Analysis of the King Street Traffic Pilot Project on Improving the Reliability, Speed, and Capacity of Transportation*

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The paper provides a detailed analysis of the King Street transport pilot project, which aims to assess the impact of prioritizing trams over private cars on transport reliability, speed and capacity. Through the modeling and improvement of traffic data, the study gradually optimized the model variables and found that the model after logarithmic transformation performed best, with R-Square = 0.6345, which significantly improved the explanatory power of traffic flow changes. The pilot policy has achieved significant results in reducing traffic pressure at specific intersections and reducing interference from private cars. The effect of the policy is particularly significant on road sections with heavy traffic and during peak hours. In addition, the impact of different time periods and intersection characteristics on traffic patterns shows complex dynamic characteristics, which further indicates that targeted adjustment of traffic signals and optimization of priority policy implementation strategies will help further improve policy effects.

1 Introduction

The King Street Transit Pilot(General Manager, Transportation Services, Chief Planner & Executive Director, City Planning, and Chief Customer Officer, Toronto Transit Commission 2019) is a focused project designed to assess the impact of prioritizing trams over private vehicles on key transportation metrics, including reliability, speed, and capacity. Launched on November 12, 2017, between Bathurst Street and Jarvis Street, the project represents a critical effort to address Toronto's urban mobility challenges in its busiest transit corridor. To evaluate the pilot's effectiveness, baseline traffic and pedestrian data were collected in October and early November 2017. The study employs advanced statistical modeling to analyze traffic

*Code and data are available at: https://github.com/zilin1017/King-Street-Traffic-Pilot-Project.

flow changes, with a specific focus on identifying the impact of the transit-first policy at critical intersections and during peak hours. Through iterative modeling improvements, the study identified that a log-transformed model with provided the strongest explanatory power, highlighting the policy's effectiveness in reducing congestion and enhancing transit efficiency.

The results demonstrate that prioritizing trams significantly reduces private vehicle interference, particularly at high-traffic intersections, and improves overall traffic flow during peak periods. However, the policy's impact varies across different time periods and road sections, revealing complex dynamic characteristics that necessitate targeted adjustments. For example, intersections like Bathurst and Jarvis benefited notably, yet other areas showed less pronounced effects, emphasizing the need for localized signal adjustments and strategy refinements. These findings underline the importance of continuous monitoring and adaptive policy-making to maximize the pilot's benefits. By showcasing how targeted priority measures can enhance urban transit, the study provides actionable insights for refining the King Street project and offers a framework for similar initiatives in other cities.

The overall structure of the paper is arranged as follows. Section 2 introduces the data required for the study, including the data source, the main content of the data, descriptions of all variables, and a detailed introduction and visual analysis of the important variables required in the modeling stage. Section 3 builds a model based on the selected variables, and improves the model in turn through model diagnosis to obtain the final applicable model. The logarithm of the variable is used as the dependent variable of the regression model, and the remaining variables are used as binary variables or multi-classification variables for modeling. Section 4 explains the specific results of the final model and the comparison of the results of the three improved models. Section 5 the final model is diagnosed to illustrate the effectiveness of the model. In the fifth part, the article discusses and analyzes the above results, and introduces the shortcomings of the article in modeling and discussion as well as the direction for future improvement.

2 Data

2.1 Survey Data

This survey data is titled About King St. Transit Pilot - Traffic & Pedestrian Volumes Summary and is available on Open Data Toronto at https://open.toronto.ca/dataset/king-st-transit-pilot-traffic-pedestrian-volumes-summary/. It can be downloaded programmatically via the API, with example `R` code provided in the file "00-download_data.R".This dataset pertains to the King Street Transit Pilot, which commenced on November 12, 2017Toronto (2017b), and was implemented along King Street between Bathurst Street and Jarvis Street. The pilot aimed to prioritize streetcar traffic over private vehicles to improve transit reliability, speed, and capacity. The dataset provides monthly updates on traffic and pedestrian volumes recorded within the pilot area throughout the project, offering valuable data for analyzing the impacts of this transit initiative. It serves as a critical resource for evaluating the effectiveness of the pilot in optimizing urban transit and informing future city planning and transportation policies.

The dataset provides detailed monthly updates on traffic and pedestrian volumes within the King Street Transit Pilot area, covering the stretch between Bathurst Street and Jarvis Street. Data collection was conducted at 21 intersections in the pilot area using a video-based counting system. The collected volumes are categorized into three main groups: vehicles, bicycles, and pedestrians.Each month, data captures approximately one week of activity, with more intensive data collection carried out during the initial months of the pilot. The counts are presented in a structured format, including breakdowns by specific time periods (e.g., AM peak, PM peak) and by intersection approach legs (North, South, East, West) as well as direction of travel (Northbound, Southbound, Eastbound, Westbound).

