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Master Thesis

以參數相關性潛在類別雙變量一般化依序普羅比模型分析市區路口雙方事故嚴重度

Investigating the two-party crash severity at street intersections by the Latent Class Parameterized Correlation Bivariate Generalized Ordered Probit

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摘要

交岔路口事故通常涉及雙方(雙車、車與行人)。我國之機車路權與行人環境長期遭到漠視，使弱勢使用者較易涉入嚴重事故，然現有改善措施成效不彰，是以透過分析釐清事故嚴重度之影響因素，並對此作出改善。涉入事故的雙方可能會遭受完全不同程度的傷害，要正確辨認雙方事故的真正因果關係，有必要同時評估雙方事故的嚴重度。在事故嚴重度研究中，已使用各種潛在類別依序模型來捕捉事故發生的異質性。然而，多數研究為單變量，並不適用雙車事故。本研究提出一種潛在類別參數化相關性雙變量依序普羅比模型，以研究交岔路口的雙方事故。

本研究以2018至2020年間32,308件臺北市路口雙方事故作為分析對象，將嚴重度分為財損、輕傷/可能受傷、致命/明顯受傷三個等級。透過潛在類別模式確定兩群為最佳群數，是為低風險群與高風險群。本模型不僅可參數化雙方事故嚴重度的門檻值和事故相關性，還可根據特徵將雙方事故分類為不同的風險群，從而更好地理解雙方事故下的變數。普通事故群(OCS)主要涉及雙車碰撞之機車事故；高嚴重事故群(HCS)由行人與機車騎士等弱勢使用者組成，推測主要出現在車流量大的地區。

基於估計結果指出一些潛在因素，例如駕駛(老年人)、違規行為(安全裝備、讓車或肇逃)和運具類型(四輪車輛、二輪車輛或行人)，交通工程三要素中，人、車、路皆存在為影響嚴重度之風險因素。透過彈性效應，OCS群於致命/明顯受傷之彈性值高於HCS群，變數型態則以運具類型的致命/明顯受傷值最高，強調其影響性。本研究藉此希望減少路口違規行為，並預防大型車輛事故。

結果說明特定某方因素對嚴重度的影響大於雙方通用因素，並對路口事故提供寶貴的見解，透過結合傳統交通3E(工程、教育、執法)與鼓勵成為第4E，制定相應的安全措施，以降低未來事故發生件數與嚴重度，建議相關單位執行本研究提出之策略，並提升全民之行車觀念。本研究最後透過分析事故嚴重度與肇責釐清事故因果關係，可使保險相關風險得到管控。

關鍵字：雙方事故、參數化相關性雙變量依序普羅比、事故嚴重度、彈性

ABSTRACT

Street intersection crashes often involve two parties (vehicle-vehicle and vehicle-pedestrian). The disregard for the right-of-way of motorcycles and the pedestrian environment in our country has been ignored, making vulnerable users more prone to serious accidents. However, existing improvement has been proven ineffective. Therefore, it is necessary to analyze the factors affecting the injury severity and to make improvements accordingly. The parties involved in crashes can vary considerably. To accurately identify the causality of a two-party crash, it is necessary to assess the damage of both parties simultaneously. While the latent class ordinal model has been used in crash severity studies to capture heterogeneity in crash propensity, most are univariate. They are inappropriate for the context of two-vehicle crashes. We propose a latent class parameterized correlation bivariate generalized ordered probit (LC*p*-BGOP) model to examine two-party crashes at intersections in the study.

This study collected 32,308 cases of two-party crashes at street intersections in Taipei City from 2018 to 2020. Injury severity is categorized into three levels: property damage only, minor/possible injury, and fatal/evident injury. Here are two classes, low-risk and high-risk, determined as the optimal class number through the latent class method. The LC*p*-BGOP parameterizes the thresholds and within-crash correlations of two-party crash severity, and it classifies the crashes into distinct risk groups based on risk variables, thereby better understanding variables in intersection crashes. According to our model, the Ordinary Crash Severity (OCS) group mainly involves two-vehicle crashes colliding with motorcycles; the High Crash Severity (HCS) group comprises vulnerable road users like pedestrians and cyclists, mainly in mixed traffic with high volumes.

Our model-based estimation points out several potential factors, such as drivers (elderly), violations (safety equipment, yielding to vehicles, or hit-and-run), and modes (four-wheeled vehicles, two-wheeled vehicles, or pedestrians). Three elements of traffic engineering, namely people, vehicles, and roads, are some existing risk factors that can influence severity. Through the elasticity effects, the OCS group has a higher magnitude of fatal/evident injury than the HCS does. By variable patterns, the mode of mobility exhibits the highest fatal/evident injury values, underscoring its significant influence. Accordingly, we hope to reduce violations at intersections and prevent large vehicle crashes.

The results show that the party-specific factors contribute to injury severity more than generic factors do, providing invaluable insight into intersection crashes from the perspective of reducing two-party collisions. By integrating the traditional traffic 3E (Engineering, Education, and Enforcement) with Encouragement into 4E, we develop the corresponding safety measures to reduce the frequency and severity of future crashes. It is recommended that authorities implement the strategies proposed in this study and enhance public awareness of driving. Finally, this study clarifies causal relationships in accidents by analyzing crash severity and fault determination, enabling risk management for insurance.

Keywords: Two-party Crashes, Latent Class Parameterized Correlation Bivariate Generalized Ordered Probit, Crash Severity, Elasticities

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In TDM, NCKU

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CHAPTER 1 INTRODUCTION

1.1 Research Background

As the domestic economy grows, the number of private vehicles increases due to heightened transportation demand, causing traffic congestion and rising accidents. Traffic accidents lead to casualties and property damage. Furthermore, some unexpected barriers may interfere with pedestrian movement, especially at city/street intersections (hereafter intersections). In such instances, pedestrians may resort to jaywalking when faced with blocked paths, leading to potential collisions.

Intersections are frequently the site of road accidents, particularly conflicts involving two parties, such as two vehicles or pedestrian-vehicle accidents (Chiou et al., 2013; Eluru et al., 2008; Esmaili et al., 2022; Li & Fan, 2019; Schneider et al., 2012; Xiao et al., 2022). According to statistics from the Ministry of Transportation and Communications (MOTC) in Taiwan, there were approximately 3,000 fatalities annually from 2008 to 2022 (MOTC, 2023). Nearly 60% of these road crashes occurred at intersections, underscoring the critical safety concern associated with road casualties at these locations (NPA, 2022). Despite continuous safety advocacy campaigns and engineering projects initiated by policymakers to reduce accidents at intersections, the observed decrease in accidents has been disheartening. A prominent contributing factor to this issue is the insufficient attention given to pedestrians' right of way, contributing to the notoriety of Taiwanese city streets as a "living hell" (Chang, 2022).

Additionally, the sample scope of Chiou et al. (2013) focused on signalized intersections, with a notable exclusion of unsignalized. Vehicle-pedestrian crashes that recently gained more attention on Taiwanese city streets are also excluded, so there may be a further need to review the crashes at intersections with the recent data, including unsignalized intersections and vehicle-pedestrian crashes.

Aside from the unresolved issues (Chen et al., 2019; de Lapparent, 2008; Russo et al., 2014; Russo et al., 2023; Weiss, 1993; Yamamoto & Shankar, 2004), most literature constrains the correlation parameter as a constant within the framework of bivariate models, thereby limiting the discussion of the correlation between injuries sustained by two parties. In contrast, this study defines the correlation parameter, enabling an exploration of potential covariates associated with within-crash correlation. The results are anticipated to provide policymakers with more insightful perspectives on effective strategies for reducing crash severity.

Consequently, this study serves as a sequel to the work of Chiou et al. (2013) aimed at addressing the aforementioned unresolved issues. Notably, the research introduces two novel BGOP extension models not explored in the literature: Parameterized Correlation BGOP (*p*-BGOP) and Latent Class Parameterized Correlation BGOP (LC*p*-BGOP). The LC*p*-BGOP model, in particular, goes beyond merely parameterizing thresholds and within-crash correlations of two parties' severities; it also categorizes crashes into different patterns based on crash characteristics. This approach enhances our understanding of associated risk factors. Furthermore, the study utilizes more comprehensive and representative samples to estimate both models, delving deeper into the factors influencing the crash severity of both parties. The ultimate goal is to develop more nuanced safety countermeasures for preventing intersection crashes, focusing on vehicle-pedestrian accidents.

Drivers purchase vehicle insurance to mitigate the potential financial consequences of road traffic accidents (RTAs). Blows et al. (2003) discovered that uninsured drivers faced notably higher odds of sustaining car crash injuries compared to insured drivers. The causal relationship between insurance status and car crash injuries remains elusive. A minor fraction of uninsured drivers in developed nations pose a considerable public health concern warranting deeper inquiry.

However, insurance has mandatory and voluntary types in Taiwan. Drivers have the autonomy to determine whether they wish to acquire voluntary insurance and the level of coverage. Hsu et al. (2015) found that policyholders with a poorer claims history tend to purchase more insurance coverage, and those with higher coverage are found to submit more claims. Consequently, crash data can provide valuable insight into formulating insurance.

1.2 Research Objectives

This study investigates factors influencing accident occurrence at intersections and offers suggestions for improvement. It delves into the varying severity levels experienced by both parties in the same accident, stemming from distinct driving behaviors, vehicle attributes, traffic conditions, and other risk factors. By examining these differences, we aim to propose effective improvement strategies.

This research aims to tackle the aforementioned unresolved issues by introducing two novel BGOP extension models: the parameterized correlation BGOP and latent class parameterized correlation BGOP. These models are unprecedented in the literature. Notably, the proposed approach enables the parameterized thresholds and within-crash correlations of two-party crash severity. Moreover, it categorizes two-party crashes into different risk occurrence patterns based on characteristics, enhancing our understanding of crash variables in the context of two-party crashes. Furthermore, the study utilizes comprehensive and representative samples to estimate both models. This allows for exploring the factors affecting the crash severity of both parties and diving into safety countermeasures to prevent intersection crashes, especially vehicle-pedestrian crashes.

The main objectives of this study are as follows:

1. Investigate the factors influencing the severity of both drivers and compare the differences between the *p*-BGOP and LC*p*-BGOP models.
2. Establish a novel LC*p*-BGOP model to analyze the observable heterogeneity and explore the factors affecting the severity of both drivers.
3. Improve strategies to serve as references for enhancing traffic safety based on the model estimation results.
4. Clarify causal relationships in accidents by analyzing crash severity and fault determination, effectively enabling risk management for insurance.

1.3 Research Issues

The following is a summary of the issues applied in this study:

1. Data collection and processing

   The study collected crash data at intersections in Taipei City from 2018 to 2020 and conducted basic statistics on driver, mode, crash, temporal, and environmental characteristics for modeling purposes.

2. Accident model construction

   The proposed model identified affecting factors and classified two-party crashes into different risk occurrence patterns based on characteristics, facilitating a better understanding of crash variables in the context of two-party crashes.

3. Development of advanced strategy

   Based on the LC*p*-BGOP model, the significant variables affecting the severity of accidents were studied to develop advanced strategies for the 4Es of traffic safety, including engineering, education, enforcement, and encouragement.

4. Clarification of causal relationships

   This study clarifies causal relationships in accidents by analyzing crash severity and fault determination, enabling risk management for insurance.

1.4 Research Framework

1. Introduction

   Describe the background and objective of the study and the desired research methodology, and finally explain the research flowchart and framework.

2. Literature review

   Review studies related to models and improvements in injury severity, research on bivariate models, heterogeneous thresholds ordinal models, and summarize the current applications of latent class models.

3. Methodology

   Based on the analysis of intersection accident characteristics, *p*-BGOP and LC*p*-BGOP models are constructed to identify affecting factors and to examine the suitability of accident analysis.

4. Empirical setting and data

   The study collected data at intersection crashes in Taipei City from 2018 to 2020 and conducted basic statistics on driver, mode, crash, temporal, and environmental characteristics for modeling purposes.

5. Estimation results

   Explain the estimation results and variable discussions for the LC*p*-BGOP model, make the group analysis, and calculate the elasticity effects of variables on severity.

6. Discussions

   The discussion pointed to some findings for specific variables causing two-party severe crashes at the intersections. Based on the estimation results, implications show that pedestrian safety urgently needs improvement.

7. Conclusions

   The conclusion of this study synthesizes the empirical findings to create helpful, actionable recommendations for further research as well as its limitations.

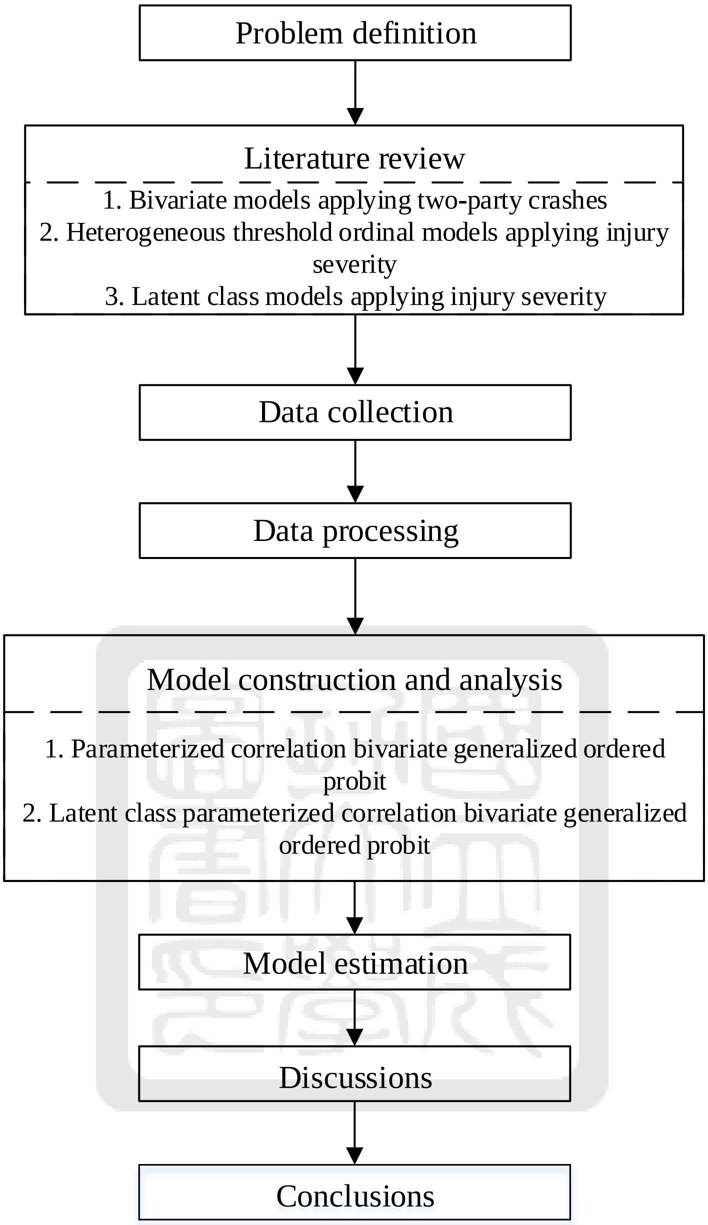


Figure 1.1 Research flowchart

CHAPTER 2 LITERATURE REVIEW

The main objective of this study is to examine the patterns of crashes occurring at intersections, exploring their heterogeneity and analyzing the factors that influence these crashes. The research involves a review of existing literature on crash severity and various research models. Ultimately, the study applies a specific model to analyze the severity of these crashes.

2.1 Bivariate Models Applying Two-party Crashes

Several crash studies have utilized bivariate models to examine the complex relationship between two involved drivers, driver/passenger pairs, or different injury components of the same individual, aiming to assess injury severity within the context of the same crash.

Given the inherent complexities in modeling crash severity data, involving factors such as parameter heterogeneity, omitted variables, endogeneity, within-crash correlation, etc., the involved drivers in multivehicle crashes may bear completely different injury severities (Mannering & Bhat, 2014; Savolainen et al., 2011). In cases involving two-party drivers, the first-party drivers (typically determined at fault by investigating police) might inflict significant injury severity upon second-party drivers (typically deemed not at fault) when an accident occurs. Under this circumstance, the first-party drivers may not suffer any injuries. To accurately discern the causal dynamics of a two-party crash, it becomes imperative to concurrently assess the crash severity levels of both parties (Chiou et al., 2020; Chiou et al., 2013; Mannering & Bhat, 2014).

The two parties (e.g. drivers/riders) involved in the same crash may experience injuries with varying levels of severity (Chiou & Fu, 2013; Chiou et al., 2020) due to their inherent physical characteristics (e.g., old adults vs. younger) and relevant aggressive driver behavior (e.g. alcohol use). Focusing solely on the party with the most severe injuries can lead to a loss of precise determination. Moreover, ignoring the interdependence of the two parties' severities results in model endogeneity issues, erroneous parameters, and bewildering causality (Mannering & Bhat, 2014; Savolainen et al., 2011). Undoubtedly, to draw meaningful conclusions from reported collision data and propose effective safety measures, it is imperative to consider the characteristics of each party and the pertinent surrounding conditions.

The suitable approach is to employ the various bivariate models to investigate the perplexing relationship between the two involved parties' injury severities. The bivariate ordered probit (BOP) is a typical paradigm that can model an interrelationship between two parties' severities with its hierarchical system of two latent propensity functions (Yamamoto & Shankar, 2004). The model approach has been employed to analyze the perplexing relationship between the two outcomes involved in the crash, such as the two-party drivers' severities (Chen et al., 2019; Chiou et al., 2020; Chiou et al., 2013; Russo et al., 2014; Russo et al., 2023; Schneider et al., 2012; Song et al., 2023), driver-passenger severities (Yamamoto & Shankar, 2004), pedestrian-vehicle conflicts (Phuksuksakul et al., 2023; Zhang et al., 2022), driving behavior and crash (de Lapparent, 2008; Wali et al., 2017), and even the two different injuries of the same individual (Weiss, 1993; Zhou et al., 2022).

Additionally, recent research (Chen et al., 2019; Phuksuksakul et al., 2023; Russo et al., 2014; Song et al., 2023; Zhang et al., 2022) has demonstrated that the BOP with random parameter specification can gain statistical advantages and invaluable safety insight by accommodating unobservable heterogeneity. This finding proves there is still substantial potential for developing bivariate models. Specifically, the above research (Chen et al., 2019; de Lapparent, 2008; Russo et al., 2014; Russo et al., 2023; Song et al., 2023; Weiss, 1993; Yamamoto & Shankar, 2004) examines the within-crash correlation with a constant correlation parameter. The effects of such a correlation between two parties involving the same crash are generally attributed to unknown and intrinsic sources. The setting confines the correlation parameter to a constant in the context of bivariate models, limiting the discussion of the correlation between two parties' injuries to some extent. Instead of typical constant correlation parameters, the current study proposes a parameterized correlation function to characterize the unobserved interrelationship, allowing for an exploration of covariates associated with within-crash correlation. The findings aim to provide policymakers with more insightful perspectives on reducing crash severity.

Weiss (1993) established a bivariate ordered probit model to analyze the effectiveness of helmets in reducing the severity of motorcycle accidents. The study simultaneously modeled body and head or neck injuries because riders were checked for head or neck injuries when they received a body injury. The estimation showed that helmets are effective in reducing the worst head or neck injuries but have a minor effect on overall injuries, especially body injuries. Yamamoto and Shankar (2004) studied both the driver's and passengers' injury severities in collisions with fixed objects via a bivariate ordered-response probit. It is necessary to model their severity simultaneously to find the most severe injury because it will have occurred to the driver or the passenger in such crashes. Although the results from the correlation parameter showed that the severity between the driver and the most severely injured passenger is positively correlated, the most severe injuries are not transferable across single and multi-occupant crash contexts.

de Lapparent (2008) analyzes the willingness to fasten the seatbelt in a car and the crash severity (if any have occurred) through bivariate ordered probit. The linkage between these factors is recursive: seatbelt choice influences injury severity, but injury severity does not impact seatbelt choice. The results for three types of car users (drivers, front and rear passengers) show that fastening the seatbelt is related to decreasing severe injuries. Schneider et al. (2012) used a multivariate probit model assessing the interrelationships among drivers/riders at fault and other dangerous behaviors in two-vehicle motorcycle crashes. Given that those factors by the riders or other involved drivers frequently occur in combination during motorcycle crashes, it is difficult to separate the effects of individual factors contributing to the crash outcome. Their finding also indicated that motorcyclist injury severity was correlated with alcohol use and wearing a helmet but not with the determination of fault. Russo et al. (2014) employed a random parameter bivariate ordered probit (RPBOP) model to assess the level of injury sustained by drivers involved in angular collisions in consideration of fault status. This model accounts for possible within-crash correlation due to common unobservable factors (such as impact speed) assumed to exist at the same crash. Furthermore, the model can address the unobserved heterogeneity (unobserved factors varying systematically across the observations), which reflects parameter effects that vary across individuals and crashes.

Wali et al. (2017) used a bivariate ordered probit model to investigate the relationship between speed limits and drunk driving laws across countries. Their results assert the preceding association, as they found some explanatory variables, such as fatalities per thousand registered vehicles, hospital beds per hundred thousand population, and road safety policy indicators, are associated with a likely medium or high effectiveness of enforcement levels of the speed limit and drunk driving laws. Chen et al. (2019) applied the random parameter bivariate ordered probit to address the within-crash correlation and to examine risk factors for crash injuries sustained by both drivers of two cars involved in the same rear-end crash. Additionally, the correlation parameter reveals that some unobserved risk factors are positively related to the severity levels of the two drivers in the same crash.

Zhou et al. (2022) investigate the effectiveness of a helmet policy on e-bike cycling behavior. They conducted a questionnaire survey and collected 1,048 riders' survey data to analyze the number of crashes while wearing helmets that those riders reported. The result shows a negative correlation between helmet-wearing and e-bike accident rates. Russo et al. (2023) utilize a bivariate ordered probit model that accommodates potential within-crash correlation in two-vehicle intersection-related rear-end crashes. Their findings revealed that although at-fault and not-at-fault drivers have several different characteristics, their injury severity is positively correlated.

