Assessing the Effects of Snow and Ice Control Operations: The Interdependency between Weather Variables, Maintenance Operations, Pavement Friction, and Collisions

BY

AHMED ABOHASSAN

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

TRANSPORTATION ENGINEERING

DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

UNIVERSITY OF ALBERTA

ABSTRACT

An effective winter road maintenance (WRM) program is essential for cities that face severe winter conditions. Snowstorms create slippery road surface conditions (RSC) that disrupt traffic flows and endanger motorists. To combat this, municipalities use a variety of tools to improve the driving conditions such as applying anti-icing agents before snowstorms, de-icing and snow plowing operations during and after snowstorms. Although these tools are common, the degree to which they improve RSC and traffic safety is an area that has not yet been fully investigated. In this thesis, a safety assessment of achieving bare pavement conditions is studied by examining the interconnection between a multitude of key influencing factors including weather variables, maintenance operations, pavement frictions, and collision frequency in the event of a snowstorm. The primary objectives of this study were to better understand the roles of maintenance operations in improving winter road safety and restoring bare pavement after snowstorms. These objectives were achieved by employing a location-specific and event-based framework to investigate the impacts of the different weather variables as well as maintenance operations on pavement friction and collision counts during snowstorms in urban environments.

Using multi-linear regression, it was shown that the total precipitation during snowstorms, extremely low temperatures, and the potential for black-ice formation all have a negative consequence on pavement friction. By comparison, snowplowing operations, application of anti-icing agents, and the frequency of de-icing operations all have positive effects on improving pavement friction.

Another important relationship explored was how pavement friction affected collision frequency, and for this, Negative Binomial regression models were used. The results of this investigation highlighted three ranges of pavement friction coefficients: pavement friction above 0.6, which led

to a significant reduction in collisions, pavement friction between 0.6 and 0.35, which had an insignificant reduction in collisions, and pavement friction below 0.35 that resulted in a significant increase in collisions. Furthermore, arterial roads were found to experience more collisions compared to collector roads which could possibly be attributed to their profoundly varying road characteristics such as higher traffic volumes, higher speed limits, and the difference in drivers' behavior while traveling on them.

After establishing that the pavement friction coefficient *"G"* can be explained using weather and maintenance operations data, and that pavement friction is a significant factor in influencing collisions during snowstorms, structural equation modeling (SEM) was used to simultaneously model the two relationships in one framework. By using pavement friction as a mediating variable, the indirect influences of the independent variables on road safety were identified. The findings suggest that precipitation, extremely low temperatures, and black-ice potentials all had indirect but significant negative effects on road safety. On the contrary, snowplowing and anti-icing operations were shown to have significantly improved road safety indirectly.

The SEM model developed was used to demonstrate its key features by applying it to a hypothetical snowstorm scenario. The results of the analysis indicate that applying anti-icing agents onto roads before snowstorms could result in a 14% reduction in collisions, snowplowing operations can reduce collisions by 33%, and by combining the two tools together collisions can be reduced by up to 42%. These reductions in collisions can further increase exponentially with higher traffic exposure.

The models developed and findings demonstrated in this thesis can help transportation agencies make more informed and timely decisions to reduce winter weather-related collisions while maximizing the efficacy of existing WRM services and resources.

PREFACE

Part of the work presented in this thesis is being prepared for journal publication.

1. **Abohassan, A.**, El-Basyouny, K., and Kwon, T.J. " *Factors Influencing Pavement Friction During Snowstorms* "
2. **Abohassan, A.**, El-Basyouny, K., and Kwon, T.J. " *Factors Influencing Road Safety During Snowstorms* "
3. **Abohassan, A.**, El-Basyouny, K., and Kwon, T.J. " *Exploring the Associations between Winter Maintenance Operations, Weather Variables, Surface Condition, and Road Safety: A Path Analysis Approach* "

ACKNOWLEDGMENTS

I would like to express my utmost gratitude to my supervisors Dr. Karim El-Basyouny and Dr. Tae Kwon. They never spared any knowledge or expertise; without their trust, efforts, and continuous support and guidance, this research would not have materialized.

I am deeply indebted to all the professors at the department of transportation engineering at the University of Alberta for giving me a safe space to discuss my ideas and thoughts, and for providing me with the technical knowledge and tools that helped me in my research. My thanks also go to Maged Gouda, Amr Shalkamy, and Mohammed Kayed for helping me with my studies, and starting my life in Canada.

I am extremely grateful to my parents and my brother for their wise counsel, and unconditional support. I would also like to thank all my friends back in Egypt for keeping in touch throughout my graduate studies. I would like to particularly single out Mohamed Khaled and Ahmed Hesham for lending me an understanding ear and always keeping by my side in all my downfalls.

Acknowledgments are extended to Dr. Mustafa Gul and Dr. Evan Davies for being part of my examination committee.

Finally, I would also like to thank the City of Edmonton for sponsoring this project, offering their experience, and providing the data used in this study.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. INTRODUCTION

This chapter offers an introduction to the thesis and is divided into four subsections. The first subsection is the background which explains and highlights the magnitude of the problem. In the second subsection, the research motivation and the limitations of the previous studies are discussed. The objectives and expected outcomes of this study are, then, presented in the third subsection. Finally, the fourth subsection sets out the thesis structure.

1.1 Background

With the globalization of world trade, billions of dollars worth of goods navigate their way around the world every day [1]. Depending on a solid infrastructure of maritime, aerial, and terrestrial transportation systems, the volume of world trade reached $18.89 trillion in 2019 and is expected to grow steadily according to the world trade organization [1]. Furthermore, the onset of lowered travel costs, readily accessible road networks, and the prevalence of more accessible modes of transportation have resulted in a massive increase in people's travel demands. This is seen in the ever-increasing number of registered vehicles, and annual million vehicle kilometers traveled [2]–[4]. Despite the concerted efforts of engineers and policy makers trying to maintain the safety and capacity of the transportation systems, the rapid increase in freight volumes and people's travel demands have come at a cost.

In such a fast-paced world, the timely delivery, and efficient movement of goods and people on the transportation networks are extremely important. Events that cause delays on the networks put the system under massive strains and can create huge waves of economical losses that ripple throughout the world. This was recently magnified when unfavorable wind conditions caused the massive Ever Given container ship to run aground, and block the Suez Canal for six full days [5]. The blockage of such a vital maritime freight route resulted in delaying an estimated $9.6 billion worth of goods daily, and enormous losses to the world trade [6].

Likewise, as a result of the rapid increase in demand, the safety of passengers, drivers, and pedestrians was put to the test. With this increased exposure, road collision injuries have emerged as one of the major causes of death in the world for all age groups, and the leading source for deaths among children and young adults aged 5 to 29 years old [7]. According to the world health organization, 1.35 million people die annually on the road, and over half of these fatalities occur to vulnerable road users [7]. The combined societal, hospitalization, and losses of labor costs due to collisions are estimated to take up to $1.8 trillion of the global economy between the years 2015 to 2030 [8], not to mention the difficulty of losing loved ones or living with permanent injuries.

Taking all of this into consideration, the inevitable need for innovative solutions to such problems has surfaced. Municipalities and departments of transportation around the world started working together to create plans, and strategies to be better prepared for current and future challenges [9]–[13]. The goals of these plans are to improve the infrastructure to meet the growing demand, restore the movement on the transportation networks after natural or man-made events, and reduce the downtimes and delays caused, all while improving the safety and livability on the streets.

On a national level, cities across Canada suffer from inclement weather conditions specifically during the winter seasons. Severe weather events characterized by low temperatures and visibility with a potential of freezing rain or snow create hazardous driving situations. In these conditions, drivers require longer stopping sight distances to be able to safely navigate the road network. In fact, reports have consistently shown an increasing trend in road collisions during the winter months [14]–[16]. Furthermore, the snow and ice left on the road in the aftermath of snowstorms can cause speed reductions, increased travel times, reduced highway capacity, and, in extreme cases, can lead to complete traffic lockdowns [16]–[20]. The financial losses due to weather-related traffic delays exceed $8 billion annually [21], while the yearly societal costs associated with weather-related collisions can reach up to CAD 1 billion [22].

The high economic impact associated with these adverse weather conditions has forced municipalities to progressively increase their investments in the winter road maintenance (WRM) programs. Canada and the United States spend over $1 billion and $2 billion, respectively each year on WRM [23], [24]. With such high levels of investment, municipalities have been increasingly exploring options to improve the overall performance of their maintenance programs with the primary goal of reducing the time to restore bare pavement conditions following a major snowstorm. It is, therefore, critical for municipalities to continuously explore ways to improve their decision-making processes while optimizing their maintenance programs over allocating additional resources.

In this regard, cities have initiated multiple programs to improve the safety, and mobility of their road network during the unfavorable weather conditions of its snowstorms [12]. Many of these initiatives fall under the 'Vision Zero' strategy [25], which is a multi-disciplinary campaign that started in Sweden, with the goal of eliminating fatal and major injury collisions from the roads [26]. It involves city planners, traffic engineers, law enforcement officers, and policy makers working together towards the common goals of this campaign. This is usually done through a process that mainly focus on two principles; continuously analyzing collision data, and implementing appropriate countermeasures that target collision prone sites. Since WRM can help achieve the goals of 'Vision Zero' a thorough evaluation of the WRM operations is needed. The aim is to better understand the roles of the maintenance operations in improving winter road safety and restoring bare pavement after snowstorms.

1.2 Research Motivation

A WRM program usually encompasses the staff, equipment, material, and policies used in the maintenance operations which all work in harmony to clear snow and ice off the roads and restore mobility on road networks after snowstorms. Typically, maintenance operations start with de-icing, which is the application of sand and salt mixtures to fresh snow after storms to help break its bonds and restore some traction on the roads. The percentage of salt in the applied mixture depends on the ambient and road surface temperature where more salt is added at higher temperatures, while 100% sand mixtures are used at extremely low temperatures (below -15°C) [27]–[29]. Depending on the function and priority of each road, plowing operations start once the snow has reached a pre-set trigger depth [30].

An alternative yet proactive method of road maintenance is to apply anti-icing chemicals to roads shortly before snowstorms are forecasted. This approach has been progressively adopted by several road jurisdictions. Anti-icing offers several advantages as it is anecdotally believed to restore bare pavement quicker and reduce the amount of material needed in de-icing. However, anti-icing application remains a controversial topic due to its environmental impacts, dependence on successful snowstorm forecasting [31], and the fact that its significance in improving pavement traction or traffic safety has not yet been thoroughly studied.

Despite experiencing almost similar weather conditions during the winter, there is a great deal of variation between the practices used by different Canadian cities [32]. This is evident from the different materials used and plowing policies adopted by each city. This lack of consistency among practices can be attributed to the fact that there is limited research on the influence of the different toolboxes used in WRM programs to improve pavement friction and road safety.

In 2017, the city of Edmonton launched a pilot project by adding anti-icing to its WRM toolbox to test its impacts on improving pavement friction and road safety. In collaboration with the University of Alberta, collision data was collected from 100 arterial, and collector maintenance routes. Then, a before-and-after Empirical Bayes approach was adopted to study the added benefit of using anti-icing in improving road safety over conventional de-icing methods [33]. Even though the project showed great success in significantly reducing all types of collisions on all types of roads, the study had two major drawbacks. It was a macroscopic study where a lot of snowstorm events information was lost due to aggregation; and it failed to capture the additional advantage of using anti-icing, compared to the conventional de-icing operations in obtaining bare pavement.

This research addresses the drawbacks of the previous studies, and the gap in the literature by employing an event-based and location-specific framework to look at snowstorms at a disaggregated level. Using friction and maintenance operations data as well as historical weather records and collision data, the microscopic analysis offered in this study is capable of isolating the conditions during individual snowstorm events rather than an aggregated analysis.

1.3 Research Objectives

Without a doubt, the WRM operations which are conducted every winter season help improve the safety and mobility of traffic on the road networks. Nevertheless, the impacts of the different tools used in the maintenance operations on improving the road surface conditions (RSC) and road safety have not been fully studied.

Therefore, the primary objective of this thesis is a methodological advancement for conducting a thorough safety assessment of achieving bare-pavement conditions by investigating the effects that the different WRM operations have on RSC during snow storms. In completing this primary objective, several secondary objectives can also be addressed such as

- Understanding the relationship between pavement friction and road safety in urban environments;

- Enumerating the benefits of the current WRM policies, strategies, and practices in improving pavement friction and road safety; and
- Studying the mobility benefits of clearing snow and ice from the roads using the different WRM tools.

Completing the objectives of this research can help improve our understanding of winter road safety and the important role of road maintenance in winter cities. By modeling road safety using collision counts as indicators, and by modeling RSC using pavement friction coefficient as the response variables, the benefits of the different maintenance tools in achieving bare pavement and improving traffic safety during and after snowstorms can be quantified. Moreover, the results of the analysis can help municipalities and transportation agencies make more informed decisions and better plan their maintenance programs. The tools provided can also help the authorities determine the outcomes of forecasted weather events, justify the use of more aggressive measures, and help decide the best course of action to use their limited resources.

1.4 Thesis Structure

The thesis is divided into seven chapters. The first chapter offers an introduction that highlights the magnitude of the problem, and defines the motivation, objectives, and expected outcomes of the study.

The second chapter gives a literature review of previous studies related to WRM, winter traffic safety, and the methodologies adopted in these studies.

Chapter three describes the WRM program, and how the data needed for this study was collected from different sources, processed, filtered, and fused.

Chapters four to six describe the different methodologies adopted to accomplish the goals of the study as well as include the results of each analysis.

The seventh chapter highlights the main findings of the study, the research contributions and illustrates a number of future research directions.

2. LITERATURE REVIEW

This chapter reviews previous studies related to winter road maintenance (WRM), road surface modeling, winter traffic safety, and their limitations. It is divided into four subsections. The first subsection discusses the efforts, and the different methodologies adopted for modeling the road surface. The second subsection shows the findings of previous research relating winter weather to road safety. The third shows the importance of the WRM operations. The final subsection gives a summary of the findings from the literature.

2.1 Road Surface Conditions Modeling

Monitoring and predicting road surface conditions (RSC) have been popular subjects of research as RSC plays a major role in determining the safety, free-flow speeds, and capacity of road networks [18], [34], [35]. In fact, Heinijoki et al. [36] found that drivers were not always able to correctly identify the RSC while driving where fewer than a third of drivers were able to identify the RSC correctly. What made matters worse, was that as RSC got poorer, the drivers reported observations deviated more from the true values. For this reason and more, researchers have developed multiple ways to describe the RSC, and numerous methods to model them.

With the widespread use of stationary and mobile road weather information systems (RWIS), RSC data became readily available for researchers to analyze. Generally speaking, RWIS sensors can describe the RSC as dry, moist, wet, ice-covered, or snow-covered in addition to their ability to read the road surface temperature. Gu et al. [37], [38] used mobile and stationary RWIS data to model and estimate the RSC in various weather conditions using surface temperature as a surrogate measure. In both studies, the authors deployed the geostatistical technique of regression kriging to describe the RSC using road surface temperature readings from RWIS. In the regression part of their analysis, they found that the longitude, altitude, slope, and vegetation index are all significant factors in describing the variation in the road surface temperatures.

The Finnish government managed to formulate a model that can predict road surface temperature, road surface conditions, as well as the friction coefficient on roads [39]. Called RoadSurf, it was developed in 2000 and has been in operation since then. The model works on the principle of energy balance, by inputting the weather forecasts, several outputs can be obtained including road surface temperature and friction. In their study, the authors used linear regression models that can predict the coefficient of friction using weather forecasts. Hippi et al. [40] explained the derivation of the surface friction models used in the RoadSurf model in a separate paper. They used independent variables like the temperature, equivalent water precipitation, as well as the thickness of the precipitated layers of snow, ice, and water in their analysis. However high the R^2 values of the models they produced, these models could only predict the worst-case scenario of when the roads receive no treatment at all. This is because the impacts of the maintenance operations were never incorporated in their analysis.

In another research, Feng et al. [41] used friction measurements to classify the RSC during snowstorms. In their study, the authors identified 7 road surface conditions, then developed binary logit models to determine, and categorize these conditions based on their probability of occurrence using the observed friction measurements. The logistic models developed were successful in accounting for the uncertainties and variations associated with the friction measurements.

On a different note, Omer et al. [42] attempted to use road photography in the classification of winter RSC. In their study, the researchers mounted RGB cameras on regular vehicles to record and transfer road imagery to a central server. Then, a support vector machine algorithm trained in extracting the proper imagery and classification of surface conditions was used to interpret these surface conditions. Despite showing great potential, their model classified RSC into only 3 categories which were bare, snow-covered, and tracks. Therefore, a high degree of uncertainty remained as each category could include a wide variety of surface conditions.

Usman et al. [34], [35] attempted to describe the variation in RSC during each hour of the snowstorm using a friction surrogate measure, road surface index (RSI). Ontario maintenance personnel patrol the maintenance routes multiple times during snowstorms, and each time, they classify the RSC of the routes as one of 7 categories which are bare and dry, bare and wet, partly snow-covered, snow-covered, snow-packed, slushy, and icy. The authors used these discrete classifications and converted them into a continuous friction surrogate measure, RSI. RSI is a continuous variable that ranges from 1 to 0, with 1 being the best RSC. Hours of snowstorms with observed RSI were populated, then all hours with missing RSI information were estimated based on two assumptions: RSI at the hour right after the maintenance operations were conducted was 0.45, and RSI varied linearly between the observed values. Although the assumptions used by the authors can mask a lot of the information pertaining to the maintenance operations, the framework used paved a new way for modeling RSC using an event-based analysis.

Even though many ways have been developed to describe and model RSC as discussed above, pavement friction remains the most accurate and objective measurement tool. Pavement friction is the resistive force to relative motion between the vehicles' tires and the road surface [43], [44]. The value of the friction coefficient depends on several factors that include the pavement surface characteristics, vehicle operating parameters, tire properties, and weather conditions. Unlike the subjective discrete classifications used by RWIS measurements or video records, the friction coefficient is a continuous linear variable that can describe the RSC objectively. Friction coefficient values range from 0G and up to 1G or higher which makes its interpretation logical and easy. Friction coefficient values of 1G or higher represent the best road surface, and tire traction conditions, while values around the lower end of the spectrum represent worse pavement traction. When the friction coefficient reaches 0G, it is an indication of extremely slippery pavement surfaces where there is no tire traction recorded.

In an early study conducted by Nixon et al. [44] in 1998, the authors suggested the use of friction coefficients as WRM indicators. In their analysis, and review of the literature, they indicated that the costs associated with buying the friction measurement devices, and friction coefficient data collection would offset the benefits it would return in material savings. In a worked example, a benefit to cost ratio of 3.38 was obtained in employing such a system to aid decision-makers in identifying the amounts of materials to be used in the maintenance operations.