2.2 Overview

After introducing the source and background of the data, here we will explain how to use the `R` language (R Core Team 2024) functions and some additional packages learned in the course to process the data. Here is a unified overview. The `dplyr` package (Hadley Wickham and dplyr Development Team 2024) is a grammar of data manipulation, providing a consistent set of verbs that help us solve the most common data manipulation challenges. In this package, this article mainly uses the `mutate` function and the `filter`(Tidyverse Development Team 2024a) function, where the `mutate`(Tidyverse Development Team 2024b) function creates new columns that are functions of existing variables. The `filter` function is used to subset a data frame, retaining all rows that satisfy conditions.In the visualization stage, this article uses the `ggplot`(Hadley Wickham and ggplot2 Development Team 2024) package to draw graphics, and when analyzing the results, in order to see the output results more intuitively, this article also uses the `xtable`(David B. Dahl and xtable Development Team 2024) package to convert the results into `LaTex` format for output. Finally, in order to output the variable data that needs to be analyzed, this article also draws on the `arrow`(Apache Arrow Development Team 2024) package recommended in the course to output data in `parquet` format.

2.3 Measurement

First, in order to better understand the data variables, the variable names and their specific explanations are given in Table 1.

After further analysis of the data set, we found that the first column, named `id`, indicates the number of data in the data set, and the second column, named `aggregation_period`, indicates the time when the data was collected. These are irrelevant to the variables required for model building, so they are no longer used in subsequent data analysis. The third column, named

Variable Name	Description
aggregation_period	Month or baseline period for the data collection. Represents the time frame of aggregated counts.
int_id	Unique identifier for each intersection. Can be linked to the intersection geometry dataset.
intersection_name	Name of the intersection where data was collected.
px	Traffic signal ID, which can be joined to the traffic signal dataset for additional details.
classification	Category of observed traffic users. Differentiates between pedestrians, vehicles, and cyclists.
dir	Direction of travel at the intersection, including Northbound (NB), Southbound (SB), Eastbound (EB), and Westbound (WB).
period_name	The time period during which data was collected.
volume	Observed count of users (vehicles, bicycles, or pedestrians) during the specified period.

Table 1: Variable descriptions for the King Street Transit Pilot dataset.

intersection_name, indicates the intersection where the data was collected. Since we are verifying Bathurst Street and Jarvis Street, we assign 1 to the intersection where one of these two streets exists in the data, otherwise 0, to construct a binary dummy variable(contributors n.d.). The fourth column, named px, corresponds to intersection_name, so it is no longer considered again. The fifth column, named classification, indicates Differentiates between pedestrians, vehicles, and cyclists. It is treated as a multi-classification (3-classification) variable in the model building. The last two variables, period_name and volume, cannot be considered as a single period because period_name can distinguish many time periods (subsequent model improvements are also based on this). Therefore, they are considered as multi-classification variables. Finally, volume, a numerical data, is constructed as the dependent variable of the model. At the same time, the data can be transformed accordingly and put into the model (such as logarithmic transformation).

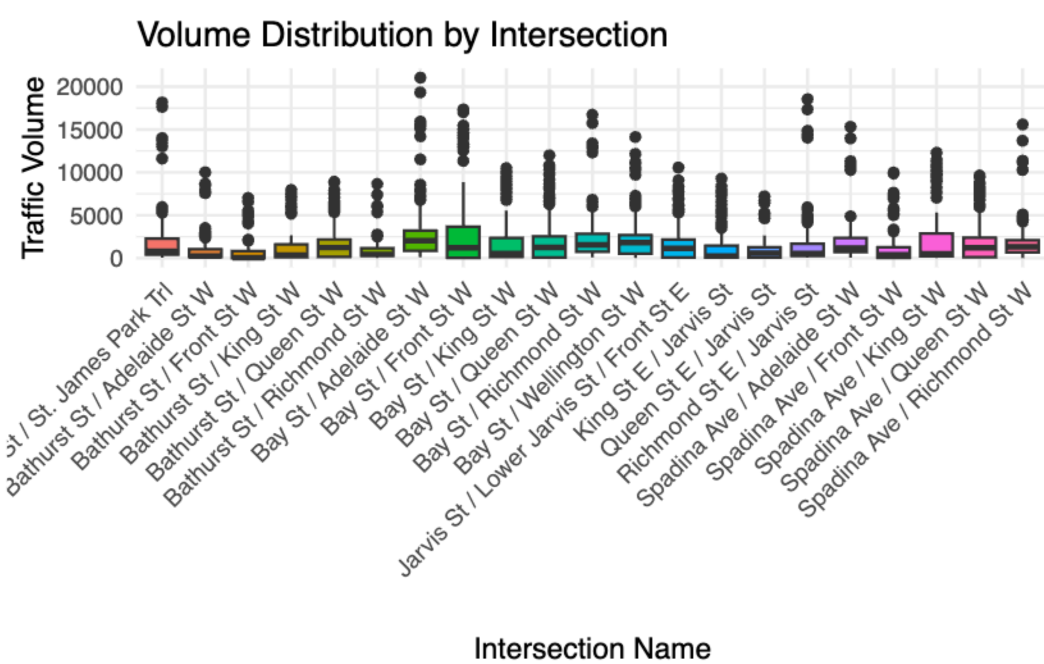
2.4 Statistical analysis of important variables

2.4.1 Variable 1:Intersection_name

The dataset contains 21 unique intersections,as shown in Table 2. The different intersections and statistical numbers are shown in the following table.

