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Does real-time transit information reduce waiting time? An empirical analysis

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A R T I C L E I N F O

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A B S T R A C T

A claimed benefit of real-time information (RTI) apps in public transit systems is the reduction of waiting time by allowing passengers to appropriately time their arrivals at transit stops. Although previous research investigated the overall impact of RTI on waiting time, few studies examine the mechanisms underlying these claims, and variations in its effectiveness over time and space. In this paper, we theorize and validate the sources of RTI-based users' waiting time penalties: *reclaimed delay* (bus drivers compensating for being behind schedule) and *discontinuity delay* (an artifact of the update frequency of RTI). We compare two RTI-based strategies – the greedy strategy used by popular trip planning apps and a prudent strategy with an insurance buffer – with non-RTI benchmarks of arbitrary arrival and following the schedule. Using real-time bus location data from a medium-sized US city, we calculate the empirical waiting times and risk of missing a bus for each trip planning strategy. We find that the best RTI strategy, a prudent tactic with an optimized insurance time buffer, performs roughly the same as the simple, follow-the-schedule tactic that does not use RTI. However, relative performance varies over time and space. Moreover, the greedy tactic in common transit apps is the worst strategy, even worse than showing up at a bus stop arbitrarily. These results suggest limitations on claims that RTI reduces public transit waiting times.

1. Introduction

Capabilities for collecting and sharing real-time information about transportation systems is changing how people navigate and travel through cities. Apps and services such as Google Traffic, INRIX and Waze provide departure time and route suggestions for automobile-based travel based on current and predicted traffic and travel times, allowing users to avoid traffic congestion, minimize travel time and arrive on-time more frequently (Cabannes et al., 2018). Correspondingly, many public transit agencies are sharing schedule and real-time vehicle location data to enable navigation apps that make public transit more convivial and useful to users.

Public transit navigation apps allow users to discover and navigate public transit systems with complex routes and schedules (Dutzik et al., 2013). Public transit apps often provide real-time information (RTI) on vehicle locations and arrival times to make the system feel more convivial to users. RTI can help users reduce the amount of time they must wait for public transit at stops; this is crucial since waiting time is perceived as onerous by users and cited as a major reason why people do not like using public transit (Algers et al., 1975; Gkioulou, 2013). The rationale behind the saved waiting time is that RTI allows users to determine the best time to

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leave their home, workplace, or similar location to travel (typically, by walking) to a public stop. RTI users can access frequently updated data on bus location and arrival times at stops, adjusting their departure time accordingly (Brakewood et al., 2015; Cats and Gkioulou, 2017; Watkins et al., 2011). RTI can be especially important for systems with sparser timetable and longer headways such as those in medium and smaller urban areas. In public transit systems that cannot sustain high frequency service due to limited resources, RTI can play an important role as a substitute to shorten waiting times despite infrequent service (Cats and Loutos, 2016a).

Popular RTI apps aim to diminish waiting time to zero: the user's expected arrival time at a stop is the same as the bus arrival time in most transit planning apps' suggested routes. However, this attempted minimization of wait time can be risky. After a person decides to leave their home, the actual arrival time of the bus may change. For example, if a bus is behind schedule, the operator may reduce the delay by speeding up. In addition, RTI apps update vehicle location and arrival times only at fixed time intervals. The discrepancies between the RTI and reality may make the user miss the bus, incurring a longer wait time – at least as long as the service headway. Paradoxically, the misuse of RTI may increase waiting times based on the realized performance of the public transit system.

In this paper, we examine the impacts of RTI on public transit users' waiting time based on the empirical performance of a public transit system. We compare two RTI-based strategies – the greedy strategy used by popular trip planning apps and a prudent strategy with an insurance buffer – with non-RTI benchmarks of arbitrary arrival and following the schedule. We compare the performance of these strategies using high-resolution schedule and real-time vehicle location data for a popular bus route operated by the Central Ohio Transit Authority (COTA) in Columbus, Ohio, USA. We find that the greedy strategy has the worst waiting time. The best RTI strategy, a prudent tactic with an optimized insurance time buffer, only performs roughly the same as a simple, follow-the-schedule tactic that does not use RTI. However, relative performance varies depending on time of day, distance to the bus stop, and the location of the stop along the bus route. Although RTI can have other benefits (such as reassuring users), these results suggest limitations on the value of current RTI prediction scheme in reducing user wait time.

In the next section of this paper, we will review previous research about the impact of mobile RTI on waiting time. The subsequent section introduces our data sources, a theory of the mechanisms that underlie RTI users' waiting time penalties, and two RTI-based strategies used in trip planning and two typical benchmarks strategies without RTI. We demonstrate each strategy's overall performance and performance with respect to time, distance to bus stop, and location of the bus stop within the route. We conclude this paper with a discussion of major findings, their significance for science and planning, and potential next research steps.

2. Literature review

In this section, we provide a comprehensive review on the impact of mobile real-time information. The deployment of automated vehicle location system, open data policies, and the widespread adoption of the mobile telephony has generated a widespread use of RTI by public transit agencies and users. Correspondingly, the body of literature on RTI in public transit is growing. We will first review the methods of quantifying the impacts of RTI on waiting time and report these studies' findings.

2.1. Methods

Survey-based methods are the most common among RTI impact studies. These methods can moreover be classified into two categories: self-reported survey (Chow et al., 2014; Ferris et al., 2010; Watkins et al., 2011) and observation (Papangelis et al., 2016). Self-reported surveys are the most direct methods to assess transit system use and especially useful to measure user experience and perceptions. Survey data can also help assess individual differences based on gender, demographic and social attributes (Neuman and Robson, 2004). However, despite extremely useful under the mentioned circumstances, the results of self-reported surveys could be inconsistent with *actual waiting time,* since they measure *perceived waiting time* (Brakewood et al., 2014). Observation survey by a third-party researcher or a sensor can better measure the actual waiting time. For example, in Seattle, RTI users' self-reported average perceived waiting time was 7.54 min compared to non-RTI users' 9.86 min, while the average actual waiting time obtained by observers for RTI users was 9.23 min compared to non-RTI users' 11.21 min (Watkins et al., 2011).

Another approach to analyzing the impacts of RTI on waiting times is mathematical simulation. Agent-based modeling represents the simultaneous actions and interactions of various agents in intricate and complicated systems such as public transit (Gkioulou, 2013). For example, Cats and Gkioulou (2017) adopted an agent-based model to simulate the influence of transit reliability and real-time information on waiting time uncertainty. With more abundant and accurate real-time data, many studies also simulated the real-time arrival time prediction schemes and investigated the added-value of RTI on real-time users. For example, Cats and Loutos (2016a, b) introduced a new bus arrival prediction scheme and compared its performance with the schedule and a common prediction scheme.

2.2. Findings

Numerous studies investigated RTI's impact on public transit users and drawn different conclusions on the effectiveness of RTI for different regions and different RTI media. In this section, we will focus on impact of personal devices RTI and summarize prior quantitative findings.

