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Factors influencing pedestrian injury severity in Chile: A hierarchical probit ordered model approach

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ABSTRACT

Introduction: Traffic crashes remain a leading cause of fatalities worldwide, with higher fatality and injury rates in non-developed countries. Understanding the relationship among variables influencing traffic crashes and its outcome, measured as crash severity, is crucial for developing effective and targeted countermeasures to mitigate this problem. Method: In this study, we analyze traffic crashes involving pedestrians in Chile from 2022 to 2023. This allowed us to consider the entire country rather than a specific urban area, which is the first of its kind for a Latin American country. A Hierarchical Ordered Probit (HOPIT) model was estimated to model both risk propensity and severity of pedestrian and vehicle crashes while maintaining an ordered threshold structure. Findings reveal that pedestrian and driver characteristics significantly influence crash severity. Results: Male drivers have a higher probability of being involved in more severe crashes. Meanwhile, older pedestrians present a higher risk of severe and fatal injuries. Crash severity is significantly influenced by variables related to vehicle type and environmental factors. Pedestrians hit by heavy-duty vehicles have a 60% and 30% higher chance of suffering fatal or severe injuries, respectively. Highways exhibit a 421% higher chance of fatal injuries, followed by crashes at night and crashes in rural areas with 380% and 267%, respectively. Practical Applications: This research indicates the need for targeted safety measures addressing pedestrian and driver demographics and behavior, vehicle types, and environmental factors to effectively reduce pedestrian injury severity.

1. Introduction

Annually, approximately 1.19 million people die from traffic crashes. More than half of these deaths correspond to vulnerable users, such as pedestrians, cyclists, and motorcyclists (WHO, 2023). According to the World Health Organization (2023), traffic collisions are the twelfth cause of death for people of all ages. However, for children and young people aged 5 to 29, traffic crashes are the leading cause of death, constituting a public health problem that impacts both the quality of life and the economic stability of the regions.

If we take into account demographic characteristics such as age and gender. It is observed that the number of deaths of men is three times greater than that of women, and more than 60% of fatalities occur in productive ages, that is, between 18 and 59 years old. Of these statistics, 23% of fatalities correspond to pedestrians, 6% to cyclists, and 3% to micromobility users, such as e-scooters (WHO, 2023). In OECD countries, the rate of deaths in traffic crashes is approximately 5.5 deaths per 100,000 inhabitants. In contrast, Latin American countries such as Brazil and Colombia have considerably higher rates, with 19.7 and 15.8 deaths per 100,000 inhabitants, respectively. Although Chile has a lower rate compared to these two countries, with 10.8 deaths per 100,000 inhabitants, this figure continues to be worrying. Furthermore, when comparing the death rate to the number of motorized vehicles, Chile is in second place with a rate of 3.5 deaths per 100,000 registered vehicles, while Colombia is in first place with 4.5 deaths per 100,000 (ITF, International Transport Forum, 2023).

Latin American countries have worked to strengthen their road safety management and policies by establishing dedicated agencies, launching strategies, allocating budgets, and creating observatories. Colombia and the Dominican Republic have successfully created and implemented new national agencies. However, these efforts often have not led to effective actions or reductions in traffic crashes (Marin et al., 2023; Ramírez & Scartascini, 2024). Contributing factors include insufficient political commitment, high agency turnover causing loss of expertise, limited authority of organizations to enact legislative changes, strategies not aligned with institutional realities and resources, and overly ambitious goals. Additionally, national agencies

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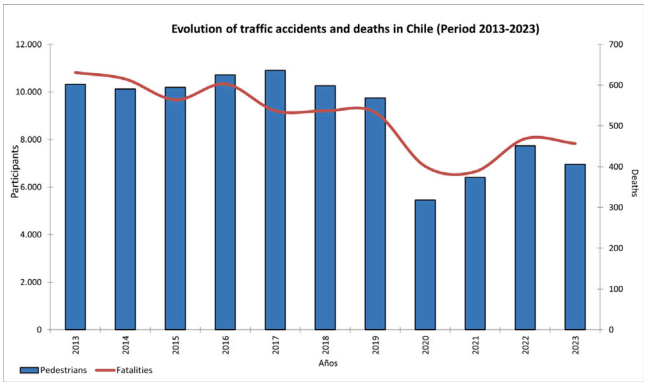

Fig. 1. Evolution of pedestrians involved in crashes and fatalities in the last ten years.

face challenges in influencing local road safety measures, especially in urban areas where most fatalities occur (Marin et al., 2023; Ramírez & Scartascini, 2024).

In recent years, Chile has also implemented various measures to reduce its high crash rates. Among these, reducing the maximum speed allowed in urban areas to 50 km/h stands out, as well as the National Road Safety Strategy 2021–2030, which presents five strategic pillars involving users, infrastructure, and current legislation (CONASET, Comisión Nacional de Seguridad de Tránsito, 2021). Despite these measures, the number of collisions involving pedestrians with motor vehicles has remained relatively constant in recent years. Between 2013 and 2019, nearly 10,000 pedestrians were involved per year. During 2020, this number decreased drastically to 5455 pedestrians due to the mobility restrictions imposed by the COVID-19 pandemic, and it has remained constant between 7739 and 6959 pedestrians in recent years (see Fig. 1). According to statistics analyzed in the last ten years, approximately 500 pedestrians die annually in the country, representing about 6% of the total pedestrians involved in traffic crashes (CONASET, Comisión Nacional de Seguridad de Tránsito, 2023).