Intersection Name	Record Count
Spadina Ave / King St W	432
Queen St E / Jarvis St	384
Jarvis St / Lower Jarvis St / Front St E	384
Spadina Ave / Front St W	384
Bathurst St / King St W	384
Bay St / Front St W	384
Bathurst St / Queen St W	384
Bay St / King St W	384
Spadina Ave / Queen St W	384
King St E / Jarvis St	384
Bay St / Queen St W	384
Bathurst St / Front St W	384
Bathurst St / Richmond St W	256
Richmond St E / Jarvis St	256
Spadina Ave / Richmond St W	256
Bay St / Wellington St W	256
Bay St / Adelaide St W	256
Spadina Ave / Adelaide St W	256
Adelaide St E / Jarvis St / St. James Park Trl	256
Bay St / Richmond St W	256
Bathurst St / Adelaide St W	252

Table 2: Intersection Name Statistics



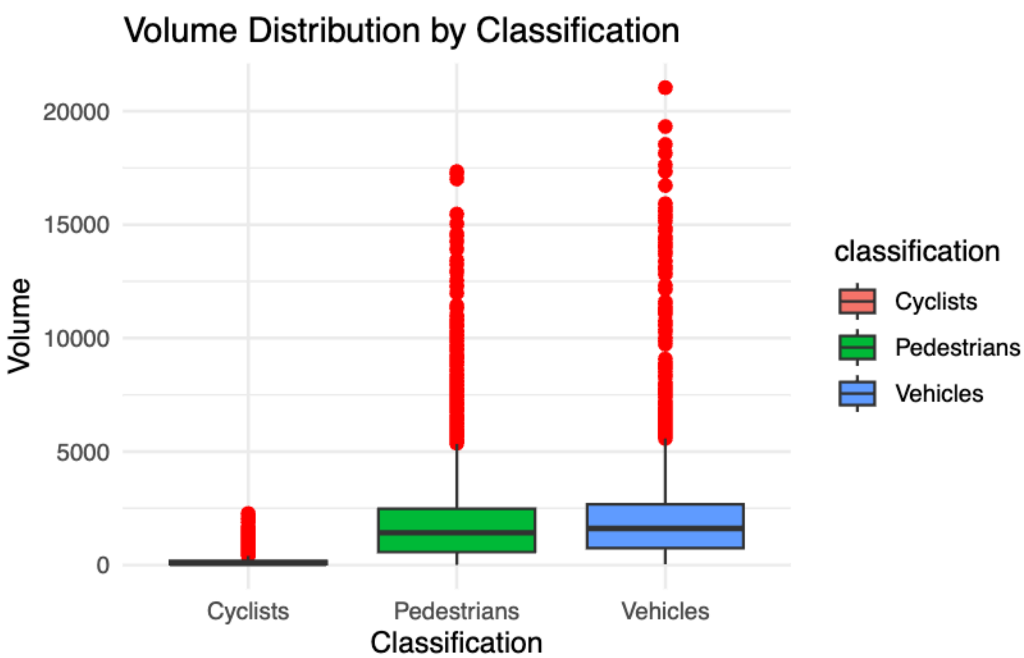
2.4.2 Variable 2:Classification

The dataset contains 3 unique classifications,as shown in Table 3.

Classification	Record Count
Pedestrians	2702
Cyclists	2127
Vehicles	2127

Table 3: Classification Statistics

The box plot of volume distribution by classification reveals distinct traffic patterns, with Vehicles showing the highest median traffic volume of 1,611.0, indicating that vehicles dominate traffic activity in the dataset. The interquartile range (IQR) for vehicles spans approximately 900 to 2,800, suggesting significant variability in vehicle activity across different periods or locations. Pedestrians follow with a median volume of 1,422.5 and a narrower IQR of 800 to 2,200, reflecting consistent foot traffic but at slightly lower volumes than vehicles. Cyclists, on the other hand, have the lowest median volume of 74.0, with an IQR of 50 to 150, indicating limited bicycle activity in comparison to the other classifications. Outliers are particularly noticeable for vehicles, with some volumes exceeding 5,000, likely representing peak traffic or specific high-demand events.