Most studies reported that RTI can reduce *perceived waiting time* by using self-reported surveys. Ferris et al. (2010) concluded that 91% of RTI users spent less time waiting in Seattle. Brakewood et al. (2014) conducted behavioral experiment in Tampa to test the self-reported waiting time and found that RTI user reported 1.5 min less than the control group. Similar conclusions were drawn in other contexts besides urban transit systems for commuting. Papangelis et al. (2016) found an average self-reported waiting time reduction of 7 min in rural Scotland. Some studies also concluded that RTI has positive impact on the *actual waiting time* by observation and simulation. Watkins et al. (2011) found that RTI users could save 2 min than non-RTI users by observation. Cats and Loutos (2016a,b) introduced a better RTI prediction scheme that can save waiting time equivalent to introducing a 60% increase in service frequency in Stockholm. Cats and Loutos (2016b) also concluded that RTI could make waiting time estimate twice as close to the actual time than the schedule.

However, some studies concluded that RTI has limited impact on both perceived and actual waiting time in some cities. Brakewood et al. (2015) explored the impact of mobile platform RTI on Boston commuter rail services and concluded that perceived waiting time did not have a statistically significant difference between RTI and non-RTI users on the survey days. Fries et al. (2011) used video feed to construct simulation model of waiting time and found pre-trip travel time savings, which is part of actual wait time, were small; the major benefit of RTI is anxiety reduction.

Although the overall impact of RTI on waiting time is well-explored, few studies investigate the variance of these impacts (Brakewood and Watkins, 2019). Most studies focus on the overall average actual waiting time, perceived waiting time, or predicted time deviation; however, few studies investigated the variance of this impact on actual waiting time relative to transit system's actual on-time performance. Empirical performance matters because on-time performance and delays can be heterogeneous within a system and even within a single route (Park et al., 2019). In addition, a key decision of public transit users is when to leave home (or other origin) to travel to a stop; therefore, the impact of RTI on waiting times may vary with walking time to the stop (Cats and Loutos, 2016a). Due to the heterogeneity of on-time performance, the impact of RTI may also vary by the location of the stop within a route. This paper fills this research gap by analyzing the overall and disaggregated performance of different trip planning strategies that both ignore and exploit transit RTI based on the actual performance of a public transit system.

3. Methodology

In this section, we introduce our data sources. Next, we conceptualize synchronization process between the user and the vehicle, and introduce the concepts of *reclaimed delay* and *discontinuity delay*: the former related to over-estimation of bus arrival time, the later related to the RTI updating frequency. Both can have impacts on RTI users. Based on the synchronization theory, we propose and model several trip planning strategies representing the possible behaviors of users. We also optimize the RTI apps user's strategy based on real-time data; this represents an ideal RTI app that provides pro-active advice to users. We also calculate the waiting time difference between RTI apps users and non-RTI users.

Our study site is Columbus, Ohio and the Central Ohio Transit Authority (COTA). COTA bus system's average headways are considerably large, meaning that public transit waiting time is a significant factor in this system. Also, as a typical car-oriented American city, the case study can be easily expanded to other cities and larger scales with same data support and methodologies.

3.1. Data

We use two data sources to represent two major actors in a public transit system: General Transit Feed Specification (GTFS) real-time data corresponding to the information available to users and automated passenger counter data to represent the actual on-time performance behavior of the transit system.

General Transit Feed Specification (GTFS) real-time provides a standard protocol to effectively transmit transit real-time information with normalized standard. Most RTI apps use the estimated arrival time provided by GTFS trip update for the buses' real-time information (Google Developers, 2018; Transit app, 2019). Therefore, we simulate RTI users' behavior from the GTFS trip update data. We collected the COTA GTFS data in MongoDB and Python environment from May 2018 to May 2019; for GTFS real-time, we archived the streamed data with frequency of one minute for the same time period.

A one minute update interval in our study represents a typical trip planning app update frequency. Table 1 shows the update frequency of all publicly available transit systems in the US that provide GTFS real-time feed from OpenMobilityData.org (OpenMobilityData, 2020). We use the GTFS real-time validator (Center for Urban Transportation Research @ USF, 2020) to measure the update frequency of each GTFS real-time feed as of May 2020. The table shows that the majority of the transit systems still have non-

Table 1
GTFS real-time update frequency for 20 transit systems in the United States.

Transit system	GTFS update interval (secs)	Transit system	GTFS update interval (secs)
MBTA, Boston, MA	~5	Go Metro, Cincinnati, OH	~30
Community transit, Seattle, WA	~10	DCTA, Denton, TX	~30
CATA, Lansing, MI	10–20	VIA, San Antonio, TX	~30
MST, Monterey, CA	10–20	HART, Tampa, FL	~30
RTC, Southern Nevada	10–20	LTD, Eugene, OR	~30
Votran, Daytona Beach, FL	10–20	Metro Transit, Madison, WI	~30
ART, Arlington, VA	20–30	MTA, MD	~30
Big Blue Bus, Los Angeles, CA	20–30	RTA, Riverside, CA	~30
Calgary Transit, Calgary, Alberta, Canada	~30	Capital metro, Austin, TX	~60
BART, San Francisco, CA	~30	CT Transit, Hartford, CT	>60

trivial interval between each update.

Although GTFS data's resolution is relatively high, its *temporal accuracy* can be improved for determining realized wait times. Temporal accuracy measures difference between the measure's recorded time and the actual time (Liu and Miller, 2020); this represents the systematic error caused by the temporal delay of measurement. Since GTFS data is updated at a fixed interval, the reported times of bus arrivals at stops could be different from the actual arrival times. To improve temporal accuracy for estimating wait times, we used automated passenger counter (APC) data. These data are event-driven: rather than updated at a fixed temporal interval, they are updated when the arrival/departure event at a stop occurs. However, because the APC devices are not installed on every bus, the system coverage is not 100% like GTFS. Correspondingly, we merged the APC data and GTFS to achieve both higher temporal accuracy and 100% system coverage: for every trip and stop, query in the APC database and overwrite the GTFS record if APC record exists (Liu and Miller, 2020). We obtained APC data from COTA for the period May 2018 to May 2019.

3.2. *Synchronization*

We conceptualize catching a bus as a synchronization process between the walking trip to the target stop and the target bus's *trip sequence array*. Trip sequence array is the collection of trips running on the same route and in the same direction as the target bus.

Depending on user's arrival time at the stop *t*, the actual bus that user will take can be different from the scheduled one. We use the same concept in the transfer synchronization process: *desynchronization degree* (DD), to measure the desynchronization between the bus and user at the stop (Liu and Miller, 2020). DD is an integer indicator that represents how many buses the user loses in the trip sequence array: it represents the order number of the actual bus before/after the scheduled bus. For example, if the actual bus is the *n-th* bus after the scheduled bus, the DD is *n*; if the actual bus is the *n-th* bus before the scheduled bus, the DD is -*n*; if the actual bus is the scheduled bus, then the DD is 0.

