Spatio-Temporal Analysis of Roundabout Traffic Crashes in the Region of Waterloo

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Roundabouts are increasingly implemented as safer alternatives to stop-controlled and signalised intersections, with the goal of reducing the severity and frequency of traffic crashes. The safety performance of roundabouts, however, is influenced by their geometric design, and the effects of geometric design variables on safety can vary across different countries and regions. Despite this, there is limited research on these safety impacts within the Canadian context. This study addresses this gap by using data from the Region of Waterloo, Ontario, to develop a safety performance function (SPF) using a negative binomial regression model. The model identified significant geometric design variables affecting collision frequency, such as inscribed circle diameter (ICD), entry angle, entry lane width and number of entry lanes. The findings suggest that the safety impacts of geometric design in Canada may differ from those observed in other countries, highlighting the need for region-specific SPFs. Additionally, in areas where roundabouts are relatively new, it is expected that the safety performance of roundabouts may fluctuate over time and across different locations. However, spatio-temporal variations in roundabout safety have not been extensively studied. To fill this gap, a spatio-temporal analysis was conducted using Bayesian hierarchical models to capture spatial and temporal variations in collision frequency. The results reveal significant spatial autocorrelation, while no strong temporal patterns or novelty effect were detected within the scope of the data and modelling approach used in this analysis. This research advances the understanding of how geometric design and spatio-temporal factors influence roundabout safety, providing important insights for the planning and design of roundabouts. Moreover, it is pioneering in its application of spatio-temporal interaction effects in road safety analysis, demonstrating the potential for this approach in future studies.

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Chapter 1

Introduction

1.1 Background

Road safety remains a critical concern both globally and in Canada. Globally, an estimated 1.3 million people die from road collisions each year, and approximately 50 million more people suffer non-fatal injuries (World Health Organization, 2021). In Canada, while the number of collisions, fatalities and injuries has been declining over the past decades, road collisions still pose significant challenges. Figure 1.1 shows the recent statistics of fatalities and serious injuries, as a result of road crashes. In 2022, 1,746 fatal and 89,787 injury collisions occurred in Canada, resulting in 1,931 fatalities and 118,853 injuries of which 8,851 were serious (Transport Canada, 2024).

The repercussions of road collisions extend beyond the immediate victims and their families, imposing significant economic burdens on communities and countries. The financial losses due to property damage and the associated repair costs represent substantial avoidable economic costs. Additionally, road injuries place a considerable strain on the healthcare systems, and lead to substantial productivity losses due to traffic delays. Globally, the macroeconomic cost of road fatalities and injuries is estimated to be 0.12% of the global gross domestic product, with an estimated total of $1.8 trillion USD in 2015–2030 (Chen, Kuhn, Prettner, & Bloom, 2019). In Canada, the social cost of vehicle collisions in 2020 was estimated at approximately $36 billion CAD, constituting more than 1.9% of the Canadian GDP (Transport Canada, 2023).

To address such issues, there has been significant interest in improving road safety. At the global level, the United Nations and the World Health Organization (2021)

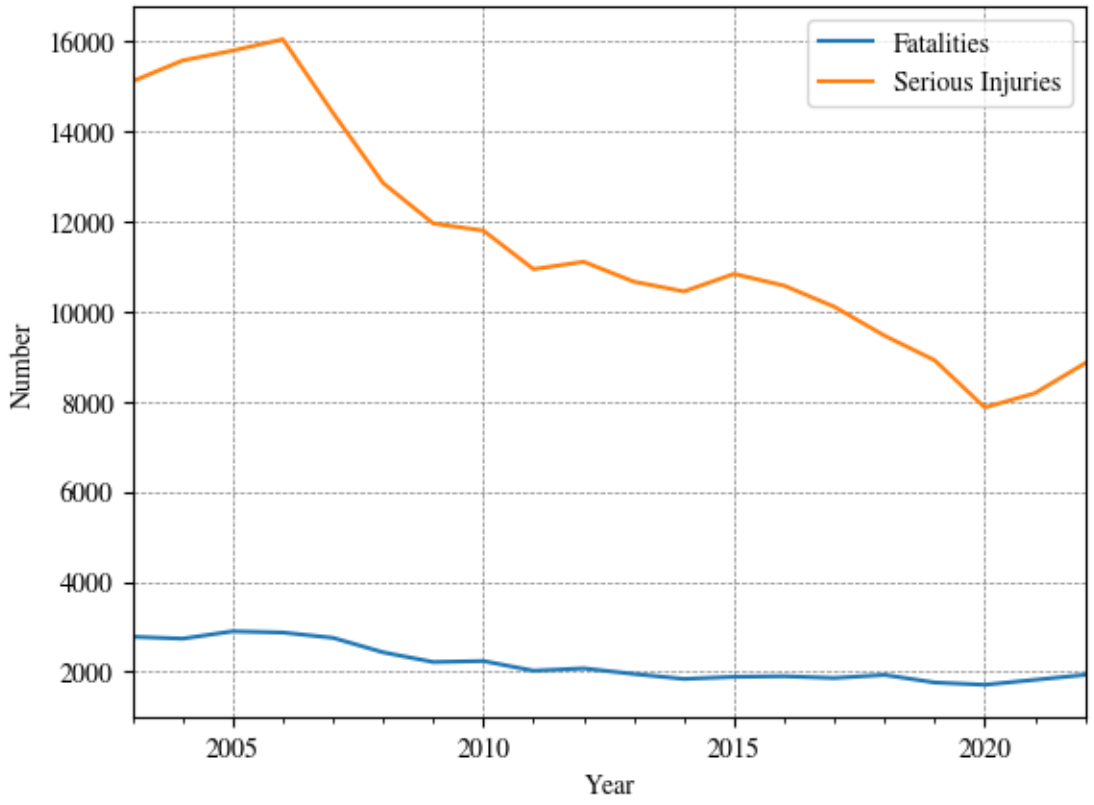


Figure 1.1: Number of Fatalities and Serious Injuries due to Collisions in Canada (Data Source: Transport Canada (2024))

have established "Global Plan Decade of Action for Road Safety 2021–2030", which aims for a 50% reduction in traffic deaths and injuries during the period of 2021 and 2030. In Canada, the Canadian Council of Motor Transport Administrators (2016) has adopted "Road Safety Strategy 2025", which seeks to continuously reduce the rate-based number of deaths and serious injuries due to road collisions, with a long-term vision of eliminating them. Both initiatives, among others, are grounded in the concepts of Vision Zero and the Safe System Approach.

Vision Zero, first introduced in Sweden in 1997 and later adopted by many other countries, is a long-term policy for the design and functioning of the road transport system. It sees deaths and serious injuries as unacceptable outcomes of road collisions, and aims to ultimately eliminate such risks from the road transport system (Transportation Association of Canada, 2023). The approach places a larger

emphasis on preventing deaths and serious injuries, unlike traditional road design philosophies that primarily aimed at preventing crashes without necessarily addressing the severity of outcomes (R. Johansson, 2009). Vision Zero emphasises understanding human tolerance to kinetic energy that can cause chronic health impairment and building a road transport system that prevents such energy threshold from being exceeded.

The Safe System Approach, often discussed alongside Vision Zero, proposes an integrated, comprehensive process to improve road safety. A key component of the Safe System Approach is recognising human fallibility and advocating for road designs that ensure small mistakes by drivers do not lead to collisions, or if collisions do occur, they do not result in fatalities or serious injuries (Transportation Association of Canada, 2023).

Roundabouts, a form of intersection control, have seen continuous adoption in North America as part of Vision Zero and the Safe System Approach due to their improved safety performance compared to stop-controlled or signal-controlled intersections. The history of roundabouts in North America dates back to 1905 when the first so-called "traffic circle" was introduced in the New York City. However, traffic circles at the time differed from modern roundabouts in that right-of-way rules were not well established, and larger central islands were often recommended to facilitate higher speeds and capacity, sometimes resulting in gridlocks (Todd, 1988). Modern roundabouts, featuring "offside priority" rules that require entering traffic to yield to circulating traffic and designed with smaller central islands and larger entry curvature to slow down vehicles at entry, appeared in the United Kingdom after 1966 (Robinson et al., 2000). Such modern roundabouts have demonstrated improved operational and safety performance compared to the old "traffic circles", and have been widely adopted in other countries (Robinson et al., 2000).

1.2 Roundabout Safety and Problem Statement

Roundabouts have been demonstrated to reduce injury and fatality collisions compared to stop-controlled or signal-controlled intersections, according to numerous comparative studies (Elvik, 2017), as detailed in Section 2.1.1.

However, the safety effects of roundabouts vary subject to various factors. One of such factors is the geometric design of roundabouts, and there has been extensive research in Europe and some in the United States, Asia and Australia, to investigate how different geometric design variables impact safety. For detailed analysis of

existing studies, refer to Section 2.1.2. Currently, there is limited research on roundabout safety in Canada, and the Canadian Roundabout Safety Guide bases their geometric and safety consideration on the UK and US guide (Chartier et al., 2017; Highways England, 2020; Robinson et al., 2000; Transportation Research Board & National Academies of Sciences, Engineering, and Medicine, 2019). However, safety outcomes differ between countries, most likely due to differences in driver behaviours, environments and climate conditions.

Additionally, it is plausible that the safety of roundabouts also exhibits spatial and temporal variability. In Canada, where roundabouts have been relatively recently introduced as a traffic control measure, road users are still adapting to this new infrastructure. As a result, the safety impacts of roundabouts are likely to differ between the initial implementation phase and subsequent years. Additionally, the installation patterns of roundabouts in Canada vary, with some being clustered within certain corridors and others being isolated. This geographical variability can potentially lead to different safety outcomes. Despite extensive research on the geometric design of roundabouts, existing studies often assume constant spatial and temporal variations in safety effects. Although some research on roundabout have considered spatio-temporal effects, they mostly remain observational, with very few considering spatial and temporal effects simultaneously, and variations in the context of new implementations in regions like Canada, remain under-explored. Refer to Section 2.1.4 and Section 2.1.5 for detailed discussions.

The limited research on roundabouts in Canada, and the insufficient consideration of spatial and temporal variations in their safety effects, may result in sub-optimal implementation strategies. In Canada, where roundabouts have been rapidly deployed, considering these variations can potentially improve the design of roundabouts, contributing to improved road safety in alignment with Vision Zero and the Safe System Approach.

It is worth noting here that roundabouts are designed in various forms to accommodate different traffic conditions, geographic constraints and advancements in design. The Canadian Roundabout Design Guide (Chartier et al., 2017) classifies roundabouts into three categories based on geometric design: mini-roundabouts, single-lane roundabouts and multi-lane roundabouts. Additionally, innovative designs such as turbo roundabouts and signal-controlled roundabouts have emerged. Turbo roundabouts, which aim to combine the capacity of dual-lane roundabouts with the safety of single-lane roundabouts, have been widely adopted in Europe since the late 1990s (Fortuijn, 2009; Tollazzi, 2015). Signal-controlled roundabouts, which are effective in managing unbalanced traffic flows, have also been popular in

Europe since the 1990s (Tollazzi, 2015). Non-motorised transport modes also navigate roundabouts in various ways. For example, cyclists may share the road with vehicles or use separated pathways through pedestrian crossings (Sakshaug, Laureshyn, Svensson, & Hydén, 2010). Different roundabout designs exhibit varying safety effects, as evidenced by studies on turbo roundabouts (Fortuijn, 2009) and different cyclist pathways (Sakshaug et al., 2010). Therefore, this research will focus on single-lane and multi-lane roundabouts in an urban setting.

1.3 Research Objectives

This research aims to achieve two primary objectives. Firstly, it seeks to improve the understanding of the effects of roundabout geometry on safety performance. Secondly, it seeks to investigate the effects of spatial and temporal factors of roundabouts on safety performance. Specifically, the research aims to determine whether the duration of roundabout operation and the geographical clustering of installations have discernible effects on collision frequency. By exploring these aspects, this study aspires to provide valuable insights that can inform and enhance road design policies and strategies.

1.4 Thesis Organisation

This thesis is organised into six chapters.

- Chapter 1 provides an introduction to road safety, roundabouts and their safety performance. It also outlines the research objectives and the structure of the thesis.
- Chapter 2 provides a comprehensive literature review on roundabout safety, methods of roundabout safety analysis, and spatio-temporal effects in road safety. It identifies the research gaps and discusses potential methodologies to address these gaps.
- Chapter 3 introduces the data used in this research, and presents an exploratory analysis of the data.

- Chapter 4 investigates the effects of roundabout geometric design on safety performance. It develops safety performance functions (SPFs) using negative binomial regression to model the relationship between collision frequency and geometric design variables.
- Chapter 5 explores the effects of spatial and temporal factors of roundabouts on safety performance. It develops spatio-temporal SPFs using Bayesian hierarchical models with spatial and temporal random effects to assess their significance.
- Chapter 6 summarises the research contributions, discusses the limitations of the study, and provides recommendations for future research.

Chapter 2

Literature Review

This chapter presents a comprehensive literature review on roundabout safety analysis and spatio-temporal variation in road safety. It is organised into three sections. The first section reviews studies that have investigated the safety impacts of roundabouts from multiple perspectives. The second section examines the various methodologies employed in the analysis of roundabout safety. The third section explores the literature on temporal and spatial variability in road safety.

2.1 Roundabout Safety

2.1.1 Comparison with Other Control Types

One important aspect of safety analysis for roundabouts involves comparative studies that evaluate the effectiveness of roundabouts relative to other intersection control types, such as stop controls and signal controls.

The most common methodology for these studies is the before-after study, where the safety performance before and after the conversion is compared for intersections that were converted from stop or signal controls to roundabouts. There are various approaches to conducting before-after studies. The simplest method compares the number of collisions of specific types before and after conversion without considering changes in traffic volume. An example of this approach is Flannery and Datta (1996), where six conversions from stop-controlled or signal-controlled intersections to roundabouts were examined without accounting for changes in traffic volume and conditions.

To account for changes in traffic volume and conditions, some studies incorporate non-treatment sites as a comparison group. This comparison group includes overall trends in crash frequency or severity into the analysis, which are presumed to impact both treatment and non-treatment sites equally (American Association of State Highway and Transportation Officials, 2010). An example of this method is Hu, McCartt, Jermakian, and Mandavilli (2014), which examined two roundabouts converted from stop-controlled and signal-controlled intersections, using five and eight comparison intersections with similar traffic control types, intersection layouts, and traffic volumes to those of the pre-conversion intersections.

However, analyses using non-treatment sites as comparison groups can be susceptible to regression-to-mean bias, especially when sites were converted due to a high number of collisions rather than being randomly selected (Hauer, 1986). High collision numbers can be partially due to randomness, and in such case, since the number of collisions tends to decrease even without treatment, the analysis may overestimate the effect of treatment. Empirical Bayes methods are widely used to counteract regression-to-mean bias, utilising safety performance functions (SPFs) to estimate the expected number of collisions (Hauer, Harwood, Council, & Griffith, 2002). Most before-after analyses on roundabouts have employed empirical Bayes methods (Elvik, 2017).

Although limited in number, some comparative or cross-sectional studies examine the performance of roundabouts versus other controlled intersection types by assessing relative collision rates of intersections and roundabouts existing concurrently over the same period (Elvik, 2003; American Association of State Highway and Transportation Officials, 2010).

Elvik (2017) conducted a comprehensive meta-analysis of 44 before-and-after studies spanning from 1975 to 2014 across countries including Australia, Belgium, Denmark, Germany, Great Britain, the Netherlands, Norway, Sweden, Switzerland, the United States. The analysis came to several main conclusions. Firstly, converting intersections from stop or signal controls to roundabouts resulted in an approximately 40% reduction in injury collisions and an approximately 65% decrease in fatal collisions. Secondly, although slight reduction in the number of property-damage-only (PDO) collisions was found, it was less certain, with some studies reporting a significant increase.

From a meta-analysis of 28 studies, Elvik (2003) showed that the conversion's effectiveness was greater at intersections previously controlled by stop signs rather than signals, and at four-legged intersections compared to three-legged ones, although results varied.

Among notable before-after studies, De Brabander and Vereeck (2007) examined collision data from 95 roundabouts in Flanders, Belgium, covering the period from 1991 to 2001. The analysis found that converting stop- and signal-controlled intersections to roundabouts reduced injury collisions by 39%, with a more significant reduction in minor injuries compared to serious injuries, although it did not state the reduction in fatal collisions. The effect was more pronounced at intersections that were previously stop-controlled and those with higher speed limits.

Jensen (2013) studied 332 intersections in Denmark that had been converted from stop or signal controls to roundabouts. The findings indicated a 27% reduction in crashes, a 60% reduction in injuries, and an 87% reduction in fatalities. Again, the reductions were more significant at intersections that were previously non-signalised and those with higher speed limits.

In the United States, Gross, Lyon, Persaud, and Srinivasan (2013) conducted a before-after analysis of 28 cases where signalised intersections had been converted to roundabouts. Their study found a significant reduction of 20.8% in the number of crashes, with a more substantial decrease of 65.8% in injury collisions, and a greater reduction at four-legged intersections compared to three-legged intersections.

The enhanced safety benefits of roundabouts compared to stop- or signal-controlled intersections can be attributed to three key factors. Firstly, roundabouts have fewer conflict points, and virtually remove the potential for high-severity head-on and broadside collisions (Chartier et al., 2017). Secondly, roundabouts promote lower vehicle speeds, which diminishes both the likelihood and severity of collisions (Antov, Abel, Sürje, Rõuk, & Rõivas, 2009). Thirdly, roundabouts simplify the decision-making process for drivers by segmenting decisions into smaller steps over time and space, and by eliminating the need for traffic control devices that drivers may develop habitual responses to (Chartier et al., 2017).

However, despite the overall safety improvement of roundabouts compared to stop- or signal-controlled intersections, their effect on the safety of vulnerable road users may not be as positive. De Brabander and Vereeck (2007) reported an increase in collisions involving vulnerable road users at some intersections that were previously signalised, along with an overall rise in the likelihood of serious injuries. Similarly, Jensen (2013) observed that cyclist collisions and injuries increased by 65% and 40%, respectively, following the conversion from stop- or signal-controlled intersections.

In summary, literature shows that converting stop- or signal-controlled intersections to roundabouts significantly reduces injury and fatal collisions. However, the impact on vulnerable road users can be less positive, with increases in collisions and injuries reported in some studies.

2.1.2 Geometric Effects

The safety effects of roundabouts are influenced by their geometric features, which can impact safety in several ways. Firstly, the number of lanes can alter the number of conflict points, thereby affecting potential collision scenarios. Secondly, the geometric design, particularly the entry design, has been shown to affect vehicle speeds (Antov et al., 2009), which in turn influences the risk and severity of collisions. Thirdly, the overall geometric layout can influence visibility, which is crucial for safe navigation through the roundabout. A number of research aimed at understanding the relationships between geometric design and safety has primarily been conducted for two purposes: identifying factors influencing the safety of roundabouts to enhance geometric design, and predicting the frequency of collisions to optimise design selection and construction. While numerous studies directly analyse the relationships between geometric design and safety, there are also studies that use speed or visibility as independent variables, which are partly dependent on geometric designs.

The most commonly used method for evaluating the impact of geometric design on roundabout safety is through the use of SPFs. SPFs typically estimate the expected number of collisions over a specified period, usually one year, at a particular location using regression models that incorporate various independent variables associated with roundabouts. These models often include an exposure variable, such as the vehicle volume or bicyclist volume, which accounts for the number of at-risk road users. However, some studies, such as Kim and Choi (2013), use the number of collisions per unit traffic volume as the dependent variable, thus excluding the exposure variable from the independent variables.

The most basic regression model employed in SPFs is the Poisson regression due to their ability to handle non-negative integer collision data. However, collision data are often over-dispersed or under-dispersed, and negative binomial regression and gamma regression are used to accommodate such dispersion (Lord & Mannering, 2010). Some studies also employ zero-inflated Poisson and zero-inflated negative binomial regression models to account for the excessive zeros present in collision data (Lord & Mannering, 2010). This is further detailed in Section 4.1.1.

For roundabouts, SPFs can be constructed at either the leg level or the intersection level. At the leg level, separate SPFs are developed for each leg of the roundabout. At the intersection level, a single SPF is formulated to represent the entire roundabout.

SPFs can also be developed for different types of collisions. The most common classifications of collision types in the literature are based on severity, type of road

user involved, and the action being taken by the involved party. Severity classifications typically include fatality, serious injury, and minor injury, though definitions can vary between studies. For types of road users, most studies consider vehicles, cyclists, and pedestrians, with some further subdividing categories to include other vehicle types such as heavy vehicles and mopeds. Regarding the actions taken by road users, typical roundabout studies consider entering-circulating, circulating-exiting, rear-end, and single-vehicle collisions (Chartier et al., 2017), although different studies may consider various other action types.

A notable example of an leg-level study is the work by Maycock and Hall (1984). Using injury collisions between 1974 and 1979 at 84 roundabouts in the UK, they constructed SPFs for four collision types: entering-circulating, approaching, single-vehicle, pedestrian and other. The study considered 26 geometric variables, including entry path curvature, entry width, approach half-width, and the angle between arms, for each roundabout arm.

