TRB Annual Meeting

Analyzing Spatiotemporal Patterns of Transit Service Reliability and its Association with Ridership Using GTFS and Real-Time Transit Data

--Manuscript Draft--

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ANALYZING SPATIOTEMPORAL PATTERNS OF TRANSIT SERVICE RELIABILITY AND ITS ASSOCIATION WITH RIDERSHIP USING GTFS AND REAL-TIME TRANSIT DATA

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ABSTRACT
Public transportation plays a vital role in urban mobility, and reliable transit service is crucial for attracting and retaining passengers. This study examines the spatiotemporal patterns of transit service reliability of the Miami-Dade Transit system using GTFS realtime data and explores how bus service reliability impacts transit ridership. We use four measures to evaluate service reliability: service adherence (ratio of actual trips and scheduled trips), on-time performance, headway adherence, and travel time reliability. We identified which routes and stops have the worst service reliability, and when and where delayed trips happen. Furthermore, we developed a time-fixed effects model to examine the association of service reliability with transit ridership. We found service frequency was a significant determinant of ridership. Short headways and daily number of trips have positive impact on the ridership, but the ridership has reverse causation effect on the on-time rate. Overall, the study results offer empirical evidence to justify the need for dedicated bus lanes and bus signal priority in high-density areas (e.g., Miami downtown and Miami beach), especially during afternoon peak hours on weekdays.

Keywords: On-time Performance; Bus Ridership; Service Reliability; Public Transit; Time-fixed effects

INTRODUCTION

Service reliability of public transportation systems plays a major role in determining whether a traveler would use transit for their trips (*1*). Public transit agencies and operators are expected to ensure high service reliability to create a positive experience for passengers and encourage more people to choose buses as a preferred travel mode. However, buses are vulnerable to delay due to traffic congestion, weather conditions, and other special events (*2*). If buses are frequently delayed or arrive earlier than scheduled, passengers may feel frustrated and seek other travel alternatives (e.g., private vehicles), which can increase vehicle volume and exacerbates traffic congestion, further reducing the reliability of public transportation services (*3*). Hence, service reliability has been a key performance measure of transit operations used by transit agencies around the world to guide decision-making.

Transit service reliability measures the extent to which the transit services provided by a system adhere to their schedule and provide consistent and predictable travel experiences for the riders. The commonly used measurements include on-time performance (OTP) and headway adherence. OTP indicates whether a transit vehicle arrives at or departs from a stop within a predefined window of time, often defined as two minutes before or five minutes after the scheduled arrival/departure time. Headway adherence measures whether the time interval between successive vehicles on a route maintains the specified headway intervals. For example, if the headway of a route is 30 minutes, headway adherence measures the percentage of trips adhering to this interval. Both OTP and headway adherence focus on measuring passengers' wait time experience. In this paper, we define the concept of service reliability more broadly to include service adherence (whether scheduled trips were a fulfilled) and travel time reliability (whether the estimated travel time was accurate).

Traditional approaches for measuring service reliability often involve manual observations (i.e., transit agency staff monitoring vehicle arrivals and departures at designated stops) and surveys. These approaches are labor-intensive, making them unsuitable to evaluate a large number of transit routes and stops. In recent years, the widespread adoption of vehicle tracking systems such as Automatic Vehicle Location (AVL) enables agencies to track vehicle locations, speeds, and movements in real time, allowing them to easily determine vehicle arrival and departure time at each stop. Furthermore, the emergence of GTFS (General Transit Feed Specification) Realtime also simplifies the technical steps required to efficiently compute service reliability measures, such as OPT and headway adherence, across the entire transit network. Despite the increasing adoption of GTFS Realtime, there is a lack of empirical work that applies such data to assess the service reliability of a transit system and identify routes and stops with low performance.

This paper examines the spatiotemporal patterns of service reliability of the Miami-Dade Transit (MDT) system and its association to transit ridership. We first adopted some measurements to evaluate the service reliability of MDT, including service adherence, OTP, headway adherence, and travel time reliability. Then we developed a time-fixed effects regression model to explore how bus service reliability affects ridership at the route level. Based on the results, we offer insights and practical recommendations for strengthening the MDT system's service reliability, with the goal of ultimately improving the travel experience for local passengers.

The remainder of this paper is organized as follows. Section 2 provides an overview of related literature, highlighting the measurements of bus service reliability and its impact on passenger ridership. Section 3 introduces the applicable context and datasets. Section 4 presents the methodology employed for evaluating OTP and exploring the determinants of bus ridership. Section 5 discusses the results and findings. Finally, Section 6 concludes the paper by summarizing the key insights and suggesting future research directions and policy implications.

LITERATURE REVIEW

Bus Service Reliability Measurements

In recent years, some studies have been conducted to evaluate bus service reliability and OTP (*4*). There are several indicators to define transit reliability, which can be grouped into five categories: travel time indicators, schedule adherence indicators, headway regularity indicators, wait time indicators, and composite indicators (*5*). Zhang et al. (6) used travel time deviation and indicator and travel time on-time accuracy model to evaluate the travel time reliability in Xi'an city. Saberi et al. (7) investigated the distribution of delays and headway deviations with headway regularity indicators and schedule adherence indicators, such as Earliness Index and Width Index. Godachevich and Tirachini (8) focused on headway variability at bus dispatching to measure the service reliability of buses in Santiago, Chile with three indicators: standard deviation, modified index per observation and an ad-hoc measure. Ishaq and Cats (9) calculated the coefficient of variation of the headway as a measurement of OTP of the Matronit Bus Rapid Transit (BRT) system in Haifa. These studies suggested that schedule adherence and headway regularity are the primary focuses of bus service reliability analysis. However, lots of studies do not provide a clear picture of the spatiotemporal pattern of bus OTP.