Intersection accidents involving two parties may lead to injuries of varying severity levels (Chen et al., 2019; Russo et al., 2014; Russo et al., 2023; Schneider et al., 2012). Solely focusing on the most severely injured party may obscure the true causality of the accident. Therefore, it is imperative to consider the characteristics of both parties and the surrounding conditions when analyzing collision data and proposing safety measures. Previous studies have developed and applied bivariate models to assess within-crash correlation using a correlation parameter. However, the factors contributing to this correlation are often inadequately described or attributed to unobservable variables.

2.2 Heterogeneous Thresholds Ordinal Models Applying Injury Severity

Since the ordered-response model ranked as the prevalent KABCO scale (e.g., no injury, minor/possible injury, fatal/evident injury), it is widely used in examining crash severity (Savolainen et al., 2011). Due to the inherent limitation of consistent impacts on interior outcomes (Washington et al., 2020), recent studies have explored accident severity by incorporating observable variables into thresholds (cut-off) to mitigate potential bias and erroneous statistical conclusions from the actual data (Chiou et al., 2013; Eluru et al., 2008; Yasmin & Eluru, 2013; Yasmin et al., 2014; Zhang et al., 2023). These approaches are called generalized ordered outcome models (Eluru & Yasmin, 2015), in which those thresholds are specified as a function of exogenous variables. Apart from these exogenous variables, random and correlated effects are also allowed in the thresholds (Fountas & Anastasopoulos, 2017). Typically, the thresholds are treated as constants for two ordinal injury levels, indicating the homogeneity of injury risk propensity across involved drivers. The inherent restriction fails to reflect the possible endogeneity between thresholds and risk factors. Srinivasan (2002), Eluru et al. (2008), and Razi-Ardakani et al. (2020) utilized generalized ordered-based models to examine crash severity from the General Estimates System (GES). Their findings indicated that exogenous variables (e.g., gender, speed limit, alcohol use, frontal impact, elder, etc.) impact both latent propensity and thresholds of crash severity in both observed and unobserved manners. Building upon the generalized ordered-response model, subsequent studies (Eluru et al., 2008; Fountas & Anastasopoulos, 2017; Yasmin & Eluru, 2013; Yasmin et al., 2014) have proposed the random parameter and latent class versions of the generalized ordered-response model in the road safety research.

While previous studies have addressed heterogeneous thresholds in analyzing crash severity, few have tried incorporating them into a bivariate or multivariate model framework. Chiou et al. (2013) introduced a bivariate generalized ordered probit (BGOP) model to explore crash risk factors in latent and threshold functions, considering the interrelationship of two-party drivers' characteristics and common crash factors. The elasticity effects estimated by BGOP with heterogeneous thresholds may exhibit a bi-modal pattern compared to those without them. Furthermore, Zhang et al. (2022) expanded the BGOP to the mixed bivariate generalized ordered probit (MBGOP) to assess consecutive pedestrian-vehicle conflicts at intersections in China. The MBGOP model offers a more comprehensive understanding of potential heterogeneity. Both studies employing BGOP showed that parameterized thresholds in the context of the BOP model are a preferred method for examining crash characteristics involving two parties.

According to Chiou et al. (2013), the random coefficient specification and latent class method can improve the BGOP model. Zhang et al. (2022) have proposed the MBGOP for consecutive pedestrian-vehicle conflicts based on this concept. The latent class version has not yet been proposed in an empirical crash prevention context. Recent studies in transportation, including road safety, have employed the latent class segmentation-based severity model (Kim, 2023; Kim & Mokhtarian, 2023) to capture inherent heterogeneity and identify risk segmentation, such as high-risk and low-risk. The latent class modeling approach offers the flexibility to integrate various model structures, including multinomial logit (Cerwick et al., 2014; Esmaili et al., 2022; Hua et al., 2023; Shaheed & Gkritza, 2014; Xiao et al., 2022), ordinal logit (Eluru et al., 2012), ordinal probit (Fountas et al., 2018; Li et al., 2021; Salehian et al., 2023), random parameter ordered logit (Chang et al., 2021), and generalized ordinal logit (Li & Fan, 2019; Yasmin et al., 2014) model. These models can aid in developing effective accident avoidance strategies for intersections. A more elaborate latent class modeling application in traffic safety refers to a systematic review conducted by Kim (2023).

In addition to the methodological concerns mentioned above, the sample scope of Chiou et al. (2013) excluded the unsignalized intersections far more than the signalized ones. Vehicle-pedestrian conflicts at intersections that recently gained more attention (Esmaili et al., 2022; Phuksuksakul et al., 2023; Salehian et al., 2023; Xiao et al., 2022; Zhang et al., 2022; Zhang et al., 2023) are also omitted, which underscores the necessity of investigating recent crash data at intersections in Taiwan, including unsignalized intersections and vehicle-pedestrian crashes. Aside from this, Taiwan boasts the highest density of motorcycles globally, including scooters and mopeds, with two-thirds of Taiwanese owning these vehicles (Eccarius & Lu, 2020). As Taiwan is a scooter-dominant urban area (Chen, Fu, & Siao, 2023), examining two-party crash severity at intersections in this setting offers valuable insights into reducing crash severity, particularly for emerging countries like India, Indonesia, and Pakistan.

Srinivasan (2002), Eluru et al. (2008), and Razi-Ardakani et al. (2020) have successively developed or employed generalized ordered-based models to assess crash severity, in which the threshold parameters are formulated as a linear function of exogenous variables. Apart from incorporating the covariates, random and correlation effects are also allowed in the thresholds. Their empirical crash data is also from the General Estimates System (GES) compiled from U.S. police reports. It divided crash severity into four categories: no injury, non-incapacitating injury, incapacitating injury, and fatality. Their results showed that exogenous variables (e.g., gender, speed limit, alcohol use, frontal impact, elder, etc.) impact both latent propensity and thresholds of crash severity in observed and unobserved manners.

Yasmin and Eluru (2013) compared the mixed generalized ordered logit (MGOL) and mixed logit (ML) in modeling driver injury severity, indicating that the MGOL model is comparable to the ML model in terms of statistical performance, elasticity measures, and underreported crash data. Yasmin et al. (2014) formulated the latent segmentation-based generalized ordered logit (LSGOL) model to examine driver injury severity in Victorian Australia. Their results exhibited a substantial difference in crash characteristics between the two distinguished segments (high-risk and low-risk segments). Additionally, the magnitude and sign of variables in injury severity components between the two segments differed for some variables (e.g., gender, weather, season, traffic control device, etc.). Yasmin et al. (2015) applied the MGOL to assess the survival duration of traffic accident victims who suffered from fatal crashes. The residuals from another Emergency Medical Service (EMS) model are included in the MGOL to address the endogeneity. Furthermore, the factors contributing to a decrease or increase in the likelihood of early death are compared according to the model results.

Fountas and Anastasopoulos (2017) proposed a random threshold OP model comparing it with other OP-type models while analyzing single-vehicle crashes on the highway in the State of Washington. Further, the constants in thresholds were specified as random parameters and found to have significant effects, highlighting the existence of threshold-specific unobserved heterogeneity. Zou et al. (2017) employed the spatial generalized ordered probit model (RPSORP) to analyze the severity of single-vehicle and multi-vehicle truck crash injuries. According to their model estimation, the spatial dependency and temporal effects proved to have a significant impact on the crash. Xin et al. (2017) proposed a random parameter generalized ordered probit model, incorporating heterogeneity in means and variances, to analyze pedestrian-vehicle crashes in Florida. They identified significant heterogeneity in mean and variance for the indicator representing elderly pedestrians (ages 50 to 65), particularly in association with intersection indicators. Balusu et al. (2018) investigated the effect of different random parameter specifications on threshold correlation structures. The five scenarios are simulated, showing that correlations result in fewer random parameters in higher order thresholds and bias or loss of accuracy for a few parameter estimates. However, ignoring correlations causes other parameter estimates to be adjusted so that overall likelihood values, predicted percentage shares, and marginal effects are similar to those from models that include correlations.

Zhang et al. (2022) proposed the mixed bivariate generalized ordered probit (MBGOP) model to assess consecutive pedestrian-vehicle conflicts at intersections, heterogeneity in the MBGOP model is now more thoroughly elucidated. Zhang et al. (2023) employed a panel random threshold OP model for the jaywalking crossing behavior. Unlike the previous literature, the model identifies the influencing factors of sequential conflicts, which could account for the panel effects and unobserved heterogeneity simultaneously.

2.3 Latent Class Models Applying Injury Severity

The study by Chiou et al. (2013) has shown that ignorance of the interrelationships between two-party drivers may result in model endogeneity issues, erroneous parameters, and bewildering causality. Therefore, more robust modeling approaches should incorporate the characteristics of all drivers involved in crashes and relevant shared conditions. Given that the previous study mainly focused on signalized intersections and excluded unsignalized intersections and vehicle-pedestrian crashes, there is a need for further investigation using recent data that includes these types of crashes. Recently, many crash severity studies (Cerwick et al., 2014; Chang et al., 2021; Eluru et al., 2012; Fountas et al., 2018; Li et al., 2021; Li & Fan, 2019) adopted latent class ordered probit (LCOP) model for capturing the heterogeneity in crash propensities. The LCOP, grounded in the ordered probit model, posits that crashes can be divided into multiple classes characterized by homogeneous crash propensities within each class. Relevant covariates are employed to delineate these classes.

Eluru et al. (2012) employed a novel latent segmentation-based ordered logit (LSOL) model to assess the impacts of different factors on vehicle drivers' injury severity. Their study emphasized the presence of risk segmentation within the affected grade crossing population due to active warning devices. Cerwick et al. (2014) examined the distinctions between mixed logit and latent class approaches in handling individual unobserved heterogeneity. Their findings indicated an advantage of the latent class method regarding model fit. Shaheed and Gkritza (2014) employed a latent class multinomial logit model to study the determinants of crash severity outcomes in single-vehicle motorcycle crashes. They addressed unobserved heterogeneity by distinguishing two separate crash data classes with homogeneous attributes. Unobserved heterogeneity was acknowledged as a crucial point in traffic safety research that has not been fully solved and often failed to notice. Yasmin et al. (2014) developed and estimated an econometric model known as the latent segmentation-based generalized ordered logit (LSGOL) model to analyze driver injury severity. This model segmented drivers into different injury severity classes according to crash types, acknowledging that the exogenous variables' effects on severity levels may vary among drivers.

Fountas et al. (2018) employed two latent class modeling approaches, namely segment-based and accident-based LCOP models with class probability functions. The comparison between these approaches revealed that the segment-based approach offers a superior overall statistical fit. Li and Fan (2019) were the first to utilize a latent class clustering approach to identify latent classes and categorize crashes based on varying distribution characteristics of contributing factors to pedestrian-vehicle collisions. Chang et al. (2021) conducted a comparative analysis of latent class clustering and latent segmentation-based random parameter models to investigate crash injury severity outcomes. They initially explored the random parameter variant of ordered modeling structure within a latent segmentation modeling framework. Li et al. (2021) examined the impact of rider characteristics, road conditions, pre-crash situations, and crash features on motorcycle severities across various numbers of vehicles involved. Their findings revealed significant variations in severity based on the number of vehicles involved in the crash.

Chu et al. (2022) employed a latent class model to categorize individuals into two classes: red-light-respectful and disrespectful road users. This classification was according to recognize red-light running (RLR) as a significant violation contributing to traffic accidents and injuries. Esmaili et al. (2022) discovered pedestrian crash patterns and uncovered random parameters within the dataset. They employed a two-step approach that combined latent class cluster analysis (LCA) with the mixed logit model to consider unobserved heterogeneity. The results showed that some factors are associated with pedestrian injuries. Xiao et al. (2022) employed latent class cluster analysis alongside an unbalanced panel mixed ordered probit model to explore the severity of injuries in pedestrian-vehicle collisions and discern the factors influencing them. This model offers an alternative approach to identify the determinants of injury severity and address the challenge of heterogeneity within the data.

Gaweesh et al. (2023) conducted a comparative analysis of underlying crash factors using various statistical methods. They utilized structural equation modeling to evaluate latent factors influencing the severity of crashes involving large trucks. Hua et al. (2023) employed latent class clustering and random parameter logit model to identify factors potentially influencing the severity of injuries in SUV overturn crashes. This research is crucial given the irreparable nature of fatal or incapacitating injuries resulting from such crashes. Kim (2023) reviewed the selection of class numbers in empirical applications and the methods used for determination. In safety analyses, it is typical to select the class number according to judgment rather than quantitative measures like BIC. It suggests that the explainability of the latent class model by researchers is crucial, as solutions with numerous classes can complicate the interpretation of models. Kim and Mokhtarian (2023) explored the infinite mixture modeling (latent class modeling) framework, which has garnered attention as an appealing approach. Their study aimed to offer a comprehensive view of its usage landscape and provide insights into its detailed components. Salehian et al. (2023) examined the pedestrian injury severity on UK rural roads and proposed several strategies to alleviate the severity of pedestrian-vehicle collisions. These measures are enhancing lighting conditions, improving pedestrian infrastructure, lowering speed limits in crash-prone areas, and fostering education and awareness among pedestrians and drivers.

2.4 Summary

Chiou et al. (2013) introduced a bivariate generalized ordered probit (BGOP) model to analyze crash risk factors in latent and threshold functions. This model accounts for the interrelationships of two-party drivers' characteristics and common crash factors. The elasticity effects estimated by BGOP with heterogeneous thresholds may demonstrate a bi-modal pattern compared to those without them.

Yasmin et al. (2014) developed the latent segmentation-based generalized ordered logit (LSGOL) model to investigate driver injury severity. Their findings revealed two latent segments. In contrast, this study utilized a latent class bivariate generalized ordered probit model with parameterized correlation, similarly partitioned into two latent classes. The distinction primarily lies in the variable aspect (univariate and bivariate), with both models predicting the likelihood of event occurrence using either logit or probit methods, differing solely in distribution assumptions.

Moreover, Zhang et al. (2022) expanded on the BGOP model, introducing the mixed bivariate generalized ordered probit (MBGOP), which was employed to analyze consecutive pedestrian-vehicle conflicts at intersections in China. The MBGOP model offers a more comprehensive understanding of potential heterogeneity. Both studies utilizing the BGOP model demonstrated that parameterized thresholds within a bivariate ordered response framework could provide valuable insights for proposing safety countermeasures.

Based on the above research, it is evident that the variables related to the intersection crash injury severity encompass various factors, including driver, violation, mode, crash, temporal, and environmental features. This study compiles the literature review's research methods, objectives, severity levels, and crucial variables in Table 2.1.

Table 2.1 Literature summary

Author (Year)	Research Objective	Severity Levels	Crucial Variables						Methodology		
			DR	VI	MO	CR/CO	TE/RO	EN	B	G	LC
Weiss (1993)	Effectiveness of helmets in reducing the severity	6		✓		✓			✓		
Yamamoto and Shankar (2004)	Driver's and passengers' injury severities	5	✓	✓	✓		✓	✓	✓ (BORP)		
de Lapparent (2008)	Willingness to fasten the seatbelt	4	✓			✓	✓		✓		
Schneider et al. (2012)	Interrelationships among drivers/riders at fault and other dangerous behaviors	5	✓		✓	✓	✓		✓ (MP)		
Russo et al. (2014)	Level of injury sustained by drivers	4	✓	✓			✓		✓ (RPBOP)		
Wali et al. (2017)	Relationship between speed limits and drunk driving laws	4		✓					✓		
Chen et al. (2019)	Within-crash correlation and examine risk factors	4	✓	✓			✓	✓	✓ (RPBOP)		
Zhou et al. (2022)	Effectiveness of a helmet policy	5 (usage frequency)					✓		✓		
Russo et al. (2023)	Potential within-crash correlation	4	✓		✓		✓	✓	✓		
Srinivasan (2002)	Assess crash severity, in which the threshold	4	✓		✓	✓	✓			✓	

Author (Year)	Research Objective	Severity Levels	Crucial Variables						Methodology		
			DR	VI	MO	CR/CO	TE/RO	EN	B	G	LC
Eluru et al. (2008)	parameters are formulated as a linear function of exogenous variables	4	✓	✓	✓	✓	✓	✓		✓	
Razi-Ardakani et al. (2020)		4	✓	✓	✓	✓	✓	✓		✓	
Yasmin and Eluru (2013)	Compare the MGOL and ML models in modeling driver injury severity	4	✓	✓	✓	✓	✓	✓		✓ (MGOL)	
Yasmin et al. (2015)	Assess the survival duration of traffic accident victims	7 (fatal injury)	✓			✓	✓	✓		✓ (MGOL)	
Fountas and Anastasopoulos (2017)	Analyze single-vehicle crashes on the highway	4	✓	✓	✓		✓			✓ (RTOP)	
Xin et al. (2017)	Analyze Florida pedestrian-vehicle crashes	5		✓			✓	✓		✓ (RPGOP)	
Zou et al. (2017)	Analyze the severity of crash injuries	4	✓				✓	✓		✓ (SGOP)	
Balusu et al. (2018)	Investigate the effect of different random parameter specifications on threshold correlation structures	4	✓							✓ (MGORP)	
Zhang et al. (2023)	Employ a model for the jaywalking crossing behavior	3 (conflict severity)			✓					✓ (RTOP)	
Eluru et al. (2012)	Identify the different factors that influence the injury severity	3	✓		✓		✓				✓ (2) (LSOL)

Author (Year)	Research Objective	Severity Levels	Crucial Variables						Methodology		
			DR	VI	MO	CR/CO	TE/RO	EN	B	G	LC
Cerwick et al. (2014)	Investigate the differences between the two preferred methods	3	✓	✓	✓	✓	✓	✓			✓ (2)
Shaheed and Gkritza (2014)	Explore the factors that influence the severity of single-vehicle motorcycle collisions	3	✓	✓			✓	✓			✓ (2) (LCMNL)
Fountas et al. (2018)	Compare segment- versus accident-based latent class ordered probit models	4	✓	✓	✓		✓	✓			✓ (2)
Li and Fan (2019)	Identify and classify the crashes with different distribution characteristics	4	✓	✓	✓		✓				✓ (6)
Chang et al. (2021)	Compare the performance of latent class clustering and latent segmentation-based random parameter models	4	✓	✓	✓	✓	✓	✓			✓ (2) (LCROL)
Li et al. (2021)	Investigate the effects of factors on motorcycle severities	5			✓		✓	✓			✓ (2)
Chu et al. (2022)	Explore the effects of observable and unobservable factors on red-light running	4 (RLR frequency)									✓ (2)
Esmaili et al. (2022)	Recognize pedestrian crash patterns and reveal the random parameters	3	✓	✓	✓		✓	✓			✓ (4)

Author (Year)	Research Objective	Severity Levels	Crucial Variables						Methodology		
			DR	VI	MO	CR/CO	TE/RO	EN	B	G	LC
Xiao et al. (2022)	Examine the pedestrian-vehicle crash injury severity	4	✓	✓			✓				✓ (2)
Gaweesh et al. (2023)	Assess latent factors affecting the crash severity of large trucks	2	✓			✓	✓				✓ (2)
Hua et al. (2023)	Identify potential factors that affect the injury severity of overturn crashes involving SUVs	3	✓	✓			✓	✓			✓ (6)
Kim (2023)	Explore how to examine heterogeneity in traffic safety analyses	-									✓ (-)
Kim and Mokhtarian (2023)	Examine the finite mixture modeling framework	-									✓ (-)
Salehian et al. (2023)	Investigate the pedestrian injury severity on rural roads	3	✓		✓	✓	✓	✓			✓ (4)
Chiou et al. (2013)	Enhance the explanation of crash causality under the bivariate model framework	4	✓	✓	✓	✓	✓	✓	✓	✓	
Yasmin et al. (2014)	Examine driver injury severity	3	✓		✓	✓	✓	✓		✓ (LSGOL)	✓ (2)
Zhang et al. (2022)	Assess consecutive pedestrian-vehicle conflicts	3 (conflict severity)			✓				✓	✓	

Author (Year)	Research Objective	Severity Levels	Crucial Variables						Methodology		
			DR	VI	MO	CR/CO	TE/RO	EN	B	G	LC
Notes	Abbreviation for critical variables DR: Driver type VI: Violation type MO: Mode of mobility CR/CO: Crash/collision type TE/RO: Temporal/roadway conditions EN: Environmental B: Bivariate model G: Heterogeneous threshold model LC: Latent class model (2): Two latent classes										

CHAPTER 3 METHODOLOGY

This chapter elaborates on the formulation and estimation for the proposed Parameterized Correlation BGOP, Latent Class Parameterized Correlation BGOP, model identification, and elasticity effects.

3.1 Parameterized Correlation BGOP

The *p*-BGOP is derived from the bivariate ordered probit (BOP). The BOP is a hierarchical system consisting of two severity latent propensity functions that can be employed to model an interrelationship between two-party drivers' injury severities and explore the crash causality (Savolainen et al., 2011). The model approach has been widely utilized in studies of crash severity (Chen et al., 2019; Russo et al., 2014; Russo et al., 2023; Schneider et al., 2012; Wali et al., 2017; Yamamoto & Shankar, 2004; Zhou et al., 2022). However, most literature has constrained the correlation parameter to be constant, thus limiting the discussion on the correlation between injuries sustained by the two parties. By parameterizing the correlation, we can investigate potential causes such as speeding, alcohol, and violations leading to injury correlation between the two parties and how the at-fault driver may cause severe injuries to the victims. The insights gained from these findings would be invaluable for preventing severe crashes.

Let q_n (n = 1, 2) be an index describing two drivers affected in the same accident q (q = 1, 2, …, Q). First-party drivers are typically considered at fault as they take more responsibility for the accident as determined by the police. Suppose $y_{q,n}$ is the observed injury severity that expresses drivers' latent severity propensity. u_{q1} and u_{q2} are threshold values to determine each party driver's observed injury severity levels relative to his corresponding injury propensity in the q crash.