Liu et al. [45] conducted a controlled experiment to study the effects of temperature and humidity on the coefficient of friction of icy roads. In their experiment, they simulated the conditions of icy rain and showers to imitate the traffic conditions during winter. Then, by manipulating the temperature and humidity, they plotted their relationships with their corresponding recorded friction coefficients. The range of temperatures they tested was from 0°C to -16°C, while the range of relative humidity they simulated was from 50% to 85%. Using the results from their tests, they formulated several regression models to predict the value of friction at icy RSC using temperature and humidity as independent variables. The results of their analysis showed that humidity is not a significant variable in describing the friction coefficient and that the best fit models with the highest R^2 values were obtained using the temperature as the main predictor in a one-dimensional non-linear model.

In a controlled study on the University of Alberta test road facility, Salimi et al. [46] investigated the effects of snow, ice, speeds, temperatures, and the number of traffic passes on the friction as compared to bare pavement conditions. The results of the analysis showed that speeds had no significant effects on the variation of friction. However, it was reported that the friction dropped significantly once snow and ice were present on the pavement surface. It appeared that friction dropped by 55%, 69%, 75%, and 81% on surfaces covered by ice, light, moderate, and heavy snow respectively. Moreover, low temperatures and the number of passes were found as significant factors in reducing the friction.

Table 1. A Summary of Road Surface Modeling Studies.

Authors	Study Area	Methodology	Findings	Limitations
Heinijoki et al. [36]	Finland	-	Drivers are not capable of identifying how dangerous the RSC are by eye.	-
Gu et al. [37], [38]	Edmonton	Regression Kriging	Modeled RSC using road surface temperature.	Maintenance operations were not included.
Hippi et al. [39], [40]	Finland	Linear regression	Temperature, equivalent water precipitation, and thickness of snow layers are significant factors in predicting RSC.	Maintenance operations were not included.
Feng et al. [41]	Ontario	Binary logit models	Described RSC using friction measurements.	-

Omer et al. [42]	Ontario	Support vector machine algorithm	Road photography can be used to categorize RSC.	Only 3 categories of RSC could be identified.
Usman et al. [34], [35]	Ontario	Linear interpolation	Described RSC using a continuous linear RSI depending on maintenance personnel observations.	Impacts of the maintenance operations were assumed not deduced.
Nixon et al. [44]	-	Benefit to cost ratio	Investing in employing friction measurement devices can aid decision-makers in saving material.	No realistic framework was provided.
Liu et al. [45]	Closed labs	Linear regression	Described pavement friction as a function of temperature.	Controlled study and maintenance operations were not included.
Salimi et al. [46]	Edmonton	Statistical comparisons	Friction drops significantly on surfaces covered by ice and snow, and during extremely low temperatures.	Controlled study and maintenance operations were not included.

2.2 Winter Weather & Traffic Safety

Due to the restricted visibility and slippery road surface conditions, driving during and after snowstorms can be very dangerous. The literature shows that weather variables that include precipitation intensities, precipitation types, temperatures, wind speeds, and visibility can all influence traffic safety in the winter seasons [41].

Numerous countries studied the risk of collisions under deteriorating RSC. Earlier studies relied mostly on rudimentary methods such as collision trends and naïve before and after analyses in drawing conclusions rather than sophisticated statistical frameworks. In Germany [47], it was found that as roads got wetter, the collision risk increased. In France [47], a similar study was done on skid-prone sites, the study concluded that as the friction coefficient decreased, the collision proportion rose sharply. In Denmark [48], collision rates were found to be indirectly proportional to friction coefficients.

Nordic countries' researchers are among the most interested in the effects of WRM and the RSC on collision risk [36], [48]–[50]. Norrman et al. [49] studied collisions that occurred on slippery roads in southern Sweden. They attempted to associate collisions with different types of slippery RSC to come up with the risk of driving during these conditions. Although their study was not backed up statistically, they found that certain RSC were linked with higher collision risks.

The Ministry of Transport of Ontario conducted a field study to demonstrate how snowfall can lead to hazardous driving conditions [51]. In this study, a vehicle with an initial velocity of 80 kilometers per hour was allowed to brake sharply to a complete stop in different environments representing different RSC. The stopping distances were recorded, and the pavement friction coefficients were measured after each attempt. The results showed a significant increase in the stopping distances as friction coefficients decreased.

Table 2. Stopping Distances Versus Friction Coefficients [51]

Road Condition	Friction Coefficient	Stopping Distance in Meters
Bare Pavement	0.7	35.9
Snow Packed	0.276	91.2
Snow Packed	0.184	136.8
Bare Ice	0.128	196.6
Bare Ice	0.125	201.4

One of the earliest attempts to understand the importance of friction and bare pavement in controlling the number of collisions was done by Preus in the early 1970s [52]. The author analyzed the safety benefits of using studded tires on winter streets as a means to increase vehicle traction on slippery surfaces. Unfortunately, the study was unsuccessful in obtaining a clear idea of the effects of this tire alteration because it was difficult to isolate the effects of a single factor due to the lack of sufficient data at the time.

Since then, with the advancements in data collection technologies, numerous studies have been conducted to make better use of these datasets by employing different statistical techniques. Depending on the nature of the datasets, the level of aggregation, and the type of dependent variable that needed to be modeled, researchers used various statistical models to adapt to the data. In a review of the most popular statistical analysis methods used in traffic safety, Lord et al. [53] reported that the Negative Binomial, Negative Multinomial random-parameters bivariate, and zero-inflated Poisson and Negative Binomial models are the most widely used distributions in collision modeling. This is mainly due to the ability of these models to account for most of the confounding factors and inherent problems associated with collision data.

In recent years, researchers tried incorporating the use of Tobit regression in modeling collision rates. Anastasopoulos et al. [54] conducted an aggregate collision modeling study on 5 interstate highways in Indiana. Despite using aggregated collision data over 5 years, the authors were able to include variables describing the pavement condition by dividing the highways into 337 homogeneous segments. The results of their analysis showed the significant positive effect of having better pavement friction in reducing collision rates. Chen et al. [55] conducted a similar study but using a disaggregated dataset on a select portion of highway I-25 in the state of Colorado. With the help of refined data collection methods, they were able to formulate a random-effects Tobit collision rate prediction model using real-time traffic and weather data. The random-effects Tobit model was able to account for the unobserved heterogeneity across observations, and space and time-varying variables like hourly traffic volume, wet surface conditions, and visibility. It should be noted that even though both studies used different levels of aggregation, they both concluded that RSC was a significant factor in influencing collision rates.

In a study done by Usman et al. [56], the authors explored the effect of aggregating time-varying variables like precipitation, and RSC throughout a snowstorm event, and compared the results with a disaggregated 1-hour model. The results not only showed that aggregation could cause loss of information, and result in biased parameter estimates, it also showed that some statistically significant variables in modeling collisions become insignificant as a result of aggregation. These findings opened the door for more disaggregated traffic safety studies, and researchers from around the world took a special interest in this framework.

Collision risk models are among the research areas that exploite real-time traffic and weather data. Using random forests, and Bayesian logistic regression, Theofilatos et al. [57] studied the factors that affect the collision likelihood and severity on two urban arterials in Greece. By including real-time traffic and weather data in their analysis, the authors found that weather variables had neither positive nor negative influence on determining the likelihood or severity of collisions. Nevertheless, real-time traffic volume and speed data had proven significant in explaining collisions. In another study done by Pham et al. [58] rear-end collision risk was assessed using several traffic, geometric and weather variables on a highway in Switzerland. A disaggregate 5-min interval dataset was compiled and utilized to create clusters of non-collision traffic situations and pre-collision traffic situations. The results of the analysis accredited rear-end collisions mainly to the speed difference between the two lanes of the roadway, with little influence given to weather conditions. The insignificant influence of the weather variables on collisions that was reported in these two studies was mainly attributed to the mild winter conditions in the countries where the studies were conducted.

Knapp et al. [20] performed a comprehensive study on the impacts of snowstorm events on traffic mobility, and safety in Iowa. In their study, severe snowstorm events on segments of 3 national highways were defined and analyzed for their impacts on traffic volumes and collisions. Severe snowstorms were identified as hours when RWIS sensors on these segments recorded snowfall intensity of 0.2 inches per hour or more, wet pavement surface, below-freezing air, and pavement temperatures. Preliminary analysis of the data showed a dramatic increase in the hourly collision rate during these severe storms that reached an average of 1,303%. Furthermore, when collision counts during the identified severe snowstorms were modeled using a Poisson regression model, the exposure, snowstorm duration, and snowfall intensity were all found to be statistically significant variables in increasing collision frequencies during snowstorms. Additionally, regression analysis showed statistically significant volume reductions whenever snowfall and wind gust speed increased.

Perhaps the most established studies on the effect of RSC on road safety were done by Usman et al. [34], [35]. The authors compiled enormous weather, traffic, and collision datasets to conduct a disaggregate 1-hour collision frequency modeling on select 4 highway maintenance routes, then repeated the study on a larger scale of 31 highway maintenance routes in Ontario. By defining the start and end time of snowstorm events, they recorded weather variables such as precipitation, visibility, and temperature, as well as traffic volumes, RSC, and collisions that occurred during every hour of the defined snowstorm events. The results of the studies were consistent with previous studies which provided evidence that the RSC is among the most significant factors influencing the occurrence of collisions in countries with harsh winter weather. This proved, once again, the importance of the WRM operations in reducing collision counts and saving lives.

Table 3. A Summary of Winter Weather & Collision Modeling Studies.

Authors	Study Area	Methodology	Findings	Limitations
Schulze et al. [47]	Germany, and France	Descriptive statistics	Collision risk increased as roads got wetter, and friction coefficients decreased.	No statistical methods were deployed.
Hemdorff et al. [48]	Denmark	Descriptive statistics	Collision risk increased as friction coefficients decreased.	No statistical methods were deployed.
Norrman et al. [49]	Northern Sweeden	Descriptive statistics	Collision risk increased in certain road surface conditions.	No statistical methods were deployed.

Comfort et al. [51]	Ontario	Descriptive statistics	Stopping distances increased dramatically as friction coefficients decreased.	No statistical methods were deployed.
Preus [52]	Minnesota	-	Inconclusive results due to lack of information	-
Anastasopoulos et al. [54]	Indiana	Tobit regression	Segments with better pavement friction witnessed fewer collisions.	Aggregate study
Chen et al. [55]	Colorado	Random-effects Tobit model	Real-time weather and traffic data are significant factors in influencing collisions.	Maintenance operations impacts were not included.
Usman et al. [56]	Ontario	General Negative Binomial models	Aggregating data can result in biased parameter estimates.	-
Theofilatos et al. [57]	Greece	Random Forests, and Bayesian logistic regression	Weather variables were insignificant in influencing collisions.	Mild winter conditions in Greece.
Pham et al. [58]	Switzerland	Random Forests and Clustering by K-means	Weather variables were insignificant in influencing collisions.	Mild winter conditions in Switzerland.
Knapp et al. [20]	Iowa	Poisson models	Snowfall intensity was a significant variable in increasing collision counts.	Maintenance operations impacts were not included.

Usman et al. [34], [35]	Ontario	Various generalized linear models	Weather variables and RSC play a significant role in determining road safety during snowstorms.	Maintenance operations impacts were assumed not deducted.

2.3 Importance of Winter Road Maintenance (WRM)

The deterioration of RSC and accumulation of snow during the winter seasons of northern countries not only increase the likelihood of collisions but also affects the mobility of traffic as a whole. For these reasons, understanding the importance of the multi-million WRM operations was essential. Ye et al. [59] conducted a study to quantify the overall societal welfare of winter maintenance operations in Minnesota. By incorporating factors such as safety, mobility, and fuel-saving benefits. The authors estimated financial savings of over $220 million per winter season. They also calculated the benefit-to-cost ratio by including the total cost of the operations to be 6.2 which showed the significant role of the WRM operations.

In another study, Kwon et al. [60] investigated the reductions of free-flow speeds, and the capacity of freeways that are associated with snowstorms. When compared with dry road surfaces, it was reported that the saturation flow rates can decrease by up to 25%, and free-flow speeds can decrease by up to 23% due to the accumulation of snow and other unfavorable RSC during and after snowfalls [18]. Without WRM operations, these reductions in capacities, and speeds can reduce the levels of service on the road network leading to increased traffic delays.

In a different study, it was also suggested that WRM is vital in reducing collision risk [50]. This was shown by investigating collision frequencies during and after snowfalls. It was found that collision risks can increase by up to 12 times in the 2 hours before starting the maintenance operations. In Norway, a 20% reduction in collisions was reported after converting from unsalted to salted winter operations.

Salami et al. [61] attempted to evaluate the effectiveness of the plowing and sanding operations in WRM by quantifying the improvement in the lateral coefficient of friction. Interestingly, it was found that sanding and plowing operations can have contradicting outcomes depending on the condition of the road surface. Sanding seemed to significantly reduce pavement friction when used on a bare dry road surface, while plowing was ineffective in improving friction when done on ice-covered surfaces. On the other hand, when roads were covered with ice or snow, sanding significantly improved the pavement friction on these surfaces. Likewise, plowing was crucial in improving friction when the road surface was snow-covered.

Attempting to understand the role of WRM on traffic safety, Gouda et al. [33] employed an Empirical Bayes framework to quantify the safety benefits of using anti-icing in winter maintenance operations. Their study focused on comparing anti-icing to the conventional de-icing methods on urban roads in Edmonton. Even though the project showed great success in significantly reducing all types of collisions, the study had two major drawbacks. It was a macroscopic study where a lot of information was lost due to aggregation, and it failed to identify the advantages that anti-icing operations have over de-icing operations.

In the study done by Usman et al. [34], after showing that the RSI is a significant predictor of collision counts during snowstorms, the authors proceeded to show the importance of WRM operations in reducing collisions. Based on the assumption that maintenance operations improved the RSI of roads by an average of 0.8, the mean number of collisions at each hour of the event was calculated. On top of that, the predicted number of collisions was cut in half by reducing the bare pavement regain time from eight to four hours, which highlighted the value of speedy winter maintenance services.

Table 4. A Summary of the Importance of WRM operations Studies.

Authors	Study Area	Methodology	Findings	Limitations
Ye et al. [59]	Minnesota	-	WRM provides a benefit to cost ratio of 6.2	-
Kwon et al. [18], [60]	Ontario	Synchro/VISSIM	Snowstorms decrease flow rates and free-flow speeds by 25%, 23% respectively.	The importance of WRM operations was not highlighted.

Wallman et al. [50]	Norway	Descriptive statistics	Converting from unsalted to salted winter operations results in a 20% collision reduction.	No statistical methodology to support the claim
Salami et al. [61]	Edmonton	Statistical comparisons	Plowing and sanding are effective in improving pavement friction in specific conditions only.	A controlled study, operational variations were not considered.
Gouda et al. [33]	Edmonton	Empirical Bayes, and Negative Binomial models	Application of anti-icing before snowstorms results in a significant reduction of collisions of all types and a decrease in injury severity.	Aggregated study where the influences of WRM can be masked.
Usman et al. [34]	Ontario	Various generalized linear models	50% of snowstorm collisions can be avoided if the WRM response time was reduced from eight to four hours.	Impacts of the maintenance operations on RSC were assumed.

2.4 Summary

This chapter gave an overview of studies that focused on RSC modeling, winter weather and road safety, and the benefits of the WRM operations.

Even though RSC has been modeled using various techniques and metrics, pavement friction remained the most accurate way to represent and model the road surface conditions. Several studies in the past attempted to model pavement friction; however, they had the limitations of assuming the influence that the WRM operations had on pavement friction, studied rural isolated highways, or drawing conclusions from controlled experiments. The analysis presented in this thesis addresses this problem by offering a pavement friction model that represents the RSC at an operational level where the influences of the different tools of the maintenance operations were studied and quantified in an urban environment.

The influence of winter weather on road safety has also been studied multiple times in the past; nevertheless, there were significant limitations in these studies. Among these limitations are: the relationship between pavement friction and collision counts was not fully investigated, the studies aggregation level made it impossible to isolate the interactions that occur during individual snowstorm events, and the role of WRM operations in improving traffic safety remained unknown.

By developing a proposed event-based and location-specific framework, the influence of pavement friction on deciding the road safety level can be readily identified. Furthermore, by using the Structural Equation Modeling (SEM) statistical technique, it will be possible to quantify the direct and indirect effects of the different weather and maintenance operations factors during snowstorms and their associated effect on winter road safety.

3. WINTER ROAD MAINTENACE PROGRAM & DATA DESCRIPTION

This chapter describes the winter road maintenance (WRM) program, and how the data needed for this study was collected from different sources, processed, filtered, and fused. The chapter is divided into six subsections. The first subsection talks about the study area and describes how the WRM program operates in Edmonton. The following five subsections explain how the historical weather data was used to create events, how pavement friction and maintenance operations data and collision data were processed and filtered, then fused with the created events datasets.

3.1 Study Area & Program Description

The study area for this research is the city of Edmonton which is the fifth-largest city in Canada and the capital of the province of Alberta. The city has adverse weather conditions during the winter seasons with the daily average temperature reaching -10.4°C in January and could drop to -48.3°C on the coldest day of the year and the average snow depths during the winter months are as high as 17 cm [62].

The WRM crew in Edmonton must maintain the streets of the road network both during and after snowstorms. The two primary objectives of the maintenance program are to clear snow off the roads to restore mobility and to maintain the roads to bare pavement conditions within a certain number of hours after the end of snowfall. To achieve these goals, the maintenance operators have several tools under their disposal, which include de-icing and snowplowing operations while the application of anti-icing was briefly introduced between 2017 and 2019 then was discontinued. The city also adopts a transportation network priority hierarchy where certain roads receive maintenance more rapidly and frequently as summarized in Table 5.

To conduct an event-based and location-specific microscopic analysis, multiple datasets from different sources had to be combined to create a series of centralized databases, where each includes certain information that serves the function of modeling specific variables as discussed in the subsequent sections.

Table 5. Transportation Network Priority Hierarchy Adopted by the City of Edmonton [63].

Priority Level	Sublevels	Roads	Maintenance policy	Clearing starts
Priority 1	A	Prioritized sidewalks, trails, and bike routes	Restore to a bare pavement standard within 24 hours from the end of snowfall.	Once 2-3 cm of snow has accumulated.
	B	Freeways, arterials, business districts, busways	Restore to a bare pavement standard within 36 hours from the end of snowfall.	
	C	Bus stops adjacent to city property	Restore to a bare pavement standard within 48 hours from the end of snowfall.	
Priority 2	-	Collectors, bus routes, transit parks, and ride access roads	Restore to a bare pavement standard within 48 hours from the end of snowfall.	Once 2-3 cm of snow has accumulated.
Priority 3	-	Local industrial roadways	Restore to a bare pavement standard within 5 days from the end of snowfall.	Once 2-3 cm of snow has accumulated.
Priority 4	-	Residential roadways, and alleys	Blade level snowpack, start within 48 hours after snowfall and complete in 5 days.	Once 5 cm of snowpack has formed.

