Measuring Disruptions’ Impacts on the Unreliability of Public Transit Accessibility: Example of COVID-19 and College Football Games

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# Introduction

Accessibility is the primary indicator of a public transit system’s useability. It determines passengers’ ability to reach opportunities given a fixed amount of time [CITATION NEEDED]. However, high reliability of public transit systems’ accessibility is a primary disadvantage compared to other transportation systems. Transit systems are highly dynamic and time-dependent, and their actual arrival time and accessibility can be significantly different from the scheduled time. On-time performance loss worsens the useability and user experience of transit systems, and it is one of the most important reasons why people do not favor public transit among other mobility options [CITATION NEEDED].

A major cause of unreliability is public transit systems’ vulnerability to outer disruptions, including short-term and long-term disruptions. Short-term disruptions introduce temporary disturbances usually in only a part of the system. Prominent examples are traffic jams, extreme weather, and major social events. Short-term disruptions affect accessibility primarily by influencing the on-time performance, in the form of delayed or early arrivals. Long-term disruptions have persistent impacts on the reliability of the whole system, such as the COVID-19 pandemic and schedule changes caused by budget cut. Besides the on-time performance, long-term disruptions can also change the schedule, which create more nuanced patterns of unreliability.

Some prior studies discussed public transit’s accessibility unreliability. Wessel, Allen, & Farber and Wessel & Farber (*1*, *2*) assessed the unreliability of schedule-based accessibility with respect to retrospective real-time accessibility; they calculate schedule-based measure from transit schedule data and calculate retrospective real-time accessibility from historical real-time vehicle location data. They find significant unreliability in schedule-based accessibility. Nevertheless, retrospective measure assumes users know *a priori* the actual arrival time (*1*), which is only attainable after the event happens. Therefore, retrospective accessibility cannot be realized by a user. It does not represent the actual accessibility that a user experiences during operation, and the deviation of retrospective accessibility from schedule-based accessibility cannot accurately reflect accessibility unreliability.

In this paper, we use *realizable real-time accessibility* – a space-time prism measure that can be achieved by ordinary users (*3*). It uses both schedule and real-time data to simulate the decision-making process of users. It acknowledges users’ inability to use the actual arrival time *a priori* when planning their trips. The measure is a more accurate representation of users’ actual accessibility experience, and its deviation from schedule-based accessibility can be a good indicator for the reliability of the public transit system.

# Literature review

We review relevant literature in this section.

The definition of disruptions are heterogenous and diverse. Depending on the effects, persistency, and frequency of the event, we can categorize all disruptions with multiple standards: 1) Short-term versus long-term; 2) planned and unplanned (*4*); 3) Recurring and non-recurring (for short-term, traffic-related disruptions). In this paper, we use the short/long-term categorization to classify disruptions.

## Short-term Disruption

We define short-term disruption with several standards: 1) the event should be short in time span and will not exceed a day, which is the time unit of the operation of most transit systems; 2) the event usually will not change the schedule of the transit system. In that sense, short-term disruptions usually influence the unreliability by only on-time performance, i.e., delays and early arrival.

A primary example is traffic. As most public transit systems share same roads with other vehicles (except systems with dedicated bus lanes and subways), traffic on roads can significantly impact the on-time performance of the buses. The research on traffic as a disruption is abundant.

Another example is weather, such as rain, snow, or fog. These events can also worsen on-time performance and reliability.

Finally, major social events can also create unexpected disruptions to public transit, such as large social gatherings. There are very few studies on the large events’ impacts.

## Long-term Disruption

We define long-term disruptions with several standards: 1) the disruptions are longer in time span, which last from weeks to multiple years. 2) the disruptions affect both the on-time performance and the timetable.

The COVID-19 pandemic is a major disruption, if not the most important one in this century, that has huge impacts on the public transit systems in the entire world.

Extreme weather events can also incur persistent disruption to the public transit system.

# Method

We present our method in this section.

## Data

The primary data source in this paper is General Transit Feed Specification (GTFS) data. It is the de facto standard to transmit real-time information (*5*, *6*). The data have two data standard, GTFS static and GTFS real-time data, which contain the schedule timetable and real-time timetable, respectively (*7*, *8*). Based on the two data, we can calculate the scheduled and actual arrival time for any buses at any stop. We focus our study area to Central Ohio Transit Authority (COTA) bus system in Columbus, Ohio, USA. We collected GTFS static and GTFS real-time data from COTA’s application programming interface (API) from May 2018.