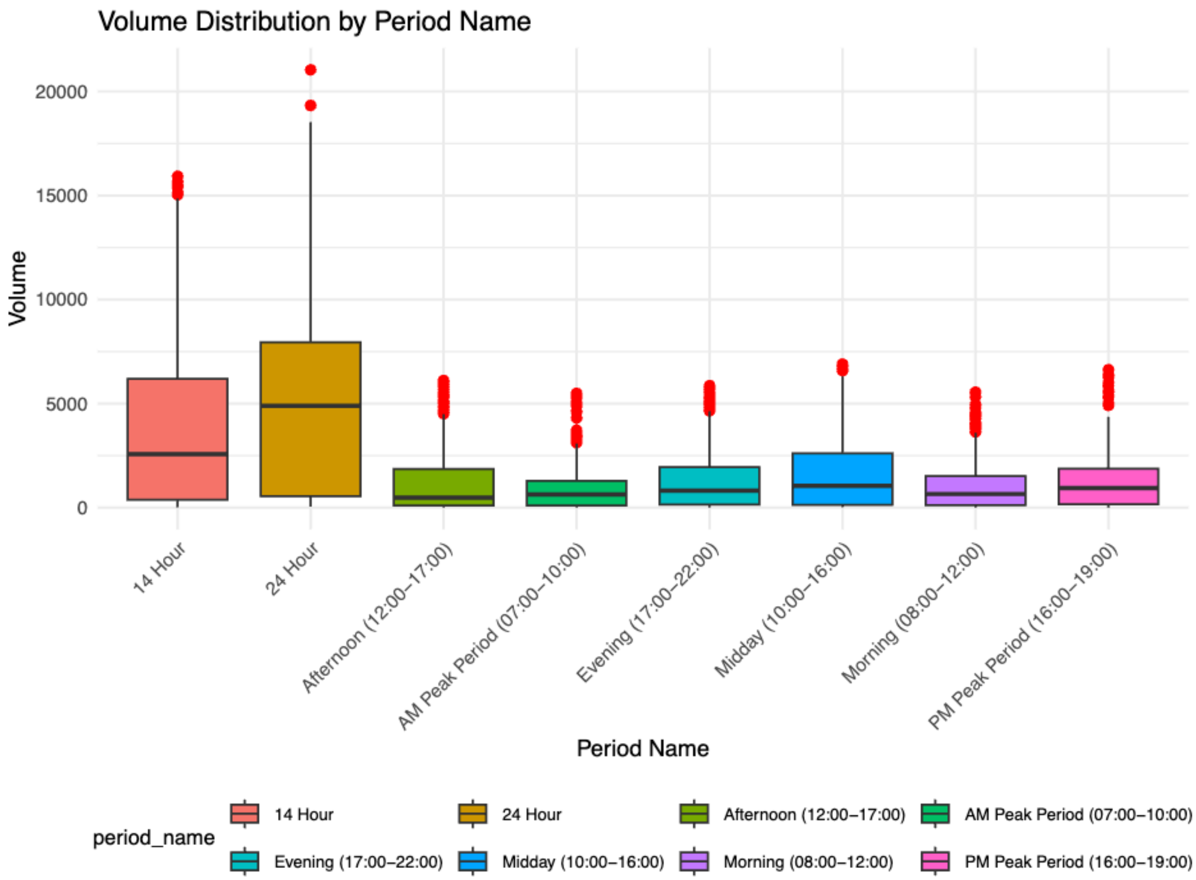
2.4.3 Variable 3:Period_Name

The dataset contains 8 unique period_names,as shown in Table 4.

Period Name	**Record Count**
Afternoon (12:00-17:00)	1080
AM Peak Period (07:00-10:00)	1080
Evening (17:00-22:00)	1080
Morning (08:00-12:00)	1080
PM Peak Period (16:00-19:00)	1080
14 Hour	672
Midday (10:00-16:00)	672
24 Hour	212

Table 4: Period Name Statistics

The box plot of traffic volume by period_name reveals significant differences in traffic patterns across time periods. For example, “PM Peak Period (16:00-19:00)” shows the highest median traffic volume at approximately 2,500, with an interquartile range (IQR) between 1,500 and 4,000, indicating consistent high activity during evening rush hours. Conversely, “24 Hour” has the lowest median volume at around 800, with a narrower IQR (500–1,200), reflecting reduced overall activity over a full day. Outliers are most prominent in “Morning (08:00-12:00)” and “14 Hour”, where some volumes exceed 10,000, potentially due to events or anomalies. Variability is highest during “Afternoon (12:00-17:00)” and “Evening (17:00-22:00)”, with whiskers extending over a wide range.



3 Model

3.1 Model Building

According to the dataset introduction, selection of important datasets, and visualization of single and interactive datasets, we hope to build a model to verify whether the pilot project launched between Bathurst Street and Jarvis Street has improved the reliability, speed and capacity of traffic. Therefor, this article first builds the model as follows: classification (Pedestrians, Cyclists, Vehicles) is used as a categorical variable, and a dummy variable is generated. For the Intersection_name variable containing "Bathurst" or "Jarvis", it is used as a 1-0 variable. If the Intersection_name variable contains "Bathurst" or "Jarvis", we set it to 1, otherwise it is 0. Volume is modeled as the dependent variable, and its mathematical expression is

$$volume = \beta_0 + \beta_1 Pedestrians + \beta_2 Vehicles + \beta_3 interaction_{binary} + \epsilon \tag{1}$$

In the expression, volume represents the dependent variable (traffic volume), Pedestrians represents a dummy variable (indicates whether it is pedestrian data, then the value is 1, otherwise it is 0. Vehicles is also a dummy variable (indicates whether it is vehicle data, if yes, the value is 1, otherwise 0). cyclists is used as the reference group. intersection_binary is a binary variable, indicating whether the intersection is "Bathurst" or "Jarvis". ϵ represents random error, which generally obeys a normal distribution.