This persistent issue emphasizes the need to understand the factors influencing the severity of crashes involving pedestrians. Previous studies have identified that the factors that influence the severity of crashes involving pedestrians can be grouped into four categories: (i) characteristics of the pedestrian, (ii) characteristics of the driver and the motor vehicle involved, (iii) attributes of the environment, and (iv) geometric characteristics of the road (Bhat, Astroza, & Lavieri, 2017; Eluru, Bhat, & Hensher, 2008; Kim, Kho, & Kim, 2017; Kim, Ulfarsson, Shankar, & Kim, 2008; Park & Bae, 2020; Rahman, Kockelman, & Perrine, 2022). A recurring cause in many crash severity studies is associated with the influence of alcohol on drivers of motor vehicles, especially when they are intoxicated (Christoforou, Karlaftis, & Yannis, 2013; Eluru et al., 2008; Kemnitzer et al., 2019; Pour-Rouholamin & Zhou, 2016). Likewise, if a pedestrian is hit by a motor vehicle, the severity of the crash is more significant, with a greater probability of suffering serious injuries and even death (Ballesteros, Dischinger, & Langenberg, 2004; Roudsari et al., 2004).

Studies on the factors influencing the severity of crashes involving pedestrians are scarce in the Global South (Blazquez & Celis, 2013; Blazquez, Lee, & Zegras, 2016; Pineda-Jaramillo, Barrera-Jiménez, & Mesa-Arango, 2022; Rampinelli et al., 2022; Silva, Cunto, Gomes, & Ferreira, 2023; Zewdie et al., 2024). Moreover, these studies rely on descriptive analysis and multivariate modeling. Therefore, they do not recognize the discrete and ordinal nature of injury severity since crashes are usually classified into distinctive and increasingly severe injury categories that a continuous variable cannot adequately describe (Savolainen, Mannering, Lord, & Quddus, 2011). A recent model that considers injury severity as an ordinal variable was conducted by Torres, Nodari, and Larrañaga (2024). They estimate ordinal logit models with fixed and random parameters to study the effect of the built environment on the severity of collisions occurring in school surroundings in Porto Alegre, Brazil. However, although this is the first study that uses ordinal models for crash severity in Latin America, its modeling approach does not consider that the thresholds dividing each severity category could vary across observations depending on the explanatory variables, adding a restriction to the ordinal logit model that could affect the results. This could lead to inaccurate conclusions about the effect of the explanatory variables on crash severity and, therefore, to potentially misleading policy recommendations.

This study aims to identify factors contributing to the severity of crashes involving pedestrians and motorized vehicles in Chile between 2022 and 2023. We focus on the individual characteristics of the pedestrians and drivers, the specific circumstances of the collision, and the location and characteristics of the road infrastructure in which the crash occurred. To achieve this objective, we applied a random hierarchical ordered probit model, where the propensity for pedestrian injury is classified on a scale from 1 to 4, with 1 representing no injury and 4 representing pedestrian fatality. This model allows us to examine how factors related to the crash, the pedestrian, the vehicle, the environment, and the driver affect injury severity.

2. Methodology

2.1. Methodological approach

The literature presents a diverse range of modeling approaches to estimate factors affecting the probability of different levels of severity in traffic crashes (Savolainen et al., 2011; Washington, Karlaftis, Mannering, & Anastasopoulos, 2020). These models aim to link individual characteristics, crash conditions, and environmental factors to the severity of injuries. They employ several methodologies, from basic logit models to more sophisticated approaches like mixed logit models, ordered models, and hierarchical ordered probit (HOPIT) models. These approaches can be categorized based on how the response variable is treated: ordinal or discrete.

Logit models treat the outcome categories as nominal, assuming that these categories are unrelated and independent (Savolainen et al., 2011; Washington et al., 2020). However, these models could lead to potentially biased and inefficient results due to the oversight of the ordinal nature of injury severity, where the outcomes follow a natural progression from less severe to more severe injuries. On the other hand, ordered models (such as ordered logit or ordered probit) are commonly used to address the ordinal nature of the categories (Greene & Hensher, 2010; Savolainen et al., 2011; Washington et al., 2020). However, these models rely on the proportional odds (or parallel regression) assumption, which means that the same set of independent variables is assumed to affect all severity levels similarly. This assumption can be limiting because the impact of independent variables may not be uniform across different levels of severity, and their effects may vary between lower and higher severity outcomes. Generalized ordered logit models (Eluru et al., 2008; Kaplan & Prato, 2012; Williams, 2006; Yasmin, Eluru, & Pinjari, 2015) have been introduced to relax the proportional odds assumption, allowing different sets of variables to affect each injury severity level in distinct ways. However, this model's limitation is that it can sometimes predict negative probabilities.

In response to these limitations, the hierarchical ordered probit (HOPIT) model, first developed by Greene and Hensher (2010), and Greene, Harris, Hollingsworth, and Weterings (2014), has been used to model injury severity (Forbes & Habib, 2015; Yu, Ma, & Shen, 2021). This model not only eliminates the possibility of negative probabilities but also ensures that the thresholds are always positive and ordered. Moreover, the thresholds are heterogeneous, as they are a function of a unique set of parameters that do not necessarily directly affect the probability of the resulting severity category. Extensions of this model exist, incorporating heterogeneity in the thresholds and the observed variables (Fountas & Anastasopoulos, 2017; Fountas, Fonzone, Gharavi, & Rye, 2020; Rahimi, Shamshiripour, Samimi, & Mohammadian, 2020). Note, however, that the term "hierarchical" does not imply the existence of a hierarchy in the data structure; it was named this way by Greene (2007) because it refers to the model's ability to allow thresholds to be heterogeneous and systematically decomposed as a result of the inclusion of exogenous variables, which may differ for each threshold (Greene, 2024; Greene & Hensher, 2010).

Therefore, to effectively model injury severity in pedestrian-related crashes, we adopt the hierarchical ordered probit (HOPIT) model. In the following subsection, we detail the modeling framework of the HOPIT approach, explaining its mathematical formulation and how it accommodates the heterogeneity in thresholds.

