Journal of Public Transportation 27 (2025) 100139

Contents lists available at ScienceDirect

Journal of Public Transportation

journal homepage: www.journals.elsevier.com/journal-of-public-transportation

Measuring the operational impacts of a new Bus Rapid Transit (BRT) in Montreal, Canada

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ARTICLE INFO

Keywords:
BRT
Running time
Schedule deviation
Headway deviation
Transit operations

ABSTRACT

Recent research on Bus Rapid Transit (BRT) systems has mostly focused on ridership forecasting and scheduled travel time gains, with little empirical evidence on potential operational improvements. This study examines the short-term impacts of implementing a new BRT corridor in Montreal, Canada, on key bus performance indicators: running time, running time deviation, and headway deviation. Using Automatic Vehicle Location (AVL) and Automated Passenger Count (APC) data from 2022 to 2023, we compare the performance of the BRT to a parallel local bus route operating along the same corridor, before and after the BRT implementation. Our findings indicate that the BRT significantly reduced trip durations (about four minutes on average) primarily due to infrastructure features such as dedicated lanes and all-door boarding policy. The local route experienced modest running time improvements post-BRT, suggesting potential corridor-wide benefits. However, run time deviation was significantly higher for the BRT, particularly during peak periods while headway deviation worsened along the corridor compared to pre-BRT conditions. These findings highlight the importance of integrating infrastructure investments with dynamic operational strategies such as real-time dispatching and headway control. It emphasizes the need for schedule calibration following implementation to ensure that planned service aligns with actual performance. These findings offer practical insights for transit agencies planning or managing BRT systems.

1. Introduction

Bus Rapid Transit (BRT) systems have emerged as a high-quality, cost-effective alternative to rail-based transit options, particularly in Global South countries (Wirasinghe et al., 2013). By combining features such as dedicated rights-of-way, limited stop service, and all-door boarding policy, BRT systems can offer travel speeds and capacities (Levinson et al., 2002; Venter et al., 2017) similar to light rail or metro systems while requiring significant lower capital investment (Currie and Delbosc, 2014; Deng and Nelson, 2011). As a result, BRT has gained popularity globally, with more than 190 cities, 23 of them in North America, implementing BRT corridors to improve urban mobility (BRT Data, 2023).

Research on BRT implementation has typically emphasized outcomes such as ridership forecasting (Baker and Linovski, 2022; Ingvardson and Nielsen, 2017; Stewart et al., 2017; Umlauf et al., 2016), modal shift (Currie, 2006; Ingvardson and Nielsen, 2017), or scheduled travel time gains (Pereira, 2019; Singh et al., 2022). However, fewer studies have focused on the operational performance of BRT systems once they are in service. Specifically, empirical analysis of how BRT affects actual running times, schedule deviation, and headway regularity remain limited, despite these metrics being central for understanding service reliability, which influence user experiences (Cao et al., 2015) and ridership retention and growth (Allen et al., 2018; Chou & Kim, 2009).

To date, some efforts have been made to assess these dimensions, but they often rely on less granular data sources. Schramm et al. (2010) used schedules to evaluate the travel time changes across 19 BRT systems. While Andrew et al. (2022) used limited field observation data to measure travel time performance between BRTs, conventional buses,

This paper has not been published previously, and it is not under consideration for publication elsewhere. Its publication is approved by all authors.

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https://doi.org/10.1016/j.jpubtr.2025.100139
Received 14 May 2025; Received in revised form 11 September 2025; Accepted 22 September 2025
Available online 26 September 2025

and private automobiles along a 10.2 kilometer arterial segment in Dar es Salaam. While these studies offer valuable insights, the use of Automatic Vehicle Location (AVL) and Automatic Passenger Counter (APC) systems can support providing more robust before-and-after evaluations of new BRT systems, as they enable precise, detailed monitoring of transit performance.

Most existing studies adopt cross-sectional designs, evaluating performance post-implementation without a true pre-BRT baseline. Consequently, the extent to which BRT implementation improves, or undermines, operational performance relative to previous service remains unclear. A further complication is that BRT services often partially replace or run in parallel to existing bus routes. In such cases, operational changes may extend beyond the BRT route itself, producing spillover effects that impact local routes and network-wide service quality similar to what was found with the implementation of new express bus services (Diab & El-Geneidy, 2012; El-Geneidy & Surprenant-Legault, 2010; Surprenant-Legault & El-Geneidy, 2011).

This paper addresses these gaps by evaluating the operational impacts of the Pie-IX BRT corridor in Montreal, Canada, implemented in November 2022. Leveraging AVL/APC data from before and after the corridor's inauguration, we quantify the impact of introducing the BRT route on operational performance (running time, schedule deviation, and headway deviation) along and parallel to the corridor, providing new empirical insights into how BRT systems alter local transit operations. In doing so, this study contributes to a more comprehensive understanding of BRT effectiveness and supports data-driven transit planning and scheduling practices.

2. Literature review

2.1. Running time

Running time refers to the time it takes for a bus to travel between two points on a route. It is a foundational performance metric in transit operations, directly influencing in-vehicle travel time (El-Geneidy et al., 2006). Running time is shaped by a combination of internal operational factors, such as passenger activity, onboard passenger load, distance travelled, delay at the beginning of the trip, number of stops made, and vehicle type, as well as external conditions including traffic congestion, weather, and time of day (Abkowitz and Engelstein, 1983; Levinson, 1983; Strathman et al., 2000).

Transit agencies have implemented several strategies to reduce running time, including dedicated bus lanes, limited-stop services, and transit signal priority (TSP) (Diab and El-Geneidy, 2012), all of which are core features of Bus Rapid Transit (BRT) systems. Other strategies, such as operating articulated buses to accommodate higher demand, can have mixed effects on running time (El-Geneidy and Vijayakumar, 2011). While articulated buses require more time for acceleration and deceleration due to their weight, employing all-door boarding can lead to substantial time savings due to the presence of three doors (El-Geneidy et al., 2017).