Furthermore, the indices k (k = 1, 2, ..., K) and l (l = 1, 2, ..., L) denote ordinal categories of injury severity that the two-party drivers suffered. Consequently, these drivers' latent injury severity propensities reflect their actual severity, as demonstrated in the following equations:

$$\begin{aligned} y_{q1}^{*} &= k; if\ u_{1,k-1} < y_{q1}^{*} < u_{1,k} \\ y_{q2}^{*} &= l; if\ u_{2,l-1} < y_{q2}^{*} < u_{2,l} \end{aligned} \quad (3.1)$$

Afterward, the simultaneous equation system obtained by modeling the two drivers' injury severity engaged in a two-party crash is represented as Equation (3.2) respectively:

$$
\begin{aligned}
y_{q1}^* &= \beta_{q1}' X_{q1} + \varepsilon_{q1} \\
y_{q2}^* &= \beta_{q2}' X_{q2} + \varepsilon_{q2}
\end{aligned}
\tag{3.2}
$$

where X_{qn} is the estimable variable vector incorporating common causes and two-party individual driving characteristics engaged in the same crash *q*; β_{qn} is the corresponding parameter vector, and ε_{qn} denotes the random components that capture all unobservable errors associated with the two engaged party drivers. Given the bivariate normal distribution $\Phi_2(\cdot)$ assumption in random errors, the joint probability of two drivers (n = 1, 2) engaged in the same accident may be defined accordingly:

$$
\begin{aligned}
&Pr(u_{1,k-1} < y_{q1}^* < u_{1,k};\ u_{2,\ell-1} < y_{q2}^* < u_{2,\ell}) \\
&= Pr(u_{1,k-1} < \beta_1' X_{q1} + \varepsilon_{q1} < u_{1,k};\ u_{2,\ell-1} < \beta_2' X_{q2} + \varepsilon_{q2} < u_{2,\ell}) \\
&= Pr(u_{1,k-1} - \beta_1' X_{q1} < \varepsilon_{q1} < u_{1,k} - \beta_1' X_{q1};\ u_{2,\ell-1} - \beta_2' X_{q2} < \varepsilon_{q2} < u_{2,\ell} - \beta_2' X_{q2}) \\
&= \Phi_2(u_{1,k} - \beta_1' X_{q1}, u_{2,\ell} - \beta_2' X_{q2}\,; \rho) - \Phi_2(u_{1,k-1} - \beta_1' X_{q1}, u_{2,\ell} - \beta_2' X_{q2}\,; \rho) \\
&- \Phi_2(u_{1,k} - \beta_1' X_{q1}, u_{2,\ell-1} - \beta_2' X_{q2}\,; \rho) + \Phi_2(u_{1,k-1} - \beta_1' X_{q1}, u_{2,\ell-1} - \beta_2' X_{q2}\,; \rho)
\end{aligned}
\tag{3.3}
$$

where ρ is an estimated correlation parameter between ε_{q1} and ε_{q2}, moreover, a parameterized correlation formulated as a current parameterized function: $\tilde{\rho} = \kappa + \varphi\tau$, in addition, κ is the constant; τ is the covariate vector that includes shared factors between two parties, and φ is the associated parameter vector. Through this, rewrites the Equation (3.3) as:

$$
\begin{aligned}
&Pr(u_{1,k-1} < y_{q1}^* < u_{1,k};\ u_{2,\ell-1} < y_{q2}^* < u_{2,\ell}) \\
&= \Phi_2(u_{1,k} - \beta_1' X_{q1}, u_{2,\ell} - \beta_2' X_{q2}\,; \tilde{\rho}(\tau)) - \Phi_2(u_{1,k-1} - \beta_1' X_{q1}, u_{2,\ell} - \beta_2' X_{q2}\,; \tilde{\rho}(\tau)) \\
&- \Phi_2(u_{1,k} - \beta_1' X_{q1}, u_{2,\ell-1} - \beta_2' X_{q2}\,; \tilde{\rho}(\tau)) + \Phi_2(u_{1,k-1} - \beta_1' X_{q1}, u_{2,\ell-1} - \beta_2' X_{q2}\,; \tilde{\rho}(\tau))
\end{aligned}
\tag{3.4}
$$

The formulation of Bivariate Generalized Ordered Probit (BGOP) is adopted from the study by Chiou et al. (2013). Typically, the thresholds $u_{1,k}$ and $u_{2,\ell}$ in the BOP are expressed as the fixed constants for any two ordinal injury levels, representing the probability at specific observable injury levels. These constant thresholds assume homogeneity of injury risk propensity for each involved driver, which may not capture the potential endogeneity between thresholds and certain variables. Therefore, the current study assumed that the two thresholds subscripted by index q vary across crashes for each involved driver to account for individual intrinsic features in injury risk propensity (Eluru et al., 2008).

$$
\begin{aligned}
&y_{q1}^{*} = k, if\ \tilde{u}_{q1,k-1} < y_{q1,k}^{*} < \tilde{u}_{q1,k} \\
&y_{q2}^{*} = l, if\ \tilde{u}_{q2,l-1} < y_{q2,l}^{*} < \tilde{u}_{q2,l}
\end{aligned} \tag{3.5}
$$

For each crash q, parametric functions are set for two-party drivers' thresholds. The boundary ranges between the thresholds of the two parties are expressed as ($-\infty < \tilde{u}_{q1,1} < \tilde{u}_{q1,2} < \ldots < \tilde{u}_{q1,K-1} < \infty$) and ($-\infty < \tilde{u}_{q2,1} < \tilde{u}_{q2,2} < \ldots < \tilde{u}_{q2,L-1} < \infty$) to satisfy the ordering conditions. For the two-party drivers, their threshold functions are:

$$
\begin{aligned}
&\tilde{u}_{q1,k} = \tilde{u}_{q1,k-1} + exp(\alpha_k + \gamma_{q,k}'.Z_{q,k}) \\
&\tilde{u}_{q2,l} = \tilde{u}_{q2,l-1} + exp(\theta_\ell + \delta_{q,l}'.Z_{q,l})
\end{aligned} \tag{3.6}
$$

where $\gamma_{q,k}'$ and $\delta_{q,l}'$ injury level-specific row parameterizing vectors are to be estimated, $Z_{q,k}$ and $Z_{q,l}$ are corresponding column vectors of exogenous variable. $\alpha_{q,k}$ and $\theta_{q,l}$ are constants included in these threshold functions. $\tilde{u}_{q1,k}$ and $\tilde{u}_{q2,l}$ are corresponding thresholds linking to the preceding parameters and exogenous variable vector.

The study uses the Maximum Likelihood Estimation (MLE) to estimate the parameters mentioned above $\beta_1', \beta_2', \tilde{u}_{q1}(\gamma_k', \alpha_{q,k}), \tilde{u}_{q2}(\theta_k', \varsigma_{q,k})$, and $\tilde{\rho}(\tau)$. Considering both parties, the log-likelihood of the BGOP model is:

$$
\begin{aligned}
&LL = \sum Ln\{\Phi_2\big(\tilde{u}_{q1,k} - \beta_1'X_{q1}, \tilde{u}_{q2,l} - \beta_2'X_{q2}\,; \tilde{\rho}(\tau)\big)\} \\
&- \Phi_2(\tilde{u}_{q1,k-1} - \beta_1'X_{q1}, \tilde{u}_{q2,l} - \beta_2'X_{q2}\,; \tilde{\rho}(\tau)) \\
&- \Phi_2(\tilde{u}_{q1,k} - \beta_1'X_{q1}, \tilde{u}_{q2,l-1} - \beta_2'X_{q2}\,; \tilde{\rho}(\tau)) \\
&+ \Phi_2(\tilde{u}_{q1,k-1} - \beta_1'X_{q1}, \tilde{u}_{q2,l-1} - \beta_2'X_{q2}\,; \tilde{\rho}(\tau))\big\}
\end{aligned} \tag{3.7}
$$

where the coefficients (β_1', β_2') with positive or negative signs represent the increase (decrease) in the severity of the latent injury risk propensity, the coefficients ($\gamma_k', \alpha_{q,k}$,

$\theta_k', \varsigma_{q,k}$) of the threshold variable are estimated to determine the cut-off values varying across drivers, capturing the heterogeneity within them.

Furthermore, the above model parameters are estimated by the maximum likelihood method through the GAUSS software, and the coefficients are obtained through an iterative process based on BGOP through trial and error for the optimal solution. Since the model estimation process is programmed, it is directly written in the likelihood function to make it clear. For identification, the first thresholds $\tilde{u}_{q1,1}$ and $\tilde{u}_{q2,1}$ are typically set to zero for the party drivers' severity at the same crash. In addition, the *p*-BGOP model restricts all non-constant parameters in the threshold function to zero.

3.2 Latent Class Parameterized Correlation BGOP

The LCp-BGOP formulation draws inspiration from the BGOP and the latent segmentation-based generalized ordered logit (LSGOL) model developed by Yasmin et al. (2014). In our study, two-party severities (driver, motorcyclist, biker, or pedestrian) can be classified into multiple classes or segments based on crash characteristics. These classes demonstrate a relatively homogeneous crash propensity for two parties within each class but exhibit inherent differences in the pattern of injury severity across different segments (Eluru et al., 2012).

The LCp-BGOP can be separated into two distinct components. The first represents the probability that characterizes latent crash severity propensities within a class, as determined by the parameterized correlation BGOP (p-BGOP). The parameters estimated by p-BGOP for any two-party crash remain identical within the classes but vary across classes. The second manifests the probability that a two-party crash belongs to a given class, formulated in multinomial logit form (MNL) (Chang et al., 2021; Eluru et al., 2012; Yasmin et al., 2014).

Let c be the index for classes (c = 1, 2, …, C), and q_n be the index describing two parties affected at the intersection crash q (q = 1, 2, …, Q), where n denotes the specific party (i.e. q_1, q_2). The first parties are commonly referred to as at-fault, as they take more responsibility for the accident as determined by the police. k (k = 1, 2, ..., K) and l (l = 1, 2, ..., L) are indices expressing ordinal categories of injury severity by the two parties. Therefore, the probability $P_q(k,l)$ of the two parties sustaining injury severity (k,l) is formulated as:

$$P_q(k,l) = \sum_{c=1}^{C} P_q(q_1 = k, q_2 = l|c) \cdot M_q(c) \tag{3.8}$$

where $P_q\left(q_1 = k, q_2 = l\middle|c\right)$ represents the conditional probability for class c that the two parties (q_1, q_2) sustained injury severity k and l in the crash q, respectively. The class membership component $M_q(c)$ indicates the probability that the two-party crash q belongs to class c. The formulation of both class-specific and class-membership probabilities is detailed as follows:

For a specific class c, the observed discrete injury severity of two parties, $y_{q1,k}$ and $y_{q2,l}$, is assumed to be mapped to their latent and continuous injury propensities, $y^*_{q1,k|c}$ and $y^*_{q2,l|c}$, as follows:

$$\begin{aligned} &y^*_{q1,k|c} = X_{q1}\beta_{1|c} + \varepsilon_{q1,k|c}, y_{q1|c} = k, if\ \tilde{u}_{q1,k-1|c} < y^*_{q1,k} < \tilde{u}_{q1,k|c} \\ &y^*_{q2,l|c} = X_{q2}\beta_{2|c} + \varepsilon_{q2,l|c}, y_{q2|c} = l, if\ \tilde{u}_{q2,l-1|c} < y^*_{q2,l} < \tilde{u}_{q2,l|c} \end{aligned} \tag{3.9}$$

where $X_{qn=1,2}$ is the exogenous variable vector (including constants as its first element) incorporating generic factors, as well as individual and driving characteristics for the two parties involved in the crash q, $\beta_{1|c}$ and $\beta_{2|c}$ are corresponding column vectors of unknown parameters specific to class c. $\varepsilon_{q1|c}$ and $\varepsilon_{q2|c}$ are class-specific random error components that capture all unobserved factors regarding two parties.

The heterogeneous thresholds, $\tilde{u}_{q1,k|c}$ and $\tilde{u}_{q2,l|c}$ $(\tilde{u}_{q1,0|c} = -\infty, \tilde{u}_{q1,k|c} = \infty;\ \tilde{u}_{q2,0|c} = -\infty, \tilde{u}_{q2,l|c} = \infty)$ are related to the severity levels k and l, given the class-specific upper threshold. These heterogeneous thresholds are parametric functions and represent the boundary range between the thresholds of the two parties, expressed as $(-\infty < \tilde{u}_{q1,1|c} < \tilde{u}_{q1,2|c} < \ldots < \tilde{u}_{q1,K-1|c} < \infty)$ and $(-\infty < \tilde{u}_{q2,1|c} < \tilde{u}_{q2,2|c} < \ldots < \tilde{u}_{q2,L-1|c} < \infty)\ \forall\ c = 1, 2, \ldots, C$ to satisfy the ordering conditions. Additionally, $\tilde{u}_{q1,k|c}$ and $\tilde{u}_{q2,l|c}$ are formulated as linear combinations in an exponential form to meet the above conditions (Chiou et al., 2013; Yasmin et al., 2014), as shown in the following equations:

$$\begin{aligned} &\tilde{u}_{q1,k|c} = \tilde{u}_{q1,k-1|c} + exp(\alpha_{q1,k|c} Z_{q1,k|c}) \\ &\tilde{u}_{q2,l|c} = \tilde{u}_{q2,l-1|c} + exp(\alpha_{q2,l|c} Z_{q2,l|c}) \end{aligned} \tag{3.10}$$

where $\alpha_{q1,k|c}$ and $\alpha_{q2,l|c}$ are injury level-specific row vectors of estimable parameters conditional on class c, utilized to determine the intrinsic heterogeneity within injury risk propensity. $Z_{q1,k|c}$ and $Z_{q2,l|c}$ are corresponding column vectors of exogenous variable (including constants as its first element) associated with the inherent systematic variation in injury risk propensity. $\tilde{u}_{q1,k-1|c}$ and $\tilde{u}_{q2,l-1|c}$ represent the thresholds for the two-party severity levels described above.

Furthermore, under the bivariate normal distribution $\Phi_2(\cdot)$ assumption in random errors and the formulation above, the joint probability $P_q(k, l|c)$ that the two parties suffer two specific injury severity levels ($q_1 = k,\ q_2 = l$) belonging to class c in the q intersection crash is:

$$
\begin{aligned}
&P_q(q_1 = k, q_2 = l|c) \\
&= \tilde{u}_{q1,k-1|c} < y^*_{q1,k} < \tilde{u}_{q1,k|c}\,;\, \tilde{u}_{q2,l-1|c} < y^*_{q2,l} < \tilde{u}_{q2,l|c} \\
&= \Phi_2(\tilde{u}_{q1,k|c} - X_{q1}\beta_{1|c}, \tilde{u}_{q2,l|c} - X_{q2}\beta_{2|c}\,;\tilde{\rho}_{q|c}) \\
&- \Phi_2(\tilde{u}_{q1,k-1|c} - X_{q1}\beta_{1|c}, \tilde{u}_{q2,l|c} - X_{q2}\beta_{2|c}\,;\tilde{\rho}_{q|c}) \\
&- \Phi_2(\tilde{u}_{q1,k|c} - X_{q1}\beta_{1|c}, \tilde{u}_{q2,l-1|c} - X_{q2}\beta_{2|c}\,;\tilde{\rho}_{q|c}) \\
&+ \Phi_2(\tilde{u}_{q1,k-1|c} - X_{q1}\beta_{1|c}, \tilde{u}_{q2,l-1|c} - X_{q2}\beta_{2|c}\,;\tilde{\rho}_{q|c})
\end{aligned}
\tag{3.11}
$$

where $\tilde{\rho}_{qc}$ is specified as a non-linear parameterized correlation function rather than a constant, which significantly differentiates from the BGOP as follows:

$$\tilde{\rho}_{q|c} = Ln\big(exp(\gamma_{q|c}\varpi_{q|c})\big) \tag{3.12}$$

where $\varpi_{q|c}$ represents the covariate vector (including a constant as its first element) consisting of exogenous variables that characterize the unobservable factor regarding the correlation between ε_{q1} and ε_{q2}; $\gamma_{q|c}$ denotes the corresponding parameter vector. The correlation pattern of both-party severities $\tilde{\rho}_{q|c}$ remains identical within a specific class but varies across classes.

As mentioned above, the $M_q(c)$ is the probability that the two-party crash q belongs to class c. In the typical MNL, the class membership component can be expressed as follows:

$$M_q(c) = \frac{exp(\theta_c\eta_q)}{\sum_{c=1}^{C} exp(\theta_c\eta_q)} \tag{3.13}$$

where η_q is a vector of covariates (including a constant as its first element) that captures class-specific characteristics and determines the class probabilities for each crash q, θ_c is a vector of the corresponding membership function of class c. Using the membership function, we can derive the probability of any two-party crash belonging to that class. The class size is calculated as the average membership probability of each collision.

3.3 Model Identification and Estimation

The study employs MLE to estimate the aforementioned parametric vectors in the following log-likelihood function:

$$LL = \sum_{q=1}^{Q} Ln\{\sum_{c=1}^{C} P_q(\beta_1, \beta_2, \tilde{u}_{q1,k}(\alpha_{q1,k}), \tilde{u}_{q2,l}(\alpha_{q2,l}), \tilde{\rho}_q(\gamma_q)|c) \cdot M_q(\theta|c)\} \quad (3.14)$$

For identification, the first thresholds $\tilde{u}_{q1,1}$ and $\tilde{u}_{q2,1}$ in the crash latent propensity are set to zero, and the θ_c vector for the base class in the membership function. Since the number of classes is unknown to analysts, this study determines the desirable class number based on the highest improvement in goodness-of-fit and many significant coefficients. As such, the model information criteria (Chang et al., 2021; Eluru et al., 2012; Esmaili et al., 2022; Shaheed & Gkritza, 2014), such as the Bayesian information criterion (BIC), the constrained Akaike information criterion (CAIC), are employed, alongside class sizes and the number of significant variables (Chen, Fu, & Chen, 2023). The greater the number of classes, the less goodness-of-fit can be achieved, accompanied by more insignificant variables within and across classes. In addition, the entropy value ranging from 0 to 1 serves as another criterion for selecting the latent class number (Ramaswamy et al., 1993). A higher entropy value means a better model fit and the class number of interests. These metrics are defined as follows.

$$\rho^2 = [LL(\beta) - LL(C)]/LL(C) \quad (3.15)$$

Here, $LL(\beta)$ represents the log-likelihood function value with all significant variables and the constant; $LL(C)$ represents the log-likelihood function value when the model only considers the constant. A higher ρ^2 value indicates a better overall fit.

$$BIC = -2LL(\beta) + C_j(Ln(Q)) \quad (3.16)$$

$$CAIC = -2LL(\beta) + C_j(Ln(Q) + 1) \quad (3.17)$$

$$Entropy = 1 - \frac{\sum_q \sum_c(-\hat{P}_{qc} Ln\hat{P}_{qc})}{qLn(c)} \quad (3.18)$$

Here, C_j represents the number of parameters, and Q is the total sample size. BIC and CAIC initially decrease as the number of sample classes increases. However, as the number of classes grows, they increase due to the penalty for parameters. Therefore, the optimal number of sample classes is when BIC and CAIC approach their minimum values.

As Bhat (1997) suggested, estimating the log-likelihood function using typical routines in the Latent Class model can be computationally unstable. Therefore, relying on simple models and computationally tractable values may be necessary. The *p*-BGOP is a degenerate case of the LC*p*-BGOP constrained to one class (c = 1), and its results can identify significant estimates to offer good initial values for the LC*p*-BGOP model estimations. With a pre-specified number of classes, the LC*p*-BGOP can implement estimations via the Gauss Matrix programming language in the current estimation work.

Table 3.1 The evolution of models

Model	Difference	Objective
OP	Univariate	Address ordinality in independent variables
BOP	Bivariate	Handle two ordinal variables simultaneously
BGOP	Threshold	Observe the significance of the variables' net effect
p-BGOP	Parameterized	Explain the sources of heterogeneity among classes
LC*p*-BGOP	Latent class	Examine the correlation between the severity

3.4 Elasticity Effects

To further comprehend the influence of variables on severity, calculate elasticity utilizing the following equation:

$$E_{X_{i,k}}^{P(k)} = \frac{\partial P(k)}{\partial X_{i,k}} \times \frac{X_{i,k}}{P(k)} \tag{3.19}$$

$$E_{X_{i,k}}^{P(k)} = \frac{\partial lnP(y_{q,n,k}=k)}{\partial lnX_{q,k}} = \frac{\Phi(u_{q,n,k-1} - \beta' x_{q,n}) - \Phi(u_{q,n,k} - \beta' x_{q,n})}{\Phi(u_{q,n,k} - \beta' x_{q,n}) - \Phi(u_{q,n,k-1} - \beta' x_{q,n})} \beta x_{q,n} \tag{3.20}$$

In this equation, $E_{X_{i,k}}^{P(k)}$ denotes the elasticity percentage of the variable *i* on severity level k, $P(k)$ represents the probability of severity level *k*, and $X_{i,k}$ signifies the impact of variable *i* on severity level *k*.