2.2. Modeling framework

A hierarchical ordered probit (HOPIT) model with random parameters is used in the present study (Greene, 2024; Greene & Hensher, 2010). In this modeling approach, the latent injury risk propensity is a function of exogenous variables, including pedestrian characteristics, driver attributes, and the environment and motor vehicle features. For a pedestrian q and an injury severity level j, the hierarchical ordered probit model is defined as follows:

$$z_q = \beta x_q + \epsilon_q, \quad y_q = j \;\text{ if }\; \mu_{j-1} < y_q < \mu_j, \quad j = 1, 2, \ldots, J, \tag{1}$$

where z_q represents the latent injury risk propensity for pedestrian q involved in a given crash, y_q is an integer that represent the observed injury severity levels, x_q is a vector of explanatory variables, β is a vector of parameters to be estimated, μ are threshold parameters that define y_q and are estimated along with β and ϵ is an error term assumed to be normally distributed with mean zero and variance one.

The thresholds can vary as a function of a set of explanatory parameters defined as:

$$\mu_{q,j} = \mu_{q,j-1} + \exp(\alpha_j + \gamma_j S_j), \tag{2}$$

where α_j represents the intercept for each threshold, S is a vector of variables affecting the thresholds, and γ_j is a vector of parameters to be estimated for S.

The model also allows for the incorporation of heterogeneity in the effect of exogenous variables on the latent injury risk propensity, which refers to the underlying probability of a pedestrian being injured, by including a random parameter as follows:

$$\beta_q = \beta + \Gamma \omega_q \tag{3}$$

where β represents the mean of the random parameters vectors, Γ the diagonal matrix of standard deviations, and ω_q is a term distributed normally with mean zero and variance one (Fountas & Anastasopoulos, 2017).

The ordered probability of each injury severity level j for each crash observation can be calculated using the following formulation (Washington et al., 2020):

$$P(y = j) = \Phi(\mu_j - \beta x_q) - \Phi(\mu_{j+1} - \beta x_q), \tag{4}$$

where $P(y = j)$ is the probability of the injury severity level j, Φ represents the cumulative distribution function of the standard normal distribution, and μ defines the marginal threshold for outcome j. To ensure model identifiability, a normalization is adopted where $\mu_0 = 0$ for all q, hence only $j - 2$ thresholds are estimated (Eluru et al., 2008; Fountas & Anastasopoulos, 2017). The parameters β, γ, and α are estimated by means of log-likelihood maximization using Apollo 0.3.0 (Hess & Palma, 2019).

Table 1
Distribution of pedestrian injury severity levels.

Injury severity category	Distribution
No injury	738 (6.88%)
Slight injury	5657 (52.71%)
Moderate injury	924 (8.61%)
Severe injury	2599 (24.22%)
Fatal injury	814 (7,58%)
Total	10,732 (100%)

3. Data

The data used for this analysis are based on the public record of traffic crashes in Chile between 2022 and 2023, provided by the Technical and Road Safety Prefecture of the Chilean Carabineros. These records cover incidents across the country's 16 regions and are categorized by crash type, involved individual's role, and vehicle type involved. This period was selected as it marks a return to regular activities following the COVID-19 pandemic, thus offering the most current data on post-pandemic collisions. The data comprises details of 164,288 crashes involving 14,698 pedestrians and 293,322 vehicles, both motorized and non-motorized.

3.1. Database description

This study focuses on crashes involving pedestrians and motorized vehicles, which account for approximately 8% of all recorded incidents. Specifically, we concentrate on cases involving just one pedestrian being hit by one motorized vehicle. Consequently, the modeling database comprises 10,732 collisions. This final dataset was derived after a thorough review and subsequent cleansing of the initial records, eliminating instances where (i) the driver was under 16 years old (the minimum legal driving age in the country), (ii) crashes involving more than one pedestrian, and (iii) records with incomplete information about the type of vehicle involved or driver characteristics.

Each report includes a severity level for the involved parties (driver, pedestrian, or passenger), categorized on a five-point ordinal scale: (1) no injury, (2) slight injury, (3) moderate injury, (4) severe injury, and (5) fatal injury. Detailed definitions of these five severity levels are provided in Annex A.[1]

In most studies analyzing traffic crash data, the severity levels are often imbalanced, particularly in cases involving fatalities (Bhat et al., 2017; Eluru et al., 2008; Fountas & Anastasopoulos, 2017; Li, Yang, et al., 2023). Table 1 shows the distribution of crash severity for pedestrians, where it is evident that the "moderated injury" category accounts for a low percentage of crashes (8.61%). Considering that both "slight injury" and "moderated injury" involve days counted as incapacitation, these two categories were combined into a single category called "incapacitating injury", reducing the categories for modeling to four levels: (1) no injury, (2) incapacitating injury, (3) severe injury, and (4) fatal injury, as shown in Fig. 2.

[1] In Chile, crashes are reported as follows: an officer from "Carabineros de Chile" reports the traffic crash. The officer must call an ambulance if the incident involves more than just vehicle damage, meaning there is a person who is potentially injured as a result of the crash. While the officer records the crash's details, a medical professional provides the final assessment. This assessment depends on the severity of the injuries. It is based on the scale provided by the Traffic Law, which, for example, categorizes injuries according to the number of days the person will be on medical leave. For more information, visit CarabinerosChile.