Over time, the modelling of bus running times has evolved. Early studies relied on manually collected data to estimate trip duration and factors influencing variability (Levinson, 1983). More recent research has leveraged archived data from AVL and APC systems, which offer more granular and continuous observations of bus movements. These technologies enable more robust modelling of operational performance under real-world conditions (Kimpel, 2001; Kimpel et al., 2005; Tétreault and El-Geneidy, 2010). For example, Diab and El-Geneidy (2012) demonstrated that a combination of service improvements, like all-door boarding and TSP, significantly reduced running times along major bus routes in Montreal. Kathuria et al. (2020) expanded this research by analyzing travel time variability using GPS data from Ahmedabad's BRT network. Their study highlighted the role of system design and intersection density in shaping travel time variability patterns while reinforcing the value of real-time data for evaluating BRT performance. However, their focus was limited to the BRT corridor itself and does not incorporate comparisons to parallel local bus services or changes over time.

2.2. Schedule deviation

Schedule deviation, or running time deviation, refers to the difference between scheduled and actual travel times (Cats, 2019). High schedule deviations can result in increased passenger waiting times and missed transfers. Continued negative experiences with transit can lead to decreased trust in the transit system, influencing ridership (Calvo & Ferrer, 2018; Cao et al., 2015; Saxena et al., 2024; Singh and Kathuria, 2023; Wan et al., 2016). The determinants of bus running time deviation are well established in the literature matching the determinants of running time (Cats, 2019; El-Geneidy et al., 2011). BRT systems are often implemented with the goal of reducing such variability through features like dedicated lanes and reduced number of stops. However, while these elements are assumed to enhance schedule adherence, few empirical studies rigorously evaluate whether the implementation of a BRT corridor actually reduces schedule deviation using real-time performance data.

Two main approaches are commonly used to measure deviation using AVL data. The first method assesses absolute deviation between actual and scheduled running times (Cats, 2019), interpreted in seconds or minutes. The second, more robust method expresses the deviation as a ratio of actual to scheduled run time, accounting for variation in scheduled trip lengths (El-Geneidy et al., 2011). The latter is particularly effective when comparing routes or trips with different distances or time allocations. Despite the availability of these methods and data sources, schedule deviation remains an underexplored dimension in BRT performance evaluations, particularly in studies adopting a longitudinal or comparative framework.

2.3. Headway deviation

Headway deviation refers to the inconsistency between scheduled and actual intervals (headways) between consecutive buses on the same route (Vuchic, 2017). It is a measured as the ratio between the actual headway, calculated with AVL data, and the scheduled headway (El-Geneidy et al., 2011; Tirachini et al., 2022). Deviations in headways can lead to inefficiencies in bus operation, such as bus bunching (Chen et al., 2022; Daganzo, 2009). Bus bunching is well studied in the public transit literature, leading to uneven passenger load and to reduced route productivity (Tirachini et al., 2022). This practice has a direct impact on waiting time (Durán-Hormazábal and Tirachini, 2016) affecting seat availability (Babaei et al., 2014) and rider satisfaction. Additionally, bus bunching has been shown to impact running times (Verbich et al., 2016).

A wide range of operational and environmental factors influence headway deviation being similar to the determinants of running time and running time deviation (Strathman et al., 2003; Tirachini et al., 2022). While most BRT systems are designed to minimize these disruptions, through measures like exclusive lanes, off-board fare collection, and dedicated stations with at level boarding, achieving consistent headway in practice can remain a challenge, especially in mixed traffic segments. Despite the operational importance of headway adherence, few empirical studies assess changes in headway deviation resulting from BRT implementation, particularly using comparative or longitudinal studies. Moreover, evaluations have typically overlooked whether BRT corridors have improved headway regularity relative to services they replaced, leaving unanswered questions about the net benefits of the investment in terms of reliability.

A substantial body of research has explored strategies to mitigate headway deviation, generally through real-time control mechanisms tested in both simulation and field settings. Early work emphasized threshold-based holding, showing that simple headway control rules (whether defined by the preceding bus alone or by both preceding and following buses using real-time data) can stabilize service when applied at strategic locations, particularly high-demand stops near the route midpoint (Fu & Yang, 2002). Focused on dedicated corridors, such as BRT infrastructure, more advanced approaches introduced deterministic and predictive holding strategies (Muñoz et al., 2013), which differ in how they treat passenger demand and travel-time variability. Deterministic control assumes relatively stable conditions and is particularly effective on crowded routes, as it minimizes passenger wait times and prevents downstream overloads. Predictive control, by contrast, accounts for random variations and is better suited to less crowded routes, as it prioritizes keeping headways even and avoiding bunching. Robust model predictive control (MPC) approaches build on these methods by explicitly accounting for operational uncertainties, such as fluctuating passenger demand and variable running times, through continuous real-time feedback (Ma et al., 2021).

Recent studies have introduced probabilistic dispatching to guide holding decisions under uncertainty (Berrebi et al., 2015). Other research has highlighted complementary tactics, including conditional signal priority (i.e., requesting intersection priority only when it improves headway or schedule stability) (Anderson & Daganzo, 2020), short-turning as a more effective alternative to conventional holding on congested routes (Tian et al., 2022), and integrated tactic libraries that combine holding, skip-stops, and speed adjustments to improve reliability and transfers (Nesheli & Ceder, 2017). Collectively, these studies underscore that while no single strategy fully resolves headway deviations, data-driven and context-specific interventions can significantly improve reliability. Yet, much of this work remains theoretical or simulation-based, and relatively little is known about how these mechanisms translate into real-world outcomes when new infrastructure such as BRT corridors are introduced.

While significant research has documented the theoretical advantages of BRTs, most studies rely on scheduled data, simulated scenarios, or post-implementation snapshots. Few have leveraged detailed AVL and APC data to examine how key operational metrics, such as running time, schedule deviation, and headway deviation, change with the introduction of a BRT corridor. Even fewer have adopted before-and-after designs or compared BRT services to parallel local routes, despite the implications for broader network efficiency. These gaps limit our understanding of how BRT investments perform under real-world conditions and how they affect the overall reliability of transit operations along the corridor where they operate. This research addresses these limitations by studying the introduction of the Pie-IX BRT in Montreal, Canada, contributing new empirical evidence to support performance-based transit planning.