3.2 Weather Data

Historical hourly weather data is recorded and stored on the province of Alberta website [64]. There are two weather stations within the city limits; namely Blatchford and South Campus weather stations which are shown in Figure 1. Hourly weather data from 2017 to 2019 were downloaded and compiled from each weather station. The downloaded datasets include the following information: minimum and maximum air temperature, average air temperature, dew point temperature, average humidity, total equivalent precipitation in mm, average wind speed, and average wind direction. All of this information is recorded during each hour of the day.

3.3 Pavement Friction and Maintenance Operations Data

The maintenance operators conducted friction testing on 21 urban routes in the city during the winter seasons from 2017/18 to 2019/20. The city used the Vericom Brakemeter 4000 device to calculate the friction coefficient for each route. To calculate each friction coefficient value, the following standard procedure was used:

1- The testing vehicle was mounted with the Vericom Brakemeter 4000 device, and the device was calibrated.
2- The testing vehicle accelerated to a target speed of 30 ± 5 km/h, then brakes were applied fully until the vehicle came to a complete stop.
3- The device automatically calculated and stored the friction coefficient using equation (1).

$$d = \frac{v^2}{2\mu g} \tag{1}$$

where d is the stopping distance, μ is the coefficient of friction, v is the velocity at the time when braking started, and g is the gravitational acceleration constant.

The 21 testing routes include 13 arterial segments and 8 collector segments from different areas and neighborhoods of the city. During friction testing runs in the two winter seasons of 2017/18, and 2018/19, information about the status of the WRM operations on each route was recorded. Such information included whether anti-icing chemicals had been applied before/after the snowstorm and whether the road had been plowed. A total of 351 pavement friction records were collected in the three winter seasons. However, only the 234 records that were collected during the first two winter seasons included information about the status of the WRM operations. Figure 1 shows the 21 friction testing routes included in the study, and Table 6 gives a summary of information about the routes.

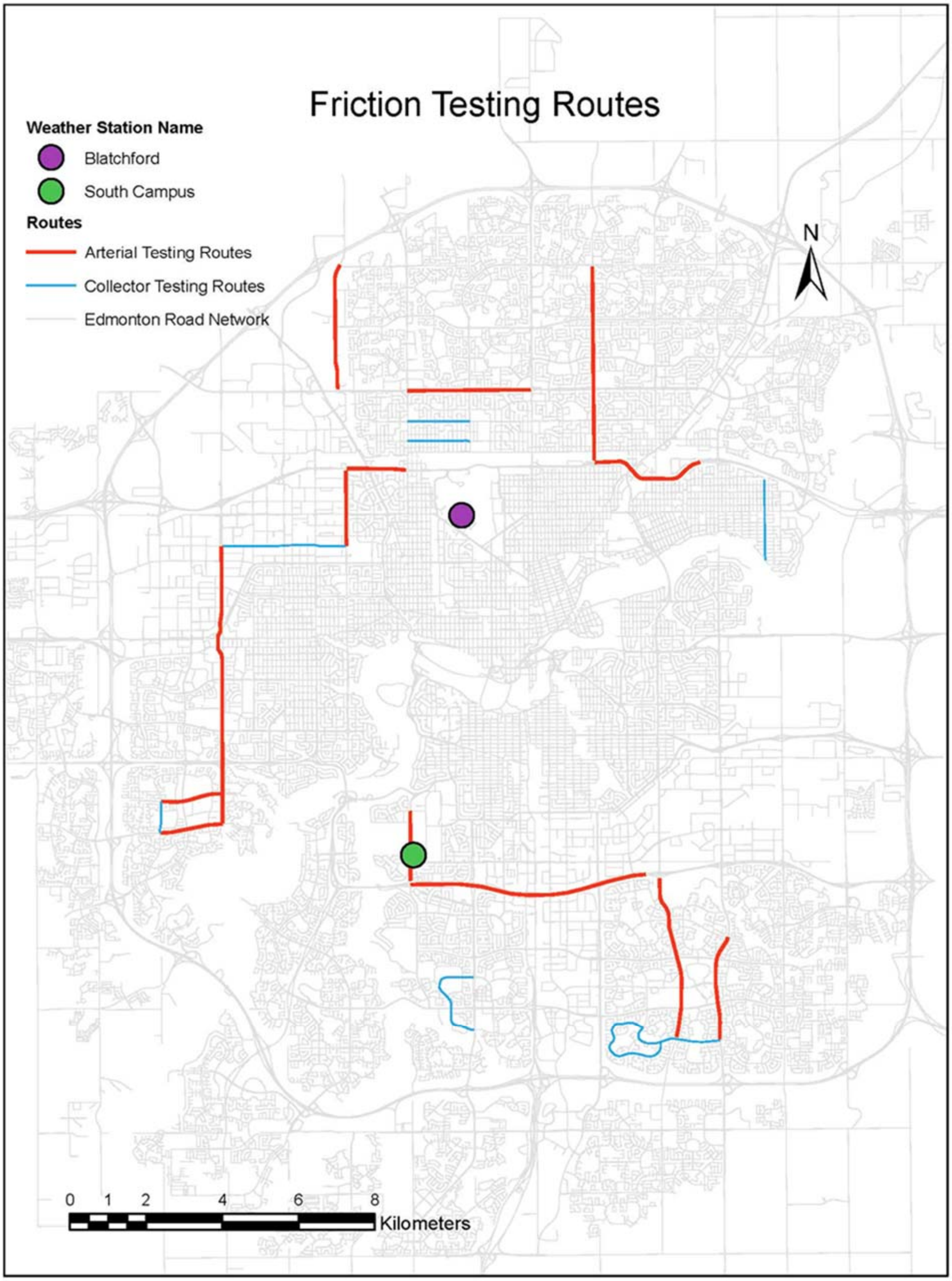

Figure 1. Weather Station Locations, and Friction Testing Routes

Table 6. A Summary of the 21 Friction Testing Routes.

Route number	Location	Segment Length in Kilometers	Route Classification
1	Yellowhead Trail between 55 st and 82 st	3.07	Arterial
2	82 st between Yellowhead Trail and 167ave	5.07	Arterial
3	137 ave between 97 st and 127 st	3.23	Arterial
4	132 ave between 113a st and 127 st	1.63	Collector
5	Yellowhead Trail between 127 st and 142 st	1.55	Arterial
6	142 st between 114 ave and Yellowhead Trail	1.97	Arterial
7	114 ave between 142 st and 170 st	3.24	Collector
8	170 st between 69 ave and 114 ave	7.30	Arterial
9	Callingwood Rd between 170 st and 184 st	1.65	Arterial
10	69 ave between 170 st and 184 st	1.61	Arterial
11	122 st between Whitemud Drive and 63 ave	1.82	Arterial
12	Whitemud Drive between 75 st and 122 st	6.25	Arterial
13	66/75 st between Millwoods Rd and Whitemud Drive	4.28	Arterial
14	Knottwood Rd	3.14	Collector
15	50 st between Millwoods Rd and 38 ave	2.74	Arterial
16	129 ave between 113a st and 127 st	1.63	Collector
17	142 st between 137 ave and 167 ave	3.28	Arterial
18	Saddleback Rd/19 ave	2.72	Collector
19	184 st between Callingwood Rd and 69 ave	0.83	Collector
20	Millwoods Rd between Knottwood Rd and 50 st	2.53	Collector
21	38 st between 105 ave and 123 ave	2.12	Collector

3.4 Events Definition

A critical part of the analysis depended on the definition of the snowstorm events. Using the hourly weather data, the start and end of a snowstorm are identified, as per the literature [30], [34], [35], [56], based on the following criteria:

1- Snowstorm events start if the precipitation value during an hour is more than 0, and the average temperature during the same hour is equal to or less than 5°C, and

2- Snowstorm events would continue until the precipitation stopped for 3 consecutive hours.

A MATLAB code was developed and used to process the hourly weather data collected from the two weather stations (i.e., Blatchford and South Campus) using the conditions described above, and a dataset of all the snowstorm events that occurred during the period from 2017 to 2019 was compiled. Figures 2-4 illustrate the frequencies and severities of snowstorms during the study period.

The final dataset included the following information about each snowstorm: start date and time of each event, duration of the event, average temperature, average dew temperature, total equivalent precipitation in mm, average humidity, average wind speed, and average wind direction during each event.

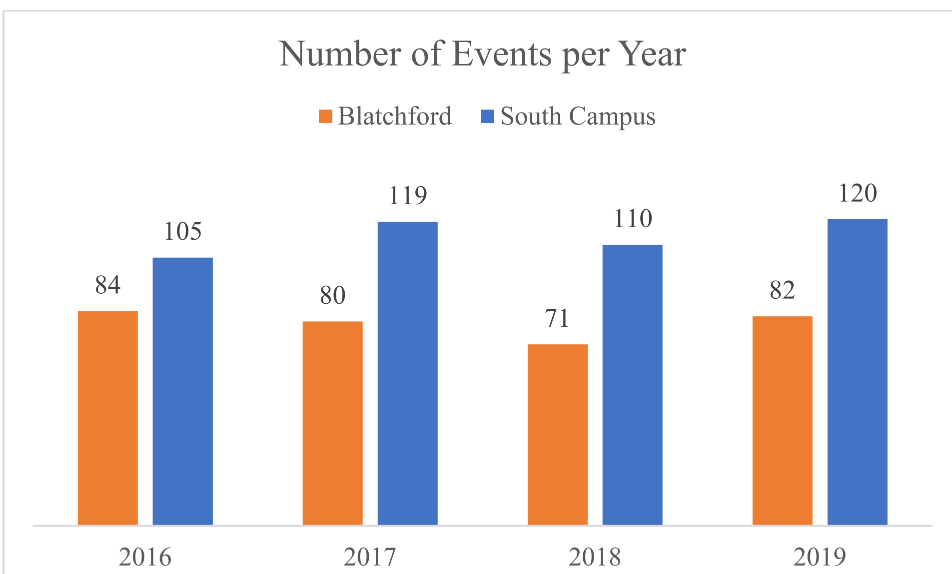

Figure 2. Number of Snowstorm Events According to the Two Weather Stations.

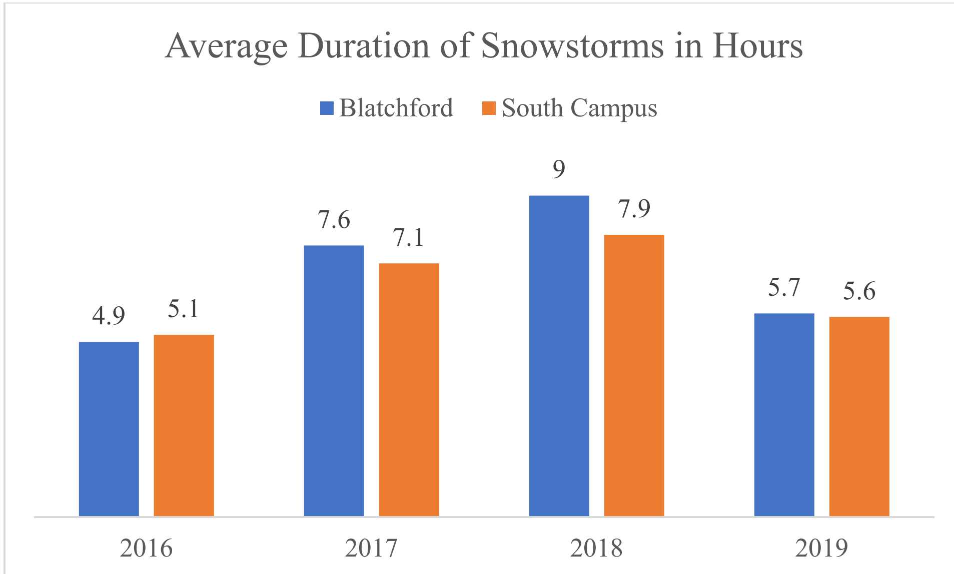

Figure 3. Average Snowstorm Duration According to the Two Weather Stations.

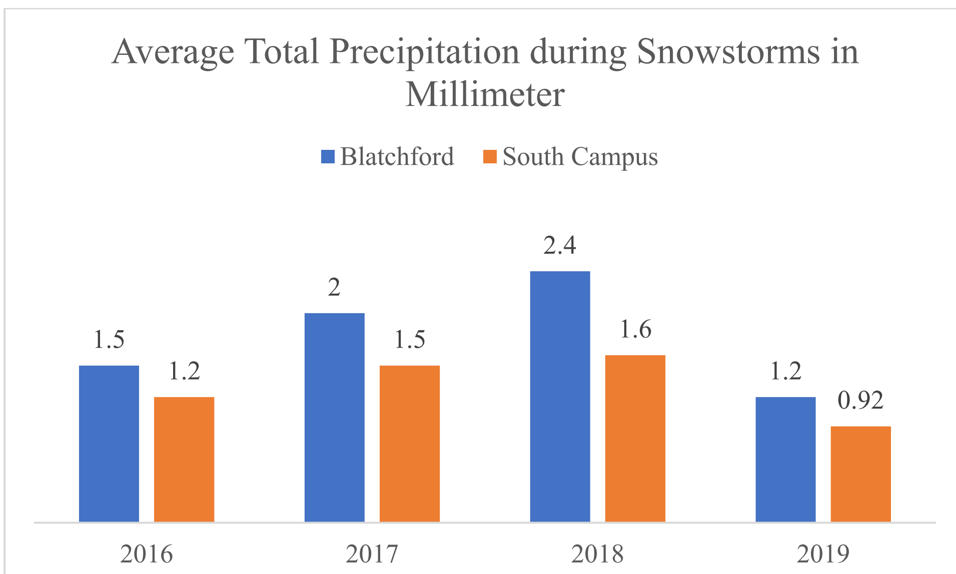

Figure 4. Average Total Equivalent Precipitation During Snowstorms According to the Two Weather Stations.

3.5 Collision Data

Large datasets of collisions were provided by the city of Edmonton. Collisions are recorded by the Edmonton police service whenever they result in an estimated damage of $2,000 or more. The collected datasets include the date and time of each collision, number of vehicles involved, collision location (at a midblock, or an intersection), collision severity, and collision address.

Collision data were processed and filtered for the purpose of this study as follows:

1- Duplicates of the same collision record were filtered out using the police report number field.
2- Collisions that occurred at an unknown location or ones that occurred in residential or local streets were filtered out using the location code. Only collisions that occurred in intersections or mid-blocks were kept.
3- The remaining subset of filtered collisions was further filtered out using Esri's ArcGIS [65], to keep only collisions that occurred on any of the 21 friction testing routes.

The resulting dataset included a total of 3,853 collisions that occurred on the 21 friction testing routes throughout the study period. The breakdown of the annual collisions per friction route is shown in Figure 5, while the breakdown of the annual collisions per road type is shown in Figure 6.

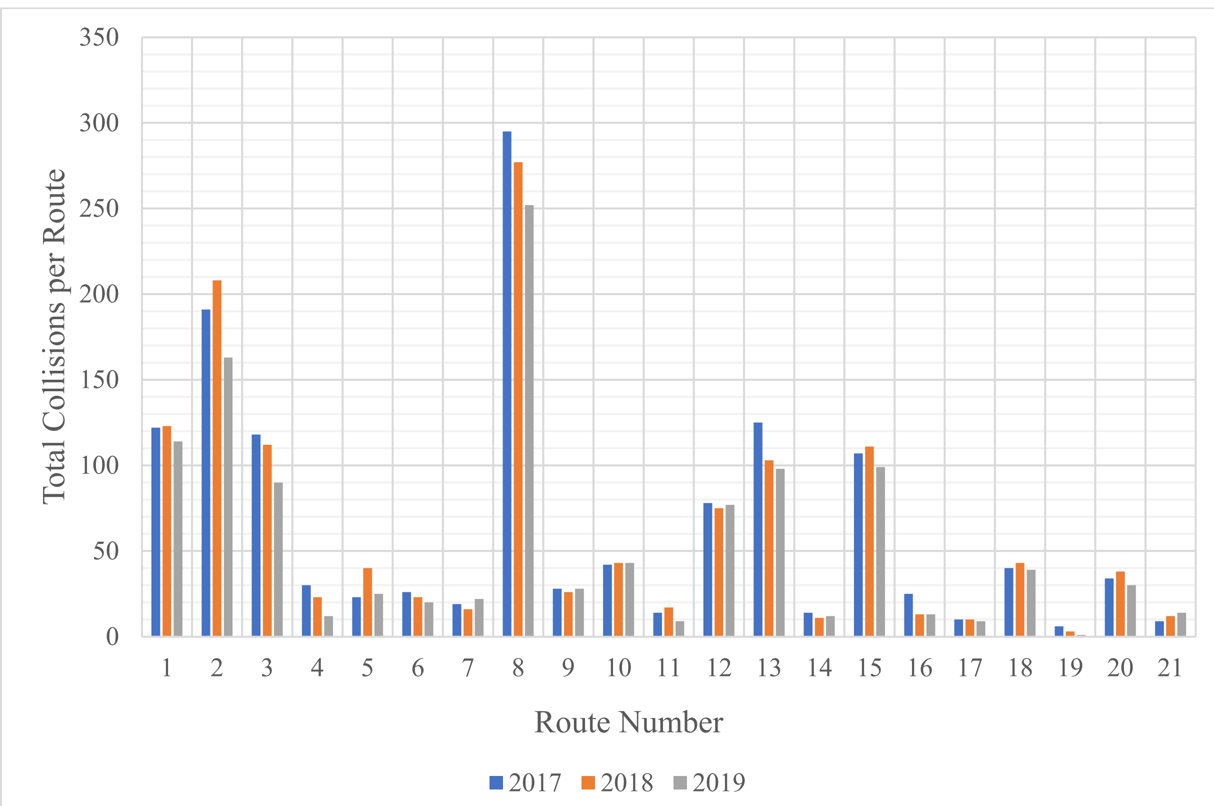

Figure 5. Total Annual Number of Collisions per Route.