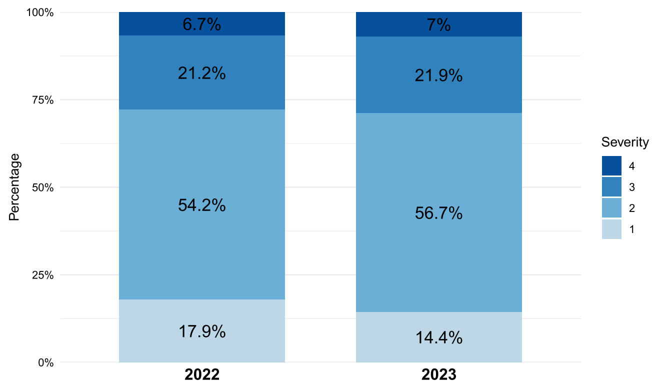

Fig. 2. Distribution of pedestrians injury-severity levels per year (2022–2023).

Table 2
Crash determinants for modeling purpose.

Cause	Base line cause
Alcohol in driver	Driving under the influence of alcohol Driving while intoxicated Driving under the influence of drugs or narcotics
Pedestrian imprudence	Pedestrian crosses the road suddenly or carelessly Pedestrian crosses the road outside the crosswalk Pedestrian crosses the road or highway without caution Pedestrian imprudence Pedestrian remains on the road
Reckless speed	Excessive speed in restricted areas Speed exceeding the maximum limit Speed below the minimum limit Speed that is neither reasonable nor prudent Speed not reduced at intersections, crests, curves, etc.
Other cause	Those not specifically detailed

3.2. Variables considered

Our research process was comprehensive, considering several variables in the modeling process, including crash characteristics (such as, causes and type of the crash), driver attributes, pedestrian features, characteristics of the involved vehicles, and environmental factors. The absence of geometric features of the road and weather condition in the crash reports was a limitation we acknowledged and worked with.

The variables considered in this study are derived from the information provided in the Traffic Crash Report by the Technical and Road Safety Prefecture. The report is divided into three files. The first includes data on the characteristics of the individuals involved in the crash (driver, pedestrian, or passenger), such as age and gender, as well as the outcome of the crash based on severity. The second provides information on the types of vehicles involved in the crash, grouped into 12 major categories, and the type of service, such as school transport, private vehicles, taxis, among others.[2] The third contains detailed information on the type of traffic crash, causes, relative location, number of participants involved, their respective injury severity outcomes, and the court where the crash will be recorded. It is important to note that all three databases share common information, including the crash ID, exact date, month, time, municipality, and region where the incident occurred, making it straightforward and precise to cross-reference data across the three sources.

Using these comprehensive datasets, we extracted and organized the variables relevant to our analysis. *Pedestrian* and *driver characteristics* include demographic information such as age and gender. The characteristics of *motorized vehicles* are divided into four categories: (i) compact or small vehicles, including cars, pickup trucks, jeeps, and vans; (ii) motorcycles; (iii) heavy-duty vehicles such as trucks of various sizes, buses including articulated ones, and agricultural or industrial machinery; (iv) other types of vehicles, which are reported as unclassified, including micro electric, vehicles animal or human-powered vehicles and those not identified because they fled the scene. In preliminary analyses, attempts were made to classify more specifically, such as the type of trucks and micro-mobility. Still, no statistically significant parameters were obtained, likely due to insufficient data compared with compact cars.

Regarding *crash location*, the data includes whether the crash occurred in an urban or rural setting. Additionally, detailed location information is provided in three distinct forms:

- Exact Address: The specific street name and number are provided, indicating that the crash occurred at a precise location on the road, such as in front of a house.
- Intersection Information: The names of two intersecting streets are provided (without street numbers), indicating that the crash occurred at an intersection (used as "*intersection*" for modeling purposes).
- Highway Location: The route's name is recorded, indicating that the crash occurred on a highway. In most cases, the specific kilometer marker is also recorded (used as a "*highway*" for modeling purposes).

Since these three categories are mutually exclusive, only two will appear in the model, with the base category interpreted as "other location". There are no details on road design, such as width or number of lanes, so only available information is included.

The *crash determinant* considered in the modeling is derived from the 59 cause categories provided by CONASET (2024).[3] Based on this information, we grouped possible causes, considering the quantity of data for each and their relevance within the model, as shown in Table 2.

Finally, among the *environmental factors* associated with the crash, the time of the collision is considered, grouped into a variable that identifies if it occurred between 9 PM and 6 AM compared to the rest of the day. We also consider the day of the week, comparing crashes occurring on weekends to other days. Table 3 presents the descriptive statistics of variables used in model estimation.

4. Results

In this study, we conducted a systematic estimation process to identify the best specification for an ordinal model. We began with an ordinal probit model with fixed parameters, which allowed us to identify the significant variables for the latent injury risk propensity. Building on this initial model, we proceeded to estimate a model with random parameters in the explanatory variables. Subsequently, we estimated a hierarchical ordered probit model (HOPIT) to assess how certain variables affect the severity thresholds. Finally, we specified a HOPIT model incorporating random parameters in both the thresholds and the explanatory variables. During the estimation process, we compared the four models using a likelihood ratio test, the Akaike Information Criterion (AIC), and the correct prediction percentages to evaluate the overall statistical fit. The results indicated that the HOPIT model with random parameters shows statistical superiority; therefore, the results of this model are presented in this section.

[2] The twelve major groups are car, bicycle, bus/taxi-bus, truck, pickup, hit-and-run, van, SUV, minibus, motorcycle, pedestrian, others. For more details, visit (CONASET, 2024).

[3] For more detail of each cause and base line cause see Table 7 in Appendix B.

Table 3
Descriptive statistics of variables used in estimation model.