3. Case Study

The Pie-IX BRT corridor runs through the east side of Montreal, Canada. The $523 M CAD project spans over 13 km along Pie-IX boulevard with fourteen operational stations. The corridor runs in the north-south direction, connecting residential areas to major east-west commuter routes on the island of Montreal. Service along the corridor is currently provided by two routes: the recently implemented BRT service (route 439) and the local route 139, which operated as the primary service along Pie-IX prior to the BRT's inauguration in November 2022. While the 439 operates primarily in a dedicated bus-only lane in the middle of the Pie-IX boulevard with enhanced infrastructure, such as dedicated stations, and transit signal priority (TSP), route 139 continues to run in mixed traffic along the same boulevard and is not permitted to enter the BRT's exclusive lanes. Moreover, the BRT route serves every station along the corridor, while the local route operates on a request-stop basis. Fig. 1 provides an overview of the infrastructure configuration for both routes along the Pie-IX boulevard.

Before the BRT's opening, route 139 served approximately 29,500 riders per day in 2019. However, this figure dropped significantly since the COVID-19 pandemic, with ridership falling to around 11,500 riders per day in 2022 before the BRT started operations. Following the introduction of the BRT route, early 2023 data indicate that route 439 was carrying approximately 30,000 passengers daily, while the local route 139 retained only about 3000 passengers. This shift in ridership illustrates not only the operational significance of the BRT route but also its potential to reshape transit usage along the corridor with around 3500 new daily users at a time when the transit system in Montreal did not fully recover from the COVID-19 pandemic.

Schedules for both route 139 and the BRT were stable throughout the study period, with only minor month-to-month variation across periods of the day. For instance, in the before period, Route 139 showed a median AM peak frequency of 13 min, ranging from 10 to 15 min over the year. After the implementation of the corridor, schedules remained consistent, with the BRT operating at 10-minute intervals and route 139 at 30-minute intervals in the AM peak. The BRT operates a range of trip patterns, with variations in starting and ending points depending on the time of the day. The BRT runs in mixed traffic at both the southern and northern ends of some trip patterns. While the northern section is not planned to receive a dedicated corridor, the corridor is being extended further south. To ensure consistency in analysis, this study focuses exclusively on the segment shared across all route patterns. This common section spans approximately ten kilometers from Pierre du Coubertin station in the southern portion of the route to Amos station in the northern portion, as illustrated in Fig. 2. It is important to note that, immediately following the corridor's inauguration, a short section of the BRT alignment was rerouted due to ongoing construction at Jean-Talon station, which will later connect through a tunnel to a future extension of the blue metro line in the region.

The Pie-IX corridor offers a unique setting to evaluate the operational outcomes of BRT implementation. It enables comparison between bus rapid service and a legacy local route operating in mixed traffic. The configuration allows for a before-and-after evaluation using AVL/APC data, providing insight into how the BRT infrastructure affects running time, schedule deviation, and headway deviation relative to both past conditions and current local service.

4. Data source

The data used in this study was obtained from Société de Transport de Montréal (STM) through a formal access-to-information request submitted in 2023. The dataset consists of operational records drawn from STM's AVL/APC systems. The AVL systems records bus locations at frequent intervals, which are processed into stop-level arrival and departure timestamps. The APC systems automatically log the number of passengers boarding and alighting at each stop using infrared sensors at vehicle doors. The use of AVL/APC data is well established in the transit

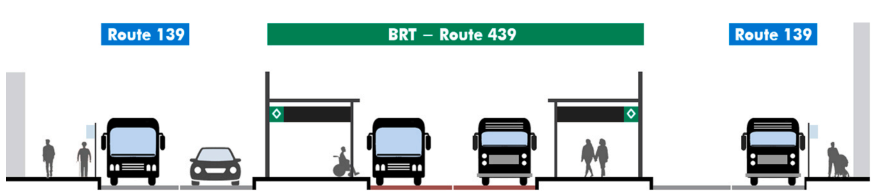

Fig. 1. Configuration of the Pie-IX boulevard (Routes 139 and 439).