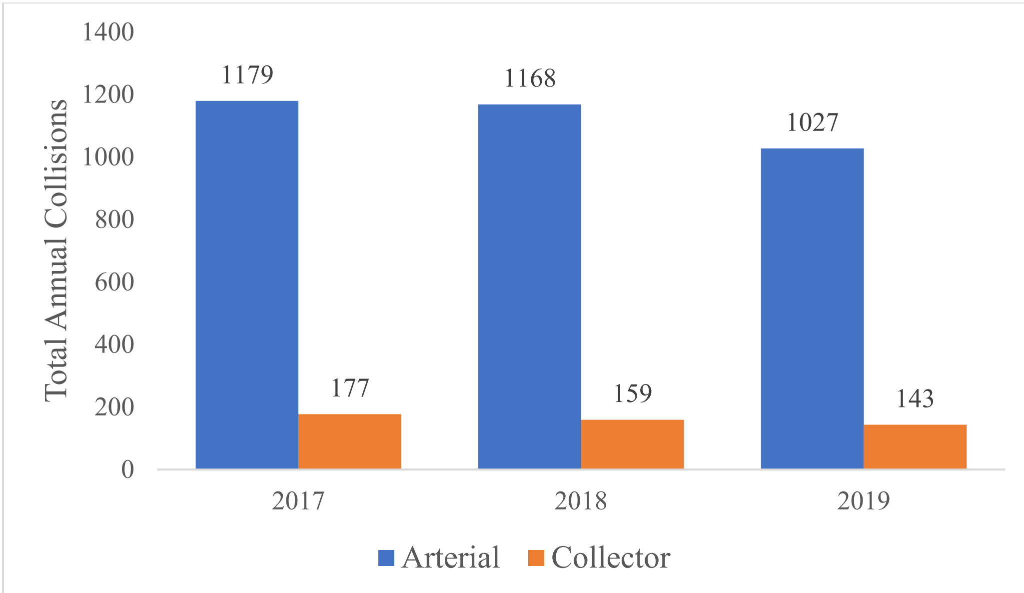

Figure 6. Total Annual Number of Collisions per Route Type.

3.6 Data Fusion

Each friction testing route was assigned to the closest weather station to ensure that each route was associated with the most accurate weather conditions during each snowstorm. Then, using the timestamp and location of each friction testing record, and using the date, time, duration, and location information for each event in the dataset, friction coefficient records were assigned to the snowstorm events. Similarly, collision counts that occurred during each snowstorm event were added to the dataset.

Dummy events were created to make use of pavement friction records obtained between subsequent snowstorms by executing the following procedures:

1- For the friction modeling dataset, 4-hour dummy events with no precipitation were created.
2- For the collision modeling dataset:
    i- If plowing operations had been conducted at the time of the friction testing record, then, the dummy events created would extend to a duration up until the following snowstorm. The assumption here was that the pavement friction coefficient would remain unchanged in these conditions.

ii- If plowing operations had not been conducted at the time of the friction testing record, then 4-hour dummy events with no precipitation were created. The assumption here was that the pavement friction coefficient could change and improve significantly once plowing operations start.

All snowstorm events without friction coefficient records were filtered out of the analysis, leaving 351 snowstorm events. A subset dataset of the 234 snowstorm events that occurred during the first two winter seasons was separated to be used for friction modeling. These events include information about the status of the maintenance operations at the time of friction testing which is critical in describing and predicting pavement friction. The larger dataset was still used to associate the risks of collision occurrence at specific thresholds of pavement friction. The dataset that contains all the 351 events is to be called "Dataset 1", and then the subset dataset that contains the 234 events with maintenance information is named "Dataset 2". Summaries of both datasets are shown in Tables 7 and 8.

To create a dataset that would be useful in modeling collisions, information regarding both the maintenance operations and traffic data needed to be present. There was no traffic volume information available for the friction testing route number 17 (142 st between 137 ave and 167 ave). Hence, snowstorm events that occurred on this route were discarded from the subset dataset, leaving 231 records to be used in quantifying the benefits of WRM operations in improving traffic safety. This dataset is to be called "Dataset 3". A summary of Dataset 3 is shown in Table 9.

Three additional variables were created and added to the three datasets; *BI*, *T15*, and *I*. *BI* is a dummy variable that describes the potential for black ice formation; taking a value of 1 when the average dew point temperature is within 2 degrees of the average ambient temperature during a snowstorm. *T15* is a dummy variable that describes an event with an average temperature that is equal to or less than -15°C, while *I* is the precipitation intensity variable, which was obtained using equation (2). A flowchart that describes the sequence of how the datasets were created is shown in Figure 7.

$$I = \frac{\mathrm{P}}{D} \tag{2}$$

where *P* is the total equivalent precipitation in mm, and *D* is the total snowstorm event duration.

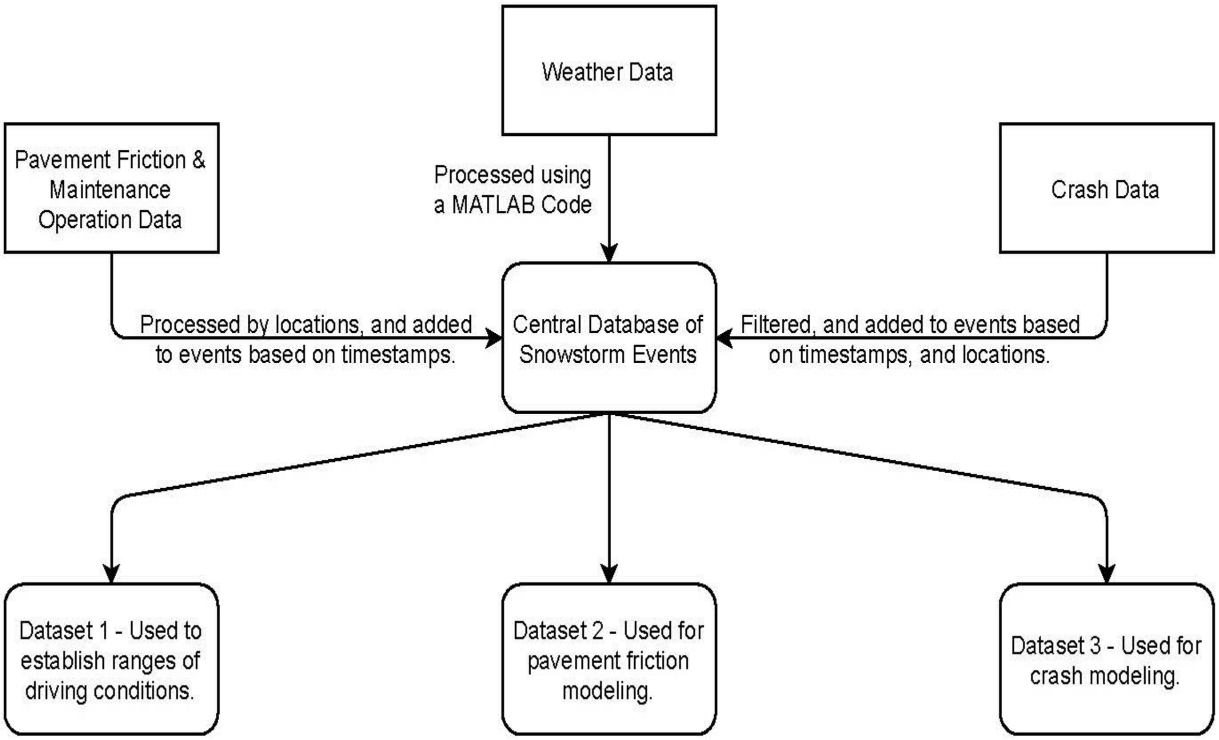

Figure 7. A Schematic Workflow of Data Processing.

Table 7. The Descriptive Statistics of the Full Dataset – Dataset 1.

Variable	Mean	Minimum	Maximum	Range	St. Deviation
T	-14.42	-31.05	0.68	31.73	7.588
H	80.50	62.55	96.93	34.38	8.227
P	1.83	0	11.8	11.8	2.643
W	10.63	1.75	23.48	21.73	4.707
D	11.49	4	40	36	9.573
I	0.11	0	0.36	0.36	0.094
T15	0.45	0	1	1	0.498
Dew	-17.35	-33.78	-2.96	30.82	8.053
BI	0.23	0	1	1	0.419
Arterial	0.77	0	1	1	0.424
G	0.482	0.190	0.833	0.643	0.154
Length	3.26	0.83	7.30	6.48	1.736
ADT	25367.88	1433	74523	73090	23488.211
MVK	37.19	0.95	170.09	169.14	48.156
Collisions	0.30	0	11	11	0.898

Table 8. The Descriptive Statistics of the Subset Dataset - Dataset 2.

Variable	Mean	Minimum	Maximum	Range	St. Deviation
T	-17.40	-31.05	0.68	31.73	6.975
H	77.69	62.55	94.66	32.11	7.870
P	2.30	0	11.8	11.80	3.073
W	10.96	1.75	23.48	21.73	4.789
D	13.32	4	40	36	10.939
I	0.12	0	0.36	0.36	0.108
T15	0.64	0	1	1	0.482
Dew	-20.57	-33.78	-4.70	29.08	7.296
BI	0.21	0	1	1	0.408
Arterial	0.75	0	1	1	0.435
AI	0.14	0	1	1	0.349
Maint	0.36	0	1	1	0.479
G	0.448	0.199	0.816	0.617	0.143

Table 9. The Descriptive Statistics of Dataset 3.

Variable	Mean	Minimum	Maximum	Range	St. Deviation
T	-17.09	-31.05	1.85	32.9	7.358
H	76.56	58.8	94.66	35.86	8.952
P	1.93	0	11.8	11.8	2.972
W	10.68	1.75	21.64	19.89	4.460
D	16.45	4	98	94	15.672
I	0.10	0	0.36	0.36	0.111
T15	0.61	0	1	1	0.488
Dew	-20.48	-33.78	-6.58	27.2	7.578
BI	0.14	0	1	1	0.351
Arterial	0.74	0	1	1	0.437
AI	0.14	0	1	1	0.346
Maint	0.35	0	1	1	0.480
G	0.448	0.199	0.816	0.617	0.144
Length	3.32	0.83	7.301	6.476	1.642
ADT	25339.45	1433	74523	73090	23406.75
MVK	37.14	0.95	170.09	169.14	47.127
Crashes	0.39	0	11	11	1.069

T = Average temperature in Celsius; *H* = Average humidity in %; *P* = Total equivalent precipitation in mm; *W* = Average wind speed in km/hr; *D* = Total duration in hours; *I* = Precipitation intensity in mm/hr; *T15* = Dummy variable describing events with an average temperature less than or equal -15°C; *Dew* = Average dew point temperature in Celsius; *BI* = Dummy variable describing the potential for black ice formation; *Arterial* = Dummy variable describing the segment function; *AI* = Dummy variable describing the application of anti-icing; *Maint* = Dummy variable describing the plowing operations; *G* = Coefficient of friction; *Length* = Route length in KM; *ADT* = Average daily traffic on each route; *MVK* = Exposure variable, Million vehicle kilometer; *Collisions/Crashes* = Collision counts.

4. PAVEMENT FRICTION MODELING

This chapter discusses the pavement friction model. Using a multi-linear regression model, the impacts of the different weather and maintenance operation variables on pavement friction were obtained. The chapter is divided into three subsections. In the first subsection a brief introduction about the goal of the analysis and the methodology used is provided; the linear regression methodology for pavement friction modeling is presented in the second subsection; while in the third subsection, the results and discussion of the developed model are illustrated.

4.1 Introduction

The primary goal of this analysis was to quantify the impacts of the different weather and maintenance operation variables on road surface conditions during snowstorms. There was an obvious linear trend between pavement friction and the rest of the independent variables, which is why multi-linear regression was deemed the best way to represent this relationship.

Although more sophisticated methodologies could have been used to study this interaction and result in better data fits such as geostatistical analysis [18], [37], [60] or machine learning algorithms [42], multi-linear regression had been preferred because of its ability to quantify and draw associations between the independent and response variables. Had the goal of this analysis been purely predictive, however, one of the pre-mentioned methodologies would have been more appropriate.

Multi-linear regression is a parametric statistical technique used to understand the effects of independent variables on a response variable by constructing a linear relationship between them [66]. It helps quantify the impact of each of the independent variables as well as the magnitude and significance of their impact on the dependent variable under study. Furthermore, the resulting model can be used to predict the average value of the response variable under certain conditions as described by the independent variables. This technique has been widely used in many fields as it is easy to formulate and, if properly specified, can result in models with a very good statistical fit and very high predicting powers. Multi-linear regression is used extensively in the field of transportation engineering. In transportation planning, it is mainly used in demand forecasting [67]–[69]; while in traffic engineering, its applications include traffic predictions, and speed and flow rate estimations [70]–[72]; it is also used in road surface modeling [39], [40], [45].

4.2 Methodology

Multi-linear regression models take the form of equation (3), where y is the dependent variable under study, β_0 is the intercept or the mean value of the dependent variable when all predictor variables are equal 0, X_i is a vector of predictor variables, β_i is a vector of regression coefficients. ε is an error term which is defined as the difference between the observed and expected values of the dependent variable, as per the model, at each observation. ε is a random variable that is assumed to be uncorrelated within observations, and to follow a normal distribution with parameters $\varepsilon \sim N(0, \sigma^2)$. The regression coefficient vector β_i represents the marginal change in the dependent variable y per unit change in the predictor variable X_i when all other variables are kept constant.

$$y = \beta_0 + \beta_i X_i + \varepsilon \qquad (3)$$

Estimates of the regression coefficients were determined using the ordinary least square method. The method calculates the regression coefficients by minimizing the sum of the squares of the error terms. The sum of the squares of the error terms S is calculated as in equation (4), then using the partial derivatives of S with respect to the regression parameters, β_0 and β_i are calculated as in equations (5) and (6) respectively by simultaneously solving the resulting equations.

$$S(\beta_0, \beta_i) = \sum_{n=1}^{n} \varepsilon_n^2 = \sum_{n=1}^{n} (Y_n - \beta_0 - \sum_{i=1}^{i} \beta_i X_i)^2 \qquad (4)$$

$$\frac{\partial S}{\partial \beta_0} | \beta_0, \beta_i \;=\; -2 \sum_{n=1}^{n} \left(Y_n - \beta_0 - \sum_{i=1}^{i} \beta_i X_i \right) = 0 \qquad (5)$$

$$\frac{\partial S}{\partial \beta_i} | \beta_0, \beta_i \;=\; -2 \sum_{n=1}^{n} \left(Y_n - \beta_0 - \sum_{i=1}^{i} \beta_i X_i \right) = 0 \qquad (6)$$

All the variables included in the final accepted model met a certain pre-set statistical significance level α. A t-test was conducted for all the independent variables used in the model, and variables with p-values of more than 0.05 were dropped using a backward stepwise variable selection. Finally, residual plots of all the selected predictor variables were examined to make sure that there were no patterns in the random error terms (i.e. homoscedastic errors).

The overall goodness of fit of the model was judged using the coefficient of determination (R^2). R^2 measures the percentage of the variability in the dependent variable that is explained using the independent variables and is equal to the ratio of the regression sum of squares SSreg to the total sum squares SYY. R^2, SSreg, and SYY are calculated as in equations (7-9) respectively. SAS statistical software [73] was used for model calibration and processing.

$$R^2 = \frac{SSreg}{SYY} \tag{7}$$

$$SSreg = \sum_{n=1}^{n} (y_n - \bar{y})^2 \tag{8}$$

$$SSreg = \sum_{n=1}^{n} (Y_n - \bar{y})^2 \tag{9}$$

where y_n, Y_n, $\bar{y}$ are the predicted, observed, and mean values of the dependent variable respectively.

In this analysis, Dataset 2 was used, the response variable under study was the coefficient of pavement friction "*G*", while the independent variables (i.e., weather and maintenance) used to predict it are summarized in Table 8.

4.3 Results & Discussion

The results of the friction coefficient model are summarized in Table 10 and presented in equation 10. As shown in the table, all the variables were statistically significant at the 99% confidence level. The model had an R^2 of 0.7233 and an adjusted R^2 of 0.716 which demonstrated a good fit [74], [75]. This indicates that the predictor variables included in the model can explain 72.33% of the variation of pavement friction during snowstorms. Residual plots for all the independent variables, shown in the appendix, were inspected, and no trends nor patterns were found, further confirming the validity of the developed model.

Table 10. The Results of the Pavement Friction Regression Model.

Variable	Parameter Estimate	Standard Error	t-value	p-value
Intercept	0.4444	0.0153	28.87	<.0001
P	-0.0086	0.0019	-4.44	<.0001
T15	-0.1098	0.0129	-8.53	<.0001
BI	-0.1166	0.0159	-7.35	<.0001
Arterial	0.0768	0.0117	6.59	<.0001
AI	0.0577	0.0153	3.77	0.0002
Maint	0.1484	0.0119	12.49	<.0001

$$\boldsymbol{G} = 0.44 - 0.009\,\boldsymbol{P} - 0.110\,\boldsymbol{T15} - 0.117\,\boldsymbol{BI} + 0.077\,\boldsymbol{Arterial} + 0.058\,\boldsymbol{AI} + 0.148\,\boldsymbol{Maint} \tag{10}$$

The model results show that the precipitation variable *P* had a negative effect on pavement friction. This is understandable because the snow that accumulates on the roads during snowstorms is the main factor that worsens the road surface conditions (RSC). Snow makes roads more slippery, and therefore, reduces the friction coefficient. Hence, it should be expected that snowstorms with more snowfall would result in lower friction coefficient values. The model predicts that the friction coefficient drops by -0.0086 for each 1 equivalent millimeter of precipitation.

Temperature was also found to be a significant factor in predicting friction coefficients for the roads during snowstorms. The resulting model suggests that friction coefficient drops by an average value of -0.1098 in snowstorm events with an average temperature of equal to or less than -15°C. This finding is consistent with what had been found in prior studies attesting that the efficiency of salt in breaking up the bonds between snow and pavement decreases as temperatures decrease [27]–[29].

The formation of black ice on road surfaces can be very dangerous as it makes the pavement surface extremely slippery. In fact, the model suggests that the friction coefficient during snowstorms, when there is a possibility for black ice formation is, on average, 0.1166 less than snowstorms without the potential for black ice formation.

Like many cities in North America, the City of Edmonton adopts a priority plan for the winter road maintenance (WRM) operations which gives precedence to roads based on their function [63]. Accordingly, arterial roads have better maintenance response times and receive de-icing operations more frequently than collector roads. This was shown in the results of the model developed here as, on average, the friction coefficient on arterial roads is expected to be higher than collector roads subjected to the same snowstorm by 0.0768.

The application of anti-icing chemicals before snowstorms has always been anecdotally associated with higher levels of service, and better overall RSC. The model finally confirms this notion with empirical evidence as it predicts that roads that receive anti-icing treatments before snowstorms shall have a 0.0577 better friction coefficient than their counterparts.

Moreover, the model quantifies the impact of the plowing operations on pavement friction as it improves friction by 0.1484. This makes intuitive sense as plowing is essentially the main and most important maintenance operation tool for snow clearance.

Finally, the model predicts that the average value of pavement friction on arterial roads is 0.5212 when there is no precipitation, the temperature is above -15°C, the conditions for black ice formation are not met, and no maintenance operations are conducted. On the other hand, the model predicts that the average value of friction coefficient on collector roads under the same conditions is 0.4444.

Interestingly, among all the variables included in the model, the plowing operations represented in the variable *Maint* had the highest impact on pavement friction. According to the model, plowing improves pavement friction by an average of 0.1484, which shows its utmost importance in restoring bare pavement conditions. In contrast, temperatures during snowstorms play a major role in worsening pavement friction. Road friction during snowstorms with average air temperatures below -15°C and dew point temperatures within 2 degrees of the air temperature is expected to drop by 0.2264. As such, decision-makers should pay extra attention to these snowstorms as these events would result in highly hazardous driving conditions for motorists.

