Long-Term Impacts of Bike-Sharing Systems on Public Systems: A Time-Series Analysis of Toronto Area

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1. Introduction

Bike-sharing systems (BSS) have rapidly expanded in many countries in recent years as a crucial component of urban green transportation. As a cornerstone of sustainable commute option, it not only offers an eco-friendly alternative than private vehicles, and also provides physical exercise that modern population keen for(Pelechrinis et al., 2017). Despite their rapid adoption globally, much of the existing research has focused on short-term impacts or cities with warm climates, leaving significant gaps in understanding the long-term implications of BSS, particularly in colder regions.

Toronto, characterized by harsh winters, presents a unique opportunity to explore these effects over an extended period. As a city with a publicly funded healthcare system, the implications of BSS adoption on public health, traffic safety, and urban planning are particularly significant. (Liu & Allen, 2024)Unlike cities with mild climates, where cycling is a year-round activity, Toronto's seasonal variability influences ridership patterns and potentially affects the broader public systems.

This paper aims to investigate the long-term impact of Toronto's BSS on public systems, focusing on its relationship with traffic safety, air pollution, and mortality rates. By

employing time-series analysis and linear regression, the study examines multi-year trends in BSS ridership, key safety indicators, air quality, and mortality rates. The findings aim to bridge the research gap in cold-climate cities and provide actionable insights for policymakers and urban planners to integrate sustainable transportation policies with broader public health and urban development initiatives.

2. Literature Review

Previous studies of BSS indicate that converting commuters who would otherwise rely on private cars or public transport into bike-share users can not only reduce traffic congestion and air pollution but also significantly increase physical activity levels(Babagoli et al., 2019). Consequently, this helps prevent chronic conditions such as cardiovascular disease, obesity, and type 2 diabetes. For cities, the potential health dividends of bike sharing include lowering public health expenditures and mitigating the economic burden of traffic accidents and chronic illnesses, thereby alleviating pressures on healthcare systems(Otero et al., 2018).

However, these benefits do not manifest equally in every region. In cold-climate locales like Toronto, seasonal changes in ridership present challenges to fully realizing the potential of BSS. Harsh winter conditions can impede cycling activity, necessitating substantial investment in infrastructure maintenance and safety measures to sustain ridership rates. Moreover, Toronto's publicly funded healthcare system adds a unique

dimension to understanding the economic and health impacts of BSS. While reduced automobile usage and the associated health benefits may ease the burden on public healthcare, the interplay between seasonal ridership fluctuations and traffic incidents warrants further investigation.

Past research commonly employs a Health Impact Assessment (HIA) framework to estimate these benefits, yet such models may not fully capture the complex, long-term interactions among BSS usage, air pollution, traffic safety, and mortality. By utilizing robust empirical methods grounded in time-series data, this study addresses that gap and offers deeper insights into the cumulative effects of BSS on public systems under cold-climate conditions(Clockston & Rojas-Rueda, 2021).

Furthermore, a review of existing studies reveals a notable gap in research connecting bike-sharing systems (BSS) with mortality rates. According to Howland (2020), in contexts where public health challenges are not adequately controlled—particularly during large-scale infectious disease outbreaks—high utilization of public systems could potentially correlate positively with mortality. Despite the growing attention on BSS and active transportation, there remains a lack of systematic investigations into how such systems might influence overall death rates, whether through changes in exposure patterns or other indirect mechanisms.

Similarly, there has been little scholarly work examining traffic-related accident rates

in conjunction with BSS usage. While some literature touches on road safety and "safety in numbers" effects, few, if any, studies quantitatively assess whether an increase in shared bike ridership leads to higher or lower incidence of traffic injuries and fatalities(Pelechrinis et al., 2017). These gaps underscore the need to expand current research frameworks—especially in cities facing public health stressors or seasonal riding fluctuations—to incorporate more direct evaluations of mortality and traffic-accident outcomes linked to bike-sharing.

3. Proposed Methodology

This study aims to explore the potential relationship between bike-sharing system (BSS) usage rates and mortality rates, integrating multiple datasets to uncover the dynamic connection between the two. Data sources include monthly ridership data from the BSS, Air Quality Health Index (AQHI) metrics, urban demographic statistics, severe injury and fatal accident records(KSI), and overall mortality counts.