Influencing factors of Bus Ridership

A number of studies have focused on the impacting factors of bus ridership (*10*). These factors can be categorized into both internal factors and external factors. Internal factors mainly include route network design, vehicle revenue miles, fares, and especially OTP and service reliability (*11, 12*). Chakrabarti and Giuliano (13) found out that better schedule adherence can potentially promote passenger ridership, especially during weekday peak hours. Mucci and Erhardt (14) and Berrebi et al. (15) concluded the significance of frequent service frequency in improving bus ridership. Cervero et al. (16) found that the daily number of buses has a positive effect on station-level ridership. External factors impacting ridership typically include several categories: built environment, socioeconomic characteristics, land use pattern, and transit accessibility (*17, 18*). Some sociodemographic variables have been found to influence stop-level ridership positively, such as population density, households without vehicles, and employment rate, while some have a negative impact on ridership, such as median income and white population (*19–21*). Land use patterns and built environments have been identified to influence bus ridership, as urbanization, residential and commercial zones, pedestrian-friendly intersections, walk and bike connectivity, are usually associated with the increment of bus ridership (*22, 23*). A few studies have explored that accessibility and safety play a vital role in increasing transit usage and ridership (*24, 25*). Previous studies have applied a variety of statistical modeling approaches to explore the relative importance of these factors, the interaction between them, and their impact on transit ridership (*26*). These models typically include geographically weighted regression (GWR), ordinary least squares (OLS), Poisson regressions, time-fixed effect, and pooling regression (*27–29*). At this level of analysis, external factors usually predominate (*11*).

Previous studies have commonly used system or stop level as unit of analysis. For example, Tao et al. (30) modeled the effects of local weather conditions on bus ridership at stop level. Cui et al. (20) measured the relationship between accessibility and stop-level ridership. Compared with stop-level studies, few literature has studied route-level ridership. Studies on route-level ridership helped identify routes with the highest demand and determine the appropriate service frequency and timing for buses, hence improving the overall performance and effectiveness of the transit system. This paper filled the research gaps of modeling transit ridership at the route level and exploring the impacts of OTP indicators on ridership.

DATA

Our study focused on the Miami-Dade Transit system (MDT), the primary public transit system serving the Miami region in Florida. MDT is the largest transit system in Florida that operates four main types of services: Metrobus, paratransit, Metrorail and Metromover. The Metrobus network provides bus service throughout Miami-Dade County, which includes about 93 routes and 880 buses. Metromover is a free, elevated, automated mass transit people mover that runs on three loops in Miami Downtown area. Metrorail is a heavy rail rapid transit system that serves the urban core of Miami. Paratransit provides transportation options for people with a mental or physical disability who cannot ride Metrobus, Metrorail, or Metromover.

The main datasets used in this study include the OTP data, speed data, ridership data, and GTFS static. Both the OTP data and speed data are collected through Swiftly APIs from all the weekdays during October 2022 to March 2023 for Miami-Dade Transit. OTP data provides schedule-adherence information on all routes in the system, such as scheduled arrival time, actual arrival time, and their arrival time differences. This dataset also includes detailed trip information such as arrival stops, vehicle ID, bus routes, direction, trip destination, stop sequence, as well as status (delay or not). Speed data is collected at the route segment and stop level, including travel distance, travel and dwell time. Ridership data is requested from Miami-Dade Department of Transportation & Public Works (DTPW), which includes daily (weekdays/weekends) and monthly ridership of all bus routes. GTFS static data contains the complete scheduled operations of a transit agency during a specific period, including transit routes, stops, trip schedules, and associated geographic data. The GTFS static data can be compared to the OTP data to show the difference between actual trips and scheduled trips, especially in terms of daily transit service time and daily number of transit vehicles serving each stop.

METHODOLOGY

We perform a spatiotemporal analysis of transit service reliability. We then explored how these factors impact route-level bus ridership with the time-fixed effect model.

Descriptive Analysis of Service Reliability

As discussed above, there are various measurements to evaluate service reliability. This study utilizes the following measurements to analyze the service reliability of MDT from both spatial and temporal aspects as Figure 1 indicates: service adherence, on-time performance, headway adherence, and travel time reliability.

Service adherence indicates the extent to which a transit agency delivers the scheduled trips, measured by the ratio of the number of actual trips (available from the GTFS Realtime data) and the number of scheduled trips (available from the GTFS Static data). With a lower value indicating more cancelled trips, the measure can empirically assess the “ghost bus" issue. While this measure has not been commonly used to evaluate service reliability (which is often due to a lack of data), it is particularly important in recent years due to increasing service disruptions caused by the driver