The results of the model further suggest that there are two sets of variables that influence pavement friction during snowstorms. On one hand, there are the weather variables, represented by *P*, *T15*, and *BI*, which worsen the pavement friction coefficient on roads. These variables vary from one snowstorm to another depending on the weather forecast. On the other hand, there are the efforts of the maintenance operators, which are represented by the variables *Arterial*, *AI*, and *Maint*. Unlike the weather variables, the maintenance operation variables improve the pavement friction and can be controlled by decision-makers' policies.

5. TRAFFIC COLLISION MODELING

This chapter discusses the collision count models. Collisions were modeled using Negative Binomial count models to understand the influences of the different predictor or independent variables on road safety. The chapter is divided into four subsections. In the first subsection, a brief introduction about the goals of the analysis and methodology used is presented, then the Negative Binomial methodology used for collision modeling is explained in subsection two. In the third subsection, the results and discussion of the developed models are illustrated. Finally, the fourth subsection shows how the created models can be used.

5.1 Introduction

Collisions are rare and random phenomena which can be modeled using discrete count distributions models [76], [77]. Safety performance functions (SPFs) are mathematical models that aim to explain some of the structured randomness in crash occurrence using various influencing variables [76], [77]. In order to construct good representative SPFs, a wide range of hierarchical models and methodologies have been developed. The most popular frameworks used in the literature to model collisions are Poisson and Negative Binomial models [53]. This is because these structures are easy to model and can account for the most common issues found in collision data.

Negative Binomial SPFs are more robust than the Poisson as they are capable of dealing with the overdispersion found in most collision datasets. Overdispersion occurs when the variance of the data is larger than the mean. Poisson models are structured such that the variance is assumed to be equal to the mean. If this assumption does not hold, biased parameter estimates will be generated leading to wrong conclusions and bad goodness of fit. Negative Binomial models are an extension of Poisson models where the variance, mean equality restriction is not assumed. Instead, Negative Binomial models allow the variance to exceed the mean by a factor of $\frac{\mu^2}{k}$ (see equations 11-19). By allowing the variance to deviate from the mean Negative Binomial SPF usually results in superior goodness of fit and more accurate inferences [53], [78]–[81]. Hence, Negative binomial models were used predominantly in this analysis.

Using SPFs, the relationship between the pavement friction coefficient with collision counts during snowstorms was examined. The main objectives of this analysis were to: understand the influence of pavement friction on road safety, and establish pavement friction intervals where collision counts significantly increased and decreased. The first part of the analysis was conducted by including the pavement friction coefficient variable *"G"* as an independent variable that can explain collisions during snowstorms.

To conduct the second part of the analysis, dummy variables of pavement friction were created at 0.05 increments. These dummy variables represent the upper and lower limits of road surface conditions where collisions become more and less likely to occur respectively. The significance of these dummy variables in influencing collision counts was tested one at a time until significant changes in collision risk were reported.

5.2 Methodology

To derive the Negative Binomial SPFs, the observed number of collisions per snowstorm Y_n is assumed to follow a Poisson distribution with parameter θ_n; $Y_n | \theta_n \sim Poisson(\theta_n)$ where θ_n is the mean number of collisions per snowstorm. The probability distribution function of Y_n can then be described as shown in equations (11), and the expected value of the distribution and its variance are shown in equations (12,13) respectively.

$$P(Y|\theta) = \frac{\theta^{Y} e^{-\theta}}{Y!} \tag{11}$$

$$E(Y|\theta) = \theta \tag{12}$$

$$Var(Y|\theta) = \theta \tag{13}$$

The mean number of collisions per snowstorm θ_n is, then, assumed to follow a gamma distribution with a shape parameter k and scale parameter k/μ; $\theta \sim$ Gamma $(k, k/\mu)$ where μ is the predicted number of collisions per snowstorm. The probability distribution function of θ can be described as shown in equation (14), and the expected value of the distribution and its variance are shown in equations (15,16) respectively.

$$f(\theta) = \frac{(\frac{k}{\mu})^{k}\, \theta^{k-1}\, e^{-\theta\,(k/\mu)}}{\Gamma(\mathrm{k})} \tag{14}$$

$$E(\theta) = \mu \tag{15}$$

$$Var(\theta) = \frac{\mu^2}{k} \tag{16}$$

The resulting product of the two probability functions is a Negative Binomial distribution with a probability distribution function shown in equation (17), and an expected value and variance described in equations (18,19) respectively.

$$P(Y_n|\mu_n, k) = \frac{\Gamma(Y_n + k)}{Y_n!\ \Gamma(k)} \left(\frac{k}{k + \mu_n}\right)^k \left(\frac{\mu_n}{k + \mu_n}\right)^{Y_n} \tag{17}$$

$$E(Y) = \mu \tag{18}$$

$$Var(Y) = \mu + \frac{\mu^2}{k} \tag{19}$$

The predicted number of collisions per snowstorm μ_i is assumed to be a function of independent variables that take the form as shown in Equation (20). μ_i is the collision count during each snowstorm which is the dependent variable under study, β_0 is the intercept, X_i is a vector of predictor variables, β_i is a vector of regression coefficients, and ε is an error term, which is a random variable that is assumed to follow a Negative Binomial distribution. The error term ε accounts for the randomness that is associated with the collision occurrence. The exposure and snowstorm duration terms were left outside of the exponential function because if either was equal to zero, then we would not expect any collisions to occur.

$$\mu_i = duration.\ exposure^{\beta}.\ e^{\beta 0 + \beta i\, Xi + \varepsilon} \tag{20}$$

The model's regression coefficients were calibrated using the maximum likelihood estimation method, while the overall goodness of fit of the models were judged by comparing Pearson's X^2 and the scaled deviance (SD) to the chi-square of α = 0.05; $X^2_{.05}$. Pearson's X^2 and the SD are calculated for each created model using the equations (21,22) respectively. SAS statistical software was used for model calibration and processing [73].

$$Pearson\ X^2 = \sum_{n=1}^{n} \frac{[Y_n - E(\theta_n)]^2}{Var(Y_n)} \tag{21}$$

$$SD = 2\sum_{n=1}^{n} \left\{ Y_n\, ln\left[\frac{Y_n}{E(\theta_n)}\right] - (Y_n + k)\, ln\left[\frac{Y_n + k}{E(\theta_n) + k}\right] \right\} \tag{22}$$

All the variables included in the final models were ensured to meet a minimum pre-set statistical significance level of 0.05. *t*-tests were conducted for all the independent variables used in the models, and variables with *p*-values of more than 0.05 were dropped.

Dataset 1 was used for this study where "*Collisions*" was the dependent variable, and the independent variables were all the other variables summarized in Table 7, in addition to the friction dummy increment variables previously described. Considering how pavement friction was shown to be correlated with the weather and maintenance operations variables in the previous chapter, a forward stepwise variable selection was opted this time. This was done to ensure that pavement friction was among the variables that remained in the final model while any other variable that might be correlated would be removed.

5.3 Results & Discussion

First, the relationship between pavement friction and road safety was hypothesized and tested. This was done by investigating the impacts and significance of the friction coefficient values on collision counts during snowstorms. The model shown in Table 11 and presented in equation (23) was created.

As shown in Table 11, all the variables were statistically significant at the 99% confidence level. Additionally, the dispersion parameter estimate was less than 1 which confirmed the presence of overdispersion within the data and justified the use of a Negative Binomial model in the analysis. The goodness of fit of the model was judged using the Scaled Deviance and Pearson's chi-squared values. Since both, the Scaled deviance (178.1916), and Pearson's chi-squared (342.8055) were less than $X^2(347, 0.05) = 391.43$ the model was considered a good fit for the data.

Table 11. The Results of the First Collision Count Model.

Variable	Parameter Estimate	Standard Error	p-value
Intercept	-4.9063	0.6743	<.0001
lnMVK	0.3357	0.1232	0.0064
G	-3.6712	0.9341	<.0001
Arterial	1.7665	0.6729	0.0087
Dispersion	0.7545	0.3081	-

$$\textit{\textbf{Collision counts}} = 7.4\,x\,10^{-3}\boldsymbol{D}\,.\,\boldsymbol{MVK}^{\,0.34}.\ exp^{-3.67\,\boldsymbol{G}\,+\,1.77\,\boldsymbol{arterial}} \tag{23}$$

The model suggests that collisions during snowstorms increase as the exposure variable *lnMVK* increases. This is intuitive and in line with previous studies [33]–[35] because when there is more traffic on the road, there are more chances for collisions to occur. Moreover, the pavement friction coefficient was found to be a significant factor in predicting collision counts. Since pavement friction is an indicator of road surface conditions (RSC), it was predicted that the number of collisions would decrease as pavement friction increased. In fact, previous studies reported similar results when modeling collisions using RSC indicators [34], [35]. Finally, Arterial roads were found to witness more collisions than collector roads which was attributed to the higher traffic volumes that these roads receive, the higher speed limits that they have, and the difference in drivers' behavior while traveling on them.

Once pavement friction was found to have a significant impact on road safety, further analysis to establish pavement friction thresholds where roads are significantly safer or less safe was pursued. The upper bound of pavement friction that signifies unsafe driving conditions was established by creating SPFs using dummy variables that take the value of 1 whenever the friction coefficient was below a certain threshold. Unsafe driving conditions were defined in this context as the pavement friction coefficient value when a significant increase in collisions was predicted. Friction coefficient increments of 0.05 were used until the upper bound was reached. Similarly, the lower bound of pavement friction that signifies safe driving conditions or a significant reduction in collisions was evaluated. The results of the models created are shown in Tables 12 - 14, and equations (24 - 26).

Table 12. The Goodness of Fit Results of the Pavement Friction Thresholds Models.

Model	SD*	Pearson's $\boldsymbol{X}^{\,2}$	$\boldsymbol{X^2(348, 0.05)}$
1	186.469	334.678	392.5
2	185.729	314.34	392.5
3	179.609	304.086	392.5

Examining the results of the models summarized in Table 12, several findings can be deduced. Firstly, the goodness of fits of all three models included in this analysis were significant at the 95% confidence level. Secondly, the overdispersion assumption was confirmed in all the models as the dispersion parameters were all less than 1. Thirdly, the models showed three distinct ranges of pavement friction coefficients when it comes to road safety. The first range is when the friction coefficient is equal to or less than 0.35. In these conditions, the results showed that there was a significant increase in collisions. This means that the pavement friction coefficient value of 0.35 signifies the start of dangerous driving conditions and that collisions are expected to increase exponentially at lower friction coefficients. The second range is when the friction coefficient is between [0.35, 0.6]. At this interval, driving conditions were relatively safer, however, there was not a significant reduction in collisions predicted. Finally, the third range is when the friction coefficient is more than or equal to 0.6. In these conditions, there was a significant decrease in the number of collisions as per the model. Similar to the first range, the trend of collision reduction continued at pavement friction values higher than 0.6.

These results show that not only collisions are expected to increase whenever pavement friction on the roads decreases, but also that there are specific ranges of pavement friction where driving conditions can be considered safe or dangerous. Using the friction ranges established in the three models above, driving conditions can be categorized into three categories as shown in Table 15. Interestingly, the concluded driving categories are found in line with the standard categories of driving conditions that the city of Edmonton had previously set (Shown in Table 16) based solely on experience. In comparison, the new thresholds of categories that were established in this analysis would have the advantage of being backed by empirical data and statistical methodology in addition to field experience.

Table 13. The Results of the Analysis of the Pavement Friction Thresholds Models.

Model Number	Variable	Estimate	S.E.	p-value
1	***Intercept***	-7.298	0.6837	<.0001
	lnMVK	0.2821	0.1192	0.018
	G1(=<0.35)	0.5857	0.2672	0.0284
	Arterial	1.8213	0.6727	0.0068
	T	-0.0448	0.0162	0.0057
	Dispersion	0.65	0.3	-
2	***Intercept***	-7.0015	0.6692	<.0001
	lnMVK	0.2685	0.1201	0.0254
	G2 (0.6-0.35)	-0.135	0.2493	0.5882
	Arterial	1.671	0.6748	0.0133
	T	-0.0532	0.0162	0.001
	Dispersion	0.7466	0.3278	-
3	***Intercept***	-6.6797	0.6869	<.0001
	lnMVK	0.2811	0.122	0.0212
	G3 (>=0.6)	-0.8426	0.4265	0.0482
	Arterial	1.6326	0.67	0.0148
	T	-0.036	0.018	0.0463
	Dispersion	0.7878	0.3256	-

Table 14. The Pavement Friction Thresholds Models.

Model Number	Equation Form	Equation Number
1	***Collision Counts*** = $6.77\ x\ 10^{-4}.\boldsymbol{D}\ .\ \boldsymbol{MVK}^{\,0.28}.\ exp^{0.59\ \boldsymbol{G1}\ +\ 1.82\ \boldsymbol{arterial}\ -0.04\ \boldsymbol{T}}$	(24)
2	***Collision Counts*** = $9.11\ x\ 10^{-4}\ .\boldsymbol{D}\ .\ \boldsymbol{MVK}^{\,0.27}.\ exp^{-0.14\ \boldsymbol{G2}\ +\ 1.67\ \boldsymbol{arterial}\ -0.05\ \boldsymbol{T}}$	(25)
3	***Collision Counts*** = $1.26\ x\ 10^{-3}.\boldsymbol{D}\ .\ \boldsymbol{MVK}^{\,0.28}.\ exp^{-0.84\ \boldsymbol{G3}\ +\ 1.63\ \boldsymbol{arterial}\ -0.04\ \boldsymbol{T}}$	(26)

Table 15. The Three Categories of Driving Conditions as Per the Models.

Pavement Friction Range	Observations	Comments
G>=0.6	Significant reduction in collisions	Safe driving conditions
G = [0.35, 0.6]	Insignificant reduction in collisions	Fair driving conditions
G<=0.35	Significant increase in collisions	Dangerous/unsafe driving conditions

Table 16. The Old Driving Conditions Categories as Per the City.

Pavement Friction Range	Verdict
G>=0.8	Excellent driving conditions
G = [0.6, 0.8]	Good driving conditions
G = [0.4, 0.6]	Fair driving conditions
G<=0.4	Poor driving conditions

5.4 Model Application

To demonstrate how the created collision prediction model summarized in Table 11 and equation (23) can be used to estimate the safety outcome during a snowstorm, consider the following hypothetical scenario. Say a moderate to severe snowstorm event with a duration of 21 hours was expected to hit a highway in Edmonton with an average exposure of 37.19 million vehicle kilometers (MVK). The relationship between the number of predicted collisions during the hypothetical snowstorm and the expected value of pavement friction coefficient after using various winter road maintenance (WRM) operations on the two road types can be plotted as shown in Figure 8.

The graph highlights the significance of the pavement friction coefficient in determining the safety outcome of snowstorms. As can be seen, the expected number of collisions during the hypothetical snowstorm increases exponentially as the pavement friction coefficient decreases which means that whenever the RSC deteriorates, road safety is compromised dramatically. However, relatively safer driving conditions can be restored swiftly once the WRM operations start and bare pavement is achieved.

This can be shown numerically on the graph. On arterial roads, the expected number of collisions drops from 2.12 collisions per snowstorm at $G = 0.1$ to 0.49 collisions per snowstorm at

G = 0.5. On the other hand, the expected number of collisions drops from 0.36 collisions per snowstorm at G = 0.1 to 0.08 collisions per snowstorm at G = 0.5 on collector roads.

Moreover, the inherent differences in road safety between arterial and collector roads are emphasized in this graph. Even after fixing the exposure on the two types of roads, the arterial road is shown to experience significantly more collisions than the collector road. At a similar average pavement friction coefficient G = 0.1, the expected number of collisions on the arterial road is 2.12 collisions per snowstorm, while on a similar collector road, 0.36 collisions per snowstorm are expected. This finding can justify, on a scientific basis, why arterials take precedence over collector roads in receiving the maintenance operations as per the transportation network priority hierarchy adopted by the city shown in Table 5.

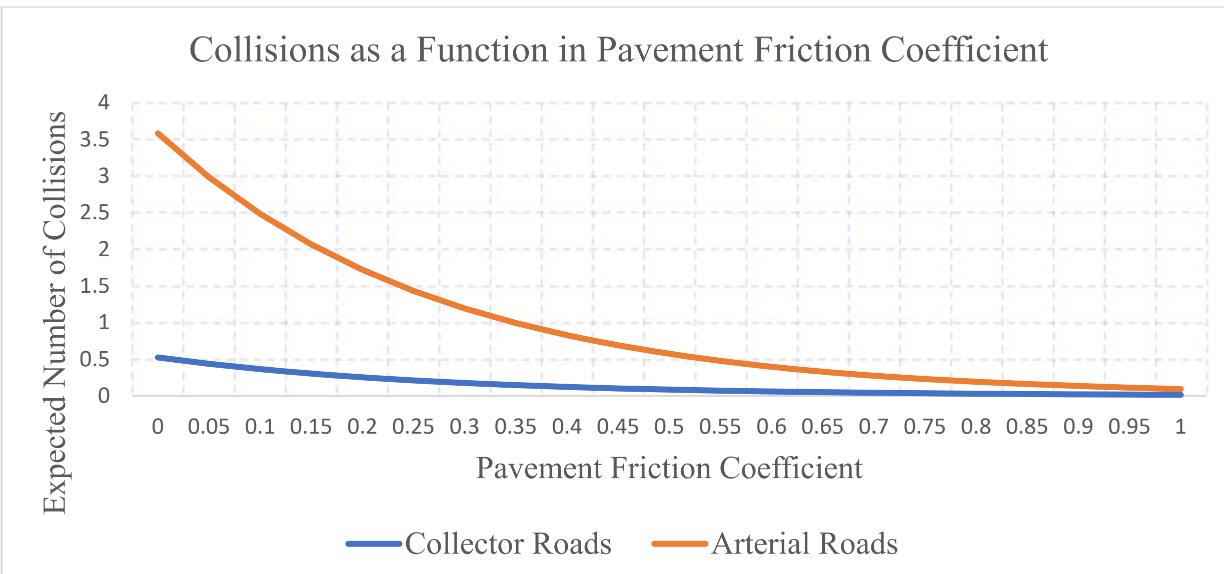

Figure 8. The Expected Number of Collisions During a 21-Hour Long Snowstorm

6. QUANTIFYING THE IMPACTS OF WINTER ROAD MAINTENANCE OPERATIONS ON ROAD SAFETY

This chapter describes how pavement friction and collision modeling were combined into a single hierarchical model. Using structural equation modeling (SEM) and path analysis, the direct and indirect effects of the different independent variables on road safety were summarized. The chapter is divided into four subsections. In the first subsection, a brief introduction about the goals of the analysis and methodology is provided. The SEM methodology is explained in the second subsection. In the third subsection, the results and discussion of the developed models are illustrated. Finally, the fourth subsection shows how the created models can be used.