Elasticity refers to the percentage change in the probability $P(k)$ of severity level *k* when the explanatory variable $X_{q,k}$ changes by 1%. However, when $X_{q,k}$ is a dummy variable, the traditional definition of elasticity may lead to biased and distorted results. In such cases, it becomes necessary to calculate the pseudo elasticity, as shown in Equation (3.21). This expression illustrates the percentage effect of changing the variable from 0 to 1, where $x_{q,n,i}$ denotes the *i*th variable of the *n*th party and $\beta_{q,i}$ represents the corresponding variable vector.

$$E_{X_{i,k}}^{P(k)} = \frac{\begin{gathered}\Phi\left[u_{q,n,k} - \left(\beta_q' x_{q,n} + \beta_{q,i}'\left(1 - x_{q,n,i}\right)\right)\right] - \Phi\left[u_{q,n,k-1} - \left(\beta_q' x_{q,n} + \beta_{q,i}'\left(1 - x_{q,n,i}\right)\right)\right] \\ - \Phi\left[u_{q,n,k} - \left(\beta_q' x_{q,n} - \beta_{q,i}' x_{q,n,i}\right)\right] + \Phi\left[u_{q,n,k-1} - \left(\beta_q' x_{q,n} - \beta_{q,i}' x_{q,n,i}\right)\right]\end{gathered}}{\Phi(u_{q,n,k} - \beta_q' x_{q,n}) - \Phi(u_{q,n,k-1} - \beta_q' x_{q,n})} \tag{3.21}$$

CHAPTER 4 EMPIRICAL SETTING AND DATA

4.1 Data Sources and Crash Severity Classification

From 2018 to 2020, there are 59,001 crashes in Taipei City with marked crash location information. Among these, 33,740 occurred within intersections (about 57.2% of all crashes). This study focused on 32,308 two-party intersection crashes, excluding self-collision and crashes involving more than two parties. The analyzed dataset includes 28,863 two-vehicle accidents (about 90% of those crashes) and 3,445 vehicle-pedestrian crashes, to examine the crash severity involving two parties. The parties involved in the collisions were drivers, riders, and pedestrians, with passengers excluded from consideration.

Based on the information provided in the Taiwanese official road accident investigation report, the dataset initially classifies crash severity into three categories: A1 (death within 24 hours), A2 (injury or death occurred between 2 and 30 days), and A3 (property damage only). However, due to the uneven distribution of crash counts and the scarcity of fatalities (0.1% for the first party; 0.3% for the second party) under this classification, the study categorizes crash severity into three levels referring to the KABCO scale (Eluru et al., 2008; Kim et al., 2010; Li & Fan, 2019): property damage only (PDO), minor/possible injury ("C"), and fatal/evident injury ("K/A/B"). Among these, the "fatal/evident" injury crashes comprise those involving "death within 24 hours", "death occurred between 2 and 30 days", and those involving "head, neck, chest, and multiple body parts" injuries. The remaining crashes are minor/possible injuries.

Due to the limitation on the injury status in the Taiwanese official road accident investigation report, the severity status was categorized as "death within 24 hours", "death occurred between 2 and 30 days", "injured", "not injured", and "unknown". The current analysis excludes those crashes whose injury status is unknown.

Table 4.1 presents the cross-tabulation of the two-party severity levels. The total number of cases involving PDO for the first party is higher than those for the second party (i.e., 20,228 vs. 6,863). In contrast, the fatalities and injuries for the first party are fewer than those of the second party (i.e., minor/possible: 11,637 vs. 23,560; fatal/evident: 443 vs. 1,885). Since the first parties are usually deemed at fault, leading to the injury of the second party, the finding may confirm the assertion less or more. It underscores the necessity of modeling the interrelationship of the two-party injuries since the factors of the two-party crashes are intertwined rather than modeling the party with a higher injury.

Table 4.1 Cross-tabulation by the severity levels of two parties

First party (1st)	Second party (2nd)							
	PDO		Minor/Possible		Fatal/Evident		Total	
PDO	122	(0.6%)	18,514	(91.5%)	1,592	(7.9%)	20,228	(62.6%)
"C"	6,493	(55.8%)	4,889	(42.0%)	255	(2.2%)	11,637	(36.0%)
"K/A/B"	248	(56.0%)	157	(35.4%)	38	(8.6%)	443	(1.4%)
Total	6,863	(21.2%)	23,560	(72.9%)	1,885	(5.8%)	32,308	(100.0%)

Table 4.2 summarizes the sample characteristics of the crash variables in the estimation dataset. After excluding the data beyond the research scope, the dataset comprises two-party crashes occurring at intersections. The crash variables considered in the study can be classified into eight categories. Certain variables, such as driver type, violation type, mode of mobility, and collision impact, are collected from either party. The remaining variable types, including crash, temporal, roadway, and environmental factors, are cross-party.

Among these crashes, males (*DM*) account for more than 65% in both parties. Elderly (*DO*) constitute nearly 10% of both parties. Young individuals (*DY*) are more than 15% of both parties, with the second party even at 30%. Regarding violation type, "not yielding to the right-of-way vehicles (*VLOY*)", "turning without following the right-of-way (*VLOT*)", and "inattentive to the vehicles ahead (*VLOI*)" are the top three violations involving the first party, each accounting for nearly or more than 10% of cases, while "speeding (*VLOS*)", "not wearing safety equipment (helmet, seatbelt) (*VLOE*)", and "inattentive to the vehicles ahead (*VLOI*)" are the top three violations involving the second party, each near or exceeding 8%. It is noteworthy that the top two violations for each party vary. In terms of the mode of mobility, "small vehicle (*VHS*)" and "motorcycle/moped (*VHM*)" are the top two modes involved in crashes for both parties. In particular, the percentage of the first party involved in *VHS* crashes is nearly 50%, remarkably higher than the second party (17%). Conversely, the second party involved in *VHM* crashes is almost 70%, significantly higher than the first (44%). Notably, "pedestrians (*VHP*)" are involved in nearly 10% of crashes where they constitute the second party. As for the collision portion of each vehicle, frontal and side collisions for two-wheel vehicles (*COFT/COST*) are prevalent, accounting for more than 17% of such crashes. The percentage of the second party involved in two-wheeled vehicle crashes is higher than that of the first party. Notably, side collisions in four-wheeled vehicles (*COSF*) account for 14% of first-party collisions.

The following crash variables are generic. The top three crash-type variables are "T-bone (*CST*, 28%)", "sideswipe-same direction (*CSS*, 14%)", and "angular (*CSA*, 13%)". As for the roadway conditions, more than half of crashes are at four-leg intersections (*RFI*), accounting for 64%, followed by three-leg intersections (*RTI*, 31%). 35% of intersections have traffic signals (*RTS*) or physical median strips (*RPM*). Lane marking lines (*RLM*) are present in over half of the intersections (66.2%). Most crashes (79.8%) occur on the dry road surfaces (*RD*). Regarding the environment, 65.6% occur on sunny days (*ES*). Nearly 32% of crashes occur at illuminated intersections at night (*EL*).

Based on research conducted by Benlagha and Charfeddine (2020), male drivers exhibit a higher propensity for engaging in extreme risk-taking behavior. With the empirical insights, a novel approach to rate-making is proposed to enhance road safety and prevention.

Additionally, Shannon et al. (2018) discovered that the relative velocity at impact and dark conditions contribute to increased predicted costs, while crashes such as rear-end, truck involved, and occurring during turns result in lower predicted compensations, the availability of airbags in the vehicle emerged as a significant factor. Therefore, the variables affecting injury severity can offer better information to insurance as a basis for compensation.

Table 4.2 Descriptive statistics for crash variables

Variables	Description (Scale)	1st	2nd	Cross
Driver type				
DM	if the driver is male (1) or female (0)*	75.3%	67.5%	
DY	if the driver's age is between 18 and 24 years old (1) or not (0)*	15.4%	31.6%	
DO	if the driver's age is equal to or greater than 65 years old (1) or not (0)*	10.2%	9.2%	
Violation type				
VLOE	if the driver/rider does not wear safety equipment (helmet, seatbelt) (1) or not (0)*	2.9%	12.1%	
VLOL	if the driver/rider is unlicensed (1) or not (0)*	4.1%	3.0%	
VLOD	if the driver/rider is drunk driving (1) or not (0)*	0.5%	1.3%	
VLOY	if the driver/rider does not yield to the right-of-way vehicles (1) or not (0)*	24.0%	2.2%	
VLOT	if the driver/rider turns without following the right of way (1) or not (0)*	19.2%	2.2%	
VLOR	if the driver/rider makes a U-turn without permission (1) or not (0)*	2.6%	0.2%	
VLOS	if the driver/rider speeding (1) or not (0)*	1.3%	15.0%	
VLOC	if the driver/rider fails to give the right-of-way to pedestrians (1) or not (0)*	5.5%	0.2%	
VLOK	if the driver/rider fails to keep a safe distance while driving/riding (1) or not (0)*	2.2%	1.3%	
VLOI	if the driver/rider is inattentive to the vehicles ahead (1) or not (0)*	9.3%	7.8%	
VLOR	if the driver/rider runs red lights (1) or not (0)*	6.5%	1.6%	
VLOSP	if the driver/rider does not comply with the posted traffic sign and marking (1) or not (0)*	2.3%	1.8%	
VLOH	if the driver/rider commits hit-and-run (1) or not (0)*	4.1%	0.3%	
VLOP	if the driver/rider parks without permission (1) or not (0)*	0.1%	0.3%	
VLOPE	if the pedestrian fails to comply with regulation while crossing (1) or not (0)*	0.7%	2.3%	
Mode of mobility				
VHL	if the involved vehicle is a large vehicle (bus, truck, or trailer) (1) or not (0)*	1.6%	0.5%	
VHS	if the involved vehicle is a small vehicle (passenger car or light truck) (1) or not (0)*	50.5%	16.7%	
VHM	if the involved vehicle is a motorcycle or moped (1) or not (0)*	44.4%	69.3%	
VHB	if the involved vehicle is a bike (bicycle or motorbike) (1) or not (0)*	2.3%	3.6%	
VHP	if a pedestrian is involved in the crash (1) or not (0)*	0.9%	9.3%	
Crash type (collision over two vehicles)				
CSH	if the involved crash is a head-on collision (1) or not (0)*			0.3%

Variables	Description (Scale)	1st	2nd	Cross
CSO	if the involved crash is an opposite-direction sideswipe collision (1) or not (0)*			3.9%
CSS	if the involved crash is a same-direction sideswipe collision (1) or not (0)*			13.9%
CSR	if the involved crash is a rear-ended collision (1) or not (0)*			6.0%
CSA	if the involved crash is an angular collision (1) or not (0)*			13.0%
CST	if the involved crash is a T-bone collision (1) or not (0)*			28.2%
Collision type (Collision portion of each vehicle)				
COFF	if the collision type is on the front of a four-wheel vehicle (1) or not (0)*	9.3%	3.6%	
COSF	if the collision type is on the side of a four-wheel vehicle (1) or not (0)*	14.3%	4.0%	
CORF	if the collision type is on the rear of a four-wheel vehicle (1) or not (0)*	0.7%	1.1%	
COFT	if the collision type is on the front of a two-wheel vehicle (1) or not (0)*	17.7%	29.7%	
COST	if the collision type is on the side of a two-wheel vehicle (1) or not (0)*	20.2%	30.7%	
CORT	if the collision type is on the rear of a two-wheel vehicle (1) or not (0)*	2.7%	5.1%	
Temporal				
TW	if the crash occurred on the weekend (1) or not (0)*			22.0%
TND	if the crash occurred during the late night to dawn of the next day (1) or not (0)*			4.8%
Roadway conditions				
RPR	if the crash occurred on a provincial-level road (with a relatively high design speed and sight distance, compared to municipal-level) (1) or not (0)*			11.5%
RMR	if the crash occurred on a municipal-level road (with a relatively low design speed and sight distance, compared to provincial-level) (1) or not (0)*			2.5%
RLK	if the speed limits are less than or equal to 30 kph (1) or not (0)*			15.6%
RHK	if the speed limits are greater than or equal to 60 kph (1) or not (0)*			0.8%
RTI	if the crash occurred at a three-leg intersection (1) or not (0)*			31.5%
RFI	if the crash occurred at a four-leg intersection (1) or not (0)*			62.4%
RMI	if the crash occurred at a multiple-leg intersection (1) or not (0)*			6.1%
RV	if the intersection visibility is poor (1) or not (0)*			2.0%
RTS	if the intersection has no traffic signal (1) or not (0)*			35.7%
RPM	if the intersection has physical median strips (1) or not (0)*			34.2%
RLM	if the intersection has no lane marking (1) or not (0)*			66.2%
RD	if the crash occurred on a dry road surface (1) wet or other surfaces (0)*			79.8%

Variables	Description (Scale)	1st	2nd	Cross
RW	if the crash occurred on a wet road surface (1) dry or other surfaces (0)*			20.1%
Environment				
ES	if the crash is on a sunny day (1) cloudy and rainy (0)*			65.6%
EC	if the crash is on a cloudy day (1) sunny and rainy (0)*			16.8%
ER	if the crash is on a rainy day (1) sunny and cloudy (0)*			17.7%
EL	if the crash is at an illuminated intersection in the night (1) or not (0)*			31.9%

* Base categories (level)

4.2 Variable Description

The collected variables were categorized into five main categories based on the literature: driver characteristics, vehicle characteristics, crash characteristics, temporal characteristics, and roadway/environment characteristics, as shown in the following arrangement.

1. Driver characteristics

   A. Gender: Male and female drivers were divided into two groups to analyze the relationship between gender and injury severity. Males were more likely to be at fault, with a higher percentage of PDO, while females were more likely to be involved in level "K/A/B" injuries than males.

Table 4.3 Injury severity table by driver's gender

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
Male	16,461 (67.7%)	7,571 (31.1%)	296 (1.2%)	24,328	5,758 (26.4%)	15,008 (68.8%)	1,045 (4.8%)	21,811
Female	3,767 (47.2%)	4,066 (51.0%)	147 (1.8%)	7,980	1,105 (10.5%)	8,552 (81.5%)	840 (8.0%)	10,497

   B. Age: Grouped by driver age, there was a high proportion of PDOs when the first-party driver was between ages 25 and 64, and a higher proportion of level "K/A/B" injuries when the second-party driver was under 18 or older than 65.

Table 4.4 Injury severity table by driver's age

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
Age < 18	61 (25.2%)	176 (72.7%)	5 (2.1%)	242	16 (4.7%)	290 (85.0%)	35 (10.3%)	341
18 to 24	1,822 (36.5%)	3,103 (62.2%)	63 (1.3%)	4,988	698 (9.5%)	6,340 (86.4%)	300 (4.1%)	7,338
25 to 64	16,321 (68.6%)	7,172 (30.2%)	293 (1.2%)	23,786	5,647 (26.1%)	14,922 (68.9%)	1,102 (5.1%)	21,671
Age ≥ 65	2,024 (61.5%)	1,186 (36.0%)	82 (2.5%)	3,292	502 (17.0%)	2,008 (67.9%)	448 (15.1%)	2,958

C. Alcohol use: When the driver has been driving under the influence of alcohol, a higher percentage of level "K/A/B" injuries will occur, based on the alcohol concentration detected in the police drunk driving test.

Table 4.5 Injury severity table by driver's drinking status

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
No	20,140 (62.7%)	11,589 (36.1%)	406 (1.3%)	32,135	6,851 (21.3%)	23,497 (72.9%)	1,874 (5.8%)	32,222
Yes	88 (50.9%)	48 (27.7%)	37 (21.4%)	173	12 (14.0%)	63 (73.3%)	11 (12.8%)	86

D. Speeding: When the first party engages in speeding behavior, it increases the risk of injury to itself.

Table 4.6 Injury severity table by speeding situation

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
No	20,104 (63.1%)	11,328 (35.5%)	440 (1.4%)	31,872	6,099 (22.2%)	19,659 (71.6%)	1,715 (6.2%)	27,473
Yes	124 (28.4%)	309 (70.9%)	3 (0.7%)	436	764 (15.8%)	3,901 (80.7%)	170 (3.5%)	4,835

E. Running a red light: Drivers who run a red light slightly increase their risk of injury.

Table 4.7 Injury severity table by running a red light situation

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
No	18,526 (62.9%)	10,562 (35.8%)	382 (1.3%)	29,470	6,639 (21.3%)	22,757 (72.9%)	1,820 (5.8%)	31,216
Yes	1,702 (60.0%)	1,075 (37.9%)	61 (2.1%)	2,838	224 (20.5%)	803 (73.5%)	65 (6.0%)	1,092

F. Use of safety equipment: Driving without protective equipment, such as helmets or seatbelts, increases the risk of injury.

Table 4.8 Injury severity table by safety equipment status

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
No	225 (24.1%)	618 (66.2%)	90 (9.6%)	933	140 (3.6%)	3,100 (79.3%)	668 (17.1%)	3,908
Yes	20,003 (63.8%)	11,019 (35.1%)	353 (1.1%)	31,375	6,723 (23.7%)	20,460 (72.0%)	1,217 (4.3%)	28,400

2. Vehicle characteristics

A. Mode of mobility: There are almost PDOs when driving a four-wheeled vehicle. When a crash involves a two-wheeled vehicle, the percentage of level "K/A/B" injuries is higher than a four-wheeled vehicle. The severity of the injuries is greater when pedestrians are involved.

Table 4.9 Injury severity table by mode of mobility

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
Large vehicle	531 (99.6%)	1 (0.2%)	1 (0.2%)	533	163 (98.2%)	0 (0.0%)	3 (1.8%)	166
Small vehicle	16,061 (98.4%)	171 (1.0%)	82 (0.5%)	16,314	5,111 (94.6%)	158 (2.9%)	135 (2.5%)	5,404
Motorcycle	3,379 (23.5%)	10,712 (74.6%)	265 (1.9%)	14,356	1,465 (6.5%)	19,896 (88.9%)	1,013 (4.5%)	22,374
Bicycle	141 (19.1%)	554 (75.1%)	43 (5.8%)	738	38 (3.3%)	980 (83.9%)	150 (12.8%)	1,168
Pedestrian	53 (18.3%)	188 (64.8%)	49 (16.9%)	290	48 (1.6%)	2,485 (82.8%)	468 (15.6%)	3,001
Others	63 (81.8%)	11 (14.3%)	3 (3.9%)	77	38 (19.5%)	41 (21.0%)	116 (59.5%)	195

3. Crash characteristics (28,863 cases)

A. Crash type: Depending on the crash type, there are head-on, sideswipe (opposite direction and same direction), rear-end, angular, and T-bone crashes. For first-party crashes, the proportion of level “C” injuries is higher in rear-end and angular ones. For the second party, rear-ends have the highest percentage of PDOs and level “K/A/B” injuries of all crash types.

Table 4.10 Injury severity table by crash type

Sort	1st			2nd			
	PDO	C	K/A/B	PDO	C	K/A/B	Total
Head-on	35 (35.0%)	64 (64.0%)	1 (1.0%)	34 (34.0%)	61 (61.0%)	5 (5.0%)	100
Sideswipe (opposite)	858 (68.6%)	378 (30.2%)	15 (1.2%)	182 (14.5%)	1,020 (81.5%)	49 (3.9%)	1,251
Sideswipe (same)	2,987 (66.6%)	1,440 (32.1%)	55 (1.2%)	920 (20.5%)	3,354 (74.8%)	208 (4.6%)	4,482
Rear-end	704 (36.4%)	1,187 (61.4%)	43 (2.2%)	833 (43.1%)	978 (50.6%)	123 (6.4%)	1,934
Angular	1,788 (42.5%)	2,325 (55.3%)	91 (2.2%)	1,355 (32.2%)	2,665 (63.4%)	184 (4.4%)	4,204
T-bone	5,854 (64.3%)	3,150 (34.6%)	106 (1.2%)	1,746 (19.2%)	6,924 (76.0%)	440 (4.8%)	9,110
Others	5,239 (67.3%)	2,479 (31.9%)	64 (0.8%)	1,607 (20.7%)	5,884 (75.6%)	291 (3.7%)	7,782

B. Collision impact type: The collision impact types include frontal, side, and rear impacts, categorized into four-wheeled and two-wheeled vehicles. Cross-tabulation analysis reveals that rear impact has higher "K/A/B" level injuries for both four-wheeled and two-wheeled vehicles.

Table 4.11 Injury severity table by collision impact type (four-wheeled vehicle)

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
Frontal impact	2,962 (98.1%)	40 (1.3%)	17 (0.6%)	3,019	1,085 (94.0%)	40 (3.5%)	29 (2.5%)	1,154
Side impact	4,542 (98.1%)	60 (1.3%)	28 (0.6%)	4,630	1,233 (94.6%)	33 (2.5%)	38 (2.9%)	1,304
Rear impact	210 (97.7%)	2 (0.9%)	3 (1.4%)	215	320 (89.1%)	18 (5.0%)	21 (5.8%)	359

Table 4.12 Injury severity table by collision impact type (two-wheeled vehicle)

Sort	1st				2nd			
	PDO	C	K/A/B	Total	PDO	C	K/A/B	Total
Frontal impact	984 (17.2%)	4,592 (80.2%)	153 (1.7%)	5,729	403 (4.2%)	8,760 (91.3%)	437 (4.6%)	9,600
Side impact	1,148 (17.6%)	5,283 (80.9%)	99 (1.5%)	6,530	546 (5.5%)	8,953 (90.3%)	414 (4.2%)	9,913
Rear impact	365 (41.1%)	516 (58.1%)	7 (0.8%)	888	328 (19.9%)	1,198 (72.7%)	121 (7.3%)	1,647

4. Temporal characteristics

A. Day of week: There was no significant difference in injury severity between the two parties regarding the percentage of crashes according to the day of the weekday and the weekend.

Table 4.13 Injury severity table by day of week

Sort	1st			2nd			
	PDO	C	K/A/B	PDO	C	K/A/B	Total
Weekday	15,745 (62.5%)	9,139 (36.3%)	326 (1.3%)	5,322 (21.1%)	18,403 (73.0%)	1,485 (5.9%)	25,210
Weekend	4,483 (63.2%)	2,498 (35.2%)	17 (1.6%)	1,541 (21.7%)	5,157 (72.7%)	400 (5.6%)	7,098

B. Time: Depending on the time of day the crash occurs, it is divided into the late night (00:00~06:00), daytime (06:00~18:00), and night hours (18:00~00:00). When comparing the two parties, the second party has a higher percentage of level "K/A/B" injuries; in terms of the period, the proportion of level "K/A/B" injuries is higher in the late night.