Their developed equations are:

$$y \mid \alpha, \mu \sim \text{Negative Binomial}(\alpha, \frac{\alpha}{\alpha + \mu}) \tag{2.1}$$

for entering-circulating crashes:

$$\begin{aligned} \mu = \exp \Bigg(& -2.957 + 0.7 \ln(Q_{en}) + 0.4 \ln(Q_c) - 40 C_{en} \\ & + 0.14 W_{en} - 0.007 EV - RF + 0.2 P_m - 0.01 \theta_a \Bigg) \end{aligned} \tag{2.2}$$

for approaching injury crashes:

$$\mu = \exp\left(-5.174 + 1.7 \ln(Q_{en}) + 20 C_{en} - 0.1 W_{en}\right) \tag{2.3}$$

for single-vehicle injury crashes:

$$\mu = \exp\left(-5.046 + 0.8 \ln(Q_{en}) + 25 C_{en} + 0.2 W_{app} - 45 C_{app}\right) \tag{2.4}$$

where

$$
\begin{aligned}
y &: \text{number of injury collisions per year} \\
\alpha &: \text{dispersion parameter} \\
\mu &: \text{expected number of injury collisions per year} \\
Q_{en} &: \text{entering flow (thousands of vehicles per 24 hours)} \\
Q_c &: \text{circulating flow (thousands of vehicles per 24 hours)} \\
C_{app} &: \text{approach curvature } \left(m^{-1}\right) \\
C_{en} &: \text{entry curvature } \left(m^{-1}\right) \\
W_{app} &: \text{approach width } (m) \\
W_{en} &: \text{entry lane width } (m) \\
EV &= 0.14 \left(1 - \frac{W_{app}}{20}\right) W_{en} \\
RF &= \frac{1}{1 + \exp\left(4\frac{ICD}{CID} - 7\right)} \\
ICD &: \text{inscribed circle diameter } (m) \\
CID &: \text{central island diameter } (m) \\
P_m &: \text{proportion of motorcycles } (\%) \\
\theta_{arm} &: \text{angle between arms (degrees).}
\end{aligned}
$$

A notable example of intersection-level analysis is provided by Daniels, Brijs, Nuyts, and Wets (2011). The analysis developed SPFs for roundabouts in Belgium using data from 148 roundabouts. They considered a total of 37 independent variables, including geometric variables such as the presence of a raised central island, presence of traversable truck aprons, apron width, central island diameter, inscribed circle diameter, number of legs, and number of circulating lanes. In addition to these geometric variables, they also included independent variables related to the surrounding area and the geometric symmetry of the roundabout. They developed eight different models based on the type of involved party in the collision, distinguishing between single-vehicle and multiple-vehicle collisions. Both Poisson and gamma regression models were evaluated to determine the most effective modelling approach.

Negative binomial regression model for all crashes is:

$$y \mid \alpha, \mu \sim \text{Gamma}(\alpha, \frac{\alpha}{\mu}) \tag{2.5}$$

$$\mu = \exp\left(-10.64 + 1.10\ln(ADT) + 0.08\ln(BIC) - 0.33CP + 0.59Leg_3\right) \tag{2.6}$$

where

$$\begin{aligned}
y &: \text{number of injury collisions per year,} \\
\alpha &: \text{dispersion parameter,} \\
\mu &: \text{expected number of injury collisions per year,} \\
ADT &: \text{Volume of motor-vehicles (vehicles per 8:00–18:00),} \\
BIC &: \text{volume of bicyclists (bicycles per 8:00–18:00),} \\
CP &: \text{presence of cycle paths,} \\
\text{Leg}_3 &: \text{three-leg roundabouts.}
\end{aligned}$$

Another notable example of intersection-level analysis is provided by Ambros et al. (2016), who developed safety performance models in Central European countries using data from 72 roundabouts. This study utilised injury and fatality collision data from 2009 to 2013 and employed a negative binomial regression model to explain variations in crash rates. The independent variables considered included traffic volume, inscribed circle diameter, central island diameter, entry width, exit width, circulating width, apron width, entry angle, deviation angle, and the presence of pedestrian crossings or cycle paths. Two final models were developed based on whether entry angle or deviation angle was used as an indicator of deflection.

$$y \mid \alpha, \mu \sim \text{Negative Binomial}(\alpha, \frac{\alpha}{\alpha + \mu}) \tag{2.7}$$

for entry angle-based models,

$$\mu = 0.004 \cdot I^{0.424} \cdot \exp(0.369 \cdot W_{apr} - 0.034 \cdot A_{en}) \tag{2.8}$$

for deviation angle-based models,

$$\mu = 0.001 \cdot I^{0.639} \cdot \exp(0.402 \cdot W_{apr} - 0.031 \cdot A_d) \tag{2.9}$$

where

y : number of injury collisions per year,
α : dispersion parameter,
μ : expected number of injury collisions per year,
I : traffic volume (vehicles per day),
W_{apr} : apron width (metres),
A_{en} : entry angle (degrees),
A_d : deviation angle (degrees).

A notable example of directly using vehicle speeds and visibility to explain differences in roundabout safety performance is Turner, Roozenburg, and Smith (2009). They used injury and collision data from 104 roundabouts in New Zealand to perform a leg-level negative binomial regression analysis.

For instance, the model for entering-circulating crash type they developed is:

$$y \mid \alpha, \mu \sim \text{Negative Binomial}(\alpha, \frac{\alpha}{\alpha + \mu}) \tag{2.10}$$

$$\mu = 6.12 \cdot 10^{-8} {Q_{en}}^{0.47} \cdot {Q_c}^{0.26} \cdot {S_c}^{2.13} \tag{2.11}$$

where

y : number of injury collisions per year,
α : dispersion parameter,
μ : expected number of injury collisions per year,
Q_{en} : entering flow (vehicles per day),
Q_c : circulating flow (vehicles per day),
S_c : free mean speed of circulating vehicles as they pass the approach (km/h).

The results from 14 similar studies conducted in Europe, Australia, the United States, India, and Korea are summarised in the Appendix A. Due to slightly varying model structures, direct comparison between model coefficients was not possible. However, by examining the signs of the model coefficients, it was possible to determine whether an increase in each variable was associated with an increase or decrease in the expected collision frequency. In the table, a variable is indicated with a (+) if its increase is associated with an increase in expected collision frequency, and with a (−) if its increase is associated with a reduction in expected collision frequency.

Comparing the results from different studies, the effects of some variables on roundabout safety are consistent, while others vary. For instance, all relevant literature agrees that vehicle volume is positively associated with collision frequency, and all studies that considered the number of circulating and entry lanes found a similar positive association with collision frequency. However, while Brude (2000), Kim and Choi (2013), and Transportation Research Board and National Academies of Sciences, Engineering, and Medicine (2019) identified a positive correlation between the number of legs and collision frequency, Daniels et al. (2011) found a negative correlation, and Qin, Khan, Bill, and Noyce (2011) and Šenk and Ambros (2011) found it to be insignificant. Similarly, while Kamla, Parry, and Dawson (2016) reported a positive correlation between the inscribed circle diameter (ICD) and collision frequency, Maycock and Hall (1984) and Transportation Research Board and National Academies of Sciences, Engineering, and Medicine (2019) found the opposite, with Ambros et al. (2016), Anjana and Anjaneyulu (2015), Daniels et al. (2011), Kim and Choi (2013), Novák, Ambros, and Frič (2018) and Qin et al. (2011) finding it to be insignificant. Varying effects of a variable are also observed within the same study, depending on the crash type; for example, Maycock and Hall (1984) found that the entry radius had a positive relationship with entering-circulating collisions, a negative relationship with approaching or single-vehicle collisions, and was insignificant for other or pedestrian collisions.

2.1.3 Regional Variations

A number of studies acknowledge the varying safety effects of roundabouts between different countries or regions. In the before-after studies summarised in Section 2.1.1, Elvik (2017) found that the conversion of intersections to roundabouts was more effective in North America and Australia than in other parts of the world.

In SPF studies discussed in Section 2.1.2, several researchers have highlighted differences in the relationship between geometric design and safety across different countries or regions. For instance, National Academies of Sciences, Engineering, and Medicine (2007) investigated the applicability of European models, specifically those from Sweden, the UK, and France, to data from the United States by assessing the goodness of fit for predicting the number of collisions, and found that the European models did not adequately fit the US data. Consequently, the report concluded that using existing European models to predict intersection-level collisions in the United States is not advisable. Transportation Research Board and National Academies of Sciences, Engineering, and Medicine (2019) introduced calibration variables in SPFs

to indicate the state and jurisdiction for which the model is developed, reflecting the variation in safety effects across different locations. On a regional scale, several studies have identified the urban or rural setting as a significant factor affecting safety, with the majority finding better safety outcomes in urban areas (Daniels et al., 2011; Transportation Research Board & National Academies of Sciences, Engineering, and Medicine, 2019; Novák et al., 2018; Gross et al., 2013; Jensen, 2013).

Such varying effects can be attributed to several factors. One factor is the difference in road user behaviour between countries. For instance, Elvik (2017) speculated that the enhanced effectiveness of roundabouts in North America might be due to the high prevalence of stop-controlled intersections and the habituation of drivers to stopping, which may enhance the effectiveness of roundabouts in these regions. National Academies of Sciences, Engineering, and Medicine (2007) found that American drivers use roundabouts less efficiently than European drivers. Although this observation was concerned with the operational aspect of roundabouts, it is plausible that behavioural differences also contribute to varying safety outcomes.

Another factor is the differing design principles. For example, while double-lane roundabouts are not particularly discouraged and are widely seen in Canada, they are strongly discouraged in some European countries (Chartier et al., 2017); France and Germany have limited design guidance for these (Kennedy, 2007), and the Netherlands and Slovenia have banned the construction of standard multi-lane roundabouts (Tollazzi, 2015). In fact, studies on geometric effects in Europe predominantly included more single-lane roundabouts than multi-lane roundabouts: 26 dual-lane roundabouts versus 58 single-lane roundabouts in Maycock and Hall (1984), 15 versus 133 in Daniels et al. (2011), and 23 versus 177 in Novák et al. (2018). Additionally, continental Europe generally prefers tighter geometric designs; for example, the recommended ICD for urban single-lane roundabouts is 28-60 metres in Canada (Chartier et al., 2017), whereas it is 26-35 metres in Germany (Kennedy, 2007).

A third factor is the environmental conditions. For instance, snowfalls have been shown to affect road safety in general (Theofilatos & Yannis, 2014). Although Canada and the US follow similar design guidelines, prolonged wintry conditions in Canada may result in distinct safety outcomes.

2.1.4 Spatial Effects

Several studies have examined the spatial effects on roundabout safety, particularly the proximity to certain infrastructure or geological features. For example, Novák et

al. (2018) included the presence of public transport stops, car parks, and access points or intersections within 100 metres of roundabouts as binary independent variables in their SPFs, although these factors were not significant. Transportation Research Board and National Academies of Sciences, Engineering, and Medicine (2019) included the number of unsignalised access points within 250 feet of roundabouts in their SPFs, finding that a higher number of access points was associated with a higher frequency of collisions. Hydén and Várhelyi (2000) found that for a group of 21 small roundabouts in Sweden, roundabouts located within 300 metres of each other had a speed reduction effect on the connecting link. Although the study did not find a significant reduction in collisions, lower speeds are often associated with fewer collisions, suggesting that closely spaced roundabouts have the potential to reduce collisions within the system.

2.1.5 Temporal Effects

Several studies have examined the temporal effects on roundabout safety, particularly focusing on the phenomenon known as the novelty effect. This effect refers to the observation that the safety impacts of roundabouts during the initial years following their installation differ from those in subsequent years. This novelty effect, also termed the "adaptation effect" or "learning curve effect", is attributed to changes in road user behaviour as drivers become more accustomed to navigating roundabouts.

For instance, Joerger et al. (2007) investigated the first urban multi-lane roundabout in the State of Oregon, the US, and monitored driving errors using video recordings and on-site analysis. The analysis revealed that the number of driving errors decreased over time, following a logarithmic learning curve.

Novelty effects are considered in both before-after studies and SPF studies. For instance, Coffey, Park, and Zoccoli (2016) studied 11 converted sites in Pennsylvania, the US, and reported that some intersections converted to roundabouts experienced a significant increase in collisions during the first two years after installation. However, overall, there was no noticeable yearly trend. Similarly, Jensen (2013), who studied 332 converted sites in Denmark, identified an adaptation effect wherein the number of single-vehicle collisions and the severity of multi-vehicle collisions decreased and stabilised a few years after installation. The safety effect from three to nine years after installation was found to be 12–13% better than in the first two years for all types of injuries in both urban and rural settings. In before-after studies, a post-implementation period of at least three years is commonly used to mitigate the impact of such initial effects (De Brabander, Nuyts, & Vereeck, 2005).

In SPF studies, some researchers have included temporal variables in their analyses. For example, Daniels et al. (2011) incorporated the year of construction of each roundabout as a numeric variable in the SPFs. This variable was found to be significant for crashes involving mopeds, motorcycles, and multi-vehicle incidents, although it was insignificant for other types of crashes. The coefficients indicated that the number of collisions was lower for newer roundabouts. Conversely, some studies have excluded data from the first few years post-installation due to fluctuations. For instance, Turner et al. (2009) excluded data from the first five years after installation in their modelling process, acknowledging that this period may not be representative of the roundabout's long-term safety performance.

Contrary to the findings of some studies, other research did not observe significant initial temporal effects. For example, Transportation Research Board and National Academies of Sciences, Engineering, and Medicine (2019) investigated the temporal effects within the first five years post-installation at 109 sites in the United States by incorporating a variable that indicated the age of the roundabouts into their model. The analysis did not reveal any statistically significant evidence of a learning effect on an annual basis. Similarly, Qin et al. (2011), utilising data from 41 roundabouts in Wisconsin, United States, examined the 'novelty effect' at six-month intervals but did not find any significant results.

Moreover, after the initial few years, the safety effects of roundabouts appear to be quite consistent. Elvik (2017) found that the safety improvements from converting stop- or signal-controlled intersections to roundabouts have remained consistent from 1975 to 2014.

2.1.6 Research Gap

Canadian roundabouts are largely designed based on the guidelines from Chartier et al. (2017). The geometric design guidance is derived from guidelines in the United States (Robinson et al., 2000) and the United Kingdom (Highways England, 2020), while the safety analysis is based on studies conducted in the United States (Robinson et al., 2000; Transportation Research Board & National Academies of Sciences, Engineering, and Medicine, 2019). However, the varying safety results observed globally suggest that findings from other countries may not be directly applicable to the Canadian context, underscoring the necessity for developing SPFs tailored to the unique conditions present in Canada.

Additionally, safety outcomes at roundabouts in Canada are likely to exhibit some spatio-temporal variability due to the relatively recent adoption of roundabouts and

the ongoing process of road user adaptation. Although some of the literature has considered the micro-level spatial and temporal effects of roundabout safety, most of these studies were observational and included few statistical analyses of varying effects. More significantly, no literature has examined the combined effects of spatial and temporal variability. This highlights the need for a more rigorous analysis of the spatio-temporal variability of roundabout safety, particularly in the context of new installations.

2.2 Methods of Roundabout Safety Analysis

Road safety analysis, particularly the analysis of roundabout safety, can be approached through various methodologies, including empirical studies, simulation studies and user experience studies. Below is a brief summary of each methodology type, along with their respective advantages and disadvantages.

2.2.1 Collision-based Empirical Studies

Traditionally, crash data have been used as a measurement of the safety of particular road facilities. These data are the most direct measure of road safety, and in the context of the Vision Zero approach, measuring safety in terms of the number of injury collisions is particularly relevant. All literature introduced in Section 2.1 is based on collision-based empirical studies.

However, using collision data has some drawbacks. Firstly, crashes are rare events, and obtaining a sufficient sample size for statistical analysis poses a challenge (Lord & Mannering, 2010). Secondly, the analysis can be affected by under-reporting of crashes, which has been shown to occur at all levels of injury severity with varying degrees between car occupants and cyclists (Elvik & Mysen, 1999). Lastly, this approach is reactive rather than proactive, as an analysis can only be done after collisions have already occurred, which raises ethical concerns.

2.2.2 Conflict-based Empirical Studies

Conflict-based studies focus on identifying and analysing potential collision or near-miss situations, known as conflict situations, to assess safety in roundabouts.

In empirical studies, conflicts are identified from road user trajectory data, which can be typically obtained from video, LiDAR or Bluetooth technology. Video analysis involves recording road users at roundabouts and subsequently analysing the footage using computer vision technology to track road user movements. Most existing conflict-based research has used video technology, as seen in the examples of St-Aubin, Saunier, and Miranda-Moreno (2015). Both LiDAR and Bluetooth technology may also be used to accurately capture the trajectories of vehicles, cyclists, and pedestrians, although most applications in roundabout so far have been in operation and not in safety (Li, Zhang, Xu, Yang, & Lu, 2024). Trajectory data can be obtained from simulation models which replicate real-world traffic conditions and driver behaviours instead of using empirical data, which are detailed in Section 2.2.3.

From trajectory data, conflicts are identified and measured in various measurements. The most commonly used measurements are time to collision (TTC) and post encroachment time (PET) (Zheng, Sayed, & Mannering, 2021). TTC is defined as the time remaining before two road users would collide if they continued at their current speeds and trajectories (Hayward, 1972), and in used in roundabout analysis such as Deveaux et al. (2021), Sadeq and Sayed (2016) and St-Aubin et al. (2015). PET is defines as, for the potential conflict point, the time difference between the moment the preceding road user passes and the following road user passes (Cooper, 1984), and used in Karwand et al. (2023).

One of the primary advantages of conflict-based empirical studies is that conflicts occur more often than crashes, allowing for larger sample sizes compared to collision-based studies (Zheng et al., 2021). Additionally, conflict-based studies avoid the under-reporting of collisions commonly seen in collision-based studies, as they automatically record conflicts regardless of the behaviour of the road users or the police, potentially offering a more comprehensive picture of safety (Johnsson, Laureshyn, & De Ceunynck, 2018). Another significant advantage is that these studies are more proactive than collision-based studies and do not require waiting for fatalities or injuries to occur before conducting an analysis (Zheng et al., 2021).

However, conflicts are surrogate safety measures used in lieu of crashes, and the types of conflict measurements and the thresholds for these measurements to be considered conflicts need careful examination. Li et al. (2024) identified several issues with current conflict analysis at roundabouts. Firstly, roundabouts exhibit distinct collision patterns compared to other intersection types, such as a higher prevalence of multi-vehicle collisions. Therefore, commonly-used conflict criteria may not be the best indicators of potential collisions. Secondly, although vehicle size and mass are considered to affect the severity of collisions, these factors are usually not

considered in existing conflict-based analyses. Thirdly, existing research employs varying thresholds for conflicts and the associated risk of collisions. The use of overly lenient or strict thresholds can lead to an inaccurate representation of safety.

Moreover, although there are large datasets of conflict data at roundabouts available, such as Zhan et al. (2019) and Breuer, Termöhlen, Homoceanu, and Fingscheidt (2020), they typically span from a few hours to a few days, limiting the scope for larger temporal analysis. This constraint can hinder the ability to study long-term trends and the effectiveness of interventions over extended periods.

2.2.3 Simulation Studies

Simulation studies replicate roundabout geometries, traffic and, in case of signalised roundabouts, signal timing in computational models to analyse traffic operation and safety under various conditions. They typically employ microscopic traffic simulation software such as VISSIM and SUMO to model individual driver behaviour and obtain vehicle trajectories, allowing for analysis of conflict data and surrogate safety measures. Although traffic simulation software simulates the behaviour of individual drivers through mathematical functions such as car-following models and gap acceptance models, some studies use results from driving simulators, as seen in the case of Orsini, Gecchele, Gastaldi, and Rossi (2019) for roundabouts.

One notable example of roundabout safety analysis using simulation is the study by Saccomanno, Cunto, Guido, and Vitale (2008), which used microscopic simulation in VISSIM and surrogate measures to compare the risk of rear-end conflicts at signalised intersections and roundabouts. The study found that roundabouts have a lower percentage of vehicles in conflict, indicating fewer rear-end conflicts.

One of the primary benefits of simulation studies over other methods is the ability to assess the safety of a hypothetical scenario. This allows for testing new designs without exposing real road users to potentially hazardous scenarios and at a smaller cost. For instance, Gallelli, Perri, and Vaiana (2021) simulated the safety performance of a hypothetical egg turbo roundabout to identify potential advantages and disadvantages of converting from the current roundabout or previous intersection Simulation studies are also particularly useful for analysing connected or autonomous vehicle situations, as seen in the study by Zohdy and Rakha (2016).

Additionally, simulation studies offer control over variables, enabling researchers to systematically vary specific factors to isolate their effects on safety. This level of control is exemplified in the work of Saleem, Persaud, Shalaby, and Ariza (2014),

where the researchers were able to adjust traffic volume from and to each arm of roundabouts to simulate safety outcomes in varying traffic conditions. Furthermore, simulation studies provide detailed vehicle trajectories and interactions, allowing for a deep understanding of the mechanisms behind traffic conflicts and crashes. This is often not possible with other methodologies, especially collision-based studies, which typically only provide the location of crashes without the exact trajectories leading to them.

However, simulation studies have some drawbacks. Since simulated conflicts are surrogate safety measures of real-life conflicts, which themselves are surrogate safety measures of real-life crashes, model calibration and validation are crucial. Extensive efforts in model calibration and validation, such as those described by Saccomanno et al. (2008) and Saulino, Persaud, and Bassani (2015), have shown satisfactory results but highlight the complexity and effort required. Some research suggests discrepancies between simulated and real-world conditions. Huang, Liu, Yu, and Wang (2013) found that although systematic calibration of microscopic simulation improved fitting between simulated and observed conflicts, simulated conflicts are not good indicators of the traffic conflicts generated by unexpected driving manoeuvres. They also found that rear-end conflicts were better simulated than crossing and lane change conflicts, indicating that simulating conflicts at roundabouts presents more challenges.

2.2.4 User Experience Studies

User experience studies focus on the subjective perceptions and behaviours of road users, such as drivers, cyclists, and pedestrians, in roundabout environments. These studies often employ a variety of qualitative and quantitative methods to gather data. Common methodologies include structured interviews, focus groups, surveys, on-site observations, and driving simulator experiments.

One of the primary advantages of user experience studies is their ability to provide direct feedback from road users, which can highlight issues that might not be apparent through empirical data alone. For instance, Lord, van Schalkwyk, Chrysler, and Staplin (2007) conducted structured interviews with older drivers to evaluate their comfort and safety perceptions regarding roundabout design elements, such as advance warning signs and lane control signs.

User experience studies can also reveal how different user groups, especially vulnerable road users, perceive and interact with roundabouts. For instance, Ashmead,

Guth, Wall, Long, and Ponchillia (2005) found varying operational and safety outcomes between sighted and blind pedestrians crossing roundabouts, and Møller and Hels (2008) found variations in perceived risk of roundabouts between cyclists of different ages. Such differences in individual behaviour are often not captured in simulation studies.