The preliminary modeling results are as follows

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	508.9107	47.3276	10.75	0.0000
classificationPedestrians	1824.9326	55.8484	32.68	0.0000
classificationVehicles	2126.6516	59.0786	36.00	0.0000
intersection_binary	-709.9550	46.2475	-15.35	0.0000

Table 5: Modeling results of the initial model

After linearity, homogeneity of variance, and residual normality tests, it was found that the results were not ideal. From the visualization diagram((Appendix B_1), it can be seen intuitively that it does not meet the assumptions required by the linear model, so the model needs to be improved.

3.2 Model Improvements

In order to further improve the model, we consider adding the period_name variable. Because the volume of different time periods varies greatly, we add the period_name variable as a multi-classification variable to the original model for modeling in the improved model. Its mathematical expression is

$$volume = \beta_0 + \beta_1 Pedestrians + \beta_2 Vehicles + \beta_3 interaction_{binary} + \sum_{k=1}^{K-1} \beta_{k+3} period_{name_k} + \epsilon \tag{2}$$

In the expression, the former variable has the same interpretation as in model 1, and $period_{name_k}$ is a time period classification variable containing K categories, where K is 8.

The results of the improved model are as follows

After linearity, homogeneity of variance, and residual normality tests, the results are still not ideal. From the visualization diagram(Appendix B_2), we can intuitively see that although it is improved compared to the first model, it still does not meet the basic assumptions required by the linear model. Therefore, the model needs to be further improved.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	2904.2470	70.4428	41.23	0.0000
classificationPedestrians	1828.1000	46.3646	39.43	0.0000
classificationVehicles	2126.6516	49.0462	43.36	0.0000
intersection_binary	-688.9816	38.3977	-17.94	0.0000
period_name24 Hour	1309.1426	125.9938	10.39	0.0000
period_nameAfternoon (12:00-17:00)	-2846.9106	78.5888	-36.23	0.0000
period_nameAM Peak Period (07:00-10:00)	-3056.8523	78.5888	-38.90	0.0000
period_nameEvening (17:00-22:00)	-2697.8773	78.5888	-34.33	0.0000
period_nameMidday (10:00-16:00)	-2333.5967	87.2579	-26.74	0.0000
period_nameMorning (08:00-12:00)	-2970.3300	78.5888	-37.80	0.0000
period_namePM Peak Period (16:00-19:00)	-2733.2106	78.5888	-34.78	0.0000

Table 6: Improved model building results

3.3 Further Model Improvements

Based on the previous two models, due to the large difference in volume, in this model, I took the logarithm of the volume value for modeling analysis. The specific mathematical expression is as follows

$$\log volume = \beta_0 + \beta_1 Pedestrians + \beta_2 Vehicles + \beta_3 interaction_{binary} + \sum_{k=1}^{K-1} \beta_{k+3} period_{name_k} + \epsilon \tag{3}$$

This expression follows the previous results, and for the dependent variable, the logarithm is taken as the dependent variable of the new model, and this model is used as the final model for modeling. The results of the modeling will be elaborated in detail in the next section.

4 Results

Through the above modeling, we obtained a linear model with log-volume as the dependent variable, and binary and multi-classification variables as the independent variables. In this section, we will give the results of the final model, and re-test the assumptions required by the model and give corresponding discussions.

4.1 Model Results

By running the R code, the estimated coefficients, standard deviations, t-values, and p-values of the independent variables are first given.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	5.7476	0.0460	124.84	0.0000
classificationPedestrians	2.6326	0.0303	86.88	0.0000
classificationVehicles	2.8213	0.0321	88.01	0.0000
intersection_binary	-0.5716	0.0251	-22.78	0.0000
period_name24 Hour	0.3836	0.0823	4.66	0.0000
period_nameAfternoon (12:00-17:00)	-1.3993	0.0514	-27.24	0.0000
period_nameAM Peak Period (07:00-10:00)	-1.4924	0.0514	-29.06	0.0000
period_nameEvening (17:00-22:00)	-1.0790	0.0514	-21.01	0.0000
period_nameMidday (10:00-16:00)	-0.9272	0.0570	-16.26	0.0000
period_nameMorning (08:00-12:00)	-1.3773	0.0514	-26.81	0.0000
period_namePM Peak Period (16:00-19:00)	-1.0947	0.0514	-21.31	0.0000

Table 7: Final modeling results

Table 8: Comparison of R^2 Values for Different Models

Model	R^2
model_1	0.2051
model_2	0.4527
log_model	0.6345

The model equation satisfied by the data is

$$\begin{aligned}\log volume = 5.75 + 2.63 Pedestrians + 2.82 Vehicles - 0.57 interaction_{binary} + 0.38 period_{24Hour} \\ -1.40 period_{Afternoon} - 1.08 period_{AMPeak} - 0.928 period_{Midday} \\ -1.37 period_{Morning} - 1.09 period_{PMPeak}\end{aligned} \tag{4}$$

The R^2 values of the three models established are 0.2051, 0.4527, and 0.6345 respectively. From the perspective of R^2, the logarithmic model is the best choice.