When synchronizing, users can control the stop arrival time only by selecting their home departure time. Except for very crowded conditions in dense cities, we can assume walking time is linear with respect to distance. In contrast, the actual real-time performance of the bus is non-linear: the bus will not run at a fixed velocity and the expected time of arrival of bus at the stop is constantly changing. The vehicle operator can change the vehicle's speed based on conditions in real-time. Most relevant to our question, a vehicle operator can make up for an initial delay by increasing speed. Indeed, public transit agencies value on-time performance and may incentivize drivers to compensate for delays when possible, considering speed limits and safety considerations.

We therefore introduce the concept of *reclaimed delay*. Similar to delay propagation (Park et al., 2019) and riding time deviation (Cats, 2019), it is the time difference between the estimated time of departure estimated before the bus arrival and the actual time of departure at the target stop. It measures the over-estimation caused by bus accelerating, short signals, and skipping stops between two stops. Many studies reported the impact of the delay propagation on transit performance (Cats, 2019; Park et al., 2019), ridership and running time (El-Geneidy et al., 2006; El-Geneidy et al., 2011). In this paper, we are going to discuss the impact on waiting time specifically. Fig. 1 shows corresponding space–time diagram of the expected synchronization, the actual desynchronization, and delay reclamation process. After the user leaves home, the actual bus trip (blue line) will diverge from the expected bus trip (red line) and converge with the scheduled bus trip (yellow line): since the bus has an initial delay near the user's home, the bus accelerates and catches up the delay with the schedule. However, the user's walking trip is still aiming for the expected bus trip. Consequently, the bus

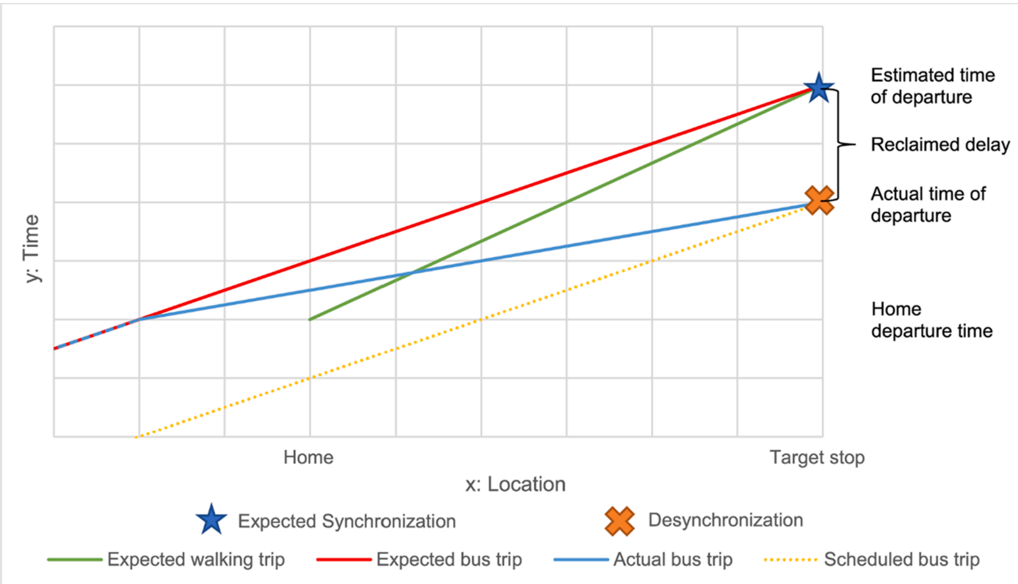

Fig. 1. Space–time diagram of the expected synchronization and the actual desynchronization.

arrives earlier than the user's expected time and the user will miss the bus. The reclaimed delay could be small but critical for RTI apps users: if expecting the user and the bus to always arrive at the same moment, the RTI apps user could miss the bus and suffer waiting time penalty for a relatively long time. Thus, the synchronization of these two processes is highly unstable.

Besides reclaimed delay, due to the discrete nature of the GTFS real-time data, there are *discontinuity delays* for all RTI-based trip planning strategies: if RTI apps do not interpolate the gap between the data feeds and their corresponding timestamp, the RTI-based users will wait until the data is updated. However, when the data is updated, the RTI-based user may already be late for the bus. Similarly, if the user decides to leave between two updates, although the RTI apps will show a good result based on the last update, in reality the user will miss the bus. Either scenario is the consequence of discontinuity of the real-time data. Exactly like reclaimed delay, although the discontinuity delay could be very small in value, it still can result in desynchronization and significantly long waiting time. Both reclaimed delay and discontinuity delay produce potential missed risk for RTI-based users.

3.3. Trip planning strategies

A trip planning strategy is a tactic for a user to plan and execute a transit trip. There are different trip planning strategies for both RTI apps and non-RTI users to determine their home departure time. Assuming no disturbance on user's walking and boarding process, different trip planning strategies have only one controllable factor to determine the actual waiting time, namely, the home departure time:

$$w(\tau) = \pi^a(\tau) - \tau = \pi^a(t + \delta t) - (t + \delta t) \tag{1}$$

where τ is the passenger's arrival time at the stop, t is the home departure time, δt is the walking time, and $\pi^a(\tau)$ is the corresponding actual boarding bus departure time which depends on when the passenger arrives at the stop. We examined the sensitivity of the linear walking time assumption against the counterargument that users could mitigate the risk of missing a bus by running if they see it. Using parameters based on average human running speed and duration, and the visibility of bus route signage at distance, our sensitivity analysis suggests that the results are relatively stable with respect to linear walking time. Therefore, we define each trip planning strategy by giving the formula of either its actual waiting time or its home departure time.

We define two simple non-RTI benchmark strategies, arbitrary arrival and following the schedule, and two RTI strategies: a greedy strategy followed by popular trip planning apps and a prudent strategy based on an optimized insurance buffer.

3.3.1. Arbitrary tactic

The simplest strategy is to arbitrarily walk to a stop and catch the subsequent bus that arrives; this is a common pattern for users' arrival time with short headways (Bowman and Turnquist, 1981). Since we have access to the real-time vehicle departure time data, we can directly calculate the waiting time as the median of the departure time of target bus and its previous bus without calculating the home departure time due to random uniform distribution:

$$w = \frac{1}{2} \cdot (\pi_0^a - \pi_{-1}^a) \tag{2}$$

where: δt is waiting time, π_0^a is the bus's actual real-time departure time with desynchronization degree = 0, and π^a_{-1} is the previous bus's actual real-time departure time with desynchronization degree = −1.

Theoretically, this strategy is not very efficient since it is always the half of the buses' actual headway. Therefore, it is a good benchmark for other trip planning strategies: if another trip planning strategy performance is even worse than arbitrary tactic, we can assert that it is not effective.

3.3.2. Schedule tactic

These timetable-dependent users make their home departure time decisions based on the schedule published to the public:

$$t = \pi^t - \delta t \tag{3}$$

where: δt is the walking time from user's home to the stop, π^t is the scheduled bus departure time.

A schedule tactic is another common benchmark (Cats and Loutos, 2016a) because it is the default strategy to use public transit and it has the lowest risk of missing a bus. Although schedule tactic users do not benefit from waiting time reduction based on RTI, they are unlikely to miss a bus: many public transit systems have explicit policies restricting vehicle operators from leaving stop ahead of schedule, including COTA (COTA, 2019).