3.1 Mortality Rate Vs. Ridership Rate

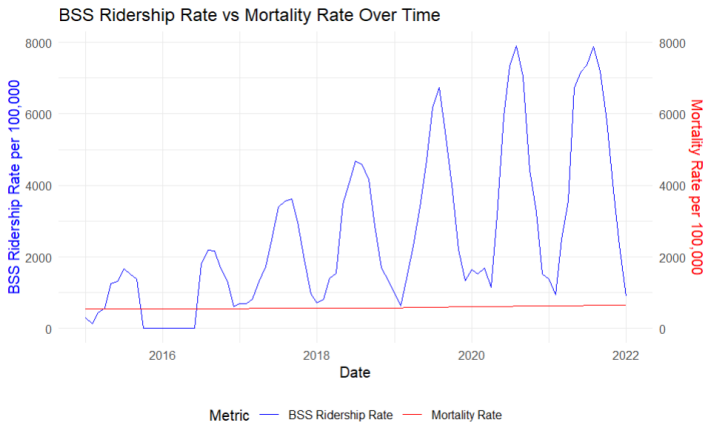
The first step are cleaning, standardizing, and converting data into a uniform monthly time series format. Missing values were imputed using interpolation techniques to ensure the completeness and accuracy of the analysis. Key indicators, such as ridership rates and mortality rates per 100,000 population, were calculated to mitigate biases arising from population size differences, enabling a more precise depiction of the

relationship between BSS usage and mortality rates.

$$\text{Mortality Rate per 100,000 Population} = \frac{\text{Death Number}}{\text{Population}} \times 100{,}000$$

$$\text{Ridership Rate per 100,000 Population} = \frac{\text{BSS Ride}}{\text{Population}} \times 100{,}000$$

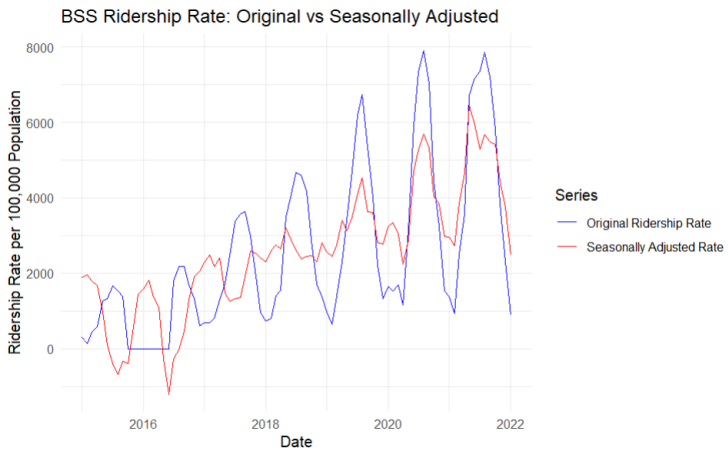
Time-series decomposition was employed to analyze the long-term trends, cyclical variations, and random components of the variables, shedding light on the seasonal characteristics and potential correlations between BSS usage and mortality rates. The study also performed correlation analysis to quantify the linear relationship between ridership rates and mortality rates. To further validate this relationship, regression models were used to determine the significance and directionality of the association.



Graph 1: BSS Ridership Rate vs Mortality Rate

In addition, seasonal adjustments were made to the BSS ridership rates to remove the influence of short-term fluctuations, enabling a clearer representation of their long-term trend correlations with mortality rates. By comparing the raw and seasonally adjusted

ridership rates, the study demonstrated that adjusted data more accurately reflect the connection with mortality trends. Regression modeling was then applied to the adjusted ridership rates to confirm their significant relationship with mortality rates and explore possible causal links.



Graph2: Ridership Rate vs Adjusted Ridership Rate

3.2 KSI Rate Vs. Ridership Rate

KSI stands for "Killed or Seriously Injured," a common metric used in traffic safety studies to quantify the severity of traffic accidents. It includes all incidents where individuals have been killed or suffered serious injuries due to traffic-related events. KSI is often used as an indicator to evaluate road safety and the effectiveness of transportation policies.

In this phase of the research, the relationship between KSI rates and bike-sharing system (BSS) ridership rates was analyzed. The primary goal was to determine whether

changes in ridership rates are associated with changes in traffic accident rates involving fatalities or serious injuries. To account for population growth over time and ensure accurate comparisons, the analysis used the KSI Rate per 100,000 Population as the main variable of interest, calculated as:

$$\text{KSI Rate per 100,000 Population} = \frac{\text{KSI}}{\text{Population}} \times 100{,}000$$

By standardizing the data to population size, the study aimed to eliminate potential biases introduced by population changes, providing a clearer understanding of the dynamic relationship between cycling activity and accident rates.