6.1 Introduction

SEM is a statistical analysis technique that allows us to account for the interrelated dependencies between variables through a single hierarchical model. The path analysis, which is a part of SEM, takes into consideration the direct and indirect effects that the independent variables have on the dependent variable through mediator variables [82].

SEM is inherently different from regression analysis in that regression models are focused primarily on predicting the change in a certain phenomenon by constructing linear relationships between the dependent and independent variables [83]. Independent variables are principally added or removed from the model based on their contribution towards explaining the variation in the dependent variable. On the other hand, in SEM, models are formulated based on a prior assumption of causal effects between the independent and dependent variables. Additionally, SEM makes it possible to test several relationships at the same time. For these reasons, SEM requires a sample size of at least 200 records to report any significant results [84].

SEM allows researchers to add unmeasurable or observed variables into the analysis as latent variables [82], [85]. Because of this and its ability to account for mediating factors, it has been intensively used in a variety of fields including psychology, medicine, ecology, business and economics, as well as, engineering [86]–[90]. In traffic safety, SEM has been beneficial in helping understand the complicated relationships between driver, vehicle, and environment. Combining the capabilities of SEM of allowing latent and mediating variables in the analysis allowed researchers to uncover some important relationships such as the effects of increased accessibility, blood alcohol level, variation in housing-employment balance, traffic congestion, and road geometric characteristics on traffic safety [90]–[93].

The main objective of this analysis was to study the direct and indirect effects that the different tools of winter road maintenance (WRM) have on collisions. Dataset 3 was used which included over 200 records (231 observations), the variable "*Crashes"* was the main dependent variable, while all the other variables summarized in Table 9 were assumed to have either a direct or an indirect effect on it through pavement friction "*G*". The underlying assumption is that "*G*" is an endogenous variable which is influenced directly by both the weather and maintenance operations variables while all other variables are exogenous variables that are not influenced by any other variables in the analysis. Figure 9 shows the initial model specification as a path diagram.

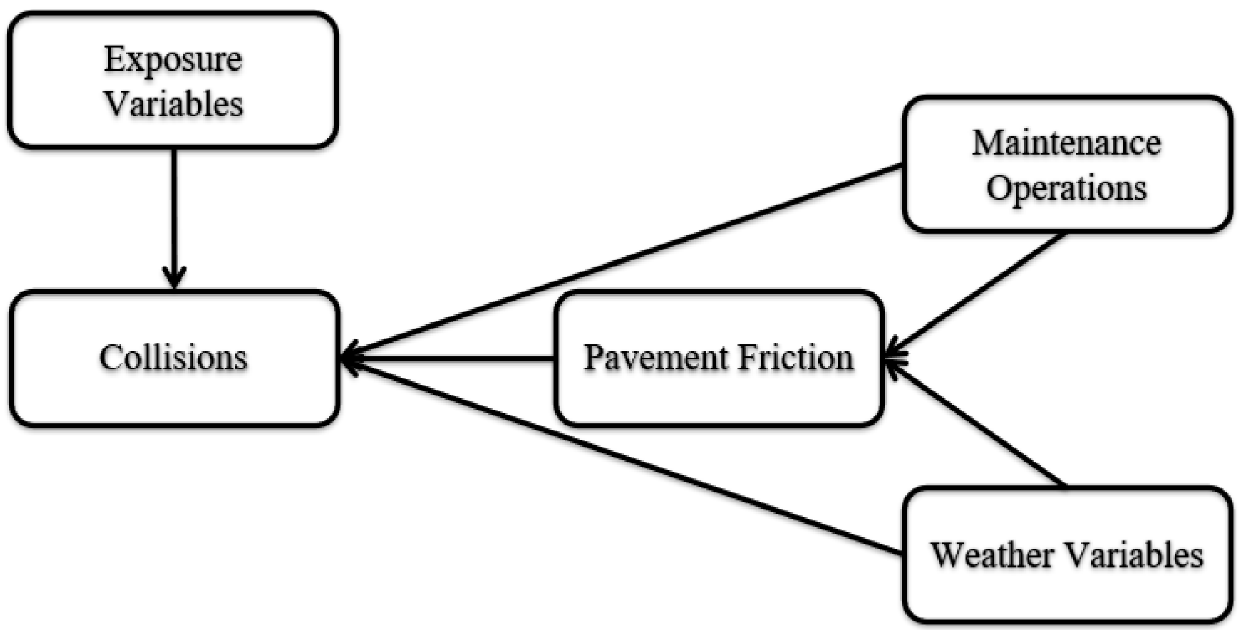

Figure 9. Initial Model Specification Path Diagram

6.2 Methodology

The software used to construct the SEM statistical models is MPlus version 6 [94]. The first dependent variable in this analysis was *"G"*. It was assigned to a Normal distribution variable formulated as $G_i \sim N(\bar{G}, \sigma^2)$, where $\bar{G}$ is the mean pavement friction during snowstorms, and σ^2 is the standard deviation. $\bar{G}$ is assumed to be a function as shown in Equation (27), where β_0 is the intercept, X_i is a vector of predictor variables, β_i is a vector of regression coefficients, and ε is an error term which is a random variable that is assumed to follow a normal distribution. Estimates of the regression coefficients were determined using the ordinary least square method.

$$G = \beta_0 + \beta_i X_i + \varepsilon \quad (27)$$

The second dependent variable in this analysis was "*Crashes"*. It was assigned to a count variable using a Negative Binomial distribution formulated as $Y_i \sim NB(\mu_i, \alpha)$, where Y_i is the number of collisions that occurred during snowstorm i, μ_i is the mean collision count, and α is the overdispersion parameter. The mean collision count μ_i is assumed to be a function of independent variables and takes the form as in Equation (28).

$$\mu_i = exposure^{\beta}.duration^{\beta 1}.\ e^{\beta 0 + \beta i\, Xi + \varepsilon} \quad (28)$$

where μ_i is the collision counts during each snowstorm which is the dependent variable under study, β_0 is the intercept, X_i is a vector of predictor variables which include all the variables in dataset 3, β_i is a vector of regression coefficients, and ε is an error term, which is a random variable that is assumed to follow a Negative Binomial distribution. The parameters in the collision count model were estimated using the maximum likelihood with robust standard errors method. The indirect effects of the variables that describe pavement friction on collisions were calculated using the product of the parameter estimates [85], while their standard errors were calculated using the delta method [95].

As with the previous analyses, all the variables included in the final models met a minimum pre-set statistical significance level of 0.1. t-tests were conducted for all the independent variables used in the models, and variables with p-values of more than 0.1 were dropped using a backward stepwise variable elimination.

6.3 Results & Discussion

After establishing that the pavement friction coefficient *"G"* can be explained using weather and maintenance operations data, and that pavement friction is a significant factor in influencing collisions during snowstorms, SEM was used to simultaneously model these two relationships in one framework. Multiple paths had been investigated starting from the general one shown in Figure 9. Insignificant variables were removed from the analysis in a backward step elimination process until the final significant path was obtained. The resulting final path is shown in Figure 10, its associated parameter estimates are shown in Table 17, and the model is shown in equations 29,30.

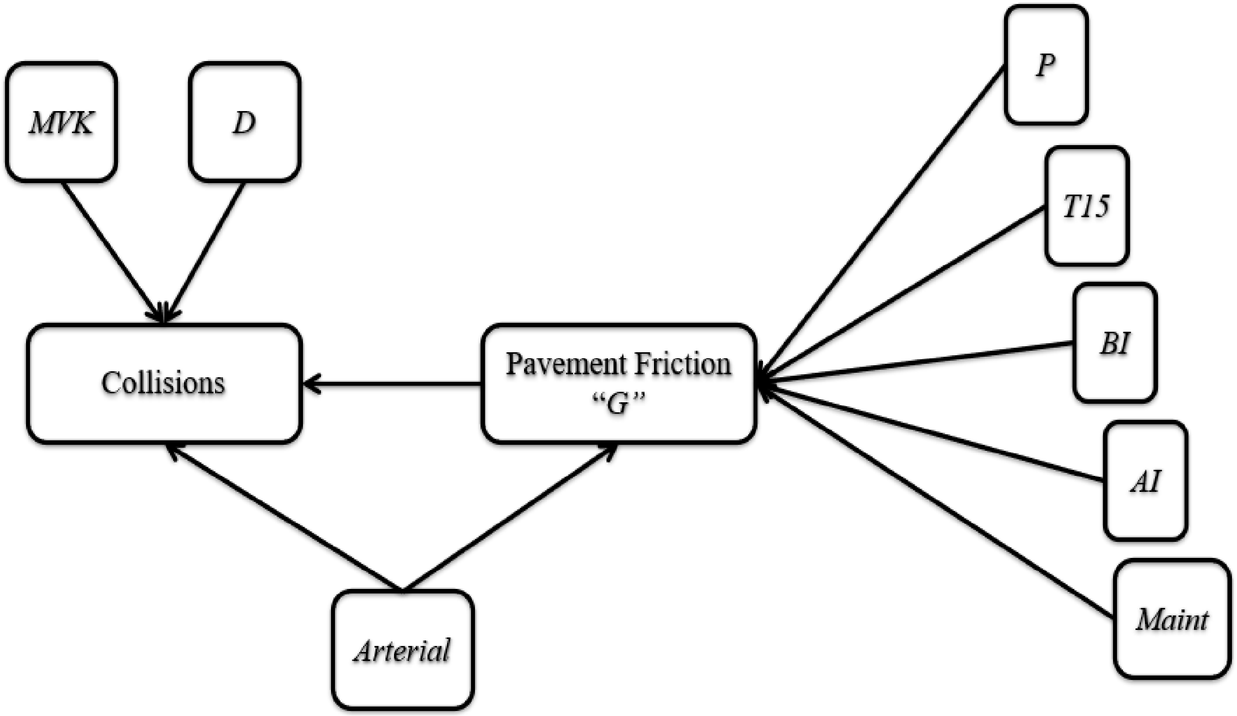

Figure 10. The Significant SEM Model Path

All the variables in the final model were at least significant on the 95% confidence level except *lnMVK* which was significant on the 90% confidence level. The goodness of fit of the model was evaluated by comparing the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of the fitted Negative Binomial model with a Poisson, and non-parametric models, where the best model is the one with the lowest AIC and BIC values. The AIC and BIC values of the Negative Binomial fitted model (AIC = -192.753, BIC = -144.559) were smaller than those of both the Poisson model (AIC = -174.699, BIC = -129.948), and the non-parametric model (AIC = 125.116, BIC = 138.886), which confirmed the superior fit of the Negative Binomial model.

Table 17. The Results of the SEM Model.

	Variable	Parameter Estimate	Standard Error	p-value
Effects on G	***P***	-0.005	0.002	0.004
	T15	-0.127	0.016	<.0001
	BI	-0.144	0.019	<.0001
	Arterial	0.087	0.012	<.0001
	Maint	0.124	0.014	<.0001
	AI	0.046	0.017	0.006
Direct Effects on Crashes	***G***	-3.271	1.079	0.002
	Arterial	1.801	0.741	0.015
	lnMVK	0.25	0.147	0.089
	lnD	1.103	0.177	<.0001
Indirect Effects on Crashes	***P***	0.016	0.008	0.044
	T15	0.414	0.145	0.004
	BI	0.472	0.164	0.004
	Arterial	-0.285	0.1	0.004
	Maint	-0.406	0.145	0.005
	AI	-0.151	0.074	0.04
Intercepts	***G***	0.441	0.016	<.0001
	Crashes	-5.11	0.832	<.0001
Residual Variances	***G***	0.006	0.001	<.0001
Dispersion	***Crashes***	0.953	0.437	0.029

$$\boldsymbol{G} = 0.44 - 0.005\,\boldsymbol{P} - 0.13\,\boldsymbol{T15} - 0.14\,\boldsymbol{BI} + 0.09\,\boldsymbol{Arterial} + 0.05\,\boldsymbol{AI} + 0.12\,\boldsymbol{Maint} \quad (29)$$

$$\boldsymbol{Collision\ Counts} = 6\ x\ 10^{-3}\ \boldsymbol{D}^{1.10}.\ \boldsymbol{MVK}^{0.25}.\ \boldsymbol{exp}^{-3.27\,\boldsymbol{G} + 1.80\,\boldsymbol{arterial}} \quad (30)$$

The results of the model were in line with the previous analyses shown in this thesis. As previously concluded in the pavement friction regression model, weather and maintenance operation variables had significant effects on pavement friction. Moreover, the effects of pavement friction as well as exposure variables on collision counts during snowstorms were further consolidated as predicted by the collision count models. Therefore, and to avoid redundancy, the additional effects that the independent variables had on *Crashes* will be the sole focus of discussion in this section.

The model showed two types of variables. The first type was exogenous variables which were not influenced by any other variable in the analysis. These include *P, T15, BI, Arterial, Maint, AI, T, lnMVK, lnD, and T.* The second type was endogenous variables which depended on other variables in the analysis and were represented by *G* in the model. Although previous collision count models, presented in this study, were unsuccessful in finding a statistically significant relationship between most independent variables and collisions (possibly due to their small sample size), in this framework, pavement friction successfully mediated these relationships. In other words, the variables *P, T15, BI, AI,* and *Maint* were found to have an indirect effect on collisions through influencing the pavement friction coefficient variable *G* while exposure variables *lnD* and *lnMVK* had a direct effect on collisions. Additionally, the variable *Arterial* demonstrated two effects on collisions, a direct effect and an indirect effect through *G*. All these effects are discussed fully later.

The model successfully demonstrated the indirect effect of precipitation on collisions. Precipitation was found to have a statistically significant negative effect on collisions through pavement friction. This means that as precipitation during snowstorms increases, pavement friction worsens, which increases collision counts. This finding is in line with the conclusions of previous papers that studied the direct effect of precipitation on collisions [20], [34], [35], [56].

Similarly, temperature showed a statistically significant indirect effect on collisions through pavement friction. As expected, snowstorms with lower temperatures result in poorer road surface conditions (RSC), which in return, increases the risk of collisions as indicated by the model.

Equally important, the formation of black ice on the road surface was confirmed to be a very dangerous phenomenon for drivers. Slippery conditions left by black ice, not only worsen pavement friction but also indirectly increase collision risks during snowstorms as shown by the model.

The significant impacts of the WRM operations in reducing collision counts were seen in the indirect effects of anti-icing and plowing operations on collisions. Although both variables were found to have no statistically significant direct impacts on collisions (as reported previously in the thesis), using pavement friction as a mediator showed a positive indirect effect of both variables on collisions. This means that whenever anti-icing chemicals are applied, or plowing operations are conducted, both pavement friction, as well as road safety are shown to improve. This is the first time that the impacts of the different tools of the WRM program had been studied and quantified.

Interestingly, the variable *Arterial* was shown to have two different and conflicting effects on road safety, a direct and indirect effect through pavement friction. As discussed in the previous chapter, the higher traffic volumes that arterials receive, combined with the higher speed limits that they have, and the inherent difference in drivers' behavior while traveling on them, all make them relatively more susceptible to collisions than collector roads. This effect was captured in the SEM model as a direct negative effect which shows the relatively higher risk of driving on arterial roads (compared to their collector counterparts). However, since arterial roads have better maintenance response times and receive de-icing operations more frequently than collector roads, they were found safer than collector roads indirectly through the mediator variable pavement friction. When combining the direct and indirect effects of the variable *Arterial* on collision counts, the total effect leaned towards increasing collisions due to the higher impact of the direct effects of the variable. This finding alone can justify why arterial roads should be prioritized over collectors in any WRM hierarchy plan.

6.4 Model Application

To demonstrate how the SEM model summarized in Table 17 can be used to estimate the safety outcome of a snowstorm, consider the following hypothetical scenario. Say a moderate to severe snowstorm event with a duration of 21 hours was expected to hit the city. During the hypothetical snowstorm, the temperature is expected to drop below -15°C, total precipitation is forecasted to be 5mm of equivalent snow, and the conditions suggest the potential formation of black ice on the roads. The relationship between the predicted number of collisions on arterials during this snowstorm and the exposure variable MVK can be plotted as shown in Figure 11.

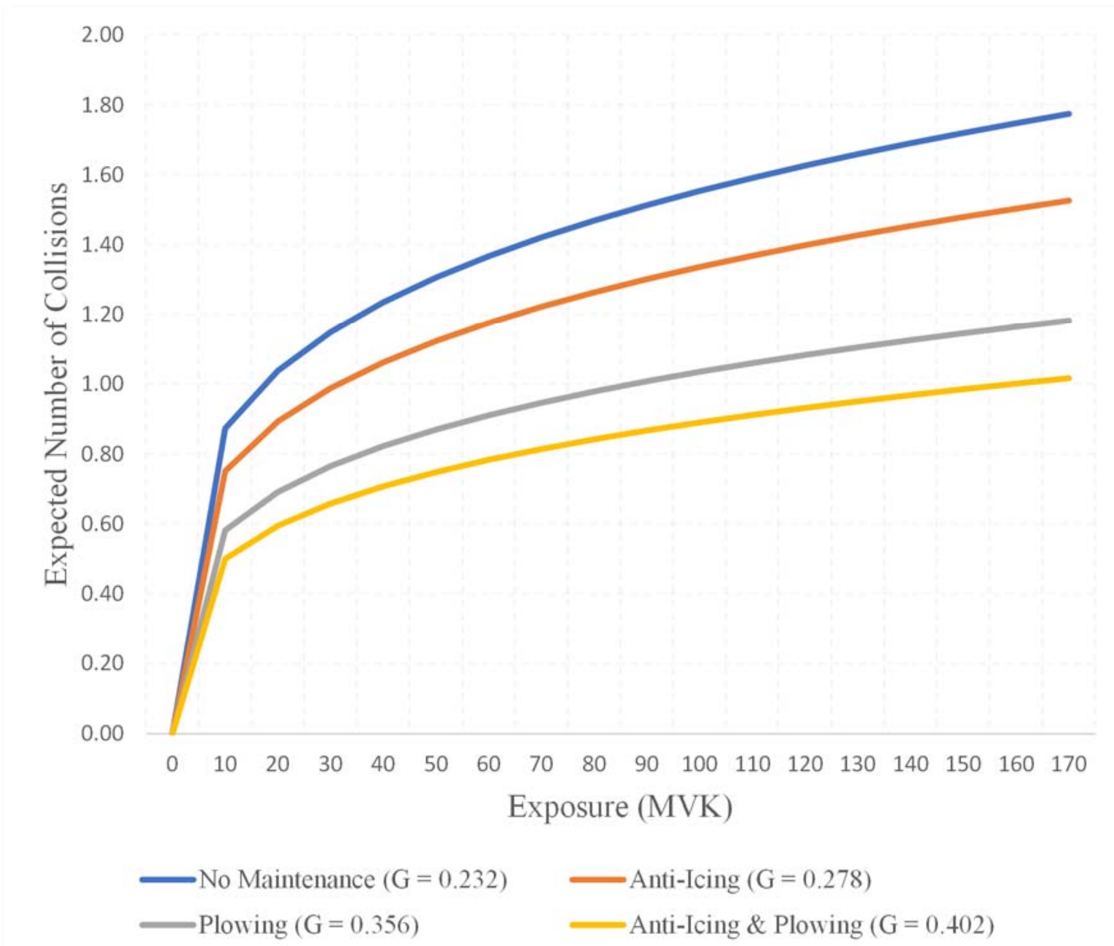

Figure 11. The Expected Number of Collisions on Arterials During a 21-Hour Long Snowstorm

The graph highlights the role of the WRM operations in improving traffic safety during snowstorms. According to the graph, the expected number of collisions on arterials that do not receive any maintenance operations is significantly higher than on roads that receive plowing or anti-icing operations. During a moderate to severe snowstorm that lasts 21 hours with weather conditions as described above, the expected pavement friction coefficient on arterial roads that receive no maintenance operations would be 0.232, which would result in 1.72 collisions per snowstorm at 150 MVK. Arterial roads with the same exposure where they receive anti-icing, plowing, or both would have varying pavement friction coefficients of 0.278, 0.356, and 0.402, respectively. This will result in a significantly fewer expected number of collisions of 1.48, 1.15, and 1 collisions per snowstorm, respectively.