3.3.3. Greedy tactic

Greedy tactic is a strategy used by many real-time transit planning apps and algorithms. The routing and timing advice provided by these apps is such that the user will arrive at the same time as the bus at a stop, thus achieving shortest waiting time. This can be checked empirically by comparing the user arrival time at stops with the bus departure time on popular apps. Therefore, based on the same logic, a greedy tactic user will check the relationship between suggested home departure time and current time, leaving home when the bus's estimated time of departure is equal to or greater than walking time plus current time. The pseudo code is for this strategy is:

$$\begin{array}{l} \textbf{\textit{while}}\ \textit{there is a new update}\ \textbf{\textit{do}} \\ \quad \textbf{\textit{if}}\ t' + \delta t \geq \pi^p \\ \qquad \textit{return}\ t = t' \\ \quad \textbf{\textit{else}} \\ \qquad \textit{wait until next update} \end{array} \tag{4}$$

where: π^p is the scheduled bus's estimated time of departure given by RTI app and t' is the current time when a new update is available.

Ideally, this strategy can achieve a minimal wait time if no disturbance as shown in Fig. 1. However, due to the instability of transit system, its risk of missing a bus is also the highest. Due to the possible reclaimed delay and discontinuity delay, the bus may leave the stop earlier than the estimated time of departure. Consequently, we consider an alternative, prudent, RTI-based strategy.

3.3.4. Prudent tactic

To manage the risk of missing a bus, a RTI user may want to leave home earlier than the greedy tactic. This is a common strategy to avoid risk of missing a bus, such as using the 95th percentile waiting time as budgeted waiting time (Furth and Muller, 2006). An *insurance buffer* trades some time to reduce risk of missing a bus. Given a user-designated insurance buffer *IB,* the pseudo code for home departure time *t* is:

$$\begin{array}{l} \textbf{\textit{while}}\ \textit{there is a new update}\ \textbf{\textit{do}} \\ \quad \textbf{\textit{if}}\ t' + \delta t + IB \geq \pi^p \\ \qquad \textit{return}\ t = t' \\ \quad \textbf{\textit{else}} \\ \qquad \textit{wait until next update} \end{array} \tag{5}$$

The insurance buffer is an indicator of the transit users' risk attitude: it represents how much time the user is willing to gamble to gain the waiting time reduction. The less insurance buffer, the more risk-seeking the user. We can consider prudent and greedy tactic as part of a *prudent tactic family*, since the greedy tactic is a special case with insurance buffer of 0.

We can optimize the insurance buffer to achieve minimal waiting time by users based on the empirical performance of the transit system. This requires four steps that could be accomplished by a trip planning app on the server side:

- Calculation: Designate a set of buffers (e.g., 0–300 s) and walking time ranges (e.g., 0–9 min). Calculate the performance for all designated buffers. The results contain user's arrival time at the stop and the actual taken bus's departure time for users with different walking time.

Fig. 2. Bus route 2′s standard and frequent service map.

Table 2
Overall performance of trip planning strategy; waiting time and missed risk's mean and deviation.

Strategy class	Trip planning strategy	Waiting time		Risk of missing bus	
		Mean	Standard deviation	Mean	Standard deviation
No real-time information	Arbitrary Tactic (AT)	510 s	–	–	–
	Schedule Tactic (ST)	252 s	345 s	6.28%	16.55%
Real-time information	Greedy Tactic (GT)	751 s	707 s	74.63%	74.50%
	Prudent Tactic (PT)	282 s	381 s	10.18%	17.70%

- Optimization: Find the smallest waiting time and the corresponding buffer each day. If there are multiple smallest waiting time, designate the one with smaller buffer to guarantee least waiting time.
- Finalization: For each day, reduce all past days' buffers into one by finding the maximum of the optimal buffers. We aim to find the smallest buffers while most trips are synchronized. To accommodate changes in the schedule, we will restart the process whenever a change is implemented.
- Revalidation: Based on the finalized buffers, calculate the performance of each day.

However, the number of insurance buffers is large: we minimize waiting time over each IB_{ijk}, which represents a different buffer for each trip i, each stop j, and each walking time k from the stop (0 – 10 min). Meanwhile, the collected transit system data volume for the period May 2018 to May 2019 is terabyte-scale; to deal with the consequent large computational cost, we selected the representative bus route No.2 to study and parallelized the outmost loops (buffers × dates) on a workstation with 40 virtual CPU cores. We also select another five major routes in the COTA systems in a typical week and conduct the same PT optimization process to test the generalizability of the research.

4. Analysis

In this section, we focus on the performance of different trip planning strategy based on scheduled and actual bus arrivals at stops

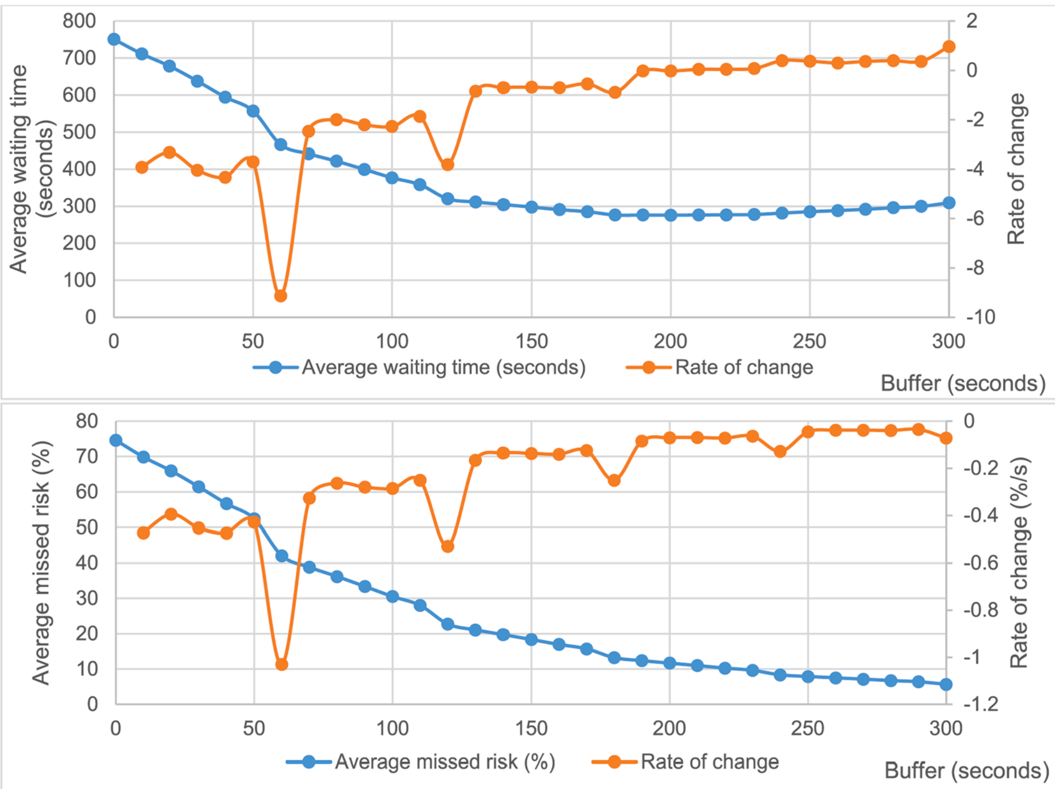

Fig. 3. Average waiting time/missed risk and their changing rates' relationship with the uniform buffer.

along one bus route in the Columbus, Ohio, USA Central Ohio Transit Authority (COTA) system: route No. 2. We chose this route for its popularity (it is the one of the busiest routes in the system) and coverage (it traverses a long spatial transect of the city and has a long service temporal span). Fig. 2 provides a map of COTA bus No. 2 from Southeast to Northwest during the period May 2018 to May 2019. The bus route has two schedules: the frequent schedule originates from the red circled stop in Fig. 2 with headways of 10–15 min, while the standard (non-frequent) schedule originates from blue circled stop with headways of 20–30 min.