However, it is crucial to recognise that the subjective nature of the studies, as participants' perceptions may not always align with actual safety performance. Additionally, under-represented/over-represented groups can cause biases in the data, which could hinder the validity of the research (Møller & Hels, 2008).

2.2.5 Comparison of Study Methods

All four study methods considered here have advantages and disadvantages. Here, each study method is discussed in the context of this study.

User experience studies purely investigate road users' perceptions of roundabouts and do not examine the outcomes, thus they are not suitable for studying variations in safety outcomes. However, it is expected that understanding road user behaviour through user experience studies can contribute to comprehending the variation in roundabout safety performance. This approach would be particularly useful as some of the varying effects are possibly caused by differences in road user behaviours.

Simulation studies can replicate roundabout geometric designs and account for varying design standards across countries. They also have the potential to simulate variations in road user behaviours. Nevertheless, calibrating simulations to accurately reflect real-world conditions presents a significant challenge, and investigating geometric effects specific to Canada, as well as examining spatio-temporal effects, is not yet feasible with current simulation methodologies.

Although conflict data would be useful with a sufficiently large dataset, the conflict data for roundabouts is not extensive enough, both in terms of the number of roundabouts and the duration, to capture spatio-temporal effects adequately. Additionally, translating conflict data into collision data presents difficulties, particularly for roundabouts.

Therefore, collision-based empirical studies are suggested as the most appropriate method for this study. Despite several challenges, collision data remains the most standard and direct method of road safety analysis.

2.3 Spatio-Temporal Effects in Road Safety

Road crashes are complex events that have a multitude of causes. Although SPF studies aim to estimate the frequency of collisions based on a number of important factors, not all factors associated with crashes can be included in the model due to limitation in data availability, causing unobserved instability. Examples of such factors include road user characteristics such as gender and age, vehicle characteristics such as vehicle type and safety features, roadway and traffic characteristics, and environmental characteristics such as weather.

One example of unobserved instability in traditional models is the spatial and temporal effect. Traditionally in SPFs, parameters for independent variables in the model, such as road geometry, were considered to be spatially and temporally homogeneous and stable. However, it has been shown that in many cases, model parameters are temporally and spatially unstable (Lord & Mannering, 2010). Here, a review of research on spatial and temporal instability in road safety is provided, focusing on the causes of these instabilities and how to account for them.

2.3.1 Cause and Effects of Spatio-Temporal Instability

The temporal and spatial instability is likely to be caused, in large part, by variance in road user behaviours. Mannering (2018) discusses, based on studies in a number of fields such as psychology, neuroscience, economics, and cognitive science, that road user behaviour varies due to factors such as socioeconomic conditions and information gathered through driving experience and media. The variation in road user behaviour can be temporal at the same location. For instance, Ruhm (2000) found, from state-level data in the United States, that recession is associated with fewer instances of intoxicated driving and fewer road collision fatalities. This can be partly attributed to the change in perceptions of risk during economic downturns (Mannering, 2018). The variation in road user behaviour can also be spatial within the same time period. As an example of local or regional level variation, Loo and Anderson (2015) introduces examples in which variance in the socioeconomic status of a geographical area, such as employment, income, ethnicity, and educational level, is associated with variance in collision frequency.

A part of the spatio-temporal variation in roundabout safety, discussed in Section 2.1.4 and Section 2.1.5, can be attributed to variation in road user behaviour. National Academies of Sciences, Engineering, and Medicine (2007) identified operational differences likely due to variations in driver behaviour, and it is reasonable to

assume that similar variations in driver behaviour affect the safety of roundabouts differently in various countries. The temporal safety pattern of new roundabouts, if observed, is likely caused by drivers' adaptation to navigating through roundabouts, as shown in the example by Hydén and Várhelyi (2000).

The temporal and spatial instability as an underlying factor may have two effects on collision frequency. Firstly, it manifests as heterogeneity, contributing to the over-dispersion of data commonly observed in road collision statistics (Hauer, 2001). Secondly, autocorrelation may occur between collision occurrences at spatially or temporally proximate situations (Wang & Kockelman, 2013). It is plausible that observations close in space or time will show similar results due to underlying factors related to temporal or spatial variables, which violates the independent observations in data assumed in many traditional crash prediction models.

2.3.2 Approaches to Spatio-Temporal Effects

There has been a considerable amount of research aimed at improving models to address the issue of heterogeneity and enhance model fitting. A commonly used approach is to extend the Poisson regression model to a negative binomial model by including a gamma-distributed unstructured random effect. However, for panel data consisting of measurements in both spatial and temporal dimensions, this approach does not necessarily capture heterogeneity in both dimensions.

The simplest approach is to incorporate spatial or temporal information as fixed effects. Some roundabout safety research has included fixed effects to account for spatial heterogeneity in SPFs. A commonly used approach is to include the area description of the roundabout location, such as rural, suburban, and urban, as categorical variables (Daniels et al., 2011; Transportation Research Board & National Academies of Sciences, Engineering, and Medicine, 2019; Novák et al., 2018). Incorporating the location as a fixed-effects variable is also utilised. For instance, Qin et al. (2011), when analysing roundabout safety performance in Wisconsin, included the area within the state as fixed effects.

However, fixed-effects models greatly increase the number of parameters to estimate and reduce the model degrees of freedom. Therefore, random effect models are more widely used to model panel-structured collision data. Random intercept models add a random variable as an intercept to capture unobserved heterogeneity. For instance, P. Johansson (1996) employed a random intercept model to study the relationship between speed limits and the number of collisions in Sweden. Shankar,

Albin, Milton, and Mannering (1998) studied the number of median crossover collisions, comparing the performance of negative binomial and random intercept negative binomial models, with random effect capturing location and time effects. Miaou and Lord (2003) examined the relationships between crashes and flow at intersections using random intercept Poisson models. Estimation of parameters can be done through the maximum likelihood method, empirical Bayes method, or full Bayes method. For estimation, P. Johansson (1996) and Shankar et al. (1998) used the maximum likelihood method, while Miaou and Lord (2003) compared the performance of the empirical Bayes and full Bayes methods.

Although random intercept models capture underlying heterogeneity among varying settings, model coefficients remain constant for all instances. By introducing variability in the estimated model parameters in addition to the model intercepts, which are typically assumed to follow normal, lognormal, or gamma distributions, random effect models allow greater flexibility. Anastasopoulos and Mannering (2009) applied random coefficient Poisson and random-parameters negative binomial models to rural interstate highway collision data in Indiana. Random parameters were used for variables such as pavement, geometric, and traffic characteristics. El-Basyouny and Sayed (2009) employed random-parameters Poisson-lognormal models to model collision frequency at road segments in British Columbia. These models allowed coefficients for variables such as land use and crosswalk density to vary amongst corridors, although they remained constant amongst segments within the same corridor. Liu, Zhao, Li, and Sharma (2018) used multivariate random-parameters zero-inflated negative binomial regression with segment-specific parameters to study urban mid-block crashes in Lincoln, Omaha, and Nebraska. In roundabout safety analysis, Kamla et al. (2016) developed random intercept negative binomial regression using roundabout-specific random parameters for geometric design variables and found improved fitting compared to fixed-effects models. Due to the complex functional structure, a simulation-based maximum likelihood method (Anastasopoulos & Mannering, 2009), empirical Bayes method, or full Bayes method (El-Basyouny & Sayed, 2009; Liu et al., 2018) are used for random-parameter estimation.

Although random effect models incorporate the heterogeneity associated with spatio-temporal variation, they do not capture the autocorrelation between neighbouring spaces or times. A number of models that account for time-space autocorrelation were developed in epidemiology and have recently seen significant application in road safety analysis. In particular, the Bayesian hierarchical model framework proposed by Knorr-Held (2000), in which the spatio-temporal effects are decomposed into three components: the spatial component, the temporal component, and the

component that captures the interaction between spatial and temporal components, is widely used. For each of the spatial and temporal components, a combination of the structured term and non-structured term is used to capture both autocorrelation and heterogeneity, originally proposed by Besag, York, and Mollié (1991) and often referred to as the Besag-York-Mollié (BYM) model. Each is used as a prior in the Bayesian hierarchical model, and typically solved using the Markov Chain Monte Carlo (MCMC) method. However, for complex models, the integrated nested Laplace approximation (INLA) method proposed by Rue, Martino, and Chopin (2009) serves as a numerical approximation (Bakka et al., 2018; Liu & Sharma, 2017).

For the structured spatial component, the conditional autoregressive (CAR) structure, formulated by (Besag, 1975), is predominantly used. The CAR model imposes a neighbourhood structure on the random effect variable using a spatial weight matrix. It was first introduced in road safety analysis by Aguero-Valverde and Jovanis (2006) and has since seen wide usage (Barua, El-Basyouny, & Islam, 2014; Boulieri, Liverani, Hoogh, & Blangiardo, 2017; Cai, Abdel-Aty, Lee, Wang, & Wang, 2018; Liu & Sharma, 2017; Siddiqui, Abdel-Aty, & Choi, 2012; Wang & Kockelman, 2013). The CAR model has mainly two variations: the intrinsic conditional autoregressive (ICAR) model and the proper conditional autoregressive (pCAR) model. The ICAR model is an improper model, and the spatial parameters need to sum to zero. The pCAR model overcomes the shortcomings of the ICAR model by adding a strength variable for autocorrelation and allowing for negative autocorrelation, although it may pose interpretative and computational challenges. It is recommended that the ICAR model be used if the BYM structure is adopted and an unstructured spatial component is included, to allow for separate estimation of the two variables (Haining & Li, 2020). Although some studies in traffic safety analysis have used the pCAR model, most have employed the ICAR model to reduce computational issues and allow for the BYM structure. Several methods to capture spatial proximity in the weight matrix have been proposed, but for the case of intersections and road segments, Aguero-Valverde and Jovanis (2010) compared the effectiveness of adjacency, distance, and route information-based models.

It is worth noting that, in addition to spatial autocorrelation, spatial spillover effects can also be considered. Unlike spatial autocorrelation, where outcomes at a location are influenced by unobserved variables of neighbouring locations, spatial spillover refers to a phenomenon where outcomes at a location depend on the outcomes or the values of observable variables at neighbouring locations, or where the regression error at a location depends on the errors at neighbouring locations. Several spatial econometric models have been proposed to capture spatial spillover effects

depending on their type, such as the spatial lag model (SLM), the spatially-lagged covariates model (SLX), the spatial error model (SEM), and the spatial Durbin model (SDM). For instance, Quddus (2008) used the SLX model and the SEM model to capture the spillover effects of injury collisions in the census wards of Greater London. Wen, Zhang, Zeng, Lee, and Yuan (2019) applied the CAR and SLM models simultaneously to freeway crash data in China.

For the temporal component, the linear time trend model, the quadratic time trend model, the first-order random walk (RW1) model and the first-order autoregressive (AR1) model have been used (Cheng, Gill, Zhang, & Cao, 2018; Liu & Sharma, 2017, 2018; Ma, Chen, & Chen, 2017). The linear trend model captures simplistic increasing, decreasing, or stable time trends. The quadratic time trend model follows the same principle as the linear model, but adds complexity to allow for a non-linear trend. The RW1 model essentially models a temporal adaptive process and temporal smoothing, where information is borrowed from the previous and subsequent time steps to reflect positive autocorrelation. It can be considered the temporal equivalent of the spatial ICAR model (Fahrmeir & Lang, 2001). The second-order random walk model (RW2) can also be considered, where values from the two neighbouring time periods are used, although it has not seen usage in road safety analysis. The AR1 model adds a parameter that measures the strength of autocorrelation to the RW1 model. Although requiring more computation, the AR1 model adds flexibility in the strength of autocorrelation as well as allowing for negative autocorrelation (Haining & Li, 2020). Cheng et al. (2018) compared the performance of the linear trend, quadratic trend, RW1, and AR1 models using rural roadway crash data from California and found that the RW1 model provided the best fitting.

For the spatio-temporal interaction component, Knorr-Held (2000) outlined four possible structures.

I. No dependence structure is assumed for the space-time parameters.

II. The temporal dependence structure is assumed within each space unit, but it varies independently of spatial proximity.

III. The spatial dependence structure is assumed within each time unit, but it varies independently of temporal proximity.

IV. The space-time parameters are fully spatio-temporally dependent. There are three main forms of this dependency structure. Firstly, the temporal depen-

dence structure is assumed within each space unit, and the temporal dependency pattern depends on spatial proximity. Secondly, the spatial dependence is assumed within each time unit, and the spatial dependency pattern depends on temporal proximity. Thirdly, the parameters depend on the structure matrix of both the spatial and temporal components.

Despite significant applications of the spatial and temporal components, the spatio-temporal interaction component has not seen widespread use in road safety research. Liu and Sharma (2017) and Liu and Sharma (2018) employed a Type I interaction component using a random effect variable following a zero-mean normal distribution. Wen, Zhang, Zeng, and Sze (2019) appears to have used a simplified Type IV interaction, in which the ICAR model and the temporal variable was multiplied.

Most studies employed a few different approaches and compared their performance. Given that the heterogeneity and autocorrelation due to unobserved parameters in the spatio-temporal space are the focus of this study, it is suggested that Bayesian spatio-temporal hierarchical models with spatio-temporal random effects using the ICAR and linear, quadratic, RW1, or AR1 models be tested for analysis. Refer to Section 5.1.1 for a detailed discussion of the models.

Chapter 3

Exploratory Analysis

In this chapter, the data used in this research is first described. An exploratory analysis is then conducted to understand the overview of the collision data and the geometric design variables of roundabouts.

3.1 Data Description

In this research, a case study was conducted using data from the Regional Municipality of Waterloo — a metropolitan area of Southern Ontario, Canada, consisting of the cities of Kitchener, Waterloo and Cambridge, and the townships of North Dumfries, Wellesley, Wilmot and Woolwich. There are a total of 39 roundabouts on the regional roads under the jurisdiction of the regional municipality, as of 2021. Traffic calming circles and small roundabouts on local collectors were not included in the analysis, due to the unavailability of data and the need for different analyses for varying types of roundabouts. Although there is no official statistics on the current total number of roundabouts, there were estimated to be around 400 roundabouts in Canada in 2015 (Tollazzi, 2015). To the author's knowledge, the Region of Waterloo has the highest number of roundabouts in any local jurisdiction in Southern Ontario, followed by the Region of York and the Region of Durham, making it the ideal location to conduct a detailed safety analysis of roundabouts in the Canadian context.

The region has compiled and made available collision data based on police records obtained through the Ministry of Transportation, covering the period from 2000 to 2020, on intersections and roads under the jurisdiction of the region. This dataset

consists of fatal and injury collisions, excluding property-damage-only (PDO) collisions. Fatal collisions are defined as those resulting in the death of involved road users within 30 days of the incident. Each incident report includes details such as location in the form of street segment or intersection name, date, time, involved modes of transport, and weather conditions. Collisions on public roadways are classified as "at intersection", "intersection-related" or "non-intersection". Crashes that occurred within 50 m of intersections are typically classified as "at intersection" or "intersection-related", although the decision is made at the discretion of the attending police officer. Due to the limited cases of crashes involving pedestrians or bicyclists as discussed in Section 3.2.2, all vehicle-to-vehicle collisions which occurred at roundabouts with "at intersection" or "intersection-related" classes were extracted for the analysis.

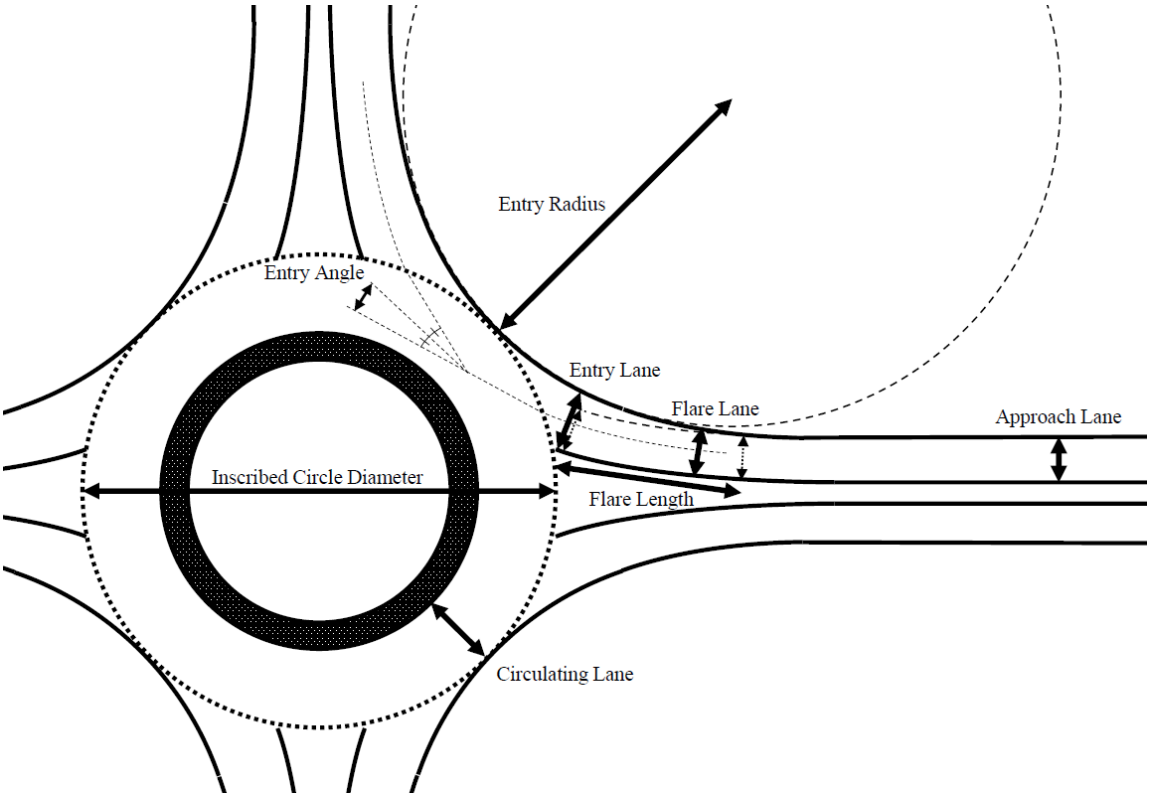


Figure 3.1: Geometric Design Variables of Roundabouts

The region has also provided the geometric design variables of roundabouts as printed CAD files. Some of the geometric variables are intersection-level, such as the

number of legs and the number of circulating lanes. Others are leg-specific, which include the inscribed circle diameter (ICD), entry radius, flare length, entry angle, number of entry lanes, entry lane width, number of flare lanes, flare lane width, number of approach lanes, approach lane width, and the number of right-turning bypass lanes along with their entry widths. The geometric variables are depicted in Figure 3.1.

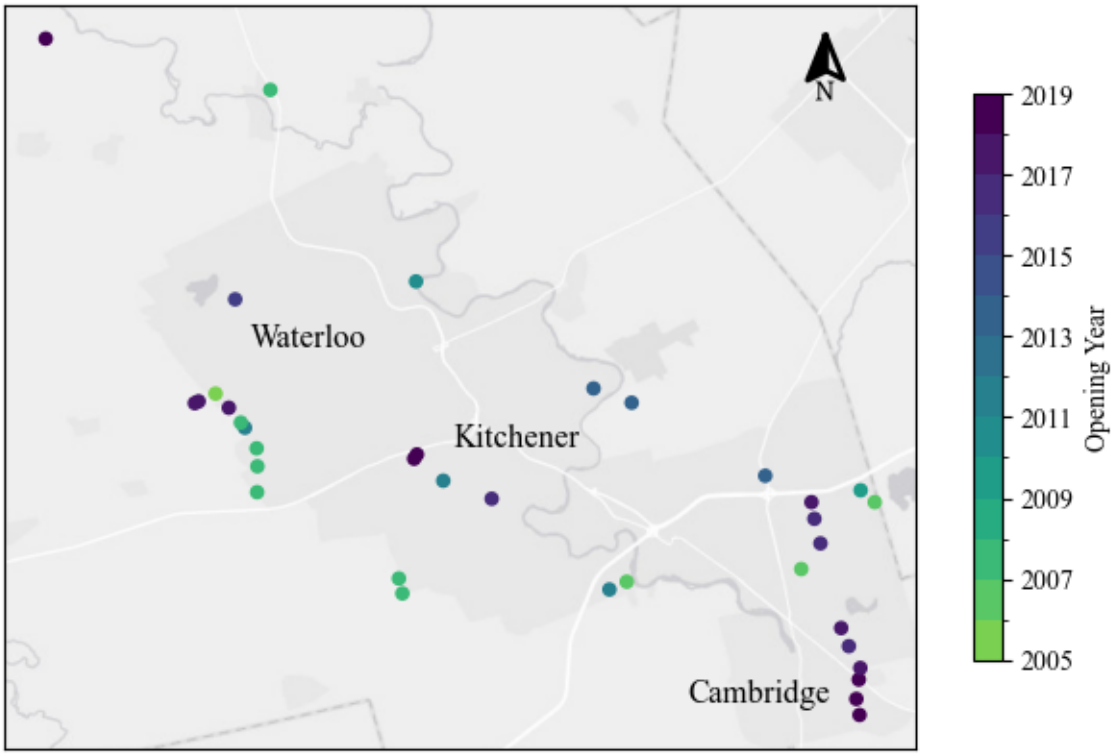


Figure 3.2: Opening Year of Roundabouts in Waterloo Region

The Region also provided the opening years of roundabouts and the intersection-level annual average daily traffic (AADT). The region does not document the month and date of the openings; hence, only the year has been used for the analysis. The locations and opening years of roundabouts within the scope of this study are shown in Figure 3.2. The AADT data from 2012 to 2015 were provided, with the "current" AADT the Region continues to use, without disclosing the specific year from which the data were taken. Linear regression analysis using the AADT data from 2012 to 2015 indicated that the predicted AADT for 2016 had a significantly better fit to the "current" AADT than the predicted AADT for 2017. Thus, the "current" AADT

was assumed to be from 2016. Additionally, the AADT from 2017 and 2018 were interpolated using a simple linear regression model. This was considered sufficiently accurate since the fluctuation of the AADT at roundabouts within the period was not significant.