The significance of the WRM operations can be further emphasized if we calculate the expected percent of collision reduction that is associated with deploying each tool of the maintenance operations. Using the same hypothetical snowstorm described above, the expected reduction in collisions per snowstorm on arterials where anti-icing chemicals have been applied is 14%. Plowing operations would reduce the expected number of collisions per snowstorm by 33%. Ultimately, combining the two tools would further reduce the expected number of collisions per snowstorm by 42%.

The expected reductions in collisions can be translated into dollar values. On average, there are 80 snowstorms per year in Edmonton. Assuming that at least 20 of them would be as severe as the hypothetical example, then it can be assumed that 14.4 collisions per arterial road per year would be eliminated from the roads when WRM operations are conducted (reduction of 0.72 collisions per snowstorm multiplied by the number of similar severe snowstorms per year). Assuming that there are at least 100 arterial roads in Edmonton and that the average cost of property damage only collisions in Alberta is $10,900 [96], it can be demonstrated that WRM directly saves over $15 million annually from road safety alone.

It is also worth noting that the expected percent of collision reduction and the expected financial savings would increase exponentially if roads with higher exposure were selected or if more severe snowstorms were forecasted, or more severe collisions were considered.

7. CONCLUSIONS

This chapter summarizes all the major findings of the thesis, identifies the limitations, and provides an insight into future research directions. The chapter is divided into four subsections. The first subsection gives an overview of the thesis, the second subsection provides a summary of all the key findings, the third subsection illustrates the research contributions, and the final subsection shows the limitations and future research.

7.1 Overview of Thesis

There is a need to quantify the benefits of different maintenance operations tools in achieving bare pavement and improving road safety. This will potentially improve decision-making in choosing the appropriate winter maintenance strategies and optimizing limited resources. This thesis presents a data-driven and evidence-based framework for predicting the variation in the coefficient of pavement friction on winter roads and understanding the impacts of the winter road maintenance (WRM) program in improving pavement friction and road safety during snowstorms. The framework used is an event-based and location-specific methodology that serves to isolate the events of interest in a disaggregated analysis.

Several data sources were combined to conduct such a microscopic analysis. Historical weather data was collected and processed, then, snowstorm events were defined and created. Using the timestamps of the start of snowstorms and their durations, maintenance operations data, friction testing data, and collision data were merged with the snowstorm datasets to create a series of unified databases for the study.

7.2 Summary of Key Findings

The work in this thesis focused on understanding the importance of WRM operations in improving road surface conditions (RSC) and road safety during snowstorms. This was addressed by pursuing three objectives:

Pavement Friction Modeling

Firstly, multi-linear regression was used to model the response variable "*G*" which stands for the pavement friction coefficient on roads during snowstorms. The developed model used a combination of weather variables and maintenance operations variables to explain the variability in the coefficient of friction for urban roads during snowstorms. As evident from the R^2 value of

0.7233, the model had high explanatory and predicting powers and was found to be a good fit for the data.

The results showed that the plowing operations during snowstorms and the application of anti-icing chemicals before snowstorms had a statistically significant impact on improving the friction coefficient on winter roads. Moreover, the frequency of applying the de-icing chemicals and the response time of the maintenance operators to start plowing roads were also found to be significant factors in predicting pavement friction. Contrarily, precipitation, extremely low temperatures, and the potential for black ice formation all had statistically significant negative effects on pavement friction.

Traffic Collision Modeling

Likewise, the impacts of pavement friction and the WRM program on traffic safety were studied using safety performance functions or collision prediction models. Several models were created using different statistical modeling techniques, each tailored to explain certain aspects of the driving conditions and collision occurrence during snowstorms.

The preliminary models showed a strong statistically significant relationship between pavement friction and road safety. This was demonstrated multiple times as collision counts were always found to increase whenever pavement friction declined. Further, it was shown that the risks of driving during snowstorms vary dramatically depending on the friction coefficients on the roads. According to the models, collisions were expected to significantly decrease whenever pavement friction was above 0.6, while at conditions where pavement friction deteriorated to below 0.35, collisions were predicted to significantly increased. These findings, as documented in the thesis, along with the pavement friction prediction model can be used to predict and assess the safety of arterial and collector roads during snowstorms. Also, by adopting a minimum pavement friction value of 0.35 as the threshold for safe driving, these findings could prove invaluable in decision-making. If a severe snowstorm event is forecasted, and the friction coefficient on the roads is predicted to drop below this value, aggressive proactive measures could be taken to mitigate the effects of such snowstorms. These measures could include the use of anti-icing chemicals before the snowstorm, increasing the frequency of the de-icing operations, or requesting additional plowing resources depending on forecasted snowstorms severities. Furthermore, the cut-off values for each level of service category of driving conditions could be used as performance indicators by the WRM operators. By calculating the average times in which the road network remained at each category of the defined levels of service, the performance and effectiveness of the program can be evaluated and compared with previous years or even other jurisdictions.

Quantifying The Impacts of WRM Operations on Road Safety

Structural equation modeling (SEM) and path analysis statistical techniques were used to combine the different relationships established to describe pavement friction and collision occurrence into one model that can tell the whole story. SEM allowed us to investigate the direct and indirect relationships between the independent variables and road safety. By using pavement friction as a mediating variable, the indirect influences of the independent variables on road safety were identified. It was revealed that precipitation, extremely low temperatures, and the black ice potentials all had indirect significant negative effects on road safety. On the contrary, plowing operations and the application of anti-icing were shown to have significantly improved road safety indirectly. Interestingly, one variable in particular (*Arterial)* appeared to have both a direct and an indirect relationship with collisions. By examining the magnitude of both impacts, the resulting total effect leaned towards increasing collisions. Had SEM not been implemented and used in this study, these significant indirect impacts would have remained hidden, and the influences of the different tools of WRM on road safety would have continued to be unknown to date.

It is worthwhile mentioning that SEM helped improve our understanding of how the different variables can affect road safety during snowstorms either directly or indirectly. Snowstorms can now be viewed as closed systems where inputs of variables are added to impact the driving conditions and result in an outcome of collisions. In the framework described, exogenous variables, which include weather, maintenance operations, and exposure variables are added to the system and allowed to interact. This interaction results in an immediate impact on the system which can be observed as a decline in the pavement friction coefficient. Ultimately, this causes the deterioration of the RSC which could result in unfavorable outcomes which is the occurrence of collisions. Different inputs to the system could influence the outcomes in different ways. Some inputs directly increase the chance of collisions while others only influence collisions indirectly by affecting the driving conditions. Additionally, some variables could have both effects as depicted in an easy-to-understand diagram.

7.3 Research Contributions

The methodological framework constructed, and the models developed in this thesis have various academic and practical contributions. The findings can help transportation agencies make more informed decisions to promote an efficient mobilization of existing WRM services and resources while improving the safety of the traveling public during the winter months. Furthermore, the work presented in this thesis has, *methodologically and practically*, contributed the followings:

- **Quantified the benefits that the different tools used in WRM have in improving RSC and traffic safety.** Very limited research attempted to answer this question of understanding how WRM operations help improve RSC and traffic safety. All the studies that attempted to understand the influence of WRM have been conducted in a controlled manner. The work shown in this research directly answers this question by showing how plowing, anti-icing, and salting and sanding operations contribute to improving driving conditions during snowstorms.
- **Illustrated the weather factors that significantly affect RSC and urban road safety during snowstorm events.** Previously, the research done in this area has been limited to lab experiments, controlled field studies, or rural highways where the driving behavior and conditions are inherently different. The work in this research focused on urban arterial and collector roads within the limits of the city of Edmonton. In a city with such adverse weather conditions, all the weather variables that can significantly influence pavement friction and traffic safety have been identified. Furthermore, using weather and maintenance operations factors, models were created that can predict how severe snowstorms can worsen driving conditions by compromising pavement friction.
- **Established ranges of pavement friction coefficients where roads were significantly safer or more dangerous for drivers.** The city has historically adopted pavement friction coefficient ranges where roads were deemed safe or unsafe for driving which was based mainly on experience. In this research, scientifically backed new ranges were proposed.
- **Justified the hierarchical priority plan most cities use in prioritizing arterial roads over collectors.** Historically, cities maintain arterial roads more rapidly and frequently when compared to collectors. This was mainly done because arterials carry more traffic volumes. In return, this has resulted in that arterials have, on average, better pavement friction than collectors. It was shown in this research that despite receiving more

maintenance and having better than average pavement friction, arterials remain more vulnerable to winter collisions than collector roads.

- **Quantified the direct and indirect effects of different factors on road safety during snowstorms using the statistical technique of SEM.** There has been very limited research that deploys this statistical analysis technique in the field of road safety. In this research, SEM was utilized, and its capabilities of obtaining the direct and indirect effects of weather and maintenance operations variables in influencing collisions. Without using SEM, the effects of the different tools of the WRM operations on road safety would have remained unknown.
- **Constructed an event-based and location-specific framework that can isolate the weather, maintenance operations, and RSC during the time of snowstorms.** Advanced the use of the event-based and location-specific framework that was previously shown in the literature by incorporating more datasets into the analysis and asking different research questions.

7.4 Limitations & Future Research

The event-based and location-specific study presented herein is disaggregate and microscopic in nature that aims to isolate and analyze the conditions of each individual snowstorm. For this reason, the analysis was very reliant on the high granularity of data, and due to the occasional lack of supporting datasets, several assumptions had to be made. For instance, the actual timing of the plowing maintenance operations had to be assumed in several snowstorm events. Whenever this assumption was made, it was based on the city's snow clearing policy and the recorded RSC during the pavement friction testing. In addition, the annual average daily traffic volumes were used as a surrogate traffic demand measure in lieu of the actual traffic volumes during snowstorms which were not recorded.

The work can be extended in several directions. Since the framework presented could easily be replicated and expanded to include more variables and effects that influence pavement friction and road safety during snowstorms, more frequent data collections accompanied by larger pavement friction testing routes as well as traffic counting on shorter intervals would be recommended. These would result in a more refined and conclusive analysis and a better understanding of the winter maintenance operations' effects on road safety. The framework provided can also be used to study how adverse weather conditions during snowstorms or similar events can increase delays on the road network, and how it affects driving behavior and trends.

Moreover, equipping the pavement friction testing vehicle with GPS trackers and onboard cameras that can record the RSC could be very beneficial. The combination of video footage and GPS timestamps can help create geocoded maps of the RSC during snowstorms which in return can result in modeling of the RSC over two analysis domains - *space* and *time*.

BIBLIOGRAPHY

[1] "WTO | Trade Statistics - World Trade Statistical Review 2020." https://www.wto.org/english/res_e/statis_e/wts2020_e/wts20_toc_e.htm (accessed Apr. 26, 2021).

[2] United States. Department Of Transportation. Bureau Of Transportation Statistics, "Transportation Statistics Annual Report 2018," 2018, doi: 10.21949/1502596.

[3] S. C. Government of Canada, "Vehicle registrations, by type of vehicle," Sep. 10, 2020. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=2310006701 (accessed Apr. 26, 2021).

[4] "Canada: road vehicle mileage," *Statista*. https://www.statista.com/statistics/485450/road-vehicle-mileage-in-canada/ (accessed Apr. 26, 2021).

[5] "Suez Canal Traffic Backlog Finally Cleared Following the Ever Given Saga," *NPR.org*. https://www.npr.org/2021/04/03/984111501/suez-canal-traffic-backlog-finally-cleared-following-the-ever-given-saga (accessed Apr. 26, 2021).

[6] "Suez blockage is holding up $9.6bn of goods a day," *BBC News*, Mar. 26, 2021. Accessed: Apr. 26, 2021. [Online]. Available: https://www.bbc.com/news/business-56533250

[7] World Health Organization, *Global status report on road safety 2018*. Geneva: World Health Organization, 2018. Accessed: Apr. 26, 2021. [Online]. Available: http://www.freefullpdf.com/#gsc.tab=0&gsc.q=traffic%20safety%20ISBN%202019&gsc.sort=

[8] S. Chen, M. Kuhn, K. Prettner, and D. E. Bloom, "The global macroeconomic burden of road injuries: estimates and projections for 166 countries," *Lancet Planet. Health*, vol. 3, no. 9, pp. e390–e398, Sep. 2019, doi: 10.1016/S2542-5196(19)30170-6.

[9] E. L. Chao, "National Freight Strategic Plan," p. 118.

[10] OECD, "Highlights of the International Transport Forum 2013." 2014. [Online]. Available: https://www.oecd-ilibrary.org/content/publication/itf_highlights-2013-en

[11] C. of Edmonton, "The Way We Move: Transportation Master Plan," May 06, 2021. https://www.edmonton.ca/city_government/city_vision_and_strategic_plan/the-way-we-move.aspx (accessed Jun. 05, 2021).

[12] C. of Edmonton, “Safe Mobility Strategy,” Jun. 05, 2021. https://www.edmonton.ca/transportation/traffic_safety/safe-mobility-strategy.aspx (accessed Jun. 05, 2021).

[13] C. of Edmonton, “ConnectEdmonton,” Jun. 05, 2021. https://www.edmonton.ca/city_government/city_vision_and_strategic_plan/connectedmonton.aspx (accessed Jun. 05, 2021).

[14] C. of Edmonton, “Motor Vehicle Collisions,” Mar. 13, 2021. https://www.edmonton.ca/transportation/traffic_safety/motor-vehicle-collisions.aspx (accessed Mar. 13, 2021).

[15] L. Qiu and W. A. Nixon, “Effects of Adverse Weather on Traffic Crashes: Systematic Review and Meta-Analysis,” *Transp. Res. Rec.*, vol. 2055, no. 1, pp. 139–146, Jan. 2008, doi: 10.3141/2055-16.

[16] “Snow & Ice - FHWA Road Weather Management.” https://ops.fhwa.dot.gov/weather/weather_events/snow_ice.htm (accessed Mar. 13, 2021).

[17] D. Akin, V. P. Sisiopiku, and A. Skabardonis, “Impacts of Weather on Traffic Flow Characteristics of Urban Freeways in Istanbul,” *Procedia - Soc. Behav. Sci.*, vol. 16, pp. 89–99, Jan. 2011, doi: 10.1016/j.sbspro.2011.04.432.

[18] Z. Lu, T. J. Kwon, and L. Fu, “Effects of winter weather on traffic operations and optimization of signalized intersections,” *J. Traffic Transp. Eng. Engl. Ed.*, vol. 6, no. 2, pp. 196–208, Apr. 2019, doi: 10.1016/j.jtte.2018.02.002.

[19] A. D. Stern, V. Shah, and L. C. Goodwin, “Analysis of Weather Impacts on Traffic Flow in Metropolitan Washington, DC,” Jan. 2003, [Online]. Available: https://rosap.ntl.bts.gov/view/dot/51762

[20] K. Knapp, D. Kroeger, and K. Giese, “Mobility and Safety Impacts of Winter Storm Events in a Freeway Environment,” p. 86.

[21] “Regional Assessment of Weather Impacts on Freight: Chapter 1 Introduction.” https://ops.fhwa.dot.gov/publications/fhwahop16044/chap1.htm (accessed Mar. 13, 2021).

[22] D. J. Andrey, “Weather Information and Road Safety,” p. 39.

[23] “FHWA Road Weather Management - Winter Maintenance Virtual Clearinghouse: Technical Briefs.” https://ops.fhwa.dot.gov/weather/resources/publications/tech_briefs/tech_briefs.htm (accessed Mar. 13, 2021).

[24] “Salt Smart Transportation Association of Canada,” *yumpu.com*. https://www.yumpu.com/en/document/view/11245246/salt-smart-transportation-association-of-canada (accessed Mar. 13, 2021).

[25] C. of Edmonton, “Vision Zero,” Apr. 21, 2021. https://www.edmonton.ca/transportation/traffic-safety.aspx (accessed Apr. 22, 2021).

[26] “What is Vision Zero?” https://visionzeronetwork.org/about/what-is-vision-zero/ (accessed Apr. 26, 2021).

[27] “How It Works: Road salt and de-icing,” *Driving*, Dec. 14, 2016. https://driving.ca/auto-news/news/how-it-works-road-salt-and-de-icing (accessed Feb. 25, 2021).

[28] W. R. Trenouth, B. Gharabaghi, and N. Perera, “Road salt application planning tool for winter de-icing operations,” *J. Hydrol.*, vol. 524, pp. 401–410, May 2015, doi: 10.1016/j.jhydrol.2015.03.004.

[29] R. R. Blackburn, National Cooperative Highway Research Program, National Research Council (U.S.), American Association of State Highway and Transportation Officials, and United States, Eds., *Snow and ice control: guidelines for materials and methods*. Washington, D.C: Transportation Research Board, 2004.

[30] *Sustainable Winter Road Operations*, 1st ed. John Wiley & Sons, Ltd, 2018. doi: 10.1002/9781119185161.

[31] X. Shi, “Winter road maintenance: Best practices, emerging challenges and research needs,” *J. Public Works Infrastruct.*, vol. 2, pp. 226–318, Jan. 2010.

[32] S. Nassiri, A. Bayat, and S. Salimi, “Survey of Practice and Literature Review on Municipal Road Winter Maintenance in Canada,” *J. Cold Reg. Eng.*, vol. 29, no. 3, p. 04014015, Sep. 2015, doi: 10.1061/(ASCE)CR.1943-5495.0000082.