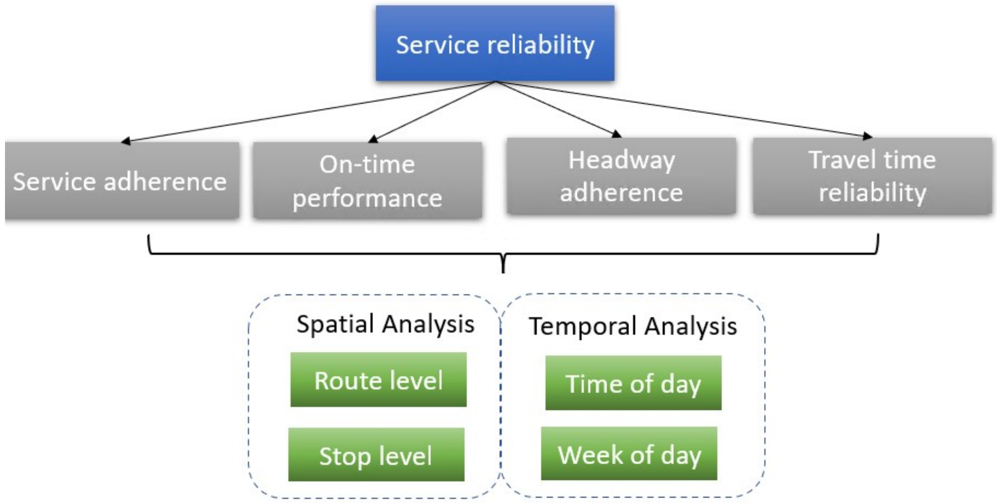

FIGURE 1 Flow chart of the descriptive analysis

shortage issue. The ideal value of the ratio should 1, meaning that the actual trips follow strictly its schedule without more or less bus dispatching. We measured service adherence at both the route and stop levels.

On-time performance (OTP) and headway adherence are other key measurements to evaluate bus service reliability. We then evaluated the bus OTP and headway adherence based on the arrival time difference and headway difference respectively. Arrival time difference refers to the difference between scheduled and actual arrival time. This measure reflects the experience of passengers who checks the bus schedule. A negative or positive value suggests the magnitude of an unreliable bus service. The ideal value of arrival time difference is zero, while a positive value means that the bus arrives later than the schedule, and a negative value suggests earlier arrival than the schedule. We measured the arrival time difference by routes and day of time. Headway difference refers to the difference between actual headway and scheduled headway. The headway is calculated by identifying the time difference between two continuous trips with the same destination, passing by the same stop on the same route and on the same date. The headway difference measures the experience for passengers who do not check the transit schedule but have some sense of the headway of the routes they take. If the transit system has perfect on-time performance, the headway difference value should be close to 0 with little variation, suggesting that the actual bus operation strictly follows its schedule.

Travel time reliability is measured by the ratio of actual trip time and scheduled trip time. The trip time ratio is to measure whether the travel time is reliable as passengers expected. Reliable services are expected to adhere closely to their schedules, ensuring that customers or passengers can rely on them to arrive and depart at the expected times. A higher ratio (greater than 1) signifies poorer reliability, as the service is experiencing delays or unpredictability. On the other hand, a ratio close to 1 suggests a reliable service that consistently operates as the schedule.

Analysis of Bus Ridership Determinants

To examine the impact of service reliability indicators on bus ridership, we modeled the bus ridership as a function of temporal characteristics using time-fixed effects models on longitudinal route-level data. Table 1 presents the summary statistics for the different variables in this model. The outcome variable is the bus ridership per route of average weekday during October 2022 - March 2023. The monthly variation of bus ridership is shown in Figure 1. Figure 1 (a) shows the median, 25th and 75th percentile of the monthly route-level ridership. The overall ridership remained stable from October to December 2022, increased since January 2023, and reached the top in February at a median ridership of about 2200. Then the overall ridership decreased slightly in March. The trend of the ridership reflects the seasonal and holiday effects. Winter and holidays (e.g. Thanksgiving in November and Christmas in December) may result in a decrease in ridership. Figure 1 (b) shows a significant variation in the monthly average ridership across different routes, with the highest ridership at about 10000 and the lowest ridership at less than 100. The monthly ridership of most routes ranges from 1000 to 4000.

The independent variables include the on-time rate, average daily trip number, and a dummy variable to identify routes with headway greater than 30 minutes. On-time rate (%) is the percentage of buses arriving within an acceptable threshold from their schedules (early arrival within 2 minutes and late arrival within 5 minutes). We also added a dummy variable to identify whether the bus headway is greater than 30 minutes, which takes a value of 1 if the bus headway is smaller than 30 minutes and 0 otherwise. All variables were tested for multicollinearity before executing the models to ensure no highly correlated variables are included in the final models.

TABLE 1 Descriptive statistics for all the variables

Variable	Category(%)	Mean	SD	Min	25th Pctl	75th Pctl	Max
Outcome variable							
Ridership		2082.09	2221.61	20	428.25	2756	10501
Independent variable							
On-time rate (%)		55.76	11.17	24.21	49.16	61.80	96.05
Headway smaller than 30 min	Yes(1) - 35 % No(0) - 65%						
Average daily trip number		62.67	37.44	1	35.60	84.48	170.76

