pedestrians are less likely than for male drivers. Similarly, Zhang et al. (2013) have found Chinese male drivers over-represented in crashes in which traffic violations were recorded. On the other hand, in this study, inattention driving-related crashes are more likely for female drivers. However, there is a higher likelihood of injuries/casualties to vehicle occupants when female drivers are involved in crashes with aberrant behaviors, following an opposite tendency with respect to speeding. This aspect may require further investigation (see also Ulfarsson & Mannering, 2004). In fact, generally, female drivers are underrepresented in fatal crashes (see e.g., Bose et al., 2011, and reports from the Italian National Institute of Statistics, relevant to this study) even if they are more likely to be severely injured compared to male drivers (Fu et al., 2021). Note also that less pedestrian casualties were found here for female with respect to male pedestrians.

Finally, concerning the relationship between crash type and vehicle occupant injury severity related to aberrant behaviors, rear-end, angle and head-on crashes are more likely to lead to injuries and casualties than run-off/fixed object crashes. This was to be expected since most of run-off crashes on city-managed roads generally occur at low speeds, thus they may not be as severe as on rural roads, where they generally represent a major concern (Montella et al., 2021).

4.2. Variability of crash specific factors across cities for different crash circumstances

Previous literature (see e.g., Woods & Masthoff, 2017) has highlighted that driving behaviors may differ between cities of the same country or different countries, which can result in differences in the circumstances surrounding traffic accidents in the cities. However, in this study, based on the calculated intra-class correlation coefficients reported in Table 3, there is no evidence of significant differences between the 10 major Italian cities concerning the relationships between crash factors and the recorded crash circumstances (i.e., illegal maneuvering, speeding and wrong interactions with pedestrians). Note that this result is based on fatal + injury crashes only, since property-damage-only crashes were not available in the dataset.

However, some variability in crash specific factors was noted between the 10 largest Italian cities for the inattention-related crash circumstance, based on the employed statistical approach. Table 9 reports the statistically significant coefficients of the mixed model developed for inattentive driving (and the associated odds ratios) for each of the 10 Italian cities studied, provides ground for some interesting remarks. In fact, in some cases, the effect of a specific factor for a given city is opposite to the average (nationwide) effect, implying a different city-specific tendency.

These city-specific tendencies are more evident when looking at the graphical outputs in Fig. 3, where coefficient boxplots and a dendrogram obtained from a hierarchical clustering analysis of coefficients (both analyses were run in the SPSS software environment) are reported. In fact, it is evident that there are groups of cities that behave differently from the other cities. For example, it is possible to highlight the Torino-Firenze group, which exhibits (low) outlier coefficients for some intersection types and for motorcycles and the Napoli-Genova group, which exhibits positive outlier coefficients for all intersection types, on the

Table 9
Statistically significant coefficients (odds ratios in parenthesis) of the mixed model developed for crash circumstances (dependent variable: inattentive driving) varying across the cities in the sample (coefficients with opposite sign with respect to the corresponding mean coefficient estimate are reported in bold).