Table 4.14 Injury severity table by the time

Sort	1st			2nd			
	PDO	C	K/A/B	PDO	C	K/A/B	Total
00:00~06:00	972 (62.3%)	537 (34.4%)	50 (3.2%)	338 (21.7%)	1,114 (71.5%)	107 (6.9%)	1,559
06:00~18:00	13,748 (62.1%)	8,112 (36.6%)	278 (1.3%)	4,870 (22.0%)	15,988 (72.2%)	1,280 (5.8%)	22,138
18:00~00:00	5,508 (64.0%)	2,988 (34.7%)	30 (1.5%)	1,655 (19.2%)	6,458 (75.0%)	498 (5.8%)	8,611

5. Roadway/environment characteristics

A. Road class: Based on the road class, there is little difference in the severity of the first party on provincial, municipal roads, and city streets. However, the second party experiences slightly higher severity on provincial and municipal roads of higher road grades, primarily because they account for a smaller proportion.

Table 4.15 Injury severity table by road class

Sort	1st			2nd			
	PDO	C	K/A/B	PDO	C	K/A/B	Total
Provincial	2,354 (63.4%)	1,310 (35.3%)	49 (1.3%)	774 (20.8%)	2,705 (72.9%)	234 (6.3%)	3,713
Municipal	533 (65.2%)	276 (33.7%)	9 (1.1%)	159 (19.4%)	588 (71.9%)	71 (8.7%)	818
Others	17,341 (62.4%)	10,051 (36.2%)	385 (1.4%)	5,930 (21.3%)	20,267 (73.0%)	1,580 (5.7%)	27,777

B. Intersection type: Three, four, and multiple-leg intersections were the different categories. When comparing the consequences of intersection types, the differences between the two-party injury severity were extremely slight.

Table 4.16 Injury severity table by intersection type

Sort	1st			2nd			
	PDO	C	K/A/B	PDO	C	K/A/B	Total
Three-leg	6,632 (65.2%)	3,411 (33.5%)	133 (1.3%)	1,988 (19.5%)	7,634 (75.0%)	554 (5.4%)	10,176
Four-leg	12,347 (61.2%)	7,545 (37.4%)	280 (1.4%)	4,449 (22.1%)	14,518 (72.0%)	1,205 (6.0%)	20,172
Multiple-leg	1,249 (63.7%)	681 (34.7%)	30 (1.5%)	426 (21.7%)	1,408 (71.8%)	126 (6.4%)	1,960

C. Weather conditions: Weather conditions affect visibility and coefficient of friction of road surfaces, and rainy days are slightly more severe than sunny or cloudy days.

Table 4.17 Injury severity table by weather conditions

Sort	1st			2nd			
	PDO	C	K/A/B	PDO	C	K/A/B	Total
Sunny	13,027 (61.5%)	7,886 (37.2%)	284 (1.3%)	4,624 (21.8%)	15,386 (72.6%)	1,187 (5.6%)	21,197
Cloudy	3,362 (62.1%)	1,976 (36.5%)	75 (1.4%)	1,149 (21.2%)	3,941 (72.8%)	323 (6.0%)	5,413
Rainy	3,839 (67.4%)	1,775 (31.2%)	84 (1.5%)	1,090 (19.1%)	4,233 (74.3%)	375 (6.6%)	5,698

CHAPTER 5 ESTIMATION RESULTS

This chapter conducted estimations and comparisons between the *p*-BGOP and LC*p*-BGOP models to discern the factors influencing both parties' crash severity. It underscored the necessity of integrating heterogeneous thresholds and parameterized correlation into the modeling process. Moreover, the study offered policy implications derived from the estimation results. The discussion on the results of the LC*p*-BGOP model focused on its unique model components, including group analysis and elasticity effects.

5.1 The Model Estimation

The estimation results for the two models are reported from Table 5.3 to Table 5.5. The model measures of performance (such as ρ^2, BIC, CAIC, and entropy) of LC*p*-BGOP outperform the *p*-BGOP model, showing the necessity of latent class. Considering all these things, the LC*p*-BGOP model findings provide the basis for discussion and implications.

As previously mentioned, we first estimated the *p*-BGOP for assistance in calibrating the LC*p*-BGOP model, as shown in Table 5.3. The variable specification in the *p*-BGOP has attempted to be a restricted (nested) version of the LC*p*-BGOP for the need for a log-likelihood ratio (LR) test. The *p*-BGOP model has retained variables that reached a strict statistical significance level (t > 1.96) except for constants. The goodness-of-fit of the *p*-BGOP model is 58.3%, implying that the current model might explain substantial heterogeneity. The study specifies the LC*p*-BGOP formulation with different classes based on the current *p*-BGOP. As the number of classes increased to three, the parameter estimates became extremely unstable and challenging to interpret due to a large number of estimates (adding at least 50 coefficients for each additional class) and small class probabilities. The initial model estimation allowed for latent propensity, parametric thresholds, and across-class correlations. Drawing from our experience, we learn that parametric thresholds involve numerous covariates that may influence the estimation of latent propensity while estimating LC*p*-BGOP. The estimation challenge mentioned above with sophisticated latent segmentation models, as earlier studies discussed (Eluru et al., 2012; Sobhani et al., 2013; Wen et al., 2013; Yasmin et al., 2014). According to the above studies, reducing the number of estimated coefficients and latent classes and restricting certain parameters to be identical across different classes are feasible solutions to obtain stable estimates. As a result, unlike previous research (Li & Fan, 2019; Yasmin et al., 2014) in the univariate context, the current estimation imposes identical parametric thresholds across classes to simplify the estimation procedure and obtain computationally stable estimates.

As shown in Table 5.1, the study attempted the LC*p*-BGOP models with 2 to 5 classes. The ideal class number was according to the goodness-of-fit estimates. After considering these performance estimates, the study used the two-class model and calculated a variant 2-class LC*p*-BGOP model (LC*p*-2R) for enhancement. In contrast to the LC*p*-2 model, the LC*p*-2R model is estimated with additional significant crash variables in the membership function with *t* values greater than 1.645. Although the class sizes between the two models were similar, the assessment metrics of the two-class models, such as BIC, CAIC, and entropy, favored the estimation of LC*p*-2R. Among the various latent class models, the LC*p*-2R is considered desirable. It exhibited the lowest BIC and CAIC values, more significant estimates (including 140 variables; 135 of them, nearly 96.4%, are statistically significant), and sufficient class size (all greater than 15%). Interestingly, most road safety studies (Cerwick et al., 2014; Chang et al., 2021; Eluru et al., 2012; Shaheed & Gkritza, 2014; Xiao et al., 2022; Yasmin et al., 2014) recommend two classes as the best fit when applying LC models in the context of univariate analysis, which is in line with our findings in the context of bivariate analysis.

In addition, the *p*-BGOP is a restricted version of LC*p*-2R. A log-likelihood test is performed and shows a significant increase in goodness-of-fit (1,273.76 > $\chi^2_{(40-1,0.001)}$= 72.06). This comparison indicated good statistical performance of the LC*p*-2R model compared to *p*-BGOP, suggesting the superiority of accommodating latent segmentation. Accordingly, the results, discussion, and conclusions are based on LC*p*-2R results.

Table 5.2 provides the class size estimates across the two classes and the overall injury severity shares within each class based on the LC*p*-2R estimation. LC*p*-2R displays that two-party crashes are divided into Class 1 (82.7%) and Class 2 (17.3%), with the former being four times greater than the latter in size. Compared to Class 1, crashes in Class 2 show a higher frequency of fatal/evident (“K/A/B”) injuries. However, the percentage of PDOs in Class 1 is higher than in Class 2. As a result, Class 1 is known as the Ordinary Crash Severity (OCS) group, as it is often PDO and minor/possible (“C”) injury on both sides of the crash. Class 2 is referred to as the High Crash Severity (HCS) group, and it is more likely to be type “C” and “K/A/B” injuries on both sides of the collision. To ensure the model is applicable, this study uses hit ratio, root mean square error (RMSE), and mean absolute percentage error (MAPE) to compare different models. The *p*-BGOP and LC*p*-2R models all have a hit ratio above 93%, saying that the models have a great prediction of severity levels.

Among the variables examined, those associated with the OCS 2^{nd} *VHL* are not statistically significant (*t*-values of 1.18 and -0.62, respectively). Despite their lack of statistical significance, removing these variables would substantially impact the model. Therefore, we should retain these variables in the model.

To facilitate the discussion of the variables considered, the LC*p*-2R consists of nine functions: four for latent propensities, one for class membership, two for parameterized thresholds, and two for parameterized correlations. The covariates in the LC*p*-2R model are separated into two tables: Table 5.4 for the parametric threshold/correlation and Table 5.5 for the latent propensity/class membership function.

Table 5.5 shows that the OCS group has more variables than the HCS group, and the variables belonging to the second party are more than the first. The estimated latent class propensity coefficients vary for two sides and classes. A positive (negative) sign indicates that an increase in a specific variable unambiguously increases (decreases) the probability of level “K/A/B” injury while decreasing (increasing) the PDO probability (Washington et al., 2020).

The class membership component determines the probability of assigning two-vehicle crashes to either class based on crash characteristics. As the HCS group serves as the base, its function coefficients are constrained to zero, so its result is omitted (Table 5.5). Furthermore, a positive (negative) coefficient in this function indicates that crashes between two parties with this characteristic are more (less) likely to be assigned to the OCS group. The membership function includes six variables to explain the common factors in both classes. It is noted that a mixture model with a sophisticated kernel is less likely to have more exogenous variables in the membership function, as parametric thresholds and correlations have clarified considerable heterogeneity, as discussed in relevant studies (Chang et al., 2021; Yasmin et al., 2014).

The thresholds of the LC*p*-2R, as shown in Table 5.4, are parameterized functions rather than constants. Three injury levels (i.e., PDO, "C" injury, and "K/A/B" injury) require two thresholds for identification: zero for the first, and the second demarcates level "C" injury from level "K/A/B" injury. The factors in the second threshold reflect exogenous effects on the shift between "C" and "K/A/B" injury levels. The last row of Table 5.4 provides the mean threshold values. The second threshold (4.389) is greater than the first (2.234), representing that the second party typically sustains more injuries than the first. As described in Table 4.1, the percentage of level "C" injury for the second party is 72.9%, while for the first party, it is 36.0%. Most threshold coefficients are negative and related to the first party, leading to leftward contraction of the thresholds (between levels of "C" and "K/A/B"), increasing the likelihood of level "K/A/B" injury and vice versa. Figure 5.1 illustrates that the net effect of two-party crash severity should be fully accounted for by the associated coefficients on both latent crash propensity and threshold.

The correlation is parameterized by twelve variables that vary across the two classes, allowing for exogenous effects on the within-crash correlation without the typical constant constraint. Table 5.4 displays a high negative correlation (-0.792) and a lower standard deviation (0.13) in the OCS group, while an insignificant correlation (0.078) with a high standard deviation (0.22) in the HCS group. The result confirms a significantly negative correlation for two-party injuries within Class 1 but is unclear in Class 2. With 80% of the samples belonging to the OCS group, most crashes have an inverse severity relationship between the parties involved. This finding may contradict the previous study by Chiou et al. (2013), as our sample includes unsignalized intersections and vehicle-pedestrian crashes. Furthermore, most collisions shown in Table 4.1 result in PDOs for the first party but injuries or fatalities for the second party. However, most parametric correlation coefficients are positive, indicating heterogeneity within this negative within-crash correlation framework.

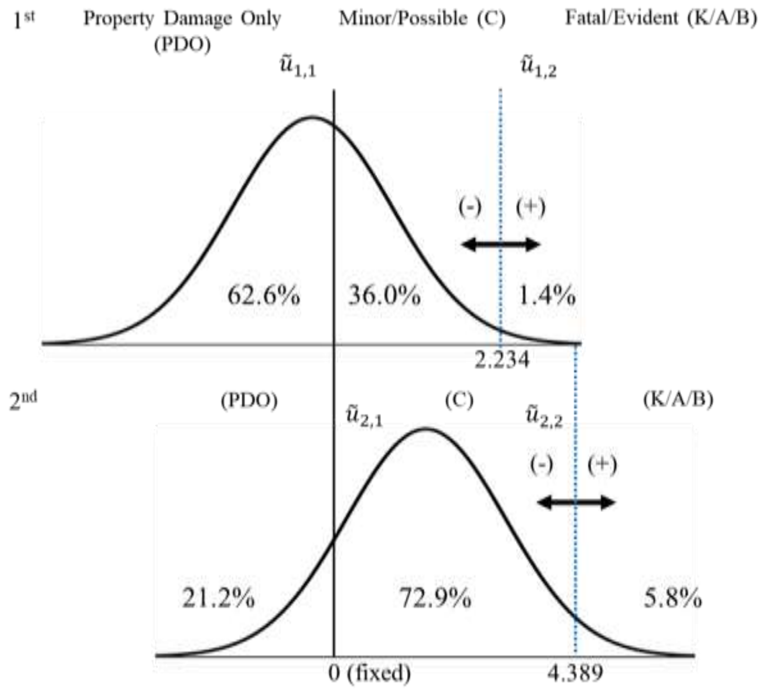


Figure 5.1 The illustration of the net effect on crash latent propensity

Table 5.1 Determination of class number

Class	C_j (C_j / *Sig.* C_j) [b]	Log-likelihood	BIC	CAIC	Entropy	Class size
p-BGOP	100 (99.0%)	-17,240.50	35,519.30	35,619.30	1	100.0%
LC*p*-2	158 (81.0%)	-16,636.46	34,913.45	35,071.45	0.318	81.9%, 18.1%
LC*p*-2R[a]	140 (96.4%)	-16,603.62	34,660.87	34,800.87	0.339	82.7%, 17.3%
LC*p*-3	220 (61.4%)	-16,554.48	35,393.24	35,613.24	0.405	79.2%, 11.8%, 9.0%
LC*p*-4	282 (42.2%)	-16,383.72	35,695.46	35,977.46	0.378	73.6%, 7.3%, 11.2%, 8.0%
LC*p*-5	344 (30.8%)	-16,234.50	36,040.78	36,384.78	0.408	71.9%, 3.9%, 12.7%, 5.5%, 6.0%

Note:

(a). LC*p*-2R is the variant of LC*p*-2, determined from the individual characteristics in the membership functions and the significant estimates in the class-specific functions (excluding constant)

(b). C_j: Number of estimates; *Sig.:* Number of significant estimates with *t* value greater than 1.645

Table 5.2 Validation between *p*-BGOP and LC*p*-BGOP

Injury severity	Actual share		*p*-BGOP		LC*p*-2R					
	Cross-Party		Cross-Party		Cross-Party (Weighted)		Class 1		Class 2	
Injury severity Probability (%)	1st	2nd	1st	2nd	1st	2nd	1st	2nd	1st	2nd
PDO	62.61	21.24	62.55	21.26	62.58	21.22	64.11	22.15	55.29	16.75
"C"	36.02	72.92	36.00	72.84	36.00	72.98	35.25	74.96	39.59	63.53
"K/A/B"	1.37	5.83	1.44	5.90	1.42	5.80	0.64	2.89	5.12	19.72
Hit-ratio										
PDO			90.9%	94.3%	90.8%	94.4%				
"C"			90.2%	90.8%	90.1%	90.9%				
"K/A/B"			98.7%	95.8%	98.7%	95.8%				
Overall			93.2%	93.6%	93.2%	93.7%				
RMSE										
PDO			0.412	0.353	0.413	0.354				
"C"			0.400	0.351	0.401	0.352				
"K/A/B"			0.039	0.129	0.038	0.129				
Overall			0.576	0.515	0.577	0.515				
MAPE										
PDO			0.624	1.272	0.624	1.277				
"C"			1.051	0.377	1.052	0.381				
"K/A/B"			1.176	0.922	1.132	0.932				
Overall			2.852	2.571	2.808	2.589				
Class size		100.0%		100.0%		100.0%		82.7%		17.3%
Log-likelihood test							1,273.76 > $\chi^2_{(40-1,0.001)}$ = 72.06			
ρ^2				0.583		0.599				

5.2 Variable Discussion

The variables specifying various parameterized functions within the same model framework may intuitively overlap in the residuals. Since the specification for these variables is assumed to be a linear combination, the heteroscedastic effects may still need to be fully resolved. Furthermore, various functions under the same model framework have different explanations. The latent propensity of ordered probit aims to explain the mean effects of the independent variable, the threshold function accounts for variance, and the parameterized correlation to clarify the interrelationship between two dependent variables. Consequently, it is acceptable for the same variables to exist simultaneously in different parts of functions within an integrated model framework.

The previous model may have exhibited bias during processing. Specifically, the sign of the same variable could vary across different classes, and various variables might have displayed different levels of significance across distinct classes. The LC*p*-2R comprises 140 variables, with 32 explaining the thresholds invariant across the two classes. The remaining 108 variables vary over two classes (12 for parameterized correlation, 6 for the membership function, and 90 for crash latent propensity). In addition to the threshold function, 68 variables have been included for the OCS and 40 for the HCS, as the former group has a higher class probability. Further discussion is elaborated below.

Driver type

Actual injuries on both sides include both latent propensities and threshold shifts (Yasmin et al., 2014). The injuries are specific to the physical conditions of the parties, such as gender (Russo et al., 2014; Russo et al., 2023; Srinivasan, 2002) and age (Fountas & Anastasopoulos, 2017; Phuksuksakul et al., 2023; Razi-Ardakani et al., 2020; Russo et al., 2023). Males (*DM*) are likely to resist more injuries and be responsible for injury to the opposite party due to their incorrect and aggressive reaction during the crash (Chen et al., 2019; de Lapparent, 2008; Yamamoto & Shankar, 2004), and their inherent physical conditions and aggressive driving attitude, especially in the usual setting (OCS group) (Eluru et al., 2012; Shaheed & Gkritza, 2014). Thresholds for *DMs* denote a leftward shift (negative value) in the injury severity of their own, suggesting that their presence increases the likelihood of level "K/A/B" injuries, consistent with the previous study by Chiou et al. (2013).

In both classes, crashes tend to result in less injury to young second-party 2^{nd} *DY*, as indicated by a negative coefficient. However, the positive sign for the first party in the OCS group suggests that young second parties (aged 18 and 24) may be responsible for the injuries of first at-fault parties due to some liability in the crash. A leftward threshold for 1^{st} *DY* expresses a reduced likelihood of level "K/A/B" injury resulting from a better physical condition to withstand injury (Chen et al., 2019; Gaweesh et al., 2023; Russo et al., 2014; Shaheed & Gkritza, 2014; Yamamoto & Shankar, 2004).

The membership function specifies a positive 2^{nd} *DO* for second parties aged above 65 years old, indicating that they are more likely to belong to the OCS group (Chang et al., 2021; Phuksuksakul et al., 2023; Razi-Ardakani et al., 2020; Russo et al., 2023; Yasmin et al., 2014). Elders of both sides in the two groups have a higher propensity to be involved in high-injury crashes, in line with previous studies (Chiou et al., 2013; de Lapparent, 2008; Hua et al., 2023; Russo et al., 2014; Yamamoto & Shankar, 2004). The negative 1^{st} *DO* of the OCS group manifests that elders at fault may cause lower injuries to others due to their typically conservative driving behavior, as they take into consideration their physical conditions, thus reducing the possibility of severe injury.

Violation type

Violation-type variables covered numerous forbidden or illegal behaviors that the Taiwanese government prohibited for all road users, such as drunk driving, being unlicensed, and failing to wear safety equipment (helmet, seatbelt). Among these prohibited behaviors, such as "not yielding to the right-of-way vehicles" (*VLOY*), "turning without following the right-of-way" (*VLOT*), and "failing to keep a safe distance" (*VLOK*), are discussed less in the literature. These variables are typically attributed to the first party, but in most cases, both parties may be more or less accountable. Thus, this study analyses two-party injuries simultaneously to avoid assigning complete blame to either one. For instance, a second-party pedestrian in the accident who crossed the intersection arbitrarily (2^{nd} *VLOPE*) caused injury to a first-party driver who committed other violations concurrently, which led to being distracted and unable to react to the unexpected jaywalking (Zhang et al., 2023). Compared to Chiou et al. (2013), this study includes additional modes, such as bikes and pedestrians, which extends the discussion to include more violations.

First and foremost, the negative 2nd *VLOE* in the membership function suggests that those without safety equipment like helmets or seatbelts probably belong to the HCS group (Phuksuksakul et al., 2023; Razi-Ardakani et al., 2020; Srinivasan, 2002). A positive 2nd *VLOE* in the latent propensity of the HCS group is in line with the preceding classification results and previous research (Chen et al., 2019; Fountas et al., 2018; Russo et al., 2014; Yamamoto & Shankar, 2004; Yasmin et al., 2014). In the OCS group, "*VLOE*" for both parties with perplexingly negative signs shows a reduction of injuries for themselves and the opposite parties. It may represent the sample profile for motorcyclists, bike riders, pedestrians, and typically those without wearing safety equipment involved in the crashes (first party: 47.6%; second party: 82.2%), which is substantial. The leftward shift of the 1st *VLOE* thresholds for both sides indicates that the absences of safety equipment in the first party reduce the level "C" range and increase the likelihood of level "K/A/B" injury. Generally, wearing safety equipment is crucial to preventing a higher risk of injury across both crash occurrence groups.

In the OCS group, drivers or riders will be likely to express aggressive driving or riding attitudes and behaviors while they are unlicensed (Chang et al., 2021), intoxicated (Chen et al., 2019; Chiou et al., 2013; Eluru et al., 2008; Fountas et al., 2018; Russo et al., 2014; Shaheed & Gkritza, 2014; Yamamoto & Shankar, 2004; Yasmin & Eluru, 2013), and speeding (Fountas & Anastasopoulos, 2017; Razi-Ardakani et al., 2020; Shaheed & Gkritza, 2014). Unlicensed first parties (1st *VLOL*) contribute to the injury of second-party crashes. Moreover, the significant parametric correlation coefficient for the 1st *VLOL* exhibits a positive correlation with injury in a two-party crash. The two leftward thresholds of *VLOD* for each party point to intoxication as more likely leading to a level "K/A/B" crash. 1st *VLOS* indicates that the first party is at risk of injury due to speeding. The injury severity of the opposite party for 1st *VLOS* may be reduced as the research focuses on intersections where most road users may be alert or cautious when crossing, resulting in safety compensation effects (Fountas & Anastasopoulos, 2017; Russo et al., 2014).