Variables	Number of observations
Pedestrian characteristics	
Male	5346 (49.81%)
Age	
<26 years	2755 (25.67%)
26–55 years	4507 (42.00%)
>55 years (base)	
Driver characteristics	
Male	9194 (85.67%)
Vehicle attributes	
Compact vehicle	8346 (77.77%)
Motorcycle	557 (5.19%)
Heavy-duty (base)	
Other vehicle	570 (5.31%)
Crash Location	
Urban (base)	
Rural	1324 (12.34%)
Type of infrastructure	
Other (base)	
Intersection	6940 (64.66%)
Highway	1249 (11.64%)
Crash determinant	
Others (base)	
Pedestrian imprudence	1851 (17.25%)
Exceeding maximum speed	117 (1.09%)
Alcohol in driver	291 (2.71%)
Environmental factors	
Time of the day	
06:00–21:00 (base)	
21:00–06:00	1580 (14.72%)
Type of day	
Weekday (base)	
Weekend	4055 (37.78%)
Total number of observations	**10,732**

However, during estimation, we did not find statistical significance in the random parameters of the thresholds. As a result, the final model includes heterogeneity only in the explanatory variables. We used this random parameters Hierarchical Ordered Probit (HOPIT) model to estimate the factors influencing the severity of traffic crashes involving pedestrians and motorized vehicles.

Table 4 presents the final model specification. The first column displays the coefficients β that characterize the injury risk propensity and the parameters α and γ of the threshold functions. The last column corresponds to the robust t-statistic. The sign of the parameters presented in Table 4 are interpreted as follows: a positive (negative) sign in a risk propensity parameter indicates that the corresponding variable increases (reduces) the severity of the injury. On the other hand, a positive (negative) sign in a threshold parameter reduces the probability of the more (less) severe injury category associated with that threshold, thus indicating a reduction (increase) in the injury severity.

4.1. Measures of fit

As previously detailed, a set of models was estimated to find the one that best fits the data. We used a likelihood ratio (LR) test to compare each pair of models, considering that one is the restricted version of the other (Train, 2009). The statistic for the LR test is defined as:

$$LR = -2[LL(\beta_R) - LL(\beta_U)] \sim \chi_r^2, \tag{5}$$

where $LL(\beta_R)$ is the log-likelihood at the convergence of the "restricted" model, and $LL(\beta_U)$ is the log-likelihood at convergence for the "unrestricted" model. Under the null hypothesis, the LR statistic defined above is asymptotically chi-square distributed with r degrees

Table 4
Hierarchical ordered probit model results.

Variable	Latent risk propensity	Robust t-test
Constant	2.185	35.94
Pedestrian characteristics		
Male	0.068	2.82
Age		
<26 years	−0.479	−15.37
26–55 years	−0.371	−12.49
>55 years (base)	–	–
Vehicle attributes		
Compact vehicle	−0.451	−10.12
Motorcycle	−0.405	−6.06
Heavy duty (base)	–	–
Other vehicle	−0.507	−7.95
Road Location		
Urban (base)	–	–
Rural	0.487	3.82
Standard deviation of rural parameter	0.449	2.53
Type of infrastructure		
Other (base)	–	–
Intersection	−0.057	−1.97
Crash determinant		
Others (base)	–	–
Pedestrian imprudence	0.099	2.96
Standard deviation of pedestrian imprudence parameter	0.469	7.41
Environmental factors		
Time of the day		
06:00–21:00 (base)	–	–
21:00–06:00	0.451	11.53
Standard deviation of time of the day parameter	0.723	12.09
Thresholds parameters		
Threshold between no injury and incapacitating injury	***fixed***	–
Threshold between incapacitating and severe injury (μ_{q2})		
Constant (α_2)	0.838	43.68
Highway (base other type of infrastructure)	−0.169	−2.73
Exceeding maximum speed	−0.079	−1.42
Type of day		
Weekday (base)	–	–
Weekend	−0.031	−2.87
Alcohol/drugs (1 if driver was under influence)	−0.027	−0.65
Male driver	−0.053	−2.95
Threshold between severe and fatal injury (μ_{q3})		
Constant (α_3)	0.427	7.58
Highway (base other type of infrastructure)	−0.424	−2.72
Type of day		
Weekday (base)	–	–
Weekend	−0.063	−1.72
Alcohol/drugs (1 if driver was under influence)	−0.337	−2.93
Male driver	−0.111	−1.94
Log-likelihood at convergence	**−10028.09**	
AIC	**20 106.18**	
Number of observations	**10732**	

of freedom, where r corresponds to the number of linear restrictions required to transform the more generic model into its restricted version. For instance, the log-likelihood at convergence for the model presented in Table 4 is −10028.09, while the corresponding value for the HOPIT model without heterogeneity is −10068.45.[4] The value obtained using the LR test is 96.72, significantly higher than 11.34, which is the chi-square value with 3 degrees of freedom at the 99% confidence level. This result unequivocally demonstrates the statistical superiority of the HOPIT model with heterogeneity over its restricted version. We conducted a similar comparison with the simpler ordinal models and found our model to be superior in terms of statistical fit.

We also compared the predicted and observed shares of injuries at each severity level using sample enumeration. Table 5 shows that the predicted shares are very close to the actual shares. This high level of

[4] The results of the HOPIT model without heterogeneity are not presented in the article, but are available upon request to the authors.

Table 5
Aggregate measures of fit in estimation sample.

Injury severity category	Actual shares	HOPIT predictions
No injury	6.88%	6.87%
incapacitating injury	61.32%	60.39%
Severe injury	24.22%	25.55%
Fatal injury	7,58%	7,19%
Number of observations	10,732	10,732

predictive accuracy reflects the effectiveness of our model in capturing the detailed aspects of injury severity.

4.2. Pedestrians characteristics

The effect of pedestrian characteristics on the latent injury risk propensity indicates that men and individuals over the age of 55 are more likely to suffer severe injuries compared to women and younger individuals (up to 55 years old). Similar studies have shown that older pedestrians are more likely to suffer severe injuries, potentially resulting in fatality (Batouli, Guo, Janson, & Marshall, 2020; Martínez-Ruiz et al., 2019; Park & Bae, 2020; Pour-Rouholamin & Zhou, 2016). Male pedestrians have also been found to face an elevated risk of fatality as well as a higher likelihood of causing conflicts with motor vehicles (Ma, Lu, Chien, & Hu, 2018; Martínez-Ruiz et al., 2019; Schneider, 2020).