		City										
		Roma	**Milano**	**Napoli**	**Torino**	**Palermo**	**Genova**	**Bologna**	**Firenze**	**Bari**	**Catania**	**Mean**
Day period (ref.: morning peak)	**Night**	0.476 (1.610)	0.203 (1.225)	0.268 (1.307)	**−0.072 (0.930)**	0.145 (1.156)	0.329 (1.390)	0.391 (1.478)	0.546 (1.726)	0.307 (1.359)	0.210 (1.234)	0.279 (1.322)
Year period (ref.: winter)	**Spring**	0.089 (1.093)	0.043 (1.044)	0.101 (1.106)	0.119 (1.126)	0.034 (1.035)	0.126 (1.134)	0.040 (1.041)	0.127 (1.135)	0.156 (1.169)	0.014 (1.014)	0.085 (1.089)
	Summer	0.070 (1.073)	0.102 (1.107)	0.065 (1.067)	0.053 (1.054)	0.113 (1.120)	0.065 (1.067)	0.099 (1.104)	0.054 (1.055)	0.025 (1.025)	0.131 (1.140)	0.078 (1.081)
Element type (ref.: ordinary segment)	**Crossing**	−0.603 (0.547)	−0.593 (0.553)	**0.032 (1.033)**	−1.237 (0.290)	−0.695 (0.499)	**0.209 (1.232)**	−0.777 (0.460)	−0.984 (0.374)	−0.765 (0.465)	−0.948 (0.388)	−0.638 (0.528)
	Unsignal. Intersection	−0.766 (0.465)	−0.682 (0.506)	**0.529 (1.697)**	−1.154 (0.315)	−0.466 (0.628)	**0.131 (1.140)**	−0.583 (0.558)	−1.386 (0.250)	−0.480 (0.619)	−0.654 (0.520)	−0.554 (0.575)
	Signalized intersection	−0.430 (0.651)	−0.301 (0.740)	**0.458 (1.581)**	−0.781 (0.458)	−0.320 (0.726)	**0.208 (1.231)**	−0.364 (0.695)	−0.867 (0.420)	−0.327 (0.721)	−0.430 (0.651)	−0.317 (0.728)
	Segment with issues/ tunnel	0.348 (1.416)	0.304 (1.355)	0.217 (1.242)	0.407 (1.502)	0.352 (1.422)	0.264 (1.302)	0.346 (1.413)	0.413 (1.511)	0.349 (1.418)	0.355 (1.426)	0.336 (1.399)
Vehicle type (ref.: car)	**Bicycle**	0.610 (1.840)	0.457 (1.579)	0.200 (1.221)	0.338 (1.402)	0.673 (1.960)	0.136 (1.146)	0.429 (1.536)	0.059 (1.061)	0.483 (1.621)	0.319 (1.376)	0.368 (1.445)
	Light motorcycle	0.790 (2.203)	0.439 (1.551)	0.267 (1.306)	0.035 (1.036)	0.489 (1.631)	0.346 (1.413)	0.344 (1.411)	**−0.034 (0.967)**	0.452 (1.571)	0.282 (1.326)	0.340 (1.405)
	Motorcycle	0.447 (1.564)	0.178 (1.195)	0.138 (1.148)	**−0.114 (0.892)**	0.196 (1.217)	0.163 (1.177)	0.149 (1.161)	**−0.090 (0.914)**	0.188 (1.207)	0.117 (1.124)	0.137 (1.147)