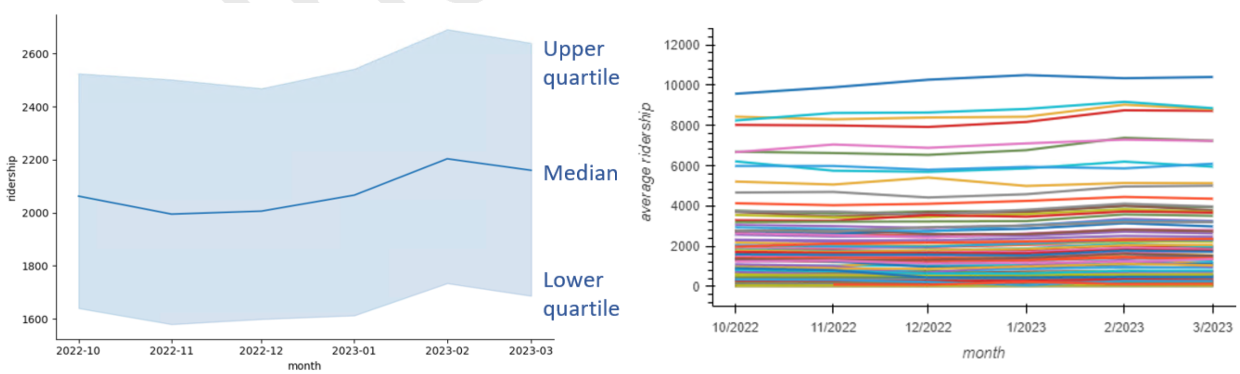

FIGURE 2 Monthly variation of bus ridership: (a). overall trend (b). average ridership per route

We used time-fixed effects model to estimate the effect of these variables on bus ridership. Time Fixed Effects Model is a statistical method used in panel data analysis to control for time-specific factors or trends in the data. Time fixed effects are particularly useful when we suspect that time-specific factors can influence the outcome variable - the bus ridership. By including time-fixed effects in the model, we can control all bus ridership that varies over month but remains constant across the bus routes. The regression equation is shown in Equation (1).

$$log(R_{i,t}) = \beta_0 + \beta_1 log(TN_{i,t}) + \beta_2 OT_{i,t} + \beta_3 HW_{i,t} + \beta_4 log(TN_{i,t}) * HW_{i,t} + \gamma_t + \xi_{i,t} \quad (1)$$

where:

- $R_{i,t}$: the bus ridership for bus route i during time t (month).
- β_0: the fixed intercept for the model.
- β_1-β_4: coefficients to be estimated.
- $TN_{i,t}$: average daily trip number.
- $OT_{i,t}$: on-time rate.
- $HW_{i,t}$: dummy variable for identifying whether the bus headway is smaller than 30 minutes.
- γ_t: the time fixed effect of t^{th} month.
- $\xi_{i,t}$: the error term.

In our model, we applied a natural-log transformation to both our dependent variable $R_{i,t}$ and the primary explanatory variable of interest $TN_{i,t}$, as these two variables are not normally distributed. We also added an interactive variable $log(TN_{i,t}) * HW_{i,t}$ in our final model, a variable measuring the number of bus trips when the headway is greater than 30 minutes. We hypothesize that all the variable coefficients should be positive and significant, as we believe that a more relatively reliable service should attract and retain a greater number of passengers.

RESULTS

Service Adherence: Scheduled Trips versus Actual Trips

To measure service adherence, we calculated the ratio of the actual daily number of trips and the scheduled daily number of trips at the route and stop levels. Figure 3 shows that for most routes, the ratio is close to one with a small level of variation, suggesting that these routes mostly adhere to their schedule. However, some routes have worse service adherence as the ratio of is smaller than 1 and have large deviations. For example, Route 200's service adherence measure has a median value of 0.75 and an extremely high level of deviation. This indicates that buses on route 200 usually dispatch fewer buses than the schedule. This will result in delays and longer waiting times for passengers easily and discomfort in passengers' travel experiences. Other routes with bad service adherence include routes 246, 1 and 248. Figure 4 suggests that, for many stops, there were about 25%-50% cancelled trips, suggesting highly unreliable services at these stops. As fewer buses pass the stops than what's been scheduled, passengers may need to wait longer than they expected and lose confidence in the service's ability to meet their travel needs consistently, leading some to seek alternative transportation options. Only a few stops in Miami downtown have relatively better service adherence, as the actual trips almost match their schedule at these stops.

On-time Performance

We measured the OTP based on the arrival time difference. We first visualized the distribution of the arrival time difference across transit routes in Figure 5. The median line of each box represents the median arrival time difference for all trips of a transit route. The length of the "box" for each transit route indicates the variation in arrival time difference; the longer a box is, the more