4.3. Crash determinants

The model results indicate that driving under the influence of alcohol significantly affects two thresholds: between incapacitating and severe, and between severe and fatal injury risk. The negative sign of this variable implies that if the driver is under the influence of alcohol (or drugs), the injury severity level increases. Several studies on accidentality and injury severity support this finding. They concluded that alcohol-impaired drivers tend to drive at higher speeds, increasing the impact of the crash and, consequently, its severity (Peck, Gebers, Voas, & Romano, 2008; Traynor, 2005). Alcohol can also reduce the driver's reaction time and overall driving skills (as judgment and vigilance, among others) (Ahlström, Zemblys, Finér, & Kircher, 2023; Dunaway, Will, & Sabo, 2011; Yadav & Velaga, 2019).

Our study also reaffirms the significance of driving above the permitted speed limit as a determinant of crashes. This behavior significantly increases the likelihood of severe consequences for pedestrians (Aarts & Van Schagen, 2006; Harris, Ahmad, Khattak, & Chakraborty, 2023). Our findings align with evidence from several studies, including a study by Hussain, Feng, Grzebieta, Brijs, and Olivier (2019) that found a mere 1 km/h increase in vehicle speed can elevate the probability of a pedestrian fatality by 11%. These findings emphasize the importance of setting and enforcing maximum speed limits in urban areas to mitigate the risk of pedestrian fatalities (Yeo, Lee, Cho, Kim, & Jang, 2020).

Pedestrian behavior also plays a significant role in latent propensity risk. In our study, pedestrian imprudence, which includes crossing the road without paying attention or in a hasty manner and crossing outside of a designated crosswalk, is a key component of this latent propensity risk.[5] Compared to other determinants of crashes, this factor leads to an increased severity of outcomes for the pedestrian injury severity (Blazquez & Celis, 2013; Rampinelli et al., 2022).

[5] For more detail, see Appendix B.

4.4. Motorized vehicle characteristics

The type of vehicle involved in a pedestrian crash significantly impacts the injury risk for the pedestrian. Compared to heavy-duty vehicles (trucks and buses), crashes involving smaller vehicles (such as sedans or SUVs) and motorcycles result in reduced severity. Other studies have also shown that heavy trucks and large passenger vehicles, especially those with tall, blunt front ends, are associated with increased pedestrian injury severity (DiMaggio, Durkin, & Richardson, 2006; Monfort, Hu, & Mueller, 2024). This can be attributed to larger vehicles having longer stopping distances and greater mass, which can impact a pedestrian more forcefully than smaller vehicles (Roudsari et al., 2004; Schubert et al., 2023). Additionally, larger vehicles have a greater impact area and are more likely to cause injuries above the knee due to their higher bumpers (Roudsari, Mock, & Kaufman, 2005).

4.5. Crash location and type of infrastructure

Our model's results indicate that the location of the crash significantly impacts the injury risk. In line with previous studies, we have found that collisions occurring in rural areas are associated with a higher injury risk propensity than those in urban areas (Gitelman, Carmel, Hendel, Pesahov, & Balasha, 2013; Islam & Jones, 2014; Marshall & Ferenchak, 2017). This higher risk can be attributed to the lack of pedestrian infrastructure in rural settings, such as crosswalks, pedestrian bridges, and crossing islands. Additionally, vehicles in rural areas typically travel at higher speeds, which increases reaction times (Saheli & Effati, 2019; Schneider, Proulx, Sanders, & Moayyed, 2021; Tay, 2015).

Contrary to previous works, we found that crashes at intersections exhibit a lower latent injury propensity than those occurring at other points in the road (Qiu & Fan, 2022; Tanishita, Sekiguchi, & Sunaga, 2023). This may be due to pedestrian traffic lights, speed control infrastructure, and other measures at urban intersections that can provide greater pedestrian safety compared to expressways at different speeds (Weiss, Kaplan, & Prato, 2014). Not surprisingly, crashes involving pedestrians on highways significantly increase the probability of fatal injuries. This is due to the higher speeds and the absence of pedestrian infrastructure on highways, which are often in rural areas (Liu, Hainen, Li, Nie, & Nambisan, 2019; Wang & Cicchino, 2020). In our model, this variable affects the thresholds, with the negative sign of the parameters indicating an increased likelihood of severe injuries and fatalities when crashes occur on highways.

4.6. Environmental factors

The analysis indicates that crashes occurring on weekdays between 9:00 PM and 6:00 AM are more severe than at other times, which is in line with previous results obtained in the United States (Alogaili & Mannering, 2022; Ferenchak, Gutierrez, & Singleton, 2022). This may be due to reduced visibility during these hours, affecting drivers' reaction times (Ferenchak & Abadi, 2021; Ferenchak et al., 2022; Schneider, 2020). Additionally, in agreement with other studies, crashes that occur on weekends are more likely to result in fatal injuries (Nasri, Aghabayk, Esmaili, & Shiwakoti, 2022; Samerei, Aghabayk, Shiwakoti, & Karimi, 2021; Song, Li, Fan, & Liu, 2021). The negative sign in both thresholds indicates an increase in the latent injury risk area under these categories. This could be due to a higher incidence of drivers under the influence of alcohol and higher driving speeds on weekends (Li, Song, & Fan, 2021; Mokhtarimousavi, Anderson, Azizinamini, & Hadi, 2020).

Table 6
Semi-elasticities of each injury category with respect to the model's variables.