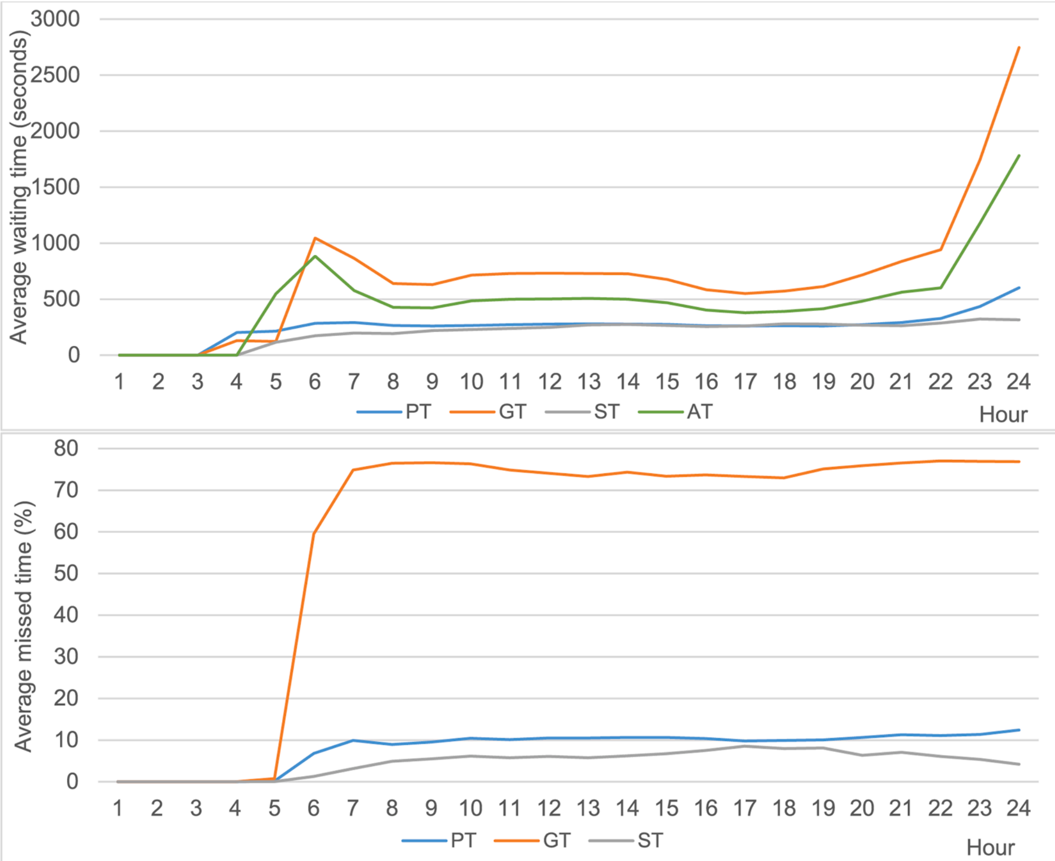

Fig. 4. Average waiting time and risk of missing bus by hour of day.

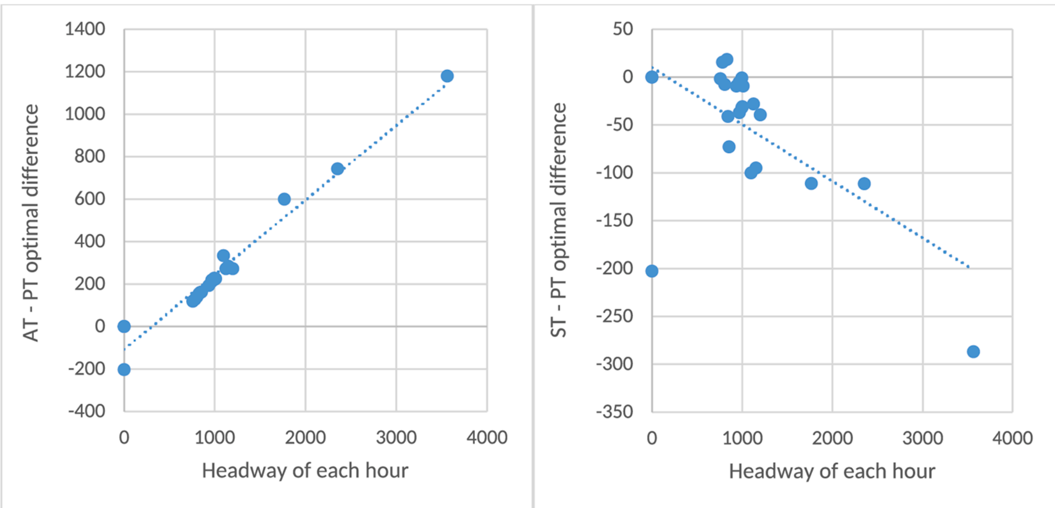

Fig. 5. Scatter plots between headway and AT- PT (left side) and ST-PT (right side) waiting time differences.

4.1. Overall performance

Table 2 shows the mean and deviation of each trip planning strategy waiting time and risk of missing a bus. Overall, the schedule tactic (ST) or the prudent tactic (PT) with optimal insurance buffer are the best strategies: these achieve roughly equivalent waiting time performance based on waiting time average and standard deviation; they also have similar performance based on bus missed risk average and standard deviation. Showing up at the bus stop at an arbitrary time (AT) has the second worst performance. AT only has average waiting time because we do not simulate the decision-making process like the other trip planning strategies but use Eq. (2). The worse strategy is the greedy tactic (GT) that is common in trip planning apps: this is a risky strategy that is harshly penalized by reclaimed delay and discontinuity delay in the RTI system. This suggests that many trip planning apps and algorithms are systematically proposing a very risky strategy with poor performance to users.