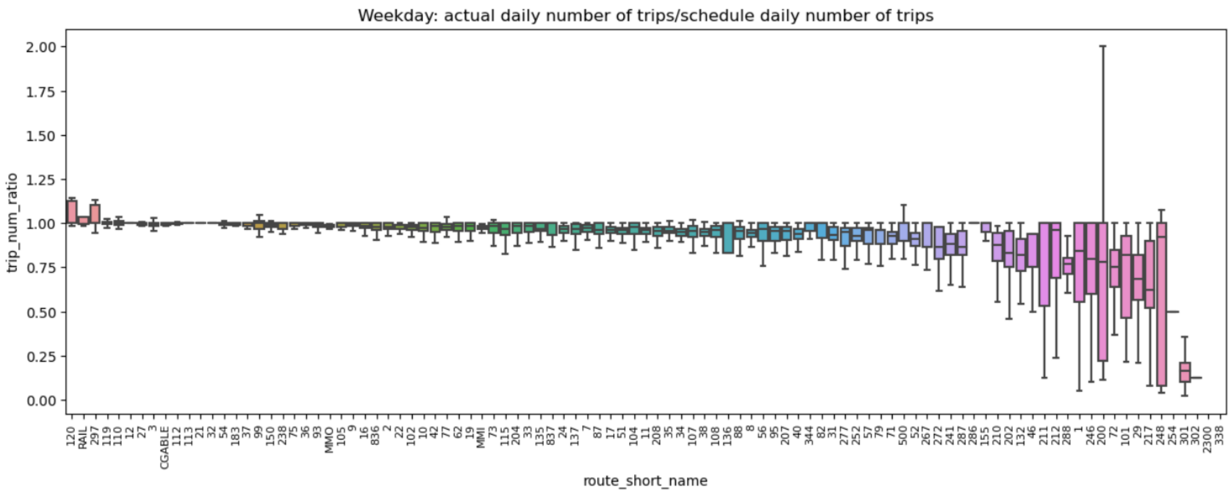

FIGURE 3 The ratio between actual and scheduled number of trips for each route

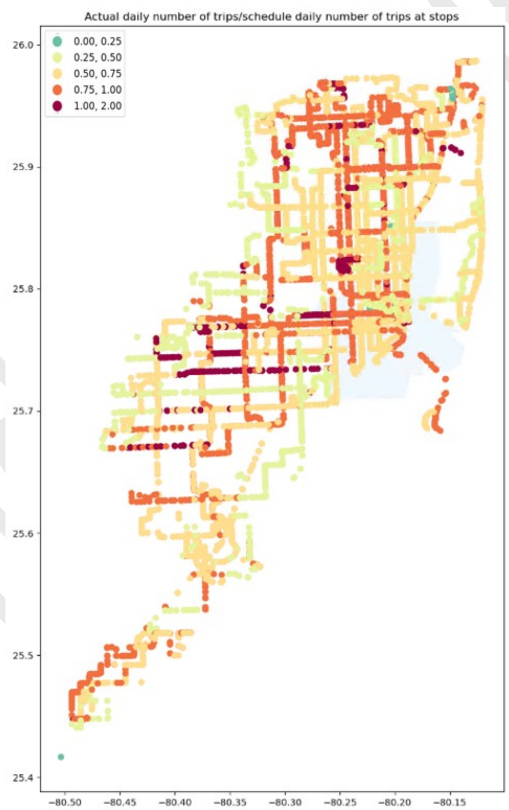

FIGURE 4 The ratio between actual and scheduled number of trips at stop level

uncertain the arrival time. The horizontal red line denotes the 0 value of arrival time difference, which is compared with the median value of each ‘box’. Ideally, the median arrival time difference should be close to the red line. Transit routes such as Route 286 and Route 155 have an arrival time difference close to zero and a low variation in arrival time, which means that they have the best on-time performance. By contrast, the worst-performing transit routes are routes 302, 29, and

57. The arrival time of these routes fluctuates a lot, with a high frequency of delays.

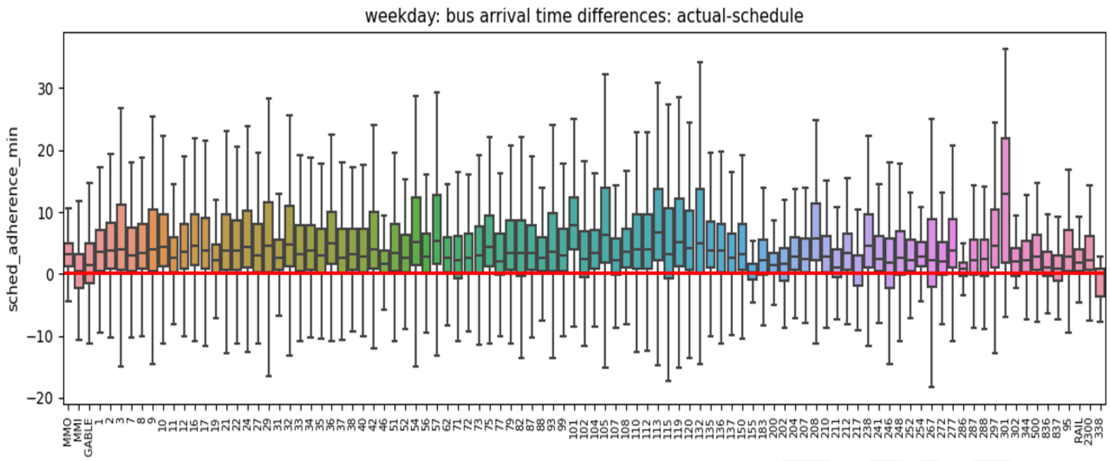

FIGURE 5 The arrival time difference between actual and schedule time by routes

We also generated pivot tables showing the mean arrival time by routes and daily hours to see when the transit service is stable. The pivot table can summarize the on-time performance dataset by grouping and aggregating the arrival time differences by hour and route. The X-axis shows the hour of day, and the Y-axis shows the route name. The average arrival time is filled at the cells, as the colormap on the right represents the arrival time difference in minutes. According to Figure 6, transit vehicles often delay for over 20 minutes during afternoon peak hours (4-7pm).

In addition to temporal analysis at week or time of day, we conducted spatial analysis of OTP at the bus stop level. In Figure 7, we map the proportion of early or late arrival for 5 minutes or more at each stop to visualize where early or late arrivals typically happen. Most stops have close to 0 percent of early arrival rate. While very few stops have an ideal on-time performance rate of less than 10% of late arrival trips, most stops have a delay rate of 30-40%. Notably, some stops at Miami Downtown have a very high delay rate at 60-80%.