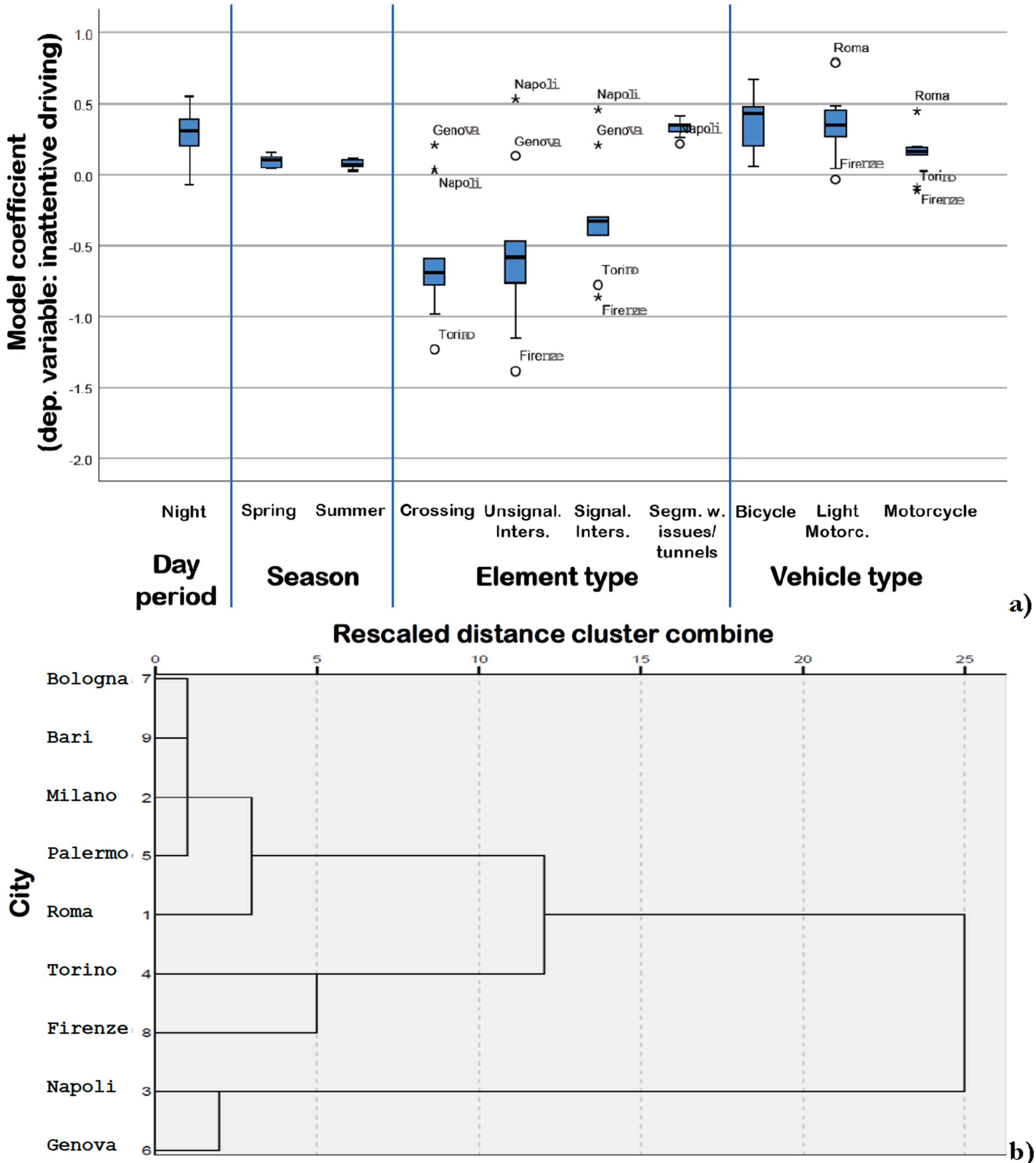

Fig. 3. Analysis of city-specific model coefficients (mixed model having inattentive driving as the dependent variable): a) boxplots of city-specific coefficients (boxes are defined by the interquartile range "IQR = Q3-Q1", whiskers represent minimum/maximum values except outliers, circles are mild outliers that are values greater than 1.5 IQR from Q1 or Q3, stars are severe outliers that are values greater than 3 IQR from Q1 or Q3; b) dendrogram obtained from hierarchical clustering of city-specific coefficients (average linkage method).

contrary to all other cities. These two groups can be identified as separate clusters with respect to the other cities (Fig. 3,b).

Analyzing these results in further detail, while on average at night, the odds of being involved in a crash while inattentive is higher than during morning peak hours, the opposite occurs in the city of Torino. Similarly, while on average the odds of being involved in a crash while inattentive is higher on ordinary segments than at intersections, the opposite occurs in the cities of Napoli and Genova. This opposite tendency is consistent for all the intersection classes (crossings, signalized and unsignalized intersections). Finally, while on average, the odds of being involved in a crash while inattentive is higher for motorcyclists than for car drivers, the opposite was noted in the cities of Firenze and

Torino (in the latter case, the opposite tendency is only valid for motorcycles but not for light motorcycles). Since these tendencies are in contrast with the average national data, these discrepancies are likely to be explained by considering the importance of local factors (see e.g., Theofilatos & Yannis, 2014).

For instance, there could be particular environmental conditions for which, in the city of Torino, drivers could be less prone to night-time inattention-related crashes, despite this being a nationwide issue. Nevertheless, a possible explanation for the cities of Napoli and Genova is that they are the coastal cities showing the highest deviation between the maximum and minimum elevations with respect to the mean elevation (together with Palermo, see Table 1, for which however this effect is not noted). In fact, they extend from the coast to areas on hilly grounds, even through steep slopes. Hence, in these cases, segments may be particularly demanding (i.e., winding and not straightforward as flat roads), thus drivers may be less likely prone to be inattentive while driving on segments included between critical sections. This could partly explain the decreased likelihood of the inattentive driving crash circumstance in segment than intersection crashes. However, since detailed road geometric data are not included in the crash dataset used in this study, this interpretation should be intended as a possible explanation of results made by the authors, needing further investigation. On the other hand, these discrepancies may also hide differences in the local officers' interpretation of traffic violations made by drivers involved in crashes that are reflected in the crash reports. In fact, even if crash data reporting processes are standardized at the national level (see ISTAT, 2018), the interpretation of aberrant behaviors is always subject to human judgment and thus may vary between individuals and also between cities (e.g., the attribution of the "inattentive" driving behavior as driver-related crash circumstance is significantly higher for Genova than for the other cities).

5. Conclusions

This study aimed to explore the most important factors that affect the odds of exhibiting specific aberrant driving behaviors (inattentive driving, illegal maneuvering, wrong interaction with pedestrians, speeding). The influence of different factors on the fatal/injury outcome for occupants of crashed vehicles in which aberrant behaviors were reported and for the involved pedestrians, was studied as well. The available crash dataset of the 10 largest Italian cities was used for this scope. The within-country variation due to the different location of cities (having different road, traffic and environmental conditions), which may result in different driving behavior and thus different crash circumstances, was investigated by using multilevel models. Besides providing a contribution to the study of the relationships between aberrant behavior-related crash circumstances/injury severity and other crash factors, findings from this study document the first attempt, to the authors' knowledge, at searching for the variability of these relationships between cities of the same country.