The results of the above logarithmic model are diagnosed from the perspectives of linearity, variance homogeneity, and residual normality. From the following figure(Appendix B_3), we can easily see that for the test of linearity (the first figure), the residuals are randomly distributed on both sides of the zero line, without obvious trends or patterns, so the linearity is satisfied. For the variance homogeneity test, it can be seen that the scattered points are evenly distributed along the zero line, satisfying the variance homogeneity. For the residual normality test, the QQ plot points are close to the reference line, so the residuals are close to the normal distribution, and the assumption is satisfied. From the histogram, the residuals are centered at 0 and are symmetrically bell-shaped, so the normality test is satisfied. All tests passed, so the logarithmic model is the final model selected in this article.

From the final expression of the model, it can be seen that when the area is selected on Bathurst Street or Jarvis Street, the volume is significantly reduced. This may be because the priority is given to trams rather than private cars in the area, resulting in a reduction in vehicles. Since this section is the busiest section, the overall actual traffic flow is unlikely to decrease, while the data volume shows a decrease. This is because people choose trams for transportation.

5 Discussion

5.1 Tram priority policy improves traffic capacity

The model results show that by gradually optimizing the model variables, the explanatory power is significantly improved: the basic model (Model 1,$R^2 = 0.2051$) only includes traffic classification and intersection characteristics, and has low explanatory power; the model adding time period variables (Model 2 , $R^2 = 0.4527$) and the model with logarithmic transformation of the dependent variable (Log Model, $R^2 = 0.6345$) can better reflect changes in traffic capacity. Combined with the coefficient analysis of traffic classification variables, the traffic volume contribution of vehicles (Vehicles) is significantly higher than that of cyclists and pedestrians, while the intersection characteristic variables indicate that the traffic volume of "Bathurst" and "Jarvis" is relatively low, which may be related to the pilot policy reduction Related to interference with private vehicle traffic. However, while prioritizing trams may have reduced traffic bottlenecks and improved traffic efficiency, whether the decline in private car traffic has a negative impact on overall traffic capacity requires further verification. From the perspective of the purpose of the policy, if the traffic reduction during peak periods is mainly concentrated on private cars and the tram traffic is stable or even increases, then the policy goal is basically achieved; but if the overall traffic flow drops significantly, the policy effect may need to be refined. analyze. Therefore, further hierarchical analysis of the flow trends of various transportation modes, especially the performance during peak periods, is the key to evaluating the effectiveness of policies.(Higgins et al. 2024)

5.2 Effects of time period and intersection characteristics on traffic reliability and speed

In the improvement of the model, the time period variable significantly improves the explanatory power of traffic flow, while the intersection characteristic variables show that at key intersections such as "Bathurst" and "Jarvis", the traffic volume decreases significantly. Combined with the objectives of the pilot policy, this may reflect improved traffic reliability by reducing tram waiting times by prioritizing tram traffic signal configuration. The variable coefficients of time periods show that traffic patterns vary greatly in different periods, and the implementation effects of priority policies may also change over time. During peak hours, reducing private vehicle traffic may significantly alleviate traffic pressure and increase tram speeds, but during off-peak periods, whether this policy leads to idle resources and low traffic efficiency requires further evaluation. Pilot policies can combine the modeling results of time periods to explore whether priority strategies can be strictly enforced during peak periods and relaxed restrictions on private cars during off-peak periods to manage traffic flow more flexibly.

5.3 Weaknesses and next steps

5.3.1 Analysis of model weaknesses

Although the three models gradually improved their explanatory power (R^2 improved from 0.2051 to 0.6345), there are still some limitations that may affect the comprehensive assessment of policy effects. First, the model only focuses on traffic volume (volume) as the dependent variable and does not directly analyze traffic reliability (such as delay time or waiting time) and speed (such as average traffic speed). Although difficult to quantify directly, these factors are critical to the assessment of policy priorities. In addition, the model assumes that the relationship between variables is linear and may fail to capture complex nonlinear interaction effects. For example, the strength of restrictions on private cars at different times or at specific intersections may significantly affect the flow of other modes of transportation. Secondly, the model does not fully consider the dynamic changes in time and space, especially the short-term or long-term impact of different time periods, weather conditions, events (such as holidays) on traffic patterns, which may lead to biased results.