To show the relationship between reclaimed delay, discontinuity delay and the risk of missing a bus, we also calculate the delay reclamation and miss risk for each specific trip. We estimate that during the whole year, when a delay reclamation occurred, there was 88.87% chance that the GT user would miss the bus. To validate the existence of discontinuity delay, we calculated 31 trip planning strategies in the PT family, each with a designated static insurance buffer from 0 (greedy tactic) to 300 s. Fig. 3 shows how the average waiting time, miss risk and rate of changes in both indicators with respect to the length of the insurance buffer. Note the dramatic changes in both indicators at the multiples of the RTI update frequency (60 s). These abrupt changes demonstrate the existence of the discontinuity delay. With better real-time data supports and policies, more transit systems are providing RTI with higher update frequency. Some can be as high as 5 s such as Massachusetts Bay Transportation Authority in Boston. However, the large majority of most transit systems still face considerable discontinuity delay larger than 30 s as shown in Table 1.

These results suggest that real-time information may have limited value with respect to minimizing waiting time and risk. A strategy that simply takes the RTI at face value (GT) is the worst performing strategy: even worse on average than showing up at a bus stop randomly (AT). Enhancing the RTI with an optimal insurance buffer helps (PT); however, this strategy is not substantially better than simply following the schedule (ST) without using RTI. However, note these results reflect overall performance. The effectiveness of these strategies can vary with respect to time and space; we examine these patterns below.

4.2. Performance over time

4.2.1. Hourly pattern

Fig. 4 illustrates the average waiting time and risk of missing a bus with respect to hour of the day. These hourly results support the

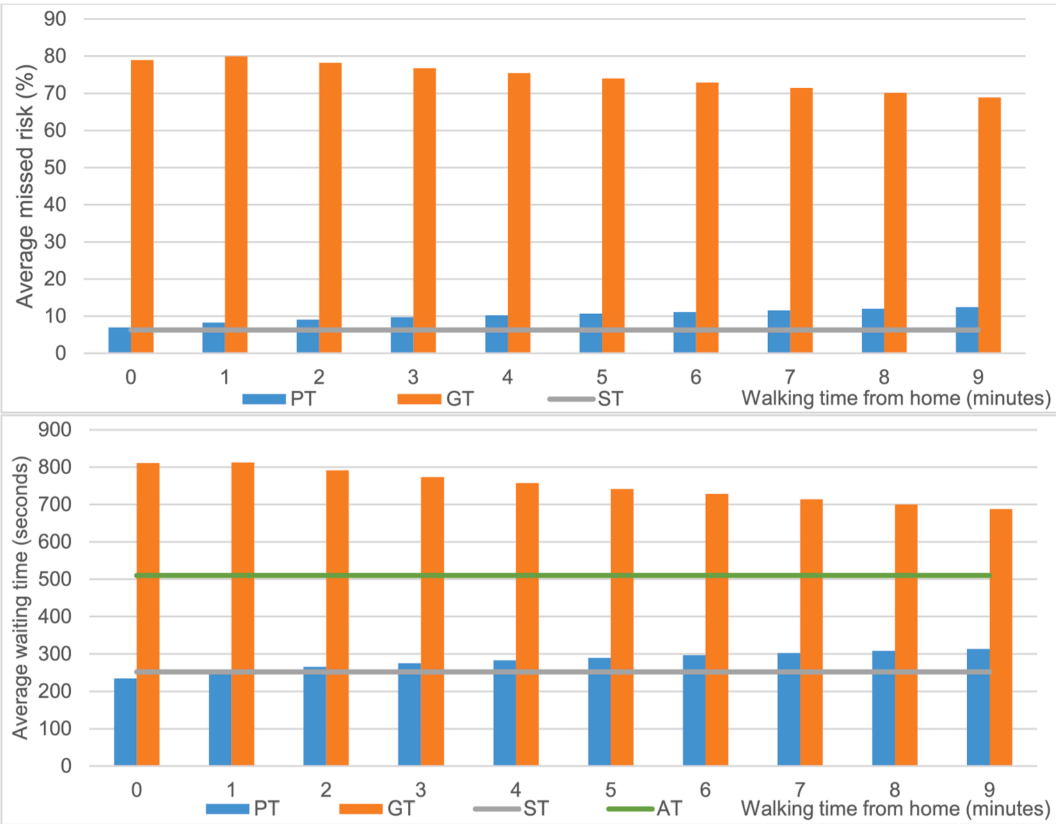

Fig. 6. PT, GT, AT, and ST’s waiting time and risk of missing bus’s relationship with the walking time.

overall results discussed above: ST and PT are consistently the best over the course of a day. AT and GT perform especially poorly during service hours with long headways (6:00 to 8:00 and 21:00 to 24:00) since the time penalties associated with missing a bus during these periods are dramatically higher. These inferior strategies perform better during short headway hours, but not better than ST and PT. GT is a very risky strategy at all times, although is not penalized as harshly during short headway hours.

Although ST and PT are always competitive, although there are some differences in their performance over the day. For long headway hours in the morning and midnight, PT performs worse than ST; while for most hours during 8:00 to 21:00, performs PT almost the same as ST; especially, for afternoon hours from 17:00 to 20:00: with higher delay in the system due to peak traffic and user-related boarding delays, PT outperforms ST. In this sense, it is generally better for transit users to follow ST in the morning commuting and follow PT in the afternoon commuting. This suggests that PT is more sensitive to the headway and delays than ST.

4.2.2. *Service headway*

As previous analyses suggest, headway is a crucial factor for the performance of trip planning strategies. Since service headway can change by hour of the day, we conduct two temporal analyses based on the average headway within each hour. The analyses suggest two empirical rules:

- The larger the headways, the *more* effective PT compared to AT. This is obvious since AT's waiting time is exactly the half of the headway. To moreover prove this, we investigated the correlation between the average waiting time difference in each hour and the average headway. The Pearson correlation indicates a strong positive correlation (coefficient $= 0.9798$ and p-value < 0.0001) as shown in Fig. 5 (left). Some former studies also suggested the same conclusion: in rural Scotland, RTI users can save 7 min in average (Papangelis et al., 2016), while in other studies in urban areas, the saved time is much less (Brakewood et al., 2014; Chow et al., 2014). RTI will flatten the radical waiting time difference between different systems caused by different scheduled frequencies.
- The larger the headways, the *less* effective PT compared to ST. Likewise, we tested the correlation between each hour's average headway and corresponding performance difference. Fig. 5 (right) shows a strong negative correlation (Pearson correlation coefficient $= -0.6201$ and p-value $= 0.0012$).

4.3. *Performance over space*

4.3.1. *Walking time to bus stops*

Fig. 6 illustrates the relationship between average waiting time and risk of missing bus based on walking time from home to the closest stop. Again, we can see that the non-RTI strategy of following the schedule (ST) and the prudent RTI strategy (PT) are generally competitive with each other with respect to average waiting time. However, as walking time to the nearest bus stop increases, the PT waiting time increases with respect to ST, which can also be observed in Fig. 7. The degradation of PT waiting time performance with increasing walk time is due to the increasing risk of missing a bus. This supports the claim that the longer distance a user lives from the stop, the more unstable their trip is: the longer walking time to the stop, the bus has a greater chance to reclaim delay; because PT trips are synchronized to RTI, they are more sensitive to reclaimed/discontinuity delays. Therefore, PT users have a greater chance to desynchronize with longer walking time. This is also consistent with prior studies about prediction horizon's impact on the waiting time (Cats and Loutos, 2016a).