Headway adherence

We then measured the service reliability by headway adherence at route level and across time. As shown in Figure 8, routes with the best service reliability should have a median headway difference value close to 0 as well as low variance in this value, such as route 286, 301 and 302 The mean of the difference between the actual and scheduled headway for most routes is close to 0, but the difference has relatively high variation (±10-20 min), such as route 9, 29, 17 and 77. The headway difference of route 132 at weekdays is about 5 minutes, which suggests that the service of Route 132 is highly unreliable, with significant delays (sometimes for about an hour) at many stops.

We also generated pivot tables showing the mean headway differences by routes and daily hours to see when the transit service is stable. The colormap on the right represents the headway difference in minutes. Ideally, most regions should appear in yellow, as the headway difference should be close to 0. Red/orange zones represent that the actual headway typically exceeds more than 10 minutes ahead of schedule headway, while blue zones represent that the actual headway typically lag behind the schedule headway for more than 10 minutes. According to Figure 9, the headway difference does not vary greatly by hour. However, route 132 and 297 have a very high

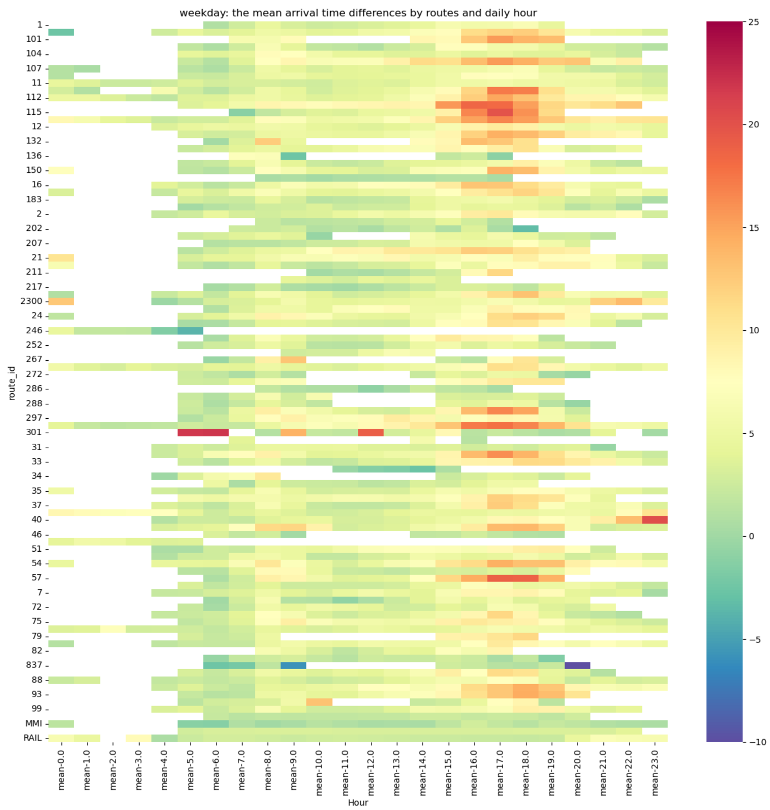

FIGURE 6 Pivot table of mean arrival time differences by routes and daily hour

headway difference at more than 15 min on weekdays. At midnight, headway difference tends to enlarge as dark red and blue appears at 11pm-1am.

Travel time Reliability: Scheduled Trip time versus Actual Trip time

We then measured travel time reliability by calculating the ratio of actual trip time and scheduled trip time. As Figure 10 shows, the trip time ratio of more than half of the routes is greater than 1, suggesting that the actual trips on these routes usually take longer than the scheduled time. This indicates bad service reliability of MDT. 301 was the route with the worst service reliability, as the median trip time ratio even exceeds 2 with a very high deviation.

Modeling outputs

Table 2 shows the model estimation results for the time-fixed effect model, including the variables, the coefficients and P-values. This model achieves an R-squared of 0.73, suggesting that about 73% of the variation in bus ridership across months can be explained by the determinants included in this model. The positive coefficients of $HW_{i,t}$ (routes with a headway of 30 minutes or shorter) and $log(TN_{i,t})$ (daily average number of trips) are reasonable, which suggests that ridership increases with greater service frequency. Transit routes with a shorter headway and more bus trips can reduce