Disregarding right-of-way rules, like running a red light (*VLOR*), not yielding to the right-of-way vehicles (*VLOY*), and turning without following the right-of-way (*VLOT*) while crossing the intersection, reflects that these prohibited behaviors tend to cause collisions, raising the risk of severe injury for both parties. *VLOY* and *VLOR* share similarities in their latent propensity to increase injury severity for both parties, for crashes mainly caused by first parties. The positive signs of the two variables are related to the latent propensity functions for both sides, indicating an increase in the severity of injury for both parties involved in the accident, especially for the second party. In the OCS group, the 2nd *VLOR* expresses the injuries caused by the second party running a red light toward the first party. This finding reminds us that crashes typically occur due to co-existing violations by two parties.

Moreover, *VLOT* in both parties' latent propensity increases injury severity for the opposite party and decreases it for oneself. The leftward thresholds confirm a high probability of level "K/A/B" injury, showing that this prohibited behavior has an intrinsically high severity injury risk. As several collision cases show, the violation frequently arises when one side makes an arbitrary turn, causing the other, driving straight ahead, to fail to stop before crashing. A consistent negative value for the latent propensity of the second party across both classes may manifest a risk compensation effect (Mannering & Bhat, 2014). If the second party commits the prohibited behavior, they may become more cautious about their crash risk, thus reducing the severity of the crash.

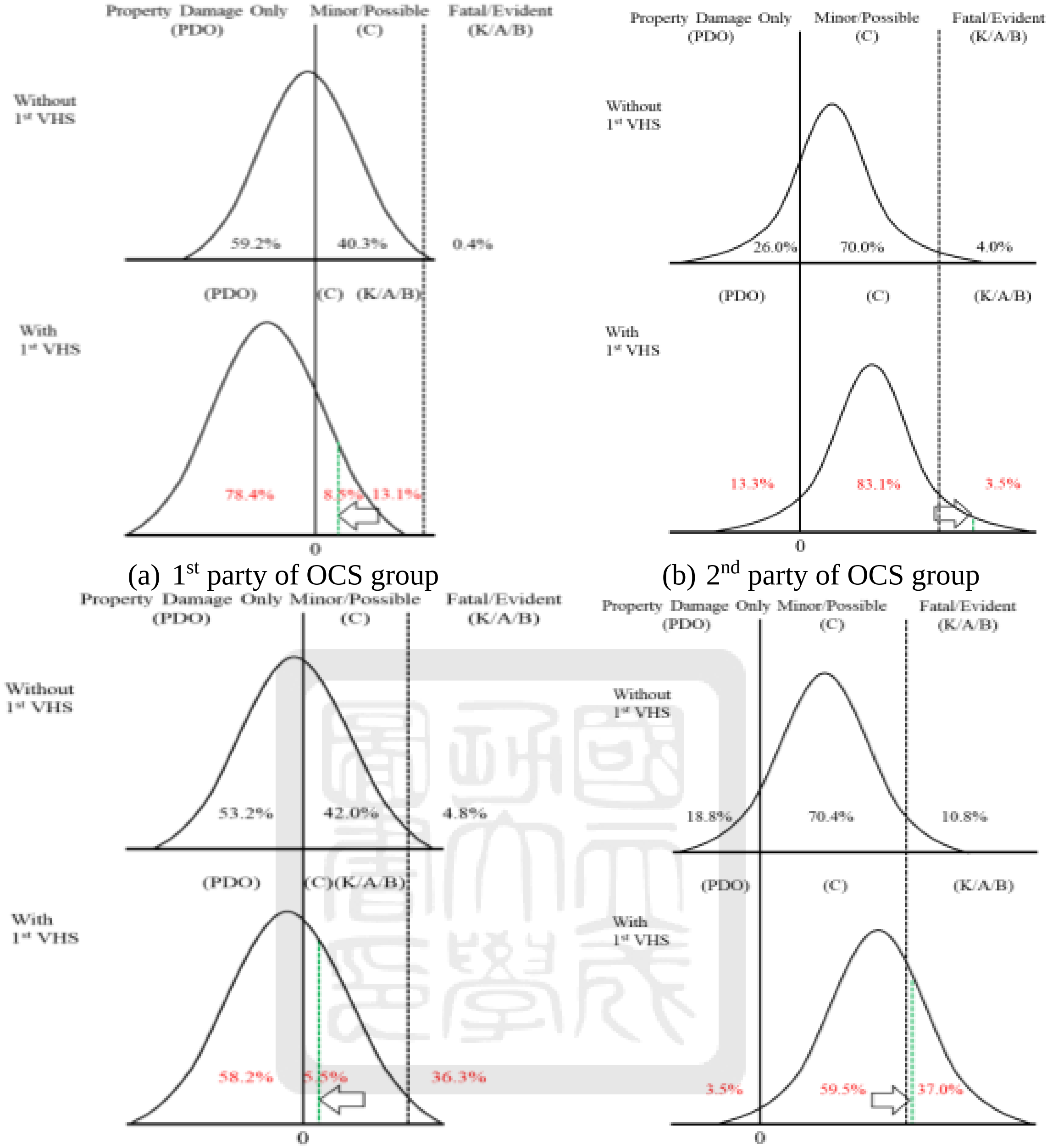
Many accidents are caused by road users not paying attention to their surroundings when crossing an intersection. The negative 2nd *VLOI* in the membership function suggests severe accidents (HCS group occurrences) happen when second parties fail to take sufficient preventive measures to reduce their injury and ignore the road situation ahead. In the OCS group, the 1st *VLOI* shows that the first parties are more likely to be injured (first latent propensity), while the second party is prone to level "K/A/B" injuries (second threshold). Similarly, the 1st *VLOK* in the second party threshold indicates a high probability that the second party (as the rear vehicle) will be seriously injured if the first party fails to keep a safe distance.

The consistent signs of 1st *VLOH* for both parties across the two groups are noteworthy: negative for the first party and positive for the second, indicating that the party at fault ran away from the scene with lower or no injury in the crash but left the disability party on site. The first parties are typically determined to be at fault, so some of them flee the scene not to be blamed, particularly for prohibited behaviors such as alcohol or drug use (Li & Fan, 2019). Noteworthy is the contracting threshold, which indicates that, in some situations, the first parties also have a higher likelihood of “K/A/B” injury than the second parties but may still engage in hit-and-run to avoid liability.

Mode of mobility

The mode of mobility significantly influences injury severity in crash scenarios involving two parties. Larger four-wheeled vehicles, equipped with comprehensive protection, tend to mitigate direct collisions more effectively than two-wheeled vehicles like motorcycles or bicycles, resulting in reduced injury severity (Fountas & Anastasopoulos, 2017; Srinivasan, 2002; Yasmin et al., 2014). Coefficients for large (*VHL*) and small (*VHS*) four-wheeled vehicles consistently indicate their latent propensity. Positive values indicate increased injuries to the opposite party, while negative values suggest decreased injuries to themselves. The latent propensity magnitudes of *VHL* are higher than *VHS*, indicating that both-party drivers sustained lower or no injuries in the larger vehicles during a crash (Chiou et al., 2013; Li & Fan, 2019). Although four-wheeled vehicles provide better driver protection, *VHS* thresholds show a reverse effect (leftward for self-parties, rightward for opposite parties), implying that level “K/A/B” injuries still occur for drivers due to violations and driver-related factors mentioned above. Figure 5.2 shows that 1st *VHS* increases the risk of level “K/A/B” injury for the first party in both groups (Figure 5.2(a) and (c)). However, its impact on the second party may differ between the two, with a decreased risk of level “K/A/B” injuries in the OCS group and an increase in the HCS (Figure 5.2(b) and (d)). Aside from this, the parameterized correlation for the OCS group reveals a positive value for 1st *VHS*, suggesting similar two-party injuries when the first parties use small vehicles.

In contrast to four-wheeled vehicles, the coefficients for two-wheeled vehicles (*VHM* and *VHB*) and pedestrians (*VHP*) show a different trend in latent propensity across the two classes, with positive values for their corresponding injuries. Pedestrians, bike riders, and motorcyclists are at risk of sustaining severe injuries in crashes (Chiou et al., 2013; Fang et al., 2024; Li et al., 2021; Russo et al., 2023; Srinivasan, 2002). Furthermore, negative coefficients for *VHB* imply reduced injuries for the opposite parties in bike collisions due to the small size and low speed of bikes. The estimated magnitudes of *VHB* and *VHP* are relatively large compared to *VHM* across the two groups, suggesting that bike riders and pedestrians are more likely to suffer severe injuries than motorcyclists due to the lack of additional protection like helmets and protective clothing.



(a) 1st party of OCS group (b) 2nd party of OCS group

(c) 1st party of HCS group (d) 2nd party of HCS group

Figure 5.2 The illustration of crash variable (1st *VHS*) on latent propensity

The thresholds for *VHM* and *VHB* help to identify the exact injury level. A rightward contraction for the 2nd *VHM* indicates that most crashes the second party sustained may be within the "C" injury. The same interpretation applies to both sides in a collision involving the first party using bikes (1st *VHB*). Variables like 2nd *VHM*, 2nd *VHB*, and 2nd *VHP* significantly influence the correlations between the two parties about the parametric correlation function. Those second non-fault parties may be vulnerable to severe collision effects due to a lack of vehicle protection. With a negative correlation of *VHM*, almost 70% of second-party crashes involve motorcycles, and about 60% of these involved collisions with large or small vehicles, resulting in high-severity injuries for the second parties but low severity for the first parties. *VHB* and *VHP* for the second party reveal a positive correlation. Crash injuries for both sides are comparable when the second party involved in a collision is either pedestrians or bike riders, and the first party is two-wheeled vehicles (motorcycles and e-bikes).

Crash/Collision

Crash types like rear-end (*CSR*), angular (*CSA*), and T-bone (*CST*) are cross-party variables. In the OCS group, *CSR* and *CSA* positively affect first-party latent propensity, indicating their prevalence in causing injuries to the first party (Chang, Haque, et al., 2022; Chiou et al., 2013). Most of these first-party injuries involve two-wheeled vehicle riders, as they are likely to suffer the entire or most of the collision impact and be ejected from their vehicles due to the lack of complete vehicle protection (Yasmin et al., 2014). However, a small proportion of four-wheeled vehicle injuries may result from airbag deployment. In the HCS group, angular (*CSA*) and T-bone (*CST*) collisions lead to severe injuries to the second parties involved in a noticeable positive correlation, as expressed in the latent propensity and parameterized correlation. This stronger relationship may stem from violations like *VLOT* and *VLOY*, with three-fourths of crashes involving small vehicles colliding with two-wheeled vehicles.

Collision types are classified for each vehicle involved in a crash according to their collision parts, front, side, and rear of four-wheeled and two-wheeled vehicles. Among the six indicator variables, only the frontal collision on the four-wheeled vehicle (*COFF*) has been confirmed, as well as three variables relating to the frontal (*COFT*), side (*COST*), and rear (*CORT*) collisions involving two-wheeled vehicles. The front bumper of a four-wheeled vehicle is designed to absorb collision impact and protect occupants from serious injury. Thus, a frontal collision with this protective device is expected to increase the likelihood of injury to the second party (de Lapparent, 2008).

Many coefficients for *COFT* and *COST* for both parties in the two classes have consistent effects across their considered functions. These variables show positive impacts on injuries for the same party and negative implications for the opposite party, similar to the effects of two-wheeled vehicle variables (Cerwick et al., 2014; Eluru et al., 2008; Srinivasan, 2002). Riding two-wheeled vehicles can expose them to high-severity crashes due to the lack of side protection, making them more likely to sustain severe crashes and be ejected from vehicles. The threshold coefficients for both variables indicate a rightward shift in severity of their own but a leftward shift that they cause to the opposite parties. This suggests that the exact injury for these crashes is mainly at the “C” level. In the OCS group, the 2nd *COFT* reveals a positive effect on parametric correlation, and both sides exhibited similar injuries in frontal impact involving two-wheeled vehicles. The remaining 2nd *CORT* expresses a leftward threshold for the second party, increasing the likelihood of “K/A/B” injury due to the absence of buffering in two-wheel vehicles.

Temporal/Roadway

Temporal and roadway variables are generic in the crash. The late-night to dawn period (*TND*) positively impacts the latent propensity of both parties across two classes (Li & Fan, 2019; Yasmin & Eluru, 2013; Zou et al., 2017). This period often sees high vehicle speeds due to low traffic volume. Meanwhile, drivers are more likely to be fatigued and distracted, which increases the injury severity from crashes (Chiou et al., 2013; Eluru et al., 2012; Eluru et al., 2008; Sun et al., 2019; Yasmin et al., 2014). Moreover, the rightward threshold for the second party suggests that being cautious during this time can decrease the likelihood of level “K/A/B” injuries in the collision.

The membership functions include roadway variables, including *RPM* and *RLM*, with inverse signs indicating that intersections with physical medians are prevalent in the HCS group, while intersections without lane markings are in the OCS group. It is important to note that *RLM* has a positive correlation in the HCS group, reflecting that serious injuries may be comparable in the absence of lane markings. Such circumstances are rare in the HCS group, as suggested by the previous classification. Some roadway variables, such as municipal-level roads (*RMR*), multiple-leg intersections (*RMI*), poor visibility (*RV*), and wet road surfaces (*RW*), increase the risk of injury to second parties. Of these variables, the first three are at the threshold; the last is at the latent propensity. The configuration related to *RMR* (de Lapparent, 2008), *RMI* (Chiou et al., 2013), and *RV* suggests that a complicated road intersection triggers a higher likelihood of level “K/A/B” injury due to insufficient sight distance and warning devices. Also, the presence of *RW* indicates that it is difficult for the second party to brake the vehicle when unexpected occasions occur, resulting in serious injury (Zou et al., 2017).

Table 5.3 Estimation result of the *p*-BGOP model

Variables	Party	*Threshold btw. "C" and "K/A/B"** 1st		2nd		*Latent propensity* 1st		2nd		*Correlation* Cross-party	
		Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value
Constant		0.932	28.00	1.230	47.49	-1.349	-8.42	0.166	1.60	-0.513	-22.91
Driver type											
DM	1st	-0.104	-7.10			-0.397	-13.22	0.191	8.18		
	2nd			-0.090	-8.98	0.316	12.70	-0.437	-12.52		
DY	1st	0.037	2.46								
	2nd					0.144	5.08	-0.097	-3.77		
DO	1st					0.174	4.48	-0.083	-2.46		
	2nd							0.224	6.34		
Violation type											
VLOE	1st	-0.135	-4.35	-0.249	-5.28			-0.551	-7.40		
	2nd					-0.366	-7.37				
VLOL	1st							0.133	2.41	0.160	2.97
VLOD	1st	-0.529	-7.85								
	2nd			-0.146	-3.21						
VLOY	1st					0.121	3.85	0.157	5.01		
VLOT	1st	-0.066	-3.25					0.149	4.37	0.094	2.83
	2nd			-0.112	-3.21	0.275	3.74	-0.313	-3.72		
VLOS	1st					0.307	3.16	-0.159	-1.99		
VLOK	1st			-0.067	-2.74						
VLOI	1st			-0.054	-4.53	0.124	2.87				
VLOR	1st					0.102	2.32	0.313	6.89		
	2nd					0.223	2.68				
VLOH	1st	-0.768	-5.66	0.253	10.16	-1.675	-16.76	1.106	9.24		
VLOPE	2nd					0.282	3.86				
Mode of mobility											
VHL	1st					-1.832	-6.12	5.012	38.03		
	2nd					1.426	11.59	-2.362	-15.15		
VHS	1st	-1.545	-20.17	0.355	15.17	-1.119	-6.96	1.623	24.28	0.087	2.97

Variables	Party	*Threshold btw. "C" and "K/A/B"*[*] 1st		2nd		*Latent propensity* 1st		2nd		*Correlation* Cross-party	
		Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value
	2nd	0.538	26.68	-1.789	-24.38	2.142	35.10	-1.926	-20.18		
VHM	1st					1.019	6.40				
	2nd			0.107	7.36			0.766	8.33		
VHB	1st	0.189	4.73	-0.154	-2.78	1.981	11.81	-0.420	-4.79		
	2nd					-0.321	-4.86	1.486	15.49	0.168	3.07
VHP	1st					2.043	12.37				
	2nd							1.635	18.48	0.265	5.71
Crash/Collision type											
CSR						0.191	3.66				
CSA						0.176	4.79	0.098	2.57	0.288	6.96
CST								0.068	2.44	0.191	6.34
COFF	1st							0.097	2.54		
COFT	1st	0.203	6.56	-0.148	-5.56	1.039	23.29	-0.324	-5.55		
	2nd							0.778	18.39	0.153	4.85
COST	1st	0.239	7.82	-0.180	-6.78	0.982	23.08	-0.515	-8.99		
	2nd	-0.073	-2.94			-0.191	-6.35	0.572	14.33		
CORT	2nd			-0.256	-13.11						
Temporal/Roadway conditions											
TND				0.051	2.66	0.113	2.25	0.299	4.32		
RMR				-0.057	-3.03						
RMI				-0.043	-3.52						
RV				-0.070	-3.59						
RW								0.057	2.22		
Aggregate Mean (std.)		1.910	(1.67)	3.579	(1.71)					-0.277	(0.16)
No. of Obs. (No. of Coef.)											32,308 (100)
Goodness-of-fit											
LL(C)											-41,377.67
LL(β)											-17,240.50
ρ^2											0.583

Table 5.4 LC*p*-2R estimation (parametric threshold and correlation)

Variables	Party	*Threshold btw. "C" and "K/A/B"**				*Correlation*			
		Cross-Class				OCS (Class 1)		HCS (Class 2)	
		1st		2nd		Cross-Party		Cross-Party	
		Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value
Constant		1.084	26.03	1.200	40.66	-0.858	-22.76	-0.167	-1.93
Driver type									
DM	1st	-0.093	-4.16						
	2nd			-0.047	-2.82				
DY	1st	0.049	2.84						
Violation type									
VLOE	1st	-0.100	-2.89	-0.110	-1.87				
VLOL	1st					0.227	2.56		
VLOD	1st	-0.594	-8.49						
	2nd			-0.181	-2.63				
VLOT	1st	-0.052	-2.34					0.218	1.95
	2nd			-0.155	-2.65				
VLOK	1st			-0.075	-2.50				
VLOI	1st			-0.057	-3.78				
VLOH	1st	-0.591	-2.98	0.287	5.11				
Mode of mobility									
VHS	1st	-1.600	-20.23	0.524	16.32	0.106	2.07		
	2nd	0.407	12.25	-1.826	-23.88				
VHM	2nd			0.191	7.94	-0.114	-2.19		
VHB	1st	0.234	4.22	-0.250	-3.71				
	2nd					0.173	2.55		
VHP	2nd					0.146	1.57		
Crash type									
CSA								0.451	3.37
CST								0.282	2.81
Impact type									
COFT	1st	0.336	7.86	-0.078	-3.19				
	2nd					0.210	2.99		
COST	1st	0.301	7.93	-0.106	-4.29				
	2nd	-0.194	-5.75						
CORT	2nd			-0.207	-6.88				
Temporal/Roadway conditions									
TND				0.088	2.64				
RMR				-0.080	-3.19				
RMI				-0.048	-3.10				
RV				-0.081	-3.07				
RLM								0.291	2.98
Aggregate mean (std.)		2.234	(1.96)	4.389	(2.26)	-0.792	(0.13)	0.078	(0.22)

Table 5.5 LC*p*-2R estimation (latent propensity and class membership)

Variables	Party	*Latent propensity*								*Membership*	
		Ordinary Crash Severity (OCS)				High Crash Severity (HCS)				OCS (Class 1)	
		1st		2nd		1st		2nd		Cross-Party	
		Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value
Constant		-1.268	-5.59	0.044	0.21	-1.290	-4.66	-0.076	-0.28	1.450	8.70
Driver type											
DM	1st	-0.476	-14.10	0.344	10.26	-0.371	-3.09				
	2nd	0.416	12.78	-0.505	-13.79			-0.251	-2.30		
DY	2nd	0.177	5.14	-0.101	-2.76			-0.158	-2.62		
DO	1st	0.166	3.23	-0.169	-3.40	0.344	2.97				
	2nd			0.208	3.87			0.932	5.35	0.492	3.26
Violation type											
VLOE	1st			-0.475	-5.93						
	2nd	-0.537	-7.40	-0.597	-6.52			1.996	7.13	-0.446	-2.82
VLOL	1st			0.212	3.11						
VLOY	1st	0.163	4.40	0.221	5.25			0.130	1.89		
VLOT	1st			0.241	5.46						
	2nd	0.310	3.29	-0.315	-3.48			-0.650	-2.12		
VLOS	1st	0.447	3.87	-0.239	-2.21						
VLOI	1st	0.175	3.37								
	2nd									-0.282	-2.17
VLOR	1st			0.341	5.13	0.532	4.49	0.384	3.63		
	2nd	0.260	2.34								
VLOH	1st	-1.944	-9.83	1.085	8.44	-1.521	-3.76	1.522	3.30		
VLOPE	2nd	0.247	2.57								
Mode of mobility											
VHL	1st	-2.134	-3.55	6.020	1.18			3.230	9.19		
	2nd	2.030	12.85	-3.201	-0.62			-0.844	-2.38		
VHS	1st	-1.338	-5.87	1.599	22.97	-0.670	-2.57	3.325	17.89		
	2nd	2.248	34.25	-1.875	-9.30	2.057	10.00	-2.412	-8.27		
VHM	1st	0.842	3.64			1.638	5.29				

Variables	Party	*Latent propensity*								*Membership*	
		Ordinary Crash Severity (OCS)				High Crash Severity (HCS)				OCS (Class 1)	
		1st		2nd		1st		2nd		Cross-Party	
		Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value	Coef.	*t*-value
	2nd			0.696	3.53			2.055	6.87		
VHB	1st	1.753	7.52	-0.480	-5.00	3.604	9.71	-0.961	-4.45		
	2nd	-0.459	-5.13	2.093	9.85						
VHP	1st	1.617	6.79			4.204	9.76				
	2nd			2.216	10.65						
Crash type											
CSR		0.245	3.92								
CSA		0.225	5.54					0.227	2.52		
CST								0.180	2.89		
Impact type											
COFF	1st			0.238	3.12						
COFT	1st	0.961	14.04	-0.348	-5.84	2.534	9.93				
	2nd			0.932	19.06			0.413	3.39		
COST	1st	0.911	13.93	-0.553	-9.41	1.980	8.42				
	2nd	-0.158	-4.59	0.610	12.85	-0.733	-5.88	0.264	2.20		
Temporal/Roadway conditions											
TND				0.288	3.90	0.380	2.49	0.743	3.22		
RPM										-0.139	-1.90
RLM										0.241	2.52
RW								0.129	2.07		
No. of Obs. (No. of Coef.)											32,308 (140)
Goodness-of-fit											
LL(C)											-41,377.67
LL(β)											-16,603.62
ρ^2											0.599

5.3 Group Analysis

The LC*p*-2R was used to assign each crash to enhance comprehension of class characteristics. Table 5.6 characterizes the corresponding features of the two identified classes based on the chi-square test, including driver, violation, mode of mobility, collision, and roadway. The characteristics of the drivers for both parties differ between the classes. In the OCS group, over two-thirds of male drivers (*DM*) are observed on both sides, whereas this percentage is lower in the HCS group (57%) for the second party. Both classes are similar in the percentages of young individuals (*DY*) across the two parties (Chang et al., 2021; Shaheed & Gkritza, 2014; Yasmin et al., 2014). However, the proportion of older adults (*DO*) as second parties in the OCS group (10.6%) is much higher than in the HCS group (1.9%), consistent with the previous classification results (Chang et al., 2021; Eluru et al., 2012; Yasmin et al., 2014). While elders are more prone to road crashes due to their reduced physical capability to react to unexpected incidents on the road, they may not sustain severe injuries in intersection crashes as expected. Furthermore, the average age of the two parties across the two classes is similar, revealing that the age of the first party is slightly higher than that of the second party.