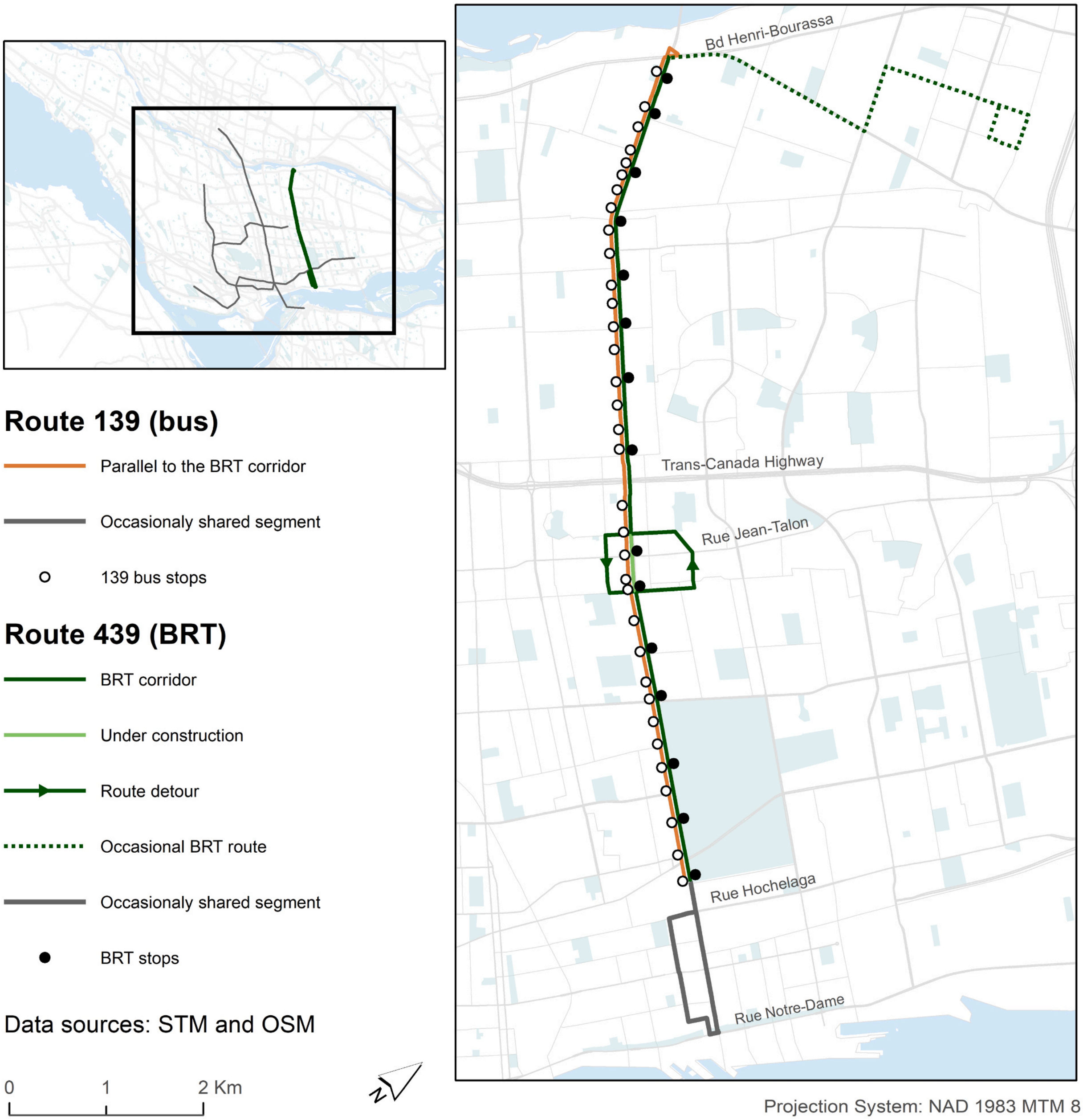

Fig. 2. Studied segment of the BRT (route 439) and route 139.

literature as a robust method for understanding the impacts of operational improvements (Dueker et al., 2004; Strathman et al., 2000; Tirachini et al., 2017). Combining these technologies yields key operational measures, including actual running times and headways between consecutive buses.

Since 2020, STM has equipped their entire bus fleet with AVL/APC technology as part of the implementation of their real-time “next arrival” passenger information system. For this study, we obtained detailed stop-level data for the local route 139 and the newly implemented BRT route 439. Specifically, we accessed archived data from January 2022 to March 2023 for route 139 (n = 1,990,578 stops) and from November 2022 to March 2023 for route 439 (n = 358,296 stops). This time window captures operational patterns both before and after the BRT implementation, allowing for a comparative assessment between both services as well as potential spillover effects. The dataset meets industry standards for AVL/APC quality. APC data were valid for

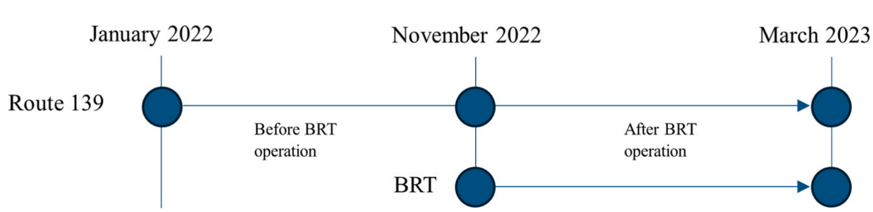

Fig. 3. Timeline of data collection.

96 % of trips and stop-pattern coverage was 99 % across the dataset. Fig. 3 presents a visual summary of the data collection period in relation to the inauguration of the Pie-IX BRT corridor. A detailed description of the variables and related descriptive statistics are provided in the following sections.

5. Methods

To assess the operational impacts of the Pie-IX BRT corridor, we estimate three multivariate linear regression models, each corresponding to a distinct performance outcome: running time, running time deviation, and headway deviation. These metrics were chosen as they reflect core operational dimensions, such as travel time and reliability (TRB, 2003), expected to be sensitive to the implementation of a BRT corridor while directly observable from AVL/APC data. The derived models allow us to quantify the effect of the BRT implementation on different dimensions of service reliability while controlling for operational, temporal, and environmental conditions. The models were estimated using generalized linear model (GLM) with a Gaussian distribution and identity link function, which is equivalent to ordinary least squares (OLS) regression. The use of OLS regression is appropriate for continuous dependent variables and facilitates clear interpretation of coefficients in the context of transit operations.

Although the dataset was originally structured at the stop level, all models are estimated at the trip level to align with the study's objectives and to ensure consistency across performance metrics. Trip-level indicators, such as total run time, cumulative passenger activity, and headway deviations were computed accordingly for the studied segment. Table 1 summarizes the dependent and independent variables used across the three models.

Running time is calculated based on the time the bus leaves the first stop along the segment till the bus arrives at the last stop along the same segment. The *BRT* and *After BRT* variables allows us to isolate the impact of the BRT corridor from general temporal trends. Interaction terms between these two indicators are included to capture the net effect of BRT implementation relative to pre-existing local service. Temporal controls account for peak and off-peak periods, while weather-related variables help isolate effects from environmental disruptions. Passenger activity is included with a quadratic term to reflect non-linear effects on dwell time and overall trip performance.

Table 1
Variable description.

Variable	Description
Run Time	Trip duration in seconds *[Dependent]*
Run Time Deviation	Ratio between actual and scheduled run time *[Dependent]*
Headway Deviation	Ratio between actual and scheduled headways at the end of the route *[Dependent]*
BRT	Equal one if bus route is 439, zero otherwise
After BRT	Equal one if date after the opening of the BRT, zero otherwise
South	Equal one if southbound, zero otherwise
Early AM	Equal one if stop time is between 3:00–6:30 am, zero otherwise
Am Peak	Equal one if stop time is between 6:30–9:30 am, zero otherwise
Midday	Equal one if stop time is between 9:30 am to 3:30 pm, zero otherwise
PM Peak	Equal one if stop time is between 3:30–6:30 pm, zero otherwise
Evening and night	Equal one if stop time is between 6:30 pm to 3:00 am, zero otherwise
Weekday	Equal one if the trip is in a business day, zero otherwise
Delay at start	The delay at the start of the route in seconds (leave – scheduled time)
Passenger activity	The sum of boardings and alighting per trip
$(\text{Passenger activity})^2$	The sum of the square of boardings plus alighting per trip
Mean temperature (°C)	Mean temperature on the day of the trip
Rain (mm)	The amount of rain (mm) on the day of the trip
Snow on the ground (cm)	Snow on the ground (cm) on the day of the trip

6. Results and discussions

6.1. Descriptive statistics

Table 2 reports descriptive statistics for key operational indicators across three service configurations: route 139 before the BRT implementation, route 139 after implementation, and route 439 (BRT).