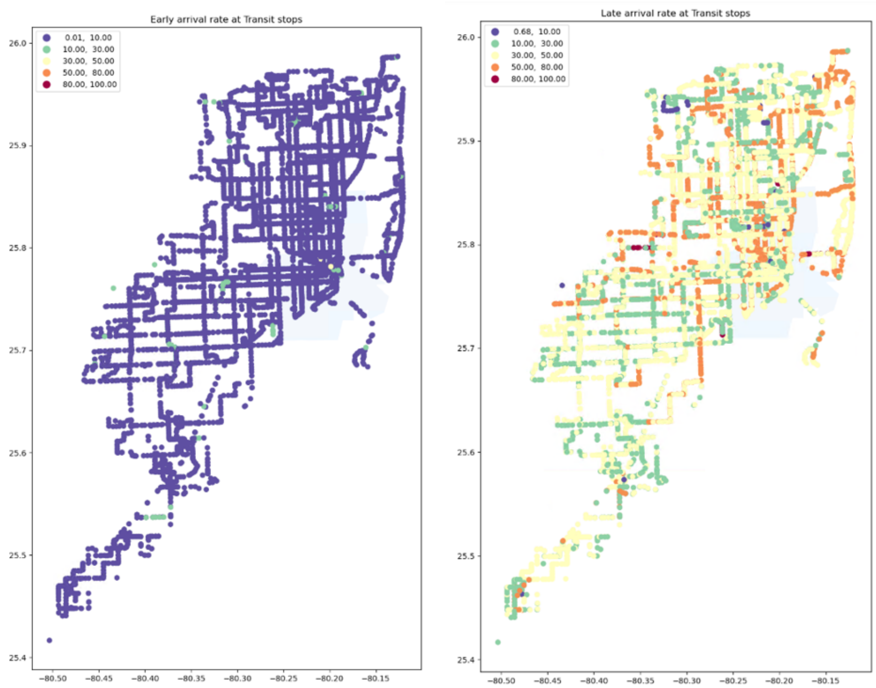

FIGURE 7 Early and late arrival rate at stop level

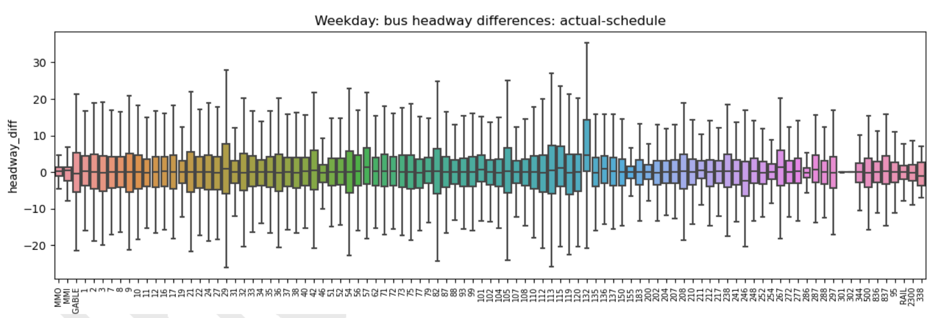

FIGURE 8 The headway difference between actual and schedule time by routes

the average waiting time of passengers and enhance the attractiveness of transit services to many travelers.

However, the coefficient of on-time rate is negative, which contradicts our hypothesis that the higher on-time rate will promote bus ridership. We offer two explanations for these results. First, it is possibly due to the issue of reverse causality, which may bias the parameter of on-time rate; in other words, the causal relationship works in the other direction: routes with a higher level of ridership tend to have a lower on-time rate. This may be because a greater number of passengers require longer boarding time, which cause delays. Second, it is due to the data issue: we have only modeled six month of data (October 2022 to March 2023). The short study period means that there is limited variation in the data, making the time-fixed effect model generating less reliable results. Moreover, the interaction term has a negative sign, which adds further evidence to the effect of reverse causality. The more frequent routes tend to have higher ridership levels and operate in