3.2 Exploratory Analysis

3.2.1 Geometric Design Variables

The geometric variables are compared in relation to the opening years of the roundabouts to identify changes in design over time within the Region. Figure 3.3 shows the variability of lane widths over time and Figure 3.4 show the variability of other continuous geometric variables over time. Some of the changes are consistent with the findings of previous studies, and may be attributed to the evolution of design guidelines and standards. For example, the entry angle seems to take less extreme values in newer roundabouts, which is consistent with the findings that moderate entry angles are associated with lower collision frequencies (Novák et al., 2018). However, the changes can also be attributed to the specific characteristics of the roundabouts, such as the geographical constraints of the site, the geometries of the intersecting roads, and the traffic conditions.

3.2.2 Collisions

Examinations of the collision statistics reveal that no fatal collision at roundabouts was documented in the period between 2000 and 2020, and all collisions subjected to analysis are of injury type. There was a total of 436 injury collisions, of which 405 were vehicle-only collisions, 22 involved bicycles, and 9 involved pedestrians. Studies by Daniels et al. (2011), Maycock and Hall (1984), and Turner et al. (2009) revealed that vehicle-only, bicyclist, and pedestrian collisions are associated with different roundabout design variables, suggesting that SPFs should be modelled separately for different types of road users involved. Due to the limited number of documented collisions involving bicyclists and pedestrians, separate analyses for these groups pose difficulties. Therefore, this study focuses exclusively on vehicle-to-vehicle collisions.

To briefly analyse the spatial variability in collision frequency at roundabouts, the occurrences of injury collisions between 2017 and 2019 for roundabouts constructed

before 2017 are plotted on the map in Figure 3.5. Some roundabouts recorded significantly higher numbers of collisions compared to others. For instance, the roundabout at Erbsville Road/Ira Needles Boulevard @ Erb Street West recorded 23 collisions, and the roundabout at Homer Watson Boulevard @ Block Line Road recorded 19 collisions, while 19 out of 24 roundabouts recorded fewer than 10 injury collisions. Although there is variation in the frequency of collisions, a discernible spatial pattern is not evident.

To briefly analyse the temporal variability in collision frequency at roundabouts, the occurrences of injury collisions are plotted against the age of roundabouts using box plots in Figure 3.6. The median collision frequency fluctuates within the range of 0 to 3, with several intersections and roundabouts recording zero injury collisions in a given year. Although there is no noticeable change in the median or 25th percentile values before and after conversions, the upper adjacent values and the number of outliers with high collision frequencies appear to reduce after conversions. Notably, two roundabouts, Franklin Boulevard @ Pinebush Road and Homer Watson Boulevard @ Ottawa Street South, recorded high collision occurrences of 18 and 21, respectively, in the year of conversion.

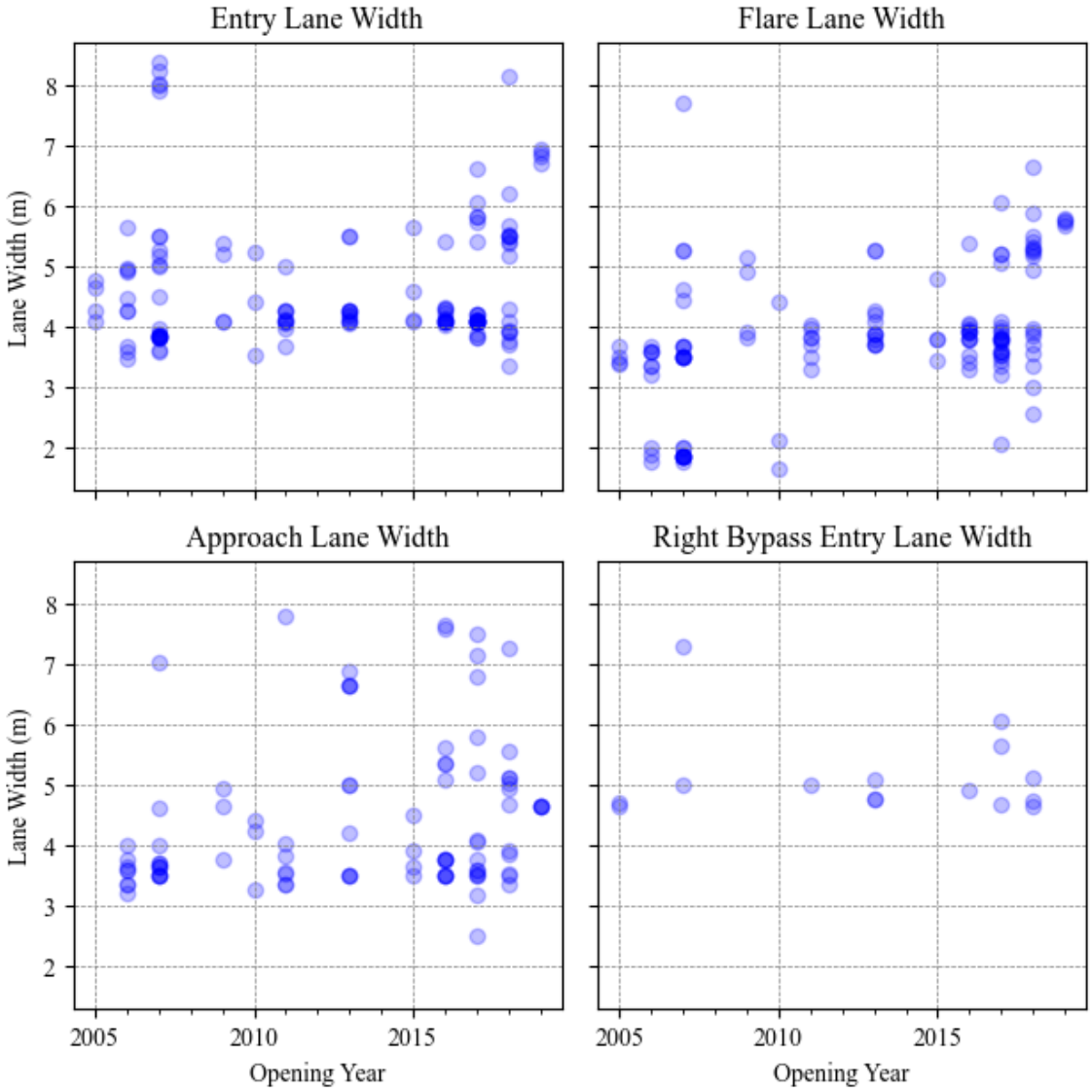


Figure 3.3: Lane Width against Opening Year of Roundabouts

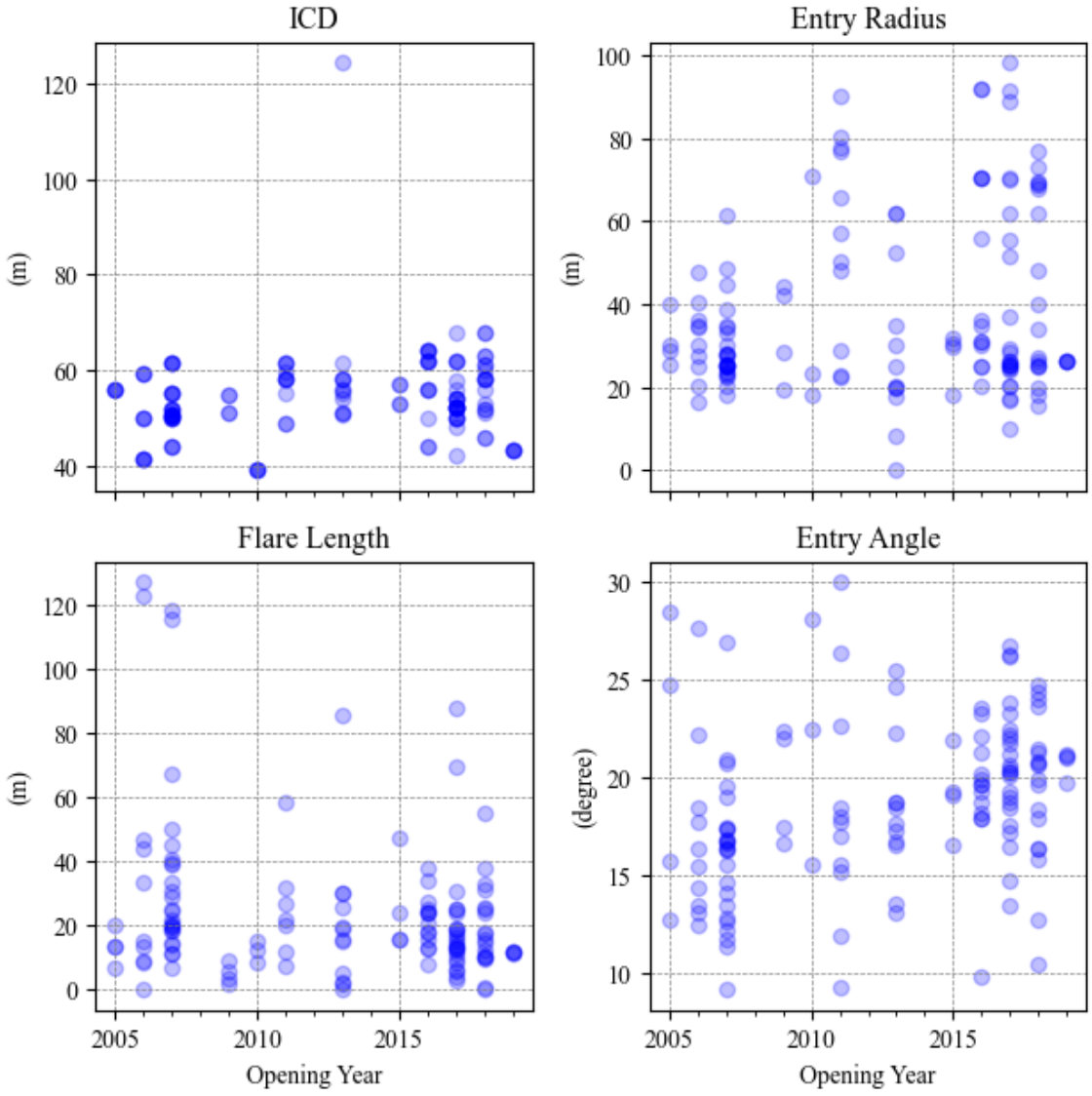


Figure 3.4: Other Geometric Variables against Opening Year of Roundabouts

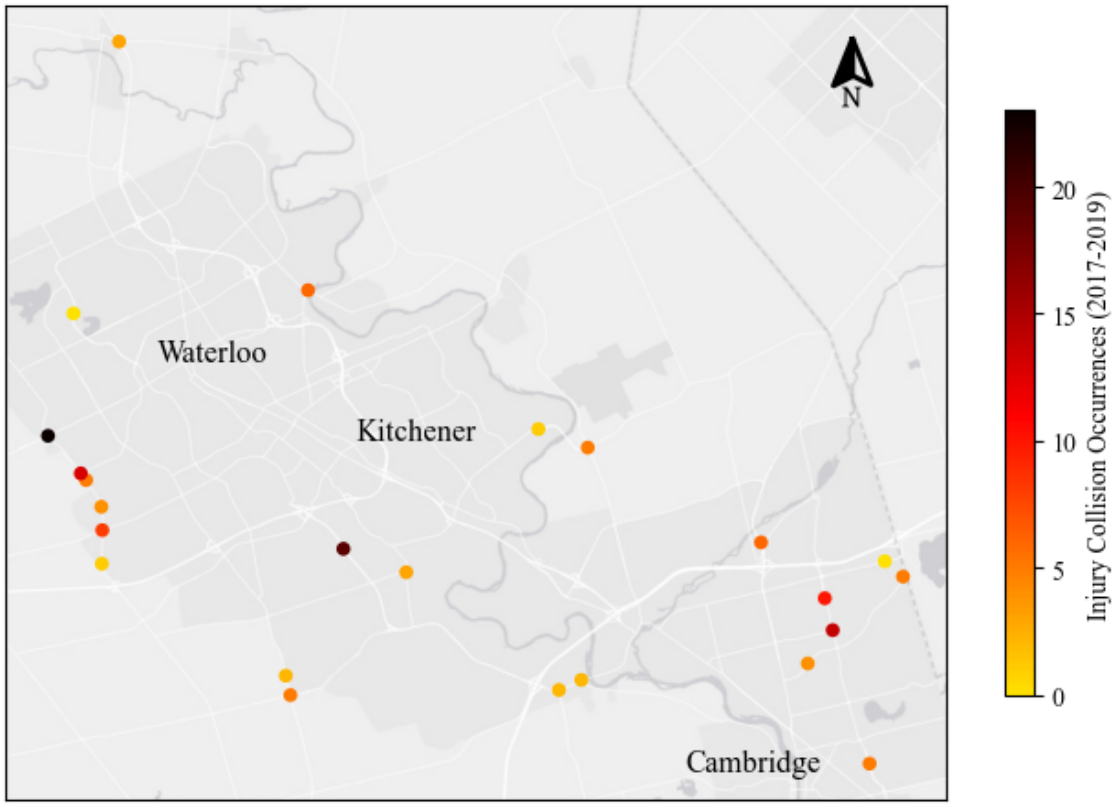


Figure 3.5: Injury Collision Occurrences (2017-2019) at Roundabouts

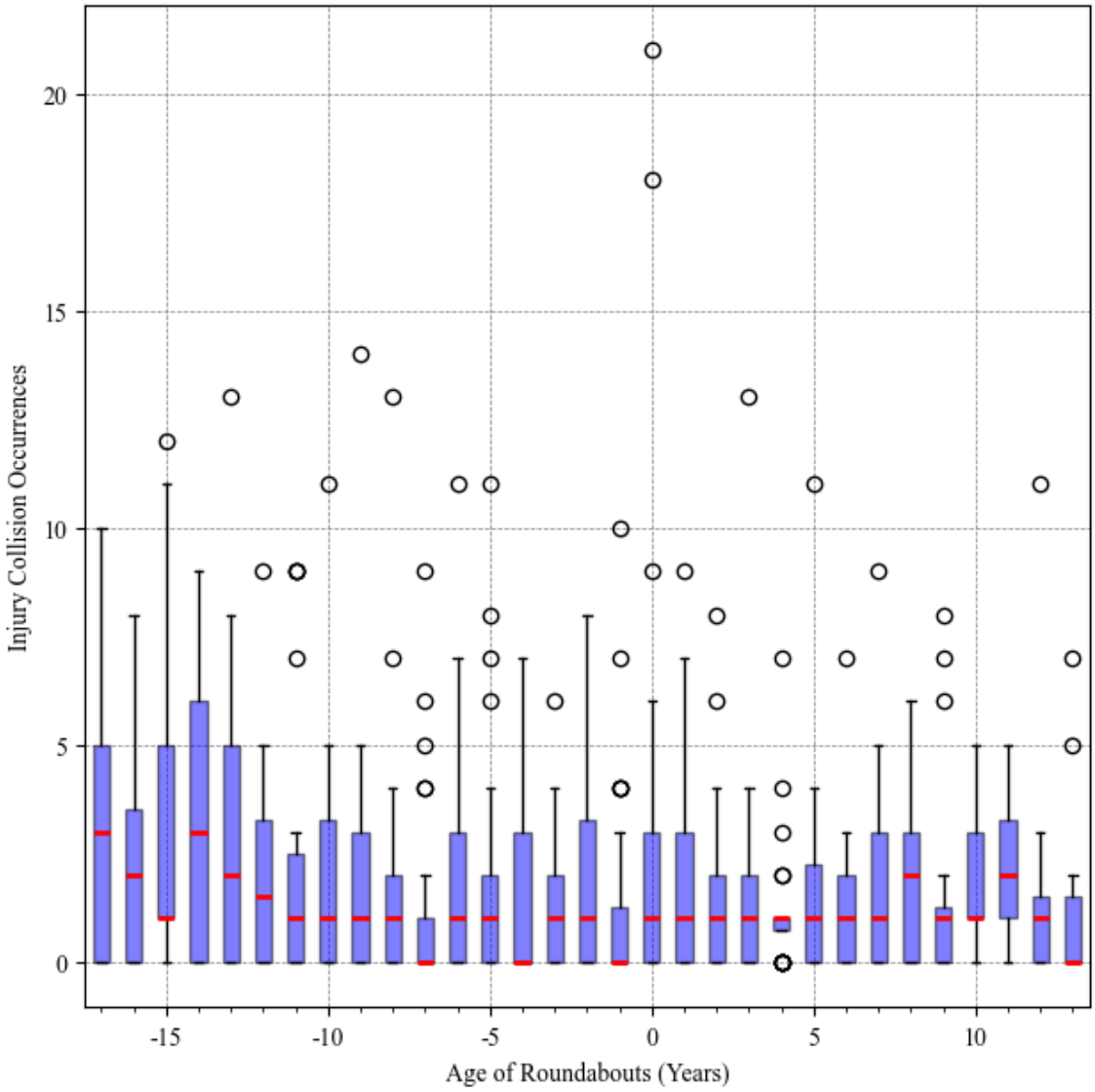


Figure 3.6: Injury Collision Occurrences against Years in Operation since Opening of Roundabouts

Chapter 4

Analysing Safety Effects of Roundabout Geometric Design

In this chapter, we address the first research question: to improve the understanding of the effects of roundabout geometry on safety performance. The chapter is divided into two sections. Section 4.1 describes the development of safety performance functions (SPFs) for roundabouts. Section 4.2 then presents the results and discussions of the developed SPFs.

4.1 Development of Safety Performance Functions

SPFs, or collision prediction models, express the expected collision frequency, i.e., the number of collisions within a certain period, typically a year, as a regression model of explanatory variables such as the annual average daily traffic (AADT) and geometric design variables. This enables the prediction of the expected collision frequency based on these explanatory variables, and allows for the analysis of how each explanatory variable may influence collision frequency.

4.1.1 Functional Form Selection

The number of road crashes is quantified as a non-negative integer, necessitating a careful examination of the error structure of the regression model. For SPFs, the employment of Poisson, negative binomial, gamma, zero-inflated Poisson and

zero-inflated negative binomial regressions are commonly used. Lord and Mannering (2010) provides an exhaustive analysis of the advantages and disadvantages associated with each of these models.

The most fundamental error term structure is Poisson regression. For roundabout i, the Poisson regression model is formulated as:

$$y_i \mid \mu_i \sim \text{Poisson}(\mu_i) \tag{4.1}$$

$$\mu_i = \exp(\beta_0) \cdot AADT_i^{\beta_1} \cdot \exp\left(\sum_{k=2} \beta_k x_{ki}\right) \tag{4.2}$$

$$= \exp\left(\beta_0 + \beta_1 \cdot \ln(AADT_i) + \sum_{k=2} \beta_k x_{ki}\right) \tag{4.3}$$

where

y : the number of injury collisions per year,
μ : the expected number of injury collisions per year,
β_k : model coefficients for x_k,
x_k : explanatory variables.

and if a random variable X is Poisson-distributed, denoted as $X \mid \mu \sim \text{Poisson}(\mu)$, the probability mass function of which is given by:

$$f(x;\mu) = \frac{\mu^x e^{-\mu}}{x!}. \tag{4.4}$$

However, Poisson regression assumes that the mean and variance are equal, which is often not the case in model fittings with road collision data. In case the variance is greater than the mean, the data is said to be over-dispersed. This is a common issue in road crash data for a number of reasons, such as the data clustering, presence of unobserved variables and the unequal probabilities of the crash process (Lord & Miranda-Moreno, 2008). Typically, negative binomial regression, also called Poisson-gamma regression, is used to counter over-dispersion. Negative binomial regression is formulated in a hierarchical structure as:

$$y_i \mid \lambda_i \sim \text{Poisson}(\lambda_i) \tag{4.5}$$

$$\lambda_i \mid \alpha, \mu_i \sim \text{Gamma}\left(\alpha, \frac{\alpha}{\mu_i}\right) \tag{4.6}$$

$$\mu_i = \exp\left(\beta_0 + \beta_1 \cdot \ln\left(AADT_i\right) + \sum_{k=2} \beta_k x_{ki}\right) \tag{4.7}$$

or, in a non-hierarchical formulation,

$$y_i \mid \mu_i \sim \text{Poisson}(\mu_i) \tag{4.8}$$

$$\mu_i = \exp\left(\beta_0 + \beta_1 \cdot \ln\left(AADT_i\right) + \sum_{k=2} \beta_k x_{ki} + \epsilon_i\right) \tag{4.9}$$

$$\exp\left(\epsilon_i\right) \mid \alpha \sim \text{Gamma}\left(\alpha, \frac{\alpha}{1}\right) \tag{4.10}$$

where if a random variable X is gamma-distributed, denoted as $X \sim \text{Gamma}(\alpha, \beta)$, the probability density function of which is given by:

$$f(x; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x} \tag{4.11}$$

for $x > 0$ and $\alpha, \beta > 0$.

Zero-inflated Poisson or negative binomial regression are used when there are excess zeros available in the data. This is commonly seen in road crash data, where many intersections do not experience collisions in a given duration. Zero-inflated models are dual-state models, consisting of two different processes: one generating zero observations and the other generating non-zero observations. Although their use often improves model fitting, it causes theoretical inconsistency with the assumption that road crashes are generated by a single process (Lord, Washington, & Ivan, 2005).

Although not common, road crash data can sometimes be under-dispersed, where the variance is less than the mean. The gamma distribution can be employed to account for under-dispersion, although its error structure does not ensure integer values for the dependent variable and it is a dual state model that may pose theoretical inconsistencies (Lord & Mannering, 2010).

4.1.2 Model Estimation and Comparison

The model parameters were estimated using the maximum likelihood method. In this research, we utilised the programming language R and the CAR library for model estimation (R Core Team, 2023; Fox & Weisberg, 2019).