Among all the factors that were revealed to influence the likelihood of exhibiting particular crash circumstances or injury severity, the most notable effects found were:

- an increase in the odds of speeding being a crash circumstance and more vehicle occupant injuries/casualties during nighttime than during morning peak hours, while at the same time a decrease in wrong interactions with pedestrians;
- an increased likelihood of illegal maneuvering crash circumstances at intersections (in particular those unsignalized) than on ordinary segments, also considering that signalized intersections show more injuries/casualties to vehicle occupants than ordinary segments;
- it is more likely to find car drivers performing illegal maneuvering and wrong interaction with pedestrian crash circumstances (but also speeding, to a lesser extent) than all other road vehicle users, while cyclists and motorcyclists are those who suffer more injuries and casualties from urban traffic crashes;
- it is more likely to observe pedestrian casualties for male, older adults, on roads different than city-managed roads, when hit by heavy vehicles than cars and on dry roads.

These findings pave the way for specific engineering countermeasures and policies that should be implemented at the urban level. In particular, the need for traffic calming measures and for protecting vulnerable road users is evident (i.e., through infrastructure and traffic control). At the same time, the regulation of unsignalized intersections or the reconfiguration of signalized intersections, together with an increase in traffic control may be useful to contrast illegal maneuvering. Moreover, nighttime traffic control should be promoted to reduce night speeding-related injury and fatal crashes. Considering that, among vehicle occupants, cyclists and motorcyclists were found to be the most exposed to injuries/casualties (as widely expected), some specific countermeasures can be the implementation of limited speed zones (e.g., 30 km/h zone, see Inada et al., 2020; Pazzini et al., 2023) and of protected bike lanes physically separated from the main carriageway (Guo et al., 2023; McNeil et al., 2015; Monsere et al., 2014). For all other vehicles, considering that a speeding/severity relationship was highlighted in several instances throughout the article, drivers' speeds could be also reduced by means of different speed tables, including raised crossings (Cherry et al., 2012) and Berlin speed cushions (Berloco et al., 2022, 2023). These measures may be useful to reduce pedestrian injury severity as well. Moreover, severe crashes fostered by drivers' illegal maneuvering, which was particularly related to intersections in this study, could be reduced through traditional enforcement policies or dedicated driver training (see e.g., Goodwin et al., 2015). However, apart from traditional measures, other possible solutions will come from the development of the V2X (Vehicle-to-Vehicle or -Infrastructure) technology related to Connected and Autonomous Vehicles (CAVs), which could be efficiently used for managing intersections (Rammohan, 2023), also unsignalized (see e.g., Deng et al., 2023).

Significant within-country variability was detected for inattentive driving only. In detail, the relationships between day period, road element type, vehicle type, and the likelihood of crashes related to inattentive driving in some Italian cities is different from the nationwide mean tendency. Hence, on one hand this study reveals that the within-country variability of crash circumstances is generally almost negligible; on the other hand, it shows the potential usefulness of applying mixed models with random parameters grouped by cities (or other relevant analysis units) in the analysis of country-wide datasets.

This study is not without its limitations, especially considering that it strives to catch human-related aspects from crash datasets, a widely used approach in safety research. In this perspective, one of the most important aspects to note is that the analysis of crash circumstances is based on police reports, which may be affected not only by clerical errors as every manually recorded information, but also by subjective judgment of the most influential circumstances, or bias due to local reporting practices, notwithstanding national reporting standard procedures. Highlighting the differences between cities, our approach could help in identifying potential issues with local reporting. Further work on the topic should address the other two issues. Since the employed dataset did not allow to provide compelling explanations of the observed differences between cities, further studies could include other variables thath may help in explaining those revealed differences. Moreover, other modeling approaches can be used to analyze crash circumstances and vehicle occupant injury severity. The use of the mixed model structure was here limited to a random parameter (grouped by city) approach, conditional to a preliminary assessment of the ICC estimate, given the specific aims of this study. Finally, the particular injury severity analysis performed can be improved and integrated in further studies, especially if more detailed crash datasets including a full scale of severity levels will be available. In particular, findings from this article should be confirmed by future analyses, including also property-damage-only crashes, which were not available in the dataset used for this study.

CRediT authorship contribution statement

Paolo Intini: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Methodology. **Nicola Berloco:** Writing – original draft, Writing – review & editing, Visualization, Investigation. **Stefano Coropulis:** Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation. **Achille Fonzone:** Writing – review & editing, Visualization, Investigation, Methodology. **Vittorio Ranieri:** Writing – review & editing, Investigation, Methodology.

Declaration of competing interest

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

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