Average running time decreased notably across configurations. For route 139, mean trip duration declined from 2452 s (40 min) before the BRT implementation to 2321 s (38 min) after implementation. Route 439 (BRT) exhibited the shortest mean run time at 1843 s (30 min), reflecting the impact of its operational design, such as dedicated lanes, transit signal priority, and limited stops. Welch two sample T-tests confirm that all differences are statistically significant. The reduction from route 139 before to after BRT implementation was highly significant ($t = -30.03$, $p < 0.001$), with a mean difference of approximately 131 s. The difference between route 139 before and route 439 was even more pronounced ($t = 281.47$, $p < 0.001$), yielding a time savings of over 600 s (10 min), demonstrating the operational efficiency of the BRT.

Changes in running time deviation followed a similar trend. The average running time deviation for route 139 improved from 9.1 to 4.5 percent after the BRT, a statistically significant reduction ($t = 28.22$, $p < 0.001$), indicating enhanced schedule adherence. However, the BRT exhibited a higher average deviation of 19.9 %, suggesting greater inconsistency during early implementation. This difference was statistically significant when compared to both route 139 before ($t = -105.3$, $p < 0.001$) and after the BRT ($t = -87.05$, $p < 0.001$). These results indicate that while the BRT delivered travel time savings, initial stability and adherence to scheduled run times remained a challenge.

In terms of headway deviation, route 139 worsened slightly from 0.957 before BRT to 0.991 after implementation, a statistically significant deterioration ($t = -10.97$, $p < 0.001$). Comparing across services, the BRT exhibited no improvement over the pre-BRT baseline. Headway deviation averaged 0.993 for route 439 versus 0.957 for route 139 before implementation, a significant difference ($t = -6.35$, $p < 0.001$). In contrast, route 439 and route 139 after implementation were statistically indistinguishable (0.993 vs. 0.991; $t = -0.12$, $p = 0.91$). These findings suggest that the BRT did not deliver measurable gains in service regularity relative to the pre-BRT local service benchmark.

Other variables show meaningful contrasts. For instance, passenger activity appears similar across groups but with greater variance for the

Table 2
Descriptive statistics.

Variable	Route 139 – Local Bus Service		Route 439 (BRT)
	Before BRT	After BRT	
Running Time	2452.3 (320.1)	2321.2 (318.9)	1843.1 (233.2)
Running Time Deviation	1.0 (0.4)	1.0 (0.2)	1.0 (0.8)
Headway Deviation	1.0 (0.5)	1.0 (0.2)	1.0 (1.0)
Early AM	0.1 (0.3)	0.1 (0.3)	0.0 (0.2)
Am Peak	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)
Midday	0.4 (0.5)	0.3 (0.5)	0.4 (0.5)
PM Peak	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)
Evening and night	0.2 (0.4)	0.3 (0.4)	0.2 (0.4)
Weekday	0.7 (0.4)	0.7 (0.5)	0.8 (0.4)
Number of stops	35.4 (1.6)	35.4 (1.6)	15.9 (0.7)
Delay at start	33.6 (86.2)	24.9 (97.1)	105.2 (146.3)
Passenger activity	113.3 (60.8)	103.4 (161.9)	107.2 (69.8)
Mean temperature (C)	7.9 (12.6)	−2.6 (5.7)	−2.3 (5.6)
Rain (mm)	2.9 (7.1)	2.8 (5.9)	2.4 (5.2)
Snow on the ground (cm)	4.2 (6.9)	13.5 (12.4)	13.1 (12.8)
Trips (n)	48,212	6,016	21,595

BRT. Environmental differences, such as higher snowfall and lower temperatures during the post-BRT period are notable and controlled for in the regression analysis.

6.2. Regression results

We estimated OLS models for running time, running time deviation, and headway deviation. OLS assumptions were assessed for normality of residuals (QQ plots), nonlinearity (Ramsey RESET test), heteroskedasticity (Breusch–Pagan test), multicollinearity (adjusted VIF), autocorrelation of residuals (Durbin–Watson test), and influential measures (Cook's distance, leverage values, and student residuals). All adjusted VIF values were below 5, indicating no problematic multicollinearity among predictors. Although we considered including the observed number of stops in the regression analysis, this variable was almost perfectly correlated with the route indicator ($r = -0.99$), creating severe multicollinearity. We therefore excluded it from the models. A small share of observations was highly influential representing mostly non-typical disruption trips, characterized by substantially higher delays, heavier passenger activity, snowfall conditions, and shorter scheduled headways. We removed these observations (running time: 3.84 %, running time deviation: 4.65 %, headway deviation: 4.60 %) and refitted the models on the remaining sample. This significantly improved residual normality and reduced leverage without substantially changing estimated effects. The resulting models therefore capture the typical pattern of operations, as opposed to the atypical conditions associated with disruption events.

To address potential nonlinearity, we estimated spline models for delay at start and passenger activity. This alternative specification yielded coefficients with the same direction and similar magnitudes as the models without influential observations. For interpretability, we report the models without influential observations (Table 3). Because tests indicated heteroskedasticity and within-day dependence (positive serial correlation), we compute route x date cluster-robust standard errors for inference and report 95 % confidence intervals and p-values based on those clustered standard errors. Robust standard errors also help mitigate potential bias concerns from small or uneven sample sizes (Judkins and Porter, 2016), such as trip counts varying across routes depending on service frequency and the observation period. No additional weighting was applied since the imbalance reflects actual operations rather than a sampling artifact.

In terms of model fit, the explanatory power varied across outcomes. The run time model explained a substantial share of variation ($R^2 = 0.76$). The run time deviation model showed a more moderate fit ($R^2 = 0.46$), while the headway deviation model captured less variation ($R^2 = 0.15$), reflecting that headway irregularities are likely influenced more by unpredictable disruptions than by systematic factors. These results are in line with expectations from previous literature (El-Geneidy et al., 2011), meaning that systematic factors explain much of the level of run times while schedule deviations and headway variability are driven to a greater extent by unobserved or random disruptions.

6.2.1. Running time

Regression results presented in Table 3 confirm the statistically significant impact of the Pie-IX BRT corridor on bus travel time performance. Compared to the baseline local service (route 139 before BRT), the BRT service (route 439) is associated with a 229-second (3.8 min) reduction in running time in the northbound direction and a 269-second (4.5 min) reduction in the southbound direction ceteris paribus. These results reflect time savings of approximately 4 min per trip, demonstrating the effectiveness of BRT infrastructure in reducing in-vehicle travel time. The greater reduction in the southbound direction may be

Table 3
Regression model results.