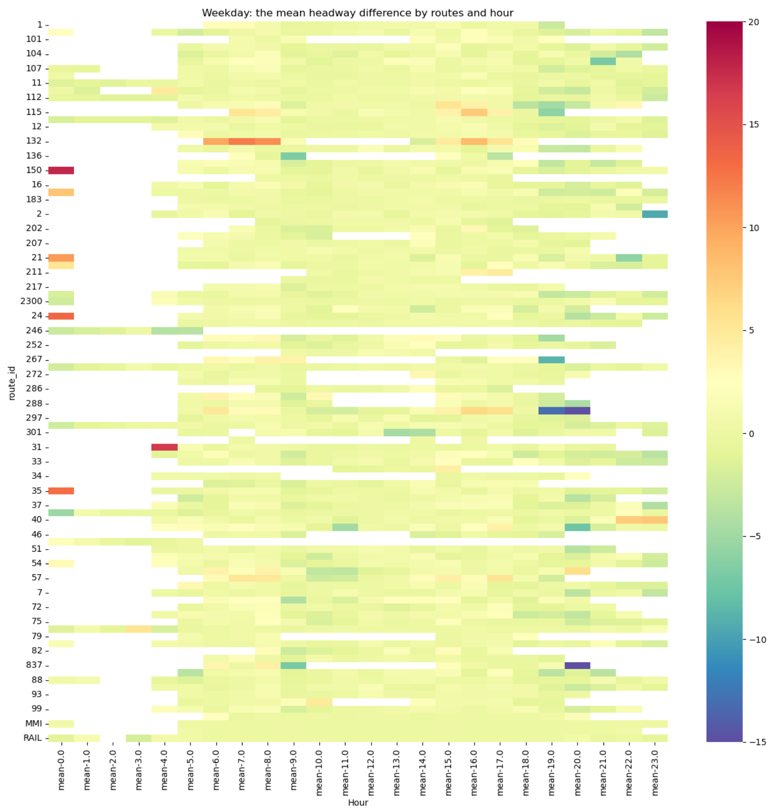

FIGURE 9 Pivot table of mean headway differences by routes and daily hour

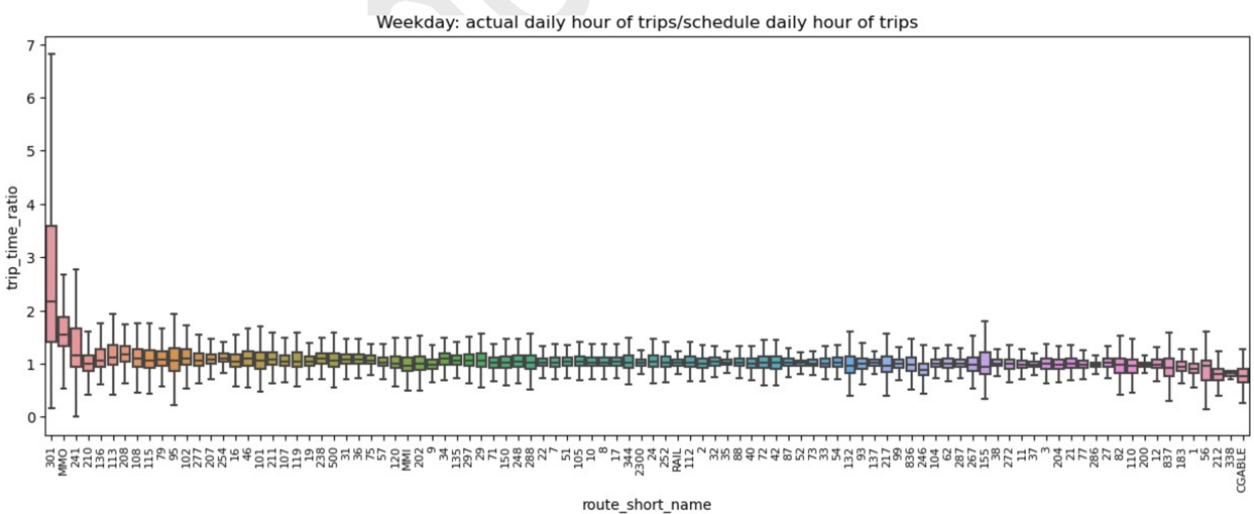

FIGURE 10 The ratio between actual and scheduled trip time for each route

more congested areas, which cause vehicle delays and consequently lower on-time rate.

TABLE 2 Time-fixed effect regression of bus transit ridership

Independent variable: $log(R_{i,t})$		
Dependent variables	**Coefficient**	**p-value**
$OT_{i,t}$	-0.0098	0.0042**
$HW_{i,t}$	1.7036	< 0.001***
$log(TN_{i,t})$	1.5210	< 0.001***
$HW_{i,t}$ * $OT_{i,t}$	-0.0285	< 0.001***

Significance codes: '***' p<0.001; '**' p<0.01; '*' p<0.05.

DISCUSSION

The proposed analytical framework provides a comprehensive evaluation of a transit system's service reliability by evaluating the complete trip experience of a transit rider. Service adherence evaluates if a passenger can do reliable trip planning, OTP and headway adherence assess the wait time experience, and travel time reliability measures if the estimated travel time is accurate and reliable. In our case study of MDT, we have identified where and when transit services are less reliable. For example, considering the median values and variance of both arrival time difference and headway difference, we found that buses on route 286 and 132 have the worst service reliability. Bus trips passing through stops at Miami downtown or Miami beach have the most frequent delays. On the temporal dimension, we found that weekdays have longer delays than weekends and that buses experience most delays during the afternoon peak hours. These results provide practical insights that can inform MDT's strategies to improve customer experience in critical areas and time periods.

This study also modeled the impact of service reliability on route-level bus ridership. The study period is six months and has less temporal variation in terms of both ridership and service reliability. We incorporated additional service reliability indicators in our model, such as the mean absolute and squared values of arrival time or headway differences during peak hours, mean and standard deviation of daily service revenue hour. However, these variables are excluded in our final model because of statistical insignificance and multicollinearity concerns. Future research could obtain stop-level data for longer periods from 2018 to 2023 from MDT. This will help capture seasonal and long-term trends of ridership and service reliability that are not evident in a shorter six-month period. To build a more robust and reliable model, besides internal factors regarding service reliability, future studies could account for spatial factors that might influence bus ridership, such as the sociodemographic variables and accessibility within bus stop buffers along the routes. The refined model will capture the spatial and temporal variation in the relationship between ridership and its associated external and internal factors.

CONCLUSION

Service reliability is one of the key factors in the acceptability of bus service, which directly impacts passenger satisfaction and perception of public transportation. In this paper, we define service reliability broadly to capture the complete transit trip experience and measure it in four dimensions: service adherence, OTP, headway adherence, and travel time reliability. We used the Miami-Dade Transit system as a case study and consider the transit's operational characteristics. The service reliability measurements we chose can effectively assess the service reliability at route or stops levels and at various temporal scales. For most transit routes, the median arrival time difference easily lags behind its schedule. The actual trip time of most routes is slightly larger than the scheduled trip time. Both the arrival time difference and headway difference have strong variations on many routes. Many stops have canceled trips, which usually range from 25% to 50% of the scheduled number of trips. Bus delays most frequently happen during weekday afternoons and at Miami downtown and Miami Beach. These results offer empirical evidence to justify the need for dedicated bus lanes and bus signal priority in these high-density areas during afternoon peak hours.

In addition, we applied a time-fixed effect model to analyze how the following factors affect route-level ridership: on-time rate, daily number of trips, and headway. All these variables have a statistically significant impact on ridership at the route level. As we expected, daily number of trips and headway less than 30 minutes have a positive effect on promoting bus ridership. However, ridership in turn affects the on-time rate, then the overall effect of on-time rate on the ridership is biased downward. The model is limited to data collected over a six-month period. Future studies should consider a longer study period and using a more comprehensive list of variables, including both internal and external factors. For example, in our ongoing work, we are evaluating the distinctive impacts of the four service reliability measures examined here on transit ridership.

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