Variable	No injury	Incapacitating injury	Severe injury	Fatality
Pedestrian characteristics				
Male	−13.1	−2.63	7.12	2.60
Age				
26 years	162.3	18.9	−38.6	−65.9
26–55 years	116.7	17.0	−29.5	−55.3
55 years (base)	–	–	–	–
Driver characteristics				
Male	–	−6.08	8.90	88.7
Vehicle attributes				
Compact vehicle	171.9	26.9	−30.5	−60.2
Motorcycle	120.3	13.4	−35.6	−60.7
Heavy duty (base)	–	–	–	–
Other vehicle	166.4	16.1	−42.7	−69.2
Road Location				
Urban (base)	–	–	–	–
Rural	−46.6	−22.8	49.9	267.2
Type of infrastructure				
Intersection	12.4	2.33	−5.41	−11.8
Highway	–	−19.5	8.65	421.1
Crash determinant				
Others (base)	–	–	–	–
Pedestrian imprudence	17.7	−7.06	12.7	84.7
Exceeding maximum speed	–	−9.79	17.7	44.9
Alcohol in driver	–	−3.31	−10.3	156.3
Environmental factors				
Time of the day				
06:00–21:00 (base)	–	–	–	–
21:00–06:00	−7.36	−23.8	42.5	380.6
Type of day				
Weekday (base)	–	–	–	–
Weekend	–	−4.83	6.44	46.5

5. Policy recommendations

The estimated parameters for the explanatory variables do not directly indicate the magnitude of the effect on the probability of each injury severity level. Nevertheless, by analyzing how a change in each variable affects the likelihood of an injury outcome, we can identify the variables that most affect injury severity and, therefore, provide targeted policy recommendations to reduce pedestrian injuries in Chile. In this case, where all model variables are dummies, we rely on the semi-elasticity effects to represent the percentage change in the likelihood of a specific injury severity category when the value of the explanatory variable changes from "0" to "1" (Fountas & Anastasopoulos, 2017; Washington et al., 2020). For example, the first value on Table 6 indicates that the probability of a male pedestrian suffering no injury during a crash is 13.1% lower than the probability of a female pedestrian suffering no injury during a collision.

Traffic crashes on highways pose the greatest risk for fatal pedestrian injuries, with a 421% increase in fatal injuries compared to non-highway crashes. This highlights the need for targeted interventions, such as improving highway infrastructure by installing pedestrian crossings and traffic calming measures. On the infrastructure side, to reduce pedestrian injuries is recommended the improvement of street lighting (Roberts et al., 2024), raised crossings and pedestrian refuge islands (Kruszyna & Matczuk-Pisarek, 2021). On the vehicle side, implementing vehicle safety technologies is recommended, such as autonomous emergency braking and external airbags (Mahdinia, Khattak, & Haque, 2022; Simms, Wood, & Fredriksson, 2014). Lastly, on the enforcement side, efforts should focus on improving alcohol abuse and speed enforcement, and the use of public awareness campaigns to reduce risky driving behaviors (Mohan, 2018).

Nighttime crashes have a higher probability of resulting in severe injuries, with a 380% and 42% higher probability of fatal injuries and severe injuries, respectively. A well-designed lighting system improves driver visibility, which reduces pedestrian crash severity in urban areas (Kakhani, Jalayer, Kidando, Roque, & Patel, 2024; Li, Wang, et al., 2023), especially at intersections and midblock crossings (Jackett & Frith, 2013; Sari & Yudhistira, 2021).

The risk of severe or fatal injury is significantly higher among older pedestrians. Pedestrians under 25 years have a 66% and 39% lower chance of suffering fatal and severe injuries, respectively. Also, they have a 162% higher probability of a no-injury outcome. Wider sidewalks, reduced crossing distances, more traffic signals at crossings and raised medians effectively reduce injury severity among older pedestrians (Gálvez-Pérez, Guirao, Ortuño, & Picado-Santos, 2022; Lv, Wang, Yao, Wu, & Fang, 2021). Education programs focusing on older adults' safety behavior can also reduce crash risks (Dommes, Cavallo, Vienne, & Aillerie, 2012; Luiu, 2021).

Alcohol consumption by drivers increases the likelihood of pedestrian fatalities by 150%. Therefore, policies aimed at reducing alcohol-related crashes, such as enforcement measures and public awareness initiatives, should be implemented (Eichelberger, McCartt, & Cicchino, 2018; Fell et al., 2016). Other options to reduce alcohol-related crashes are promoting ridesharing alternatives (Nazif-Muñoz, Batomen, Oulhote, Spengler, & Nandi, 2020) and lowering the threshold of blood alcohol concentration, even towards a zero-tolerance law (Nazif-Muñoz et al., 2020).

Vehicle type significantly influences injury severity. A pedestrian hit by a compact vehicle is 60% less likely to suffer fatal injuries and 30% less likely to suffer severe injuries compared to a crash with a heavy-duty vehicle. Hence, promoting vehicle safety technologies for larger vehicles, is essential to reuce pedestrian crash severety (Cardoso, 2012; Rosenbloom & Eldror, 2013). Other measures, like training programs for heavy-duty vehicle drivers, could also be effective in reducing the severity of pedestrian injuries (Wang et al., 2021).

6. Conclusions

Our findings provide an understanding of various factors that affect injury severity in pedestrian-involved crashes. Pedestrian and driver characteristics, type of vehicle and environmental factors have a significant impact on pedestrian injury severity. In this study, we estimated a Hierarchical Ordered Probit model, which allows the incorporation of different attributes and heterogeneity within the thresholds between injury severity categories while maintaining an ordered structure. The proposed model was applied to a traffic crash database in Chile from 2022 to 2023, which includes information regarding crash characteristics and involved actors. To the best of our knowledge, this is the first Latin-American study to consider traffic crashes across the entire country rather than a specific city, as well as the estimation of a flexible model framework, in which the thresholds of injury severity categories vary according to different variables.