Interestingly, for the greedy strategy (GT), longer walking time lowers average waiting time since the risk of missing a bus decreases with distance from a stop, which can also be observed in Fig. 8. Similar to PT's scenario, with longer walking time to the stop, the bus also has a greater chance to gain more delay; because GT trips are highly desynchronized due to a small reclaimed/

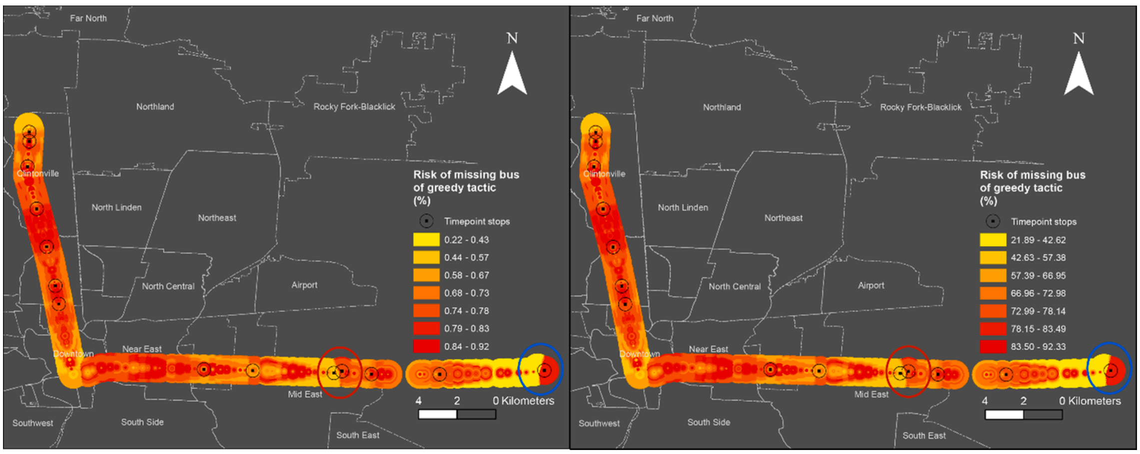

Fig. 7. Spatial pattern of average wait time (left side) and missed bus risk (right side) within a walking distance buffer for the GT strategy (black stroke: timepoints).

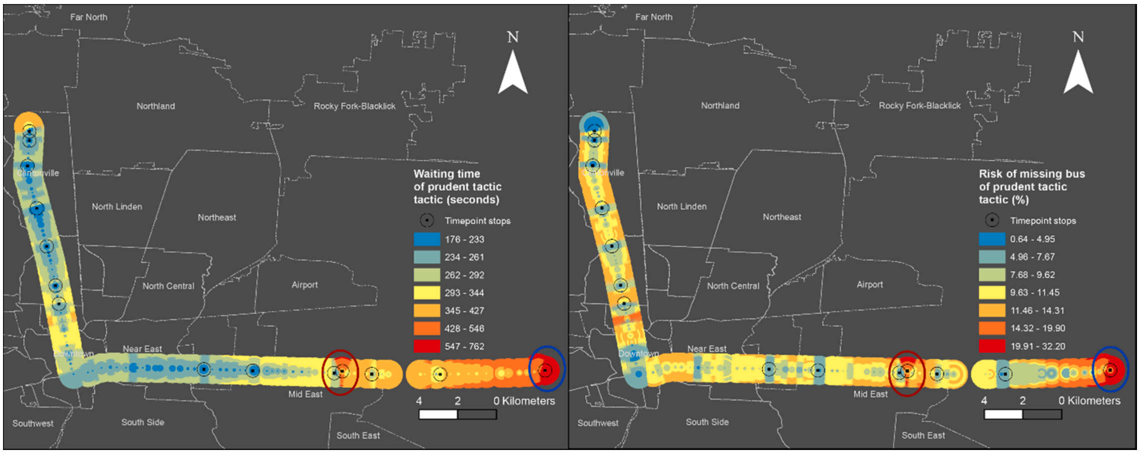

Fig. 8. Spatial pattern of average wait time (left side) and risk of missing bus (right side) within a walking distance buffer for the PT strategy.

discontinuity delay, the gained delay can offset the reclaimed/discontinuity delay, which plays a similar role as the insurance buffer. Therefore, GT users have a greater chance to resynchronize with longer walking time.

In conclusion, with longer walking distance/time, the chance of reclaiming and gaining delay will simultaneously increase while the chance of maintaining delay of the same value will decrease. PT and GT are the two polar of RTI-based trip planning strategies and their performance will converge with longer walking time: highly synchronized PT is sensitive to reclaimed delay and its performance will become worse; while highly desynchronized GT is sensitive to gaining more delay and its performance will become better.

4.3.2. Spatial patterns

As noted above, due to the heterogeneity of on-time performance over a bus route, the location of the bus stop within the route also

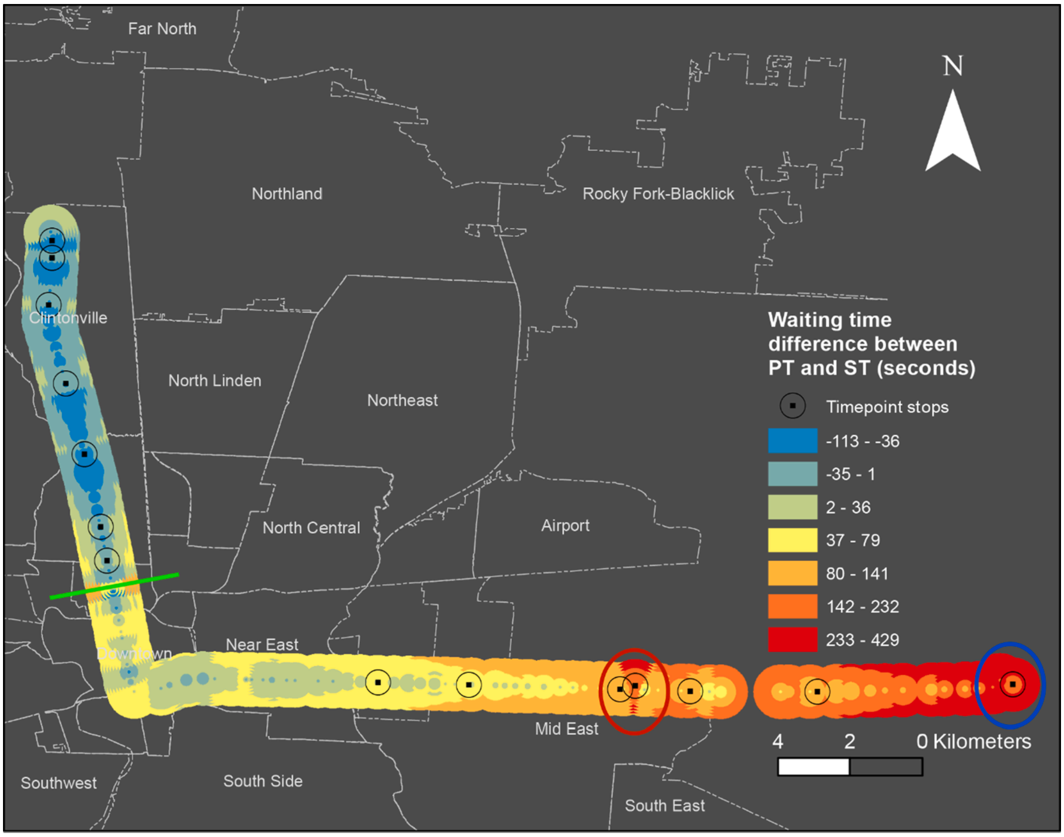

Fig. 9. PT – ST waiting time difference for each stop and walking time in COTA bus route No. 2 from Southeast to Northwest.