The goodness of fit of the models was evaluated using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The AIC is defined as:

$$AIC = -2\ln(L) + 2k \tag{4.12}$$

where L is the maximum value of the likelihood function and k is the number of estimated parameters in the model. The BIC is defined as:

$$BIC = -2\ln(L) + k \cdot \ln(n) \tag{4.13}$$

where n is the number of observations. Models with lower AIC or BIC values are preferred, with the BIC penalising the number of parameters more heavily than the AIC, except when the sample size is small. There is no definitive threshold for a significant difference in AIC or BIC values. However, as a rule of thumb, models with the AIC within 2 of the lowest value are strongly supported, while differences greater than 10 are considered significant enough to remove models from consideration (Burnham & Anderson, 2004).

4.1.3 Variable Selection

The model development procedure involved following steps. First, multicollinearity between explanatory variables was examined. Multicollinearity refers to a condition in which some explanatory variables are highly correlated to each other. This is undesirable as it may lead to inflated variances of parameter estimates, resulting in inaccurate confidence intervals and hindering the standard interpretation of regression coefficients (Washington, Karlaftis, Mannering, & Anastasopoulos, 2020). The Pearson correlation coefficient with magnitude larger than 0.8 was used as a benchmark to identify pairs of highly correlated variables. Models with all variables were constructed, then for each pair of highly correlated variables, the variable with higher variance inflation factor (VIF) was removed until all variables in the model had VIF lower than 10, which is the commonly used benchmark for high multicollinearity (Fahrmeir, Kneib, Lang, & Marx, 2021).

Second, safety performance models were developed by fitting the collision data, and both forward and backward selection of variables were performed. In forward selection, the independent variable with the lowest p-value was added to the model at each step, while in backward selection, the independent variable with the highest p-value was removed from the model at each step. The AIC and BIC were used to compare model performance, with models having the lowest information criteria being selected.

Safety performance models of roundabouts can be developed at either the intersection level or leg level as seen in Section 2.1.2. Certain geometric variables of roundabout design such as the number of lanes and entry lane width are leg-specific, which suggests that it may be preferable to develop a separate model for each leg. However, since lack of exact location information of collisions prohibited development of such models, we opted to develop models at the intersection level. For leg-specific variables, several different methods were attempted to represent such values at the intersection level. Initial attempts included the average, maximum, minimum and range values. The range value was calculated as the difference between the maximum and minimum values. However, modelling attempts with such representative values revealed high multicollinearity amongst different representative metrics. As a result, alternative models using different combinations of geometric variables are developed: models with variables **(a)** intersection-level variables and average (median) and range values of leg-specific variables, **(b)** intersection-level variables and maximum and minimum values of leg-specific variables, and **(c)** intersection-level variables and average (median) values of leg-specific variables.

Additionally, during the model development process, two different treatments of integer variables were considered. Notably, **(1)** models that treat the number of lanes and legs as discrete variables using the maximum and minimum values, and **(2)** models treating them as continuous variables were explored.

4.1.4 Model Specifications

In Chapter 4, the primary focus is on understanding the impact of geometric design variables on the safety of roundabouts. Therefore, three years of data were used to develop the SPF, minimising the impact of short-term temporal heterogeneity. This approach is consistent with the literature reviewed in Section 2.1.2, which combines at least three years of data to develop SPFs.

To allow for separate analyses between different periods, three distinct models were developed using different sets of roundabouts and analysis periods as shown in Table 4.1. Model 1 was developed using the most recent data to provide the most reliable SPF to be compared with literature and for applications. Model 2 was developed to capture the long-term temporal heterogeneity of the geometry effects and perform comparison between different time periods. Additionally, recognising the possibility that driver behaviour and attitudes towards roundabouts may evolve over time, the years in operation of roundabouts was included as an explanatory variable. Only data from 2014 onwards was used, as the number of operational

Table 4.1: Model Specifications

	Roundabouts	Analysis Period	Explanatory Variables
Model 1	Opened before 2017	2017–2019	From forward and backward selection with AIC and BIC as criteria
Model 2–1	Opened before 2014	2014–2016	Variables selected in Model 1
Model 2–2	Opened before 2014	2017–2019	Variables selected in Model 1

roundabouts prior to this period was insufficient to perform a meaningful analysis. Data from 2020 was excluded to remove the impact of COVID-19. The 2014–2016 model employed the AADT values from 2015, and the 2017–2019 models employed the AADT values from 2018.

4.2 Results and Discussion

4.2.1 Model Development

To determine the functional form of the model discussed in Section 4.1.1, a Poisson regression model was initially developed for Model 1 using only the AADT as the explanatory variable. The residual of each data point is plotted against the fitted value from the model in Figure 4.1. The graph indicates that the variance of the residuals increases with the fitted values, suggesting that the data is over-dispersed. Subsequently, another Poisson regression model was developed using all explanatory variables, with its residual plot also shown in Figure 4.1. Although some of the over-dispersion was mitigated, the variance of the residuals still increased with the fitted values. Figure 4.1 shows that the data is not under-dispersed, thus a gamma regression model was not considered. The zero-inflated Poisson and zero-inflated negative binomial models were not considered due to the lack of excess zeros in the data and the potential theoretical inconsistencies. Therefore, a negative binomial regression model was determined to be the functional form of the model.

Based on the variable selection in Section 4.1.3, models with six sets of variables, utilising three sets of leg-specific variables (a, b, c) and two treatments of the number of lanes and legs (1, 2), were developed for the analysis period of 2017–2019. The

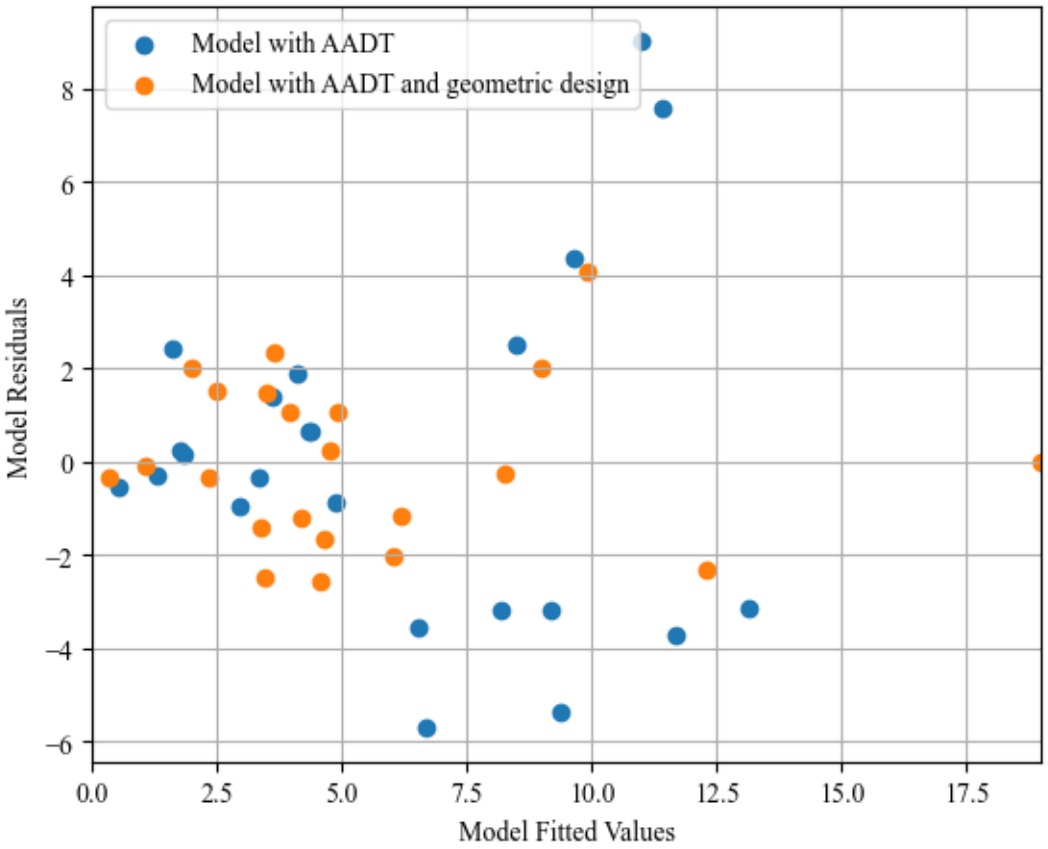


Figure 4.1: Residuals vs Fitted Values of Poisson Regression Model

AIC and BIC of the best-performing models for all model classes are presented in Table 4.2.

Although Model b-1 performed slightly better than the other models, Models b and c did not differ significantly from the other models in terms of goodness of fit. Most literature uses the direct or average values of variables while treating the number of lanes as categorical variables (Kim & Choi, 2013; Novák et al., 2018). Therefore, Model c-1 was chosen, allowing for direct comparison of the effect of each independent variable with other studies. Finally, based on Model c-1, "Average Entry Angle" was converted to a categorical variable to test whether it captures a potentially non-linear relationship between entry angle and collision frequency (Novák et al., 2018). However, the original Model c-1 was retained due to a lack of improvement in both AIC and BIC. Thus, the final models were developed using intersection-level

Table 4.2: Comparison of Variable Selection Models

Model	a-1	a-2	b-1	b-2	c-1	c-2
AIC	110.5	112.4	107.6	108.4	109.3	109.1
BIC	118.8	115.9	117.1	119.0	118.7	118.7

variables and average values of numerical leg-specific variables, and maximum and minimum values of number of lanes treated as categorical variables.

4.2.2 Model 1

Table 4.3 presents the list of variables considered for the model, and the final selected variables are shown in Table 4.4. The final selected model includes "AADT", "Average ICD", "Average Entry Angle", "Average Entry Lane Width" and "Entry Lane Minimum 2" as explanatory variables. "Entry Lane Minimum 2" is a binary variable that indicates whether minimum number of entry lanes for all legs is two or above, or fewer. These selected variables reaffirm the understanding that geometric design of roundabouts has an impact on safety of roundabouts. The variable "Years in Operation" was excluded from the final model as it was found insignificant. This suggests that either the effect of drivers getting accustomed to roundabouts does not play a significant role in influencing safety, or it is not adequately captured in the model.

Some of the estimated coefficients can be interpreted physically, although others require further investigation to understand the underlying relationships. The positive association between the AADT and collision frequency can be reasonably explained by the increase in the number of at-risk vehicles and the number of opportunities for collisions. The positive association between the number of entry lanes and collision frequency can also be reasonably explained. While one of the advantages of roundabouts is having fewer conflict points, increasing the number of entry lanes raises the number of conflict points, thereby diminishing this advantage.

Furthermore, the collision frequency shows a positive correlation with the ICD. This relationship may have several possible explanations. Firstly, larger roundabouts are more visible, and since drivers are more likely to slow down when they see a roundabout ahead, larger ICDs may reduce the speed of entering vehicles. Secondly, a larger ICD forces vehicles travelling straight through the roundabout to follow a longer deflection path, potentially reducing their speed compared to roundabouts

Table 4.3: Explanatory Variables in the Model

	Data Type	Average	Standard Deviation
AADT (2018)	Continuous	30466.920	9891.535
Average ICD (m)	Continuous	54.078	7.630
Average Entry Radius (m)	Continuous	36.694	12.620
Average Flare Length (m)	Continuous	26.941	15.261
Average Entry Angle (degree)	Continuous	17.948	2.575
Average Entry Lane Width (m)	Continuous	4.563	0.897
Average Flare Lane Width (m)	Continuous	3.569	0.919
Average Approach Lane Width (m)	Continuous	4.445	0.836
Legs (1 for 4 legs; 0 for 3 legs)	Binary	0.667	–
Entry Lane Minimum (1 for 2 or more lanes; 0 for 1 lane)	Binary	0.583	–
Approach Lane Maximum (1 for 2 or more lanes; 0 for 1 lane)	Binary	0.792	–
Right Bypass Lane Sum (1 for 1 lane or more; 0 for 0 lane)	Binary	0.250	–
Years in Operation	Continuous	6.917	3.821

with a smaller ICD, in which the path is closer to a straight line. Similar arguments are made to rationalise the positive correlation between the ICD and collision frequency in National Academies of Sciences, Engineering, and Medicine (2007).

Likewise, "Average Entry Angle" has a positive coefficient, suggesting that a larger entry angle is associated with an increase in collisions. This observation can be explained in two ways. Firstly, a smaller entry angle necessitates sharper turns at entry, likely reducing vehicle speeds and, consequently, the number of collisions. Secondly, a smaller entry angle means that vehicles merging into the roundabout are more aligned in direction, which reduces the likelihood of side-impact collisions and may result in more side-swipe collisions, which are typically less severe. An alternative perspective is provided by Arndt and Troutbeck (1998), who found that the relative speed between circulating and entering vehicles has a significant positive effect on collision frequency. Arndt and Troutbeck (1998) further suggests that the

relative speed between circulating and entering vehicles can be reduced by lowering the entry angle.

While these physical interpretations of the model results provide potential explanations for how geometric variables may influence the collision frequency, it is essential to note that these findings indicate correlations rather than causation. Further research, such conflict studies that enable precise investigation of vehicle movement leading to crashes, is required to explore the underlying mechanisms. For a more detailed discussion, refer to Section 4.2.5.

Table 4.4: Results of Variable Selection

	p value	Estimated Coefficient
Intercept	0.000	$7.269 \cdot 10^{-14}$
ln(AADT)	0.000	2.582
Average ICD	0.054	−0.032
Average Entry Radius	–	–
Average Flare Length	–	–
Average Entry Angle	0.002	0.108
Average Entry Lane Width	0.050	0.341
Average Flare Lane Width	–	–
Average Approach Lane Width	–	–
Legs = 4	–	–
Entry Lane Minimum >= 2	0.009	1.088
Approach Lane Maximum >= 2	–	–
Right Bypass Lane Sum >= 1	–	–
Years in Operation	–	–

4.2.3 Model 2

Models 2–1 and 2–2 employed an identical set of roundabouts considering the same set of explanatory variables to allow the comparison between the time periods 2014–2016 and 2017–2019. The selection of explanatory variables was based on the selection in Model 1, and model diagnostics were used to ensure their relevance and

significance in the analysis. The estimated coefficients and associated p-values are shown in Table 4.5. There was no variable in which the sign of the estimated coefficient was reversed between Model 2–1 and 2–2, with the exception of "Average ICD". The p-value for "Average ICD" was not significant at the 90% confidence level for Model 2–1, indicating temporal instabilities in the effects of the variable on the safety performance of roundabouts. The change in magnitude of parameters was small, specifically for variables "AADT", "Average Entry Angle" and "Entry Lane Minimum 2". This shows a relative consistency in the impact of geometric variables on collisions across the two time periods. However, noteworthy changes in the magnitude of estimated coefficients were observed for "Average Entry Lane Width", whose coefficient reduced from 0.624 of 2014–2016 period to 0.380 of 2017–2019 period. This may signify reduced adverse effects of large entry lane width in the frequency of collisions in the latter period.

Table 4.5: Results of Model 2

Model	AADT	Average ICD	Average Entry Angle	Average Entry Lane Width	Entry Lane Min 2
Model 2–1	2.526 (0.00)	0.016 (0.26)	0.127 (0.00)	0.624 (0.00)	1.337 (0.01)
Model 2–2	2.452 (0.00)	−0.032 (0.07)	0.124 (0.00)	0.380 (0.04)	1.237 (0.01)

4.2.4 Comparison with Literature

The estimated model coefficients were compared with values extracted from the literature to assess whether the geometric variables of the tested roundabouts had similar effects on safety as their counterparts in other parts of the world. The extract from the literature review in Appendix A is presented in Table 4.6 in comparison with the results of Models 1 and 2. The findings revealed that certain variables, such as the AADT and the number of entry lanes, aligned with previous studies in terms of their effects on safety. With the exception of studies which had different formulations and specific collision types, all investigations incorporating the AADT into their models reported positive associations between the AADT and the frequency of collisions. Similarly, six studies encompassing the number of entry lanes in their models reported a positive influence, corroborating findings from this research.

However, for the majority of geometric variables, the comparison with literature yielded somewhat contradictory results. Three studies found ICD significant and four found entry lane width significant, all of which included opposing results to the findings from this analysis. Five studies considered entry radius with inconsistent results, but it turned to be insignificant in this model. Entry angle was deemed significant by five studies, yet with varying signs and complex findings.

The presence of contradictory results may arise from several factors. Firstly, it could stem from differences in the modelling approaches. In this analysis, SPFs were developed at the intersection level, assuming linear relationships between the continuous geometric variables and collision frequency. However, other studies have developed SPFs at the leg level and incorporated non-linear relationships between variables and collision frequency. These methodological differences may contribute to the contradictory findings. For a more detailed discussion, refer to Section 4.2.5.

Secondly, differences in the design principles of roundabouts may also account for the observed contradictions. The model results are highly sensitive to the range of variable values included in the data. For instance, even if a variable has a particular optimal design value that is common across two studies, the results may differ if one study includes roundabouts with values above this optimal point while the other includes roundabouts with values below it. Such differences can lead to seemingly contradictory outcomes. Refer to Section 4.2.5 for a more detailed discussion.

Thirdly, variations in driver behaviour and environmental conditions across different regions could also explain the contradictory results. As discussed in Section 2.1.3, roundabouts in different countries and regions often exhibit varying safety outcomes, largely attributed to differences in driver behaviour and environmental conditions. It is highly likely that these variations also affect the impacts of geometric variables on safety, contributing to the observed discrepancies.

While differences in modelling approaches may play a role in producing contradictory results, it is unlikely that they are the sole cause. In this study, efforts were made to mitigate the limitations of intersection-level analysis and disadvantages of linear assumption by considering various combinations of representative values and incorporating categorical variables. Therefore, it is improbable that differences in modelling approaches alone are sufficient to explain the reversed effects of certain variables. Instead, it is more plausible that variations in the design principles and environmental conditions of roundabouts, along with differences in driver behaviour, are significant contributors to the contradictory findings. This suggests that roundabouts in Canada may exhibit unique relationships between geometric design and safety, implying that findings from studies conducted in other countries may not be

directly applicable. Consequently, development of SPFs using local data can potentially improve the safety of roundabouts by optimising roundabout design strategies.

4.2.5 Findings and Limitations

This section provides a summary of the findings from the analysis of Model 1 and Model 2. Although the models were carefully developed and the results were interpreted with caution, there are limitations in the modelling approach and the data used for the analysis. Accordingly, this section also discusses these limitations in detail.

Findings

The analysis results demonstrated that the geometric design of roundabouts significantly affects their safety performance. The analysis identified "AADT", "Average ICD", "Average Entry Angle", "Average Entry Lane Width" and "Entry Lane Minimum 2" (a binary variable that shows whether the minimum number of entry lanes is two or more) as significant variables. The final model incorporating these variables is represented as follows:

$$\begin{aligned}\text{Collisions} = 7.269 \times 10^{-14} \cdot (AADT)^{2.582} \cdot \exp\,(\\ -0.032(\text{Average ICD}) + 0.108(\text{Average Entry Angle}) \\ +0.341(\text{Average Entry Lane Width}) + 1.088(\text{Entry Lane Minimum 2}))\end{aligned} \tag{4.14}$$

A comparison with existing literature revealed both consistencies and contradictions regarding the effects of geometric variables on roundabout safety. While some contradictions may be attributed to differences in modelling approaches, these findings suggest that the impact of geometric variables on roundabout safety may vary across different regions and countries. Thus, models from other studies may not be directly applicable to the context of Canadian roundabouts.

Furthermore, a simple analysis of two SPFs based on different time periods indicated that the geometric effects are largely consistent across varying time periods, with some variations in the magnitude of these effects. However, "Average ICD" was found to be insignificant in Model 2–1, implying temporal instability in the effects of this variable.

Limitations: Modelling Approach

Several limitations lie in the modelling approach used in this research. Firstly, the model was developed at the intersection level without distinguishing between collision types, which might have led to a loss of information. For instance, Maycock and Hall (1984) demonstrated that sharper entry curves are associated with fewer entering-circulating collisions but an increased number of approaching and single-vehicle collisions. This observation aligns with intuition, as sharper curves can effectively reduce vehicle entry speeds to roundabout, thereby reducing entering-circulating collisions. However, sharper curves require more complex manoeuvres at entry, which can lead to an increase in approaching and single-vehicle collisions. This duality in the impact of entry curves could contribute to the mixed results observed regarding the effects of entry radius and entry angle on collision frequency across different locations within one roundabout and for various types of collisions. The complexity of these effects, however, may not have been fully captured in the current model.

Secondly, the model assumes a linear relationship between the continuous geometric variables and collision frequency. This approach is useful for identifying variables that have significant effects on the collision frequency and for understanding the general effects of those variables. However, it is likely that the relationships are more complex than what is captured by linear models, leaving uncaptured effects that may manifest as unstructured spatial effects. For instance, Novák et al. (2018) found that moderate entry angles are associated with the lowest collision frequency, while collisions increase if entry angles take extreme values. While an attempt was made to categorise the entry angle variable to better represent a non-linear relationship, it remains possible that the effects of other variables were inadequately captured due to the linearity assumption.

Thirdly, as with most statistical analyses, the model results indicate correlations rather than causation. For example, the negative association between "Average ICD" and collision frequency may not necessarily indicate that larger roundabouts are inherently safer; it could reflect other unobserved factors that are independently correlated with larger ICD and safer roundabouts in the data. To investigate the underlying mechanisms, further research using alternative methodologies, as discussed in Section 2.2, is needed. For instance, employing conflict analysis could provide precise insights into vehicle speeds and movements that lead to conflicts. Conducting conflict analysis at locations with varying geometries can offer information on how specific geometric variables influence vehicle speeds and movements, and subsequently, roundabout safety performance. This research serves as a foundation for such further studies, and it would be beneficial if it were combined with such alter-

native approaches to achieve a more comprehensive understanding of the effects of geometric design variables.