Predictors	Running time		Running time deviation		Headway deviation	
	Estimates	CI	Estimates	CI	Estimates	CI
Intercept	**2002.26******	1988.84–2015.68	**103.03******	102.34–103.72	**76.84******	75.07–78.60
Temporal component						
BRT	**−228.78******	−252.19 – −205.38	**13.32******	12.18–14.46	−1.00	−4.52–2.52
After BRT	**−128.55******	−141.46 – −115.64	**−5.72******	−6.34 - −5.09	**8.78******	7.48–10.07
Direction						
South	**−163.42******	−172.34 – −154.50	**−10.29******	−10.68 - −9.89	**3.06******	2.09–4.04
Time of day/week						
Early AM	**−20.80******	−1.16 – 14.06	**−0.81******	−1.23 - −0.38	**−5.57******	−6.48 - −4.65
AM Peak	**145.99******	−27.91 – −13.70	**−2.55******	−2.93 - −2.17	**−8.99******	−9.95 - −8.04
Mid-day	**242.03******	138.14 – 153.83	**−0.98******	−1.31 - −0.66	**−11.61******	−12.49 - −10.72
PM Peak	**199.81******	233.03 – 251.02	**−4.35******	−4.71 - −3.99	**−18.11******	−19.18 - −17.03
Weekday	**41.92******	190.88 – 208.74	**2.94******	2.50–3.39	**−3.35******	−4.30 - −2.39
Trip delay						
Delay at start	**−0.28******	−0.31 – −0.25	**−0.01******	−0.01 - −0.01	**0.05******	0.04–0.05
Passenger load						
Pass. activity	**3.53******	3.37 – 3.69	**0.11******	0.10–0.12	**0.26******	0.23–0.28
(Pass. activity) ^{2}	**−0.004******	−0.004 – −0.003	**0.00******	−0.00 - −0.00	**0.00******	−0.00 - −0.00
Weather						
Rain (mm)	**0.49***	0.07–0.92	**0.02 ***	0.00–0.04	−0.04	−0.08–0.01
Snow (cm)	**1.86******	1.48–2.23	**0.02******	0.01–0.04	**0.09******	0.05–0.13
Interactions						
After BRT * South	**55.59******	39.42–71.75	**7.16******	1.72–3.23	**−2.66******	−4.80 - −0.52
BRT * South	**−40.73******	−59.80 to −21.66	**2.81******	3.31–4.68	**−5.25***	−6.90 - −3.60
BRT * Early AM	**40.53******	27.19–53.87	**2.48******	2.52–3.66	**3.29***	0.48–6.10
BRT * AM Peak	**−50.98******	−63.47 to −38.49	**3.99******	6.74–7.93	**−8.21******	−10.87 - −5.54
BRT * Mid-day	**−144.70******	−156.93 to −132.47	**3.09******	−7.24 - −5.58	**−9.33******	−11.81 - −6.86
BRT * PM Peak	**−73.05******	−85.10 to −61.00	**7.34******	0.02–0.02	**−12.53******	−14.94 - −10.11
BRT * Weekday	**−28.50******	−46.85 to −10.13	**−6.41******	−0.03 - −0.01	**−12.52******	−14.90 - −10.15
BRT * Delay at start	**0.22******	0.18–0.25	**0.02******	−0.00–0.00	**0.07******	0.06–0.08
BRT * Passenger activity	**−2.05******	−2.25 to −1.85	**−0.02******	1.72–3.23	**0.05***	0.01–0.09
BRT * (Passenger activity) ^{2}	**0.002******	0.002–0.003	0.00	3.31–4.68	0.00	−0.00–0.00
Observations	72,598		71,738		70,826	
R^2	0.755		0.456		0.153	

Significance levels: * $p < 0.005$; ** $p < 0.01$; *** $p < 0.001$

attributed to the southbound route making three fewer stops compared to the northbound route. Additionally, the detour around the Jean-Talon BRT station, still under construction during the analysis period, is about five hundred meters shorter in the southbound direction.

Interestingly, a spillover effect is observed for the local route 139, which experienced shorter travel times after the BRT became operational. Specifically, trips on route 139 after implementation are 128 s shorter, with a slightly smaller benefit in the southbound direction (73 s), while keeping all values constant at their mean. This suggests corridor-level operational benefits, potentially driven by the introduction of transit signal priority and intersection redesigns that improved traffic flow for all transit services along the Pie-IX boulevard.

Running time is found to be influenced by time-of-day patterns, with trips during most periods taking longer than those during the evening/night period (the reference category), keeping everything else constant. Specifically, trips are 146 s longer during the AM peak, 242 longer during the midday period, and 200 s longer during the PM peak. These results align with expected increases in congestion during peak demand periods. However, the BRT service exhibits greater resilience to these fluctuations. Interaction terms show that, compared to local service, the BRT is 51 s faster during the AM peak, 145 s faster at midday, and 73 s faster during the PM peak. The variations in travel time for the BRT throughout the day may be partially explained by segments of the BRT that operate outside the corridor due to ongoing construction. Even so, the findings suggest that the BRT infrastructure successfully reduced the negative effects of peak-hour congestion on running times.

At the operational level, departure delays at the first stop show a compensatory effect. For every second of departure delay, total running time decreases by 0.28 s, reflecting driver attempts to make up lost time. This compensatory behavior is less pronounced for the BRT, where the same delay leads to a smaller time gain of 0.06 s. Passenger activity also significantly affects running time. Each boarding or alighting adds 3.53 s to the trip, but this effect is diminishing at higher passenger volumes, as indicated by the negative and significant squared term. On the BRT, the marginal effect of each passenger is lower, about one second less (1.48 s) likely due to the infrastructure advantages of the BRT corridor. This finding reinforces the benefits of allowing passengers to board and alight through all doors, especially on articulated buses with three doors, which operate along the BRT corridor.

Finally, weather conditions impact trip duration. Rain adds an average of 0.5 s per millimeter, and snow adds 1.86 s per centimeter. These effects are consistent across services highlighting the importance of including environmental controls in operational performance models. In sum, the BRT corridor demonstrates clear advantages in reducing running time and mitigating peak-period delays, while also enabling modest improvements to the local service.