## Accessibility Measure

Accessibility is a diverse concept that can measure different aspects of mobility (*9*); in this paper, we focus on the measure of physical accessibility in a transit system. Physical accessibility measures the physical limit of a transit user given a time budget, namely how far a user can go by using transit service. It is a primary indicator of the useability of the transit service.

We use a well-established time geography measurement – space-time prism (STP) – to quantify the physical accessibility. It represents the envelop of all potential space-time paths; we treat bus stops as single origins and calculate the prisms from each single origin with a departure time to all possible destination (*10*). In practice, we use implicit STP – the number of accessible stops from a stop give a time budget – as the accessibility measure (*3*). First, we introduce a decision variable to determine if a user can arrive at a stop within the time budget.

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| --- | --- | --- |
|  |  | (1) |

where represents whether a user can arrive at stop from stop at time point within the time budget , and is the shortest travel time between stops and starting from a time point .

Note that the travel times between two stops in the transit network are also determined by the arrival time. This is due to the time-dependent nature of transit networks (*11*, *12*). To calculate the travel time, we developed a time-dependent Dijkstra algorithm to solve this special routing problem. We use a first-in-first-out (FIFO) rule to make the generic Dijkstra algorithm, which is only applicable to static network, compatible to transit network with dynamic costs (*13*, *14*). The rule assumes a vehicle leaving an origin stop will never arrive later at the destination stop than another later vehicle. We calculate if COTA system indeed satisfies the assumption, and 95% of the buses do hold the rule.

We thus define implicit STP as:

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

where represents the implicit STP from stop at time point , while is the set of all time budgets and S is the set of stops. The implicit STP measures the accessibility to network nodes.

## Unreliability measures

We define unreliability of transit accessibility as the normalized difference between the schedule-based accessibility and the actual experienced physical accessibility. Schedule-based accessibility represents the promise that the transit authorities make to users, which cannot be perfectly kept under most circumstances due to on-time performance loss.

However, the definition of actual experienced physical accessibility can be nuanced. As we already discuss in the previous sections, retrospective real-time STPs are not feasible for ordinary users to finish in practice. To construct a realistic accessibility measure, one must only use information that is obtainable before the users use the transit system to calculate the travel times. Liu, Porr, & Miller (*3*) introduce realizable real-time accessibility. It is calculated in two steps – planning and implementation – to better represent transit users’ actual decision-making process. During the calculation process, the algorithm will first plan the trip according to buses’ scheduled arrival time and then implement the plan with actual arrival time (*3*). In other words, the realizable real-time accessibility measures the accessibility in the scenario with no real-time information, while retrospective accessibility measures the accessibility in the scenario with perfect real-time information. Realizable accessibility is a more realistic measure of users’ actual experienced physical accessibility.

We thus introduce accessibility unreliability:

|  |  |  |
| --- | --- | --- |
|  |  | (4) |

where is the scheduled STP starting from a time point , is the realizable STP, is the schedule-based number of accessible stops, and is the realizable-based number of accessible stops. The unreliability represents the accessibility a transit system loses during operation compared with the schedule.

## Short-term Disruption: College Football Games

Football is one of the most popular sports in the US; about 22 million viewers watch the final college football game in 2022 (*15*). Columbus is the seat of the Ohio State University, whose football teams are among the most competitive teams, and the Ohio Stadium in its campus is one of the biggest stadiums in the US.

Ohio State gamedays includes home and away games, which are hosted in Columbus and other cities, respectively. Columbus hosts college football games (i.e., home games) from September to December every one or two weeks, which attract more than a hundred thousand viewers to the stadium before the pandemic (*16*). Home games create high traffic around the Ohio Stadium, therefore, creating a short-term disruption to the local public transit’s on-time performance and accessibility. Away games are also popular but far less crowded than home games.

Therefore, we select all home and away game days in 2018 and 2019 and calculate the accessibility unreliability respectively.

## Long-term Disruption: the COVID-19 Pandemic

COVID-19 pandemic is a great unequalizer. COVID-19 has been

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