Limitations: Data

In addition to the limitations in the modelling approach, there are notable limitations related to the data used in this analysis. Firstly, although the Region of Waterloo had a total of 39 roundabouts as of 2021, the inclusion criteria limited the dataset to 23 roundabouts for Model 1 and only 19 for Model 2. As discussed in Section 2.2, road crashes are rare occurrences, and injury crashes are even less frequent. This limited sample size reduced the number of collisions available for analysis, resulting in inconclusive results and potentially biased estimates.

Secondly, the range of values for the variables included in the model may have influenced the results. As mentioned in Section 1.2, the study focused exclusively on single-lane and multi-lane roundabouts in an urban setting, given that different forms of roundabouts can exhibit varying safety outcomes. Additionally, the research was confined to roundabouts under the jurisdiction of the Region of Waterloo, which, despite some variations, are relatively similar in terms of design principles. This may have resulted in limited variation in the values of certain variables, potentially contributing to the insignificance of some variables in the model. Therefore, the lack of significance for certain variables should not necessarily be interpreted as an absence of the impact of those variables on roundabout safety. Rather, it shows that their impact may not be detectable within the scope of the data and methods employed in this study.

Table 4.6: Comparison with Literature

Model Number	First Author	Age	Legs	ICD	Bypass	Approach		Flare		Entry			
						Ln	LnWidth	LnWidth	Length	Ln	LnWidth	Angle	Radius
Model 1		ns	ns	−	ns	ns	ns	ns	ns	+	+	+	ns
Model 2–1		ns	ns	ns	ns	ns	ns	ns	ns	+	+	+	ns
Model 2–2		ns	ns	−	ns	ns	ns	ns	ns	+	+	+	ns
1	Ambros			ns							ns	−	
2	Ambros			ns							ns		
4	Anjana			ns			ns					+	+
8	Arndt										+	−	+
10	Daniels	ns	−	ns	ns								
12	Daniels	ns	−	ns	+								
16	Daniels	+	ns	ns	ns								
18	Daniels	ns	ns	ns	ns								
20	Daniels	ns	ns	ns	ns								
24	Daniels	+	−	ns	+								
26	Daniels	ns	ns	ns	ns								
28	Farag				ns					+	ns	ns	ns
29	Farag				ns					ns	ns	ns	ns
31	Farag				ns					ns	ns	ns	ns
32	Farag				−					+	ns	ns	ns
33	Farag				ns					ns	ns	ns	ns
34	Farag				ns					ns	ns	+	ns
35	Kamla			+						ns			
36	Kamla			+						ns			
37	Kamla			+						ns			
38	Kamla			+						ns			
39	Kamla			ns						ns			
40	Kamla			ns						ns			
41	Kim		+	ns				+	ns	+	+		ns
42	Maycock			−			+				+		+
43	Maycock						ns				−		−
44	Maycock						+				ns		−
45	Maycock						ns				ns		ns
46	Maycock						ns				ns		ns
47	NASEM		+	−									
48	NASEM		+		−					+	−		
51	NASEM			−	−								
52	NASEM			−									
53	NASEM			−									
55	NASEM			−	−								
59	NASEM									+			
60	Novak			ns	+					+		−	
61	Novak			ns	+					+		−	
62	Qin		ns	ns									
63	Senk		ns		ns					+			
68	Turner									+			

Chapter 5

Exploring Spatio-Temporal Effects in Roundabout Safety

In this chapter, we address the second research question: to investigate the effects of spatial and temporal factors of roundabouts on safety performance. The chapter is divided into two sections. Section 5.1 describes the development of SPFs integrating spatial and temporal effects. Then Section 5.2 presents the results and discussion of the developed SPFs.

5.1 Development of Spatio-Temporal Safety Performance Functions

The SPFs developed in Chapter 4 are extended to spatio-temporal SPFs to account for the spatial and temporal effects on roundabout safety. The spatio-temporal SPFs are developed using Bayesian hierarchical models, facilitating the incorporation of structured and unstructured spatial and temporal effects, and are evaluated through model fitting criteria.

5.1.1 Model Formulation

Negative binomial regression models are frequently employed to account for over-dispersion in road collision data, as discussed in Section 4.1.1. These models are

advantageous due to their closed-form marginal distribution and ability to be estimated using maximum likelihood estimation. However, in spatio-temporal analyses where Bayesian estimation is applied, Poisson log-normal regression models are also commonly employed to address over-dispersion in Poisson models. In contrast to negative binomial models where the error term follows a gamma distribution, Poisson log-normal regression models assume the error term follows a log-normal distribution, and are formulated in SPFs as:

$$y_i \mid \mu_i \sim \text{Poisson}(\mu_i) \tag{5.1}$$

$$\mu_i = \exp\left(\beta_0 + \beta_1 \cdot \ln\left(AADT_i\right) + \sum_{k=2} \beta_k x_{ik} + \epsilon_i\right) \tag{5.2}$$

$$\epsilon_i \mid \sigma \sim \text{Normal}\left(0, \sigma^2\right). \tag{5.3}$$

Poisson log-normal regression models are particularly advantageous when crash data exhibit low sample mean values and small sample sizes, compared to negative binomial models (Lord & Miranda-Moreno, 2008). The normally distributed error term further allows for direct comparison of structured and unstructured effects within the Besag-York-Mollié (BYM) model framework. Therefore, in the subsequent analysis, the error term is modelled as log-normally distributed.

The spatio-temporal effects arising from unobserved variables can be addressed by incorporating random effects into the model, as discussed in Section 2.3.2. Random intercept models allow model intercepts to vary spatially and temporally to capture the heterogeneity in the data. Following the formulation developed by Knorr-Held (2000) and Besag et al. (1991), and by incorporating structured effects as random effects, spatial and temporal autocorrelation can also be effectively captured. Thus, in the full model in which all random effects are considered simultaneously, the random effects are decomposed into the structured spatial effect, unstructured spatial effect, structured temporal effect, unstructured temporal effect, and spatio-temporal interaction effect terms. For each roundabout i and time step t from N roundabouts and T time steps, the full model that encompasses all these components is defined as follows:

$$y_{it} \mid \mu_{it} \sim \text{Poisson}(\mu_{it}) \tag{5.4}$$

$$\ln\left(\mu_{it}\right) = \beta_0 + \beta_1 \cdot \ln\left(AADT_{it}\right) + \sum_{k=2} \beta_k x_{ik} + \theta_i + \varphi_i + \upsilon_t + \nu_t + \delta_{it} \tag{5.5}$$

where

$$\begin{aligned}
\theta_i &: \text{structured spatial effect,} \\
\varphi_i &: \text{unstructured spatial effect,} \\
\upsilon_t &: \text{structured temporal effect,} \\
\nu_t &: \text{unstructured temporal effect,} \\
\delta_{it} &: \text{spatio-temporal interaction effect.}
\end{aligned}$$

In addition to the variability in intercepts captured by random intercept models, random coefficient models enable the variation of model coefficients. Although various distributions have been examined in prior road safety studies for random parameters, it has been found that the normal distribution provides the best fit (Anastasopoulos & Mannering, 2009; El-Basyouny & Sayed, 2009; Liu et al., 2018). Therefore, the normal distribution is employed in this analysis on random effects. Although all coefficients can be considered random in the formulation, in practice, only those coefficients for which σ_β is significantly different from zero are treated as random coefficients (Anastasopoulos & Mannering, 2009). The random coefficient models reduce to random intercept models in cases where only the intercept β_0 is treated as random effect and other parameters β remain fixed effect.

5.1.2 Structured Spatial Effect

To capture the structured spatial effect, or spatial autocorrelation, the conditional autoregressive (CAR) model is frequently employed, as discussed in Section 2.3.2. Specifically, the intrinsic conditional autoregressive (ICAR) model is preferred over the proper conditional autoregressive (pCAR) model due to its computational efficiency and reduced likelihood of encountering non-identifiability issues within the BYM model framework (Haining & Li, 2020). For each roundabout i, the structured spatial effect (θ_i) in the ICAR model is defined as follows:

$$\theta_i \mid \boldsymbol{\theta}_{-i}, \sigma_\theta, \boldsymbol{W}_s \sim N\left(\frac{\sum_{j\in -i} w_{ij}\theta_j}{\sum_{j\in -i} w_{ij}}, \frac{\sigma_\theta^2}{\sum_{j\in -i} w_{ij}}\right) \tag{5.6}$$

where

$\boldsymbol{W}_s$: spatial weights matrix,
w_{ij} : weight between roundabouts i and j in $\boldsymbol{W}_s$,
σ_θ : standard deviation of the spatial effect.

The spatial weights matrix $\boldsymbol{W}_s$, based on neighbouring structures, defines the proximity between roundabouts. For neighbouring structures in road safety analysis, Aguero-Valverde and Jovanis (2010) defined and compared the effectiveness of adjacency, distance order, distance exponential decay, and adjacency-route information models. Their findings suggest that while the adjacency, distance order, and adjacency-route information models consistently outperform the exponential decay model, the performance amongst these three models varies depending on the specific parameters and data employed. Although their neighbouring structures were defined for road segments rather than intersections, it is reasonable to assume that similar structures can effectively capture spatial autocorrelation between intersections. Thus, the models proposed by Aguero-Valverde and Jovanis (2010) have been slightly modified to suit intersection analysis and are applied in this study. The models and the corresponding modifications are detailed below.

Adjacency Model The adjacency level between roundabouts i and j is defined as the number of road segments separating them. Weights are then assigned as the inverse of the adjacency level between the roundabouts. For instance, if there are two road segments between roundabouts i and j, the adjacency level is second, resulting in a weight of 1/2. To eliminate the influence of local collectors, only intersections with control measures in all directions are considered when calculating adjacency.

Distance Order model The adjacency level between roundabouts i and j is defined by the distance between them, which is classified into levels based on specific thresholds. The distances are calculated using two methods: the Euclidean distance and the network distance. Two sets of somewhat arbitrary thresholds for classification were examined, following the example by Aguero-Valverde and Jovanis (2010): every 500 metres up to 5000 metres, and every 1000 metres up to 5000 metres. The latter was selected due to its superior fit. Weights are then assigned as the inverse of the adjacency level between the roundabouts.

Distance Exponential Decay Model The weights are numerically determined based on the Euclidean and network distances between roundabouts, and are defined as follows:

$$w_{ij} = \exp(-\frac{d_{ij}}{\kappa_0}) \tag{5.7}$$

where

d_{ij} : Euclidean or network distance between roundabouts i and j (in metres),

κ_0 : constant (in metres).

A threshold of 5000 metres is set, beyond which a weight of zero is assigned. Two somewhat arbitrary constants of $\kappa_0 = 1000$ and $\kappa_0 = 2000$ were examined, resulting in the selection of $\kappa_0 = 2000$ due to its superior fit.

Adjacency-Route Information Model This model incorporates route information into the adjacency framework. If two roundabouts are located on the same route, their adjacency level is elevated by one, except for first-order neighbours, which remain classified as first order. A route is defined as a road containing more than two roundabouts with no in-between turns. This model is designed to capture unobserved variables common to routes that may contribute to spatial autocorrelation.

5.1.3 Structured Temporal Effect

Four formulations for capturing structured temporal effects or temporal autocorrelation are commonly employed, as discussed in Section 2.3.2: linear time trend, quadratic time trend, first-order random walk (RW1), and first-order autoregressive (AR1) models. The AR1 model is a generalisation of the RW1 model and has the advantage of capturing both the magnitude and direction of temporal autocorrelation, as utilised by Cheng et al. (2018). However, since the focus of this study is on assessing the presence of temporal heterogeneity and autocorrelation, and negative temporal autocorrelation is not anticipated, the linear time trend, quadratic time trend, and RW1 models are considered in this analysis. The formulations of the temporal effects (υ_t) for each time step t from T time steps are described below.

Linear Time Trend Model: The model considers a linear trend over time, defined as follows:

$$\upsilon_t = \gamma \left(t - \frac{T+1}{2} \right) \tag{5.8}$$

where γ is the coefficient.

Quadratic Time Trend Model: The model considers a quadratic trend over time, defined as follows:

$$\upsilon_t = \gamma_1 \left(t - \frac{T+1}{2} \right) + \gamma_2 \left(t - \frac{T+1}{2} \right)^2 \tag{5.9}$$

where γ_1 and γ_2 are the coefficients.

First-order Random Walk (RW1) Model: The RW1 model adds complexity to the linear trend model by incorporating a temporal adaptive process, in which the temporal effect at time t (υ_t) is the sum of the temporal effect at time $t-1$ (υ_{t-1}) and a normally distributed independent noise term. Bidirectional temporal dependence can be accounted for by including the temporal effect at time $t+1$ (υ_{t+1}) in the summation, as expressed in the following equation:

$$\upsilon_t \mid \boldsymbol{\upsilon}_{(-t)}, \sigma_\upsilon \sim \begin{cases} N\left(\upsilon_{t+1}, \sigma_\upsilon^2\right) & \text{for } t = 1 \\ N\left(\dfrac{\upsilon_{t-1} + \upsilon_{t+1}}{2}, \dfrac{\sigma_\upsilon^2}{2}\right) & \text{for } t = 2, \ldots, T-1 \\ N\left(\upsilon_{t-1}, \sigma_\upsilon^2\right) & \text{for } t = T. \end{cases} \tag{5.10}$$

The random walk models are temporal analogues of the spatial ICAR model (Fahrmeir & Lang, 2001), and can be rewritten as follows:

$$\upsilon_t \mid \boldsymbol{\upsilon}_{(-t)}, \sigma_\upsilon, \boldsymbol{W}_t \sim N\left(\frac{\sum_{g=1}^{T} w_{tg}\theta_g}{\sum_{g=1}^{T} w_{tg}}, \frac{\sigma_\upsilon^2}{\sum_{g=1}^{N} w_{tg}} \right) \tag{5.11}$$

where

$\boldsymbol{W}_t$: temporal weights matrix,
w_{tg} : weight between time steps t and g in $\boldsymbol{W}_t$,
σ_υ : standard deviation of the temporal effect.

The RW1 model is the special case of this with $w_{tg} = 1$ for $|t-g| = 1$ and $w_{tg} = 0$ otherwise. Although higher-order random walk models such as the second-order random walk (RW2) model can also be considered by altering the temporal weights matrix, due to the complexity of higher-order models, the RW1 model is more commonly used in road safety analysis.

5.1.4 Unstructured Effects

Using the Poisson log-normal regression framework, both unstructured spatial and temporal effects are modelled with a normal distribution as follows:

$$\varphi_i \sim N\left(0, \sigma_\varphi^2\right), \tag{5.12}$$

$$\nu_t \sim N\left(0, \sigma_\nu^2\right). \tag{5.13}$$

The unstructured spatial effect φ captures the spatial heterogeneity due to unobserved variables relevant to spatial locations. However, it is critical to note that since each location is a roundabout with varying geometric designs, they also encompass the effects of unobserved geometric design and the effects of observed geometric design not captured appropriately by the linear regression structure.

5.1.5 Spatio-Temporal Interaction Effect

The spatio-temporal interaction effects account for the interplay between spatial and temporal effects, in which variations in both space and time are considered simultaneously. Knorr-Held (2000) proposed four possible structures for modelling these interaction effects, which are summarised below.

Type I The interaction is modelled as a combination of the unstructured spatial effect and the unstructured temporal effects. In other words, no dependence structure is assumed for the space-time parameters.

$$\delta_{it} \sim N\left(0, \sigma_\delta^2\right) \tag{5.14}$$

where σ_δ is the standard deviation of the spatio-temporal interaction effect.

Type II The interaction is modelled as a combination of the unstructured spatial effect and the structured temporal effect. In this case, a temporal dependence structure is assumed within each spatial unit, but it varies independently of spatial proximity. In other words, the structured temporal effect $\delta_{i,1:T}$ varies across locations i, but $\delta_{i,1:T}$ is independent of $\delta_{j,1:T}$ for $i \neq j$, regardless of their spatial proximity.

Type III The interaction is modelled as a combination of the structured spatial effect and the unstructured temporal effects. In this case, the spatial dependence structure is assumed within each time unit, but it varies independently of temporal proximity. In other words, the structured spatial effect $\delta_{1:N,t}$ varies due to time steps t, but $\delta_{1:N,t}$ is independent of $\delta_{1:N,t-1}$ and $\delta_{1:N,t+1}$ regardless of their temporal proximity.

Type IV The interaction is modelled as a combination of the structured spatial effect and the structured temporal effects. In this case, the spatial and temporal dependence structures are fully interdependent both spatially and temporally. Knorr-Held (2000) discusses obtaining the Kronecker product of the spatial and temporal dependence structures and developing it into a Gaussian Markov random field (GMRF) model. However, such model structures present challenges in terms of both computational complexity and interpretability. Therefore, in this analysis, the Type IV interaction effect based on the hypothesis that the structured temporal effect varies according to spatial proximity is considered. This approach would be useful for testing whether there are any spatial patterns associated with the novelty effect discussed in Section 2.1.5. Due to the model's complexity, only the linear time trend and quadratic time trend models are considered for the structured temporal effect. For instance, the interaction effect with the linear time trend (Eq. 5.8) and ICAR (Eq. 5.6) models is formulated as follows:

$$\upsilon_t = \gamma_i \left(t - \frac{T+1}{2} \right) \tag{5.15}$$

$$\gamma_i \mid \boldsymbol{\gamma}_{-i}, \sigma_\gamma, \boldsymbol{W}_s \sim N \left(\frac{\sum_{j \in -i} w_{ij} \gamma_j}{\sum_{j \in -i} w_{ij}}, \frac{\sigma_\gamma}{\sum_{j \in -i} w_{ij}} \right) \tag{5.16}$$

and the same formulation can be considered with the quadratic time trend model (Eq. 5.9) with γ_{1i} and γ_{2i} following the ICAR model (Eq. 5.6) independently.

5.1.6 Prior Distributions

Bayesian models require the specification of prior distributions for all unknown parameters in the model. If prior information or knowledge about the parameters is available, it can be incorporated into the prior distributions. However, in the absence of such prior information, non-informative or weakly informative prior distributions

are employed in this analysis to ensure that the estimation is primarily driven by the data (Gelman, Carlin, Stern, & Rubin, 1995).

For the model parameters β, normal priors are defined as follows:

$$\begin{cases} \beta_k \sim N\left(-25.0, 0.01\right) & \text{for } k = 0, \\ \beta_k \sim N\left(0, 0.0025\right) & \text{for } k > 0. \end{cases} \tag{5.17}$$

For hyperparameters, inverse-gamma distributions, uniform distributions, and half-normal distributions are commonly used. Although the use of inverse-gamma distributions as prior distributions has been subject to some criticism, they remain widely employed in epidemiology and road safety analysis (Blangiardo, Cameletti, Baio, & Rue, 2013; Cai et al., 2018). Following the approach of Boulieri et al. (2017), the following prior distributions are used for the hyperparameters:

$$\sigma_\theta, \sigma_\varphi, \sigma_\upsilon, \sigma_\nu, \sigma_\delta \sim \text{inverse-gamma}\left(0.5, 0.0005\right). \tag{5.18}$$

For prior distributions of β and σ, additional estimations are performed using varying levels of informativeness by adjusting the variance of the normal and inverse-gamma distributions. Specifically, the variance values of up to five times less variable of Eq. 5.17 and Eq. 5.18 are considered. The results are then compared to models with non-informative priors to ensure that the choice of prior distributions does not significantly influence the estimation results. All the modelling results presented in the analysis use the non-informative prior distributions shown in Eq. 5.17 and Eq. 5.18.

5.1.7 Model Estimation

The model parameters are estimated using the Markov Chain Monte Carlo (MCMC) method, a simulation-based approach that generates samples to approximate the posterior distribution. Although the integrated nested Laplace approximation (INLA) method is also commonly used in Bayesian estimation as an approximate Bayesian inference technique, with applications in road safety analysis (Liu & Sharma, 2017), the model structure and data in this analysis did not necessitate the use of INLA. The MCMC method is implemented using the WinBUGS software, which utilises the Gibbs sampling algorithm to perform Markov chain sampling (D. J. Lunn, Thomas, Best, & Spiegelhalter, 2000). The R programming language and the R2WinBUGS package are used to interface with WinBUGS and execute the MCMC chains (R

Core Team, 2023; Sturtz, Ligges, & Gelman, 2005). For the MCMC chains, the initial values for the model parameters β are derived from the maximum likelihood estimation of the negative binomial models, and the initial values for the random effects are set to near-zero values. Two chains are run for each model with varying but sensible initial values, and each chain is run for 40,000 iterations after the convergence criteria are met. To check the convergence of the MCMC chains, both visual inspection of the trace plots and the Brooks-Gelman-Rubin (BGR) diagnostic are employed (Gelman & Rubin, 1992; Brooks & Gelman, 1998). For the BGR diagnostic, values below 1.05 for all parameters are used as an indication of convergence (D. Lunn, Jackson, Best, Thomas, & Spiegelhalter, 2013).

5.1.8 Model Comparison Criteria

The performance of the models is evaluated using the deviance information criterion (DIC), defined as:

$$DIC = \bar{D} + pD, \tag{5.19}$$

where $\bar{D}$ is the posterior mean of the deviance, and pD is the effective number of estimated parameters (Spiegelhalter, Best, Carlin, & Van Der Linde, 2002). The posterior mean of the deviance is a measure of the model's goodness of fit to the data, while the effective number of parameters is a measure of the model's complexity. The DIC serves as the Bayesian equivalent of the AIC in frequentist estimation, with models having lower DIC values being preferred. Although there is no definitive rule for comparing DIC values, a commonly accepted guideline suggests that a difference of 10 in DIC effectively rules out the model with the higher DIC, a difference of 5 to 10 is considered substantial, and models are regarded as having similar performance if the difference is less than 5 (D. Lunn et al., 2013).