6.2.2. Running time deviation

The second model examines the ratio of actual to scheduled running time, an indicator of schedule adherence and operational predictability. A value of 1.0 reflects perfect alignment with the schedule, while values above 1.0 indicate that trips are running longer than expected. In the model, all coefficient estimates were multiplied by one hundred to facilitate interpretation reflecting percentage changes. The results suggest a mixed pattern: while running time deviation improved for the local service after BRT implementation, the newly introduced BRT route experienced higher variability.

Specifically, the coefficient for the "After BRT" variable is associated with a 5.7 % reduction in running time deviation relative to the baseline (route 139 before BRT) pointing to a modest gain in reliability for local service, while keeping all other values constant at their mean. In contrast, the BRT route itself shows a 13 % increase in running time deviation, signaling potential operational instability despite its infrastructure advantages, ceteris paribus. This suggests that while BRT trips are faster (as shown in the running time model), they are less consistent when it comes to adhering to scheduled times. One potential explanation is that the schedules may not have been adequately updated to reflect actual post-implementation running times, leading to persistent mismatch between planned and observed performance during the early months of operation.

These results are reinforced by exploratory analysis based on STM's service standard, which defines "on time" as trips within one minute early or three minutes late of schedule (STM, 2025). As shown in Fig. 4, 52.3 % of route 139 trips after BRT implementation were not on time, representing an improvement compared to 63.4 % before the BRT. However, 82.9 % of BRT trips fell outside of this on-time window, highlighting the reliability challenges faced during early implementation. These distributional differences support the regression findings while underscoring the need for further schedule refinement.

Directional and temporal factors further explain variations in running time. Trips in the southbound direction are associated with 10.3 % lower deviation compared to northbound trips, likely due to shorter distances, fewer stops, or more favorable traffic conditions, all else equal. However, the After BRT x South interaction suggests a significant increase (+ 7.2 %) in deviation post implementation for southbound service, likely due to delays accumulated from the northbound direction. Time-of-day effects reveal that deviation is lower during the AM peak, midday, and PM peak compared to the evening and night period (the reference category). Yet for the BRT, the interaction terms show that deviation worsens during the day, with increases of + 3.99 % in the AM peak, + 3.09 % at midday, and + 7.34 % in the PM peak compared to base level. These results point to greater unreliability for BRT during high-demand periods, likely due to bunching or station-level surges in boarding activity.

Additional model results provide insight into operator/driver response and external conditions. Departure delays at the start of a trip are associated with a slight reduction in run time deviation at baseline (–0.01 % per second), suggesting that drivers in the local route may attempt to recover time while in service. However, this effect reverses for the BRT, where the interaction term indicates a + 0.02 % increase in deviation per second of delay, keeping all else equal at their mean values. This suggests that BRT trips not only lack compensatory acceleration but may even experience worsening schedule deviation when departing late, which can be due to corridor constraints or less flexible recovery strategies available. One such constraint is that the BRT must stop at every station, unlike the local route that operates on a stop-request basis. This rigid stopping pattern reduces drivers' ability to adjust spacing in real time and may exacerbate schedule deviations when delays accumulate.

Passenger activity contributes to deviation. Each boarding or alighting adds 0.11 % to running time deviation for local service, and this effect is slightly lower for BRT trips, with the interaction term reducing 0.02 %, ceteris paribus. This suggests that BRT trips are less sensitive to passenger volume due to features like all-door boarding. Finally, weather conditions are positively associated with deviation. Each additional millimeter of rain each or centimeter of snow on the ground corresponds to a + 0.02 % increase in deviation, all else being equal.

In summary, while run time deviation improved slightly for local service, the early phase of BRT implementation was marked by increased variability, particularly during peak hours. These results emphasize the need to not only invest in infrastructure but to adapt operational strategies, such as schedule adjustments, holding strategies, or dynamic dispatching, to ensure service consistency.

6.2.3. Headway deviation

The third model assesses headway deviation, calculated as the ratio between actual and scheduled headways at the last stop along the studied segment. A value of 1.0 indicates perfect spacing between buses. Values greater than 1.0 reflect longer-than-scheduled gaps (vehicles becoming too spread out), while values below 1.0 indicate shorter-than-scheduled gaps (vehicles bunching together). Both directions signal

Fig. 4. On-time performance before and after the BRT route.

irregular service, often linked to variable dwell times, uneven passenger activity, and service delays. Similar to the running time deviation model, coefficient estimates were multiplied by 100 to reflect percentage changes.

The results show that overall headway regularity in the corridor worsened after the BRT implementation. The coefficient for the "After BRT" variable is positive and significant (+8.8 %), meaning that, across all services combined, headway deviation was higher in the post-BRT period compared to before. The BRT coefficient, by contrast, is not statistically significant, indicating that, when holding covariates constant, the BRT does not differ systematically from the local route overall. These model-based findings are consistent with the descriptive contrasts presented earlier: both the BRT and the local route after implementation show more irregular spacing than the local service before the BRT was introduced. Taken together, the evidence indicates that conditions in the corridor worsened following the BRT opening, with neither the new service nor the remaining local service matching the regularity observed before.

Directional effects add further nuance. Southbound trips were more irregular than northbound ones (+3.1 %). Yet the BRT is less exposed to this imbalance than the local service (–5.3 %). Time-of-day effects highlight improved spacing during daytime operations. Relative to the evening and night (reference category), headway deviation was lower during all other periods, with reductions of 5.6 % in the early AM, 9.0 % in the AM peak, 11.6 % midday, and 18.1 % in the PM peak. Interactions reveal that the BRT benefited more from these daytime improvements than the local route where deviation was reduced an additional 8.2 % in the AM peak, 9.3 % midday, and 12.5 % in the PM peak. On weekdays, headway deviation was lower than on weekends (–3.4 %), and the BRT gained an additional reduction of 12.5 %.

Operational and environmental conditions contributed the most to irregularity. Each second of delay at the start increased deviation by 0.05 %, and this effect was amplified for the BRT (+0.07 %). Passenger activity increased deviation by 0.26 % per boarding or alighting, with the BRT showing an additional increase of + 0.05 %. Snow accumulation reduced reliability (+0.09 % per cm), whereas rainfall had no significant effect.