As mentioned, the percentage of violations for the first party in both groups is much higher than for the second party, suggesting that the first parties are often mainly accountable for the crash. *VLOT* shows a consistent percentage across the two classes: a higher for the first party and a lower for the second party. Other than that, the percentages of the other three (*VLOC*, *VLOY*, and *VLOI*) vary between the two classes, confirming two distinct intrinsic crash injury configurations. In the OCS group, first parties exhibit relatively high percentages of *VLOY* and *VLOT*. These two violations involve the first party failing to give way to the right-of-way vehicles, which tends to increase the injuries to the second party. Compared to the OCS group, the first party in the HCS group has a relatively high percentage of *VLOC* and a great *VLOI* for both sides, particularly for the second party. The finding for *VLOC* underlines a high likelihood of severe crashes associated with pedestrians. The latter for *VLOI* emphasizes that driver attention can reduce injury severity in the event of a crash, in line with the previous classification result.

The composition of mobility modes varies between the two classes. The percentage of *VHS* for the first party is higher in the HCS group (60.7%) than in the OCS (48.4%).

However, this percentage reverses for the second party, with a high one for the OCS (18.4%) and a low one for the HCS (8.5%). Furthermore, the second parties have a relatively high percentage of *VHM* compared to the first, of which the OCS group has motorcycles up to 74.7%. In addition, crashes involving *VHB* and *VHP* with the second party have a higher proportion in the HCS group (47%) than the OCS group (6%). Nearly half of the second parties in the HCS group are pedestrians or bike riders, while over 70% of the second parties in the OCS group are motorcyclists. The HCS group, unsurprisingly, has a high severity injury occurrence due to the substantial proportion of small vehicles, pedestrians, and bike riders in crashes.

Crash-type variables are only applicable to two-vehicle crashes. T-bone collisions (*CST*) occur slightly more frequently in the OCS group than in the HCS group (Cerwick et al., 2014). The collision type on the front of a four-wheeled vehicle (*COFF*) is apparent to the first party, particularly in the HCS group. Regarding roadway conditions, provincial roads (*RPR*) with higher speed limits (Cerwick et al., 2014; Eluru et al., 2012; Shaheed & Gkritza, 2014; Yasmin et al., 2014) and sight distances, often equipped with traffic signals (*RTS*) and physical medians (*RPM*). These roadway conditions broadly point to the HCS configuration setting, which is noteworthy.

Table 5.6 Group analysis by the LC*p*-2R estimates

Variables	Ordinary Crash Severity (OCS)			High Crash Severity (HCS)		
	1st	2nd	Cross	1st	2nd	Cross
Driver type						
DM	74.8%	69.6%		77.8%	57.2%	
DY	26.0%	36.8%		23.0%	33.6%	
DO	-	10.6%		-	1.9%	
Age (in years)	42.8	39.6		43.8	38.0	
Violation type						
VLOC	2.4%	-		21.1%	-	
VLOT	19.7%	2.3%		16.8%	1.4%	
VLOI	8.7%	6.3%		12.0%	15.4%	
VLOY	27.2%	2.5%		8.5%	0.6%	
Mode of mobility						
VHS	48.4%	18.4%		60.7%	8.5%	
VHM	46.6%	74.7%		33.6%	42.6%	
VHB	-	1.9%		-	12.3%	
VHP	-	4.1%		-	34.7%	
Crash/Collision type						
CST			29.8%			20.5%
COFF	8.2%	3.9%		14.8%	1.8%	
Roadway conditions						
RPR			10.7%			15.6%
RTS			38.4%			22.3%
RPM			27.8%			65.4%
Speed (in kph)			45.3			47.6
Sample			26,858 (83.1%)			5,450 (16.9%)

5.4 Elasticity Effects

The estimated coefficients cannot directly reflect their impact on the probabilities for each injury level, as many variables simultaneously affect the class membership functions, latent propensities, threshold functions, and parameterizing correlation for the two classes. Table 5.7 and Table 5.8 calculate the aggregate elasticity effects for the variables considered in the *p*-BGOP and LC*p*-BGOP models. Elasticity effects are applied as all variables are dummy types. These effects represent the percentage change in the probability of an injury severity category due to the presence of a specific variable. The computation procedure could refer to these studies (Chiou et al., 2013; Eluru et al., 2012; Eluru et al., 2008) for detailed elaboration.

While the variable specification varies between functions within LC*p*-BGOP, these variables generally exhibit similar orientations in elasticity effects (negative/positive) across both classes when identical variables are specified simultaneously. However, the magnitudes of the variables for each injury level differ significantly between the two groups. In particular, more variables in the second party have unimodal effects, either concave or convex, at the "C" injury level than those in the first party, especially for the HCS group. The outcome is expected, as the crashes for the level "C" injury for the second party are higher than those for the first party. The same reason applies to the HCS group as well.

Moreover, the range of elasticities from calculated variables is similar to the previous study (Chiou et al., 2013), suggesting that certain variables substantially impact crash severity, particularly those concerning mode of mobility. Among these elasticity effects of considered variables greater than 100% highlight the mode of mobility variables (*VHL*, *VHS*, *VHM*, *VHB*, and *VHP*), followed by some violations such as drunk driving (*VLOD*), not wearing safety equipment (*VLOE*), and speeding (*VLOS*). The sparing main variables are the elderly (*DO*) and collision types of two-wheeled vehicles (*COFT*, *COST*, and *CORT*). While other variables, such as temporal and roadway, discussed previously, are also important, their effects are relatively modest.

Both large vehicles (*VHL*) and small vehicles (*VHS*) are four-wheeled, yet their elasticities vary across parties and classes. *VHL* in the OCS group exhibits perfect vehicle protection for the drivers of either party, reducing the likelihood of level "K/A/B" injury by nearly 100% while increasing the possibility of injury for another party by approximately

3,400%. In the HCS group, the likelihood of level “K/A/B” injury caused by the first-party *VHL* to the second-party increases to nearly 370%. Furthermore, the negative effect of *VHL* on the level “C” injury in both groups suggests that injuries for either party are likely to be levels of PDO or “K/A/B”, depending on which party is protected by *VHL*. The presence of *VHL* in the accident tremendously heightens the injuries of the second parties caused by the *VHL* of the first party and those of the first parties caused by the *VHL* of the second party. This underscores the importance of restricting the movements of large vehicles, especially tractor-trailers (dump trucks), on city streets with accident-prone intersections. Since such vehicles are typically in commercial use, equipping them with Advanced Driver Assistance Systems (ADAS) to alert drivers of potential conflicts is recommended.

Moreover, both classes of small vehicles (*VHS*) exhibit identical convex unimodal elasticities for either party, resulting in injuries skewed towards both extreme levels (i.e., PDO and “K/A/B”). Level “K/A/B” has significant magnitudes larger than PDO (Cerwick et al., 2014). Specifically, in the OCS group, the likelihood of PDO for first-party drivers caused by themselves increases by 29.88%, while that of level “K/A/B” increases by 1,988.53%. The same injury pattern is suitable for second-party drivers. However, the elasticities caused by their opposite-party drivers differ. There is a high likelihood of severe injuries for the first parties caused by second-party drivers, whereas that of the first party to the second party differs, with a 14.82% drop in level “K/A/B” in the OCS group but a 132.98% rise in the HCS group. As mentioned, the presence of *VHS* is often related to driver violations by either party, such as speeding, not yielding right-of-way vehicles, taking alcohol or drugs, not wearing safety equipment, and running red lights, among others. In such circumstances, drivers in *VHS* may be more vulnerable to severe crashes than to being well protected.

In crashes involving two-wheeled vehicle riders (*VHM* and *VHB*) and pedestrians (*VHP*) in both classes, injury elasticities for both parties increase monotonically from PDO to the “K/A/B” level. The likelihood of level “K/A/B” injury for three modes of mobility is generally higher for the first party than for the second. However, the probability of injury at the “C” level varies between parties and groups. The first-party elasticities at the “C” level for *VHP* and *VHB* in the OCS group show positive effects, whereas negative ones in the HCS. The injuries in the HCS group are more likely to suffer level “K/A/B” injuries than in the OCS, for some injuries in the OCS group shift into level “C”. Additionally, the elasticities of level “K/A/B” in the HCS group are higher for *VHP* and *VHB* than for *VHS*, indicating that first-party pedestrians and bike riders sustain more severe injuries than small vehicle drivers. Referring to the previous profile discussion for HCS, mixed traffic flow with heavy traffic volumes likely leads to conflicts between vehicles and pedestrians. The result underscores the importance of reducing these conflicts to enhance intersection safety. Although motorcycles (*VHM*) are the largest fleet in the sample, they do not show obvious high elasticities. For most motorcyclists required to wear a helmet, the measure reduces the occurrence of level “K/A/B” injuries to level “C”.

The elasticities of *VLOD* for either party across both classes exhibit a consistent convex, unimodal effect (Shaheed & Gkritza, 2014). There is a significant elasticity increase (over 100) at the “K/A/B” level, a decrease at the “C” level, and a zero at the PDO level. It is noteworthy that the zero effect for the PDO exists in cases where only the threshold functions include certain variables. This finding indicates that either party involved in drunk driving may impose a high likelihood of level “K/A/B” injuries on themselves. The elasticities of *VLOE* and *VLOS*, two types of violations mentioned, varied between the two classes. The elasticity of level “K/A/B” for *VLOE* is exceptionally high (267.58) in cases where the second party within the HCS group sustains severe injuries caused by the first parties because they do not wear safety equipment (Russo et al., 2014; Yasmin et al., 2014). For *VLOS*, it indicates a high probability of level “K/A/B” injury for the first parties when they speed in the crash (Chang et al., 2021).

Other than the above, the elasticity effects for the elder (*DO*) second party in the HCS group can be expected due to the limited physical resistance (Chang, Yasmin, et al., 2022; Eluru et al., 2012; Russo et al., 2014; Xiao et al., 2022; Yasmin et al., 2014). Three collision types involving two-wheeled vehicles (*COFT*, *COST*, and *CORT*) are greater than 100% as well (Cerwick et al., 2014). The shift in elasticity effects for both parties across classes is similar, regardless of the presence and amount of these variables. This is because two-wheeled vehicle collisions (*VHM* and *VHB*) and these collision variables are strongly correlated. First-party riders at fault in both classes are at a high risk of suffering level “K/A/B” injuries in front and side collisions. On the other hand, in side and rear crashes, the first party may seriously injure the second party riders.

Table 5.7 Elasticity effects for the *p*-BGOP model

Variables	Party	Bi.	Threshold		Latent		Corr	*p*-BGOP					
			1st	2nd	1st	2nd		1st			2nd		
			(12)	(18)	(27)	(30)	(8)	PDO	C	K/A/B	PDO	C	K/A/B
Driver type													
DM	1st		✓		✓	✓		7.08	-11.52	-19.49	-727	0.16	24.25
	2nd			✓	✓	✓		-5.73	7.79	53.84	15.59	-3.58	-11.91
DY	1st		✓					0.00	0.83	-20.69			
	2nd				✓	✓		-2.55	3.19	30.85	3.62	-0.02	-12.78
DO	1st				✓	✓		-3.06	3.76	38.72	3.15	-0.04	-10.92
	2nd					✓					-7.75	-0.59	35.19
Violation type													
VLOE	1st	✓	✓	✓		✓		0.00	-4.47	111.22	24.06	-12.57	68.47
	2nd				✓			6.78	-9.58	-54.49			
VLOL	1st					✓	✓				-4.73	-0.25	20.15
VLOD	1st		✓					0.00	-32.53	809.21			
	2nd			✓							0.00	-9.30	114.84
VLOY	1st				✓	✓		-2.15	2.72	25.14	-5.62	-0.23	23.10
VLOT	1st		✓			✓	✓	0.00	-1.82	45.26	-5.34	-0.23	22.10
	2nd	✓		✓	✓	✓		-4.78	5.55	68.70	12.81	-5.20	18.10
VLOS	1st				✓	✓		-5.33	6.07	79.16	6.20	-0.23	-19.48
VLOK	1st			✓							0.00	-3.55	43.84
VLOI	1st			✓	✓			-2.21	2.75	26.86	0.00	-2.69	33.27
VLOR	1st				✓	✓		-1.80	2.26	21.76	-10.57	-1.20	52.88
	2nd				✓			-3.90	4.62	53.67			
VLOH	1st	✓	✓	✓	✓	✓		31.10	-58.12	101.58	-31.13	7.97	13.70
VLOPE	2nd				✓			-4.91	5.66	71.64			
Mode of mobility													
VHL	1st	✓			✓	✓		32.83	-53.08	-98.52	-100.87	-100.99	1,610.38
	2nd				✓	✓		-24.73	5.41	934.58	156.16	-39.08	-80.15

Variables	Party	Bi.	Threshold		Latent		Corr	*p*-BGOP					
			1st	2nd	1st	2nd		1st			2nd		
			(12)	(18)	(27)	(30)	(8)	PDO	C	K/A/B	PDO	C	K/A/B
VHS	1st	✓	✓	✓	✓	✓	✓	26.21	-88.33	1,064.44	-57.24	11.32	66.44
	2nd	✓	✓	✓	✓	✓		-47.46	65.59	419.96	143.10	-88.53	577.45
VHM	1st				✓			-22.86	31.24	211.09			
	2nd			✓		✓					-37.97	7.30	46.62
VHB	1st	✓	✓	✓	✓	✓		-38.94	27.34	1,003.26	17.68	-7.33	26.83
	2nd				✓	✓	✓	5.93	-8.35	-48.49	-42.21	-27.35	489.82
VHP	1st				✓			-40.02	-8.76	1,947.82			
	2nd					✓	✓				-49.03	-28.67	530.59
Crash/Collision type													
CSR					✓			-3.37	4.11	43.48			
CSA					✓	✓	✓	-3.13	3.88	38.51	-3.54	-0.13	14.31
CST						✓	✓				-2.50	-0.05	9.64
COFF	1st					✓					-3.46	-0.13	14.05
COFT	1st	✓	✓	✓	✓	✓		-20.59	30.14	140.29	12.58	-7.00	41.13
	2nd					✓	✓				-29.85	-2.70	140.88
COST	1st	✓	✓	✓	✓	✓		-19.53	30.26	91.62	20.03	-8.07	27.46
	2nd	✓	✓		✓	✓		3.45	-6.22	5.73	-21.25	-1.89	99.92
CORT	2nd			✓							0.00	-19.26	237.75
Temporal/Roadway conditions													
TND				✓	✓	✓		-1.99	2.48	24.40	-10.04	1.80	13.93
RMR				✓							0.00	-2.95	36.41
RMI				✓							0.00	-2.10	25.93
RV				✓							0.00	-3.75	46.29
RW						✓					-2.08	-0.05	8.06
Note			Bi.: With at least one party that exhibits a bimodal pattern										

Table 5.8 Elasticity effects for the LCp-BGOP model

Variables	Party	Bi.	Ordinary Crash Severity (OCS)						High Crash Severity (HCS)					
			1st			2nd			1st			2nd		
			PDO	C	K/A/B	PDO	C	K/A/B	PDO	C	K/A/B	PDO	C	K/A/B
Driver type														
DM	1st	✓	8.43	-14.42	-50.20	-13.53	3.01	25.57	3.64	-5.02	-0.57			
	2nd		-7.51	12.52	62.72	18.23	-4.15	-32.01				3.61	-0.69	-0.85
DY	1st		0.00	0.40	-22.20				0.00	3.53	-27.35			
	2nd	✓	-3.11	4.99	36.84	3.82	-0.81	-8.28				2.34	4.45	-16.31
DO	1st		-2.90	4.65	34.93	6.59	-1.44	-13.11	-3.33	-3.16	60.49			
	2nd	✓				-7.37	1.39	20.49				-12.04	-35.64	125.03
Violation type														
VLOE	1st		0.00	-1.20	66.60	20.35	-5.74	-7.11	0.00	-9.12	70.54	0.00	-20.70	66.68
	2nd	✓	9.84	-16.70	-66.01	25.74	-5.66	-50.60				-45.37	-71.10	267.58
VLOL	1st					-7.47	1.37	21.81						
VLOD	1st		0.00	-27.20	1,504.88				0.00	-62.44	483.15			
	2nd					0.00	-4.02	104.21				0.00	-34.83	112.21
VLOY	1st	✓	-2.87	4.62	33.00	-7.99	1.51	22.01				-1.83	-3.87	14.03
VLOT	1st		0.00	-0.54	29.91	-8.61	1.59	24.67	0.00	-4.28	33.15			
	2nd	✓	-5.35	8.35	76.86	13.00	-4.87	26.70				12.76	-7.31	12.72
VLOS	1st		-7.64	11.60	127.06	9.61	-2.18	-17.10						
VLOK	1st					0.00	-1.16	29.97				0.00	-13.90	44.76
VLOI	1st		-3.06	4.89	37.74	0.00	-0.79	20.42				0.00	-10.36	33.38
VLOR	1st	✓	0.00	0.00	0.00	-11.66	1.95	38.82	-5.35	-5.87	103.27	-5.10	-12.64	45.05
	2nd		-4.50	7.07	62.00									
VLOH	1st	✓	32.47	-58.49	-31.73	-31.13	8.49	18.48	18.94	-36.71	79.31	-24.60	8.03	-4.97
VLOPE	2nd		-4.28	6.73	58.55									
Mode of mobility														
VHL	1st	✓	34.20	-60.42	-99.08	-101.41	-100.51	3,383.39				-78.49	-94.86	372.26
	2nd	✓	-37.39	20.32	2,638.24	225.69	-64.31	-61.86				19.35	14.61	-63.49

Variables	Party	Bi.	Ordinary Crash Severity (OCS)						High Crash Severity (HCS)					
			1st			2nd			1st			2nd		
			PDO	C	K/A/B	PDO	C	K/A/B	PDO	C	K/A/B	PDO	C	K/A/B
VHS	1st	✓	29.88	-90.30	1,988.53	-57.02	17.42	-14.82	9.01	-92.13	615.55	-91.49	-17.16	132.98
	2nd	✓	-48.71	69.49	1,056.55	131.56	-83.71	1,162.50	-39.55	33.23	170.22	146.41	-101.24	201.80
VHM	1st		-17.11	27.19	216.90				-37.48	25.62	206.73			
	2nd	✓				-33.11	9.50	7.33				-103.04	-0.82	90.16
VHB	1st	✓	-31.48	43.71	749.27	20.60	-8.23	55.45	-87.16	-45.84	1,296.46	21.73	-13.80	25.99
	2nd		8.34	-14.11	-58.89	-59.49	-15.07	846.60						
VHP	1st		-28.05	24.82	1,449.78				-94.60	-86.16	1,688.77			
	2nd					-68.19	-12.77	853.53						
Crash/Collision type														
CSR			-4.27	6.75	56.22									
CSA		✓	-3.95	6.31	48.61				-8.08	-1.11	-65.58	-23.58	-8.80	6.48
CST		✓							-0.06	-0.01	-0.50	-2.68	-5.35	19.20
COFF	1st					-8.30	1.51	24.39						
COFT	1st		-18.04	31.67	63.18	13.70	-3.80	-6.37	-64.99	37.10	415.20	0.00	-14.39	46.37
	2nd	✓				-36.27	5.17	143.89				-6.27	-12.11	44.34
COST	1st		-17.28	30.23	66.49	21.78	-5.84	-15.51	-46.82	37.16	218.38	0.00	-19.56	63.00
	2nd	✓	2.81	-7.16	113.37	-22.91	3.57	82.91	6.62	-9.51	2.12	-3.91	-7.69	28.11
CORT	2nd					0.00	-4.85	125.75				0.00	-39.61	127.59
Temporal/Roadway conditions														
TND		✓				-9.91	2.97	-1.09	-3.73	-3.75	69.32	-9.52	-7.47	32.15
RMR						0.00	-1.24	32.13				0.00	-14.84	47.79
RMI						0.00	-0.65	16.93				0.00	-8.52	27.44
RV						0.00	-1.26	32.69				0.00	-15.02	48.40
RW		✓										-1.83	-3.87	14.01
Note			Bi.: With at least one party that exhibits a bimodal pattern											

Table 5.9 Significant variables in the LC*p*-BGOP model

Variables	Party	OCS					HCS			
		1st	2nd	Corr	Thr	Mem	1st	2nd	Corr	Thr
		(25)	(28)	(6)	(12)	(5)	(13)	(20)	(4)	(18)
Driver type										
DM	1st	✓	✓		✓		✓			
	2nd	✓	✓					✓		✓
DY	1st				✓					
	2nd	✓	✓					✓		
DO	1st	✓	✓				✓			
	2nd		✓			✓		✓		
Violation type										
VLOE	1st		✓		✓					✓
	2nd	✓	✓			✓		✓		
VLOL	1st		✓	✓						
VLOD	1st				✓					
	2nd									✓
VLOY	1st	✓	✓					✓		
VLOT	1st		✓		✓				✓	
	2nd	✓	✓					✓		✓
VLOS	1st	✓	✓							
VLOK	1st									✓
VLOI	1st	✓								✓
	2nd					✓				
VLOR	1st		✓				✓	✓		
	2nd	✓								
VLOH	1st	✓	✓		✓		✓	✓		✓
VLOPE	2nd	✓								
Mode of mobility										
VHL	1st	✓	✓					✓		
	2nd	✓	✓					✓		
VHS	1st	✓	✓	✓	✓		✓	✓		✓
	2nd	✓	✓		✓		✓	✓		✓
VHM	1st	✓					✓			
	2nd		✓	✓				✓		✓
VHB	1st	✓	✓		✓		✓	✓		✓
	2nd	✓	✓	✓						
VHP	1st	✓					✓			
	2nd		✓	✓						
Crash/Collision type										
CSR		✓								
CSA		✓						✓	✓	
CST								✓	✓	
COFF	1st		✓							
COFT	1st	✓	✓		✓		✓			✓
	2nd		✓	✓				✓		
COST	1st	✓	✓		✓		✓			✓
	2nd	✓	✓		✓		✓	✓		
CORT	2nd									✓
Temporal/Roadway conditions										

TND	✓				✓	✓		✓
RMR								✓
RMI								✓
RV								✓
RPM				✓				
RLM				✓			✓	
RW						✓		

Note: Correlation (Corr), Threshold (Thr), Membership (Mem)

CHAPTER 6 DISCUSSIONS

This chapter focuses on the findings of significant coefficient, group profile, and elasticity, providing additional insights to complement the discussion of variables mentioned in the previous chapter.