In addition to the DIC, the posterior predictive distribution is used to evaluate the model's fitting to the data. The posterior predicative distribution represents the data generated from the developed model, and the appropriateness of the model is assessed by evaluating the plausibility of the observed data under this distribution (Gelman et al., 1995). The posterior predictive p-value measures the probability that the simulated data are more extreme than the observed data, and is approximated in this case as follows:

$$ppp_{it} = \frac{1}{S} \sum_{s=1}^{S} ppr_{it}^{s}, \tag{5.20}$$

where

$$ppr_{it}^{s} = \begin{cases} I\left(y_{it}^{pred,s} \geq y_{it}\right) & \text{if } y_{it} > 0 \\ I\left(y_{it}^{pred,s} = y_{it}\right) & \text{if } y_{it} = 0. \end{cases} \tag{5.21}$$

In this formulation, *ppp* is the posterior predicative p-value, I is the indicator function that returns 1 if the condition is true and 0 otherwise, $y_{it}^{pred,s}$ is the simulated value of the number of collisions at roundabout i and time step t from the posterior predictive distribution, and S is the number of simulations (Haining & Li, 2020). The number of simulation S is set to 100, and the model is considered to fit the data well if the posterior predictive p-value lies between 0.05 and 0.95 (Gelman et al., 1995).

5.1.9 Model Specifications

The model components described in Sections 5.1.2 to 5.1.5 can be combined simultaneously to develop the full model. However, given the limited number of data points, the full model may be over-parameterised, leading to computational and identifiability challenges. Therefore, several models are developed by considering different combinations of the spatial and temporal effects, with each effect assessed individually.

In most epidemiology and road safety studies, the time step t is typically defined as the calendar year, based on the assumption that temporal effects arise from unobserved variables relevant to calendar years. This assumption is also reasonable in the context of roundabout collisions, and calendar year models are developed. However, calendar year models may not be suitable for assessing the novelty effect on the number of collisions following the opening of roundabouts, as the novelty effect is concerned with the influence of the time since the roundabout's opening on the number of collisions. Therefore, operational year models are also considered, where the time step t is defined as the years in operation since the opening of roundabout.

5.2 Results and Discussion

5.2.1 Calendar Year Models

The calendar year models were developed using data from 2014 to 2018, encompassing 19 roundabouts and 5 time steps. The selection of time and location was based

on the availability of the AADT data and the need to ensure a reasonable number of data points for the analysis.

Base Model

The base model was developed with the spatio-temporal interaction term (δ_{it}) of Type I to serve as a comparison against other models. The geometric design variables from the negative binomial regression analysis in Section 4.2.2 were included as explanatory variables, specifically: "Average ICD", "Average Entry Angle", "Average Entry Lane Width", and "Entry Lane Minimum 2". The model functions as a Poisson log-normal regression model, with the assumption that the effects of unobserved variables are neither spatial nor temporal.

The 95% credible intervals for the model parameters β and δ_{it} were calculated from the MCMC chains. Based on these 95% credible intervals, all parameters except "Average ICD" were found to be significantly different from zero. The insignificance of "Average ICD" suggests spatial or temporal instability in the effects of this variable. This finding is consistent with the insignificance of "Average ICD" in model 2 from Section 4.2.3.

The base model was re-developed after removing "Average ICD" from the explanatory variables. The fitted model had a DIC value of 330.5, with $\bar{D} = 320.5$ and $pD = 10.0$. An examination of the posterior predictive distribution revealed that, out of 95 data points, 93 had a mean posterior predictive p-value between 0.05 and 0.95, indicating that the model neither significantly underestimates nor overestimates the number of collisions for those data points. This is considered a reasonable fit to the data, supporting the validity of the model.

The posterior mean, standard deviation, and 95% credible interval of the model parameters are presented in Table 5.1. For comparison, the frequentist maximum likelihood estimates of the parameters from model 1 in Section 4.2.2 are also shown in Table 5.1. The posterior means of the parameters are largely consistent with those in model 1.

Spatio-Temporal Model

It is plausible that the heterogeneity of the data follows a spatio-temporal panel structure, where the heterogeneity of each data point is simply the sum of the spatial and temporal heterogeneity. To explore this, a spatio-temporal model was developed

Table 5.1: Results of Calendar Year Base Model

	Mean	SD	2.5%	97.5%	NB Model 1
Intercept	−25.03	2.542	−30.02	−20.45	−30.25
AADT	2.106	0.242	1.667	2.580	2.582
Average ICD	ns	ns	ns	ns	−0.032
Average Entry Angle	0.099	0.028	0.043	0.156	0.108
Average Entry Lane Width	0.379	0.133	0.116	0.636	0.341
Entry Lane Minimum 2	1.039	0.275	0.511	1.588	1.088

by including the unstructured spatial effect (φ_i) and unstructured temporal effect (ν_t). The relative significance of the spatial and temporal heterogeneity was then assessed by calculating the spatial fraction of variance, defined as:

$$frac_{\varphi} = \frac{\tilde{\sigma}_{\varphi}^2}{\tilde{\sigma}_{\varphi}^2 + \tilde{\sigma}_{\nu}^2}, \tag{5.22}$$

where $\tilde{\sigma}_{\varphi}^2$ and $\tilde{\sigma}_{\nu}^2$ are the unconditional variances of the unstructured spatial and temporal effect, respectively.

The posterior distribution of the spatial fraction was skewed towards 1, with a mean of 0.68 and a median of 0.82, indicating that spatial heterogeneity is more significant than temporal heterogeneity. It should be noted again that this spatial heterogeneity include unobserved variables related to the geometric design of the roundabouts. The fitted model had a DIC value of 330.1, with $\bar{D} = 321.7$ and $pD = 8.4$. The DIC value was slightly lower than that of the base model, with similar model fit and reduced model complexity. This suggests that a portion of the unobserved heterogeneity can be attributed to spatial and temporal heterogeneity.

Additionally, the spatio-temporal interaction term δ_{it} using the Type I interaction model was incorporated into the model to further assess the significance of spatial and temporal heterogeneity. The posterior mean values of the spatial and temporal fractions of variance were calculated to be 0.44 and 0.19, respectively. These results support the argument that spatial instability is significant, although a substantial portion of the heterogeneity is not captured by the simple summation of spatial and temporal heterogeneity. The relatively low variance of the temporal unstructured term suggests that temporal instability may not be a significant factor compared to spatial and spatio-temporal instability.

Spatial BYM Model

The spatial BYM models were developed to assess the significance of spatial autocorrelation and heterogeneity in the data. The model formulation included the spatial effect θ_i with the ICAR prior (Eq. 5.6) and the unstructured spatial effect φ_i with the normal prior (Eq. 5.12). The same geometric design variables as those used in the base and spatio-temporal models were included. The relative significance of spatial autocorrelation and heterogeneity was evaluated by calculating the spatial fraction of variance, formulated as:

$$frac_\theta = \frac{\tilde{\sigma}_\theta^2}{\tilde{\sigma}_\theta^2 + \tilde{\sigma}_\varphi^2}, \tag{5.23}$$

where $\tilde{\sigma}_\theta^2$ and $\tilde{\sigma}_\varphi^2$ are the unconditional variances of the structured and unstructured spatial effects, respectively.

The model specifications and DIC values are presented in Table 5.2, in comparison to the base and spatio-temporal models. The results indicate that models using the distance order or distance exponential decay methods with the Euclidean distance between roundabouts perform the best. Both the distance order and distance exponential decay models exhibit better fitting ($\bar{D}$) and lower DIC values than the base and spatio-temporal models, suggesting the presence of spatial autocorrelation in the data. Notably, the distance order model with the Euclidean distance shows a substantially lower $\bar{D}$ value than the base and spatio-temporal models, with a DIC value lower by 4.0. The spatial fraction of variance in the distance order model with the Euclidean distance is significantly skewed towards 1, with a mean value of 0.94 and a median value of 0.98. This finding suggests that spatial autocorrelation is more significant than spatial heterogeneity, including the effects of unobserved geometric designs. However, the difference in the DIC values between the spatial BYM model and the base model is not substantial, indicating that a simpler base or spatio-temporal model may still be preferred for predictive purposes.

The posterior mean values of the structured spatial effect are presented in Figure 5.1. The figure shows that the two roundabouts on Fisher-Hallman Road and the one on Homer-Watson Boulevard at Block Line Road have higher random intercept values, in contrast to the roundabouts on Fountain Street South, which exhibit lower values.

There are numerous possible explanations for the unobserved factors related to the location of roundabouts that contribute to spatial autocorrelation in the data. One potential explanation is the behavioural differences among drivers. Due to geographical characteristics, such as proximity to certain facilities, drivers in some areas



Figure 5.1: Spatial Autocorrelation in Collision Frequency

may exhibit more aggressive driving behaviour or higher speeds. It is also plausible that drivers in certain areas are more accustomed to navigating roundabouts than those in other areas. However, this analysis only identifies the presence of effects, and determining the underlying causes of such spatial autocorrelation requires further investigation.

In addition to the structured spatial effects term θ_i, the spatio-temporal interaction term δ_{it} using the Type III interaction model was included in the distance order model to assess the temporal variation in the structured spatial effect. This addition aimed to capture temporal variation in the spatial autocorrelation, with the results also presented in Table 5.2. However, neither the model fit nor the DIC value improved. This outcome may be due to the identifiability issues related to overparameterisation of the model and does not necessarily indicate the absence of temporal variation in spatial autocorrelation. Nevertheless, within the context of the data, it is reasonable to conclude that temporal variation in spatial autocorrelation is not significant.

Table 5.2: Results of Calendar Year Spatial BYM Model

Spatial Weights Model	Distance	θ	φ	υ	ν	δ	$\bar{D}$	pD	DIC
(Base Model)						IV	320.5	10.0	330.5
(Spatio-Temporal Model)			✓		✓		321.7	8.4	330.1
Adjacency		✓	✓		✓		320.3	10.6	330.9
Distance Order	Euclidean	✓	✓		✓		315.8	10.3	326.1
	Network	✓	✓		✓		314.9	14.9	329.8
	Euclidean	✓	✓	✓		III	330.7	30.9	361.6
Distance Exponential Decay	Euclidean	✓	✓		✓		316.0	11.2	327.2
	Network	✓	✓		✓		317.4	14.2	331.6
Adjacency-Route Information		✓	✓		✓		321.1	10.7	331.8

Temporal BYM Model

The results of the spatio-temporal model suggest that temporal heterogeneity is less significant than spatial heterogeneity, and the inclusion of temporal effects in the model may not improve the model fit. However, the spatio-temporal model does not capture temporal autocorrelation, and the temporal BYM model was developed to assess the significance of temporal autocorrelation and heterogeneity in the data. The model formulation included the temporal effect υ_t, modelled using the linear trend model (Eq. 5.8), quadratic trend model (Eq. 5.9), or the RW1 prior (Eqs. 5.10 and 5.11), along with the unstructured temporal effect ν_t, modelled with the normal prior (Eq. 5.13). In the case of the RW1 model, the temporal fraction of variance was calculated as:

$$frac_{\upsilon} = \frac{\tilde{\sigma}_{\upsilon}^2}{\tilde{\sigma}_{\upsilon}^2 + \tilde{\sigma}_{\nu}^2}, \tag{5.24}$$

where $\tilde{\sigma}_{\upsilon}^2$ and $\tilde{\sigma}_{\nu}^2$ are the unconditional variances of the structured and unstructured temporal effect, respectively.

The fitting results of the temporal BYM models are presented in Table 5.3. Although the linear time trend model and the RW1 model result in lower DIC values compared to the spatio-temporal model, the improvement in the model fit and the

Table 5.3: Results of Calendar Year Temporal BYM Model

Temporal Model	θ	φ	υ	ν	δ	$\bar{D}$	pD	DIC
(Base Model)					IV	320.5	10.0	330.5
(Spatio-Temporal Model)		✓		✓		321.7	8.4	330.1
Linear		✓	✓	✓		320.7	8.5	329.2
		✓		✓	II	326.4	25.6	352.0
Quadratic		✓	✓	✓		320.9	10.2	331.1
		✓		✓	II	322.6	38.2	360.8
RW1		✓	✓	✓		320.9	9.1	330.0
		✓		✓	II	320.4	9.4	329.8

DIC values is not significant. The temporal fraction of variance exhibits a large variance, leading to inconclusive results regarding the significance of temporal autocorrelation and heterogeneity in the data. Since this model assumes identical structured temporal patterns across all roundabouts, additional models were developed with the spatio-temporal interaction term δ_{it} using the Type II interaction model. Similarly to the spatio-temporal interaction term in the spatial BYM model, the spatio-temporal interaction term δ_{it} allows for spatial variation in the structured temporal effect. However, neither the model fit nor the DIC value improved, suggesting that even with the assumption of spatial independence, the structured temporal effect is not significant. While this does not necessarily disprove the presence of a temporal pattern, it indicates that the temporal pattern is not significant in the context of the data.

Random Coefficient Model

The random coefficient models were developed to assess heterogeneity in the model coefficients, in addition to the model intercepts. Although the geometric variable "Average ICD" was excluded from the base model due to its insignificance, it is plausible that random effects on the model parameters could capture heterogeneity in the coefficients. Therefore, the original geometric parameters from the negative binomial regression analysis in Section 4.2.2, namely, "Average ICD," "Average Entry Angle," "Average Entry Lane Width," and "Entry Lane Minimum 2," were all included as explanatory variables. Using a similar formulation to the base model,

with added random effects on the model parameters β, the base random coefficient model was developed with the following formulation:

$$y_{it} \mid \mu_{it} \sim \text{Poisson}(\mu_{it}), \tag{5.25}$$

$$\ln(\mu_{it}) = (\beta_0 + \delta_{0it}) + (\beta_1 + \delta_{1it}) \cdot \ln(AADT_{it}) + \sum_{k=2} (\beta_{k0} + \delta_{kit}) x_{ki}, \tag{5.26}$$

$$\delta'_{kit} \mid \sigma_{\beta_k} \sim N\left(0, \sigma^2_{\beta_k}\right), \tag{5.27}$$

for $k = 0, \ldots, K$.

Additionally, it is plausible that the random effects can be modelled as the addition of the spatial and temporal random effects, similarly to the spatio-temporal model. Thus, the spatio-temporal random coefficient model was developed with the formulation:

$$\ln(\mu_{it}) = (\beta_0 + \varphi_{0i} + \nu_{0t}) + (\beta_1 + \varphi_{1i} + \nu_{1t}) \cdot \ln(AADT_{it}) + \sum_{k=2} (\beta_{k0} + \varphi_{ki} + \nu_{kt}) x_{ki} \tag{5.28}$$

$$\varphi_{ki} \mid \sigma_{\varphi_k} \sim N\left(0, \sigma^2_{\varphi_k}\right) \tag{5.29}$$

$$\nu_{kt} \mid \sigma_{\nu_k} \sim N\left(0, \sigma^2_{\nu_k}\right) \tag{5.30}$$

where φ_{ki} is the spatial random effect on the parameter β_k at roundabout i, and ν_{kt} is the temporal random effect on the parameter β_k at time step t.

The results of the random coefficient models are presented in Table 5.4. Although both models significantly improve the model fit compared to the base and spatio-temporal models, the increased complexity of these models leads to higher DIC values. As reasonably expected, the model with δ Type IV random effects provides a better fit to the data than the model with unstructured spatial and temporal effects; however, the benefits are offset by the increased model complexity, resulting in similar performance in terms of DIC values.

Although the above models assume random effects on all parameters, some parameters may not exhibit significant heterogeneity to justify the inclusion of random effects. An examination of the random effects and their variances revealed that the random effects on the variable "Average ICD" are larger than those on the other variables. This finding is consistent with the insignificance and subsequent removal of "Average ICD" in the base model. Consequently, a new model was developed where random effects on all geometric variables except "Average ICD" were removed. As was the case in random intercept models, it is reasonable to consider

both heterogeneity and autocorrelation in the random effects on model coefficients. Subsequently, the random effects of the variable "Average ICD" were examined to determine whether the observed instability was due to heterogeneity or autocorrelation. Although the spatial random effect on "Average ICD" exhibited no noticeable spatial pattern, the temporal random effect showed a decreasing trend, as illustrated in Figure 5.2. Therefore, another model was developed in which the spatial random effect on "Average ICD" remained unstructured, while the temporal random effect was modelled as a linear trend.

Table 5.4 shows that converting all geometric variables except "Average ICD" to fixed effects results in a better model fit and a slightly lower DIC value. This suggests that the instability in the effects of geometric variables varies depending on the variable, with "Average ICD" exhibiting the greatest instability. The unstructured nature of the spatial random effect on "Average ICD" indicates that these effects are more likely due to geometric variables not adequately captured by the linear relationship assumed in the model. Table 5.4 also shows that the model with the temporal random effect modelled as a linear trend showed a slightly better fit and a lower DIC value. This finding suggests the possibility that larger roundabouts may become safer over time, although the trend is not significant enough to justify drawing a definitive conclusion.

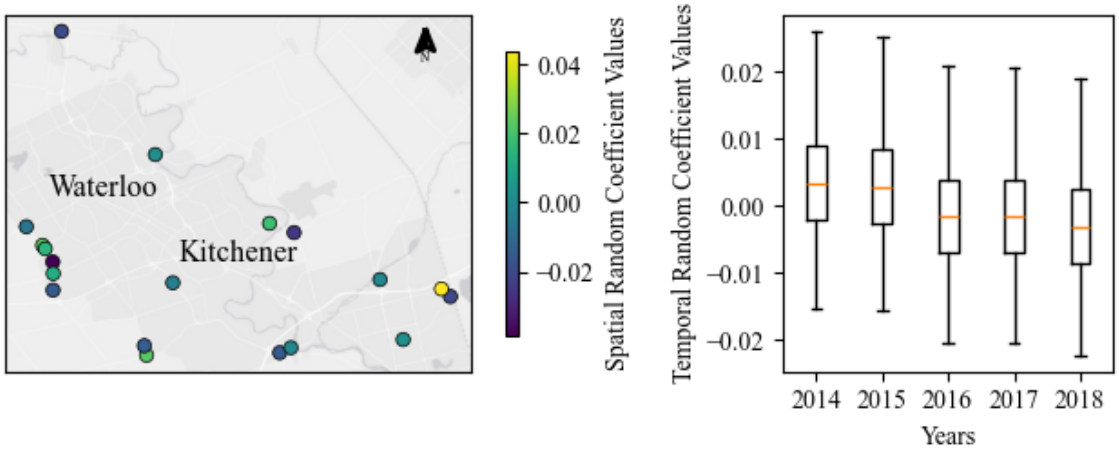


Figure 5.2: Spatial and Temporal Random Effects on Average ICD

Table 5.4: Results of Random Coefficient Models

Intercept	ln(AADT)	Average ICD	Average Entry Angle	Average Entry Lande Width	Entry Lane Min 2	$\bar{D}$	pD	DIC
(Base Model)						320.5	10.0	330.5
(Spatio-Temporal Model)						321.7	8.4	330.1
δ (IV)	δ (IV)	δ (IV)	δ (IV)	δ (IV)	δ (IV)	289.7	43.6	333.3
$\varphi + \nu$	$\varphi + \nu$	$\varphi + \nu$	$\varphi + \nu$	$\varphi + \nu$	$\varphi + \nu$	311.5	22.8	334.2
$\varphi + \nu$		$\varphi + \nu$				313.5	16.3	329.8
$\varphi + \nu$		$\varphi + \upsilon$ (linear)				312.3	16.4	328.7

5.2.2 Operational Year Models

The operational year model was developed to assess the significance of the novelty effect in the data. Instead of using the calendar year and location panel structure, the data was organised into a panel structure based on the years in operation since opening and the locations. To eliminate the influence of construction, the year in which the roundabout was opened was excluded, and data from the first three years of operation at nine roundabouts, covering the years 2010 to 2012, was used.

Due to the limited number of roundabouts available for analysis and the specific purpose of this study, only temporal variability was examined. The base model with the spatio-temporal interaction term (δ_{it}) of Type I, the spatio-temporal model, and the temporal BYM model were developed. Additionally, to test for a possible spatial pattern in the novelty effect, a model was developed to assess spatial variation in the temporal effect, incorporating the spatio-temporal interaction term δ_{it} of Type IV with the ICAR model and either the linear or quadratic time trend model.

The spatial fraction of variance in the spatio-temporal model exhibited a wide confidence interval, ranging from 0.01 to 0.99, with a median of 0.58. This suggests a relatively high significance of temporal heterogeneity in the data, in contrast to the calendar year model, where spatial heterogeneity was more pronounced than temporal heterogeneity. From this result, it can be inferred that relative temporal instability in the collision frequency is larger in the first few years after opening

Table 5.5: Results of Operational Year Models

Spatial Model	Temporal Model	θ	φ	υ	ν	δ	$\bar{D}$	pD	DIC
(Base Model)						IV	77.8	5.4	83.2
(Spatio-temporal Model)			✓		✓		78.6	5.0	83.6
	Linear		✓	✓	✓		79.4	6.2	85.5
				✓	✓	II	73.4	12.4	85.8
	Quadratic		✓	✓	✓		79.1	6.5	85.6
				✓	✓	II	70.9	15.1	86.0
	RW1		✓	✓	✓		78.5	5.1	83.5
				✓	✓	II	77.2	5.5	82.7
Distance Order Euclidean	Linear			✓		IV	79.1	6.8	85.8
	Quadratic			✓		IV	Non-convergence		

of roundabouts than the remaining years. The results in Table 5.5 indicate that the quadratic model with a Type II spatio-temporal interaction term offers better fitting, and the RW1 models have lower DIC values compared to the base and the spatio-temporal models. However, the improvement in the DIC values in either case is not significant, and the model does not provide conclusive evidence regarding the presence of the novelty effect or the spatial pattern of the novelty effect in the data.

5.2.3 Findings and Limitations

This section provides a comprehensive summary of the findings from the spatio-temporal analysis, as well as the limitations.

Findings

The spatio-temporal model indicated that spatial variability was more pronounced than temporal variability in the data. While some instability was attributed to spatial and temporal heterogeneity, a portion of the unobserved heterogeneity could not be explained by the combined effects of spatial and temporal heterogeneity.