Overall, these findings highlight that service along the Pie-IX boulevard became less reliable after the BRT was introduced. The new BRT service did not outperform the local route baseline and remains vulnerable to departure delays, passenger surges, and winter conditions. While the BRT benefited more from daytime operations and was less affected by southbound imbalance, the broader picture is one of increased irregularity in spacing compared to pre-BRT conditions. One potential contributor is the lingering construction along the corridor, including the southern extension works and the ongoing construction around Jean-Talon station. Even so, findings underscore the need for more active supervision and real-time control strategies.

6.3. *Policy implications*

The findings from the Pie-IX BRT analysis suggest several implications for the planning and operation of bus rapid transit systems. The dedicated infrastructure along much of the corridor contributed to faster and more stable running times, reinforcing the importance of priority measures in enhancing service speed. At the same time, headway regularity worsened relative to the pre-BRT baseline, indicating that infrastructure investments alone are not sufficient to guarantee reliable operations, particularly when parts of the corridor continue to operate in mixed traffic. This aligns with prior research showing that while dedicated rights-of-way reduce variability, real-time control strategies remain essential for managing headway deviation and preventing bunching (Ma et al., 2021; Muñoz et al., 2013).

A further nuance is that while the local service exhibited a modest reduction in running time deviation, the BRT itself recorded faster trips but greater variability. This pattern indicates that schedules were not fully recalibrated after implementation, leaving vehicles with limited recovery margins to absorb day-to-day fluctuations. These findings imply that STM should apply post-launch schedule adjustments, ensuring that timetables reflect actual operating conditions and prevent schedule variability from undermining the speed gains achieved by the dedicated corridor from the user perspective.

The deterioration of headway regularity along the corridor highlights the need for active headway management. Threshold-based holding strategies have long been shown to stabilize service when applied at key stops (Fu and Yang, 2002), while more advanced deterministic and predictive approaches adapt to demand and travel time variability (Muñoz et al., 2013). Robust model predictive control, which explicitly accounts for uncertainties such as fluctuating passenger demand and running times, has demonstrated substantial gains in simulation studies (Ma et al., 2021). Leveraging STM's control center to implement systematic holding and dynamic dispatching could therefore provide a practical means to stabilize headways along the Pie-IX boulevard.

The analysis showed that delays at start of trips, passenger activity, and snow accumulation significantly worsened reliability along the corridor. These results underscore the importance of strategies tailored to local conditions. Real-time probabilistic dispatching (Berrebi et al., 2015) illustrate ways of adapting dynamically to passenger surges, while targeted snow clearance along the corridor is critical to prevent weather-induced irregularity.

The local service also experienced worsening headway reliability after BRT implementation, despite not sharing stops with the BRT. This decline is likely tied to the lingering construction impacts in the southern section and around Jean-Talon station. These findings suggest the need for management plans during and after major infrastructure works, so that benefits for one service do not come at the expense of another.

Although not directly explored in the analysis, the remaining mixed-traffic sections along the corridor may still influence reliability in the dedicated segment through spillover delays at transitions or intersections. This points to the value of complementary measures such as conditional signal priority (Anderson and Daganzo, 2020) to mitigate delays at points where buses re-enter mixed flow. Overall, these implications emphasize that realizing the full potential of BRT requires combining infrastructure investments with robust real-time operational management measures.

7. Conclusions

This study provides empirical evidence of the operational impacts associated with the implementation of a new Bus Rapid Transit (BRT) corridor in Montreal, Canada using detailed AVL/APC data and a before-and-after comparative design. The results show that the Pie-IX BRT was able to improve travel time performance. Compared to the previous local service, BRT trips were four minutes faster, particularly during peak hours. These gains reflect the combined effects of the corridor's design, including dedicated bus lanes, all-door boarding, and larger vehicle capacity. In addition, modest improvements were observed for the local route operating in parallel to the BRT corridor (about 2 min), suggesting potential spillover effects related to transit signal priority and general improvements to corridor infrastructure.

Despite clear gains in travel time, the study highlights persistent challenges with respect to service regularity. While the local service showed a modest improvement in running time deviation after BRT implementation, the BRT experienced a significant increase in variability, indicating weaker schedule adherence. At the same time, headway deviation worsened across the corridor, where both the BRT and the local service after implementation displayed less regular spacing compared to the pre-BRT baseline. These patterns suggest that infrastructure upgrades alone were not sufficient to ensure consistent performance. One likely contributor is that early BRT schedules may not have been fully adapted to actual operating conditions. In addition, variability in stop-level demand, lingering construction along Pie-IX boulevard, and winter conditions likely amplified irregularities.

The findings underscore the importance of service management strategies during the initial stages of BRT implementation and the need for a more flexible scheduling approach. Infrastructure investments must be accompanied by real-time operational oversight, including schedule calibration, active dispatching, and headway control management (bus holdings), particularly during periods of high demand. Moreover, the observed benefits for the local bus route suggest that BRT implementation can contribute to broader corridor performance gains, especially when accompanied by system-wide operational enhancements such as signal priority and intersection redesign.

This study is not without limitations. It focuses on a single BRT corridor over a limited post-implementation window of five months. As such, the results primarily reflect short-term impacts and may not fully capture performance once the system has matured and stabilized. While our models control for observed weather conditions, the post-implementation data available covers only winter months. This limits our ability to assess whether the results generalize to other seasonal conditions. Future research could extend the analysis to subsequent periods to examine how operational outcomes evolved over time, particularly as construction along the route subsides and the operators gain more experience with the BRT. Further research could explore the effects of adaptive scheduling and control strategies introduced after implementation, as well as examining the relationship between operational performance and passenger satisfaction using integrated datasets. Comparative studies across other BRT corridors would help assess the generalizability of the findings from this study.

Overall, the results of this study point to the value of continued performance monitoring and adaptive management in the successful delivery of BRT systems. By aligning the BRT infrastructure with transit planning and operations, transit agencies can ensure that the benefits of speed and reliability are not only achieved but sustained.

CRediT authorship contribution statement

Thiago Carvalho: Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ahmed El-Geneidy:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare no conflict of interest.

Acknowledgement

The authors would like to thank Hisham Negm and Lancelot Rodrigue for their help with auxiliary data collection. This research was funded by Natural Sciences and Engineering Research Council of Canada grant Towards a better understanding of the determinants and satisfaction of travel among different groups in major Canadian Cities (NSERC RGPIN-2023–03852), and the Social Sciences and Humanities Research Council's partnership grant Mobilizing justice (SSHRC 895–2021–1009).

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