3.3 AHQI Vs. Ridership Rate

AQHI stands for "Air Quality Health Index," a measure used to quantify air quality based on its potential impact on human health. It considers several key air pollutants, including ground-level ozone, particulate matter (PM2.5), and nitrogen dioxide, and assigns a score reflecting the associated health risk. The AQHI is designed to help individuals make informed decisions about outdoor activities based on real-time air quality conditions.

This phase of the research focused on examining the relationship between AQHI and bike-sharing ridership rates. The objective was to determine whether changes in air quality influence the usage of the BSS. The AQHI data was specifically sourced from

the Toronto Urban Area and included only observations within the operational area of the BSS system to prevent data from outside the system's service zones from skewing the results.

By investigating this relationship, the study sought to uncover whether air quality improvements or deteriorations significantly impact cycling activity. This analysis could provide insights into how environmental conditions influence urban mobility patterns and help policymakers prioritize interventions to enhance both air quality and active transportation usage. 3.2 KSI Rate Vs. Ridership Rate

3.4 Proposed Pannal Data Regression Model Building

After exploring the relationships between each individual factor and BSS usage, a panel regression model was constructed to assess the combined impact of BSS usage on all-cause mortality rates. The Proposed model specification is as follows:

$$\boldsymbol{All - CauseMotalityRate} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}(\boldsymbol{BSSRate}) + \boldsymbol{\beta_{2(}}\boldsymbol{BSSRate} * \boldsymbol{AHQI}) + \boldsymbol{\beta_3}(\boldsymbol{AHQI}) + \boldsymbol{B_4}(\boldsymbol{KSI}) + \boldsymbol{\epsilon}$$

The term BSS Rate represents the bike-sharing system ridership rate per 100,000 population. By including this variable, the model seeks to directly assess the primary hypothesis: whether increased BSS usage significantly affects mortality rates.

The interaction term (BSS Rate × AQHI) was introduced to examine whether air quality moderates the relationship between cycling and mortality rates. Poor air quality could potentially negate the health benefits associated with cycling, while better air quality might amplify these benefits.

AQHI (Air Quality Health Index) was included as a standalone variable to account for its independent effects on mortality, given the significant role air quality plays in influencing public health.

KSI Rate (Killed or Seriously Injured Rate) was incorporated to capture the negative impacts of traffic-related accidents on overall mortality. This inclusion ensures that the potential risks of cycling-related injuries are accounted for.

The error term (ϵ) captures any unexplained variability in mortality rates not accounted for by the independent variables in the model.

The panel regression model allows for a nuanced analysis of how BSS usage interacts with environmental (AQHI) and safety (KSI) variables to influence mortality. The

inclusion of interaction terms makes it possible to explore complex dynamics, such as whether the effects of cycling depend on environmental factors like air quality.

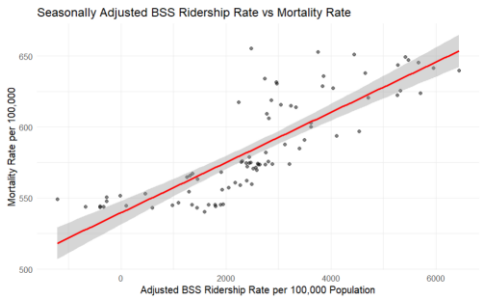
The primary objectives of this model include testing the direct effects of BSS rates on all-cause mortality rates (β_1), assessing the moderating role of AQHI (β_2), and evaluating the independent contributions of air quality (β_3) and traffic safety (β_4) on mortality outcomes.

To address potential endogeneity issues in the model (e.g., unobserved factors that could simultaneously influence BSS usage and mortality rates), diagnostic tests and robustness checks were performed. These include instrumental variable approaches to isolate causal relationships, sensitivity analyses to ensure result consistency, and the inclusion of lagged independent variables to account for time-dependent dynamics and mitigate reverse causality concerns.

Through this analytical framework, the study provides a comprehensive understanding of the health impacts of BSS usage in Toronto while considering environmental and safety-related complexities.