6.1 Variables

The above discussion has emphasized significant findings for specific variables causing two-party severe crashes at the intersections. Importantly, these findings assert that the interrelationship among risk factors is highly intertwined, which helps explain the causality. For example, certain crash types often stem from specific aggressive traffic violation behaviors. Angular (*CSA*) and T-bone (*CST*) collisions at intersections sometimes involve violations such as “turning without following the right-of-way” (*VLOT*) and “not yielding to the right-of-way vehicles” (*VLOY*). “Inattentive to the vehicles ahead” (*VLOI*) is highly inflicted with rear-end (*CSR*) crashes. Another issue characterized by the findings is that many traffic violations (e.g., speeding, running red lights, not yielding to the right-of-way vehicles, being inattentive to the vehicles ahead, and not wearing safety equipment) cause crash severity even for first-party drivers themselves. The crashes without safety equipment are likely to have a high severity level across all violations except *VLOPE*. Additionally, violations such as “not wearing safety equipment”, “not yielding to the right-of-way vehicles”, and “running red lights”, which elevate injury severity for both parties involved, warrant serious attention in enforcement efforts to deter potential violators.

Even though accidents resulting from improper door openings make up a small proportion, they should not be overlooked, and educating the public on the proper concept of opening car doors is essential. Regarding fatigue driving, as it is impossible to determine whether a driver is fatigued subjectively, it is imperative to remind drivers through promotion to ensure they are well-rested before hitting the road.

Furthermore, the correlation parameters provide insight into the relationship between injury severities of both parties and help identify potential causes. Negative values for the parameterized correlation suggest a reverse relationship between the injury severity of both parties. Since many factors associated with a violation are attributed to the first-party drivers, the crash resulted from first-party drivers, causing the second-party drivers severe injury in most cases. Road intersection prevention strategies must deter at-fault drivers from obeying the right of way in the road intersection. These findings show that the severe crashes of pedestrians involved in collisions with other vehicles will likely increase, especially if the pedestrian is deemed at fault due to jaywalking behavior. The local transportation department has taken measures to protect pedestrians by implementing various pedestrian facilities on roads, such as pedestrian refuge areas and islands, revising signal timing for pedestrians, and deploying roadside autonomous speed inspecting and warning LED systems. However, enforcement for pedestrians by the police is also needed.

In addition to pedestrians, the findings also emphasize the vulnerability of two-wheeled vehicle (motorcycle/moped, bicycle) riders, whose vehicles lack comprehensive protection, compared to four-wheeled vehicles of all sizes (bus, truck, trailer, passenger car, light truck), which are at risk of suffering injuries. Of concern is that large vehicles, usually commercial vehicles, cause severe crash injuries to small ones. Additionally, the study showed that the physical characteristics of victims (gender and age) play a crucial role in the severity of their injuries. Specifically, elderly individuals are often involved in severe accidents due to their diminished physical capabilities compared to younger individuals, especially if they are two-wheeled vehicle drivers or pedestrians. Likewise, males are less likely to be involved in a severe crash than females.

According to estimation results, pedestrian safety is noticeably in urgent need of improvement. To address pedestrian safety concerns, civil society groups have presented five essential appeals in their “Stop Killing Pedestrians” protests in August 2023. These demands include “Upgrade Pedestrian Infrastructure” (physical sidewalks, road narrowing), “Reform Driver Education” (driver training, justified licensing procedures), “Enforcement Pedestrians Rights” (stricter law enforcement against drivers not yielding to pedestrians), “Modernise Road Safety Legislation” (reconstruction of traffic regulations), and “Commit to Vision Zero”. These demands align closely with the recommendations of this study, all aimed at reducing road fatalities and ultimately achieving the Vision Zero goal, all of which depend on the execution capabilities of various government departments.

6.2 Groups

Unlike the previous BOP and BGOP models, LC*p*-BGOP incorporates a latent class model framework, allowing a better understanding of identifying unobserved segments in the crash data. This finding supports a substantial heterogeneity within the unobserved crash data. Additionally, the study highlights factors like drivers, violations, and vehicle characteristics in describing injury severities over segments, providing a comprehensive perspective beyond traditional approaches. This model is more detailed than others, considering finer elements such as parameterized correlations, threshold values, and latent classes. This comprehensive approach covers a broader range of factors.

The differences between cluster analysis and latent class won't be significant. Clusters are limited to grouping the available data; nevertheless, the latent class model is an application in econometrics, and through simulations of comparisons or preference behaviors, it can be used for prediction purposes. The model uses an endogenous approach, where the segmentation is based on unobserved characteristics that are unknown beforehand, as opposed to standard exogenous segmentation (such as gender). By using the data, the approach makes it possible to analyze heterogeneity in a more subtle and data-driven way by identifying segments.

Due to poor pedestrian environments in our country, accidents have occurred where pedestrians have not yielded the right of way. Consistent with the group analysis result, more pedestrians belong to the HCS group. Consequently, it has been called a "pedestrian hell". The MOTC has recently introduced regulations to prioritize pedestrian rights in response to this issue. Although a step in the right direction, there is still a long way to go to shed the negative image associated with car-centric traffic.

The primary factor contributing to high pedestrian severity is the protective capability. Research shows that pedestrians have a 10% fatality rate when struck by a vehicle traveling at 30 kph, which increases to 85% at 50 kph. Intersection design plays a critical role in crashes involving turning vehicles and where pedestrians may go unnoticed while crossing. Therefore, enhancing visibility and implementing traffic calming measures to reduce speeds are imperative. Features like refuge islands and sidewalks are standard road configurations in most countries, but in our country, their prevalence is low due to early planning mistakes.

It is essential to employ alternative methods to increase their prevalence and align with international safety standards.

In summary, the analysis concludes crashes involving small vehicles colliding with pedestrians and bike riders are likely to belong to the HCS group (Yasmin et al., 2014). These collisions often occur at well-designed intersections with mixed traffic, where drivers or riders crossing intersections may not yield to pedestrians and vehicles with right of way or watch the road ahead. The OCS group has a high likelihood of crashes involving two vehicles, especially motorcycles, indicating a confirmed negative correlation in two-party injuries. These collisions often occur when road users fail to yield to these vehicles with the right of way, especially in instances involving elderly individuals, who may have reduced physical capabilities to react to unexpected events from the other party. The findings for the OCS group align with previous research (Chiou et al., 2020; Chiou et al., 2013) focused on two-vehicle crashes at signalized intersections. However, this study complements the findings on bikes and pedestrians through a refined model (LC*p*-2R).

6.3 Elasticity

The presence of large vehicles (*VHL*) significantly impacts injury severity for both parties involved in accidents, offering near-perfect protection for drivers in the OCS group but increasing the risk of severe injuries to the other party. In the HCS group, the likelihood of severe injuries caused by *VHL* escalates further, underscoring the need for regulating large vehicle movements, especially in accident-prone intersections. Conversely, small vehicles (*VHS*) exhibit similar injury patterns, with injuries skewed towards extreme levels. Drivers in *VHS* are often associated with violations, making them more vulnerable to severe crashes. In accidents involving two-wheeled vehicle riders (*VHM* and *VHB*) and pedestrians (*VHP*), injuries tend to escalate from minor to severe, with pedestrians and bike riders particularly susceptible to severe accidents. Addressing conflicts between vehicles and pedestrians is crucial for improving intersection safety, while mandatory helmet-wearing for motorcyclists helps mitigate severe injuries.

The study reveals consistent trends in injury severity related to violations such as *VLOD*, with a significant increase in the likelihood of level "K/A/B" injuries for both parties involved. Additionally, those associated with *VLOE* and *VLOS* show varying elasticities between the two classes. Moreover, the *DO* in the HCS group exhibit diminished physical resilience, contributing to their injury severity. Collisions involving two-wheeled vehicles also result in high elasticities, particularly in front and side collisions, where first-party riders face a grown risk of severe injuries, while in side and rear crashes, they may cause severe injuries to second-party riders.

6.4 Summary

Therefore, the study proposed policy measures to reduce the crash severity at intersections. Engineering solutions include installing clear warning signs and establishing sidewalks, which create a safe and convenient transportation infrastructure. These efforts aim to create a people-oriented traffic environment and require ongoing maintenance and management to ensure effectiveness. In addition to engineering solutions, administrative efforts should focus on advocating for adherence to right-of-way rules and keeping safe distances when crossing intersections to prevent accidents.

A primary component of the education campaign should target high-risk groups, such as the elderly and inexperienced motorcycle riders, educating them about the concept of right-of-way and the importance of yielding to pedestrians at intersections. Education involves disseminating traffic rules, safety information, technical knowledge, and awareness to deepen the public's understanding of relevant concepts.

Since intersection violations tend to result in severe injuries, more vigorous enforcement and higher penalties for recidivists are necessary to reduce their at-fault risks. Enforcement entails the formulation of reasonable laws and regulations, the implementation of relevant ordinances, and the penalties for illegal behaviors.

Except for the traditional 3Es, the addition of encouragement results in the 4Es framework. Encouragement involves organizing events and providing incentive measures. These measures aim to strengthen the connection between public transportation options and improve transfer services. The goal is to achieve seamless transportation. For instance, encourage the adoption of policies for public bicycle usage as an initiative toward promoting green transportation. Furthermore, regular evaluation and publication of road traffic safety conditions are essential.

CHAPTER 7 CONCLUSIONS

This chapter has conclusions, limitations, and recommendations. Conclusions summary of the study's findings, limitations address concerns regarding research shortcomings, and suggestions offer ideas or plans for consideration.

7.1 Conclusions

The study employs an LC*p*-BGOP model to analyze two-party crashes at intersections. This model incorporates threshold values and within-crash correlations that vary across both classes and are parameterized as functions with exogenous variables. Notably, the within-crash correlation is found to vary across classes and is related to the exogenous covariates. The research has dived into the interrelationship of those crash variables that are party-specific or generic among the functions of LC*p*-BGOP. Our results confirm that party-specific factors (e.g., large vehicles, intoxicated, and wearing safety equipment) significantly impact each party's injury severity in both classes than generic factors (e.g., visibility, road surface, and intersection configuration).

Furthermore, our findings of two-party crashes also confirm that these risk factors are highly intertwined. Specifically, crash types frequently involved specific violations, resulting in different injuries for each party involved. For instance, angular (*CSA*) and T-bone (*CST*) intersection collisions during high crash severity occurrences are commonly associated with violations such as "turning without following the right-of-way" (*VLOT*) and "not yielding to the right-of-way vehicles" (*VLOY*). In such crashes, both parties are likely to sustain injuries classified as level "K/A/B" if the second party is a motorcyclist (*VHM*) being inattentive to the vehicles ahead (*VLOI*).

Last but not least, the study also identifies two injury severity occurrence groups: OCS and HCS. In the OCS group, crashes are likely PDOs and level "C" injuries, whereas those belonging to the HCS group are likely injuries for "C" and "K/A/B" levels. Major crash features serve as the basis for this classification, such as violations, mode of mobility, and roadway conditions. Within the OCS group, two-vehicle collisions are likely to be a negative correlation of the injury for two parties. Typically, these incidents occur when the first-party driver/rider crossing intersections fail to give way to the vehicle with the right-of-way.

Moreover, elderly individuals are often the second-party victims. Collisions within the HCS group are likely to involve small vehicles colliding with either bike riders or pedestrians because the first-party driver/rider crossing an intersection may not yield to pedestrians and vehicles with right of way or watch the road ahead. The correlation within HCS might be somewhat ambiguous, which can be illustrated by certain variables.

In the research gap, the bivariate model proposed by Chiou et al. (2013) assumes homogeneity between the two parties involved in crashes. In contrast, our model allows for the possibility of two distinct groups. Certain variables, such as small vehicles, might exhibit significance in either the first or the second group.

For further exploring the intersection crash, the current study builds upon prior research to analyze the injury severity of two-party (including pedestrian) intersection crashes. The LC*p*-BGOP model results characterize the difference in both parties' crash severities via various risk factors under an intersection setting. The model estimations show that the different sizes of vehicles (such as four-wheeled and two-wheeled vehicles) and drivers' physical characteristics differ in crash severity. Still, the model considers more factors belonging to violation types (such as running red lights, speeding, taking alcohol, hit-and-run, etc.). Moreover, two-wheeled vehicle riders, pedestrians, and the elderly are likely to be involved in a severe crash, being either a first or second party.

Many crash classes exhibit heterogeneity rather than homogeneity, which is why combining LCOP and BGOP is necessary, and the model's complexity explains this. Employing LCOP can categorize crashes into classes based on similar patterns, allow the capture of the diversity or heterogeneity present in crash scenarios, and provide a more detailed and accurate representation of the latent structures within the data.

7.2 Limitations

Injury severity has three levels: property damage only, minor/possible, and fatal/evident injury based on crash data in this study. The classification of severity does pose some issues; however, it is not directly relevant to the scope of this study. The following research can discuss this aspect. Furthermore, if future medical provides more detailed severity classifications, it could enhance the interpretability and depth of inference derived from this study.

This study focuses on intersection accidents, highlighting a notable gap in current accident investigation reports used by the police. Specifically, these reports lack critical contemporary roadway features such as auxiliary turning lanes and extended intersection corners. It is conceivable that auxiliary turning lanes, in particular, may significantly correlate with same-direction sideswipes at intersections. Moreover, the absence of exposure data related to traffic volume and phase factors limits the comprehensive analysis of accidents. Therefore, it is recommended that these variables be sensibly incorporated into the investigation forms to facilitate future research in this field. Society of Automobile Engineers (SAE) classifies automated driving into six levels. If drivers mistake lower-level driver assistance for autonomous driving, leading to accidents, there is a necessity to include these contributing factors. The National Highway Police initiated the addition of these factors in July 2023.

The primary limitation of this study stems from the available data, which allows for the determination of fault status but does not provide comprehensive insights into the specific actions of each party involved and their contribution to the severity. The data relies on police reports that offer the current status and assessment of the accidents without detailed crash reconstructions or forensic evaluations.

Moreover, the reliance on police judgment in the data introduces potential biases and limitations, as these reports are not thorough crash investigations. This reliance on police assessments represents a significant data deficiency. Despite these limitations, the study provides valuable insights into intersection crash severity and contributes to the broader understanding of traffic safety and fault determination. However, future research should aim to incorporate more detailed and precise data to overcome these limitations and offer a more comprehensive analysis.

As for future research directions, the current estimation sets the threshold parameters to be invariant across the two classes to obtain stable estimates. It may be a price for a sophisticated model specification. The adoption of a more efficient algorithm, such as the expectation-maximization (EM) algorithm (Sfeir et al., 2021; Sfeir et al., 2022), could be considered to address this issue.

Additionally, it is noteworthy that the current classification of injury severity levels combines fatal and evident injuries into fatal/evident injury (“K/A/B”) to maintain sufficient samples at the highest injury level. However, this classification fails to reflect the unique characteristics of fatal crashes. Redesigning the severity levels is desirable to study the relevant factors in fatal crashes. Also, as the sample is confined to two parties (exactly two people), many crashes involving more than two occupants and self-collisions are excluded, which may have influenced the current estimate. Perhaps a more complete study should include these cases in the context of multivariate analysis.

Lastly, the integrated model for latent class and random parameters has been developed and applied in road safety studies (Chang et al., 2019; Gaweesh et al., 2023; Song et al., 2021; Sun et al., 2022). Recent studies have also proposed various bivariate random parameter models to analyze crash severity (Chen et al., 2019; Fang et al., 2024; Russo et al., 2014; Wang et al., 2022). Thus, we can envision a more compatible model based on the LC*p*-BGOP to incorporate random effects. This approach can account for both observed exogenous variables and unobserved heterogeneity within the identified class within a bivariate model framework (Mannering et al., 2016).

7.3 Suggestions

As for suggestions, since the data explore vehicle-pedestrian and two-vehicle crashes, it is possible to focus on crashes involving pedestrians and vehicles (at intersections and on roadway segments) or to investigate crashes involving specific modes (such as bicycles). This study has identified significant differences in severity, suggesting that improving the behavior of the first-party driver may be more effective than attempting to reduce the severity of the second party. Furthermore, the impact of risk factors on crashes can serve as a reference for law enforcement and insurance agencies.

The safety implications can be group-specific and generic for reducing crash severity in the current context. As our study found in a motorcycle-dominant region, the disrespect toward the right-of-way for other road users at intersections is a critical concern revealed by the two groups. Addressing this issue requires rigorous enforcement measures and ongoing safety campaigns to enhance awareness of traffic right-of-way (i.e., stop and yield) while crossing intersections. Increasing traffic safety consciousness could decrease traffic violations as individuals strive to avoid potential conflicts.

Aside from the above education strategies, the OCS group is needed to deter violations of not giving way to a vehicle with the right of way. Thus, automatic traffic enforcement equipment, such as closed-circuit televisions, cameras, and radars, is recommended for installation at crash-prone intersections. In addition, exclusive and auxiliary turning lanes for turning vehicles may be suggested, depending on the intersection configuration.

Concerning the HCS group, a high occurrence of violations by either bike riders or pedestrians is likely in a mixed traffic flow with heavy traffic. Therefore, crash prevention strategies should aim to mitigate conflicts by implementing measures through exclusive signal timing, establishing dedicated facilities like bike-exclusive lanes and pedestrian refuge areas, and expanding existing sidewalks. Traffic calming, discussed in strategies aiming to alter driving behavior for reduced traffic volume, achieves a safe pedestrian environment through traffic engineering measures like speed humps, cushions, and raised crosswalks.

The elderly groups tend to exhibit a higher severity in latent propensity, so implementing traffic 4E measures is recommended to consider, which aim to enhance the existing roadway environment, driving habits, licensing regulations, and enforcement intensity to address the challenges posed by the current trend of population aging. The study also seeks to identify improvement measures to support the findings. Additionally, it explores the association between intersection crashes and insurance factors.

Factors such as age, driving behavior, and mode of mobility all influence the severity of accidents. Elderly drivers may involved in severe accidents. Violations like speeding and running red lights also increase the risk of accidents. Different types of vehicles cause varying damage. Generally, insurance assesses risks based on these factors and formulates corresponding insurance policies and premiums.

This study has links to the industry, as it determines fault status in insurance applications. After an accident occurs, establishing the attribution of fault is a crucial assessment within the insurance industry. This determination impacts not only the distribution of compensation but also directly relates to the formulation of insurance premium rates.

According to Hsu et al. (2015), individuals with a history of frequent claims tend to opt for higher insurance coverage. This trend suggests a correlation between insurance coverage levels and claim frequency. Therefore, crash data analysis can offer valuable insights for insurance to formulate policies. Huang and Meng (2019) have explored driving behavior variables to predict the probability of risk and claim frequency for insured vehicles. It shows the identification of significant variables and the assessment of their impacts on driving risk, confirming the considerable potential of driving behavior variables in the vehicle insurance field.

We aim to explore the practical implications and benefits for the insurance industry. These benefits may encompass the enhancement of fault determination accuracy, reduced risks for insurance, and promoted a more equitable distribution of claims. Insurance can adeptly manage risks and provide more competitive products by acquiring the factors influencing crash severity and fault status.

As for the application of autonomous vehicles, it could potentially reduce issues related to right-of-way. Once this technology becomes widespread, it might influence the nature of two-party crashes. It needs to be combined with the Internet of Vehicles (IoV) in future research as a topic.

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