influences the performance of a trip planning strategy. To illustrate this, we map the average wait time and risk of missing a bus for home locations within 0–9 min (0–756 m) distance buffer of COTA bus route #2 heading from southwest to northeast, assuming users travel to their closest bus stop. Fig. 7 shows the spatial pattern of the average waiting time and risk of missing a bus for GT. It confirms the waiting times are sensitive to the change in the headways indicated by red ovals: longer headways are correlated with longer waiting times but not risk of missing bus. Fig. 8 shows the average waiting time and risk across space for the prudent tactic optimal. Noticeably, there are two significant clusters of high waiting time/high risk near the originating stops for standard headway service (indicated by a blue oval) and frequent headway service (indicated by the red oval). These clusters occur because real-time information will not be available for these stops until the bus leaves the originating stop. By the time the real-time information is updated, the user has likely missed the bus. Consequently, PT insurance buffer will not help improve the missed risk of such trips since its effectiveness depends on accessible RTI. Meanwhile, users who live far from the stop will have higher risk of missing a bus and will consequently suffer from even more waiting time. In these areas, transit users are vulnerable and may be structurally unable to utilize real-time information.

We can also observe interesting spatial patterns at *timepoints* in Figs. 7 and 8, defined as stops where buses try to strictly observe the scheduled timetable. For GT, the waiting times at timepoints are significantly larger than nearby non-timepoint stops. Due to strict timetable policy, bus drivers may tend to reclaim more delay before these stops, making greedy tactic users' risk of missing bus larger. However, the waiting time for prudent tactic optimal at timepoints are significantly smaller than nearby non-timepoint stops, showing the effectiveness of the optimal insurance buffers.

To test the generality of these spatial patterns, we performed a similar analysis of the PT for five other bus routes in the system (specifically, COTA routes 1, 5, 7, 8, and 10). These are popular routes that have different directions, different spatial and temporal coverages within the service area. We select the time period from a typical week from 7/15/2018 – 7/21/2018, when there was no major event like football games and extreme weather. We observe the spatial distribution of the waiting time is highly similar to the results for route 2: the standard service sections have higher waiting time while the sections with frequent services have lower waiting time. These routes also have same concentric circle pattern based on walking time to stops.

4.3.3. Spatial differences between ST and PT

We now compare the performance of best RTI strategy (PT) and best non-RTI strategy (ST) with respect to space, which is a common benchmark adopted by prior research (Cats and Loutos, 2016b, 2016a). Fig. 9 shows the average wait time difference between ST and PT within a walking distance buffer of the bus route. We observe the originating stops have exceptional high waiting time due to larger headway. We can also observe that PT does not outperform ST for more than half of all stops. In fact, for most stops, especially for those stops in the upstream near the originating stops, ST performance is much better than PT. This could be because of the relatively stable performance of prudent tactic optimal and the deterioration of the on-time performance in the downstream stops. To moreover demonstrate the variations, geographically, we divide the stops into two groups at a stop (North High Street & Euclid Avenue) shown as a green line in Fig. 9. For upstream stops, PT users waited 68 s more than ST users; while for downstream stops, ST users waited 21 s more than PT users. The comparison shows the highly polarized geographic pattern of relative performance between these two strategies.

5. Conclusion

Most previous research suggests that transit real-time information (RTI) can decrease transit users' waiting time (Brakewood and Watkins, 2019). However, few studies systematically investigate the mechanisms behind this claim and the variations across time and space of RTI impact on waiting time and the risk of missing a bus. In this paper, we theorize and validate the concept of reclaimed delay and discontinuity delay during the synchronization process between users and buses. We introduce the concept of trip planning strategy and discuss four different types for both RTI and non-RTI users. We calculate the empirical wait time and risk of the different trip planning strategies using real-time bus location data for a representative bus route in a mid-sized US city. We find that the best RTI strategy, a prudent tactic (PT) with an optimized insurance buffer, performs roughly the same as a simple, follow-the-schedule tactic (ST) that does not use RTI. The analyses results show that PT users in upstream stops on a route will wait more time than the ST users, and PT users in this area may suffer from higher risk of missing a bus than ST users. We also find that PT users are more advantageous during evening peak (17:00–20:00) than ST users. These results show that although the best RTI strategy can indeed save time for certain users in certain stops and during certain hours, they cannot globally outperform simply following the published schedule. Moreover, the greedy tactic (GT) of using RTI to achieve a waiting time of zero is the worst strategy, even worse than showing up at a bus stop arbitrarily. This suggests that RTI could make users' waiting time significantly longer if apps are not using the appropriate trip planning strategy.

This study provides valuable insights for transit users, planners, and real-time transit app providers. With more access to real-time data, it is understandable that transit system navigation apps would engage with real-time performance data in addition to the published schedules. However, our results suggest that real-time performance data is not sufficient: RTI apps should also consider historical data to gauge the veracity of the RTI in reducing waiting time based on spatial and temporal context. Users should also have the option of specifying different trip planning strategy, including prudent strategies with insurance time buffers. At present, most RTI apps do not consider missed risk and implicitly promote a greedy strategy: as we have shown, this is a risky and poor performing strategy. The techniques and measure we develop in this paper can help support a more holistic and sensitive approach to public transit RTI apps.

To improve accuracy and reliability of RTI apps, transit authority or RTI apps providers can add pre-calculated insurance buffers based on stated or revealed risk attitudes of users. Also, our optimization of prudent tactic is not fully explored, there are likely better ways to find the optimal insurance buffer. Unlike simple non-RTI strategies that can be conceptualized and understood by humans from experience, RTI-based trip planning optimization can only be accomplished by the backend of the RTI apps, where more complicated and effective algorithms can be applied. Computational techniques such as machine learning and neural network could be applied to empirical performance and user data to determine effective trip planning strategies based on context and user risk preferences.

Finally, although each trip planning strategy's performance at individual level is systematically discussed in this paper, we do not empirically survey or simulate the proportions of the users using each trip planning strategy among all users. Future research should survey the different trip planning strategies user groups and the way in which they use transit apps in their decision making. This includes but is not limit to the distribution of actual insurance buffer and actual waiting time. The progress on these issues will help to understand RTI apps' collective impact on the whole population. Meanwhile, we also encourage future studies to expand the methods to more transit systems with different headway and update interval to test the transferability of the conclusions drawn from the COTA system.

CRediT authorship contribution statement

Luyu Liu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing. **Harvey J. Miller:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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