4. Results and Discussion

4.1 Mortality Rate Vs. Ridership Rate



Graph 3: LLM Adjusted Ridership vs Mortality Rate

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[1] "Linear regression with adjusted ridership rate:"

Call:
lm(formula = mortality_rate ~ ridership_rate_adjusted, data = combined_data)

Residuals:
    Min      1Q  Median      3Q     Max
-28.240 -14.641  -5.028  13.059  71.654

Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)            5.397e+02  4.136e+00  130.48   <2e-16 ***
ridership_rate_adjusted 1.767e-02  1.358e-03   13.02   <2e-16 ***
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 20.39 on 83 degrees of freedom
Multiple R-squared:  0.6712,    Adjusted R-squared:  0.6673
F-statistic: 169.4 on 1 and 83 DF,  p-value: < 2.2e-16
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Table 1: LLM Result of Ridership Rate vs Mortality Rate

Following seasonal time-series adjustments, our study revealed a significant positive correlation between bike-sharing ridership rates and mortality rates. Specifically, the linear regression model demonstrated that increases in the adjusted bike-sharing ridership rate per 100,000 population were associated with corresponding increases in the mortality rate per 100,000 population. The high R-squared value (0.6712) suggests that approximately 67% of the variation in mortality rates can be explained by the adjusted ridership rates. However, it is critical to interpret these results with caution due to several potential confounding factors.

When contextualized alongside findings from the study by Howland et al. (2020), which investigated public transportation usage and respiratory disease transmission, notable similarities and distinctions emerge. Howland et al. found no evidence of a direct association between public transit ridership and influenza/pneumonia mortality rates at the city level, challenging conventional beliefs that high-density transit use exacerbates respiratory disease spread. Their study highlights the complexity of interpreting associations between transportation systems and health outcomes due to factors such as indoor exposure dynamics, the geographic definition of cities, and

unmeasured confounders.

Moreover, just as Howland et al. highlighted limitations related to their dataset and the inability to separate influenza from pneumonia deaths, our analysis faces similar constraints. While our seasonal adjustments and standardized metrics strengthen the reliability of the findings, the absence of additional controls for confounding variables and the aggregated nature of the data limits causal inferences. For instance, increased BSS ridership in certain months may coincide with higher mortality rates due to unrelated seasonal factors, such as harsher weather conditions affecting vulnerable populations. this underscores the importance of considering broader contextual factors when evaluating the public health impact of transportation systems. While bike-sharing may increase accessibility and promote physical activity, future research should account for infrastructure quality, user demographics, and seasonal variability to better understand its net effects on public health.

5. Future Study

Although some analyses have observed a positive correlation between bike-sharing ridership and mortality, this does not inherently establish a causal relationship. One possible explanation is that higher BSS usage might increase exposure to road traffic, thereby elevating the risk of cycling-related injuries and fatalities in settings where dedicated cycling infrastructure is limited. Other factors—such as urban traffic

conditions, healthcare quality, socioeconomic inequalities, and environmental influences like air pollution—could also shape both BSS ridership and mortality rates, making it difficult to discern which element exerts the primary effect. Additionally, the potential for ecological fallacy, as highlighted by Howland et al., poses a methodological challenge: aggregating data at the city or population level may obscure the individual-level risks and behaviors that underlie complex health outcomes.

Because mortality is driven by a multitude of overlapping determinants, future investigations should adopt a more nuanced perspective on how bike-sharing usage interacts with death rates. Incorporating detailed contextual and individual-level data on cycling volume, rider demographics, and environmental conditions could help clarify whether BSS exerts a statistically significant impact on mortality. By refining methodological approaches—such as controlling for endogeneity and minimizing correlated confounders—researchers will be better positioned to determine whether the observed positive correlations are spurious or indicative of a genuine causal link.

6. Conclusion

This study explores the long-term impact of Toronto's bike-sharing system (BSS) on all-cause mortality, traffic safety, and air quality in a cold-climate context. Through time-series and panel regression analyses incorporating KSI and AQHI variables, the findings reveal a statistically significant—yet potentially confounded—positive

correlation between BSS ridership and mortality rates, indicating the complexity of achieving net health benefits. While cycling generally confers cardiovascular and environmental advantages, infrastructural limitations, harsh winter conditions, and demographic or socioeconomic disparities may influence how these benefits manifest. Echoing cautions from related research, data granularity and unmeasured confounders limit direct causal inferences; the observed association may reflect both heightened road-exposure risks and broader public health stressors. Hence, more detailed analyses, incorporating individual-level data and robust endogeneity controls, would help clarify whether the correlation truly signifies causality. On balance, BSS adoption can exert multifaceted impacts on public health, requiring thoughtful policy measures, such as bolstering dedicated cycling infrastructure, implementing winter maintenance protocols, and closely monitoring air quality to optimize its benefits. By systematically addressing these interconnected variables, policymakers and researchers can maximize the sustainability and health potential of bike-sharing in Toronto and beyond.

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