In terms of the spatial effects, the distance-order model using the Euclidean distance best captured the spatial autocorrelation present in the data, and provided

a superior fit compared to the base and spatio-temporal models. The model also found that spatial autocorrelation was more significant than spatial heterogeneity. This finding implies the existence of unobserved factors associated with geographical locations that influence collision frequency. However, incorporating temporal variability within the structured spatial effects did not improve the model fit, indicating that temporal variation in spatial autocorrelation is negligible in the data.

For the temporal effects, the structured temporal effects modelled using the linear trend, quadratic trend, and RW1 models did not show significant improvement in the model fitting. This lack of significance suggests that no strong temporal pattern exists in the collision frequency, at least within the limits of the data and modelling framework applied in this study. Similarly, analyses that incorporated temporal effects based on the years of operation of roundabouts did not enhance model performance, indicating that any novelty effects were insignificant within the scope of the available data.

Applying random effects to the "Average ICD" variable resulted in a slight improvement in the model fit. Subsequent analysis suggested a spatial heterogeneity and a decreasing temporal trend in the parameter estimates of the "Average ICD" variable. This could imply the presence of unobserved effects of "Average ICD" on safety, and that larger roundabouts may be becoming safer over time. However, the improvements in model fit were not substantial, and these findings were not definitive.

Limitations

The limitations discussed in Section 4.2.5 are also applicable to the spatio-temporal analysis presented here. Additionally, there are several specific limitations to the spatio-temporal analysis.

The geometric analysis in Chapter 4 allows for relatively straightforward interpretation of the model coefficients, due to the assumption of linear relationships between the explanatory and response variables. However, the spatio-temporal analysis in Chapter 5 is more complex, which poses challenges to the interpretability of the results. For instance, although a structured spatial effect was identified in the spatial BYM model, the model does not provide insights into the underlying causes of the spatial autocorrelation, even though factors such as driver characteristics and vehicle speeds are speculated. While this finding is useful for identifying the presence of spatial autocorrelation, the lack of interpretability limits the practical application of such results.

Additionally, the modelling approach itself has intrinsic limitations. The structural spatial and temporal effects were assumed to follow specific forms, such as the ICAR model for spatial effects and the linear time trend model for temporal effects. Although these models are well-established in the literature and various forms were tested in this research, they may not adequately capture the true structural spatio-temporal effects. For instance, the linear and quadratic time trend models assume continuous trends over time, which may fail to capture abrupt or nonlinear changes in temporal effects that could exist in the data.

Lastly, the limitations of the data used in this analysis constrain the study's findings. Although this was also discussed in Section 4.2.5, the dataset in Chapter 5 was particularly limited. The most significant data limitation was that only the opening years of roundabouts were recorded, with no information on specific months or days. As a result, data from the year in which a roundabout opened could not be utilised to analyse the novelty effect. If such a novelty effect lasted less than a year, it would not be detectable in the model. In addition to the potential biases the lack of data may have caused, it limited the complexity of models that could be developed. For example, only the linear trend model was used for the temporal structural effect of the spatio-temporal interaction term in the operational year model, which may have restricted the model's ability to capture the structural spatio-temporal effects.

Chapter 6

Conclusions

In this chapter, the main contributions, limitations, and future work are discussed based on the findings from the geometric design analysis and the spatio-temporal analysis of roundabout collision frequency data.

6.1 Contributions

Analysis of Roundabout Safety and Contributing Factors in Canadian Context

The literature review revealed that the geometric design of roundabouts has varying effects on safety performance across different countries and regions. Although Canada has seen increased adoption of roundabouts in recent years, there is limited research on their safety performance in the Canadian context. Given this gap in the literature, this research was undertaken to contribute to a better understanding of roundabout safety performance within the Canadian context.

Using data from the Region of Waterloo, a SPF with a conventional negative binomial model structure was developed. The analysis identified "AADT", "Average ICD", "Average Entry Angle", "Average Entry Lane Width" and "Entry Lane Minimum 2" as significant variables. "Average ICD" had a negative estimated coefficient, indicating that larger ICDs are associated with lower collision frequency, whereas the other variables had positive estimated coefficients, suggesting that increases in these variables are associated with higher collision frequency. A comparison of the results to the literature revealed both consistencies and contradictions. This suggests that

the effects of geometric design variables on roundabout safety in Canada may differ from those in other countries or regions, raising questions about the validity of applying SPFs from other regions to Canada and highlighting the need for developing a specific SPF tailored to the Canadian context. The developed SPF is shown below, although, again, care must be taken when applying this SPF to other regions.

$$\begin{aligned}\text{Collisions} = 7.269 \times 10^{-14} \cdot AADT^{2.582} \cdot \exp\,(\\ -0.032(\text{Average ICD}) + 0.108(\text{Average Entry Angle}) \\ +0.341(\text{Average Entry Lane Width}) + 1.088(\text{Entry Lane Minimum 2}))\end{aligned} \tag{6.1}$$

Spatial and Temporal Analysis of Roundabout Safety

Despite a large body of literature on roundabout safety, little attention has been paid to the spatial and temporal variations of roundabout safety. However, in regions such as Canada, where the adoption of roundabouts is relatively recent, it is expected that the safety performance of roundabouts may fluctuate over time and across different locations. Therefore, this research further developed the SPFs by incorporating spatial and temporal effects, capturing both the autocorrelation and heterogeneity due to unobserved factors. Spatio-temporal hierarchical Bayesian models, which are commonly used in epidemiology and have seen increasing application in road safety, were employed.

The main findings from the spatio-temporal analysis are as follows:

- Spatial variability in the collision data was found to be greater than temporal variability.
- Spatial effects were more structured than unstructured, indicating the presence of spatial autocorrelation, with the distance model using Euclidean distance best capturing these effects. The spatial autocorrelation suggests the existence of unobserved factors related to the geographical locations of the roundabouts that influence collision frequency.
- Structured temporal effects and novelty effect were not significant, suggesting that there is no significant temporal pattern in the collision frequency at least within context of the data and modelling approaches employed in the analysis.

- Applying random effects to the "Average ICD" variable slightly improved the model fit, with further analysis indicating spatial heterogeneity and a decreasing temporal trend in the random effects. This may indicate the presence of unobserved effects of "Average ICD" on safety and that larger roundabouts are becoming safer over time, although the improvement in the model fit was not substantial and the results were not conclusive.

Additionally, this research attempted to apply spatio-temporal interaction effects to road safety analysis for the first time, to the best of the author's knowledge. While this approach has been used in other fields such as epidemiology, spatio-temporal interaction has not been thoroughly examined in road safety. Although the results were not significant or conclusive, the research demonstrates the potential for applying this approach in road safety analysis.

6.2 Limitations

Although this research has contributed to the understanding of roundabout safety, several limitations are associated with the data and methodologies used in this study. Detailed discussions on these limitations are provided in Section 4.2.5 and Section 5.2.3, a summary of which is provided below.

Data Limitations

- The availability of the AADT data limited the number of roundabouts included in the analysis, potentially leading to inconclusive results and biased estimates.
- Injury and fatality collisions are rare occurrences, and the limited number of collisions available for analysis resulted potentially in inconclusive results and biased estimates.
- The study employed a single dataset from the Region of Waterloo, which may have limited the variation in the values of the geometric design variables. This may have led to insignificance of certain variables.

Modelling Limitations

- The negative binomial and Poisson log-normal regression models used in this research assume a linear relationship between the independent and dependent

variables. While categorical variables were employed in cases where non-linear relationships were suspected, the linear model may have failed to capture the relationships between the variables accurately.

- The statistical model used in this study only presents correlations between the variables and collision frequency, and does not imply causality. Thus, the analysis on the effects of geometric design variables on collision frequency does not suggest that the variation in certain variables causes the variation in collision frequency, but rather that they are associated with each other. Additionally, the spatio-temporal analysis does not provide insights into the underlying causes of the spatial autocorrelation, limiting the practical application of the results.

6.3 Future Work

Based on the contributions and limitations of this work, several directions for future research are proposed. Firstly, as discussed in Section 2.2, alternative approaches to road safety analysis could address some of the limitations of the current research. For example, the use of conflict analysis increases the number of observations, potentially enabling more statistically rigorous analysis. Additionally, simulation models allow for the examination of non-linear relationships between geometric design variables and collision frequency. Although collision analysis was employed due to the limitations associated with these methods, incorporating conflict analysis into this research could help resolve inconclusive findings and provide deeper insights into the causality of observed effects.

Secondly, the methodological framework used in this research could be applied to other forms of road safety analysis. For instance, it is reasonable to assume that there may be spatio-temporal interaction effects on collision frequency at intersections, which, to the best of the author's knowledge, have not been thoroughly examined. Additionally, exploring the interaction between safety effects on road segments, intersections, and roundabouts could be another promising area of research.

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APPENDICES

Appendix A

Literature Review on the Effects of Geometric Design on Roundabout Safety

Table A.1: Literature Reivew: Study Specifications 1

Model Number	Author and Year	Model Configuration	
		Regression Model	Level
1	Ambros et al. (2016)	NB	intersection
2			
3	Anjana and Anjaneyulu (2015)	zero-inflated NB	leg
4			
5			
6	Arndt and Troutbeck (1998)	unknown	leg
7			
8			
9	Brude (2000)	unknown	intersection
10	Daniels et al. (2011)	Poisson	intersection
11		gamma	
12		Poisson	
13		gamma	
14		Poisson	
15		gamma	
16		Poisson	
17		gamma	
18		Poisson	
19		gamma	
20		Poisson	
21		gamma	
22		Poisson	
23		gamma	
24		Poisson	
25		gamma	
26		Poisson	
27		gamma	
28	Farag and Hashim (2017)	NB	leg
29			
30			
31			
32			
33			
34			

Table A.2: Literature Reivew: Study Specifications 2

Model Number	Author and Year	Model Configuration	
		Regression Model	Level
35	Kamla et al. (2016)	NB	intersection
36		random-param NB	
37		NB	
38		random-param NB	
39		NB	leg
40		random-param NB	
41	Kim and Choi (2013)	NB	intersection
42	Maycock and Hall (1984)	NB	leg
43			
44			
45			
46			
47	National Academies of Sciences, Engineering, and Medicine (2007)	NB	hierachical
48			
49			
50			leg
51			
52			
53			
54			
55			
56			
57			
58			
59			
60	Novák et al. (2018)	NB	leg
61			
62	Qin et al. (2011)	NB	intersection
63	Šenk and Ambros (2011)	NB	intersection
64	Turner et al. (2009)	NB	leg
65			
66			
67			
68			
69			
70			
71			

Table A.3: Literature Review: Data 1

Model Number	Roundabout Data			Crash Data		
	Sample Size	Location Type	Location	Years	Severity	Type
1	72	rural and suburban	Eastern Europe	2009-2013	injury and fatality	all
2						
3	20	urban	India	2008-2010	total	all
4					injury and fatality	
5					PDO	
6	100	rural and urban	Australia	1986-1990	all	signle-vehicle
7						approaching rear-end
8						entering-circulating
9	182		Sweden	1994-1997	all	all
10	148	rural and urban	Belgium	1996-2005	injury and fatality	all
11						
12						w/ passenger vehicles
13						
14						w/ bicyclists
15						
16						w/ mopeds
17						
18						w/ motor-cycles
19						
20						w/ heavy vehicles
21						
22						w/ pedestrians
23						
24						multiple-vehicle
25						
26						single-vehicle
27						
28	15		Oman	3 years	all	all
29					injury and fatality	
30					PDO	
31					all	single-vehicle
32						rear-end
33						entering-circulating
34						circulating weaving

Table A.4: Literature Review: Data 2

Model Number	Roundabout Data			Crash Data		
	Sample Size	Location Type	Location	Years	Severity	Type
35	70	rural	UK	2002-2012	injury and fatality	all
36						
37						at circulating lanes
38						at circulating lanes
39						at approaches
40						at approaches
41	40		South Korea, US	2007 (South Korea) unknown (US)	unknown	all
42	84	semi-urban and rural	UK	1974-1979	injury and fatality	entering-circulating
43						approaching
44						single-vehicle
45						other
46						pedestrian
47	355	rural and urban	US	at least 3 years per site	injury and fatality	single-lane roundabouts
48						two-lane roundabouts
49					PDO	single-lane roundabouts
50						two-lane roundabouts
51					all	entering(one)-circulating(one)
52						entering(two)-circulating(one)
53						entering(one)-circulating(two)
54						entering(two)-circulating(two)
55						circulating-exiting
56						rear-end
57						single-vehicle
58						circulating weaving
59						all
60	200	rural and urban	Czechia	2009-2016	all	all
61					all (weighted)	
62	41		US	1994-2009	all	all
63	90	rural and urban	Czechia	2009-2010	all	all
64	104	urban	New Zealand	2001-2005	injury and fatality	all
65						entering-circulating
66						rear-end
67						loss of control
68						other motor vehicle only
69						pedestrian
70						entering-circulating cyclist
71						other motor vehicle-cyclist

Table A.5: Literature Review: Traffic Volume, Speed 1

Model Number	Traffic Volume													Speed				
	Vehicle	Vehicle Entering	Vehicle Circulating	Vehicle Exiting	Heavy Vehicle	Truck Ratio	Mopeds	Motor-Cycle	Motor-Cycle Ratio	Bicycle	Pedestrian	Posted Speed Limit	Vehicle Speed	Speed Variability	Speed Reduction
1	+														
2	+														
3	+														
4	+														
5	+														
6	+												+		+
7		+	+										+		
8		+	+											+	
9	NA											+			
10	+									ns					
11	+									ns					
12	+														
13	+														
14	+									+					
15	+									+					
16	+						+								
17	+						+								
18	+							ns							
19	+							+							
20	ns				ns										
21	ns				+										
22	+										ns				
23	+										+				
24	+									+					
25	+									+					
26	ns														
27	+														
28	+												+		
29	+												+		
30	+												ns		
31	+												+		
32	+												ns		
33	+												ns		
34	+												ns		

Table A.6: Literature Review: Traffic Volume, Speed 2

Model Number	Traffic Volume											Speed				
	Vehicle	Vehicle Entering	Vehicle Circulating	Vehicle Exiting	Heavy Vehicle	Truck Ratio	Mopeds	Motor-Cycle	Motor-Cycle Ratio	Bicycle	Pedestrian	Posted Speed Limit	Vehicle Speed	Speed Variability	Speed Reduction
35	+					+									
36	+					+									
37	ns					ns									
38	ns					+									
39	+					ns									
40	+					ns									
41	NA														
42		+	+					+							
43		+													
44		+													
45		+	+					+							
46		+		+											
47		+											+		
48		+											+		
49		+											+		
50		+											+		
51		+	+												
52		+	+												
53		+	+												
54		+	+												
55		+	+												
56		+	+												
57		+										+			
58			+												
59		+	+												
60	+														
61	+														
62	+														
63	+														
64	+												+		
65		+	+										+		
66		comp													
67		+													
68		+													
69		+									+				
70		+								+			+		
71		+								+					

Table A.7: Literature Review: Intersection-level Variables 1

Model Number	Intsersection-level Variables				Intersection-level Geometric Variables																	
	Urban	Age	Luminaires	Signals	Oval	Legs	Cycle Lane	Cycle Path	Cycle Path	Grade Separated Pavement	ICD	CID	Outer Diameter	Central Island Raised	Central Island GatedRoadway	Circulating Lane	Circulating Lane Width	Circulating Lane Width/ICD	Circulating Lane Radius	Apron	Apron Width
1								ns			ns	ns					ns				+
2								ns			ns	ns					ns				+
3											ns	+					-				
4											ns	ns					-				
5											ns	+					ns				
6																					
7																					
8												-									
9						+										+					
10	ns	ns			ns	-	ns	-		ns	ns	ns	ns	ns	ns	ns	ns			ns	
11	ns	ns			ns	-	ns	-		ns	ns	ns	ns	ns	ns	ns	ns			ns	
12	ns	ns			ns	-	ns	-		ns	ns	ns	ns	ns	ns	ns	ns			ns	
13	ns	ns			ns	-	ns	-		ns	ns	ns	ns	ns	ns	ns	ns			ns	
14	ns	ns			ns	ns	ns	-		ns	ns	ns	ns	ns	ns	ns	ns			ns	
15	ns	ns			ns	ns	ns	-		ns	ns	ns	ns	ns	ns	ns	ns			ns	
16	ns	+			ns	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
17	ns	+			ns	-	ns	ns		ns	ns	ns	ns	-	ns	ns	ns			ns	
18	ns	ns			ns	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
19	ns	ns			-	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
20	ns	ns			ns	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
21	ns	+			ns	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
22	ns	ns			ns	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
23	+	ns			ns	ns	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
24	ns	+			ns	-	-	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
25	ns	+			ns	-	ns	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
26	ns	ns			ns	ns	-	ns		ns	ns	ns	+	ns	ns	ns	ns			ns	
27	-	ns			-	ns	-	ns		ns	ns	ns	ns	ns	ns	ns	ns			ns	
28																	+	+			
29																	ns	ns			
30																	+	+			
31																	ns	+			
32																	ns	ns			
33																	+	ns			
34																	+	ns			

Table A.8: Literature Review: Intersection-level Variables 2

Model Number	Intsersection-level Variables				Intersection-level Geometric Variables																				
	Urban	Age	Luminaires	Signals	Oval	Legs	Cycle Lane	Cycle Path	Cycle Path	Grade Separated	Pavement	ICD	CID	Outer Diameter	Central Island Raised	Central Island	GatedRoadway	Circulating Lane	Circulating Lane Width	Circulating Lane Width/ICD	Circulating Lane Radius	Apron	Apron Width	
35				+								+													
36				+								+													
37				+								+													
38				+								+													
39				-								ns													
40				ns								ns													
41						+						ns						+	-			ns			
42												-	+												
43																									
44																									
45																									
46																									
47	-					+						-													
48	-					+												+							
49	-					+																			
50	-					+												+							
51												-													
52												-													
53												-							-						
54																			-						
55												-							-						
56			-																						
57																									
58																			-						
59	-																								
60	ns				ns							ns	ns					+	ns				-		
61	-				ns							ns	ns					+	ns				-		
62						ns						ns	ns					ns							
63	-					ns							ns	ns				ns					-	ns	
64																									
65																									
66																									
67																									
68																									
69																									
70																									
71																									

Table A.9: Literature Review: Leg-level Variables 1

Model Number	Leg-level Geometric Variables											
	Angle Leg	Deviation Angle	Vehicle Path Radius	Bypass	SplitterIsland Width	SplitterIsland Length	SplitterIsland Raised	SplitterIsland BarricadeMarking	SplitterIsland Marking	Pedestrian Crossing	Visibility	
1										ns		
2		-								ns		
3	-				ns	ns	-	-	+			
4	ns				ns	ns	ns	ns	ns			
5	ns				ns	ns	ns	ns	ns			
6			-									
7												
8	-											
9												
10				ns						ns		
11				ns						ns		
12				+						ns		
13				ns						ns		
14				ns						ns		
15				ns						ns		
16				ns						ns		
17				ns						ns		
18				ns						ns		
19				ns						ns		
20				ns						ns		
21				ns						ns		
22				ns						ns		
23				ns						ns		
24				+						+		
25				ns						ns		
26				ns						ns		
27				ns						ns		
28				ns			ns	ns	ns			
29				ns								
30				ns								
31				ns								
32				-								
33				ns								
34				ns								

Table A.10: Literature Review: Leg-level Variables 2

Model Number	Leg-level Geometric Variables											
	Angle Leg	Deviation Angle	Vehicle Path Radius	Bypass	SplitterIsland Width	SplitterIsland Length	SplitterIsland Raised	SplitterIsland BarricadeMarking	SplitterIsland Marking	Pedestrian Crossing	Visibility
35											
36											
37											
38											
39											
40											
41											
42	-										
43											
44											
45											
46											
47											
48				-							
49											
50											
51				-							
52	-										
53											
54	-										
55	-			-							
56											
57											
58											
59											
60		ns		+							
61		ns		+						+	
62											
63	ns			ns							
64											
65											
66											
67											+
68											
69										+	
70											
71											

Table A.11: Literature Review: Leg Variables 1

Model Number	Approach				Flaring						Entry						Exit						Comments
	Approach Lane	Approach Lane Width	Approach Gradient		Flare Lane Width	Flare Length	Weaving Width	Weaving Length			Entry Lane	Entry Lane Width	Entry Angle	Entry Radius			Exit Lane	Exit Lane Width	Exit Angle	Exit Radius			
1												ns	-					ns					
2												ns						ns					
3		ns	ns				+	+					ns	+				ns	ns	ns			
4		ns	ns				ns	+					+	+				ns	-	ns			
5		ns	ns				ns	ns					+	ns				ns	ns	+			
6																							
7																							
8												+	-	+				+					
9																							
10																							
11																							
12																							
13																							
14																							
15																							
16																							
17																							
18																							
19																							
20																							
21																							
22																							
23																							
24																							
25																							
26																							
27																							
28											+	ns	ns	ns									
29											ns	ns	ns	ns									
30											+	ns	ns	ns									
31											ns	ns	ns	ns									
32											+	ns	ns	ns									
33											ns	ns	ns	ns									
34											ns	ns	+	ns									

Table A.12: Literature Review: Leg Variables 2

Model Number	Approach				Flaring							Entry					Exit					Comments
	Approach Lane	Approach Lane Width	Approach Gradient		Flare Lane	Width Flare	Length	Weaving	Width Weaving	Length		Entry Lane	Entry Lane Width	Entry Angle	Entry Radius		Exit Lane	Exit Lane Width	Exit Angle	Exit Radius		
35												ns										
36												ns										
37												ns										
38												ns										
39												ns										
40												ns										
41						+	ns					+	+		ns							
42		+											+		+							
43		ns											-		-							
44		+											ns		-							
45		ns											ns		ns							
46		ns											ns		ns							
47																						
48												+	-									
49																						
50												+	-									
51																						
52																						
53																						
54																						
55																						
56																						
57																						
58																						
59												+					+					
60												+			-		ns		ns			Entry Angle: except for 20 degrees
61												+			-		ns		ns			Entry Angle: except for 20 degrees
62																						
63												+										
64																						
65																						
66																						
67																						
68												+										
69																						
70																						
71																						