[33] M. Gouda and K. El-Basyouny, “Before-and-After Empirical Bayes Evaluation of Achieving Bare Pavement using Anti-Icing on Urban Roads,” *Transp. Res. Rec.*, vol. 2674, no. 2, pp. 92–101, Feb. 2020, doi: 10.1177/0361198120902995.

[34] T. Usman, L. Fu, and L. F. Miranda-Moreno, “A disaggregate model for quantifying the safety effects of winter road maintenance activities at an operational level,” *Accid. Anal. Prev.*, vol. 48, pp. 368–378, Sep. 2012, doi: 10.1016/j.aap.2012.02.005.

[35] T. Usman, L. Fu, and L. F. Miranda-Moreno, “Quantifying safety benefit of winter road maintenance: Accident frequency modeling,” *Accid. Anal. Prev.*, vol. 42, no. 6, pp. 1878–1887, Nov. 2010, doi: 10.1016/j.aap.2010.05.008.

[36] H. Heinijoki, “Influence of the type and condition of tyres and drivers’ perceptions of road conditions on driving speed,” *FinnRa Rep.*, vol. 19, 1994.

[37] L. Gu, T. J. Kwon, and T. Z. Qiu, “A geostatistical approach to winter road surface condition estimation using mobile RWIS data,” *Can. J. Civ. Eng.*, vol. 46, no. 6, pp. 511–521, Jun. 2019, doi: 10.1139/cjce-2018-0341.

[38] L. Gu, M. Wu, and T. J. Kwon, “An Enhanced Spatial Statistical Method for Continuous Monitoring of Winter Road Surface Conditions,” 2020, doi: 10.1139/cjce-2019-0296.

[39] M. Kangas, M. Heikinheimo, and M. Hippi, “RoadSurf: a modelling system for predicting road weather and road surface conditions: Road weather model RoadSurf,” *Meteorol. Appl.*, vol. 22, no. 3, pp. 544–553, Jul. 2015, doi: 10.1002/met.1486.

[40] M. Hippi, M. Kangas, R. Ruuhela, J. Ruotsalainen, and S. Hartonen, “RoadSurf-Pedestrian: a sidewalk condition model to predict risk for wintertime slipping injuries,” *Meteorol. Appl.*, vol. 27, no. 5, p. e1955, 2020, doi: https://doi.org/10.1002/met.1955.

[41] F. Feng, L. Fu, and M. S. Perchanok, “Comparison of alternative models for road surface condition classification,” presented at the Transportation Research Board 89th Annual Meeting, 2010.

[42] R. Omer and L. Fu, “An automatic image recognition system for winter road surface condition classification,” in *13th International IEEE Conference on Intelligent Transportation Systems*, Sep. 2010, pp. 1375–1379. doi: 10.1109/ITSC.2010.5625290.

[43] National Cooperative Highway Research Program, Transportation Research Board, and National Academies of Sciences, Engineering, and Medicine, *Guide for Pavement Friction*. Washington, D.C.: Transportation Research Board, 2009, p. 23038. doi: 10.17226/23038.

[44] W. A. Nixon, “The Potential of Friction as a Tool for Winter Maintenance,” p. 34, 1998.

[45] J.-B. Liu and C.-G. Du, “Study on Prediction Model of Friction Coefficient of Icy Road Surface,” pp. 3389–3396, Jul. 2019, doi: 10.1061/9780784482292.293.

[46] S. Salimi, S. Nassiri, and A. Bayat, “Using lateral coefficient of friction to evaluate effectiveness of plowing and sanding operations,” *Can. J. Civ. Eng.*, vol. 41, no. 11, pp. 977–985, Nov. 2014, doi: 10.1139/cjce-2014-0076.

[47] K. H. Schulze, A. Gerbaldi, and J. Chavet, “Skidding accidents, friction numbers, and the legal aspects involved report of the PIARC technical committee on slipperiness and evenness,” *Transp. Res. Rec.*, vol. 623, pp. 1–10, 1977.

[48] S. Hemdorff, L. Leden, K. Sakshaug, M. Salusjärvi, and R. Schandersson, “Trafiksäkerhet och vägytans egenskaper (TOVE): Slutrapport (Tiedotteita 1075),” *Espoo Finl. VTT Tech. Res. Cent. Finl.*, 1989.

[49] J. Norrman, M. Eriksson, and S. Lindqvist, “Relationships between road slipperiness, traffic accident risk and winter road maintenance activity,” *Clim. Res.*, vol. 15, pp. 185–193, 2000, doi: 10.3354/cr015185.

[50] C.-G. Wallman, P. Wretling, and G. Öberg, *Effects of winter road maintenance: state-of-the-art*. Statens väg-och transportforskningsinstitut, 1997.

[51] G. Comfort, A. S. Dinovitzer, O. M. of T. Research, and D. Branch, *Traction Enhancement Provided by Sand Application on Packed Snow and Bare Ice: Summary Report*. Research & Development Branch, Ontario Ministry of Transportation, 1997. [Online]. Available: https://books.google.ca/books?id=EDm5mgEACAAJ

[52] C. Preus, “Studded tire effects on pavements and traffic safety in Minnesota,” *Highw. Res. Rec.*, no. 418, p. 44, 1972.

[53] D. Lord and F. Mannering, “The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives,” *Transp. Res. Part Policy Pract.*, vol. 44, no. 5, pp. 291–305, Jun. 2010, doi: 10.1016/j.tra.2010.02.001.

[54] P. Ch. Anastasopoulos, A. P. Tarko, and F. L. Mannering, “Tobit analysis of vehicle accident rates on interstate highways,” *Accid. Anal. Prev.*, vol. 40, no. 2, pp. 768–775, Mar. 2008, doi: 10.1016/j.aap.2007.09.006.

[55] F. Chen, X. Ma, and S. Chen, “Refined-scale panel data crash rate analysis using random-effects tobit model,” *Accid. Anal. Prev.*, vol. 73, pp. 323–332, Dec. 2014, doi: 10.1016/j.aap.2014.09.025.

[56] T. Usman, L. Fu, and L. F. Miranda-Moreno, “Accident Prediction Models for Winter Road Safety: Does Temporal Aggregation of Data Matter?,” *Transp. Res. Rec.*, Jan. 2011, doi: 10.3141/2237-16.

[57] A. Theofilatos, “Incorporating real-time traffic and weather data to explore road accident likelihood and severity in urban arterials,” *J. Safety Res.*, vol. 61, pp. 9–21, Jun. 2017, doi: 10.1016/j.jsr.2017.02.003.

[58] M.-H. Pham, A. Bhaskar, E. Chung, and A.-G. Dumont, “Random forest models for identifying motorway Rear-End Crash Risks using disaggregate data,” in *13th International IEEE Conference on Intelligent Transportation Systems*, Sep. 2010, pp. 468–473. doi: 10.1109/ITSC.2010.5625003.

[59] Z. Ye, D. Veneziano, and X. Shi, “Estimating Statewide Benefits of Winter Maintenance Operations,” *Transp. Res. Rec.*, vol. 2329, no. 1, pp. 17–23, Jan. 2013, doi: 10.3141/2329-03.

[60] T. J. Kwon, L. Fu, and C. Jiang, “Effect of Winter Weather and Road Surface Conditions on Macroscopic Traffic Parameters,” *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2329, no. 1, pp. 54–62, Jan. 2013, doi: 10.3141/2329-07.

[61] S. Salimi, S. Nassiri, A. Bayat, and D. Halliday, “Lateral coefficient of friction for characterizing winter road conditions,” *Can. J. Civ. Eng.*, vol. 43, no. 1, pp. 73–83, Jan. 2016, doi: 10.1139/cjce-2015-0222.

[62] E. and C. C. Canada, “Canadian Climate Normals 1981-2010 Station Data - Climate - Environment and Climate Change Canada,” Sep. 25, 2013. https://climate.weather.gc.ca/climate_normals/results_1981_2010_e.html?searchType=stnProx&txtRadius=25&optProxType=city&selCity=53%7C33%7C113%7C30%7CEdmonton&selPark=&txtCentralLatDeg=&txtCentralLatMin=0&txtCentralLatSec=0&txtCentralLongDeg=&txtCentralLongMin=0&txtCentralLongSec=0&txtLatDecDeg=&txtLongDecDeg=&stnID=1867&dispBack=0 (accessed Mar. 16, 2021).

[63] C. of Edmonton, “Snow Clearing Service Levels,” Mar. 23, 2021. https://www.edmonton.ca/transportation/on_your_streets/neighbourhood-roads-winter.aspx (accessed Mar. 23, 2021).

[64] “Current and Historical Alberta Weather Station Data Viewer.” https://acis.alberta.ca/weather-data-viewer.jsp (accessed Mar. 16, 2021).

[65] “About ArcGIS | Mapping & Analytics Software and Services.” https://www.esri.com/en-us/arcgis/about-arcgis/overview (accessed May 22, 2021).

[66] S. Weisberg, *Applied Linear Regression*. John Wiley & Sons, 2005.

[67] M. D. Anderson, K. Sharfi, and S. E. Gholston, “Direct Demand Forecasting Model for Small Urban Communities Using Multiple Linear Regression,” *Transp. Res. Rec.*, vol. 1981, no. 1, pp. 114–117, Jan. 2006, doi: 10.1177/0361198106198100117.

[68] L. de Grange, R. Troncoso, A. Ibeas, and F. González, “Gravity model estimation with proxy variables and the impact of endogeneity on transportation planning,” *Transp. Res. Part Policy Pract.*, vol. 43, no. 2, pp. 105–116, Feb. 2009, doi: 10.1016/j.tra.2008.07.002.

[69] K. B. Modi, D. L. B. Zala, D. F. S. Umrigar, and D. T. A. Desai, “Transportation Planning Models: A Review,” p. 6, 2011.

[70] H. Sun, H. X. Liu, H. Xiao, R. R. He, and B. Ran, “Use of Local Linear Regression Model for Short-Term Traffic Forecasting,” *Transp. Res. Rec.*, vol. 1836, no. 1, pp. 143–150, Jan. 2003, doi: 10.3141/1836-18.

[71] Z. Shan, D. Zhao, and Y. Xia, “Urban road traffic speed estimation for missing probe vehicle data based on multiple linear regression model,” in *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, Oct. 2013, pp. 118–123. doi: 10.1109/ITSC.2013.6728220.

[72] D. Branston and H. van Zuylen, “The estimation of saturation flow, effective green time and passenger car equivalents at traffic signals by multiple linear regression,” *Transp. Res.*, vol. 12, no. 1, pp. 47–53, Feb. 1978, doi: 10.1016/0041-1647(78)90107-7.

[73] “Regression with SAS Chapter 1 – Simple and Multiple Regression.” https://stats.idre.ucla.edu/sas/webbooks/reg/chapter1/regressionwith-saschapter-1-simple-and-multiple-regression/ (accessed Mar. 23, 2021).

[74] J. F. Hair, *Essentials of business research methods.*, Fourth edition. New York : Routledge, 2019.

[75] D. S. Moore, *The basic practice of statistics: instructor’s edition.*, 6th ed. /. New York : W.H. Freeman and Co., 2013.

[76] E. Hauer, *The Art of Regression Modeling in Road Safety*. Cham: Springer International Publishing, 2015. doi: 10.1007/978-3-319-12529-9.

[77] E. Hauer, *Observational before--after studies in road safety: estimating the effect of highway and traffic engineering measures on road safety*. Oxford, OX, U.K.; Tarrytown, N.Y., U.S.A.: Pergamon, 1997.

[78] K. El-Basyouny and T. Sayed, “Comparison of Two Negative Binomial Regression Techniques in Developing Accident Prediction Models,” *Transp. Res. Rec.*, vol. 1950, no. 1, pp. 9–16, Jan. 2006, doi: 10.1177/0361198106195000102.

[79] L. F. Miranda-Moreno, *Statistical Models and Methods for Identifying Hazardous Locations for Safety Improvements*. University of Waterloo, 2006.

[80] J. F. Lawless, “Negative Binomial and Mixed Poisson Regression,” *Can. J. Stat. Rev. Can. Stat.*, vol. 15, no. 3, pp. 209–225, 1987, doi: 10.2307/3314912.

[81] S.-P. Miaou, “THE RELATIONSHIP BETWEEN TRUCK ACCIDEN’I_ AND GEOMETRIC DESIGN OF ROAD _ONS: POISSON VERSUS NEGATIVE BINOMIAL REGRESSIONS,” p. 22.

[82] J. B. Ullman and P. M. Bentler, “Structural Equation Modeling,” in *Handbook of Psychology, Second Edition*, American Cancer Society, 2012. doi: 10.1002/9781118133880.hop202023.

[83] K. A. Bollen and J. Pearl, “Eight Myths About Causality and Structural Equation Models,” in *Handbook of Causal Analysis for Social Research*, S. L. Morgan, Ed. Dordrecht: Springer Netherlands, 2013, pp. 301–328. doi: 10.1007/978-94-007-6094-3_15.

[84] R. B. Kline, *Principles and Practice of Structural Equation Modeling*. Guilford Publications, 2011.

[85] A. F. Hayes, *Introduction to Mediation, Moderation, and Conditional Process Analysis, Second Edition: A Regression-Based Approach*. Guilford Publications, 2017.

[86] K. A. Bollen, *Structural Equations with Latent Variables*. John Wiley & Sons, Inc, 1989.

[87] R. Weston and P. A. Gore, “A Brief Guide to Structural Equation Modeling,” *Couns. Psychol.*, vol. 34, no. 5, pp. 719–751, Sep. 2006, doi: 10.1177/0011000006286345.

[88] Y. Fan *et al.*, “Applications of structural equation modeling (SEM) in ecological studies: an updated review,” *Ecol. Process.*, vol. 5, no. 1, p. 19, Nov. 2016, doi: 10.1186/s13717-016-0063-3.

[89] N. Venkatraman and V. Ramanujam, “Construct validation of business economic performance measures: A structural equation modeling approach,” *BEBR Fac. Work. Pap. No 1148*, 1985.

[90] K. Kim, P. Pant, and E. Yamashita, “Measuring Influence of Accessibility on Accident Severity with Structural Equation Modeling,” *Transp. Res. Rec.*, vol. 2236, no. 1, pp. 1–10, Jan. 2011, doi: 10.3141/2236-01.

[91] A. K. Yadav and N. R. Velaga, "An investigation on the risk factors associated with driving errors under the influence of alcohol using structural equation modeling," *Traffic Inj. Prev.*, vol. 21, no. 4, pp. 288–294, May 2020, doi: 10.1080/15389588.2020.1753039.

[92] P. Najaf, J.-C. Thill, W. Zhang, and M. G. Fields, "City-level urban form and traffic safety: A structural equation modeling analysis of direct and indirect effects," *J. Transp. Geogr.*, vol. 69, pp. 257–270, May 2018, doi: 10.1016/j.jtrangeo.2018.05.003.

[93] S. Gargoum and K. El-Basyouny, "Exploring the association between speed and safety: A path analysis approach," *Accid. Anal. Prev.*, vol. 93, pp. 32–40, Aug. 2016, doi: 10.1016/j.aap.2016.04.029.

[94] "Mplus at a Glance." https://www.statmodel.com/glance.shtml (accessed Jun. 07, 2021).

[95] D. P. MacKinnon, *Introduction to statistical mediation analysis*. New York, NY: Taylor & Francis Group/Lawrence Erlbaum Associates, 2008, pp. x, 477.

[96] P. Leur and L. Thue, "Collision Cost Study. Final Report. Prepared." https://docplayer.net/2395691-Collision-cost-study-final-report-prepared-for-prepared-by-paul-de-leur-phd-p-eng-road-safety-engineer-de-leur-consulting-ltd.html (accessed Jul. 17, 2021).

APPENDIX

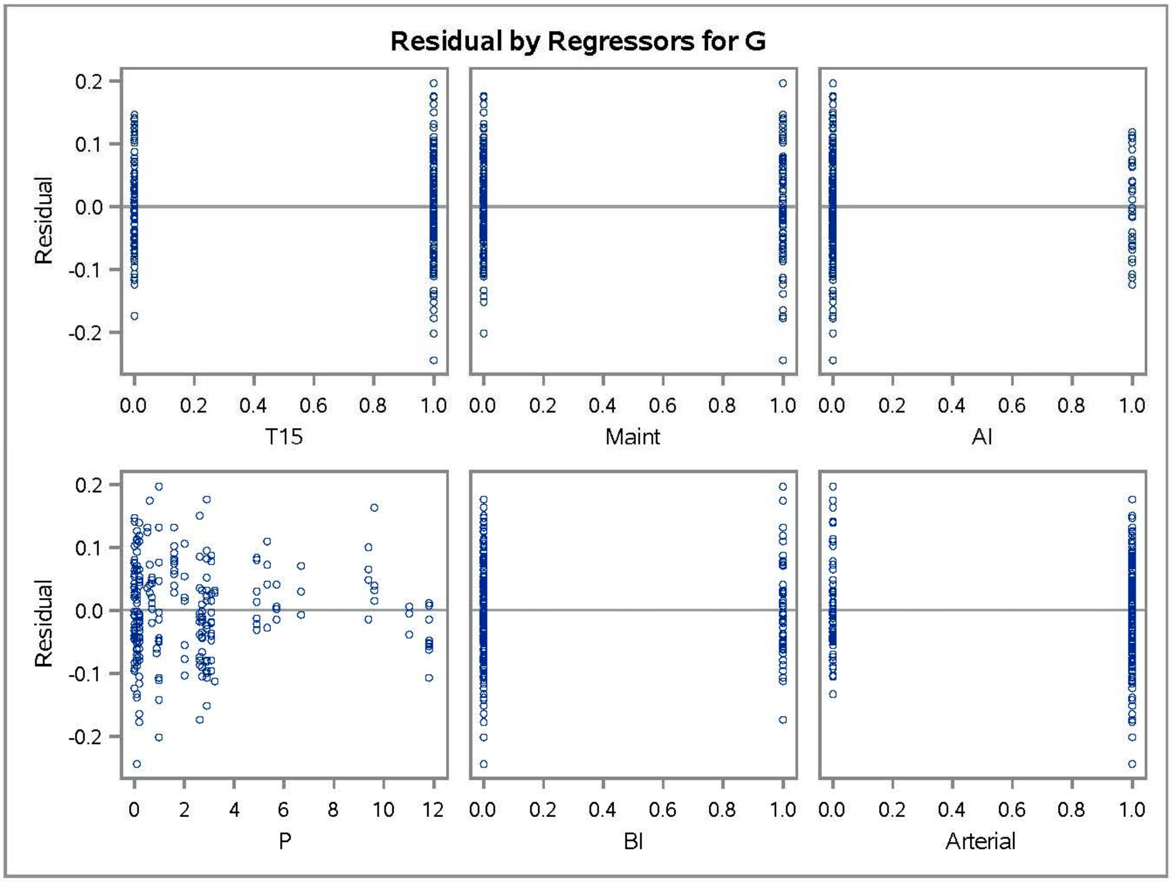

Figure A1. The Pavement Friction Model Residual Plots