5.3.2 Next steps

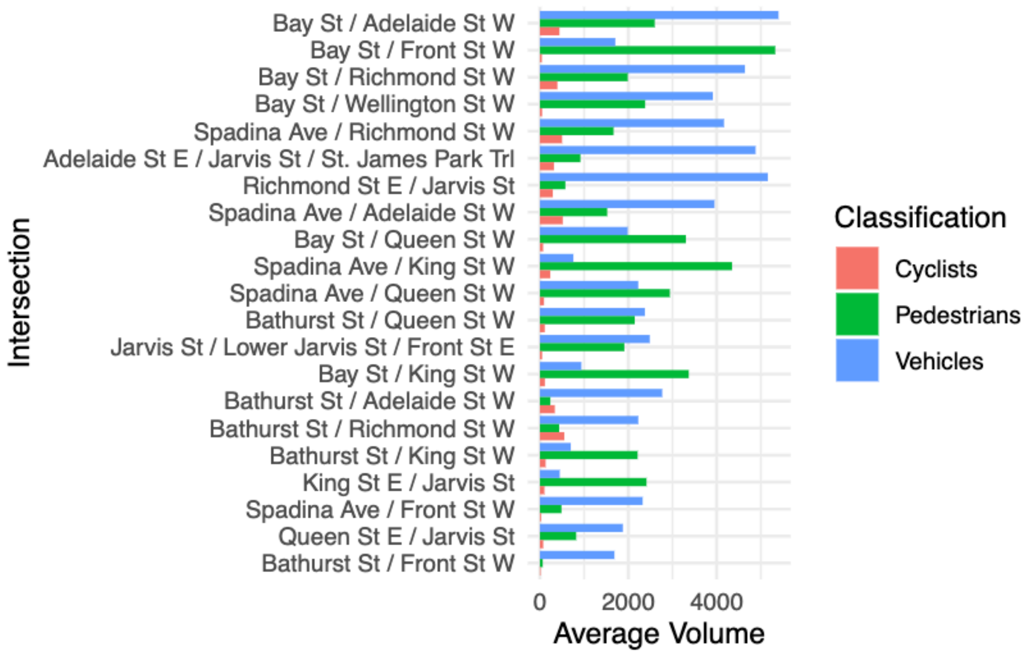
To improve the model from a more specific and small level, we can focus on the following aspects: First, introduce micro indicators such as tram punctuality, average speed per trip, and passenger volume during peak hours to quantify the impact of the policy on traffic reliability and speed, rather than relying solely on traffic volume as a single evaluation indicator. Second, at the intersection level, we can combine specific variables such as signal timing data, vehicle waiting time, and tram passing time at each intersection to analyze the changes in traffic efficiency at different intersections, providing a direct basis for optimizing priority signal control. Finally, increase observations on pedestrian and cyclist traffic, evaluate whether the tram priority policy has a negative impact on the passage of non-motor vehicles and pedestrians, and reduce potential conflicts through intersection design or diversion measures. These specific improvement measures can help more accurately identify detailed problems in policy implementation and provide targeted optimization solutions.

From the perspective of model improvement, we can consider introducing nonlinear models or interaction terms to capture the complex relationship between time periods, intersection characteristics and traffic modes, such as using generalized linear models (GLM), decision trees or random forests to better characterize the nonlinearity and high-order interactions between variables.

6 Appendix

6.1 Appendix A Interaction analysis of data

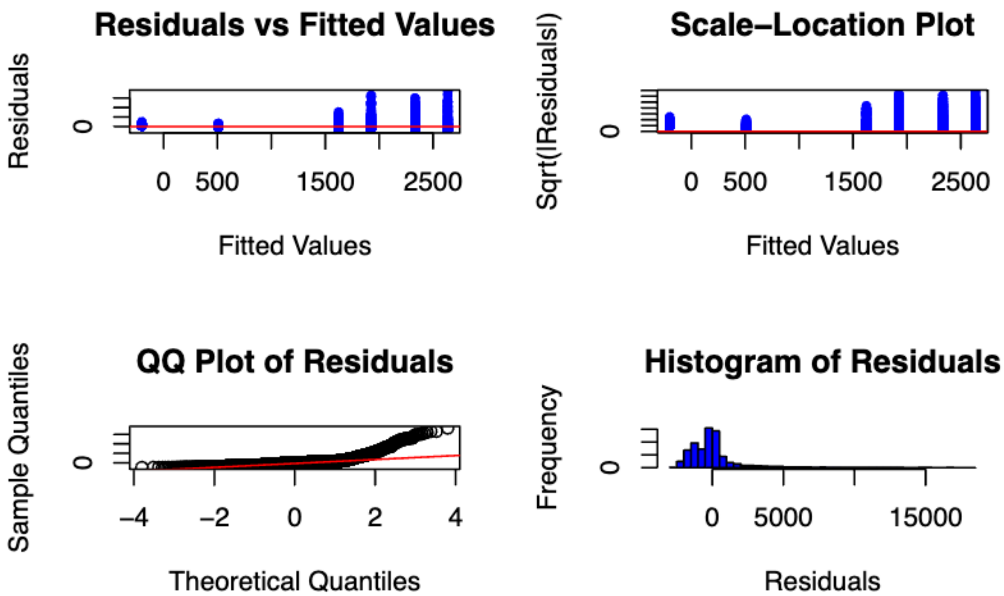
Intersection_name and Classification are combined for analysis. Through visualization, we can clearly see the detailed changes in the volume for different Classifications and different Intersection_names. It can be seen that the comparison of the volume in the pilot Bathurst and Jarvis area.This visualization is similar to the modeling result above, which is due to the negative coefficient of the variable `intersection_binary`.