The vehicle type significantly impacts severity, with smaller vehicles and motorcycles associated with lower injury severity than larger vehicles like buses or trucks. Male drivers have a higher probability of being involved in more severe crashes and older pedestrians have a higher risk of severe injuries. Regarding environmental factors, crashes occurring in rural areas tend to be more severe. Similarly, traffic crashes on highways have a higher likelihood of severe and fatal injuries. Factors such as time of day and day of the week also have a significant effect on injury severity, with a higher probability of more severe injuries in crashes that occur during nighttime and on weekends.

Table 7
Disaggregated causes of traffic crashes: 2022–2023.

Cause[a]	Base line cause[b]	Number of crashes
Alcohol in driver	Driving under the influence of alcohol	1877
	Driving while intoxicated	15,277
Drugs and/or driver fatigue	Driving under the influence of drugs or narcotics	171
	Poor physical condition (fatigue, sleepiness)	1875
Alcohol in passenger	Passenger intoxication	18
Alcohol in pedestrian	Pedestrian intoxication	285
Driver imprudence	Overtaking at intersections, curves, slopes, bridges, etc.	425
	Overtaking on the shoulder	111
	Overtaking without signaling	268
	Overtaking without sufficient space or time	3539
	Overtaking by crossing a continuous line	505
	Load spills onto the roadway	239
	Load exceeding vehicle's authorized capacity	32
	Load obstructs the driver's view	14
	Load extends beyond the vehicle's structure	158
	Sudden lane change	4710
	Driving against traffic	810
	Driving without attention to current traffic conditions	63,761
	Driving on the left side of the road	330
	Driving without maintaining a reasonable or prudent distance	12,804
	Not respecting pedestrian right of way	2275
	Not respecting vehicle right of way	3075
	Driving in reverse	2808
	Improper turns	2443
Disobedience to signage	Disobeying instructions from an officer on duty	37
	Disobeying flashing traffic light	184
	Disobeying red traffic light	4508
	Disobeying other signage	125
	Disobeying "Yield" sign	3591
	Disobeying "Stop" sign	6972
Mechanical failures	Bodywork failures	75
	Electrical failures	39
	Brake failures	927
	Engine failures	96
	Tire failures	794
	Suspension failures	29
	Vehicle breakdown without or with poor signage	46
Passenger imprudence	Passenger imprudence	240
	Passenger boards or alights from a moving vehicle	287
	Passenger rides on the vehicle's step	41
Pedestrian imprudence	Pedestrian crosses the road suddenly or carelessly	1268
	Pedestrian crosses the road outside the crosswalk	708
	Pedestrian crosses the road or highway without caution	391
	Pedestrian imprudence	746
	Pedestrian remains on the road	240
Reckless speed	Excessive speed in restricted areas	69
	Speed exceeding the maximum limit	391
	Speed below the minimum limit	15
	Speed that is neither reasonable nor prudent	9633
	Speed not reduced at intersections, crests, curves, etc.	733
Loss of vehicle control	Loss of vehicle control	3908
Road deficiencies	Loose animals on the road	1856
	Incorrectly installed or poorly maintained signage	25
	Traffic light in poor or defective condition	76
Other causes	Criminal act	568
	Other causes	3233
	Suicide	6
Undetermined causes	Undetermined causes	4297

[a] In order to facilitate understanding, CONASET has grouped the baseline causes detailed by Carabineros de Chile into 14 categories.

[b] Carabineros de Chile identifies the baseline cause as the reason why the traffic crash occurred.

This study aims to highlight the need for targeted safety measures that consider pedestrian demographics, driver behavior, vehicle type and environmental factors to effectively reduce the severity of pedestrian injuries in traffic crashes. Future works should explore the incorporation of road characteristics, such as geometric features and speed at the crash location, which were not available in our case. Additionally, incorporating detailed behavioral studies and analyzing the ex-post policy effectiveness can further refine and enhance safety measures for pedestrians. While our study provides valuable insights into pedestrian injury severity, some limitations still exist. Firstly, the assumption of temporal stability between the years (2022–2023) may overlook potential changes in behavior, policy, or infrastructure over time. Secondly, the transferability of our results to other regions should be approached with caution, as the Chilean crash characteristics, severity measurement and overall context may differ from those in other countries. Future research could extend this work by incorporating temporal dynamics and exploring if the findings could apply to different locations.

CRediT authorship contribution statement

Margareth Gutiérrez: Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Raúl Ramos:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis. **Jose J. Soto:** Writing – review & editing, Validation, Methodology. **Felisa Córdova:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare no conflict of interest.

Appendix A. Traffic crashes outcome

These five levels of severity are defined by CONASET (2024) according to the outcome of the road crash as:

- **No injury:** When the person involved remains uninjured in the crash.
- **Slight Injury:** When a person involved is slightly injured in a crash. According to Traffic Law (Art. 196), minor injuries cause illness or incapacity for no more than seven days.
- **Moderate Injury:** According to the Penal Code (Art. 399) and Traffic Law (Arts. 178, 193, and 196), this category includes individuals whose injuries result in seven to thirty days of absence from work.
- **Severe Injury:** This category refers to someone who has sustained severe injuries in a crash. The Penal Code (Art. 397) classifies injuries as severe if they lead to conditions such as insanity, permanent inability to work, impotence, disability in a vital limb, or notable disfigurement. Additionally, this category includes injuries that cause illness or incapacity to work for more than thirty days.
- **Fatal injury:** According to the records of Carabineros de Chile, this category refers to a person who died in a crash within 48 h after the incident.

Appendix B. Disaggregated causes of traffic crashes

See Table 7.

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