6.2 Appendix B Model diagnostics visualization results

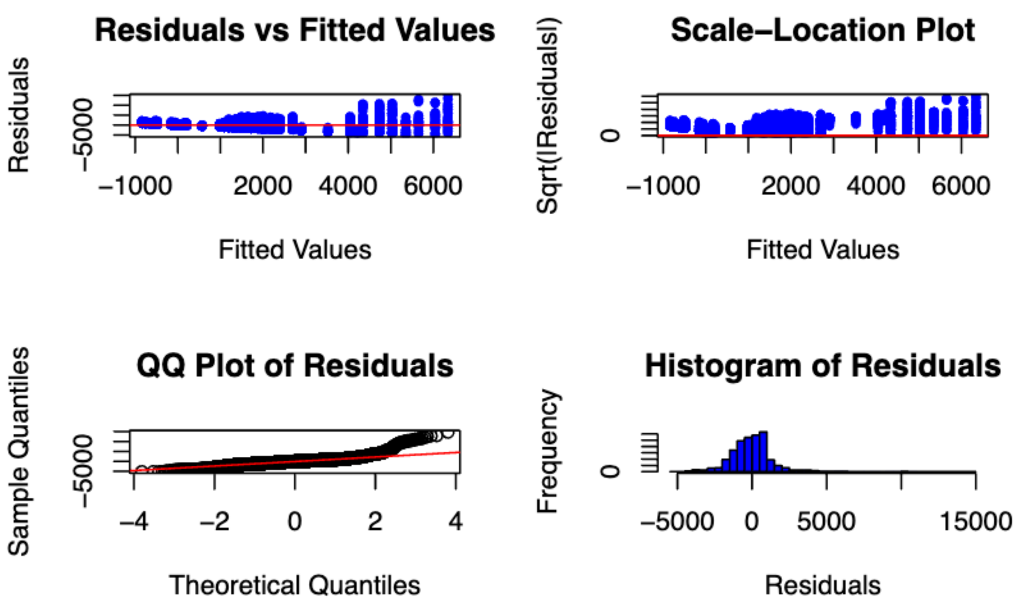
6.2.1 Initial Model Model Diagnostics

Appendix B_1:Judging from the model diagnostic results, the linear model assumptions do not seem to be met.



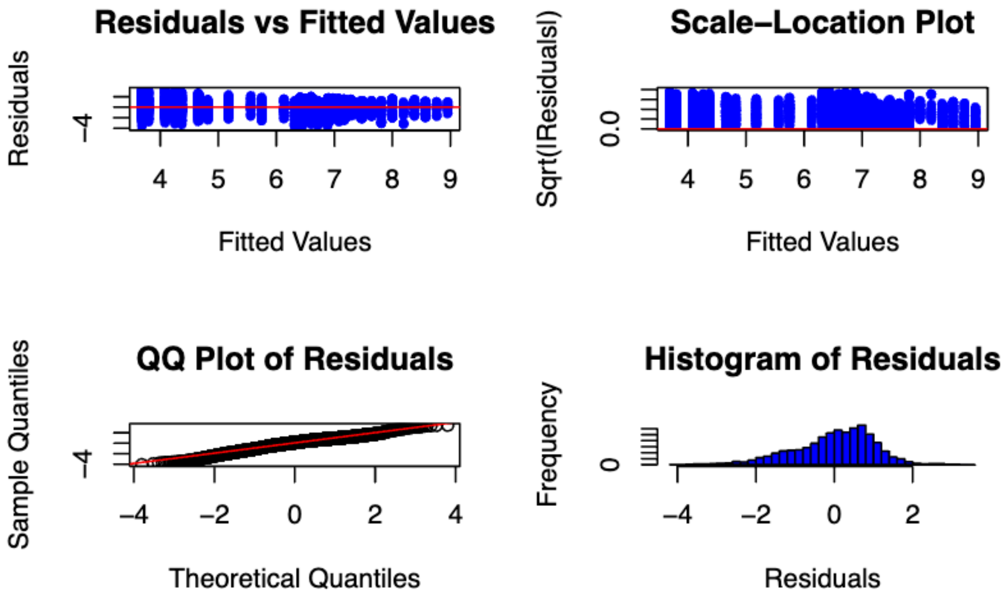
6.2.2 Improved model diagnostics

Appendix B_2:Judging from the model diagnostic results, the linear model assumptions also do not seem to be met.



6.2.3 Final Model Model Diagnostics

Appendix B_3:Judging from the model diagnosis results, the linear model assumptions can basically be met.



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